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Optimal Charging Scheduling of Electric Vehicles in Micro Grids Using Priority Algorithms and Particle Swarm Optimization

George Fernandez Savari [1] · Vijayakumar Krishnasamy [1] · Vidyasagar Sugavanam [1] · Kalyanasundaram Vakesan [1]

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Abstract

The large-scale integration of electric vehicles (EVs) into modern power grid brings both challenges and opportunities to the performance of the systems. This paper presents an optimal static (when EV is stationary) charging scheduling scheme of EVs to minimize the charging cost while complying with the constraints related to the status of the charging station. The proposed systematic charging scheme is based on "Particle Swarm Optimization (PSO)". It is compared with well-established algorithms such as "Arrival Time-Based priority (ATP) algorithm" and "SOC-Based Priority (SBP) algorithm". In addition, a microgrid scenario is further considered for reducing the consumption of energy from the grid and also, reducing the charging cost by properly shifting the EV load. Based on the study carried out for a sample test cases considered, it is found that the proposed scheme has better performance compared to the existing schemes.

Keywords Charging stations · Electric vehicles · Microgrid · Optimization · Priority algorithms

1 Introduction

Recently, much attention has been focused on replacement of conventional fuel-powered vehicles by renewables -powered vehicles in modern power system networks. Energy generation from conventional fossil fuel resources and transportation industry are responsible for about 70% of the global carbon dioxide (CO_2) production which adds to global warming [1]. In this regard, EVs have introduced a friendly transportation atmosphere compared to the traditional Internal Combustion Engine (ICE) vehicles as they can decrease CO_2 emission and solve the problem of fossil fuel resources depletion [2] because EVs use renewables in charging [3]. Currently, steady EVs deployment is noticed across the world in response to their technical and environmental merits.

However, some challenges have also arisen along with EV Charging Stations (CSs). The mileage of an EV is determined by the rated capacity of its battery. For a long range of driving, a rapid charging mechanism and a high capacity battery are needed. Fast CSs are able to charge the battery of EVs from its energy level to 80% in less than 30 minutes. In contrary, medium and slow charging stations take more time to charge a battery. A public CS is a conformist charging choice for EV drivers; particularly those who have not own chargers [4]. Also, the rapid growth of CSs can result in non-desired peaks of energy utilization, voltage deviations, overloading of the transformer and increased power loss, etc. Generally speaking, these impacts adversely affect the stability and power quality performance of power grids [5, 6]. Increasing the power generation could be the solution for the above-mentioned problems, but at a high investment cost. Instead, an EV can also deliver energy to the power grid by discharging the battery, which is also known as Vehicle to Grid (V2G) [7] technology.

An intelligent scheduling of EVs can reduce potential capital costs. Intelligent scheduling of EVs becomes a vibrant step towards the implementation of smart grid [8]. The importance of intelligent scheduling is charging the EV when the demand is low and as well as benefit the customer. In [9], the EV charging is optimized during the low-cost off-peak period. The proposed scheme achieves 28% of energy saving through optimizing the

✉ George Fernandez Savari
George.electrix@gmail.com

Vijayakumar Krishnasamy
kvijay_srm@rediffmail.com

Vidyasagar Sugavanam
mailsvs@gmail.com

Kalyanasundaram Vakesan
kalyan.srm@gmail.com

[1] Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Kattankulathur 603203, India

EV charging. In [10], a charging control algorithm is proposed to schedule the charging for large number of EVs. It allows the Plug-in-Hybrid EV (PHEV) to optimize the EV charging activities based on a price signal at the time of charging. A smart charging control strategy for residential PHEVs to minimize the peak load was presented in [11, 12]. In general, EV customers are willing to charge the battery during low-off peak electricity price at night. Moreover, 90% of EVs is parked at home ideal at night times only. Zouet al. in [13] proposed a centralized EV charging approach by considering the valley-filling effect of the supply side. The proposed scheme minimizes the charging cost of the users. The main idea of the centralized control is to use the centralized communications to gather information from all EVs considering the grid constraints. Yang et al. in [14] developed a centralized charging method for various optimization goals including cost minimization, and power loss minimization. Similarly, by considering the dynamics of EVs charging systems, the works in [15–17] developed strategies to minimize the charging cost. Cao et al. [18], a smart technique to manage EV demands is proposed based on the Time-Of-Use (TOU) price in a power market. It is observed from the results that the optimized charging model is beneficial in minimizing the price. Also, it is possible to avoid 70% of the necessary investment cost with a systematic charging as presented by Lopes et al. in [19] as the systematic charging can permit the vehicles to reach their maximum penetration level without violating the constraints. Electric power consumption in buildings can be increased by EVs charging. It can make double the average household power consumption. Passenger vehicles stand idle in the home or in the office, thusthe evening peak load coincides with the EVs charging at home particularly at the evening and night [20, 21]. The EV charging flexibility is limited by various factors such as, the available charging power ratings, battery SOC, and battery limitations. Besides, the integration with renewable system,the coordination of EV charging has been investigated on numerous scales in the existing studies [22]. The focus of EV charging optimization on the residential buildings mainly focuses on the technical (e.g., a peak shaving objective) and/or economic objectives [23]. Studies [24, 25] coordinate the EV charging in the buildings by minimizing the cost. The cost of charging infrastructure is an important parameter for widespread of charging coordination [26]. The cost of EVSEs are comparatively high. The total cost for a level-1 charging infrastructure has been reported as approximately \$400 - \$900. For a level-2 EVSE cost is more than \$75,000 and level-3 EVSEcost is higher than level-2 Electric Vehicle Supply Equipment (EVSEs) depending on the quality [27, 28].

In the literatures, a number of charging scheduling schemes have been proposed. However,

- Many of the research articles it is assumed that the charging happens at the day time. In general, EV customers may be more willing to charge the battery during low-off peak electricity price.
- These EV charging coordination strategies require the knowledge (e.g., the EV behaviour the power consumption of the buildings or private EV owners, and electricity cost) during a particular optimization and also it requires an extensive charging infrastructure which is not economical.
- Installing an individual EVSE for each vehiclein large size apartments is not possible due to economic and space constraint. Thus the existing schemes may not be suitable for the static EV charging in apartments.
- A smart priority-based static charging scheme is not developed. At present, most of the researchers still emphasize on the dynamic charging schemes which do not accommodate the pragmatic situation of vehicles being sheltered after work.
- Also, most of the research articles stress on a single charging option wherein multiple charging options (i.e, combination of slow, medium and fast charging options) can be more effective and advantageous.
- Furthermore, much attention should be paid to study the impacts of microgrid on the vehicle's market.

