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Assessment of techno-economic benefits for smart charging scheme of electric vehicle 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, 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. Salp Swarm Algorithm (SSA), 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' perspective 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 (EV), Distribution system, Salp Swarm Algorithm (SSA), Smart charging

1. Introduction

Environmental pollution, changes in climate and decreasing fossil fuel reserve continue to motivate the researchers for finding new transportation solution. 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 an Internal Combustion Engine (ICE) vehicle [4-5]. But the acceptance of EVs depends upon charging time & cost, availability of charging stations and EV owner's convenience. Charging of EVs deteriorates power quality issues like voltage fluctuation, voltage unbalance etc as well as it leads to overloading and high power losses in distribution system. Several methods have been proposed to mitigate the impact of EV charging on distribution systems. Islam et al. used 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 programme to process the investment, operation and transportability cost [7]. Masoum et al. coordinated the charging of multiple Plug-In Electric Vehicles (PEVs) using real time load management method [8]. Moradi et al. proposed a multi-objective optimization technique for allocation of charging stations and renewable energy sources [9]. Hajimiragha et al. proposed a planning method for charging the PHEVs considering different uncertainties [10]. Finn et al. discussed an optimization technique for demand-response

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strategy to improve the flexibility of distribution network [11]. Soares et al. suggested that EVs can be used as flexible load which can be charged throughout the day instead of 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 RDS.

(b) It identifies the EV location & its charging schedule which affects the residential distribution voltage 1.6cmquality and transformer loading.

(c) A smart charging scheme is proposed to directly control EV charging rates and charging time while 1.6cmminimizing the total cost of charging using Salp Swarm Algorithm (SSA). The proposed scheme shifts 1.6cmthe EV load demand to off peak hours thus mitigating loading concerns as well.

(d) The smart charging scheme mitigates the EV load impacts and benefits the EV owners & power 1.6cmsupply operators potentially.

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

2. Distribution system model

The propose method is applied to low voltage radial distribution system (RDS) of Bhubaneswar electrical division, CESU, Odisha, India. The residential RDS has 107-bus 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 107-bus RDS are given in Figure 1 to Figure 3. Hourly weight factors are used to model the load demand of RDS as shown in Figure 4. The hourly purchase rates of electrical energy for a day are given in Table 2.

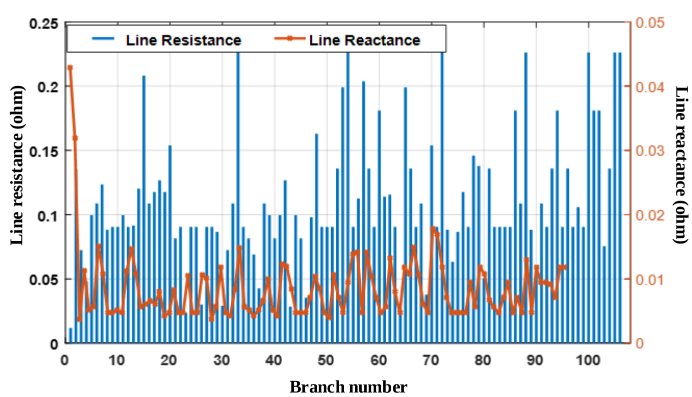

Figure 1. Line data of 107 bus RDS.

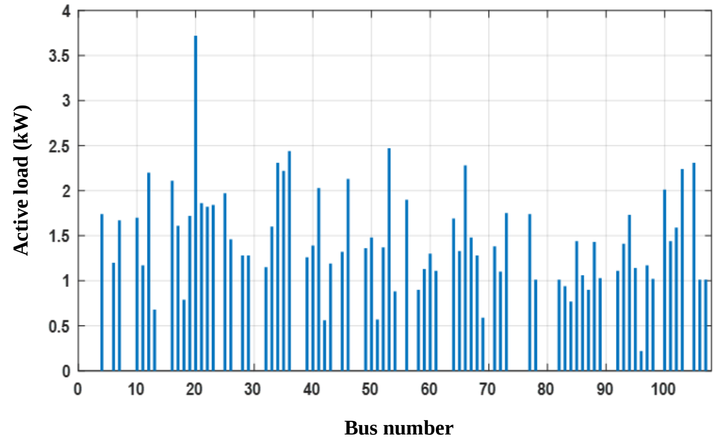

Figure 2. Active load of 107 bus RDS.

