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Savari, George Fernandez; Krishnasamy, Vijayakumar; Guerrero, Josep M.

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George Fernandez Savari[1] / Vijayakumar Krishnasamy[1] / Josep M. Guerrero[2]

# Optimal Scheduling and Economic Analysis of Hybrid Electric Vehicles in a Microgrid

[1] Department of Electrical and Electronics Engineering, SRM University, Chennai603 203, India, E-mail: George.electrix@gmail.com, kvijay_srm@rediffmail.com
[2] Department of Energy Technology, Power Electronic Systems, Aalborg University, Aalborg, Denmark, E-mail: joz@et.aau.dk

**Abstract:**
A projected high penetration of electric vehicles (EVs) in the electricity market will introduce an additional load in the grid. The foremost concern of EV owners is to reduce charging expenditure during real-time pricing. This paper presents an optimal charging schedule of the electric vehicle with the objective to minimize the charging cost and charging time. The allocation of EVs should satisfy constraints related to charging stations (CSs) status. The results obtained are compared with the two conventional algorithms and other charging algorithms: Arrival time-based priority algorithm (ATP) and SOC based priority algorithm (SPB), Particle Swarm Optimization (PSO) and Shuffled Frog Leaping Algorithm (SFLA). Also, the CS is powered by the main grid and the microgrid available in the CSs. The EVs charging schedule and the economic analysis is done for two cases: (i) With Grid only (ii) With Combined Grid & microgrid. The load shifting of EVs is done based on the grid pricing and the results obtained are compared with the other cases mentioned.

**Keywords:** electric vehicles, particle swarm optimization, microgrid, shuffled frog leaping algorithm

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## 1 Introduction

The power and transport industries together contribute approximately 70% of the worldwide carbon dioxide (CO2) production. It is a major concern due to the negative impact on the atmosphere [1]. As a solution to this crisis, implementation of EVs and green energy sources can significantly minimize the emission. Electric vehicles (EVs) have represented an atmosphere friendly transportation substitute compared to internal combustion engines (ICE). EVs can decrease the CO2 emission and as well as lessening the dependence of vestige fuels [2]. Green vehicles have a lesser fuel cost compared to ICE vehicles and they could use the nearby renewable sources for charging [3]. Due to several advantages, the number of EVs is expected to rise swiftly in the upcoming years. The mileage of EVs is determined by its rated capacity of the battery. For a long range of driving fast charging chargers and a high capacity of batteries are necessary. Fast charging stations are able to charge the battery of EVs from its available energy level of 20% to 80% under 30 min. In disparity, for medium and slow charger charging stations takes a number of hours. Public CS is a conformist charging choice for EV drivers; particularly those who haven't own chargers [4]. A large number of EVs may affect the electric power network radically, owing to the elevated power utilization. A few of the most important crisis's there in distribution systems are associated with non-desired peaks of energy utilization, overloading of the transformer and augmented power loss etc. It affects the stability of the grid [5, 6].

Increasing the power generation could be the solution for the above-mentioned problems; however, this will direct to considerable infrastructure cost. In recent times, several kinds of research have considered EV demand management on dropping peak period congestion and improving power quality [7, 8]. In recent work [9] a coordinated charging algorithm is projected to curtail the power losses. Optimal electric power distribution from the grid and regulating of the arrival rate of EV to the CS was examined in [10]. A charging scheduling scheme to minimize the waiting time in a CSs in proposed in [11]. The authors proposed a coordinated proposal to reduce the waiting time of EVs, through intelligent scheduling charging. In [12] a mathematical model of the EV charging load based on the traffic model and the queuing theory was developed to capture the dynamics of EV charging demand in a CS [13]. Authors propose a decentralized smart EV charging algorithm to resolve the Plugin EV charging crisis in a decentralized method.

The proposed decentralized algorithm retains the private user state information. They proposed a decentralized algorithm to optimally schedule electric vehicle charging. The algorithm uses the flexibility of electric

**Vijayakumar Krishnasamy** is the corresponding author.

vehicle loads for load shifting in electric load profiles [14]. Ma et al. [15] develop a decentralized computational algorithm that minimizes the electricity cost by scheduling PHEV demand to fill the overnight non-PHEV demand valley. It allows the PEV to optimize its charging activities based on a price gesture broadcast at that time of charging. W. Zou proposes a centralized charging approach by a dynamic estimation interpolation based algorithm. It takes into account the valley-filling effect of the supply side. By developing a price discount scheme it minimizes the user's cost [16]. The main initiative for centralized control is to exploit centralized communications to gather information from all EVs and centrally optimize EVs' charging allowing for the grid constraints. Jia Ying Yong [17] investigated the scheduling of EV for charging and discharging condition with solar PV in a smart parking lot. For the optimization algorithm, numerous constraints have been considered such as battery lifetime, battery SOC, charging time, irradiance probability, charging price.

The optimization algorithm gives proper Vehicle to Grid energy control to exploit both the charging and discharging, improve the SOC, reduce the net demand during peak hours, and to get the most of the inducements to EV owners who are participated. M Esmaili [18] gave a multi-objective technique to optimally manage the charging of 70 Vehicles. The author considered the electricity prices and power loss under dynamic tariff situation. J. Yang [19] developed a centralized charging method for various optimization goals, including minimizing cost, reducing CO2 emission, energy loss minimization, regulating frequency and to satisfy the EV owners, etc. By considering the dynamics of EVs' charging system reference [20–22] developed strategies for managing EVs charging to minimize the cost and for lesser EVs' detrimental impacts on the distribution network.

A pre-reservation based scheduling method as a well-organized scheduling method on CSs for chic transportation was proposed by Rezgui J, Cherkaoui S [23]. In [24] the main contribution of their scheme is that the charging stations can make a decision of charge scheduling which generates a rank by using the approximated arrival, waiting time and the energy required to charge the EV. It suggests a pre-reservation based managing technique for the CSs to choose the service order for several requests with the aim of satisfying the customers as much as possible. Based on geographical data [25] propose an assessment of EV charging scenarios. They studied a method to choose when the EVs are to be charged based on geographical numeric data. A major issue in this study was that a huge prologue of EVs in the transportation sector will be increasing the total electric power utilization. It is understandable that an uncontrolled charging of EVs can be the reason for the problems in the distribution system and the issue is to be addressed by a method to control EVs charging based on the charging behavior.

It can be calculated from the geographical numeric data. In this scheme, different charging tactics were designed and the impacts were assessed using standard load flow calculations. The result specifies that a perceptive community charging network could minimize the hassle on the distribution networks as part of the charging to be done in viable areas. Y. Cao [26] proposed a smart technique to manage EV demands in retort to TOU price in a power market. A heuristic technique was employed to reduce the charging cost. It is observed from the results that the optimized charging model is advantageous in minimizing the price and leveling the load curve. Fernandez [27] showed that it is possible to evade 70% of the necessary investment with an orderly charging. It permits to reach a maximum EV infiltration level with not defying the constraints. An analytic control-based adaptive scheduling approach was modeled by Ran Wang [28] to maximize the profits of the entire network. a centralized linear program using time-varying electricity pricing was analyzed in [29]. The result indicates that the proposed technique is used to reduce the parking lot operator's charging cost and as well as to meet customer's load.

## 2 Motivation and contributions

The main focus of this work is to reduce the total cost spent by the customer through an optimal scheduling. It includes the battery capacity of the vehicle, available SOC, the waiting period, and the real charging time. There are a number of limitations to be considered like SOC which evades a vehicle to reach the nearest CSs [30–32]. In CSs, the total time spent by the customer will be increased, when there is a number of EVs waiting for charging. If the charging rate of a charger is restricted, it could lead to extend the time of charging.

A simple and efficient algorithm to minimize EV charging cost is proposed in this paper. The main contribution of this work is as follow:

1. The formulation of EVs scheduling problem has been done for optimizing the cost and time period of the EVs.
2. Arrival time-based priority and SOC based priority algorithms were used for EVs scheduling and the results were compared with PSO and SFLA.

3. Load reallocation is also considered for benefiting the customer by reducing the electricity cost. A microgrid is considered for reducing the consumption cost of energy, when the grid cost is high.