As mentioned in the literatures, the EVs are being sheltered at home after work for over 90% of the time. So, this time can be effectively utilized to charge the EV battery. Another, problem identified from the literature articles is the availability of charging infrastructure and the cost associated with the charging premises (i.e, apartment car parking). Instead of buying individual EVSEs for all EVs, investing in a few numbers of common EVSEs would be cost beneficial. An operator can take the responsibility to charge the EVs. It should be noted that, the available EVSEs must be utilized effectively to minimize the charging time and cost. In order to overcome the problems stated above, a static charging scheme is proposed. This scheme will optimize the charging pattern (i.e.,allot different EVs to different chargers located in a CS) to reduce the charging cost and time.

The main contribution of this work is outlined as follows:

1. A smart priority-based static charging scheme is developed. Though the dynamic scenario may be more realistic in smart grids, the solutions to the static problems can be used to show potential cost savings and time minimization that can be brought by regulating the charging pattern. Moreover, they can serve as a benchmark for performance evaluation. The advantage of static charging scheme is, the parameters such as number of vehicles, available SOC in the battery, required power to charge the battery will be known before the EV charging starts.

2. A multiple charging option (fast, medium and slow) is considered for EV charging.
3. A mapping of EVs to charging points by applying scheduling algorithms is done. By doing so, EV's are charged faster, which will enhance the performance of the CS. Arrival Time-Based Priority (ATP) and SOC-Based Priority (SBP) algorithms are used for EV's scheduling and the results are compared with particle swarm optimization (PSO). Each algorithm has its own properties in terms of scheduling, but the main task is to properly allocate the charging points to each EV for a fast charging process with a minimized price in the shortest possible time. Therefore, the formulation of the EV's scheduling problem has been done.
4. A microgrid with the renewable resources scenario is considered for reducing the consumption of energy from the grid. A competitive load reallocation is done with and without the microgrid to enhance for the customers benefits by reducing the electricity cost.

This paper is categorized into 6 sections. Section 1 gives an overview of the EV charging systems with the literature review. Section 2 deals with the problem formulation and its framework. Section 3 presents the microgrid scenario used in this research in details. Section 4 discusses the proposed method and algorithm for the optimization problem. The detailed results analysis of the cases are presented in Section 5, where Case 1 gives the results of ATP algorithm, Case 2 explains the results of SBP algorithm, and the PSO results are explained in Case 3. Further, results of load reallocation are presented in Case 4. The impact of microgrid for cost reduction is explained in Case 5. Finally, the conclusions and a preview of future works are presented in Section 6.

2 Objective function framework

Within the assumed system architecture, we propose a framework consisting of twenty vehicles with various capacities and the common CS is located at charging premises (i.e, apartment car parking). The CS is equipped with five chargers; a pair of a fast charger (FC), a pair of a medium charger (MC) and a single slow charger (SC). The maximum power of the fast charging mode is 50 kW (125 A) with the maximum charging time up to 24-minutes charging duration of a 20 kWh battery [29]. The EVs will charge based on the schedule made by the operator. The objective is to minimize the charging cost and time by optimizing the charging pattern. It can be calculated as follow as:

The power required to charge theEV battery is determined in [30] is given in (1):

$$\begin{aligned} & Required\ Power \\ & = Capacity\ of\ the\ battery - Power\ left\ at\ the\ battery \end{aligned} \quad (1)$$

The time required to charge the EV battery is depend on the rated output power of the charger. So, the charging time can be calculated as given in (2)

$$R = \frac{Capacity\ of\ the\ battery - Power\ left\ at\ the\ battery}{Rated\ output\ of\ the\ charger} \quad (2)$$

where, R is the time required for charging in hours. By using (2) the charging cost of an individual EV can be calculated. It is expressed in (3).

$$Charging\ Cost\ of\ a\ vehicle = Power\ required * Ecost(t) \quad (3)$$

where, Ecost (t) is the energy cost at a particular hour. The charging cost of all the vehicles can be calculated by (4). The total charging cost $C(t)$ in Euro cent (€ct) for all vehicles at each time period (t) can be obtained as follows:

$$C(t) = \sum_{t=1}^{T} \left(\sum_{i=1}^{NF} Ci(t)R_i + \sum_{j=1}^{NM} Cj(t)R_j + \sum_{k=1}^{NS} Ck(t)R_k \right) \quad (4)$$

where, NF is the number of FCs, NM is the number of MCs, NS is the number of SCs, and T is the charging time to charge all the EVs in hours. T can be obtained by using (5):

$$T = \sum_{n=1}^{N} \left(\sum_{i=1}^{NF} \left(\frac{V_c^n - SoC(n)}{P_{ifc}} \right) + \sum_{j=1}^{NM} \left(\frac{V_c^n - SoC(n)}{P_{jmc}} \right) + \sum_{k=1}^{NS} \left(\frac{V_c^n - SoC(n)}{P_{ksc}} \right) \right) \quad (5)$$

where, N is the total number of vehicles, V_C^n is the rated capacity of a vehicle in kilowatt, SOC(n) is the SOC remaining in the nth vehicle, P_{ifc}, P_{jmc}, P_{ksc} are the output powers in kilowatts of the FC, MC and SC, respectively.

