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Assessment of techno-economic benefits for smart charging scheme of electric vehicles in residential distribution system

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Abstract: Connecting multiple electric vehicles (EVs) to a power system network for the purpose of charging has major setbacks like decrease in power quality, instability in voltage profile, and increase in power losses and thus electricity price. This paper focuses on devising an optimal charging scheme to reduce the negative impacts of EVs' presence in the distribution network by limiting the charging process to only off-peak demand periods when the electricity price is comparatively lower. The salp swarm algorithm, an efficient, fast, and reliable optimization technique, is used to obtain the optimal locations for the EVs and their charging schedule in a residential 107-bus radial distribution system (RDS). The proposed optimization technique minimizes the total charging cost of the EVs within the framework of operational constraints of a residential RDS and parking availability. This charging scheme takes care of benefit maximization from both consumer and power supply operators' perspectives by controlling the starting time of EV charging as well as the EV charging rate in order to arrive at the objective.

Key words: Electric vehicle, distribution system, salp swarm algorithm, smart charging

1. Introduction

Environmental pollution, changes in climate, and decreasing fossil fuel reserves continue to motivate researchers for finding new transportation solutions. As such, electric vehicles (EVs) have become a clean and green solution for these problems [1–3]. The main advantage of EVs is that they do not cause any environmental pollution, unlike internal combustion engine (ICE) vehicles [4,5]. However, the acceptance of EVs depends on charging time and cost, availability of charging stations, and the EV owner's convenience. Charging of EVs deteriorates power quality issues like voltage fluctuation and voltage unbalance as well as leading to overloading and high power losses in the distribution system. Several methods have been proposed to mitigate the impact of EV charging on distribution systems. Islam et al. used a binary gravitational search algorithm to optimally allocate a rapid charging station for EVs with the objective of minimizing daily EV charging cost [6]. Li et al. discussed a single objective program to process the investment, operation, and transportability cost [7]. Masoum et al. coordinated the charging of multiple plug-in electric vehicles (PEVs) using a real-time load management method [8]. Moradi et al. proposed a multiobjective optimization technique for allocation of charging stations and renewable energy sources [9]. Hajimiragha et al. proposed a planning method for charging PHEVs considering different uncertainties [10]. Finn et al. discussed an optimization technique for demand-response strategy to improve the flexibility of distribution networks [11]. Soares et al. suggested that

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EVs can be used as flexible loads, which can be charged throughout the day instead of on a rigid charging schedule [12]. The main contributions of the paper are as follows:

(a) It identifies, understands, and mitigates the impacts of EV charging on a residential radial distribution system (RDS).

(b) It identifies the EV location and its charging schedule, which affect the residential distribution voltage quality and transformer loading.

(c) A smart charging scheme is proposed to directly control EV charging rates and charging time while minimizing the total cost of charging using the salp swarm algorithm (SSA). The proposed scheme shifts the EV load demand to off-peak hours, thus mitigating loading concerns as well.

(d) The smart charging scheme mitigates the EV load impacts and potentially benefits the EV owners and power supply operators.

The rest of the paper is organized as follows. Section 2 describes the distribution system model and Section 3 presents the electric vehicle model. The problem formulation and the SSA are described in Section 4 and Section 5, respectively. The results and discussion are presented in Section 6. Finally, the conclusion is presented in Section 7.

2. Distribution system model

The proposed method is applied to the low-voltage RDS of the Bhubaneswar electrical division, CESU, Odisha, India. The residential RDS has 107 buses with a main substation transformer in which 75 individual houses are present. Each house is connected to one bus. The specifications of substation transformer are given in Table 1. The load and line data for the 107-bus RDS are given in Figures 1–3. Hourly weight factors are used to model the load demand of the RDS, as shown in Figure 4. The hourly purchase rates of electrical energy for a day are given in Table 2.

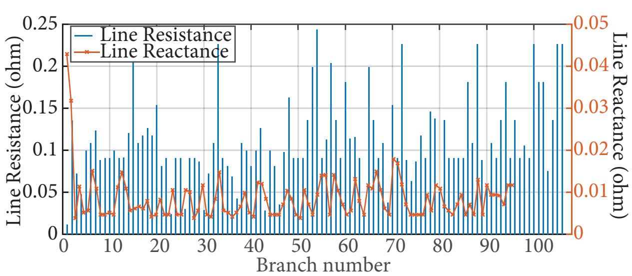

Figure 1. Line data of 107-bus RDS.