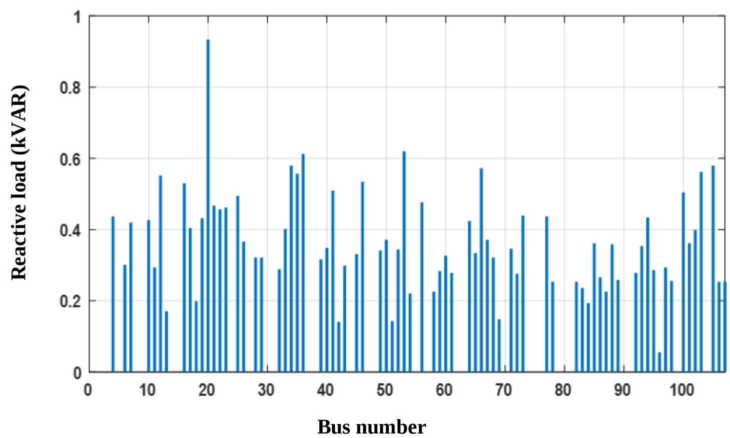

Figure 3. Reactive load of 107 bus RDS.

Table 1. Specification of three phase substation transformer.

Rated Voltage & Rated Power	10kV / 0.4 kV & 0.4 MVA
Nominal Frequency	50Hz
Short-Circuit Voltage	4.45%
Copper Losses	4.721kW

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. So available charging time is the time the EV stays at home i.e. between arrival and departure. But the problem of predicting the mobility behaviour of EVs is humungous when they are integrated with the RDS as it depends on each

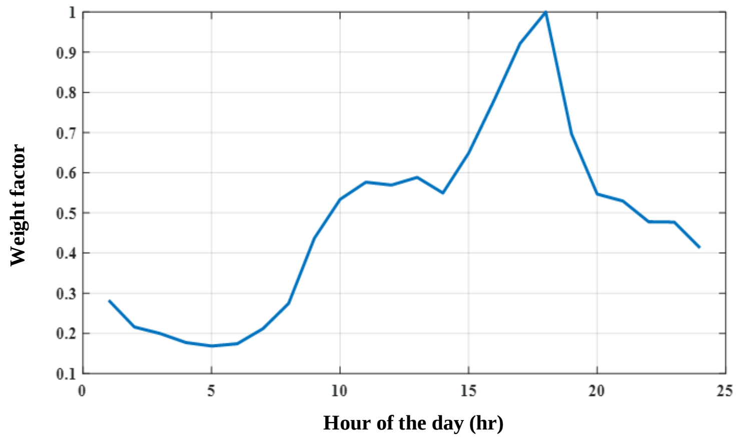

Figure 4. Hourly weight factor in a day.

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

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 time of EVs are taken into consideration to evaluate the available charging time. In this proposed method EVs are assumed to consume 0.15kWh of energy per km.Total energy needed for one day can be calculated as

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

where D is the distance covered in a day.

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. 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 14.00 hour and 22.00 hour and leave between 4.00 hour and 12.00 hour as shown in the 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 modelling [14-15]. Information of initial state of charge ($SOC_{initial}$) of EV batteries for each day is considered. Maximum charging

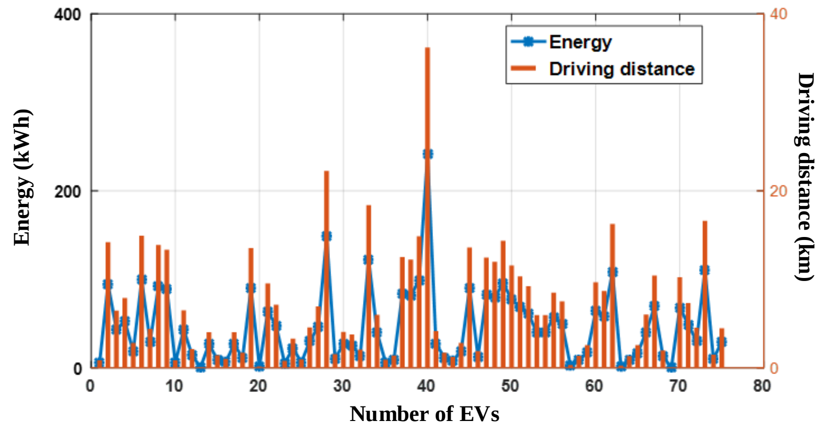

Figure 5. Stochastic data of driving distance and energy needed for each EV.

