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Efficient Plug-in Electric Vehicles Charging Scheduling to Increase Parking Lot Utilization

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Abstract: - The charging of Plug-in Electric Vehicles (PEVs) that is not properly coordinated leads to a significant decrease in voltage levels across the power grid, which affects the overall system performance, resulting in higher operational costs for both the grid and PEV users. An optimal charging schedule of PEVs is designed to maximize utilization in a car park. A fuzzy inference system is implemented to model the energy requirements of the PEVs. Particle Swarm Optimization (PSO) is then utilized to devise the optimal charging schedule for the PEVs within the car park. The charging and discharging schedule are based on maximizing PEV penetration, utilizing a combination of fuzzy logic and PSO algorithms, in the different laterals of a 33-bus distribution system. The devised strategy offers several advantages, including minimizing the total daily cost for the parking operator, reducing the network's peak load, maintaining voltage stability, and accurately calculating associated costs.

Keywords: plug in electric vehicles, optimal charging schedule, particle swarm optimization, fuzzy logic, peak to average ratio.

I. INTRODUCTION

Due to global warming and other rising environmental concerns, many nations are transitioning from conventional fuel-based transportation systems to more eco-friendly alternatives like plug-in electric vehicles (PEVs). These zero-emission vehicles serve as viable replacements for internal combustion engines. In recent years, significant advancements have been made in the design and performance of electric vehicles (EVs). EVs are gaining widespread attention for their lower emissions and improved energy efficiency, driven by the shift in global energy structures and technological progress in the automotive industry [1].

Electric Vehicle Charging Stations (EVCS) are essential infrastructure for electric vehicles (EVs), providing points for both charging and discharging. Charging stations deliver the electricity required to power EV batteries, ensuring vehicles remain functional. Discharging stations, in contrast, allow EVs to send stored energy back to the grid, a process known as Vehicle-to-Grid (V2G). This two-way energy exchange enables EVs to function as mobile energy storage units, aiding in grid stabilization during high demand and enhancing energy efficiency. Optimizing the location and scheduling of EVCS is crucial for supporting the expanding EV market while reducing the impact on the power grid. PEV owners may opt to discharge their vehicles when electricity prices are high [2].

Fuzzy logic is a useful decision-making tool for dealing with uncertain or unclear information. When it comes to charging and discharging electric vehicles (EVs), fuzzy logic helps figure out how many hours are needed based on the vehicle's state of charge (SOC) and STD for charging or discharging times. Using a fuzzy inference system, it handles uncertain inputs, like SOC levels or STD changes in energy demand, to make the best decisions about charging and discharging durations[1]. The PEV charging set up assumes that the SOC of PEVs while leaving the parking lot is always more than the SOC of PEVs when arrived [3], [4].

After the fuzzy logic system determines the required number of hours for charging and discharging electric vehicles (EVs), Particle Swarm Optimization (PSO) is employed to select how many vehicles will be assigned for the charging and discharging lot. The PSO algorithm enhances this selection process by considering various factors, including the available charging capacity and constraints. By combining fuzzy logic with PSO, the system can effectively manage the charging and discharging process[5], ensuring the number of vehicles used for charging and discharging efficiently[6]. This integration allows for a balanced approach to energy demand and grid stability, helping to optimize the use of resources while minimizing the overloading on the charging station. this approach not only improves the overall efficiency of EV charging operations but also contributes to a more reliable and sustainable energy management system, accommodating the growing number of electric vehicles.

In [4], the effects of plug-in hybrid electric vehicles (PHEVs) on voltage variations and power losses in the distribution system are studied. Local grid problems may arise from uncoordinated charging, in which cars are charged instantly after plugging in or after a certain amount of time. The coordinated charging is proposed as a

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solution to reduce power losses and maximize the primary grid load factor. **S. Deilami et al**. [7] have studied a method for managing the charging of several PEVs simultaneously within a smart grid system termed real-time smart load management, or RT-SLM. The strains, performance deterioration, and overloads that can occur from unmanaged PEV charging are all addressed by the recommended solution.

Q. Kejun et al. [8] have studied a process for modelling and evaluating the load demand that EV battery charging causes in a distribution system. A methodology is developed to determine the EV battery charging load in a distribution system include domestic charging, uncontrolled public charging, uncontrolled domestic charging, and uncontrolled off-peak domestic charging. Using time-series data from lead-acid and lithium-ion batteries. **S. Shafiee et al.** [3] have presented a thorough model for analyzing how PHEVs affect home distribution systems. By doing this, the basic attributes of PHEVs, such as their battery capacity, state of charge (SOC), and energy usage during daily travels, are accurately estimated.