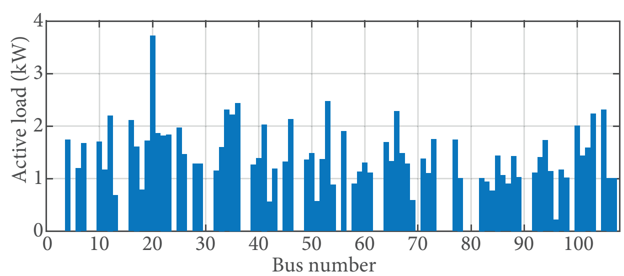

Figure 2. Active load of 107-bus RDS.

Table 1. Specifications of three-phase substation transformer.

Rated voltage & rated power	10 kV / 0.4 kV & 0.4 MVA
Nominal frequency	50 Hz
Short-circuit voltage	4.45%
Copper losses	4.721 kW

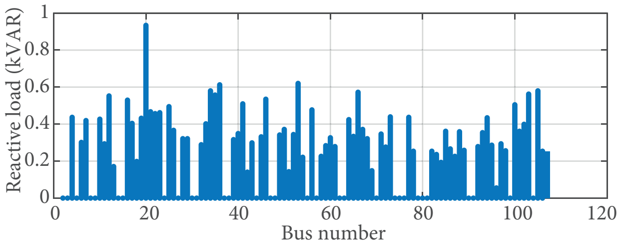

Figure 3. Reactive load of 107-bus RDS.

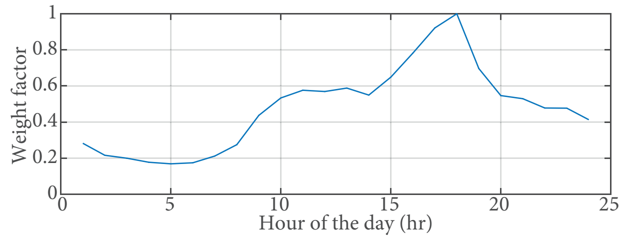

Figure 4. Hourly weight factor in a day.

Table 2. Prices for electricity.

Hour of the day	Electricity price (INR/kWh)	Hour of the day	Electricity price (INR/kWh)	Hour of the day	Electricity price (INR/kWh)	Hour of the day	Electricity price (INR/kWh)
1	2.0005	7	1.7371	13	3.2949	19	3.1014
2	1.8498	8	3.1397	14	3.2122	20	2.8174
3	1.69959	9	3.3545	15	3.1055	21	3.1428
4	1.6994	10	3.3997	16	3.2495	22	3.1501
5	1.6995	11	3.7258	17	3.2796	23	1.8171
6	1.7644	12	3.6996	18	3.2047	24	1.6994

3. Electric vehicle model

3.1. Electric vehicle user behavior

In this paper the charging hours are the hours during which EVs are parked at home. Thus, available charging time is the time the EV stays at home, i.e. between arrival and departure. However, the problem of predicting the mobility behavior of EVs is significant when they are integrated with the RDS as it depends on each individual EV owner's requirements [13]. Here, the driving patterns are studied and then used to obtain the hourly stochastic energy demand of each EV. The arrival/departure times of EVs are taken into consideration to evaluate the available charging time. In this proposed method, EVs are assumed to consume 0.15 kWh of energy per kilometer. Total energy needed for 1 day can be calculated as:

$$E = 0.15kWh/km \times D, \tag{1}$$

where D is the distance covered in a day.

The Weibull distribution is used to generate the driving distance with the distribution parameters 'a' and 'b' as 33.4061 and 0.798717, respectively. The stochastic data for driving distance and energy requirement of each EV are shown in Figure 5. A normal distribution function is used to generate arrival and departure times for each EV. From stochastic data it is observed that most of the EVs arrive home between 1400 hours and 2200 hours and leave between 0400 hours and 1200 hours, as shown in Figure 6. The parameters used in normal distribution are given in Table 3.

