Smart Grids and Sustainable Energy (2024) 9:34
https://doi.org/10.1007/s40866-024-00220-6

ORIGINAL RESEARCH PAPER

Optimization of Probabilistic EV Fleet Integration in Unbalanced Distribution System

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Received: 30 September 2023 / Accepted: 19 August 2024
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Abstract

Electrification of the transportation sector through electric vehicles (EVs) is promoted by environmentalists and government agencies in order to encourage sustainable growth. EVs as a random load may take a toll on the stability and reliability of the power system. However, they can also help to improve the grid performance if operated in coordination with the load profile. In this paper, the impact of EV fleet integration in the unbalanced distribution network has been observed. A probabilistic EV model for charging and discharging of EVs is proposed, in which both the arrival and departure time of EVs is modelled as a normal distribution and the distance travelled is modelled as a lognormal distribution taking into account the spatial temporal features of EV charging. The charging-discharging schedule of EVs is optimized using Genetic Algorithm (GA) with the aim of obtaining a flattened load profile. The developed algorithm was tested on IEEE 13-bus unbalanced test distribution network, and the results show that the optimized EV integration has resulted in flattening the load profile (gap between maximum and minimum demand reduced to ~ 18 kW), improvement in the voltage profile and reduction in the network unbalance as depicted by the decrease in the maximum neutral current drawn (~ 28%). The proposed model can be implemented for practical distribution system planning and can be an effective tool in balancing the unbalanced network in the era of rapidly increasing EVs in the real-time distribution system.

Keywords Electric vehicle · Probabilistic modelling · Unbalanced distribution system · Load curve flattening · Neutral current · Genetic algorithm

Nomenclature

Y_{prim}	Primitive Admittance Matrix
Y_{system}	Main System Admittance Matrix
I_{inj}	Injection Current
V_n	Node Voltage
I_N	Neutral Current
I_{ph1}	Current in Phase 1
I_{ph2}	Current in Phase 2
I_{ph3}	Current in Phase 3
t	Instant of time
$P_{ch}(t)$	Effective Charging Power at time t
$P_{in}(t)$	Power flowing into the storage element at time t
$P_{lossCh}(t)$	Power loss during charging at time t
$E(t)$	Energy stored in the storage element at time t
Δt_{ch}	Time period of charging
$P_{dch}(t)$	Effective Discharging Power at time t
$P_{out}(t)$	Power flowing out of the storage element at time t
$P_{lossDch}(t)$	Power loss during discharging at time t
Δt_{dch}	Time period of discharging
n	Number of EV in the fleet
t_a^n	Time of arrival of n^{th} EV
t_d^n	Time of departure of n^{th} EV
D_n	Distance travelled by n^{th} EV
f_N	Normal distribution function
X	A random variable
μ	Mean of the probability distribution
σ	Standard deviation of probability distribution
f_{LN}	Log Normal distribution function
SOC_i	Initial state of charge
SOC_{min}	Lower limit of State of Charge
SOC_{max}	Upper Limit of State of Charge

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AER	All Electric Range of the Vehicle
B	Battery Capacity
r	Rated Charge Power
t_c^n	Time taken by n[th] EV for complete charging
E_c^n	Energy required by n[th] EV to get fully charged
Actual_Load(t)	Real power demand of the test feeder at time t
Target_Load	The 24-hour average load of each phase
P^t_{bus}	Active power demand of test bus at time t
x^t_n	State of n[th] EV at time t
P_{avg}	Average load of the test bus
t_{end}^n	Time at which charging ends for n[th] EV
EV	Electric Vehicle
GA	Genetic Algorithm
BEV	Battery Electric Vehicle
CAGR	Compound Annual Growth Rate
V2G	Vehicle to Grid
G2V	Grid to Vehicle
VPP	Virtual Power Plant
ICT	Information and Communication Technologies
DER	Distributed Energy Resource
LV	Low Voltage
OpenDSS	Open Distribution System Simulator
COM	Component Object Model
3P4W	Three Phase Four Wire
A	Ampere
kW	Kilowatt