E. Sortomme et al. [9] have studied power system may be impacted by a rise in plug-in hybrid electric vehicles (PHEVs). One potential fix for these overloading, decreased efficiency, power quality, and voltage control in distribution system is coordinated PHEV charging. In the context of coordinated PHEV charging, the relationship between feeder losses, load factor, and load variance is studied. Three ideal charging algorithms that reduce the effects of PHEV charging on the linked distribution system are proposed. **W. Chenye et al.** [10] have studied then interactions among EVs help in providing frequency regulation service to the grid and designed a pricing methodology for doing so.

W. Kempton et al. [11] have studied many functions of virtual private networking (V2G) within current energy systems, highlighting how it can improve overall grid resilience, balance supply and demand, and lessen volatility from intermittent renewable sources. By serving as a distributed energy resource that absorbs excess generation during peak hours and supplies electricity during shortages, V2G integration can enable the more effective use of renewable energy. **T. Junand et al.** [5] have studied A random system based on fuzzy logic to precisely simulate the effect of PHEVs, taking into consideration the correlation between daily mileage, vehicle arrival and departure times. To integrate these driving patterns with vehicle data for load profile prediction, suggests the Load Profile Modelling Framework (LPMF).

M. Huber et al. [12] have studied the effect of integrating EV and designed a smart charging method using linear programming. **K. N. Kumar et al.** [13] have studied charging of EVs in building and developed smart energy storage (SES) in buildings. This platform can be used for leveling the intermittent outputs of renewable energy sources (RESs) and during periods of high electricity prices.

The uncoordinated charging of electric vehicles (EVs) leads to a significant decrease in voltage levels across the power grid, which affects the overall system performance and also effects the (Peak to Average Ratio) PAR and reduces the efficiency, resulting in higher operational costs for both the grid and EV users. When PEVs arrive at the parking lot, they provide their energy requirements and are assumed to stay in the parking lot for a period of 8 hours. The PEV owners may decide to charge or discharge their vehicles, or may choose to remain idle depending on what SOC they require by the time they leave the parking lot. This process of energy requirement determination is done using fuzzy inference system for initial SOC and STD. The parking operator then uses Particle Swarm Optimization (PSO) selects number of vehicles optimally, accommodating the PEVs that arrive within each hour. The operator performs this scheduling once every hour. PSO is used to determine the optimal charging schedule for parking facilities during different times of the day within the industrial and commercial laterals of the system. This scheduling results in reduced cost of operation of the parking lots and lower value of Peak to Average ratio.

II. Modelling Of Plug-In Electric Vehicles

PEV arrival driving patterns must be modelled in order to accurately calculate and efficiently manage total energy demand in a parking lot. Modelling of the Initial SOC, STD and the distance traveled each trip [14] form the major constituents. The percentage of electrical energy left in the battery of a PEV is referred to as its "state of charge" (SOC)[15]. The minimum SOC in this study is set at 20% in order to improve battery life. The distance travelled on the first journey and the driving range of the vehicle that is, its all-electric range (AER) determine the initial SOC upon arrival at the parking lot. The initial SOC for a PEV with a first trip distance of d and an AER of d_R is as follows:

Initial SOC is calculated as:

$$initial\ SOC = \begin{cases} 1-\left(\frac{d}{d_R}\right), 0 < d < 0.8d_R \\ 0.2, d \geq 0.8d_R \end{cases} \tag{1}$$

The SOC necessary for future journeys is a determining factor in estimating the SOC needed at departure time. On the other hand, calculating the overall distance to be driven before eventually pulling into your parking lot is a more feasible duty for any PEV driver. Therefore, the total mileage of all subsequent journeys made by a PEV can be considered the Subsequent Trip Distance (STD).