3.2. Electric vehicle battery charging

The rate of charge, power demand, and charging time are the main parameters for EV modeling [14,15]. Information of initial state of charge ($SOC_{initial}$) of EV batteries for each day is considered. A maximum

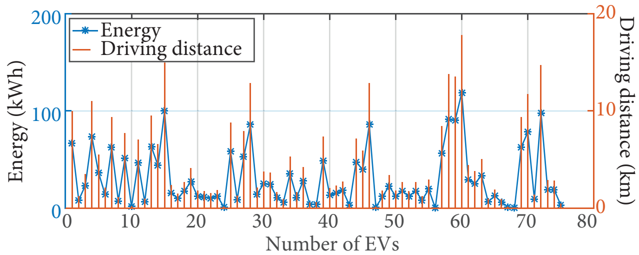

Figure 5. Stochastic data of driving distance and energy needed for each EV.

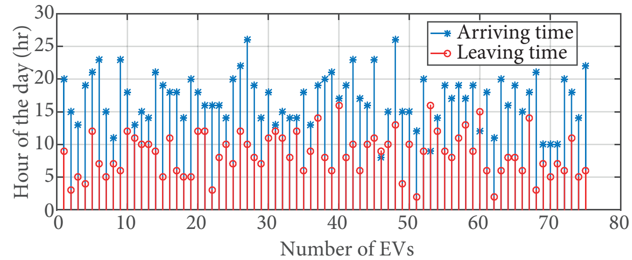

Figure 6. Stochastic data of arriving time and leaving time.

Table 3. Parameters of new fitted distribution.

Parameters	For arriving time	For leaving time
Mu (μ)	16.8461	8.8360
Sigma (δ)	8.8461	3.6019

charging rate of 11 kW is considered for this method. The state of charge (SOC) of the EV battery is updated as

$$SOC(t+1) = SOC_{initial} + \sum_{t=1}^{\mathbb{T}} SOC(t), \tag{2}$$

where SOC(t) is the state of charge at time t and T is the total time period (24 h).

3.3. Charging schemes

In this paper two different charging schedules are addressed.

(a) Dumb charging scheme

In this method, the EV owners are allowed to charge their vehicle as per their requirements [16]. When the EVs are plugged into mains, the charging starts at its maximum rate. With no control over the charging scheme it could affect the distribution system parameters. The flow chart for the dumb charging scheme is illustrated in Figure 7.

(b)Smart charging scheme

The smart charging scheme enables the system to control the charging of EVs with an aim to maximize the benefits for both EV owners and aggregators. Charging time includes both peak and off-peak hours. The charging process is delayed to avoid peak demand periods. From available charging hours, hours having lower electricity price are chosen to charge the EVs. From the generated stochastic arrival and departure time it is observed that most of the EVs are parked from 1900 hours to 0500 hours, implying that these 10 h are available charging time. The flow chart for the smart charging scheme is shown in Figure 8.

4. Electric vehicle model

4.1. Objective function

The objective function of minimizing the charging cost of EVs is defined as

$$f_{obj} = \min(C_{cp}), \tag{3}$$

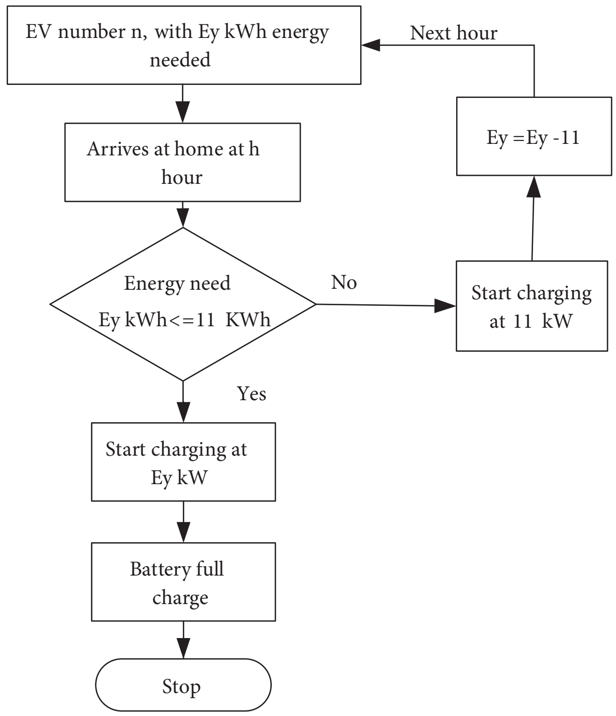

Figure 7. Flow chart for dumb charging scheme.

