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Simultaneous Compensation of Active and Reactive Power in the Power System Using Grid-Connected Electric Vehicles

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Abstract: Network-connected electric vehicles, in addition to reducing pollution, have capabilities to assist power systems. One of the most important of these capabilities is responding to the needs of the network to produce active and reactive capabilities. In this paper, considering the network constraints, technical considerations and market prices, a theoretical framework for allocating the capacity of these vehicles is presented. For this purpose, a goal function with the approach of minimizing the costs paid by the distribution system operator or DSO to the manufacturer of each of the active and reactive capabilities is proposed. Due to the fact that the problem in question is in the form of an optimization problem, new innovative solutions have been added to the algorithm to solve it from the optimization algorithm and to prevent the algorithm from getting stuck in local optimizations. In this proposed format, vehicles compete with generators to generate active and reactive power. The efficiency of the proposed method is evaluated on a low voltage network feeder with 134 subscribers and in the presence of active and reactive power generation sources, and the amount of production and costs paid for each manufacturer are determined.

Keywords: Grid-connected electric vehicles; Particle swarm optimization algorithm; Reactive power compensation; Pollution.

Introduction

One of the problems of power grids is the low efficiency of electricity production and the lack of storage facilities that are economically viable. This has led to the construction of new power plants to provide power during peak hours, which require a large amount of investment. This amount of investment is not economically viable to build power plants that operate only for a limited number of hours. The idea of using electric cars as an energy saver can be a solution to this problem. Studies on the behavior of car owners show that cars are in the parking lot for about 22 hours a day. Therefore, if these cars have the ability to connect to the grid, the energy stored in their batteries can be used to reduce peak power, provide rotating storage and adjust the frequency. This can increase the base load, reduce the maximum output, increase the load factor, increase reliability and reduce network losses and also contribute to its stability [1]. In addition, increasing the penetration of electric vehicles in the power grid can reduce the uncertainty of renewable energy sources as well as delays in the development of generation and transmission networks. Although a vehicle alone is considered as noise compared to the network load, due to their high number, the transmission power between these vehicles and the network will be significant. Therefore, the cumulative load of vehicles can participate in various markets, including the base load market, peak load, rotating reserve, frequency adjustment, reactive power, and so on [2]. The mathematical relationships of electric vehicles for participation in the markets of base load, peak load, rotating reservation and frequency regulation are presented and the amount of revenues and costs are evaluated. According to the results obtained in this reference, in the base cargo market, due to the low price, these cars do not have much chance to compete. From the network point of view, various studies have been presented in the field of charge control methods of these vehicles based on different objective functions [3]. Due to the fast charging and discharging speed, these cars can be present in the frequency tuning market. In other words, these cars are fast-moving power plants. The results of studies conducted in Sweden and Germany show that only with the participation of 5.5 % of cars in Germany and 4.2 % in Sweden, a lot of power can be used to adjust the frequency [4]. In [5] proposes the use of a dual-purpose program to adjust V2G to reduce peak and base loads during the day. In [6] a collector is presented to adjust the V2G frequency and increase its efficiency, and in [7] the issue of economic distribution is presented by considering constraints such as cost reduction and pollution of these vehicles. Various studies have been conducted on the impact of electric vehicles on distribution networks. In [8] different methods of intelligent car charging have been studied and charging electric vehicles from the network and their interaction with renewable energy sources in [9] is presented. Reference [10] has studied the advantages and challenges of electric vehicles entering the network and [11] has examined the methods of planning the integration of electric vehicles. The effect of electric vehicles on power systems has been studied for various purposes, including minimizing load variance [12], minimizing peak load [13], and maximizing operating profit [14]. Maximizing interaction with new energy sources [15], preventing frequency drop [16] and risk control [17] were mentioned. Due to the wide range of electric vehicles in different parts of the power grid, these vehicles also have great potential in the field of reactive power control. In [18] the modeling and participation of electric vehicles in the reactive power market and related costs are presented. In this reference, cars, along with other manufacturers of reactive power, participate in the market and are selected according to the offer price. In [19] the random behavior of vehicles in the network and their selection in the market is considered. In [20], the reactive power market is settled for several purposes with the aim of reducing losses and paying costs to manufacturers. Various studies have been performed on improving the quality of network power by electric vehicles [21] to [23]. For example, in [22] with the aim of improving power quality, each vehicle is modeled as a harmonic current source that can inject various harmonic components into the network. Then, using intelligent optimization algorithms, an attempt has been made to meet the two objectives of minimizing the cost of payment and reducing losses.