The below represents the energy needed by PEVs that travel a distance per day, larger than their AER:

$$SOC' = (STD/d_R) + 0.2 \quad (2)$$

$$SOC_{req} = \begin{cases} 1 - initialSOC, & SOC' > 1 \\ (SOC' - initialSOC), & initialSOC < SOC' < 1 \end{cases} \quad (3)$$

In Plug-in Electric Vehicles (PEVs), the required state of charge at the time of departure is indicated by SOC and the net state of charge needed by the PEV is denoted by SOC_{req}. The PEV owner's chosen state of charge at the time of departure affects this estimate. The energy need will increase in the event that the departure SOC is raised:

If the departure SOC is to decreased,

$$SOC' = (\mathrm{STD}/d_R) + 0.2 \quad (4)$$

$$SOC_{req} = SOC' - initialSOC \quad (5)$$

2.1 Problem Formulation using PSO

Particle Swarm Optimization (PSO) is a well-known optimization technique inspired by the social behavior observed in bird flocking and fish schooling. A swarm is made up of multiple "particles" (potential solutions) that navigate the problem space. Each particle represents a candidate solution to the optimization problem. Each particle has a position in the solution space and a velocity that determines its movement direction and speed. Particles update their positions based on their current velocity and the best positions they have discovered so far.

Objective is to minimize the Peak-to-Average Ratio (PAR) of the distribution system so that the load curve is flat enough. To minimize the PAR, this is the ratio of the maximum load (peak demand) to the average load over a period. High PAR indicates large spikes in demand that can stress the grid and necessitate costly infrastructure upgrades.

PSO optimizes the charging schedule to distribute the load more evenly over time, reducing peak demand while maintaining the same total energy consumption. By flattening the demand curve, the grid experiences less strain during peak periods, reducing the need for additional capacity and ensuring more consistent energy delivery. PAR is calculated by comparing the peak load to the average load. The PSO algorithm works to minimize peak loads by spreading charging sessions across low-demand periods.

In this optimization problem, the PSO algorithm operates under multiple constraints to ensure optimal performance:

The entire amount charged by the parking operator is divided into two categories: Charging cost ($COST_{charge}$), and the Discharging cost ($COST_{discharge}$).

$$COST_{charge} = N_c * \text{cost in kWH} \quad (6)$$

where N_c represents number of vehicles charging. The following equation determines the cost for discharge [16]

$$COST_{discharge} = N_{dc} * \text{cost in kWH} \quad (7)$$

where N_{dc} represents number of vehicles charging and cost in kWH represents cost calculated for charge or discharge the battery.

$$COST_{TOTAL} = COST_{charge} - COST_{discharge} \quad (8)$$

To prevent voltage instability, PSO ensures that the bus voltages V_{bus}, remain within a specified range:

$$V_{min} \le V_{bus} \le V_{max} \quad (9)$$

If a violation occurs, PSO adjusts the charging power to maintain voltages within acceptable limits.

The Peak-to-Average Ratio (PAR) is defined as:

$$PAR = \frac{Peak\ Load}{Average\ Load} \quad (10)$$

$$PAR = \left(\max_{t \in H} S_{total}^{t}\right) \Big/ \left(\frac{1}{T}\sum_{t=1}^{T} S_{total}^{t}\right) \quad (11)$$

PSO minimizes this value by smoothing the load profile over time, reducing peak demand and ensuring a more uniform load distribution.

$\max_{t \in H} S_{total}^{t}$ represents maximum load out of total load.

$\frac{1}{T}\sum_{t=1}^{T} S_{total}^{t}$ represents average of the total load on the system at particular duration.

2.2 PSO Algorithm Workflow

Initialization: A population of particles is initialized, each representing a possible charging schedule. Each particle has a position (charging time, energy consumption, etc.) and velocity.

Fitness Evaluation: For each particle, the cost, bus voltage stability, and PAR are evaluated. The particle's fitness is calculated based on the weighted sum of these objectives.

Update Positions and Velocities: Particles update their positions and velocities based on both their own best experience and the global best solution found by the swarm. This allows the particles to explore different schedules and converge on the optimal solution.

Constraint Handling: Voltage and PAR constraints are checked at each iteration, and if a particle violates any of these constraints, its position is adjusted to remain within feasible limits.

Convergence: The algorithm continues to iterate until the particles converge on an optimal charging schedule that minimizes cost, maintains stable bus voltages, and reduces PAR.

III. Efficient Charging Scheduling Using Fuzzy Logic And Pso

The IEEE 33 bus standard test distribution system is considered for the purpose of illustrating the effectiveness of the proposed scheduling strategy. Figure 1 represents the IEEE 33 radial distribution system [18, 19]. It consists of 33 buses; 32 feeder sections (industrial and commercial) [8] feeders and total load of 3715 kW and 2300 kVAR and the system operates at 11 kV.