$$C_{cp} = \sum_{t=1}^{\mathbb{T}} (C_t \times \sum_{n=1}^{\mathbb{N}} p_{nt}), \tag{4}$$

where C_{cp} is the total cost of charging, N is the number of EVs (= 75), C_t is the price of electricity at time t in INR, and p_{nt} is the power required to charge an EV at time t in kW. The annual cost reduction obtained in the case of the smart charging plan can be calculated as

$$C_{benefit} = 365 \times (C_{cp-dump-Ccp-smart}), \tag{5}$$

where $C_{cp\text{-}dumb}$ and $C_{cp\text{-}smart}$ are the total cost of charging for the dumb and smart charging schemes, respectively.

4.2. System operational constraints

The system operates within the framework of some equality and inequality constraints, which are explained below:

$$EV_{ch} \leq EV_{available-charging-hour}, \tag{6}$$

$$EV_{demand} = \sum_{n=1}^{\mathbb{N}} (SOC_{\max} - SOC_{initial}), \tag{7}$$

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max}, \tag{8}$$

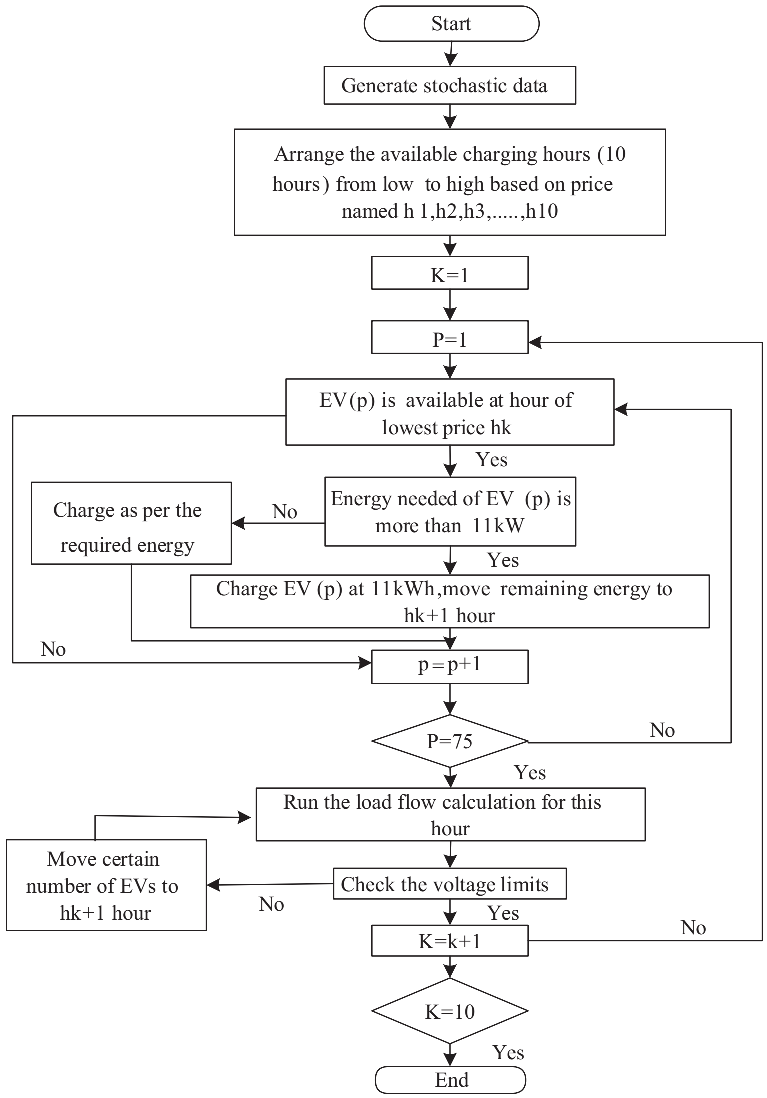

Figure 8. Flow chart for smart charging scheme.