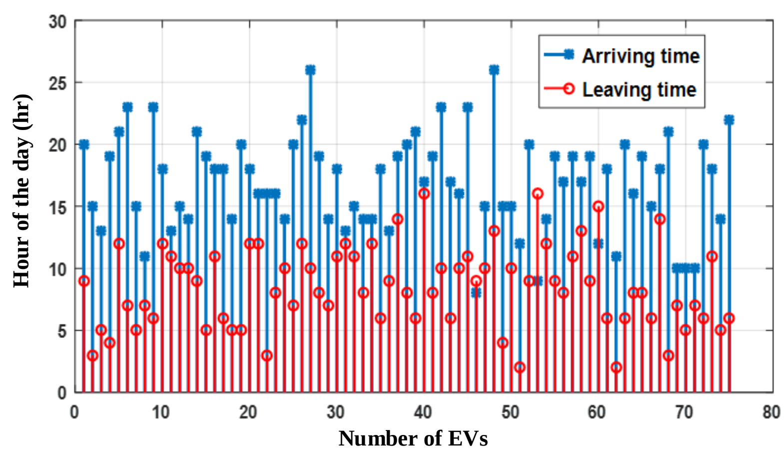

Figure 6. Stochastic data of arriving time and leaving time.

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

rate of 11kW 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(24hours).

3.3. Charging scheme

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 requirement [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 dumb charging scheme is illustrated in Figure 7.

(b)Smart charging scheme

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. 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 19.00 hours to 5.00 hours implying these 10 hours available charging time. The flow chart for smart charging scheme is shown in Figure 8.

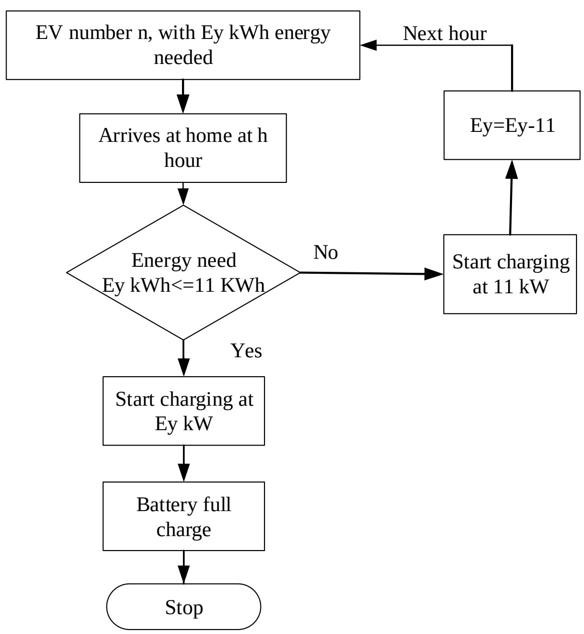

Figure 7. Flow chart for dumb charging scheme.