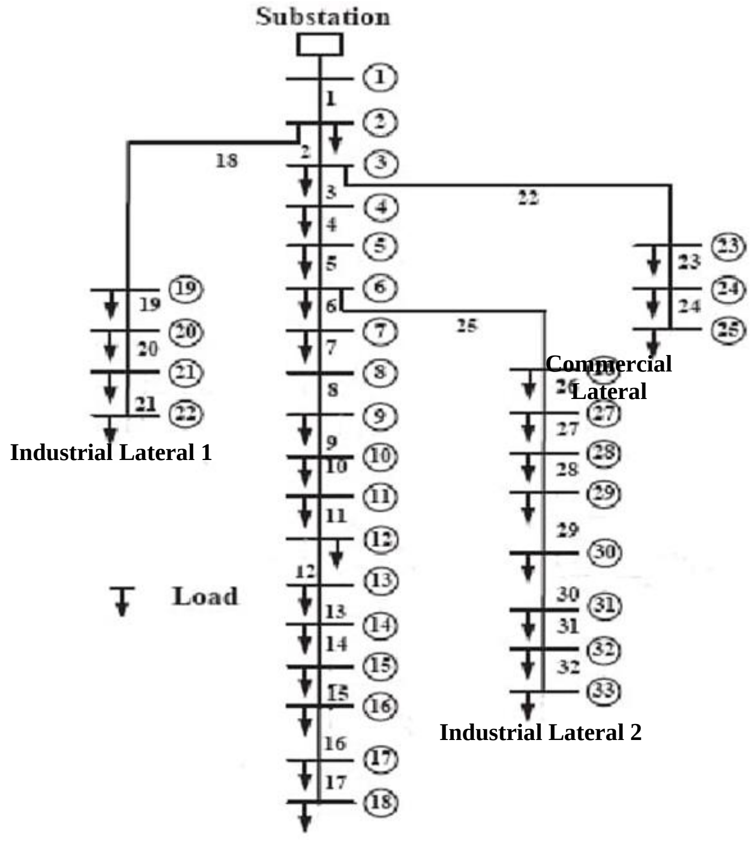

Figure 1. IEEE 33 Test Distribution System

The voltage profile, current in feeder sections and power loss are calculated using backward-forward load flow analysis [18]. This analysis enables the decision of the maximum load of PEVs that can be placed at the charging stations subject to the condition of maintaining voltage within defined limits.

Efficient Charging Scheduling focuses on optimizing the timing and distribution of EV charging to lower costs. As the number of EVs grows, it becomes essential to manage charging times and methods effectively to prevent grid overload and ensure energy is used efficiently. PSO is applied to identify optimal charging schedules by considering minimizing PAR, in turn the operating cost of the parking lot reduces. These methods help create a more sustainable and reliable EV charging system.

The industrial laterals 1 and 2 and the commercial lateral, as shown in the figure, are considered as the non-residential car parking lots, where the PEVs are considered to be charging or discharging during the day time. For industrial laterals, the working time is considered to start in two shifts from 8am or 9am and 1pm or 2pm. Each charging station (each load point) is assumed to have a capacity of 2kW and the maximum capacity of all the laterals considered for study are presented in Table 1. This indicates the maximum load after which the voltage deviation (10% deviation from 1 pu) exceeds the stipulated limit and the distribution system goes into voltage instability region.

Table 1: Maximum Capacity of charging stations

Sl. No.	**Lateral**	**Max. Capacity**	**Number of charging stations per lateral**	**Number of PEVs charging slots per station / load bus**
1	Industrial lateral 1	65 kW	4	8
2	Industrial lateral 1	65 kW	8	4
3	Commercial Lateral	60 kW	3	10

3.1 Design of Fuzzy Inference System

PEV owners can choose from three different battery conditions for their departure time when they arrive at the parking lot:

1) An increase in SOC (departure SOC > arrival SOC).

2) A decrease in SOC (departure SOC < arrival SOC).

3) No change in SOC (departure SOC = arrival SOC).

The PEVs' energy needs are established based on this decision. The SOC of PEV during arrival and the STD have an impact on the choice, although these scenarios frequently involve incorrect calculations or analysis to arrive at a decision using fuzzy inference system (FIS).

The energy needs of PEVs whose daily mileage (d) is smaller than their corresponding All-Electric Range (AER) is only determined by applying the fuzzy decision-making procedure.

The inputs given to the FIS are modelled as follows.