2.1 Constraints

- The SOC of the vehicle should be greater than the minimum value specified by the manufacturer at any time period, thus it is expressed in (6):

$$SOC_{min} \le SOC(t) \quad (6)$$

- While leaving the CS, the SOC of the nth vehicle ($SOC_n^{leaving}$) should be greater than or equal the requested

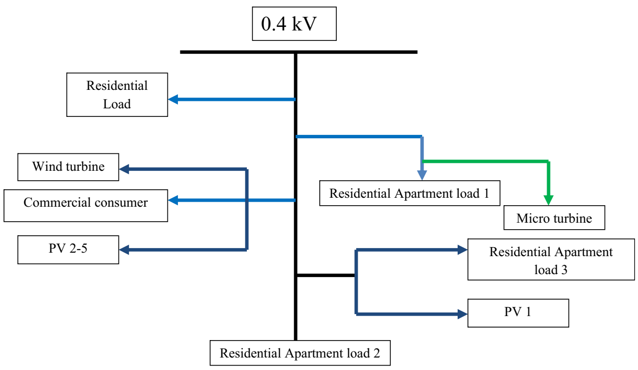


Fig. 1 Structure of the considered microgrid

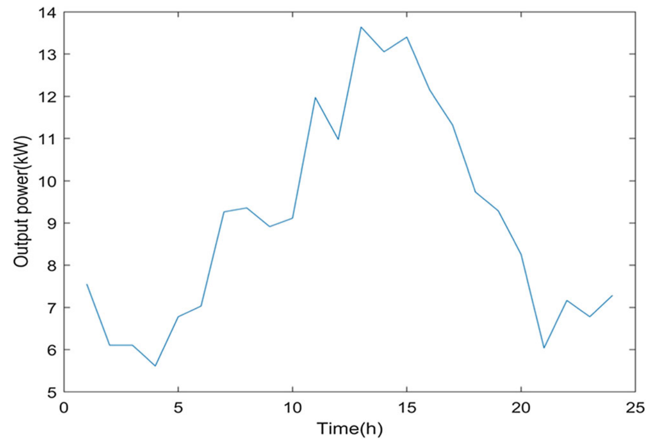


Fig. 2 Hourly microgrid output power

SOC ($SOC_n^{requested}$), but should not be more than the maximum SOC (SOC_n^{max}) which can be represented by (7).

$$SOC_n^{requested} \leq SOC_n^{leaving} \leq SOC_n^{max} \tag{7}$$

- When the microgrid scenario is taken into account, its output power (P_{mg}) should be limited between the minimum and maximum power limits, thus it can be expressed as (8):

$$P_{mg}^{min} \leq P_{mg} \leq P_{mg}^{max} \tag{8}$$

2.2 Assumptions

- The voltage of the battery is assumed to be constant.
- The battery will be at one mode at each time period, either charging or discharging.

3 Microgrid data

One of the important keys to reducing the global CO_2 production and adverse technical impacts on power grids is to encourage EV charging using renewable energy sources [29–31]. Microgrid in a LV network can determine its roles depend on the energy requirement of the network [32]. In this work, a micro turbine, wind turbine and five photovoltaic (PV) sources are considered in the microgrid as shown in Fig. 1. The maximum and minimum power generation limits of the distributed generation (DG) units are given in Table 1.

The hourly output power from all sources in the microgrid is illustrated in Fig. 2 and the same is represented as numerical in Appendix 1.1. The bid coefficients assumed from the renewable sources are given in Table 2. The 24 hour microgrid power price is calculated from the bid coefficients of the renewable sources. It can be seen that the microgrid power price is cheaper than the grid power price.

The 24 hour microgrid price is shown in Fig. 3. The renewable sources data are taken from [33, 34].

The hourly grid cost is taken on a typical day from Epex Spot [35] and is shown in Fig. 4. The battery capacities of all the 20 vehicles taken from [36] with the available SOCs. It is given in Table 3.

Table 1 Maximum and minimum power generation limits of the DG sources

DG number	Type of DG	Minimum power limit (kW)	Maximum power limit (kW)
1	Micro turbine	6	30
2	Wind turbine	3	15
3	PV1	0	3
4	PV2	0	2.5
5	PV3	0	2.5
6	PV4	0	2.5
7	PV5	0	2.5

4 The proposed algorithm

According to the EV's arrival time at the CS, number of the available chargers and the charging rate limits, the CS operator

Table 2 Bid coefficients of the renewable sources (€ct/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

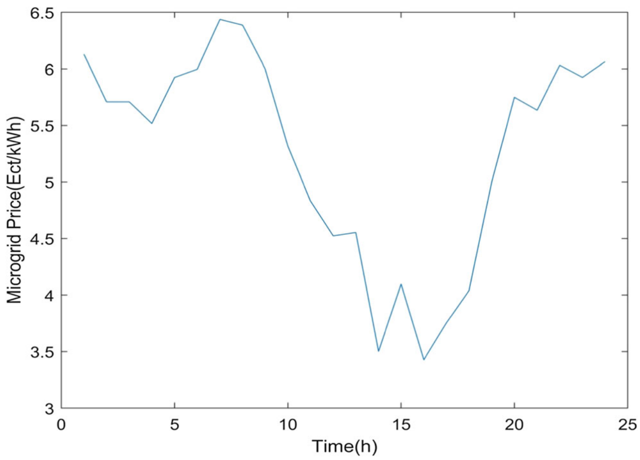


Fig. 3 Hourly microgrid power price (€ct/kWh)

needs to decide which vehicle to be charged and at what time. ATP, SBP algorithms and the PSO are used to minimize charging time and total charging cost of the twenty vehicles.

4.1 Arrival Time-based Priority (ATP) algorithm

ATP algorithm allows the vehicles into service once they arrive and hence reduces the delay time and avoids the charger to be idle. ATP algorithm lineups all vehicles to charging points until all the charging points are engaged based on the arriving time of the vehicles. Thus, the selected vehicle is allotted to a point, which makes the charging process easy and fast. Once a vehicle is allotted, it updates the waiting time for the other vehicles. The same procedure will be repeated until all the vehicles are charged. The flowchart of the ATP-based charging schedule algorithm is given in Fig. 5.