4. Electric vehicle model

4.1. Objective function

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

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

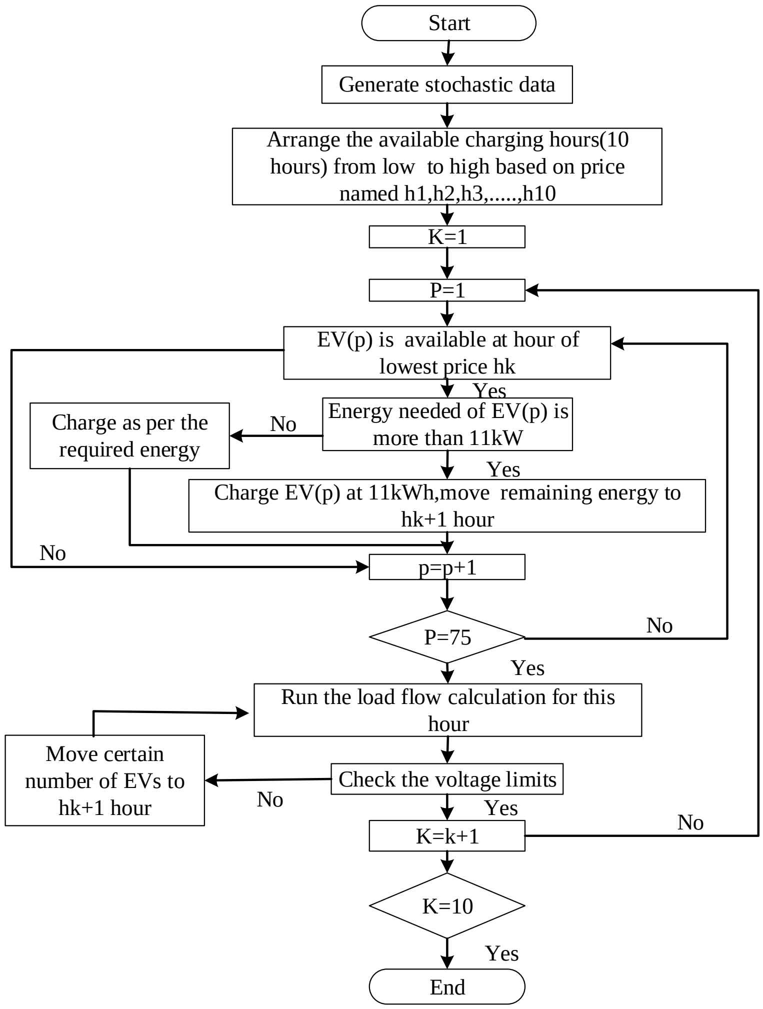

Figure 8. Flow chart for smart charging scheme.

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

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 case of smart charging plan can be calculated as

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

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

4.2. System Operational Constraints

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

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

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

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

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

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

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

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

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

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

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

5. Salp Swarm Algorithm (SSA)

Salps are oceanic creatures from Salpidae family having transparent barrel-shaped body. Salps tissues and their movements are similar to jelly fish. Water is pumped through their body propelling them to move [17]. Salps often form a swarm called salp chain to achieve better locomotion using rapid coordinated changes and foraging. This swarming behaviour of slaps can be mathematically modelled. The salps chain can be broadly divided in two groups i.e. leader and followers. The slap at the front of the chain is the leader and others are followers. As the name suggests the leader guides the swarms and the others follow each other, in a way follow 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 position 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 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 the upper and lower bounds of dimension respectively, c_1 ,c_2 and c_3 are the random numbers.c_2 and c_3 are uniformly generated between [0,1], 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 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 k^{th} follower salp in j^{th} dimension with $k \geq 2$,u_0 is the initial speed , t is the time period. If u_0=0, then (17) can be written as

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

After 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 to 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 change over iterations.

SSA algorithm saves the best solution obtained so far and assigns it to the food source variable. So 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 position with respect to each other moving gradually towards the leading salp. The gradual movements of follower salps prevent the SSA algorithm 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 exploit the search space. This algorithm has only one controlling parameter (c_1). SSA is simple and easy to implement.

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

6. Simulation result analysis

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

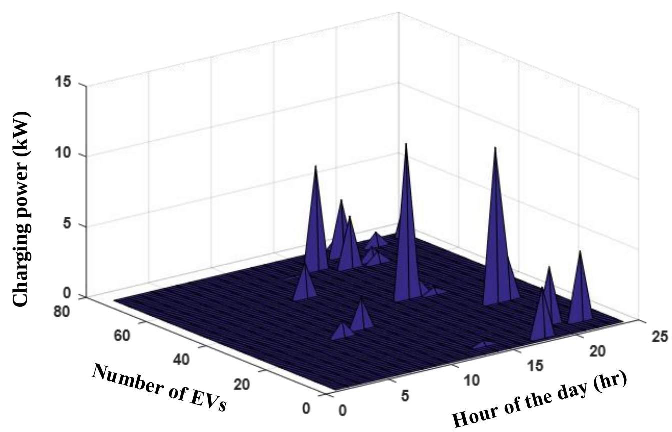

Figure 9. Charging schedules for 22 EVs in a day for dumb charging scheme.

Table 4. Optimization result.

	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

Variation of power loss and variation of voltage profile for available charging time are shown in Figure 11 & Figure 12 respectively. It is observed that due to penetration of EVs, the substation service transformer is overloaded during peak hours in case of dumb charging. During this period, most of the EVs are supposed to be plugged into RDS after their arrival at home which is between 20.00 and 24.00 hour and the electricity price is much higher during these periods. But, in case of smart charging most of the EVs are charged between 3.00 and 4.00 hour as the electricity price is lowest then which benefits both EV owners and power supply operators. So, the peak hour demand is shifted to off-peak hours resulting in peak load shaving and improving the voltage