## 3 Proposed method

By using the Arrival time-based priority and SOC based priority algorithms, the total charging cost and time including the waiting time of EVs at the CSs were reduced. In this work, instead of letting all recharges demanding EVs to choose charging points by themselves, a mapping of EVs to charging points by applying scheduling algorithms is done. By doing so, EVs are charged faster, and also enhances the performance (i.e. number of customer intake for charging by CSs) of the CSs. Each algorithm has its own properties in terms of scheduling but the main task is to properly allocate a charging point to each EV for a lesser price and time. The results of the algorithms are evaluated and compared with PSO and SFLA to reduce the cost and time significantly.

A classic case study Low Voltage network is considered [33] in this paper. A mixture of renewable sources micro turbine, a wind turbine and a few PVs are installed in the network. It is understood that every renewable generator generates true power at a power factor to unity. The operating boundaries of the DGs are specified in Table 1. The bid coefficients are given in Table 2. 24hrs output of the microgrid is given in Table 3 and Figure 1. Output from various DG's for the 24 hours is given in Table 4. Microgrid power price is given in Table 5 and Figure 2. The capacity and available SOC of each vehicle are given in Table 6. The energy cost is taken on a typical day from Epex Spot, U.K [34]. Figure 3 illustrates the 24 hours grid cost.