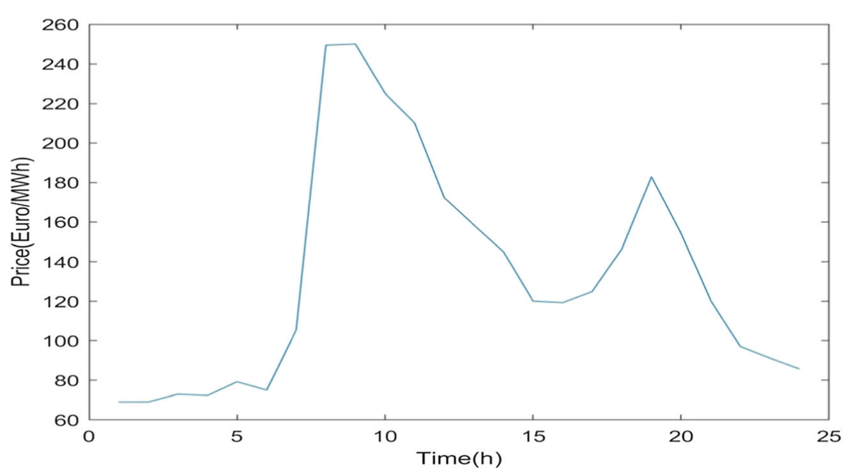
Table 3 Battery capacity of each vehicle with available SOC

Vehicle number	Capacity (kW)	Available SOC (%)
1	10	8
2	23	25
3	16.5	10
4	24	14
5	27	19
6	16	23
7	24	28
8	30	12
9	17.3	30
10	32	35
11	24	29
12	27	38
13	16	40
14	17.6	33
15	23	30
16	16.5	27
17	30	16
18	17.3	18
19	32	34
20	16.5	25

4.2 SOC-Based Priority (SBP) algorithm

This algorithm is based on the charging of EVs with the least possible charging time and cost. Unlike the ATP algorithm, SBP algorithm takes the actual charging time into consideration. It starts by assigning all EVs to the charging points in order to complete the charging at the earliest in ascending order. The same process is repeated until all the EVs are charged. The flowchart of the SBP-based charging schedule algorithm is given in Fig. 6.

Fig. 4 Grid price for a typical day from [34]



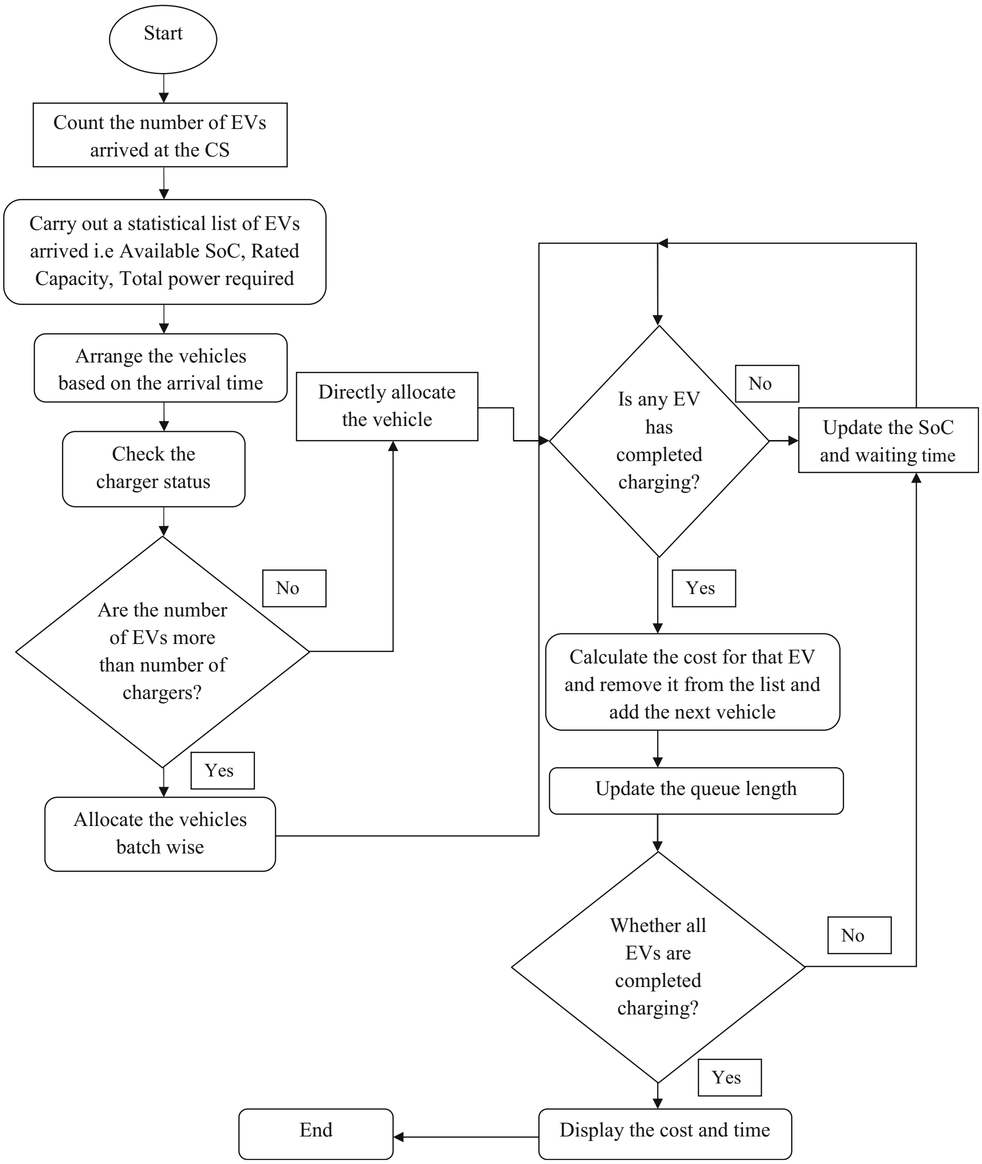


Fig. 5 Flowchart of ATP-based charging schedule algorithm

4.3 Particle Swarm Optimization (PSO)

In 1995, James Kennedy and Russell Eberhart developed an intelligent iterative swarm optimization algorithm that is inspired by the swarming behavior of fish and birds, so-called Particle Swarm Optimization (PSO) technique [37]. It conducts a generic way on how a swarm searches for food within a search space. It has gained a reputation in real-world engineering applications due to its simplicity and high efficiency. Briefly, a particle i represents a candidate in a swarm, where Ns is the swarm size. Each particle moves in the search space (modifying position) with an adaptable velocity that changes according to the individual and its neighbor's experience. Hence, based on these values, local best values are obtained. Further, out of them (by any particle in the population), the global best value is achieved [38].