$$P_{sub}(t) = P_{Load}(t) + P_{Loss}(t) + P_{EV}(t), \tag{9}$$

$$Q_{sub}(t) = Q_{Load}(t) + Q_{Loss}(t) + Q_{EV}(t), \tag{10}$$

$$P_{Load}(t) + P_{Loss}(t) + P_{EV}(t) \leq tr_{max}(t), \tag{11}$$

$$V_i^{\min} \leq V_i(t) \leq V_i^{\max}, \tag{12}$$

$$I_{ij}(t) \leq I_{ij}^{\max}, \tag{13}$$

$$S_{tr}(t) \leq S^{nominal}, \tag{14}$$

where EV_{ch} is the EV charging demand, $EV_{available\text{-}charging\text{-}hour}$ is the available charging hours, EV_{demand} is energy demand of the EV batteries, SOC_{max} and SOC_{min} are the maximum and minimum state of charge of the EV batteries, $P_{sub}(t)$ and $Q_{sub}(t)$ are respectively the active and reactive power injection of the substation at time t, $P_{Loss}(t)$ and $Q_{Loss}(t)$ are the active and reactive power losses of the branch at time t, $P_{Load}(t)$and $Q_{Load}(t)$ are the active and reactive loads of the bus at time t, $P_{EV}(t)$ and $Q_{EV}(t)$ are active and reactive charging capacity of the EV, $tr_{max}(t)$ is the peak load demand of the transformer substation at time t, ${V_i}^{min}$ and ${V_i}^{max}$ are the minimum and maximum voltage of the bus, ${I_{ij}}^{max}$ is the maximum current at branch ij, $I_{ij}(t)$ is the current at branch ij at time t, $S_{tr}(t)$ is the apparent power of the substation transformer, and $S^{nominal}$ is the nominal apparent power of the line.

5. Salp swarm algorithm (SSA)

Salps are oceanic creatures from the family Salpidae having transparent barrel-shaped bodies. Salp tissues and their movements are similar to those of jellyfish. Water is pumped through their bodies, propelling them to move [17]. Salps often form a swarm called a salp chain to achieve better locomotion using rapid coordinated changes and foraging. This swarming behavior of salps can be mathematically modeled. The salp chain can be broadly divided into two groups, i.e. the leader and followers. The salp at the front of the chain is the leader and the others are followers. As the name suggests, the leader guides the swarm and the others follow each other, thus following the leader directly or indirectly.

In this optimization technique, the salps' position is defined in an n-dimensional search space where n is the number of variables of a given problem. Hence, the positions of all salps are stored in a two-dimensional matrix called x. A food source f is assumed to be the swarm's target. The following equation is used to update the position of the leader:

$$x_{j,1} = \begin{cases} f_j + c_1((vb_j - mb_j)c_2 + mb_j, & c_3 \geq 0 \\ f_j - c_1((vb_j - mb_j)c_2 + mb_j, & c_3 < 0, \end{cases} \tag{15}$$

where j is the dimension, $x_{j,1}$ is the first slap position, f_j is the food source position, vb_j and mb_j are respectively the upper and lower bounds of the dimension, and c_1, c_2, and c_3 are random numbers. c_2 and c_3 are uniformly generated between [0,1], and c_1 can be derived as follows:

$$c_1 = 2e^{-(4i/I)^2}, \tag{16}$$

where i and I are the current and maximum iteration, respectively. The position of a follower is updated as follows:

$$x_j^k = \frac{1}{2}at^2 + u_0 t, \tag{17}$$

$$a = \frac{u_{final}}{u_0}, \tag{18}$$

$$u = \frac{x - x_0}{t}, \tag{19}$$

where x_j^k is the position of the kth follower salp in dimension j with $k \geq 2$, u_0 is the initial speed, and t is the time period. If $u_0 = 0$, then Eq. (17) can be written as

$$x_j^k = \frac{1}{2}(x_j^k + x_j^{k-1}). \tag{20}$$

After the first iteration, a swarm can be formed and it moves effectively using the proposed model. The leading salp changes its position around the food source and the follower salps gradually follow it over subsequent iterations. The food source is updated during the optimization because the salp chain model is able to find the space around it and exploit it. It is also observed that the salp chain is able to chase a moving food source. Hence, the salp chain has the potential to find the global optimum that changes over iterations.