The purpose of this paper is to provide a framework for optimally allocating vehicle capacity to the production of each of the active and reactive capabilities. For this purpose, a goal function is presented so that the distribution system operator (DSO) can provide the required capabilities at the lowest cost by considering the network and vehicle constraints. Since the problem in question is in the form of an optimization problem, the particle swarm algorithm (PSO) has been used to solve it. Also, in order to accelerate the optimization process and prevent the algorithm from getting stuck in local optimizations, new innovative solutions have been added to the algorithm. To evaluate the performance of the proposed model and algorithm, several simulations are performed on a sample network and the obtained results will be evaluated.

Materials and Methods

Presenting the Proposed Structure

DC/DC and AC/DC converters are used in the structure of the charging and discharging system of electric vehicles connected to the network, which has increased its flexibility. In order for an electric vehicle to inject any of its active and reactive currents (capabilities) into the network, no hardware changes are required and only by changing the control system can the required capabilities of the network be met. Injected into it. Therefore, in order to allocate the car's capacity to produce each of the active and reactive capabilities, a framework must be provided so that in this format, while meeting the needs of the network, the interests of car owners are also met. At the common point of connection (PCC), the mains voltage is specified and almost independent of the vehicle, so the vehicle can provide any of the required network capacities by injecting the corresponding currents. In other words, with proper flow control, the required capabilities of the network can be provided. Assuming that the network voltage at the PCC site is sinusoidal as eq. (1) and selecting the reference current as eq. (2), any of the required capacities can be generated and injected into the network.

$$\mathrm{V_{grid}} = \mathrm{V_m}\sin(\omega \mathrm{t}) \tag{1}$$

$$\mathrm{I_{ref}} = \mathrm{I_m}\sin(\omega \mathrm{t} \pm \phi) \tag{2}$$

Depending on the difference between the voltage phase and the current of the main component (φ), the following different states can occur:

• If φ = 0° or φ = 180°, then the output current of the vehicle will have a phase difference with the voltage of the co-phase network or 180°. In this case, the car can only inject or absorb active current (active power) into the network.

• If φ = 90°, then the reference current with the mains voltage has a phase difference of 90° and will cause injection or absorption of reactive power.

• If -90° ≤ φ ≤ 90°, then the reference current with the mains voltage has a phase 1 difference and according to the amount of φ can inject active and reactive current into the network or absorb from it.

Depending on the production and injection of each active and reactive capacity, costs must be paid by the DSO to the car owner, which are formulated below. Given that the distribution system operator seeks to reduce operating costs and one of the ways to reduce costs is to minimize payment costs, in this article, DSO payment minimization to car owners it is considered as a goal function. The following is the objective function with its constraints.

$$\mathrm{OF} = \min(\mathrm{P_{Cost}} + \mathrm{Q_{Cost}}) \tag{3}$$

Subject to

$$\mathrm{P_{Cost}} = \sum_{t=1}^{N_t}\sum_{j=1}^{N_v} C_{j.t}^{p} P_{j,t} \tag{4}$$

$$\mathrm{Q_{Cost}} = \sum_{t=1}^{N_t}\sum_{j=1}^{N_v} C_{j.t}^{Q} Q_{j,t} \tag{5}$$

$$P_j^{min} \le P_{j,t}^{batt} \le P_j^{max} \tag{6}$$

$$\begin{gathered} W_{j,t}^{ch} + W_{j,t}^{dch} + W_{j,t}^{idle} = 1 \\ W_{j,t}^{ch}, W_{j,t}^{dch}, W_{j,t}^{idle} \in \{0,1\} \end{gathered} \tag{7}$$

$$\left(\underbrace{P_{i,t}^{gen}}_{i=m} + \underbrace{W_{j,t}^{dch}.P_{j,t}^{PCC,dch}}_{j=m}\right) - \left(P_m^{Load} + \underbrace{W_{j,t}^{ch}.P_{j,t}^{PCC,ch}}_{j=m}\right) = |V_m| \sum_{n=1}^{NB} |V_n|.|Y_{mn}| \cos(\theta_m - \theta_n - \theta_{mn}) \tag{8}$$

$$\left(\underbrace{Q_{i,t}^{gen}}_{i=m} + \underbrace{W_{j,t}^{dch}.Q_{j,t}^{PCC,dch}}_{j=m}\right) - \left(Q_m^{Load} + \underbrace{W_{j,t}^{ch}.Q_{j,t}^{PCC,ch}}_{j=m}\right) = |V_m| \sum_{n=1}^{NB} |V_n|.|Y_{mn}| \sin(\theta_m - \theta_n - \theta_{mn}) \tag{9}$$