Each particle can be represented as an object with some characteristics. Mainly, four symbols are assigned for these characteristics: X_i as the existing position of the ith element, V_i as the velocity of the ith element with a distance in a unit time, $Pbest$ as the individual best position of the ith element (local best) and $Gbest$as the global best value obtained. Mathematically, the velocity and position of each particle are updated respectively, as follows:

$$V_{i,j}^{k+1} = \left(\omega \times V_{i,j}^{k}\right) + c_1\left(rand_1 \times \left(Pbest_{i,j} - X_{i,j}^{k}\right)\right) + c_2\left(rand_2 \times \left(Gbest_{i,j} - X_{i,j}^{k}\right)\right) \quad (9)$$

Then, $X_{i,j}^{k+1}$ can be calculated from (10)

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \quad (10)$$

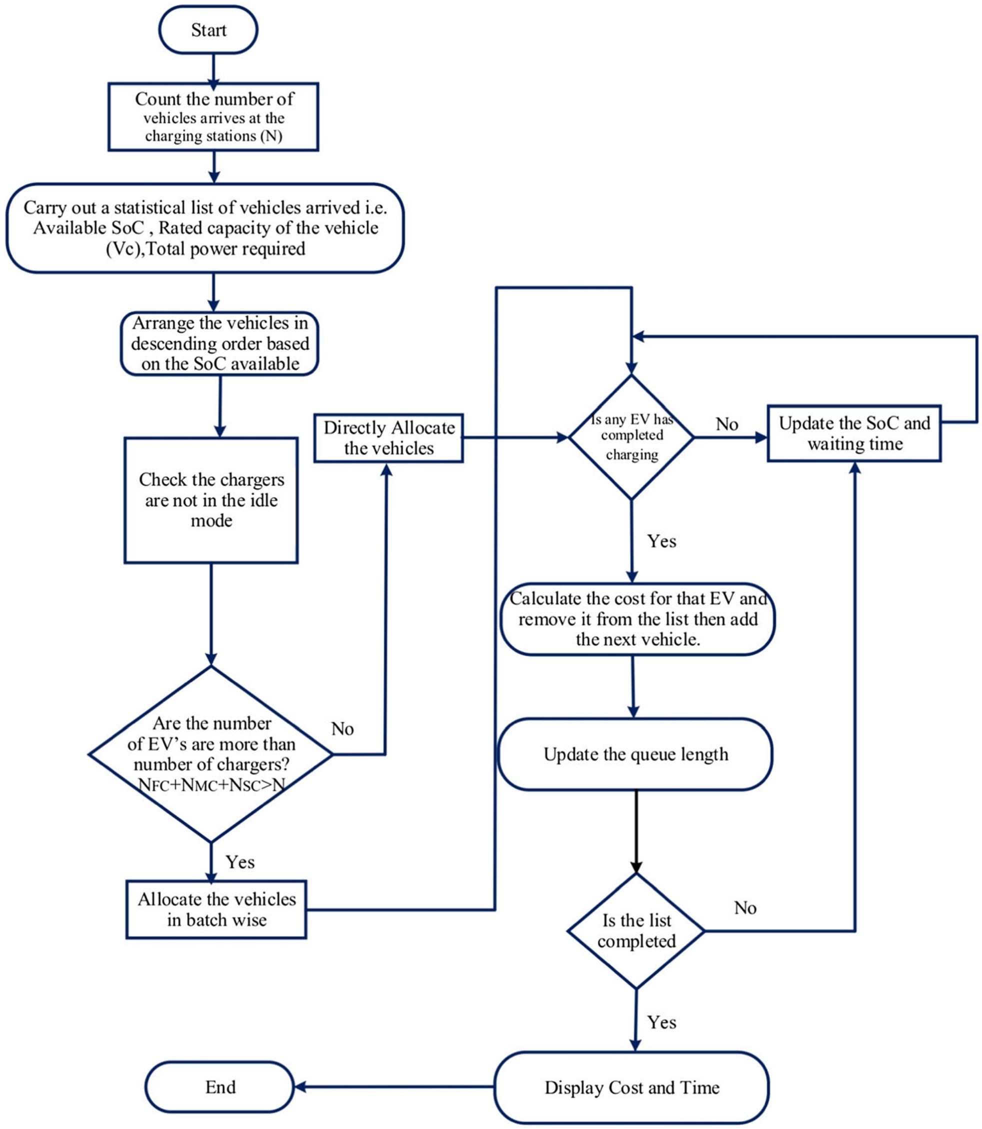


Fig. 6 Flowchart of SBP-based charging schedule algorithm

where $V_i(k)$ and $X_i(k)$ are the velocity and position of the ith particle at iteration k. They are given in the dimensional space j as follows in (11) and (12):

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

$$X_{i,j} = \left(X_{i,1'}, X_{i,2'}, \ldots.X_{i,j'}\right) \tag{12}$$

$rand_1$ and $rand_2$ are random numbers regenerated every velocity update and range between 0 and 1, c_1 and c_2 are the cognitive and social acceleration coefficients that tradeoff the impact of the local and global best solutions' on the particle's velocity. They are set to 2 in this work. The inertia weight ω that manages the sway of the velocity is linearly decreased from ω_{max} to ω_{min} with the iteration as given in (13). Finally, the fitness value will be calculated and will be further as given in (14).

$$\omega = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{k_{\max}}\right)k \tag{13}$$

$$Gbest_{i,j}(k+1) = \begin{cases} Gbest_{i,j}(k) & if\ f\left(Pbest_{i,j}(k+1)\right) \geq f\left(Gbest_{i,j}(k)\right. \\ Pbest_{i,j}(k) & if\ f\left(Pbest_{i,j}(k+1)\right) < f\left(Gbest_{i,j}(k)\right. \end{cases} \tag{14}$$

Algorithmically, the problem is addressed by the PSO algorithm. The number of variables (chargers) is five, the population size is 100 and the number of iterations is 100. The flowchart of the PSO-based charging schedule algorithm is given in Fig. 7.