Input 1: initial SOC - The membership functions for the initial State of Charge (SOC) is defined by three terms: Low, Medium, and High.

Input 2: STD - Similarly, the membership function for Subsequent Trip Distance (STD) is defined by three terms: Short, Medium, and Long.

The outputs of the FIS are modelled as follows.

Output 1: Charging - The output variables are represented by seven membership functions: Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), and Very High (VH).

Output 2: Discharging - The output variables are described by three membership functions: Low (L), Medium (M) and High (H).

Figure 2 represents initial SOC for input 1 which ranges from 20 to 80%. Figure 3 represents STD for input 2 which ranges from 0 to 50 km. Figure 4 represents charging for output 1 which ranges from 0 to 1. Figure 5 represents discharging for output 2 which ranges from 0 to 1.

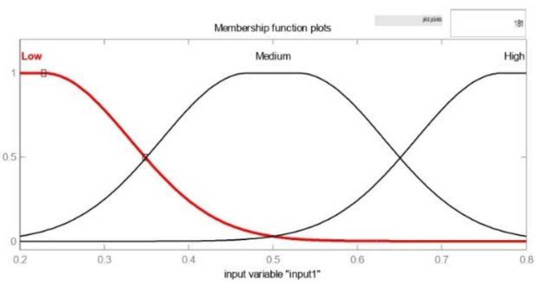

Figure 2. Initial SOC for Input 1

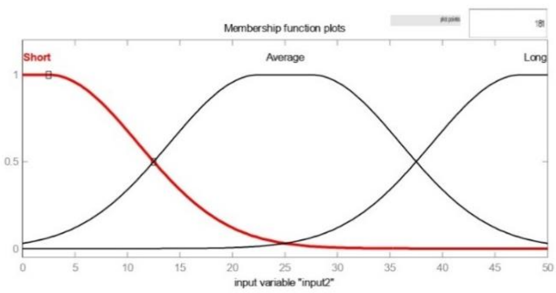

Figure 3. STD for Input 2

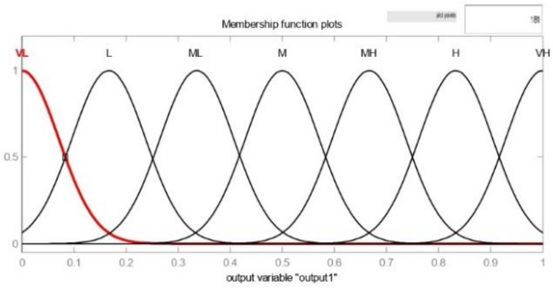

Figure 4. Charging for Output 1

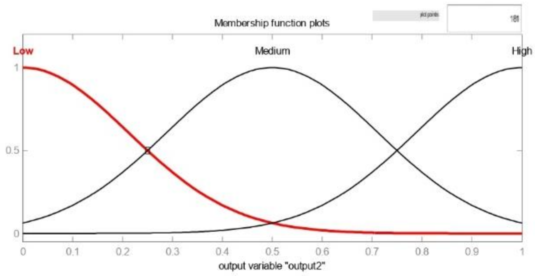

Figure 5. Discharging for Output 2

Using initial SOC and STD, an FIS is developed to represent the number of hours charging and discharging which is mentioned in Tables 2 and 3.

Table 2: Rule Base Design of FIS for charging EVs

Initial SOC	**STD**		
	Short Charging	**Average Charging**	**Long Charging**
Low	L	MH	H
Medium	VL	ML	MH
High	L	MH	H

Table 3: Rule Base Design of FIS for discharging EVs

Initial SOC	**STD**		
	Short Discharging	**Average Discharging**	**Long Discharging**
Low	L	L	L
Medium	L	L	L
High	M	L	L

Table 4 illustrates the number of vehicles incoming and number of charging and discharging points considered for Industrial lateral-1 and Industrial lateral-2 at various charging points in the morning at 8 am. The charging schedules are presented for cases without and with PSO. The case without PSO considers the maximum possible loading capacity as given in Table 1.

For Industrial lateral-1 number of vehicles incoming is 50 and number of charging points are 32 out of 32. These charging points include 30 charging points for charging out of these 10 are charging for 3 hours, 10 are charging for 2 hours and 10 are charging for 1 hour and 2 charging points are discharging for 1 hour. Number of vehicles waiting are 18.