$$\left(P_{j,t} + P_{j,t}^{loss,ch}\right)^2 + \left(Q_{j,t}\right)^2 \le \left(S_j\right)^2 \tag{10}$$

$$\left(P_{j,t} - P_{j,t}^{loss,ch}\right)^2 + \left(Q_{j,t}\right)^2 \le \left(S_j\right)^2 \tag{11}$$

$$Q_g^i \le \sqrt{\left(V_t^i, I_a^i\right)^2 - \left(P_g^i\right)^2} \tag{12}$$

$$Q_g^i \le \sqrt{\left(\frac{V_t^i, E_{aF}^i}{X_s^i}\right)^2 - \left(P_g^i\right)^2} - \frac{\left(V_t^i\right)^2}{X_s^i} \tag{13}$$

$$S_{m,n} \le S_{m,n}^{max}, m = 1, \ldots, NB, n = 1, \ldots, NB \tag{14}$$

$$V_{m,min} \le V_m \le V_{m,max} \tag{15}$$

$$P_{j,t}^{batt} = W_{j,t}^{ch}.P_{j,t}^{batt,ch} + W_{j,t}^{dch}.P_{j,t}^{batt,dch} \tag{16}$$

$$SOC_{j,t} = SOC_{j,t-1} - \frac{I_{j,t}^{batt}}{C_j^{batt}}\left(W_{j,t}^{dch} - W_{j,t}^{ch}\right) \tag{17}$$

$$SOC_j^{min} \le SOC_{j,t} \le SOC_j^{max} \tag{18}$$

$$\left|SOC_{j,t} - SOC_{j,t-1}\right| \le \frac{I_{j,t}^{batt}}{C_j^{batt}} \tag{19}$$

$$\sum_{j=1}^{N_v} \sum_{t=1}^{24} \left(W_{j,t}^{dch}.P_{j,t}^{PCC,dch}\right) + \sum_{i=1}^{N_g} \sum_{t=1}^{24} P_{i,t}^{gen} = \sum_{t=1}^{24} P_t^{load} + \sum_{j=1}^{N_v} \sum_{t=1}^{24} \left(W_{j,t}^{ch}.P_{j,t}^{PCC,ch}\right) \tag{20}$$

$$P_{j,t}^{PCC,dch} = P_{j,t}^{batt,dch} - P_{j,t}^{loss,dch} \tag{21}$$

$$P_{j,t}^{PCC,ch} = P_{j,t}^{batt,ch} + P_{j,t}^{loss,ch} \tag{22}$$

$$P_i^{min} W_{i,t}^{gen} \le P_{i,t}^{gen} \le P_i^{max} W_{i,t}^{gen},\ W_{i,t}^{gen} \in \{0,1\} \tag{23}$$

$$\lambda_t = \beta_1 + \beta_2 \alpha^{\frac{P_T - P_{avg}}{P_{avg}}} \tag{24}$$

What we have:

$P_{j,t}^{batt,\ ch}$, $P_{j,\ t}^{batt,\ dch}$: car battery power at *t* hour in discharge and charge mode, respectively

C_j^{batt}: Battery capacity of the car

P_i^{max}, P_i^{min}: Minimum and maximum generating capacity of i-th generator

$C_{j,t}^{Q}$, $C_{j,t}^{P}$: Proposed production cost for active and reactive power for j-th car at t-th time, respectively

$Q_{j,\,t}$: The reactive power produced by the j-th car at t-th

E_{af}^{i}: Generator excitation voltage i

Q^{i}: Reactive power generated by i-th generator

$I_{j,\,t}^{batt}$: Battery current of my car at t hour

Q_{cost}: The cost paid by the DSO to provide reactive power

I_a^{i}: armature current generator i

$S_{m,n}^{max}$, $S_{m,n}$: throughput and maximum throughput from line between bus n, m network

I_j^{max}, I_j^{min}: The minimum and maximum allowable current of the car

$S_{j,\,max}$: The maximum amount of apparent power of the car j

$P_{j,\,t}$: Active power produced by j-th car at t-th

SOC_j^{max}, SOC_j^{min}: The minimum and maximum allowable SOC values for the vehicle

P_j^{max}, P_j^{min}: The minimum and maximum production capacity of the car

$SOC_{j,\,t}$: The remaining charge of my car for t hours

P_m^{Load}: Bus load m-th

X_s^{i}: Synchronous reactance of i-th generator

P_i: Active power generated by the i-th generator

$V_{m,\,max}$, $V_{m,\,min}$: The minimum and maximum value of the bus voltage m-th

$P_{j,\,t}^{loss,\,dch}$, $P_{j,\,t}^{loss,\,ch}$: Losses in charge and discharge mode of j-th car at t-th time, respectively