At each iteration, the charging strategy is updated as follows:

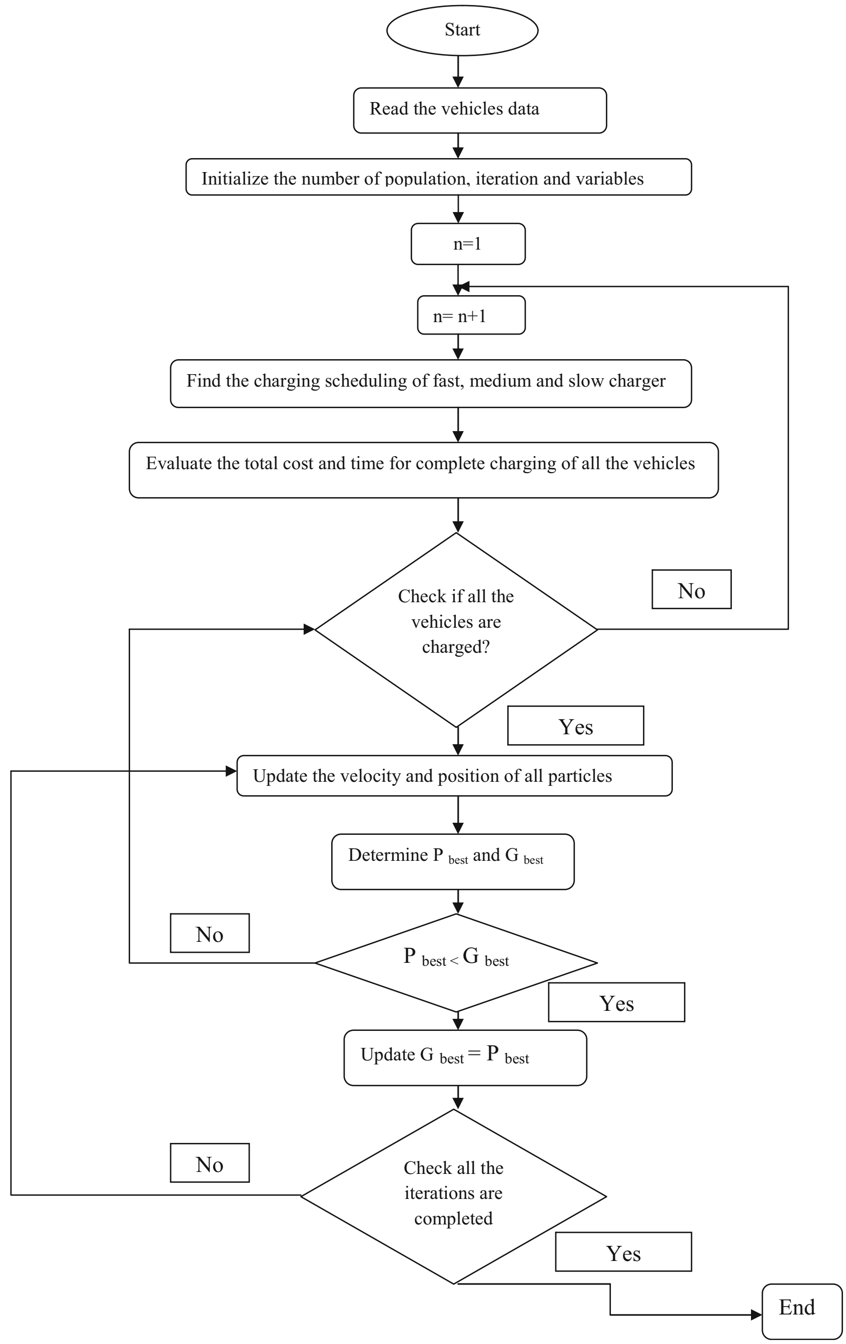


Fig. 7 Flowchart of PSO-based charging schedule algorithm

Step 1: Create a random population.
Step 2: Assign the number of iteration, variables, velocity, and position.
Step 3: Schedule the charging and find the fitness value of all population.
Step 4: Determine *Pbest* and *Gbest* from the initial population.
Step 5: Update the velocity and the particle position based on equations (7) and (8).
Step 6: Find the fitness value of the updated velocity and position.
Step 7: If the new *Pbest* is better than the previous *Gbest* then go to **Step 9**.
Step 8: In case the *Pbest* is not superior to the earlier *Gbest*, keep *Gbest* as it is.
Step 9: Update the global best.
Step 10: Repeat the procedure until the tolerance limit is reached or the maximum number of iterations is completed.

Table 4 EVs schedule using the ATP algorithm: Case 1

Vehicle Number	Available SOC (%)	Power consumed (kW)	Time (min)	Type of charger	Cost (€ct)
1	8	16.192	32.38	FC1	128.20
2	25	17.250	34.5	FC2	136.58
3	10	14.850	44.55	MC1	117.58
4	14	20.640	61.92	MC2	168.22
5	19	21.870	114.10	SC	171.79
6	23	12.320	24.64	FC1	98.54
7	28	17.280	34.56	FC2	134.91
8	12	26.400	79.2	MC1	197.56
9	30	12.110	24.22	FC1	91.40
10	35	20.800	62.4	MC2	155.55
11	29	17.040	34.08	FC2	128.10
12	38	16.740	33.48	FC1	127.48
13	40	9.6000	19.2	FC2	71.64
14	33	11.792	61.52	SC	82.54
15	30	16.1	32.2	FC1	117.49
16	27	12.045	24.09	FC2	87.03
17	16	25.2	75.6	MC1	182.06
18	18	14.18	28.36	MC2	97.30
19	34	21.12	42.24	FC2	151.26
20	25	12.375	24.75	FC1	86.45

The objective of the PSO is to minimise the charging cost and time together.

5 Results and discussion

The study is carried out in five cases. Case 1 gives the results of ATP algorithm, Case 2 gives the results of SBP algorithm, the PSO results are explained in Case 3 and the results of load reallocation is presented in Case 4. Further, results of the microgrid scenario are presented in Case 5.