Cost calculation:

Number of vehicles charging = 30

Number of vehicles discharging = 2

Cost per kWH is Rs. 20/-

Out of each charging slot is 2kW

Total cost = (number of vehicles charging – number of vehicles discharging) *20*2 = (30-2) * 40=1120/-

Table 4: Industrial Lateral Charging Station Schedule at 8 am

Charging Station	**Incoming Vehicles**	**Without PSO**			**With PSO**		
		Schedule	**Energy Requirement**	**Cost (Rs.)**	**Schedule**	**Energy Requirement**	**Cost (Rs.)**
Industrial lateral 1 (32 max.)	45	10c-3h 10c-2h 10c-1h 2d-1h 18v-w	30 charging 2 discharging	1120	10c-3h 10c-2h 5c-1h 20v-w	25 charging 0 discharging	1000

Charging Station	Incoming Vehicles	Without PSO			With PSO		
		Schedule	Energy Requirement	Cost (Rs.)	Schedule	Energy Requirement	Cost (Rs.)
Industrial lateral 2 (32 max.)	40	10c-2h 15c-1h 7d-1h 11v-w	25 charging 7 discharging	720	10c-3h 9c-1h 6d-1h 15v-w	19 charging 6 discharging	520

Similarly, for Industrial lateral-2 number of vehicles incoming is 43 and number of charging points are 32 out of 32. These charging points include 25 charging points for charging out of these 10 are charging for 2 hours and 15 are charging for 1 hour and 7 charging points are discharging for 1 hour. Number of vehicles waiting are 11. The cost calculations are done as indicated above.

Table 5 illustrates the number of vehicles incoming and number of charging and discharging points considered for Industrial lateral-1 and Industrial lateral-2 at various charging points in the morning at 9 am. The charging schedules are presented for cases without and with PSO. The case without PSO considers the maximum possible loading capacity as given in Table 1.

Table 5: Industrial Lateral Charging Station Schedule at 9 am

Charging Station	Incoming Vehicles	Without PSO			With PSO		
		Schedule	Energy Requirement	Cost (Rs.)	Schedule	Energy Requirement	Cost (Rs.)
Industrial lateral 1 (32 max.)	46	10c-2h 10c-1h 8c-3h 4d-1h 47v-w	28 charging 4 discharging	960	10c-2h 10c-1h 7c-1h 59v-w	27 charging 0 discharging	1080
Industrial lateral 2 (32 max.)	81	10c-1h 15c-3h 7d-1h 67v-w	25 charging 2 discharging	720	10c-2h 8c-1h 11d-1h 77v-w	18 charging 11 discharging	280

Table 6 illustrates the number of vehicles incoming and number of charging and discharging points considered for Industrial lateral-1 and Industrial lateral-2 at various charging points at 1 pm. The charging schedules are presented for cases without and with PSO. The case without PSO considers the maximum possible loading capacity as given in Table 1.

Table 6: Industrial Lateral Charging Station Schedule at 1 pm

Charging Station	Incoming Vehicles	Without PSO			With PSO		
		Schedule	Energy Requirement	Cost (Rs.)	Schedule	Energy Requirement	Cost (Rs.)
Industrial lateral 1 (32 max.)	100	11c-3h 10c-2h 10c-1h 1d-1h 68v-w	31 charging 1 discharging	1200	10c-3h 11c-2h 10c-1h 69v-w	31 charging 0 discharging	1240
Industrial lateral 2 (32 max.)	120	10c-3h 10c-2h 4c-1h 8d-1h 88v-w	24 charging 8 discharging	640	14c-3h 9c-2h 6d-1h 91v-w	23 charging 6 discharging	680

Table 7 illustrates the number of vehicles incoming and number of charging and discharging points considered for Industrial lateral-1 and Industrial lateral-2 at various charging points at 2 pm. The charging schedules are presented for cases without and with PSO. The case without PSO considers the maximum possible loading capacity as given in Table 1.

Table 7: Industrial Lateral Charging Station Schedule at 2 pm

Charging Station	Incoming Vehicles	Without PSO			With PSO		
		Schedule	Energy Requirement	Cost (Rs.)	Schedule	Energy Requirement	Cost (Rs.)
Industrial lateral 1 (32 max.)	93	11c-2h 10c-1h 6c-3h 5d-1h 150v-w	27 charging 5 discharging	880	10c-2h 11c-1h 3c-1h 1d-1h 158v-w	24 charging 1 discharging	920
Industrial lateral 2 (32 max.)	127	10c-2h 10c-1h 5c-3h 7d-1h 203v-w	25 charging 7 discharging	720	14c-2h 9c-1h 6d-1h 212v-w	23 charging 6 discharging	680

Table 8 illustrates the number of vehicles incoming and number of charging and discharging points considered for commercial lateral at various charging points throughout the day. The charging schedules are presented for cases without and with PSO. The case without PSO considers the maximum possible loading capacity as given in Table 1.