Introduction

The Electrical Power System is continuously evolving due to variables like – depletion of available natural reserves of fossil fuels, adoption of renewable resources along with the threat of climate change etc., which are the main causes of sustainable development approach. This change in the power system is characterized by the introduction of futuristic technology, addition of new loads (for example EVs), increased popularity of cleaner and greener sources of energy etc. The transportation sector is a major contributor to the increasing level of harmful emissions and greenhouse gases; therefore, the electrification of this sector can prove to be a propitious solution to fight global warming concerns and reduce the carbon footprint, and this would be more advantageous when these vehicles are charged using electricity produced from greener and sustainable sources such as biomass, wind or solar [1]. About 80% of Passenger rail and 50% of Freight Wagons are electrified worldwide, which do not release any direct carbon emissions into the environment [2]. With recent developments, the aviation sector is also moving towards electrification [3]. In this paper we shall focus only on Battery Electric Vehicles [4].

Unlike other loads, EVs due to their dispatchable characteristic, can provide more energy security, however, their successful implementation is hindered due to – high initial capital investment needed, lack of suitable charging infrastructure especially in developing nations, battery replacement required after a specific tenure, degradation of battery capacity etc. [5]. In spite of these reasons, the Global EV market has expanded exponentially and is expected to grow strongly in the forthcoming years [6]. The Electric Vehicle market in India is anticipated to grow at an impressive compound annual growth rate of 66.52% during the forecast period of 2022–2029 [7]. Conventionally EVs were modelled in unidirectional mode in the distribution network, which meant the energy could only flow from the grid to the vehicle (G2V). The development of the concept of Virtual Power Plants, along with advanced Information and Communication Technologies, have enabled EVs to now be modelled in a bi-directional mode in the distribution network by enabling charging through G2V while acting as a load on the grid, as well as discharging through Vehicle to grid while acting as Distributed Energy Resource [8]. This bidirectional flow of electricity can serve many purposes such as Grid Stabilization—by providing additional power during peak demand times, V2G helps to stabilize the grid and prevent blackouts or brownouts; Energy Storage—EVs can act as mobile energy storage units, storing excess energy produced during off-peak times or from renewable sources like solar and wind, and discharging it when needed, thereby enabling the integration of renewable energy resources by providing a flexible storage solution. Therefore, EVs can provide many ancillary services in the power system when utilized with an organized approach, such as – load levelling / load curve flattening, reduction in the peak load, power loss minimization etc. which will not only assist in balancing the distribution network but will also prove to be economical to the utility as well as the end-users [9]. It should be remembered that, for EVs to provide such services, there is a requirement of an EV aggregator which would regulate the participation of EVs in the electricity market and make the system more flexible [10].

The majority of research conducted on EV integration has been concerned with balanced distribution networks. In [11], only the impact of asymmetric EV charging on voltage profile of a low voltage grid has been studied, and the results show that uncoordinated EV charging can cause significant voltage imbalance; however, it does not discuss about mitigating the network imbalance and uncertainties from different possible allocations. While [12] investigates the impact of probabilistic EV charging on IEEE European LV test case which shows that optimized smart charging helps to improve the overall performance of the system; this paper also supports the fact that probabilistic methods are more appropriate and accurate than deterministic worst-case approaches due to the temporal and spatial uncertainties in EV arrivals and departures and that capturing these uncertainties can lead to better planning and management of the grid. In [13], the impact of EV fleet integration on neutral current of the system is discussed and optimized using Differential Evolution algorithm; a significant reduction in neutral current is observed along with an improve in the voltage profile of the test network; however, it does not consider a probabilistic approach to model the EVs. In [14] the combined objective of cost benefit analysis, load levelling and optimization of probabilistic EV fleet using mixed integer programming has been discussed. While [15], extends the optimization of probabilistic modelling of EVs with an aim of achieving minimum operational cost along with distribution feeder reconfiguration using GA in 33-bus radial distribution network, which is again a balanced test system. In [24], an energy management system is designed to optimize the integration of renewable energy sources and electric vehicles in microgrids. Using Support Vector Regression for precise prediction of EV charging demands and a self-adaptive dragonfly algorithm for optimization, the study addresses the significant challenge of balancing renewable energy intermittency with increasing EV charging needs. Tested on the IEEE 69-bus test system, the approach demonstrated high accuracy in demand prediction and a notable reduction in total operation costs, emphasizing its potential to enhance the efficiency and reliability of renewable microgrids while supporting the growing adoption of electric vehicles. The paper [25] proposes a framework incorporating advanced intelligent methods and evolutionary algorithms to address uncertainties related to renewable energy, EV charging, and market fluctuations. The papers [25] & [26] compare three charging schemes namely—coordinated, uncoordinated, and smart charging; and support the fact that optimal switching and smart charging results in optimization in real-time based on grid conditions, energy prices, and user preferences, offering the most significant cost reductions.