5.1 Optimal EVs scheduling using ATP algorithm: Case 1

Charging all the vehicles without scheduling is considered as arrival time-based priority method. When the management strategy is not performed, the total cost reached 2531.371 €ct, and the average time to complete the charging is 3 hours. The total energy consumed by all the vehicles is 335.91 kW. The results of vehicle allocation using ATP algorithm are given in Table 4. Result of the combination of the chargers for charging the EVs and the vehicles number is given in Table 5.

As noted from these tables, the fast chargers consume 180 kW to charge 12 vehicles which represent 60% of the total number of vehicles considered in this study. Six vehicles are charged with the medium chargers that consume 66.4 kW and 55.6 kW respectively. The slow charger charged two vehicles only and consumed about 33.6 kW.

5.2 Optimal EVs scheduling using SBP algorithm: Case 2

SBP algorithm schedules the vehicles based on the priorities to vehicles demanding less charging time. Based on number of customer intake, performance of CS will increase compared to the ATP algorithm. The total energy consumed by all vehicles is 335.91 kW. The vehicle allocation using SBP algorithm is given in Table 6. Here, both FCs consume 161.9 kW to charge 12 vehicles. Eight vehicles are charged with the medium chargers that consume 144.5 kW. The slow charger charged two vehicles only and consumed about 29.36 kW.

The SBP completes the charging of the 20 vehicles in an average time of 3.03 hours and with a cost of 2526.9 €ct. Table 7 provides the vehicles assigned to each charger by the SBP algorithm. This algorithm results in a cost reduction of 4.4 €ct compared to the ATP algorithm.

5.3 Optimal EVs scheduling using PSO algorithm: Case 3

The optimal scheduling is done using PSO algorithm and it is given in Table 8. As noted from this table, there is a significant

Table 5 Results of the chargers combination and their connected vehicles using the ATP Algorithm

Vehicles charged with FC1	Vehicles charged with FC2	Vehicles charged with MC1	Vehicles charged with MC2	Vehicles charged with SC
1	2	3	4	5
6	7	8	10	14
9	11	17	18	–
12	13	–	–	–
15	16	–	–	–
20	19	–	–	–

Table 6 EVs schedule using the SBP algorithm: Case 2

Vehicle Number	Available SOC (%)	Power consumed (kW)	Time (min)	Type of charger	Cost (€ct)
1	8	16.192	32.38	FC1	128.2
2	25	17.250	34.5	FC1	136.5
3	10	14.850	44.55	MC1	117.5
4	14	20.640	79.92	MC2	154.7
5	19	21.870	43.74	FC2	158.0
6	23	12.320	64.28	SC	97.2
7	28	17.280	51.84	MC1	128.4
8	12	26.400	79.2	MC2	183.8
9	30	12.110	36.33	MC2	95.40
10	35	20.800	41.6	FC2	154.9
11	29	17.040	88.90	SC	126.0
12	38	16.740	33.48	FC2	127.1
13	40	9.6000	19.2	FC1	71.96
14	33	11.792	23.58	FC2	93.36
15	30	16.1	48.3	MC2	124.0
16	27	12.045	36.13	MC1	95.37
17	16	25.2	75.6	MC1	176.2
18	18	14.18	28.36	FC2	112.3
19	34	21.12	42.24	FC1	158.3
20	25	12.375	24.75	FC1	86.9

Table 8 EVs schedule using the PSO algorithm: Case 3

Vehicle Number	Available SOC (%)	Power consumed (kW)	Time (min)	Type of charger	Cost (€ct)
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	SC	95.1423
17	16	25.2	50.4	FC1	183.3590
18	18	14.18	73.98	SC	105.4756
19	34	21.12	42.24	FC1	148.8069
20	25	12.375	24.75	FC2	89.4589

reduction in cost and time compared to ATP and SBP algorithms. PSO completes the charging process in an average time of 2.8 h and with a cost of 2520.7 €ct. The total energy consumed by all vehicles is 335.91 kW. Table 9 shows the vehicles scheduled for each charger. Compared to the previous cases, there is a cost reduction of 10.6 €ct compared to Case 1 and 6.2 €ct compared to Case 2.

In addition, the average time taken by each charger and their costs in the three cases are given in Table 10. It is obvious that the PSO-based scheduling algorithm takes the lowest time with the minimum charging cost for charging the 20 vehicles compared to the other algorithms. Based on these, it is found that the proposed PSO algorithm shows better performance compared to the other algorithms.

5.4 Load reallocation: Case 4

The charging costs can be significantly reduced using appropriate load reallocation (load shifting) strategy that involves shifting the energy consumption to another time period. Hence, load reallocation is considered in Case 4 in the proposed EVs charging schedule to investigate the estimated cost reduction when the energy cost is high. The optimal allocation of vehicles to the various sockets is analyzed to meet the overall demand (335.9 kW). Also, considering the operating period (hour 1 to 6) of the CS, it is observed that the price at hours 1, 2, 3 and 6 is higher than the price at hours 4 and 5. So, starting the charging process from hour 1 to hour 3.09 in Case 1 will reduce the charging cost from 649.196 €ct to 600.9 €ct. Consequentially, the charging cost of the vehicles charged by the sockets FC2, MC1, MC2 and SC will be reduced from 709.2145 €ct to 662.708 €ct, 497.384 €ct to 467.779 €ct, 421.24 €ct to 389.1 €ct and 254.337 €ct to 235.856 €ct, respectively, and the charging process will be completed in hour 5.

Among all these techniques, the maximum charging time is taken by FC1 in the PSO algorithm which is 4.127 hour. In this case, the charging process has to be started at hour 2.53 and the vehicles will complete their charging at hour 6. To

Table 7 Results of the chargers combination and their connected vehicles using the SBP Algorithm

Vehicles charged with FC1	Vehicles charged with FC2	Vehicles charged with MC1	Vehicles charged with MC2	Vehicles charged with SC
13	14	16	9	6
20	18	3	15	11
1	12	7	4	–
2	10	17	8	–
19	5	–	–	–

Table 9 Results of the chargers combination and their connected vehicles using the PSO Algorithm

Vehicles charged with FC1	Vehicles charged with FC2	Vehicles charged with MC1	Vehicles charged with MC2	Vehicles charged with SC
11	10	4	1	16
8	3	7	6	18
9	12	14	13	–
17	2	–	–	–
19	20	–	–	–
5	15	–	–	–

sum up, using load reallocation in the ATP algorithm will result in a cost reduction by 175 €ct. When the reallocation is employed in the SBP algorithm, the charging cost is reduced by 169.5 €ct and using the PSO algorithm, the charging cost is reduced by 159.2 €ct but with the advantage of less time of charging. A cost comparison of the three algorithms before and after load shifting is given in Fig. 8.