Table 8: Commercial Lateral Charging Station Schedule for the whole day

Commercial lateral (30 max.)	Incoming Vehicles	Without PSO			With PSO		
		Schedule	Energy Requirement	Cost (Rs.)	Schedule	Energy Requirement	Cost (Rs.)
Time (at 11 am)	8	15c-2h 14c-1h 0v-w	30	1200	9c-1h 11c-1h 10c-1h 22v-w	30	1200
Time (at 12 pm)		15c-1h 0v-w	30	1200	11c-1h 11c-1h 0v-w	22	880
Time (at 1 pm)	30	10c-2h 20c-1h 0v-w	30	1200	10c-2h 18c-1h 2v-w	28	1120
Time (at 2 pm)	45	10c-1h 10c-2h 10c-1h 25v-w	30	1200	10c-1h 19c-1h 28v-w	29	1160
Time (at 3 pm)	35	10c-1h 20c-1h 40v-w	30	1200	5c-2h 25c-1h 33v-w	30	1200
Time (at 4 pm)	35	10c-2h 20c-1h 45v-w	30	1200	5c-1h 25c-1h 43v-w	30	1200
Time (at 5 pm)	20	10c-1h 20c-1h 45v-w	30	1200	10c-2h 20c-1h 33v-w	30	1200
Time (at 6 pm)	27	20c-1h 10c-2h 42v-w	30	1200	10c-1h 20c-1h 40v-w	30	1200

Commercial lateral (30 max.)	**Incoming Vehicles**	**Without PSO**			**With PSO**		
		Schedule	**Energy Requirement**	**Cost (Rs.)**	**Schedule**	**Energy Requirement**	**Cost (Rs.)**
Time (at 7 pm)	26	10c-1h 20c-1h 48v-w	30	1200	20c-2h 10c-1h 36v-w	30	1200

Table 9 shows the difference in Peak to Average Ratio (PAR) and costs with and without PSO optimization across different times of the day. The total cost with PSO optimization shows a significant reduction, amounting to Rs. 41,040/- compared to Rs. 45,480/- without PSO.

Table 9: Different time durations considered for PAR and COST without and with PSO

Time	**PAR without PSO**	**PAR with PSO**	**COST without PSO**	**COST with PSO**
8 AM	4.59	4.48	3040	2720
9 AM	4.68	4.57	2720	2320
10 AM	4.72	4.60	2480	2360
11 AM	4.67	4.57	3280	3240
12 PM	4.79	4.68	2800	2440
1 PM	5.00	4.86	3040	3040
2 PM	4.94	4.80	2800	2760
3 PM	5.07	4.95	2800	2720
4 PM	4.95	4.81	3040	2600
5 PM	4.77	4.63	3120	3120
6 PM	4.71	4.58	2960	2800
7 PM	4.67	4.58	3040	2960
8 PM	4.67	4.56	2880	2080
9 PM	4.59	4.49	3440	2960
10 PM	4.59	4.47	4040	2920
TOTAL COST			45480	41040

IV. CONCLUSION

An efficient charging schedule strategy for best utilization of the PEV car parking lot has been developed. Depending on the charge of battery of PEVs during arrival and the required charge at the time of leaving the parking lot, a fuzzy based decision system is designed to address the energy consumption of PEVs in the industrial and commercial laterals of a 33-bus distribution system.

Optimal charging schedule for the car park is implemented using PSO algorithm. This scheduling approach reduces the cost of parking lot and EVs and optimize the Peak to Average Ratio (PAR). This strategy results in advantages such as reducing the operating costs of the parking lot, decreasing the peak load of the system and upholding the voltage levels of the distribution network.

The maximum capacity of a charging station is assessed using load flow study considering the maximum possible deviation on voltage allowed. Optimal scheduling using PSO aids this loading of charging stations so that the peak to average ratio is minimum while adhering to the maximum capacity constraint. Thus efficiently scheduling is done that also results in reduction of operating cost of the car parking operator.

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