V_t^{i}: i-th generator terminal voltage

P_{Cost}: DSO payment for active power supply

$|V_m|$: Bus voltage size m-th

$P_{j,\,t}$: The amount of active power generation for the j-th car at t-th hour

$W_{j,\,t}^{idle}$, $W_{j,\,t}^{dch}$, $W_{j,\,t}^{ch}$: Binary variables represent the state of charge, discharge and inertia of the car, respectively, for the hour t

$W_{i,\,t}^{gen}$: The binary variable indicates the selection of the i generator for the t clock

$P_{i,\,t}^{gen}$: The active output power of the i generator at t-th

α, $\beta 1$, $\beta 2$: Price parameters

$P_{j,\,t}^{PCC,\,dch}$: Active power injected into the PCC point in the discharge mode by the j-th car at t-th

λ_T: Energy Price ($ MWh)

P_{avg}, P_T: Demand for Total Network Average (KW), respectively

Eq. (3) is the objective function that must be minimized. The main task of a car in connecting to the network is one-way exchange of active power from the network to the car (charging), but due to the existence of scattered production sources and the availability of these cars, it is possible to exchange energy in two ways. Of course, if the car injects into the power grid, there will be costs, including the cost of converter losses, the cost of reducing battery life and replacing it, etc. These costs must be taken into account. The cost of active power generation can be obtained from eq. (4). One of the ancillary capabilities of electric vehicles is the production of reactive power. If a vehicle devotes all or part of its production capacity to reactive power generation, it must be paid by the network in accordance with eq. (5) the costs of the partnership. In optimizing the objective function presented in eq. (3), different constraints must be considered, which are presented in eqs. (7) to (24). Eq. (6) is to consider the limitation of the production capacity of cars. Due to the loss of costs and ancillary costs for cars, such as the cost of a battery for a car, the production capacity must be greater than a certain amount to be able to cover these costs. Also, due to the wiring and connections, the charging system has a high limit, which is expressed in Figure (6). The condition of the vehicle is determined by binary variables in eq. (7). The condition of the vehicle at any time can be one of charging, discharging, or stationary. In this regard, each of the variables can have a state of zero or one, and if the value of the variable is equal to one, it means that the car is in that state. Given that at a given time each car can be in the same position, so the algebraic sum of these three variables must be one, meaning that at any given time only one of the variables is one and the rest are zero. Eqs. (8) and (9) also show the constraints of the load distribution equations. Like generators, electric vehicles have limited power output due to the limited size of conductors, connectors, switches, and semiconductor diodes used in charge and discharge system converters. Constraints related to the PEV capability curve can be considered according to eqs. (10) and (11) [18]. In the charging mode, some of the power received from the network at the PCC is lost by the chargers of the charging system, so according to eq. (10) in this mode, the active power is added to the loss power and in the discharge mode to pass the power from the vehicle It is towards the network and some power is lost during the transfer, which is considered a loss with a negative sign in eq. (11). Eqs. (12) and (13) indicate the constraints related to the power curve of the generators, which are mentioned in more detail in [24]. Eq. (14) shows the apparent power limit of each vehicle. The voltage limit of each bus is calculated by eq. (15) and is calculated using eq. (16) battery power. The battery limits are set out in eqs. (17) to (19), which shows how to calculate the hourly SOC for vehicle number j. According to this relation, the SOC of each car can be increased or decreased according to the condition of the car per hour (charging or discharging). If both variables Wj,tch, Wj,tdch are equal to zero, the car SOC will remain unchanged. Eq. (18) indicates the range of SOC changes of each vehicle. Eq. (19) also shows the changes in SOC in two consecutive intervals. In other words, this relationship indicates the charge or discharge rate, which is limited by the charge or discharge current. Eq. (20) shows the balance of active power in the network. The power injected into the network at the PCC point in charge and discharge modes can be calculated from eqs. (21) and (22), respectively. The generator power limit can vary between a minimum and maximum values, which is expressed by eq. (23). Eq. (24) also shows the price of energy as a function of grid load, which is dynamic pricing.

Implementation of Optimization Problem by PSO

In the previous sections, the problem of allocating the capacity of electric vehicles that can be connected to the network to produce active and reactive capabilities was formulated in the form of an optimization problem. To solve the problem, classical optimization methods or intelligent optimization methods can be used. In classical optimization algorithms, as the number of variables increases, the convergence speed decreases, and the probability of the algorithm getting stuck in local optimizations also increases. In contrast, in intelligent optimization algorithms, by adjusting the parameters of the algorithm, in addition to increasing the convergence speed, it is possible to prevent it from getting stuck in local optimizations. For this reason, this paper uses the particle swarm algorithm, which is one of the well-known and widely used types of intelligent optimization algorithms. To speed up the optimization process and prevent the algorithm from getting stuck in local optimizations, new innovative solutions have been added to the algorithm. The structure of this algorithm is briefly described below.