It is pertinent to mention that a power distribution system is inherently unbalanced and EV fleet modelling is not deterministic. The shortage of published research on the optimized charging-discharging of EVs in an unbalanced network highlights a potential research gap. The research presented in [16], shows a deterministic approach to analyse the impact of EV fleet integration in an unbalanced distribution network. This paper presents a novel approach to model an electric vehicle (EV) fleet within an unbalanced

Table 1 Comparison Between Various Studies Conducted On EVs

Study Name	Parameters in Optimization			Stochastic Approach	Neutral Current Impact Studied	Objective of Optimization	Simulated Grid
	EV	Load	Time				
This Study	✓	✓	✓	✓	✓	Load Levelling, Reduction in Neutral Current	IEEE 13-Bus Unbalanced System
Umar, Reza, Mahmoud, Joakim & Joakim (2021)	✓	✓	✓	✓		Minimizing net-load Variance	IEEE European LV test feeder, unbalanced
Helm, Hauer, Wolter, Wenge, Balischewski & Komarnicki (2020)						An asymmetric power flow calculation analyzing the impact of uncoordinated EV charging on voltage stability	LV Grid
Islam, Lu, Hossain & Li. (2019)					✓	A method to reduce the neutral current at the supporting feeder, by optimizing the voltage unbalance	EV Penetrated Unbalanced Distribution Grid
Singh & Tiwari (2020)	✓	✓	✓	✓		Minimize losses in the system by utilizing V2G operation of the EVs	IEEE 33-Bus Balanced System
Kaur & Kaur (2022)					✓	Impact of EV deployment in unbalanced system has been observed—Deterministic Approach	IEEE 13-Bus Unbalanced System

distribution system, employing MATLAB and OpenDSS through a COM interface to establish a robust foundation. The Table 1 illustrates a comparison of different studies conducted on electric vehicles with this study.

The investigation into the impact of probabilistic EV deployment in which both the arrival and departure time of EVs are modelled as a normal distribution and the distance travelled is modelled as a lognormal distribution taking into account the spatial temporal features of EV charging, on various parameters such as active power demand, voltage profile and neutral current of the test feeder is significant.

Furthermore, the optimization of the charging-discharging schedule of the integrated EV fleet is performed using GA with an aim of achieving load levelling, which adds a unique dimension to the research and contributes novel insights to the field. The novel contribution of this work is as follows –

- The spatial temporal features of EV charging are considered in the study of EV integration on active power demand, voltage profile and network unbalance.
- Impact of EV integration is studied on unbalanced radial distribution network.
- Optimization of the charging-discharging schedule of the integrated EV fleet for load flattening is investigated.
- The impact on Neutral Current in the distribution system is studied.

System Modelling and Problem Formulation

System Modelling

In India, the three phase four wire configuration is commonly used for distribution networks. The Power Flow of Unbalanced Distribution Network solution is generated taking into consideration the limitations that arise due to high resistance to reactance ratio of the distribution feeders [17]. The power flow results are obtained by solving the equation given in (1) [18] –

$$I_{inj}(V) = Y_{system} V \tag{1}$$

The presence of unbalance in the phases, which may arise due to any reason such as load fluctuations, can lead to large neutral current in the network that causes power quality issues and decreased network efficiency. The (I_N) Neutral Current in the system is computed as –

$$I_N = I_{ph1} + I_{ph2} + I_{ph3} \tag{2}$$

Research suggests that coordinated EV charging-discharging can reduce the neutral current and hence, the unbalance in the network [13, 19].

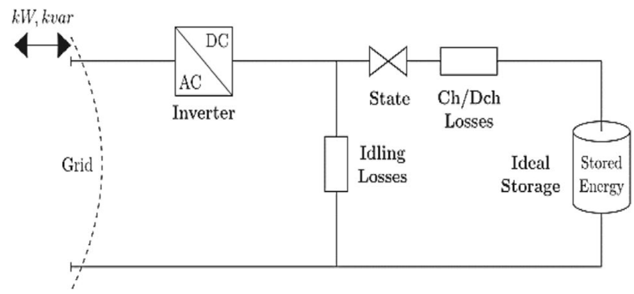


Fig. 1 Storage Element General Structure

Electric Vehicle Modelling in OpenDSS – each vehicle is modelled as a Storage Element [16] in OpenDSS and its general structure is depicted in Fig. 1 [18].