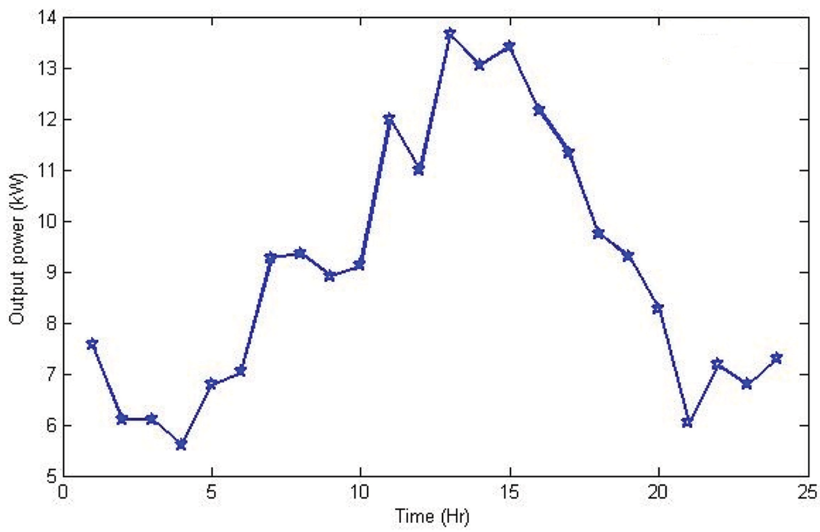


**Figure 1:** Microgrid power output for 24 hours.

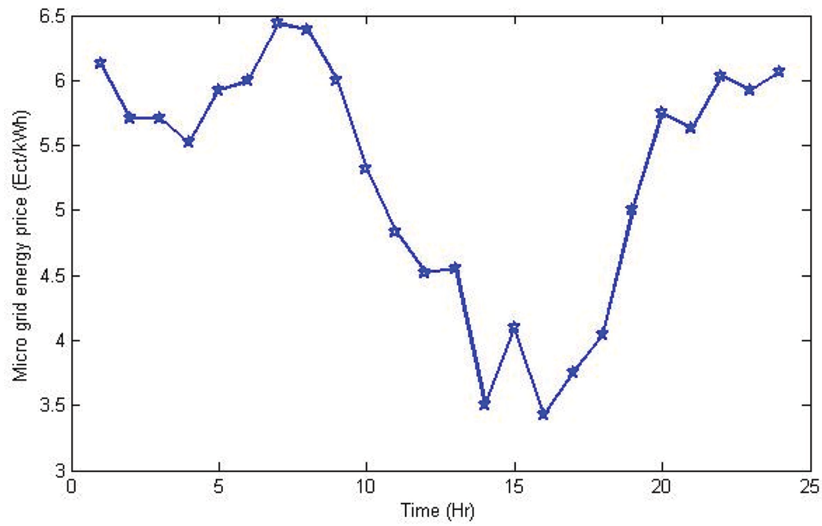


**Figure 2:** Microgrid power price for 24 hours.

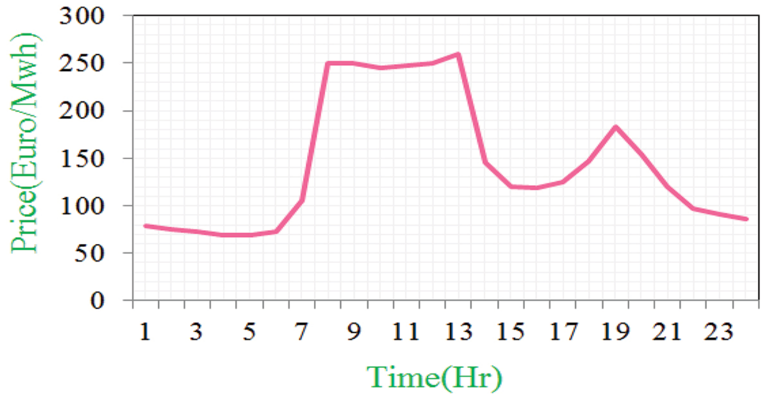


**Figure 3:** 24 hours grid price for a typical day from Epex Spot, U.K.

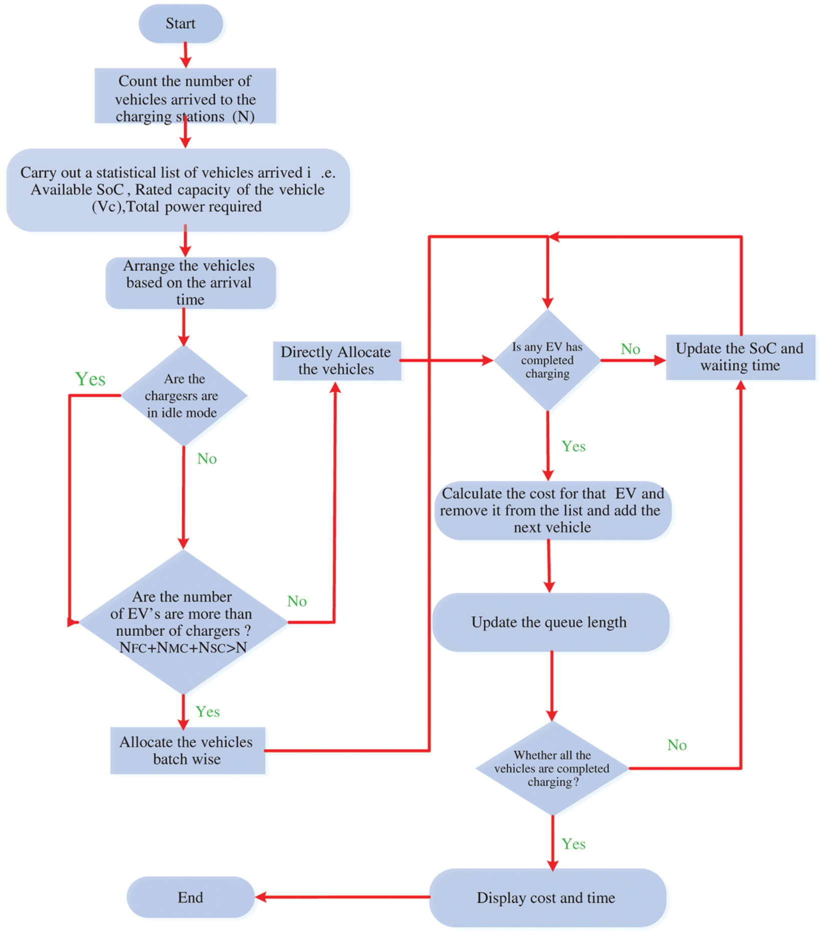


**Figure 4:** Flowchart for ATP Algorithm.

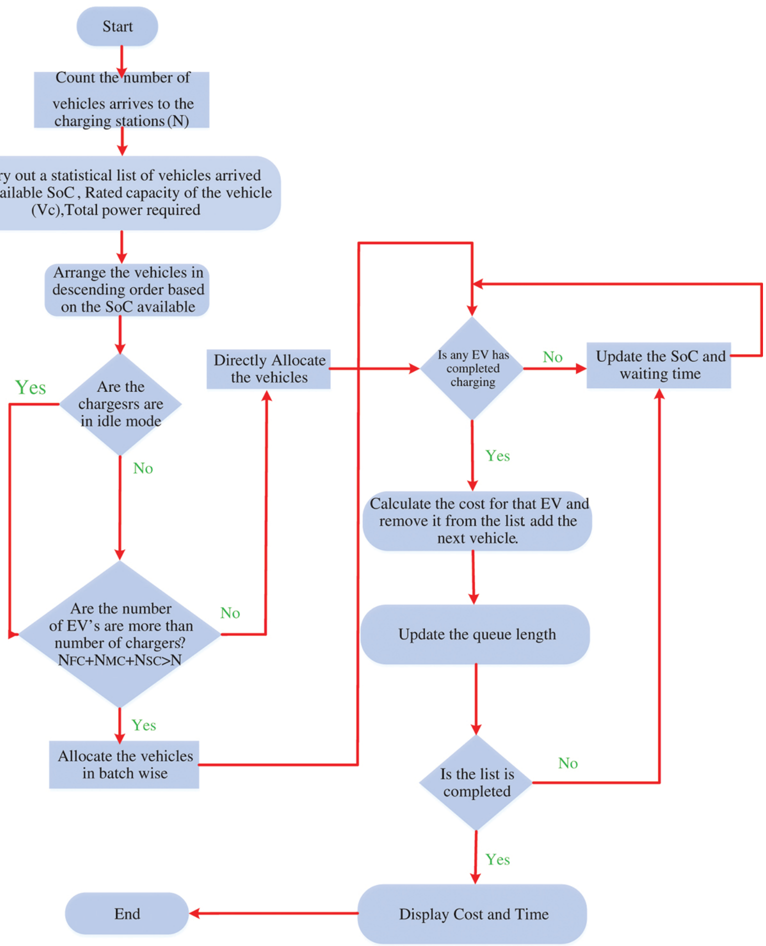


**Figure 5:** Flowchart for SPB algorithm.

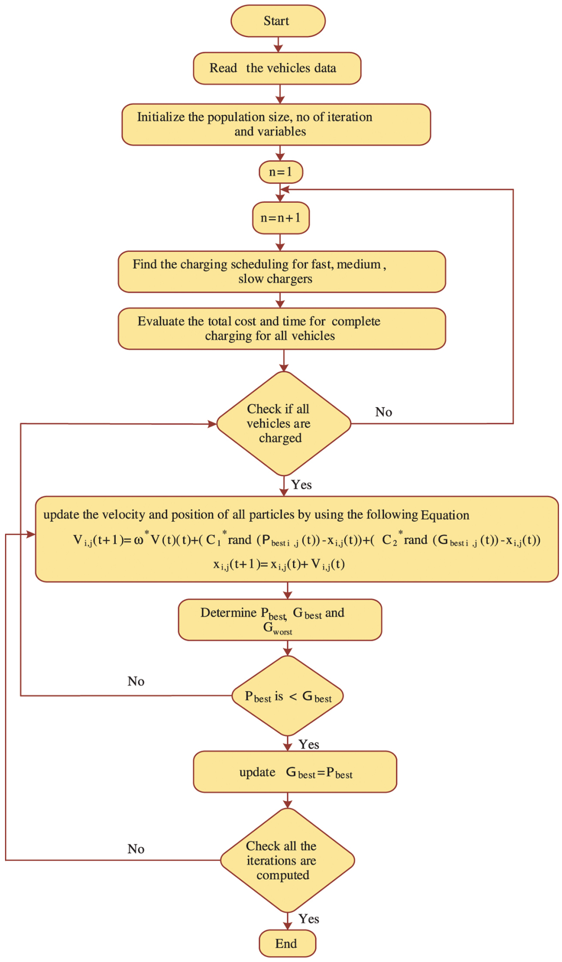


**Figure 6:** Flowchart for PSO algorithm.

**Table 1:** Maximum and Minimum Limits of DG Sources.

| DG no | Type of DG | Minimum Power limit(kW) | Maximum Power limit (kW) |
|---|---|---|---|
| 1 | Micro turbine | 6 | 30 |
| 2 | Wind turbine | 3 | 15 |
| 3 | PV 1 | 0 | 3 |
| 4 | PV 2 | 0 | 2.5 |
| 5 | PV 3 | 0 | 2.5 |
| 6 | PV 4 | 0 | 2.5 |
| 7 | PV 5 | 0 | 2.5 |

**Table 2:** Bid Coefficients of Renewable Sources (Ect/kWh).

| Type | $a_i$ | $b_i$ | $c_i$ |
|---|---|---|---|
| Micro turbine | 0.01 | 5.16 | 46.1 |
| Wind turbine | 0.01 | 7.8 | 1.1 |
| PV 1 | 0.01 | 7.8 | 1 |
| PV 2 | 0.01 | 7.8 | 1 |
| PV 3 | 0.01 | 7.8 | 1 |
| PV 4 | 0.01 | 7.8 | 0.1 |
| PV 5 | 0.01 | 7.8 | 1.2 |

Bid Coefficients of Renewable Sources (Ect/kWh)

**Table 3:** Microgrid output for 24 hours.

| Time(Hr) | O/P(kW) | Time(Hr) | O/P(kW) |
|---|---|---|---|
| 1 | 7.559 | 13 | 13.643 |
| 2 | 6.104 | 14 | 13.053 |
| 3 | 6.104 | 15 | 13.404 |
| 4 | 5.609 | 16 | 12.153 |
| 5 | 6.779 | 17 | 11.324 |
| 6 | 7.034 | 18 | 9.738 |
| 7 | 9.265 | 19 | 9.288 |
| 8 | 9.358 | 20 | 8.253 |
| 9 | 8.914 | 21 | 6.038 |
| 10 | 9.114 | 22 | 7.169 |
| 11 | 11.974 | 23 | 6.779 |
| 12 | 10.978 | 24 | 7.289 |

[1] Microgrid output for 24 hours.

**Table 4:** Power output from various DG's.

| Time(Hr) | wind | pv2 | pv3 | PV1 | PV4 | pv5 | MT |
|---|---|---|---|---|---|---|---|
| 1 | 5.46 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 2 | 4.005 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 3 | 4.005 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 4 | 3.51 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 5 | 4.68 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 6 | 4.935 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 7 | 7.14 | 0.005 | 0.005 | 0.006 | 0.005 | 0.005 | 2.099 |
| 8 | 7.155 | 0.02 | 0.02 | 0.024 | 0.02 | 0.02 | 2.099 |
| 9 | 6.36 | 0.0875 | 0.0875 | 0.105 | 0.0875 | 0.0875 | 2.099 |
| 10 | 5.715 | 0.25 | 0.25 | 0.3 | 0.25 | 0.25 | 2.099 |
| 11 | 6.885 | 0.575 | 0.575 | 0.69 | 0.575 | 0.575 | 2.099 |
| 12 | 5.85 | 0.5825 | 0.5825 | 0.699 | 0.5825 | 0.5825 | 2.099 |
| 13 | 7.41 | 0.795 | 0.795 | 0.954 | 0.795 | 0.795 | 2.099 |
| 14 | 5.325 | 1.0825 | 1.0825 | 1.299 | 1.0825 | 1.0825 | 2.099 |
| 15 | 6.495 | 0.925 | 0.925 | 1.11 | 0.925 | 0.925 | 2.099 |
| 16 | 4.815 | 1.0075 | 1.0075 | 1.209 | 1.0075 | 1.0075 | 2.099 |
| 17 | 4.935 | 0.825 | 0.825 | 0.99 | 0.825 | 0.825 | 2.099 |
| 18 | 4.545 | 0.595 | 0.595 | 0.714 | 0.595 | 0.595 | 2.099 |
| 19 | 5.46 | 0.3325 | 0.3325 | 0.399 | 0.3325 | 0.3325 | 2.099 |
| 20 | 5.595 | 0.1075 | 0.1075 | 0.129 | 0.1075 | 0.1075 | 2.099 |
| 21 | 3.9 | 0.0075 | 0.0075 | 0.009 | 0.0075 | 0.0075 | 2.099 |
| 22 | 5.07 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 23 | 4.68 | 0 | 0 | 0 | 0 | 0 | 2.099 |
| 24 | 5.19 | 0 | 0 | 0 | 0 | 0 | 2.099 |

[1] Power output from various DG's.