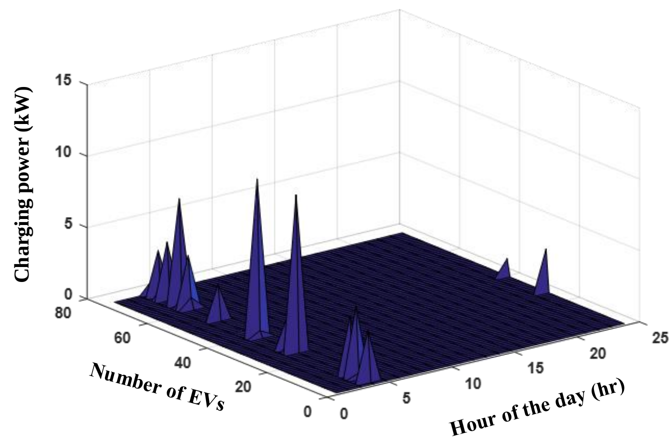

Figure 10. Charging schedules for 22 EVs in a day for smart charging scheme.

regulation. In Figure 11, it is evident that during peak hour from 20.00 hour to 22.00 hour the power loss in the system is lower in case of smart charging scheme. Figure 12 shows that in dumb charging scheme, the voltage drops distinctly during peak hours because many EVs start to charge as soon as they arrive along with peak demand of houses. Benefits offered by the smart charging scheme for EV owners are peak-shaving, to lower the peak demand charges, 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, reduce investment in transmission and distribution lines and substations.

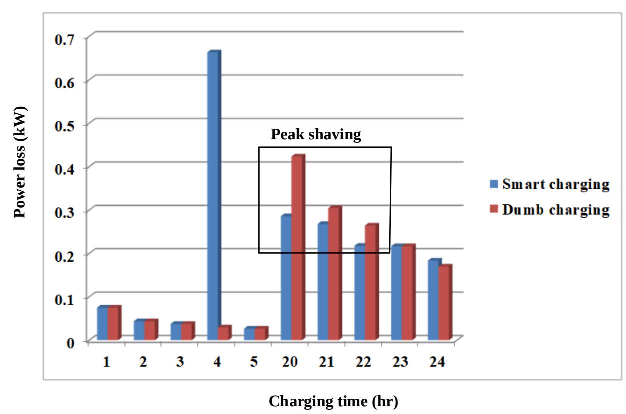

Figure 11. Power loss for charging hours.

Figure 13 shows the voltage profile of 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 EV located farther. Because a lower short-circuit

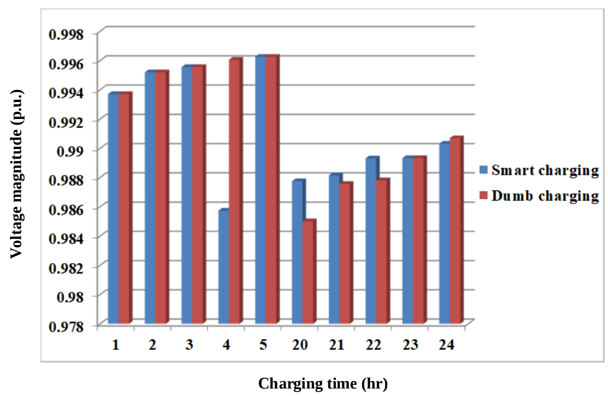

Figure 12. Voltage profile for charging hours.

capacity at the farthest load bus results in larger additional voltage drops in the secondary service voltages. Figure 14 & Figure 15 shows the voltage profiles of 107-bus RDS in a day for both dumb and smart charging scheme respectively. The minimum voltages of weakest bus 105 are 0.9587 p.u. & 0.9612 p.u. for dumb and smart charging respectively at 18.00 hrs. It is observed that the voltages of all buses are improved in smart charging scheme satisfying the secondary service voltage constraints. Variation of power loss for dumb and smart charging in a day is shown in Figure 16 & Figure 17.It is observed that the active power loss of branch 56 at 18.00 hrs 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 schemes. 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.

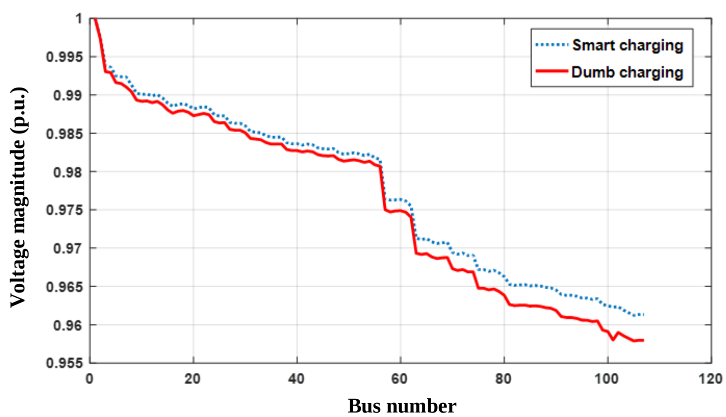

Figure 13. Voltage profile of 107-bus RDS at 18.00 hour.