The SSA algorithm saves the best solution obtained so far and assigns it to the food source variable. Thus, it never gets lost even if the whole population deteriorates. The leader salp updates its position with respect to the food source only, which is the best solution obtained so far. The follower salps update their positions with respect to each other, moving gradually towards the leading salp. The gradual movements of follower salps prevent the SSA from being stagnant at local optima. The adaptive decrease of c_1 over the course of iterations helps the SSA first to explore and then to exploit the search space. This algorithm has only one controlling parameter, (c_1). The SSA is simple and easy to implement.

This makes the SSA a theoretically and potentially viable algorithm to solve single-objective optimization problems with unknown search spaces. The adaptive mechanism of the SSA allows it to avoid local solutions and eventually find an accurate estimation of the best solution. Therefore, it can be applied to both unimodal and multimodal problems. These advantages allow the SSA to potentially outperform recently developed optimization algorithms.

6. Simulation and result analysis

The proposed technique is tested in a low-voltage 107-bus RDS. The parameters of the SSA used in simulation are number of search agents = 30 and maximum number of iterations = 200. Power flow calculation is performed using a base value of 100 MVA and 1 kV. The load bus is considered as the charging location for EVs. The bus voltage variation is limited to a maximum of 5%. Connecting all 75 EVs of rated charging power of 11 kW is not practically viable as the total load (houses' load and EVs' load) may exceed the transformer capacity. As per the rated capacity of the transformer, the maximum number of EVs that the grid can support is 22 during peak hours. The same locations for 22 EVs are considered for both dumb and smart charging schemes. $SOC_{initial}$, SOC_{max}, and SOC_{min} of EV batteries are considered as 90%, 90%, and 30%, respectively. The charging costs of the EVs along with their placements are illustrated in Table 4, which shows that the charging cost for the smart charging scheme is 44.7% less. Figures 9 and 10 show the charging schedules for 22 EVs in a day for the dumb and smart schemes, respectively.

Variation of power loss and variation of the voltage profile for the available charging time are shown in Figures 11 and 12, respectively. It is observed that due to the penetration of EVs, the substation service transformer is overloaded during peak hours in the case of dumb charging. During this period, most of the EVs are supposed to be plugged into the RDS after their arrival at home, which is between 2000 and 2400 hours, and the electricity price is much higher during these periods. In the case of smart charging, most of the EVs are charged between 0300 and 0400 hours as the electricity price is lowest then, which benefits both EV owners and power supply operators. Thus, the peak hour demand is shifted to off-peak hours, resulting in peak load

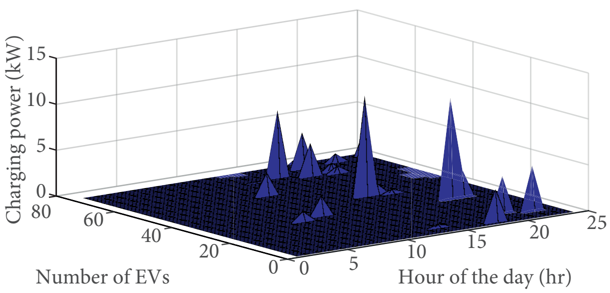

Figure 9. Charging schedules for 22 EVs in a day for dumb charging scheme.

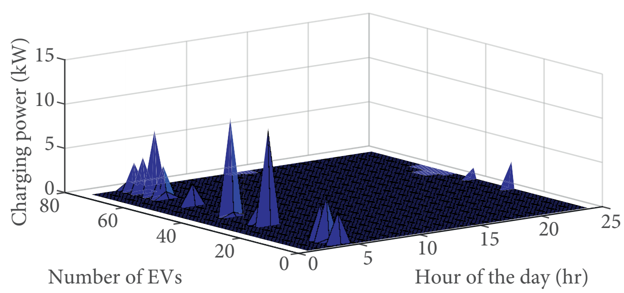

Figure 10. Charging schedules for 22 EVs in a day for smart charging scheme.