- The storage element acts as a constant power consuming load during the charging period and is represented by the equations given in (3) and (4) –

$$P_{ch}(t) = P_{in}(t) - P_{lossCh}(t) \tag{3}$$

$$E_{ch}(t + \Delta t) = E_{ch}(t) + P_{ch}(t)^{*} \Delta t_{ch} \tag{4}$$

- The storage element acts as a power generator during the discharging period which has the ability of injecting active power into the system and is represented by the equations given in (5) and (6) –

$$P_{dch}(t) = P_{out}(t) + P_{lossDch}(t) \tag{5}$$

$$E_{dch}(t + \Delta t) = E_{dch}(t) - P_{dch}(t)^{*} \Delta t_{dch} \tag{6}$$

Probabilistic EV Parameter Modelling – In this research we assume that the charging-discharging schedule is to be formulated for a residential car park where the EVs are available in the evening when the residents come home from their jobs, up until the commencement of their next trip in the following morning. The EVs are modelled probabilistically by taking into account key variables such as time of arrival and departure of EVs, AER-All Electric Range of EVs, daily distance driven etc. [15].

The arrival time of the EV (t_a) and departure time of the EV (t_d) is assumed to have a normal distribution, while the daily driven distance of the EV (D) is approximated to follow lognormal distribution taking into account the spatial temporal features of EV charging, as depicted by the forthcoming equations [15].

$$t_a = f_N\left(X_a, \mu_a, \sigma_a\right) \tag{7}$$

$$t_d = f_N(X_d, \mu_d, \sigma_d) \tag{8}$$

$$D = f_{LN}(X_D, \mu_D, \sigma_D) \tag{9}$$

Where μ is the mean and σ is the standard deviation and a, d & D are the subscripts for time of arrival, time of departure and distance driven by the Electric Vehicles respectively. These parameters are used to calculate the initial State of Charge (SOC_i) of n^{th} EV using the Eq. (10), where AER is the All-Electric Range of the vehicle and D_n is the distance driven by n^{th} EV which is calculated probabilistically as depicted in Eq. (9).

$$SOC_i = 1 - \frac{Dn}{AER} \tag{10}$$

The total time required for n^{th} EV to get fully charged (t_c^n) is calculated using the Eq. (11) and similarly the total energy required for n^{th} EV to get fully charged (E_c^n) is calculated using Eq. (12).

$$t_c^n = \frac{(1 - SOCi).B}{r} \tag{11}$$

$$E_c^n = \left|(1 - SOC_i).B\right| \tag{12}$$

Where, B is the battery Capacity of the Electric Vehicle and r is the rated charge power. We have assumed the efficiency of charging / discharging to be 100%.

Optimization of Charging-Discharging Schedule of EVs

The charging-discharging schedule of EVs is optimized with the aim of obtaining a flattened load profile through Genetic Algorithm (GA) in MATLAB [20], where the objective function is formulated on the basis of Eq. (13), subject to constraints discussed further –

$$Min\left\{Sqrt\left(\Sigma_t\left[Actual\_Load(t) - Target\_Load\right]^2\right)\right\} \tag{13}$$

Here, the Actual_Load(t) is the real power demand of the test feeder at time t, and the Target_Load is the 24-h average load of each phase. In order to achieve a flat load profile, the EVs will be required to charge during the off-peak period for Valley Filling and discharge during the peak period for peak shaving. Therefore, the fitness function is formulated in order to minimize the difference between the instantaneous load and the average load of each phase on the test bus as given in Eq. (14).

$$Min(f) = Sqrt\left(\Sigma_t\left[P^t{}_{bus} - \left\{r.\Sigma_n x^t{}_n\right\} - P_{avg}\right]^2\right) \tag{14}$$