Particle Swarm Optimization Method

The Particle Swarm Optimization Algorithm (PSO) is a population-based optimization method first proposed in 1995 by Eberhart and Kennedy [25]. In this algorithm, there are populations of particles, each of which is a possible solution to the optimization problem. The members of the community try to move towards the final solution by setting the path and moving towards the best personal experience and the best group experience. In this algorithm, the velocity of each particle at any moment consists of two parts, one is the velocity of the particle at the previous moment and the other is related to the degree of adherence to the best personal experience and the best group experience. Without the second part, the algorithm mode would be more like a random search, while without the first part, the algorithm is like a local optimization algorithm that is looking for the optimal solution in the neighborhood. Therefore, in this case, many parts of the answer space will not be searched. The PSO algorithm tries to strike a balance between global and local search by combining the two. In this algorithm, each particle at any given moment adjusts its position in the search space according to the best position it has ever been in (pbesti) and the best position ever obtained by the particle swarm (gbest). Slowly For this purpose, for each particle, a velocity vector and a position vector are defined. Then, according to eq. (32), the current position of each particle is updated according to the structure of the previous position and its current velocity [25].

$$x_i(t) = x_i(t-1) + v_i(t) \tag{25}$$

In the above relation, the constants c_2, c_1 determine the effect of each of the parameters pbest, gbest on the next position of the particle. r_2, r_1 are also random numbers in the range [0, 1] and the weight of inertia parameter (w) is also used to control the effect of velocity at the previous moment on the current velocity of the particle [26]. In other words, this parameter strikes a balance between general and local search, large amounts of the weight of inertia improve general search capability while small values improve local search capability [27]. Therefore, proper selection of this parameter can solve the problem of getting stuck in local optimizations. The coefficient c_1 also indicates how much a particle depends on its own experiences, while the coefficient c_2 determines how much the velocity of a particle depends on the experiences of its neighbors. For example, by choosing $c_2 = 0$, all particles will search for the optimal answer in the problem space based on their personal experiences, while choosing $c_1 = 0$, all particles will converge on one point. Given that at first, particles have a greater desire for new experiences, and over time this desire gives way to pursuing more of the best, so in this paper according to eqs. (27) And (28) At the beginning of the search process, we have given more importance to public search by choosing large values for c_1 and small values for c_2. Then, over time and after a sufficient number of repetitions, by decreasing the value of c_1 and increasing c_2, this effect has decreased and more importance has been given to the search based on the pursuit of the best.