**Table 5:** Microgrid Price for 24 Hrs.

| Time(Hr) | Price (Ect/kWh) | Time(Hr) | Price (Ect/kWh) | Time(Hr) | Price (Ect/kwh) | Time(Hr) | Price (Ect/kWh) |
|---|---|---|---|---|---|---|---|
| 1 | 6.129265 | 7 | 6.438081 | 13 | 4.552871 | 19 | 5.002802 |
| 2 | 5.708454 | 8 | 6.387482 | 14 | 3.501351 | 20 | 5.748534 |
| 3 | 5.708454 | 9 | 6.001008 | 15 | 4.096047 | 21 | 5.63434 |
| 4 | 5.51724 | 10 | 5.316002 | 16 | 3.426556 | 22 | 6.032647 |
| 5 | 5.925361 | 11 | 4.831752 | 17 | 3.754545 | 23 | 5.925361 |
| 6 | 5.996807 | 12 | 4.523013 | 18 | 4.040261 | 24 | 6.063433 |

[1] Microgrid Price for 24 Hrs.

**Table 6:** Capacity of the vehicle with Available SoC.

| S.No | Capacity(kW) | Available SoC(%) | S.No | Capacity(kW) | Available SoC(%) |
|---|---|---|---|---|---|
| 1 | 10 | 8 | 11 | 24 | 29 |
| 2 | 23 | 25 | 12 | 27 | 38 |
| 3 | 16.5 | 10 | 13 | 16 | 40 |
| 4 | 24 | 14 | 14 | 17.6 | 33 |
| 5 | 27 | 19 | 15 | 23 | 30 |
| 6 | 16 | 23 | 16 | 16.5 | 27 |
| 7 | 24 | 28 | 17 | 30 | 16 |
| 8 | 30 | 12 | 18 | 17.3 | 18 |
| 9 | 17.3 | 30 | 19 | 32 | 34 |
| 10 | 32 | 35 | 20 | 16.5 | 25 |

[1] Capacity of the vehicle with Available SoC.

### 3.1 Problem description

Twenty vehicles with a various range of capacity were considered for the charging schedule. The CS is equipped with a pair of a fast charger (FC), a pair of a medium charger (MC) and a single slow charger (SC). The maximum power of fast charging mode is normally identical to 50 kW (125 A) with the maximum charging time up to 24-minute charging duration of 20 kWh Battery **[**[33]**]**. SOC of the Lithium-ion battery is determined by using

$$R_i = \frac{Capacity\ of\ the\ battery\ (kW/h) - Power\ left\ at\ the\ battery\ (kW/h)}{Rated\ output\ of\ the\ charger\ (Unit/hour)} \tag{1}$$

Where,

$R_i$ is the time required for charging in hour.

Total charging cost for all the vehicles can be obtained by

$$C(t) = \sum_{t=1}^{T}\left(\sum_{i=1}^{NF} Ci(t)R_i + \sum_{j=1}^{NM} Cj(t)R_j + \sum_{k=1}^{NS} Ck(t)R_k\right) \tag{2}$$

Where,

NF - is the number of fast chargers.

NM - is the number of medium chargers.

NS - is the number of slow chargers.

T - Total time in hour.

N - Total number of vehicles.

Total charging time (T) required for all the vehicles can be obtained by,

$$T = \sum_{n=1}^{N}\left(\sum_{i=1}^{NF}\left(\frac{V_c^n - SoC(n)}{P_{ifc}}\right) + \sum_{j=1}^{NM}\left(\frac{V_c^n - SoC(n)}{P_{jmc}}\right) + \sum_{k=1}^{NS}\left(\frac{V_c^n - SoC(n)}{P_{ksc}}\right)\right) \tag{3}$$

Where,

$V_C^n$ is the rated capacity of the vehicle in kW.

$SOC\ (n)$ is the SOC left in the $n^{th}$ vehicle.

$P_{ifc}$ - is the output power of fast charger in kW.

$P_{jmc}$ - is the output power of medium charger in kW.

$P_{ksc}$ - is the output power of slow charger in kW.

### 3.2 Constraints

– The SOC of the vehicle be greater than the minimum value as specified by the manufacturer.

$$SoC_{min} \leq SoC\,(t) \tag{4}$$

– While leaving from CS the SOC of EV should be equal to the SOC, requested and should not be more than its maximum capacity.

$$SoC_n^{requested} \leq SoC_n^{leaving} \leq SoC_n^{max} \tag{5}$$

– For the microgrid output

$$P_{mg}^{min} \leq P_{mg} \leq P_{mg}^{max} \tag{6}$$

### 3.3 Assumptions

1. *Voltage of the battery is assumed to be constant*.
2. *Battery will be at one mode at a time, either charging or discharging*.

## 4 Algorithm for proposed method

According to the EVs arrived in CS, the number of available chargers and the charging rate limit, CS needs to decide which EV to charge for the current timeslot. ATP algorithm based method, SOC based method was used to calculate the minimized time and cost of vehicle charging.

### 4.1 Arrival Time based Priority (ATP) algorithm

ATP algorithm based algorithm tries to get the vehicles in service whenever it arrives which used to reduce the delay time and to avoid the charger to be idle. It allows the vehicle till all the charging points are engaged. It doesn't consider the vehicles available power, the power required to charge, the charger to be allotted and the time to complete the charge. ATP algorithm lineups all Vehicles to charging points choose the earliest vehicle based on the arriving time. So, the selected Vehicle is allotted to a point which makes charging in a quick time. Once a Vehicle is allotted, it updates the time of other Vehicles. The same procedure will be repeated until all the vehicles are charged.Flowchart for this algorithm is given in Figure 4.

### 4.2 SOC Based Priority (SBP) algorithm

This algorithm focuses on the most primitive time to complete the vehicles charging. With the available SOC, it gives priority to the customers charging as soon as possible. Unlike the arrival time-based priority algorithm, SOC based priority algorithm takes the actual charging time into consideration. It starts by aligning all EV to charging point in order to complete the charging time earlier and selects the vehicle with highest SOC. So, the chosen EV is allotted to a point which guarantees the most primitive finishing time to complete the charging process. Once a vehicle is scheduled, it updates the most primitive finish charging time of other not scheduled EVs. As allotted, the EV is included in the line of the outlet; the expected most primitive finish time of other EVs on that outlet could be modified. It repeats the same process until all the EVs are scheduled.Flowchart for this algorithm is given in Figure 5.

### 4.3 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a computational approach which optimizes any problem by iteratively. It was pioneered by Kennedy and Eberhart at 1995. PSO maintains an inhabitant of elements, where every element stands for a probable result to the optimization crisis. Cost minimization problem was solved in this paper by PSO. It is a meta-heuristic population-based optimization method that has been applied to different optimization problems in a large number [35]. The PSO method determines the dimensions of the particles, particle velocities, allocating a particle objective function, and addressing the problem constraints. The numbers of variables are 5, the population size is 100 and the numbers of iterations are 100.

Considering a dimensional space and let N is the swarm size. Each particle of i can be represented as an object with many characteristics. The following symbols are assigned for the characteristics.

The velocity of particle I for the next fitness evaluation in the subspace of the dimensional space can be calculated as

$$V_{i,j}(t+1) = w * V(t) + C_1 * rand\left(P_{best\ i,j}(t) - X_{i,j}(t)\right) + C_2 * rand\left(G_{best\ i,j}(t) - X_{i,j}(t)\right) \tag{7}$$

Where

$X_i$ is the existing position of element i

$V_i$ is the velocity of the element i with a distance in an unit time.

$P_{best}$ is the individual best position of the element i.

$G_{best}$ is the global best of the swarm.

$V_i$ (t), $X_i$ (t) is the velocity and position of the particle at $t^{th}$ iteration.