Where, f is the function to be minimized using GA, t is the time period (24 h in this study), P^t_{bus} is the active power demand of test bus at time t, n is the number of EVs in the fleet, x^t_n is the state of n^{th} EV at time t which can be 0 (idling), + 1 (discharging) or -1 (charging) and P_{avg} is the average load of the test bus. The fitness function given in (14) is an extension of equation given in (13) to our system, which is optimized subject to the following constraints.

$$x^t{}_n = 0/-1/+1 \; when \; t \in [t_a, t_d] \tag{15}$$

$$x^t{}_n = 0 \; when \; t \notin [t_a, t_d] \tag{16}$$

$$SOC_{min} < SOC < SOC_{max} \tag{17}$$

$$E_c^n = \Sigma_t x^t{}_n.r \tag{18}$$

The constraints specified in (15) and (16) describe the fundamental states of n^{th} EV when it is connected and not connected to the grid. The constraint given in (17), helps to maintain the SOC within safe limits, which are taken as $SOC_{min} = 20\%$ and $SOC_{max} = 100\%$; and it is ensured through the constraint in (18) that at the end of parking period any EV is fully charged. It is worth noting that the battery SOC is an effective optimizing constraint for EVs as it ensures battery health by preventing overcharging and

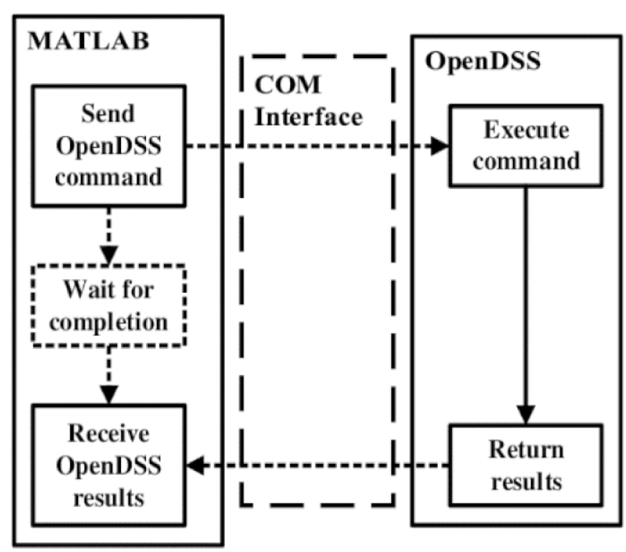


Fig. 2 COM Interface between OpenDSS and MATLAB

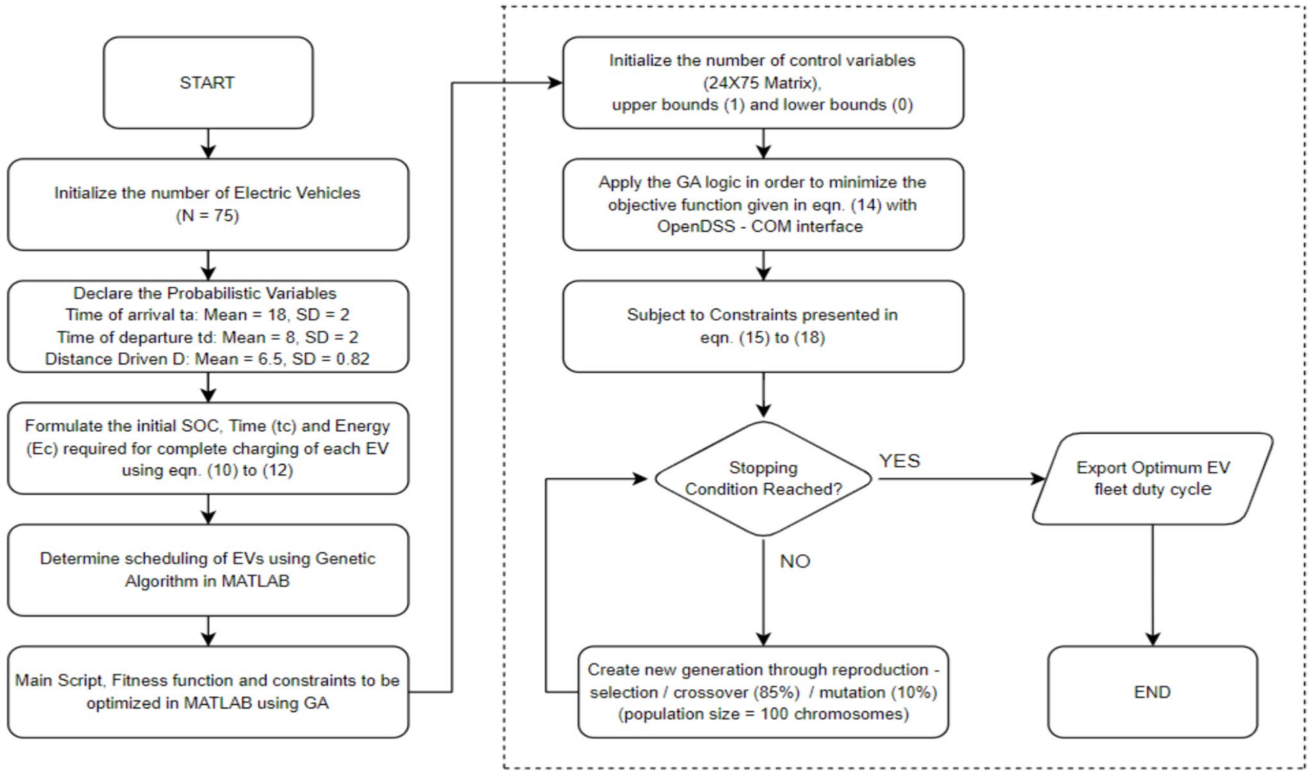


Fig. 3 Flow Chart for Optimization using GA

deep discharges. Moreover, it helps to provide predictable performance, ensuring sufficient charge for mobility needs while participating in grid services.

Methodology

For the purpose of analysis, we have used MATLAB R2015a and OpenDSS through COM interface as depicted in Fig. 2 [21].

The stepwise approach for optimization is shown in the Flow diagram presented in Fig. 3, while the steps followed for the research are summarized below –

- The network parameters such as system load, voltage regulations, maximum number of iterations, load profile etc. are declared and the 24 h load flow is run for each case.
- An EV fleet is initialized at the suitable busbar, for which the charging-discharging is optimized using GA.
- The best solution is obtained by solving and comparing the objective function given in Eq. (14), subject to constraints given in Eqs. (15) – (18), till the stopping condition is reached, which is reaching the maximum number of iterations in our case. After this, the best solution is exported to OpenDSS for running the daily load flow and the necessary computations are performed.