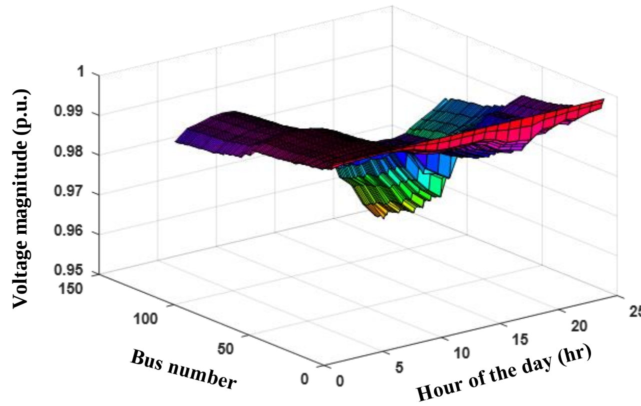

Figure 14. Variation of voltage profile of 107-bus in a day for dumb charging scheme.

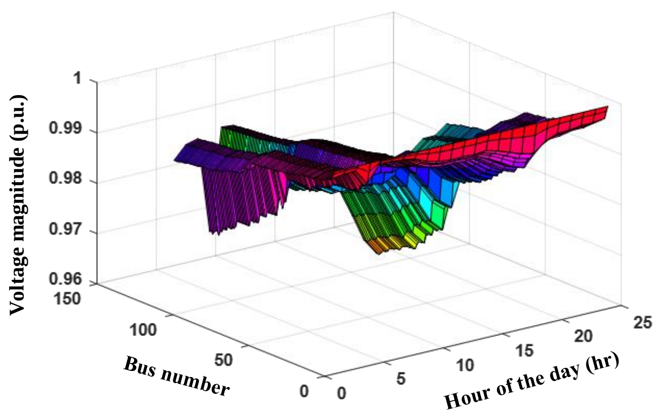

Figure 15. Variation of voltage profile of 107-bus in a day for smart charging scheme.

7. Conclusion

The impacts of EV charging on 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 addition of EV charging load causing secondary service voltage to drop.

SSA, a meta-heuristic 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.

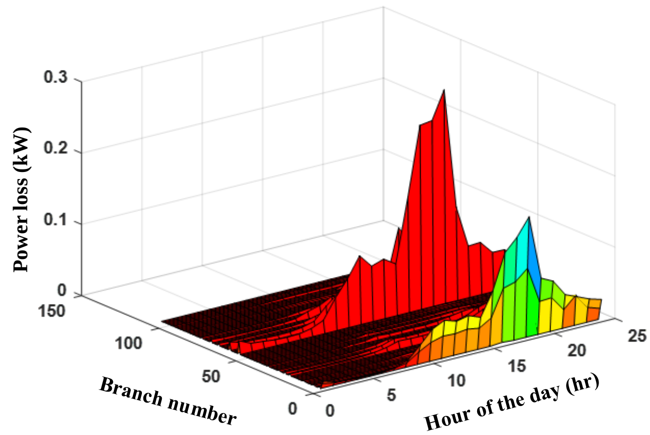

Figure 16. Variation of power loss in a day for dumb charging scheme.

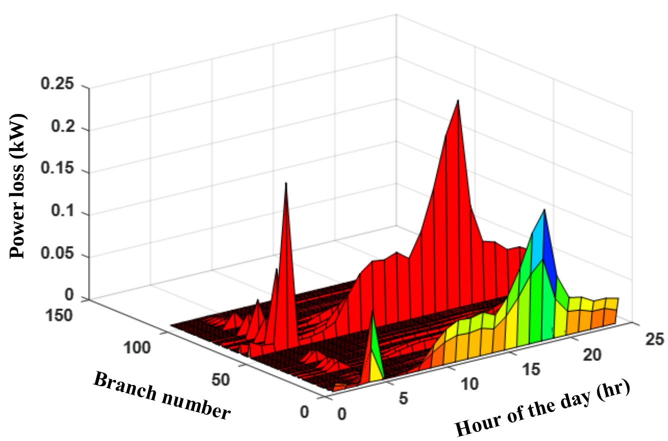

Figure 17. Variation of power loss in a day for smart charging scheme.

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