The inactivity component weight $\omega$ was taken in between 0.4 to 0.9. It manages the way of the velocity vector. The individual observation of each individual and pushing the entities to shift towards their preeminent position is represented by a component named as cognitive component represented in the eqn. The individual best position of every particle will be reached up to existing iteration in the search space. The social component which is the third part is represented by $G_{best.}$ It is the $G_{best}$ location acquired by all individuals. At all times it pushes the entity towards the global best individual established thus far. From the equation the acceleration factor determines the relative influence of the social and cognition components are determined by $C_1$, $C_2$ component. The update of their position is given as:

$$X_{i,j}(t+1) = X_{i,j}(t) + V_{i,j}(t) \tag{8}$$

Every element will calculate its fitness value. The individual finest position of each individual will be updated using the equation given below.

$$G_{best(i,j)}(t+1) = \begin{cases} G_{best(i,j)}(t)\ \ if\ f\left(P_{best(i,j)}(t+1)\right) \geqslant f(G_{best(i,j)}(t) \\ P_{best(i,j)}(t)\ \ if\ f\left(P_{best(i,j)}(t+1)\right) < f(G_{best(i,j)}(t) \end{cases} \tag{9}$$

The problem is addressed by the PSO algorithm as follows. The numbers of variables are 5, the population size is 100 and the numbers of iterations are 100. The position and velocity of $i^{th}$ particle in the dimensional space j is given as

$$X_{(i,j)} = \left(X_{i,1'}, X_{i,2'}, \ldots .X_{i,j'}\right) \tag{10}$$

$$V_{(i,j)} = \left(V_{i,1'}, V_{i,2'}, \ldots .V_{i,j'}\right) \tag{11}$$

In each iteration, the charging strategy will be updated.

Step 1: Create a population of N number randomly.

Step 2: Assign the number of iteration, variables, velocity, and position.

Step 3: Schedule the charging and find the fitness value for all population.

Step 4: Determine $P_{best}$ and $G_{best}$ from the initial population.

Step 5: Update the velocity, particle position from the equation given in the flow chart.

Step 6: Find the fitness value for the updated velocity and position.

Step 7: If the new $P_{best}$ is better than the previous $G_{best}$ then go to step 9.

Step 8: In case the novel personal best is not superior to the earlier Global best then keep Gbest as it is given in the flow chart.

Step 9: Update the Global best.

Step10: Repeat the procedure until the tolerance limit reached or the number of iterations is completed.

The flowchart for PSO algorithm based scheduling is given in Figure 6.

### 4.4 Shuffled Frog Leaping Algorithm (SFLA)

Shuffled Frog Leaping Algorithm (SFLA) is a meta-heuristic, or more accurately it is a Memetic Algorithm, which is inspired by frog leaping. SFLA is based on the model used by Shuffled Complex Evolution (SCE-UA) and incorporated the memetic evolution into it. This optimization has been applied to many optimization problems. The main advantage of SFLA is its convergence speed. The algorithm has elements of local and global search information [36]. A separate local search will be conducted for every memplex. After a particular number of memetic steps, frogs have shuffled again among the memplexes. It enables the frogs to interchange the information among different memplexes to ensure that they are moving to an optimal solution. The first step of SFLA is to initial the population of P frogs randomly with a feasible search space. The location of ith frog is represented as Fi = (Fi1, Fi2, Fi3 … .FiD). D is the total number of variables. Then, the frogs will be sorted according to the fitness value in a descending order. Now, the entire population is divided into h number of memplexes. Each population contains n number of frogs (i. e. P = h*n).

Now, the first frog will go the first memplex and the hth frog will go the hth memplex. The frog h + 1 will go the first memplex and so on. According to the rule, the position of the worst frog will be updated.

$$S_i = r.\,(X_b - X_{new}) \tag{12}$$

$$X_w^{new} = X_w^{current} + S_i \tag{13}$$

Where, $S_{imin} < S_i < S_{imax}$

The change of frog's position in one jump is Si. r is a random number generator. It is a uniform distribution between 1 and 0. The maximum and minimum allowable change of frog's position is $S_{imin}$ and $S_{imax}$.

Step 1: Create P number of random population and h number of memplex.

Step 2: Assign the number of iteration and variable.

Step 3: Find the fitness value for P number of population.

Step 4: Sort out the best (Xb), worst (Xw) and Gbest (Xg) values for each memplex.

Step 5: Calculate the new frog (Xnew) by using the eqn and replace Xw with calculated Xnew.

Step 6: If Xnew is not better than Xw go to step 5.

Step 7: Find the fitness value for all the fitness multiplex with Xnew values.

Step 8: Shuffle the Gbest value among the memplexes.

Step 9: If the convergence criteria is met then stop the process. If not repeat the procedure until the convergence criteria is met.



## 5 Results and discussion

The results are explained for 6 cases. Case 1 gives the results of arrival time-based priority algorithm, case 2 explains the results of SOC based priority algorithm, the PSO results are explained in case 3, the results obtained by shuffled frog leaping algorithms are given in case 4 and the results of load reallocation is given in case 5. The results with microgrid are considered in case 6.

### 5.1 Case 1

Charging all the vehicles without scheduling is considered here as arrival time-based priority method. When the management strategy is not performed, the total cost reaches 2531.371 Ect and the average time to complete the charging is 3.0 hours. Total energy consumed by all the vehicles is 335.91 kW. The vehicle allocation using the ATP algorithm is given in Table 7. Here, both the fast chargers consume 180 kW to charge 12 vehicles which are 60% of the total vehicles taken for this study. Table 8 shows the vehicles scheduled to various chargers by using ATP algorithm.6 vehicles were charged by the medium Chargers by consuming 66.4 kW and 55.6 kW respectively. The SC1 charged two vehicles by consuming 33.6 kW.

**Table 7:** Vehicle allocation by ATP Algorithm.

| Vehicle No | Available SoC(%) | Power consumed(kW) | Time(min) | Type of charger | Cost(Ect) |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 1 | 8 | 16.192 | 32.38 | FC1 | 128.2083 |
| 2 | 25 | 17.250 | 34.5 | FC2 | 136.5855 |
| 3 | 10 | 14.850 | 44.55 | MC1 | 117.5823 |
| 4 | 14 | 20.640 | 61.92 | MC2 | 163.1554 |
| 5 | 19 | 21.870 | 114.10 | SC1 | 168.7905 |
| 6 | 23 | 12.320 | 24.64 | FC1 | 97.5498 |
| 7 | 28 | 17.280 | 34.56 | FC2 | 134.9114 |
| 8 | 12 | 26.400 | 79.2 | MC1 | 197.5606 |
| 9 | 30 | 12.110 | 24.22 | FC1 | 91.4045 |
| 10 | 35 | 20.800 | 62.4 | MC2 | 155.5523 |
| 11 | 29 | 17.040 | 34.08 | FC2 | 127.7318 |
| 12 | 38 | 16.740 | 33.48 | FC1 | 125.4830 |
| 13 | 40 | 9.6000 | 19.2 | FC2 | 71.6492 |
| 14 | 33 | 11.792 | 61.52 | SC1 | 85.5461 |
| 15 | 30 | 16.1 | 32.2 | FC1 | 117.0912 |
| 16 | 27 | 12.045 | 24.09 | FC2 | 87.0372 |
| 17 | 16 | 25.2 | 75.6 | MC1 | 180.0681 |
| 18 | 18 | 14.18 | 28.36 | MC2 | 102.5072 |
| 19 | 34 | 21.12 | 42.24 | FC2 | 151.2649 |
| 20 | 25 | 12.375 | 24.75 | FC1 | 85.4589 |

**Table 8:** Vehicle pattern by ATP Algorithm.

| Vehicles charged by FC1 | Vehicles charged by FC2 | Vehicles charged by MC1 | Vehicles charged by MC2 | Vehicles charged by SC1 |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| 6 | 7 | 8 | 10 | 14 |
| 9 | 11 | 17 | 18 | - |
| 12 | 13 | - | - | - |
| 15 | 16 | - | - | - |
| 20 | 19 | - | - | - |

## 5.2 Case 2

SBP algorithm schedules the vehicles based on the priorities for vehicles demanding less charging times. Based on the number of customer intake, the performance of CSs will be increased compared to the ATP algorithm total energy consumed by all the vehicles is 335.91 kW. The vehicle allocation using SBP algorithm is given in Table 9. Here, both the fast chargers consume 161.9 kW to charge 10 vehicles which are 50% of the total vehicles taken for this study.8 vehicles were charged by the medium Chargers MC1 and MC2 by consuming 144.5 kW. The SC1 charged two vehicles by consuming 29.3 kW. SBP method completes the charging in an average time of 3.03 hour and with a cost of 2526.9 Ect. Table 10 provides the vehicles allotted to each charger by using SBP algorithm. It is identified from the Table 7, that compared to the first case there is a reduction of 4.4 Ect.