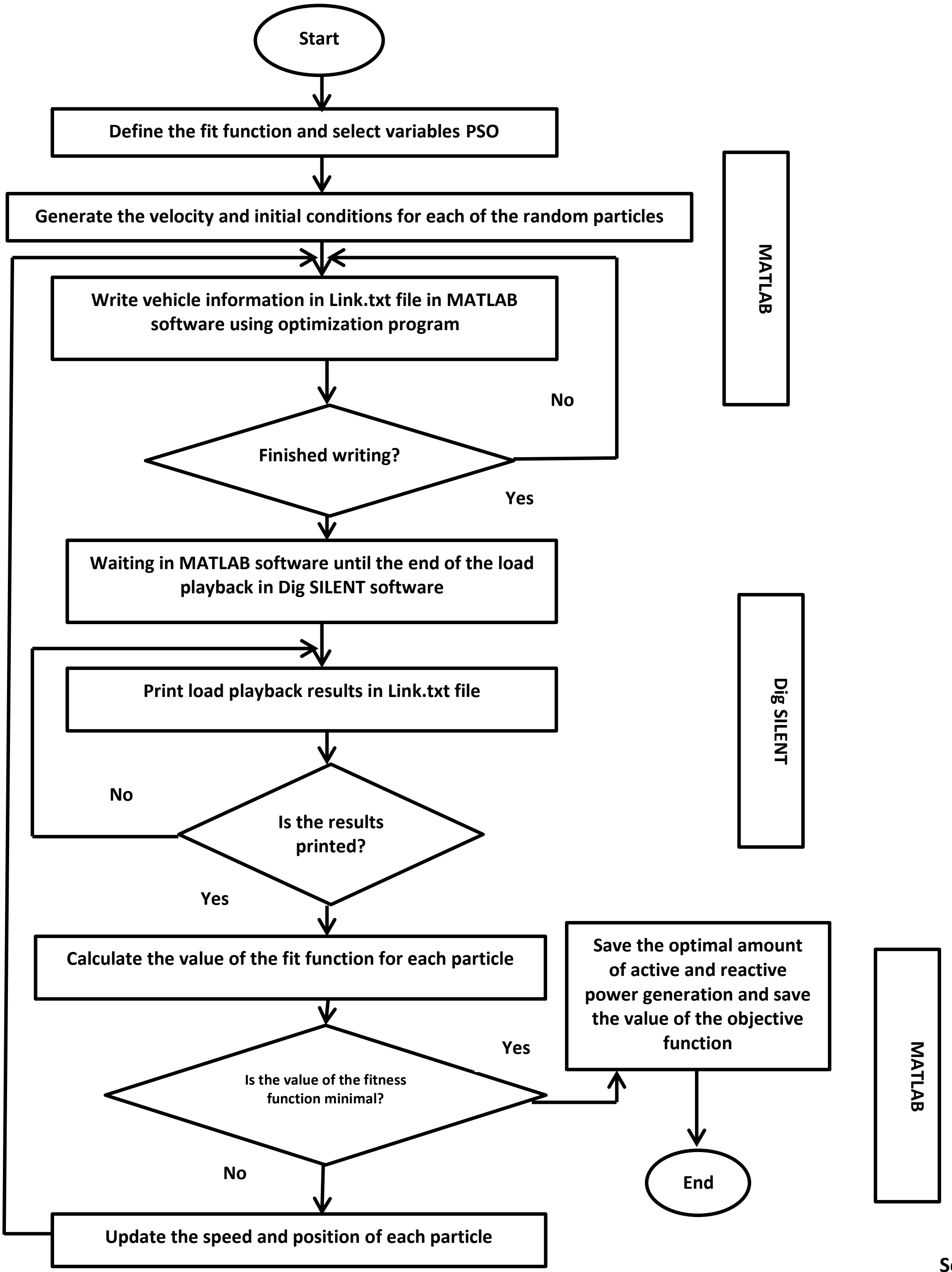

Fig. 1: Object view optimization process by two software Dig SILENT, MATLAB and using PSO algorithm.

$$c_1 = c_{min} + (c_{max} - c_{min})\frac{t}{Maxgen} \quad (27)$$

$$c_2 = c_{max} + (c_{min} - c_{max})\frac{t}{Maxgen} \quad (28)$$

In the above relation, Maxgen is the maximum number of iterations of the algorithm. According to the above relation, with increasing the number of repetitions, the value of c_1 from c_{min} starts to increase and in the last repetition, its value reaches c_{max}. While for parameter c_2, the exact opposite happens. This means that the value of this parameter will increase from c_{max} at the beginning of the algorithm to c_{min} at the end of the algorithm. For discrete variables, the position and velocity of each particle must be re-updated according to the following equations [28].

$$v_i(t) = \tan\frac{v_i t}{2} \quad (29)$$

$$x_i(t) = x_i(t-1) + \mathrm{round}(v_i(t) \times \Delta x_{max}) \quad (30)$$

Δx_{max} is the parameter of the maximum displacement value [29]. In this paper, the number of population members is equal to 30, the maximum number of replication of the algorithm is equal to 40, w = 0.6, c_{max} = 7.3, c_{min} = 0.2.

Optimization Program Modeling by PSO

The electric vehicle can produce any of the active and reactive capacities, and therefore the particle is considered as a vector.

$$X = \left[P_1, P_2, \dots, P_{N_v}, Q_1, Q_2, \dots, Q_{N_v}\right]_{1\times 2N_v} \quad (31)$$

In this relationship, N_v the number of vehicles. The process of doing the work is as follows. First, the studied network is implemented in the Dig SILENT software environment. This software has the capability of an unbalanced load distribution program [30]. Then the load distribution program is implemented and the amount of reactive and active power produced by each vehicle is obtained. According to the number of special allocations for each car, the amount of income from the point of sale of power is obtained for each car. The implementation process of the optimization algorithm by the two software SILENT and MATLAB software is shown in Fig. 1.