Table 4. Optimization results.

	Dumb charging scheme	Smart charging scheme
Bus location	3, 6, 7, 9, 14, 16, 27, 28, 30, 39, 40, 44, 53, 62, 63, 64, 65, 66, 70, 71, 73, 75	3, 6, 7, 9, 14, 16, 27, 28, 30, 39, 40, 44, 53, 62, 63, 64, 65, 66, 70, 71, 73, 75
Charging cost (INR)	906.05	500.99
$C_{benefit}$ (INR/year)	-	147846.90

shaving and improving the voltage regulation. In Figure 11, it is evident that during peak hours, from 2000 to 2200 hours, the power loss in the system is lower in the case of the smart charging scheme. Figure 12 shows that in the dumb charging scheme, the voltage drops distinctly during peak hours because many EVs start to charge as soon as they arrive along with the peak demand of houses. Benefits offered by the smart charging scheme for EV owners are peak shaving, to lower the peak demand charges, and price arbitrage in shifting peaks to lower energy charges in buying cheap electricity from off-peak hours. Benefits offered by the smart charging scheme for the power supply operator are peak shavings to reduce demand during peak hours and reduction of investment in transmission and distribution lines and substations.

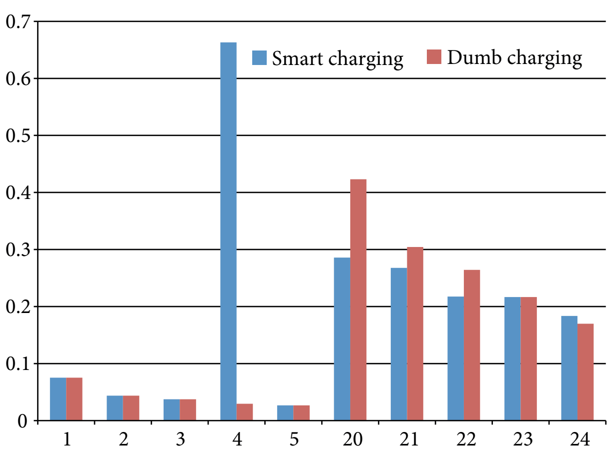

Figure 11. Power loss for charging hours.

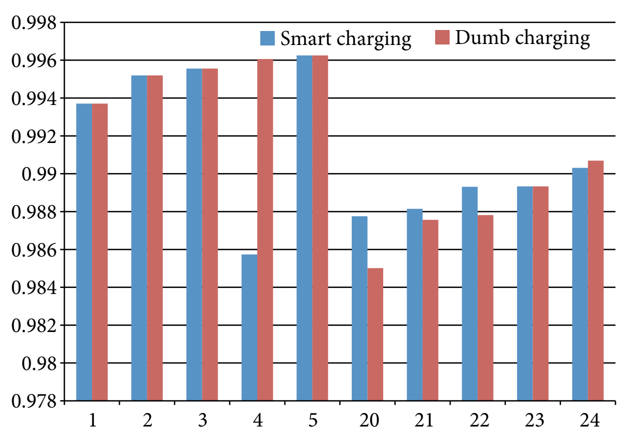

Figure 12. Voltage profile for charging hours.

Figure 13 shows the voltage profile of the 107-bus RDS for maximum loading at 18.00. The voltage profiles are noted to be enveloped within the desirable limits. Shifting from dumb charging to smart charging improves the minimum bus voltage from 0.9578 p.u. to 0.9612 p.u., but EVs located closer to the service transformer decrease the additional voltage drops in comparison to the EVs located farther away. This is because a lower short-circuit capacity at the farthest load bus results in larger additional voltage drops in the secondary service voltages. Figures 14 and 15 show the voltage profiles of the 107-bus RDS in a day for the dumb and smart charging scheme, respectively. The minimum voltages of the weakest bus, 105, are 0.9587 p.u. and 0.9612 p.u. for dumb and smart charging, respectively, at 1800 hours. It is observed that the voltages of all buses are improved in the smart charging scheme, satisfying the secondary service voltage constraints. Variation of power loss for dumb and smart charging in a day is shown in Figures 16 and 17. It is observed that the active power loss of branch 56 at 1800 hours is the maximum for both dumb and the smart charging schemes. It is 0.2989 kW for dumb and 0.2446 kW for smart charging. The smart charging scheme helps to alleviate upstream congestion by supplying power downstream, which gives rise to distribution upgrade deferral, demand charge management, and voltage regulation improvement.