**Table 9:** Vehicle allocation by SBP Algorithm.

| Vehicle No | Available SoC(%) | Power consumed(kW) | Time(min) | Type of charger | Cost(Ect) |
|---|---|---|---|---|---|
| 1 | 8 | 16.192 | 32.38 | FC1 | 124.7618 |
| 2 | 25 | 17.250 | 34.5 | FC1 | 129.3060 |
| 3 | 10 | 14.850 | 44.55 | MC1 | 114.6726 |
| 4 | 14 | 20.640 | 79.92 | MC2 | 124.0152 |
| 5 | 19 | 21.870 | 43.74 | FC2 | 158.0982 |
| 6 | 23 | 12.320 | 64.28 | SC1 | 97.2037 |
| 7 | 28 | 17.280 | 51.84 | MC1 | 128.4162 |
| 8 | 12 | 26.400 | 79.2 | MC2 | 185.8741 |
| 9 | 30 | 12.110 | 36.33 | MC2 | 95.8870 |
| 10 | 35 | 20.800 | 41.6 | FC2 | 154.9775 |
| 11 | 29 | 17.040 | 88.90 | SC1 | 126.0337 |
| 12 | 38 | 16.740 | 33.48 | FC2 | 127.1803 |

| | | | | | |
|---|---|---|---|---|---|
| 13 | 40 | 9.6000 | 19.2 | FC1 | 76.0128 |
| 14 | 33 | 11.792 | 23.58 | FC2 | 93.3691 |
| 15 | 30 | 16.1 | 48.3 | MC2 | 124.0152 |
| 16 | 27 | 12.045 | 36.13 | MC1 | 95.3723 |
| 17 | 16 | 25.2 | 75.6 | MC1 | 179.1146 |
| 18 | 18 | 14.18 | 28.36 | FC2 | 112.3247 |
| 19 | 34 | 21.12 | 42.24 | FC1 | 153.9001 |
| 20 | 25 | 12.375 | 24.75 | FC1 | 97.9853 |

**Table 10:** Vehicle pattern by SBP Algorithm.

| Vehicles charged by FC1 | Vehicles charged by FC2 | Vehicles charged by MC1 | Vehicles charged by MC2 | Vehicles charged by SC1 |
|---|---|---|---|---|
| 13 | 14 | 16 | 9 | 6 |
| 20 | 18 | 3 | 15 | 11 |
| 1 | 12 | 7 | 4 | - |
| 2 | 10 | 17 | 8 | - |
| 19 | 5 | - | - | - |

### 5.3 Case 3

When the optimization strategy is performed, there is a significant reduction in cost and time compared to both ATP and SBP algorithms. PSO completes the charging in an average time of 2.8 hours and with a cost of 2520.7 Ect. The optimal scheduling is done using PSO algorithm and it is given in Table 11. It is evident from the results given below, that PSO gives better results. Compared to the first case there is a reduction of 10.6 Ect and compared to the second case there is a reduction of 6.2 Ect. Total energy consumed by all the vehicles is 335.91 kW. Table 13 shows the vehicles scheduled to each charger.

**Table 11:** Vehicle allocation by PSO.

| Vehicle No | Available SoC(%) | Power consumed(kW) | Time(min) | Type of charger | Cost(Ect) |
|---|---|---|---|---|---|
| 1 | 8 | 16.192 | 48.57 | MC2 | 128.2083 |
| 2 | 25 | 17.250 | 34.5 | FC2 | 126.7321 |
| 3 | 10 | 14.850 | 29.7 | FC2 | 115.1980 |
| 4 | 14 | 20.640 | 61.92 | MC1 | 163.1574 |
| 5 | 19 | 21.870 | 43.74 | FC1 | 151.0024 |
| 6 | 23 | 12.320 | 36.96 | MC2 | 93.9577 |
| 7 | 28 | 17.280 | 51.84 | MC1 | 129.5309 |
| 8 | 12 | 26.400 | 52.8 | FC1 | 203.3635 |
| 9 | 30 | 12.110 | 24.22 | FC1 | 90.7766 |
| 10 | 35 | 20.800 | 41.6 | FC2 | 164.6944 |
| 11 | 29 | 17.040 | 34.08 | FC1 | 134.9227 |
| 12 | 38 | 16.740 | 33.48 | FC2 | 125.4830 |
| 13 | 40 | 9.6000 | 28.8 | MC2 | 71.9616 |
| 14 | 33 | 11.792 | 35.37 | MC1 | 85.7997 |
| 15 | 30 | 16.1 | 32.2 | FC2 | 113.7414 |
| 16 | 27 | 12.045 | 62.81 | SC1 | 95.1423 |
| 17 | 16 | 25.2 | 50.4 | FC1 | 183.3590 |
| 18 | 18 | 14.18 | 73.98 | SC1 | 105.4756 |
| 19 | 34 | 21.12 | 42.24 | FC1 | 148.8069 |
| 20 | 25 | 12.375 | 24.75 | FC2 | 89.4589 |

**Table 12:** Vehicle pattern by PSO Algorithm.

| Vehicles charged by FC1 | Vehicles charged by FC2 | Vehicles charged by MC1 | Vehicles charged by MC2 | Vehicles charged by SC1 |
|---|---|---|---|---|
| 11 | 10 | 4 | 1 | 16 |
| 8 | 3 | 7 | 6 | 18 |
| 9 | 12 | 14 | 13 | - |
| 17 | 2 | - | - | - |
| 19 | 20 | - | - | - |
| 5 | 15 | - | - | - |

## 5.4 Case 4

The results for SFLA based scheduling is given in Table 13. When compared to the ATP and SBP methods SFLA gives better results but when compared to PSO, both the results have minor differences. SFLA completes the charging with 2.8 hours as PSO did. Compared to the first case there is a reduction of 12 Ect and compared to the second case there is a reduction of 7.4 Ect. Compared to the results of PSO, 1.4 Ect can be further reduced by SFLA. Total energy consumed by all the vehicles is 335.91 kW. Table 16 shows the vehicles scheduled to each charger. Comparison of cost by the ATP, SBP, and PSO is given in Table 15.

**Table 13:** Vehicle allocation by SFL Algorithm.

| Vehicle No | Available SoC(%) | Power consumed(kW) | Time(min) | Type of charger | Cost(Ect) |
|---|---|---|---|---|---|
| 1 | 8 | 16.192 | 32.384 | FC2 | 128.208 |
| 2 | 25 | 17.25 | 34.5 | FC1 | 133.188 |
| 3 | 10 | 14.85 | 29.7 | FC2 | 107.849 |
| 4 | 14 | 20.64 | 41.28 | FC1 | 149.428 |
| 5 | 19 | 21.87 | 43.74 | FC1 | 150.969 |
| 6 | 23 | 12.32 | 36.96 | MC1 | 92.3507 |
| 7 | 28 | 17.28 | 51.84 | MC1 | 133.92 |
| 8 | 12 | 26.4 | 52.8 | FC2 | 183.839 |
| 9 | 30 | 12.11 | 24.22 | FC2 | 87.5432 |
| 10 | 35 | 20.8 | 41.6 | FC1 | 164.694 |
| 11 | 29 | 17.04 | 88.90 | SC1 | 132.585 |
| 12 | 38 | 16.74 | 33.48 | FC2 | 131.31 |
| 13 | 40 | 9.6 | 28.8 | MC1 | 76.0128 |
| 14 | 33 | 11.792 | 35.376 | MC2 | 88.3928 |
| 15 | 30 | 16.1 | 84 | SC1 | 117.978 |
| 16 | 27 | 12.045 | 36.135 | MC2 | 95.3723 |
| 17 | 16 | 25.2 | 50.4 | FC2 | 188.899 |
| 18 | 18 | 14.186 | 42.558 | MC2 | 109.695 |
| 19 | 34 | 21.12 | 42.24 | FC1 | 158.316 |
| 20 | 25 | 12.375 | 24.75 | FC1 | 88.7466 |

**Table 14:** Vehicle pattern by SFL Algorithm.

| Vehicles charged by FC1 | Vehicles charged by FC2 | Vehicles charged by MC1 | Vehicles charged by MC2 | Vehicles charged by SC1 |
|---|---|---|---|---|
| 10 | 1 | 13 | 16 | 11 |
| 2 | 12 | 7 | 18 | 15 |
| 19 | 17 | 6 | 14 | - |
| 4 | 3 | - | - | - |
| 20 | 9 | - | - | - |
| 5 | 8 | - | - | - |

**Table 15:** Charging cost for SFL, PSO, ATP and SBP Algorithm.

| S.No | Method | Cost(Ect) |
|---|---|---|
| 1 | Arrival Time Based Priority Algorithm | 2531.3 |
| 2 | Soc Based Priority Algorithm | 2526.7 |
| 3 | PSO Algorithm | 2520.7 |
| 4 | SFL Algorithm | 2519.3 |

The average time taken by each charger for all the three cases is given in Table 16. It is clear evidence that the PSO and SFLA based scheduling takes a lesser time than the other two methods. Similarly, the costs for each charger are given in Table 16. Cost for charging without load reallocation is given in Table 17. Charging cost by using SFLA,PSO,ATP and SPB methods are given in Table 18.Charging cost for each charger with load reallocation is given in Table 19.