Results and Discussion

To evaluate the capability of the proposed method, a feeder from the low voltage network has been selected according to Fig. 2. This feeder is located in Dublin, Ireland [23], and feeds 134 times a single-phase household. It is assumed that the apparent power of each household load is 1.5 KVA and their power factor is equal to 0.95 post-phase. The rated voltage of this network is equal to 230 / 400V with a voltage variation range of 5% and it is also assumed that there are 10 cars in the network. Vehicles 1, 4, 7, and 8 are connected to phase a vehicles 3, 6, and 10 are connected to phase b, and vehicles 2, 5, and 9 are connected to phase c. Another assumption is that the cars have a battery capacity of 32 kWh and the battery of these cars will be fully charged or discharged within 4 hours. In other words, these cars can power or receive 8 Kw of power to the network per hour. Also, the charge and discharge efficiency of these cars is considered to be 90 %, and it should be noted that being selected to produce each of the active and reactive capabilities and its amount will be determined by the offered price and location of the car. Table 1 shows the bid prices of these vehicles for active and reactive power generation. These prices are based on the New York market prices [31] and are considered for cars as a random number in the price range. The convergence curve of the objective function is shown in Fig. 3. According to this figure, it can be seen that the algorithm has converged to the optimal answer after about 20 repetitions. According to the figure, the minimum amount paid by the network operator is equal to 13.93 $, which must be paid to each of the producers of these capabilities to provide the active, reactive, and disturbing capabilities required by the network. Table 2 shows the results of vehicle participation in providing active and reactive capabilities. According to the results of this table, it can be seen that according to the proposed prices, car locations and network constraints, each of the manufacturers has allocated its capacity to produce each of the active or reactive capabilities.

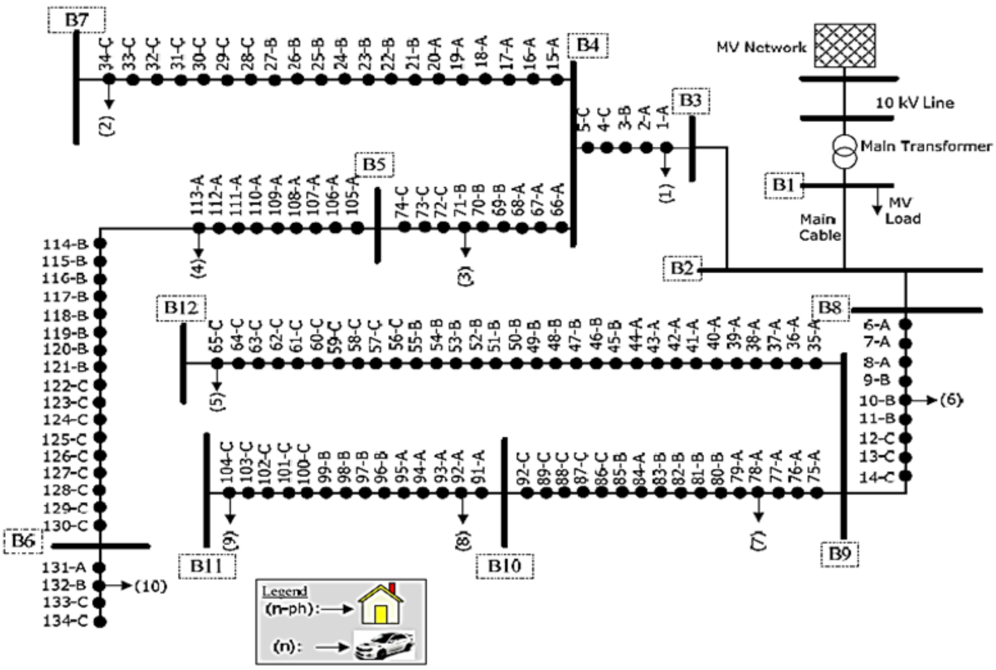

Fig. 2: Single-line diagram of a test network with 134 households and 10 electric vehicles.

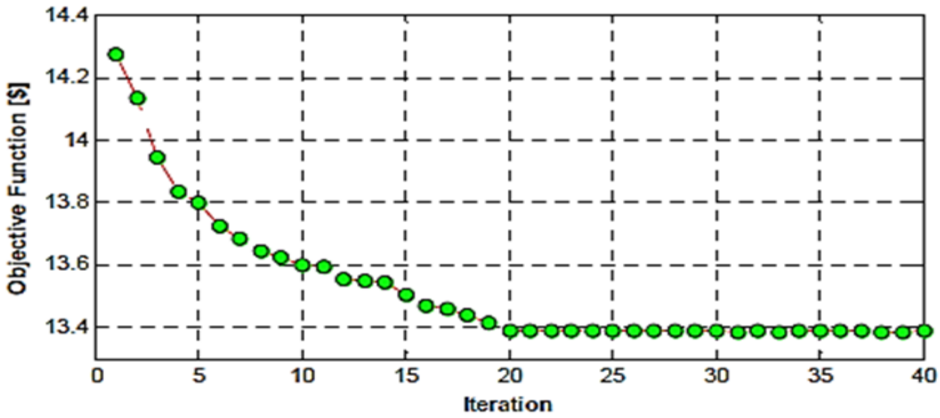

Fig. 3: Convergence curve of the objective function.