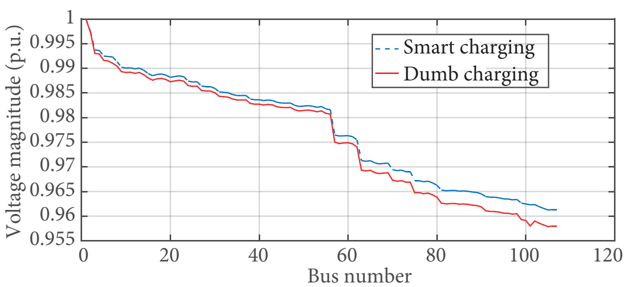

Figure 13. Voltage profile of 107-bus RDS at 1800 hours.

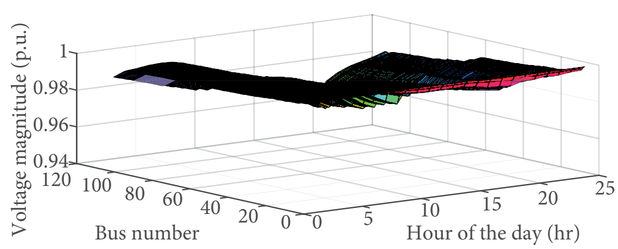

Figure 14. Variation of voltage profile of 107-bus in a day for dumb charging scheme.

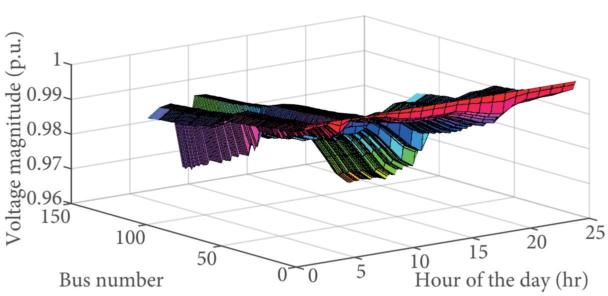

Figure 15. Variation of voltage profile of 107-bus in a day for smart charging scheme.

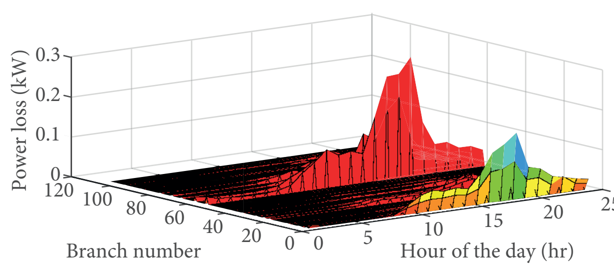

Figure 16. Variation of power loss in a day for dumb charging scheme.

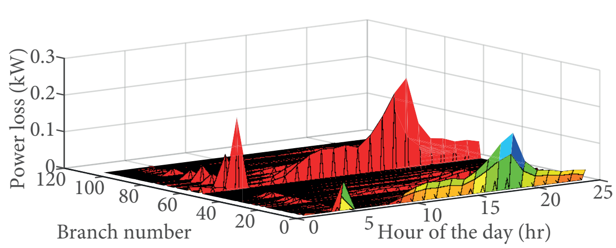

Figure 17. Variation of power loss in a day for smart charging scheme.

7. Conclusion

The impacts of EV charging on a residential RDS and techniques to mitigate them are thoroughly discussed in this paper. The study shows that residential EV charging affects the secondary distribution voltages more than the primary ones. Without the smart charging scheme the peak load demand may increase with the addition of EV charging load, causing secondary service voltage to drop.

The SSA, a metaheuristic optimization technique, is used to find the optimal EV charging profile for minimization of the total charging cost. The algorithm is found to be effective in mitigating peak loading and voltage concerns. The proposed method significantly enhances the techno-economic benefits of power system operators and EV owners.

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