5.5 Microgrid (MG) scenario: Case 5

Without considering loads reallocation in the system, the actual charging cost is 2531.3, 2526.3 and 2520.7 €ct for the ATP, SBP, and PSO algorithms respectively. However, as renewable energy is less costly than the grid, it can be utilized for further cost reduction. Using the microgrid system illustrated in Fig. 1 with the DG units connected, the cost is further reduced in all the three algorithms by 8.1%, 7.2% and 8.4% respectively. This validates that renewable energy resources integration increases the possibility of purchasing additional power from the microgrid as an alternative when the grid cost is high. Table 11 presents the charging costs in the three algorithms with and without considering the MG scenario. It should be noted that the charging time is the same for all the three cases.

6 Conclusion and future work

EVs have great potential of becoming the future of the transportation industry while saving this planet from the forthcoming misfortunes of global warming. They are a real alternative to conventional vehicles that depend directly on the diminishing fossil fuel reserves. In this work, an optimal charging scheduling of EVs is done using three algorithms (i) scheduling based on arrival time-based priority (first come, first serve basis) (ii) scheduling based on charging time (the vehicle which takes shorter charging time is charged firstly) and (iii) PSO algorithm to provide the optimal scheduling which optimizes both the charging cost and time. Also, the same analysis is extended by considering the load reallocation and microgrid scenarios. A more detailed analysis of the impact of a microgrid in the EV charging is derived from the results. The PSO-based EVs scheduling resulted in a reduction in the cost of 0.42% and 0.23% compared to ATP and SBP based approaches respectively. In addition, a microgrid scenario is further considered for reducing the consumption of energy when the grid cost is high. This scenario resulted in a cost reduction of 8.4%, 7.2% and 8.1% for the PSO, ATP and SBP based EVs scheduling problem respectively. Also, the EV charging is shifted to the time where electricity price is low. In such a condition, the cost is further reduced by 6.31% for PSO-based EVs charging algorithm. Based on the results for the different test cases considered, it is found that the proposed scheme has better results compared to the other schemes and the total charging cost and time are reduced significantly.

This research work solved the issue for static charging scenarios. The dynamic scenarios are beyond the framework of the study, and will be included in future studies. However, the solutions to the static problems presented in this work can be used to

Table 10 Comparison of costs and time taken of chargers in Cases 1, 2 and 3

Algorithm	Average time (h)	Total cost (€ct)
ATP	3.0	2531.3
SBP	3.0	2526.3
PSO	2.8	2520.7

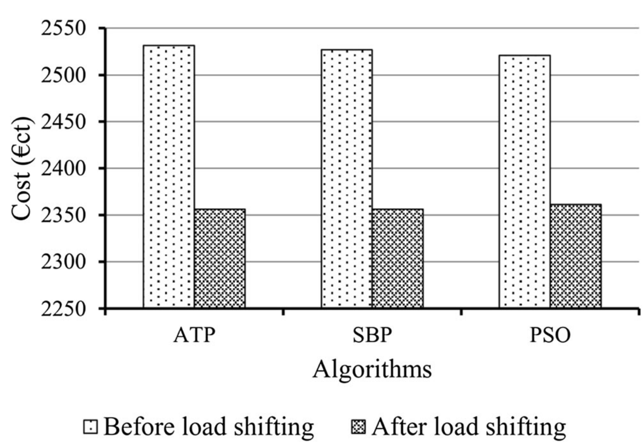


Fig. 8 Cost comparison of the three algorithms before and after load shifting: Case 4

Table 11 Costs with and without microgrid

Algorithm	Without MG		With MG		Saving in cost (%)
	Cost (€ct)	Time (h)	Cost (€ct)	Time (h)	
ATP	2531.3	3	2325.9	3	8.1
SBP	2526.3	3	2342.7	3	7.2
PSO	2520.7	2.8	2308.4	2.8	8.4

show the potential cost savings and charging time minimization that can be brought by regulating the charging pattern. Moreover, they can serve as a benchmark for performance evaluation.

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Appendix

Hourly output power of the various DG sources

Table 12 Hourly output power of the various DG sources

Time (h)	Wind	MT	PV1	PV2	PV3	PV4	PV5
1	5.46	2.099	0	0	0	0	0
2	4.005	2.099	0	0	0	0	0
3	4.005	2.099	0	0	0	0	0
4	3.51	2.099	0	0	0	0	0
5	4.68	2.099	0	0	0	0	0
6	4.935	2.099	0	0	0	0	0
7	7.14	2.099	0.006	0.005	0.005	0.005	0.005
8	7.155	2.099	0.024	0.02	0.02	0.02	0.02
9	6.36	2.099	0.105	0.0875	0.0875	0.0875	0.0875
10	5.715	2.099	0.3	0.25	0.25	0.25	0.25
11	6.885	2.099	0.69	0.575	0.575	0.575	0.575
12	5.85	2.099	0.699	0.5825	0.5825	0.5825	0.5825
13	7.41	2.099	0.954	0.795	0.795	0.795	0.795
14	5.325	2.099	1.299	1.0825	1.0825	1.0825	1.0825
15	6.495	2.099	1.11	0.925	0.925	0.925	0.925
16	4.815	2.099	1.209	1.0075	1.0075	1.0075	1.0075
17	4.935	2.099	0.99	0.825	0.825	0.825	0.825
18	4.545	2.099	0.714	0.595	0.595	0.595	0.595
19	5.46	2.099	0.399	0.3325	0.3325	0.3325	0.3325
20	5.595	2.099	0.129	0.1075	0.1075	0.1075	0.1075
21	3.9	2.099	0.009	0.0075	0.0075	0.0075	0.0075
22	5.07	2.099	0	0	0	0	0
23	4.68	2.099	0	0	0	0	0
24	5.19	2.099	0	0	0	0	0

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