**Table 16:** Comparision of time taken by each charger.

| Method | FC1 | FC2 | MC1 | MC2 | SC1 | Average time(Hr) |
|---|---|---|---|---|---|---|
| ATP | 2.8612 | 3.1443 | 3.3225 | 2.7810 | 2.9271 | 3.0 |
| SBP | 2.5512 | 2.8463 | 3.4688 | 3.7625 | 2.5530 | 3.0 |
| PSO | 4.1247 | 3.2705 | 2.4856 | 1.9056 | 2.2810 | 2.8 |
| SFLA | 3.8018 | 3.7164 | 1.96 | 1.9011 | 2.8871 | 2.8 |

**Table 17:** Cost for charging without load reallocation.

| Method | FC1 | FC2 | MC1 | MC2 | SC1 | Total cost(Ect) |
|---|---|---|---|---|---|---|
| ATP | 649.1957 | 709.1800 | 497.3844 | 421.1970 | 254.3366 | 2531.3 |
| SBP | 581.9660 | 645.9499 | 517.5756 | 558.1308 | 223.2374 | 2526.3 |
| PSO | 912.2010 | 735.3078 | 378.4880 | 294.1276 | 200.6179 | 2520.7 |
| SFLA | 845.342 | 827.649 | 302.283 | 293.46 | 250.563 | 2519.3 |

**Table 18:** Cost for SFLA, ATP, SPB, PSO methods with load reallocation.

| Vehicle No | Available SoC(%) | Power consumed(kW) | Time(min) | Type of charger | Cost(Ect) ATP | SPB | PSO | SFLA |
|---|---|---|---|---|---|---|---|---|
| 1 | 8 | 16.192 | 48.57 | MC2 | 111.7734 | 111.7815 | 111.7734 | 117.052 |
| 2 | 25 | 17.250 | 34.5 | FC2 | 119.0767 | 119.0940 | 115.5730 | 124.421 |
| 3 | 10 | 14.850 | 29.7 | FC2 | 102.5095 | 102.5164 | 102.5152 | 102.51 |
| 4 | 14 | 20.640 | 61.92 | MC1 | 142.4726 | 145.3748 | 142.4786 | 149.253 |
| 5 | 19 | 21.870 | 43.74 | FC1 | 150.9790 | 158.0982 | 152.1804 | 153.741 |
| 6 | 23 | 12.320 | 36.96 | MC2 | 85.0450 | 85.0458 | 85.0535 | 85.045 |
| 7 | 28 | 17.280 | 51.84 | MC1 | 119.2884 | 120.6580 | 119.3011 | 119.301 |
| 8 | 12 | 26.400 | 52.8 | FC1 | 182.6718 | 191.8673 | 182.2526 | 182.258 |
| 9 | 30 | 12.110 | 24.22 | FC1 | 83.6060 | 83.5953 | 83.6074 | 83.5953 |
| 10 | 35 | 20.800 | 41.6 | FC2 | 144.0712 | 144.7466 | 143.3824 | 143.585 |
| 11 | 29 | 17.040 | 34.08 | FC1 | 117.6442 | 119.7112 | 117.6271 | 117.627 |
| 12 | 38 | 16.740 | 33.48 | FC2 | 115.5730 | 115.5689 | 115.5730 | 121.223 |
| 13 | 40 | 9.6000 | 28.8 | MC2 | 66.6586 | 66.2688 | 66.2784 | 66.2688 |
| 14 | 33 | 11.792 | 35.37 | MC1 | 84.8779 | 81.4002 | 84.5684 | 81.4113 |
| 15 | 30 | 16.1 | 32.2 | FC2 | 115.5296 | 111.1465 | 116.9306 | 116.435 |
| 16 | 27 | 12.045 | 62.81 | SC1 | 87.0372 | 83.1466 | 83.72 | 83.1587 |
| 17 | 16 | 25.2 | 50.4 | FC1 | 182.6029 | 182.7989 | 180.7246 | 173.992 |
| 18 | 18 | 14.18 | 73.98 | SC1 | 102.5072 | 97.9260 | 98.9902 | 97.9401 |
| 19 | 34 | 21.12 | 42.24 | FC1 | 152.9666 | 151.1870 | 153.4718 | 152.278 |
| 20 | 25 | 12.375 | 24.75 | FC2 | 89.4589 | 85.4246 | 89.4589 | 85.4246 |

**Table 19:** Charging cost for each charger with load reallocation.

| Method | FC1 | FC2 | MC1 | MC2 | SC1 | Total cost(Ect) |
|---|---|---|---|---|---|---|
| ATP | 600.9857 | 662.6717 | 467.7792 | 389.0570 | 235.8561 | 2356.3 |
| SBP | 533.7560 | 597.7399 | 489.1200 | 531.9840 | 204.7569 | 2357.3 |
| PSO | 879.5733 | 690.2870 | 346.3480 | 263.1052 | 182.1374 | 2361.5 |
| SFLA | 653.924 | 636.362 | 419.961 | 425.754 | 220.01 | 2356 |

### 5.5 Case 5

Load reallocation is used to reduce the cost to avoid Vehicle charging during the energy cost is high. When the reallocation of the load is done for the ATP algorithm the charging cost is reduced up to 175 Ect. When reallocation of a load is done for the SBP method the charging cost is reduced up to 169.5 Ect. But, when the load reallocation is done, it is observed that there is a reduction of 175.1 Ect and 170 Ect reduction in cost is given by PSO compared to both ATP algorithm and SOC based priority algorithms and also SFLA gives a difference of 175.5 Ect, 170.9 Ect, 164 Ect compared to ATP, SBP, and PSO. .

### 5.6 Case 6

Without considering microgrid in the system, the actual charging cost is 2531.3, 2526.3, 2520.7 and 2519.3 Ect for the ATP, SBP, PSO, and SFLA. As the renewable energy costs are less than the grid price, the renewable energy can be utilized fully. With the DG installation, the cost is reduced to 8.1%, 7.2%, 8.4% and 10.3% respectively. An enhanced amount of renewable energy makes the CS purchase additional power from the microgrid as a substitute of purchasing electricity from the main grid at a high cost. So, the cost will be reduced even more. Table 20 provides the comparative effectiveness of load reallocation and Table 21 provides the effectiveness of microgrid in reducing the charging cost.