Table 1: Recommended prices of PEV and generator for production of each power component.

Participant	Symbol	Power Components	
		Reactive	Active
Electric Vehicle	PEV1	0.036	0.044
	PEV2	0.044	0.043
	PEV3	0.043	0.050
	PEV4	0.033	0.051
	PEV5	0.041	0.039
	PEV6	0.040	0.045
	PEV7	0.039	0.041
	PEV8	0.037	0.048
	PEV9	0.042	0.049
	PEV10	0.034	0.046
Generator	Gen1	0.050	0.060

Manufacturers have devoted their capacity to producing any active or reactive power. For example, due to the low bid price for reactive power generation by vehicle No. 4, this car devotes most of its capacity to reactive power generation. Also, the No. 5 vehicle will be accepted in the energy market due to its low bid price for active power generation.

Table 2: The amount of power accepted from each of the power components and for each of the manufacturers of PEVs and generators.

Participant	Symbol	Power Components	
		Reactive	Active
Electric Vehicle	PEV1	6.42	4.5
	PEV2	5.56	2.48
	PEV3	4.42	2.04
	PEV4	6.2	2
	PEV5	2.5	7.6
	PEV6	3.48	4.98
	PEV7	4.28	6.2
	PEV8	2.9	5.56
	PEV9	4.8	3
	PEV10	6.28	4.48

Generator	Gen1	15.94	148.11

The amount paid to each manufacturer to produce each of the power components is given in Table 3. According to the results in this table, the total cost paid by DSO is 13.39 $, of which $ 3.7 (1.91 for power generation +1.79 for reactive power generation) for electric vehicles and 9.69 $ (8.89 for power generation +0.80 for reactive power generation) for generators for active and reactive power generation should be paid. Table 4 shows the impact of participation and non-participation of vehicles in the production of active and reactive capabilities. According to this table, if cars are to enter the market, the DSO will have to pay 13.39 $ to the only manufacturer of reactive power, the generator, of which 11.46 $ for active power generation and 3.14 $. Also, it should be paid for reactive power generation. For this reason, the amount paid for the production of active and reactive capabilities in the absence of vehicles has been increased from 13.39 to 14.6 dollars (about 9 %).

Table 3: Costs paid to each manufacturer to produce each of the power components.

Participant	**Symbol**	**The Amount Paid to Each of the Producers**	**Total**	**Power Components**	
				Reactive	**Active**
Electric Vehicle	PEV1	3.7	0.43	0.23	0.2
	PEV2		0.35	0.24	0.11
	PEV3		0.29	0.19	0.10
	PEV4		0.30	0.20	0.10
	PEV5		0.40	0.10	0.3
	PEV6		0.36	0.14	0.22
	PEV7		0.42	0.17	0.25
	PEV8		0.38	0.11	0.27
	PEV9		0.35	0.20	0.15
	PEV10		0.42	0.21	0.21
Generator	Gen1	9.69	9.69	0.80	8.89
Total Payment		13.39	13.39	2.59	10.80

Table 4: Different costs due to participation and non-participation of vehicles in power generation.

Condition	**Participant**	**Reactive Power Cost**	**Active Power Cost**	**Total**
Vehicle Partnership	**Vehicle**	1.79	1.91	3.7
	Generator	0.80	8.89	9.69
	Total	2.59	10.80	13.39
Non-participation of vehicle	**Generator**	3.14	11.46	14.6
	Total	3.14	11.46	14.6

Conclusion

In this paper, a framework for allocating the capacity of electric vehicles to each of the active and reactive capabilities was presented. The framework was formulated in the form of an optimization problem in order to provide the required power components of the network. The main goal was to minimize the costs paid to producers under network constraints. A particle swarm algorithm was used to solve the problem. Solutions were also considered to increase the convergence speed of the algorithm and to prevent the algorithm from getting stuck in local optimizations. The problem was implemented on a low voltage sample network including 134 household subscribers and 10 electric vehicles and was evaluated for two cases with the presence of vehicles and without the participation of vehicles. The simulation results showed that in the presence of cars, the DSO would have to pay 13.39 $ to provide the required power, while if the cars were not present, the generator would be responsible for generating active and reactive power, given the relatively high bid prices. Generator for active and reactive power, in this case, DSO has to pay 14.6 $ for this purpose, which shows that the cost of payment has increased by about 9 %.

Disclosure Statement

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