**Table 20:** Charging cost and time for SFLA,PSO, ATP and SBP algorithms before and after load reallocation.

| S.No | Method | Before Load allocation | | After Load allocation | | % of Difference in Cost (Ect) |
|---|---|---|---|---|---|---|
| | | Cost(Ect) | Avg.Time(Hr) | Cost(Ect) | Avg.Time(Hr) | |
| 1 | ATP | 2531.3 | 3.0 | 2356.3 | 3.0 | 6.91 |
| 2 | SBP | 2526.3 | 3.0 | 2357.3 | 3.0 | 6.68 |
| 3 | PSO | 2520.7 | 2.8 | 2361.5 | 2.8 | 6.31 |
| 4 | SFLA | 2519.3 | 2.8 | 2356.01 | 2.8 | 6.48 |

**Table 21:** Charging cost with and without microgrid.

| S.No | Method | Without Microgrid | | With microgrid | | % of Difference in Cost (Ect) |
|---|---|---|---|---|---|---|
| | | Cost(Ect) | Avg.Time(Hr) | Cost(Ect) | Avg.Time(Hr) | |
| 1 | ATP | 2531.3 | 3.0 | 2325.9 | 3.0 | 8.1 |
| 2 | SPB | 2526.3 | 3.0 | 2342.7 | 3.0 | 7.2 |
| 3 | PSO | 2520.7 | 2.8 | 2308.4 | 2.8 | 8.4 |
| 4 | SFLA | 2519.3 | 2.8 | 2257.9 | 2.8 | 10.3 |

## 6 Conclusion

This paper presents the findings of a PSO and SFLA based scheduling of EV's during the dynamic electric price, with and without microgrid. The most economical scheduling method of EVs is derived. With a proper scheduling, load reallocation reduces the cost and time effectively. EVs can be used as a source to provide V2G service. It is possible to control Vehicle to Grid or Grid to Vehicle-based on discounts, guidelines, incentives, and put in place by the government, utilities, and manufacturers. For the smart grid environment, an advanced optimization method will be needed to track the dynamic behavior of RESs and vehicles. Furthermore, purchase and selling rates are to be considered in the scheduling, control, and optimization of EVs scheduling in a smart grid.

## References

[1] International Energy Agency (IEA). World energy outlook. Paris, France: IEA and Organization for Economic Co-operation and Development (OECD), 2008.
[2] Boulanger AG, Chu AC, Maxx S, Waltz DL. Vehicle electrification: status and issues. Proc IEEE. 2011;99:1116–38.
[3] Sortomme E, El-Sharkawi MA. Optimal charging strategies for unidirectional vehicle-to-grid. IEEE Trans Smart Gri. 2011;2:131–8.
[4] Navid R, Kashanizadeh B, Vakilian M, Barband SA. Optimal placement of fast charging station in a typical micro grid in Iran in Proc. 2013 10th IEEE Int. Conf. Eur. Energy Market (EEM), Stockholm, Sweden, 1–7.
[5] Clement-Nyns K, Haesen E, Driesen J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Trans Power Syst. 2010;25:371–80.
[6] Martinenas S, Knezovic K, Marinelli Mattia. Management of power quality issues in low voltage networks using electric vehicles: experimental validation. IEEE Trans Power Delivery. 2017;32:971–9. DOI: 10.1109/TPWRD.2016.2614582.
[7] Hu J, You S, Lind M, Ostergaard J. Coordinated charging of electric vehicles for congestion prevention in the distribution grid. IEEE Trans Smart Grid. 2014;5:703–711. DOI: 10.1109/TSG.2013.2279007.
[8] O'Connell N, Wu Q, Stergaard J, Nielsen AH, Cha ST, Ding Y. Day ahead tariffs for the alleviation of distribution grid congestion from electric vehicles. Electr Power Syst Res. 2012;92:106–14.
[9] Sortomme E, Hindi MM, James MacPherson SD. Charging of plug-in hybrid electric vehicles to minimize distribution system losses. IEEE Trans Smart Grid. 2011;2:198–205.
[10] Bayram IS, Michailidis G, Devetsikiotis M, Granelli F. Electric power allocation in a network of fast charging stations. IEEE J Sel Areas Commun. 2013;31:1235–46.
[11] Bourass A, Cherkaoui S, Khoukhi L. Secure optimal itinerary planning for electric vehicles in the smart grid. IEEE Trans Ind Inf. 2017;13:3236–45. DOI: 10.1109/TII.2017.2741347
[12] Guibin W, Zhao X, Fushuan W, Kit PW. Traffic-constrained multi objective planning of electric-vehicle charging stations. IEEE Trans Power Del. 2013;28:2363–72.
[13] Wen C-K, Chen J-C, Teng J-H, Ting P. Decentralized plug-in electric vehicle charging selection algorithm in power systems. IEEE Trans Smart Grid. 2012;3:1779–89.
[14] Xing H, Fu M, Lin Z, Mou Y. Decentralized optimal scheduling for charging and discharging of plug-in electric vehicles in smart grids. IEEE Trans Power Syst. 2016;31:4118–27.
[15] Ma Z, Callaway DS, Hiskens IA. Decentralized charging control of large populations of plug-in electric vehicles. IEEE Trans Control Syst Technol. 2013;21:67–78. DOI: 10.1109/TCST.2011.2174059.
[16] Zou W, Wu B, Liu Z. Centralized electricity markets based on spot pricing. Autom Elect Power Syst. 2011;35:62–7.
[17] Honarmand M, Zakariazadeh A, Jadid S. Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition. Energy. 2014;65:572–9.
[18] Esmaili M, Goldoust A. Multi-objective optimal charging of plugin electric vehicles in unbalanced distribution networks. Int J Electr Power Energy Syst. 2015;73:644–52.
[19] Yang J, He L, Fu S. An improved pso-based charging strategy of electric vehicles in electrical distribution grid. Appl Energy. 2014;128:82–92.
[20] Hua L, Wang J, Zhou C. Adaptive electric vehicle charging coordination on distribution network. IEEE Trans Smart Grid. 2014;5:2666–75.
[21] Kristoffersen TK, Capion K, Meibom P. Optimal charging of electric drive vehicles in a market environment. Appl Energy. 2011;88:1940–8.
[22] Moeini-Aghtaie M, Abbaspour A, Fotuhi-Firuzabad M. Online multicriteria framework for charging management of phevs. IEEE Trans Veh Technol. 2014;63:3028–37.
[23] Rezgui J, Cherkaoui S. Smart charge scheduling for EVs based on two-way communication. IEEE International conference on communications (ICC), 2016:1–6.
[24] Lee J, Park G, Kim H. Reservation-based charging service for electric vehicles. International Conference on Algorithms and Parallel Processing, LNCS 7017, Springer-Verlag, 2011:186–95.
[25] Zhou K, Fu C, Yang S. Big data driven smart energy management: from big data to big insights. Renew Sustain Energy Rev. 2016;56:215–25.
[26] Cao Y, Tang S, Li C, Zhang P, Tan Y, Zhang Z, et al. An optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid. 2012;3:388–93.
[27] Lopes JA, Soares FJ, Almeida PM. Integration of electric vehicles in the electric power system. Proc IEEE. 2011;99:168–83.

[28] Wang R, Xiao G, Wang P. Hybrid centralized-decentralized (HCD) charging control of electric vehicles. IEEE Trans Veh Tech. 2017;66:6728–41. DOI: 10.1109/TVT.2017.2668443.
[29] Jhala K, Natarajan B, Pahwa A, Erickson L. Coordinated electric vehicle charging for commercial parking lot with renewable energy sources. Electric Power Compon Syst. 2017;45:344–53. DOI: 10.1080/15325008.2016.1248253.
[30] Cao Y, Tang S, Li CB, Zhang P, Tan Y, Zhang ZK, et al. Optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid. 2012;3:388–93.
[31] Cao Y, Tang S, Li C, Zhang P, Tan Y, Zhang Z, Li J. An optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid.2015;2015:388–93. [Online]. Available at: DOI: 10.1109/TSG.2011.2159630. Accessed:23 Sep 2015.
[32] Zheng J, Wang X, Men K, Zhu C, Zhu S. Aggregation model-based optimization for electric vehicle charging strategy. IEEE Trans Smart Grid. 2013;4:1058–66. DOI: 10.1109/TSG.2013.2242207.
[33] Papathanassiou S, Hatziargyriou N, Strunz K. A benchmark LV microgrid for steady state and transient analysis, presented at the CIGRE Symp. Power system dispersed generation, Athens, Greece, Apr. 17–20, 2005.
[34] https://www.epexspot.com/en/extras/download-center/market_data. Accessed June 2017.
[35] del Valle Y, Venayagamoorthy GK, Mohagheghi S, Hernandez J-C, Harley RG. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Trans Evol Comput. 2008;12:171–95. DOI: 10.1109/TEVC.2007.896686.
[36] Selvakumar K, Vignesh RS, Vijayabalan R. Shuffled frog leaping algorithm for solving profit based unit commitment problem. 2012 International conference on computing, communication and applications. 2012 2;–. DOI: 10.1109/ICCCA.2012.6179234.