Case Study

For the purpose of this research, we have considered the IEEE 13-bus unbalanced distribution system [22], which is the most basic form of unbalanced network available for analysis. It operates at 4.16 kV and has one source, a regulator, with a number of short unbalanced transmission lines and shunt capacitors. It consists of two single-phase buses, three two-phase buses, while the rest other buses are three-phase. It should be noted that the scope of this study is limited to examining the impact of an EV fleet on the basic IEEE test system. However, future research can be extended to incorporate a real-time distribution system to obtain more realistic results.

The system modelled on MATLAB with OpenDSS COM Interface and is run under basic conditions for which the power flow results are obtained and verified with the IEEE datasheet [22]. The power flow results are computed by

OpenDSS by solving the equation given in (1) using the Fixed-Point Iteration Method as shown below –

$$V_{n+1} = \left[Y_{system}\right]^{-1} I_{inj}\left(V_n\right) \tag{19}$$

Where n varies from 0 to N, until the solution converges.

- The network is analysed for various cases as discussed further.
- GA is used to optimize the charging-discharging schedule.
- A comparison of results is presented for the various cases.

EV Fleet Size & Location

The EV modelled has three operating states, viz. (-1) charging or G2V, (+1) discharging or V2G and (0) idling [18]. The EV fleet is modelled on bus 634 which is the Low Voltage (LV) bus of the system, as shown in Fig. 4.

Table 2 EV Specifications

Spec	Rating
Battery Capacity	24 kWh
Rated Charge Power	3.3 kW (Slow Charging)
All Electric Range	315 km
No. of EVs in each phase	25

The fleet consists of 75 EV units, with 25 EVs in each phase. The EV penetration with the given number of vehicles is about 20% on bus 634. It is important to recognize that penetration level of EVs significantly influences the charging-discharging optimization. A higher EV penetration enhances demand response capabilities, facilitates the integration of intermittent renewable resources, boosts the potential for V2G services etc. Also, optimal charging strategies at higher penetration levels can lead to economic

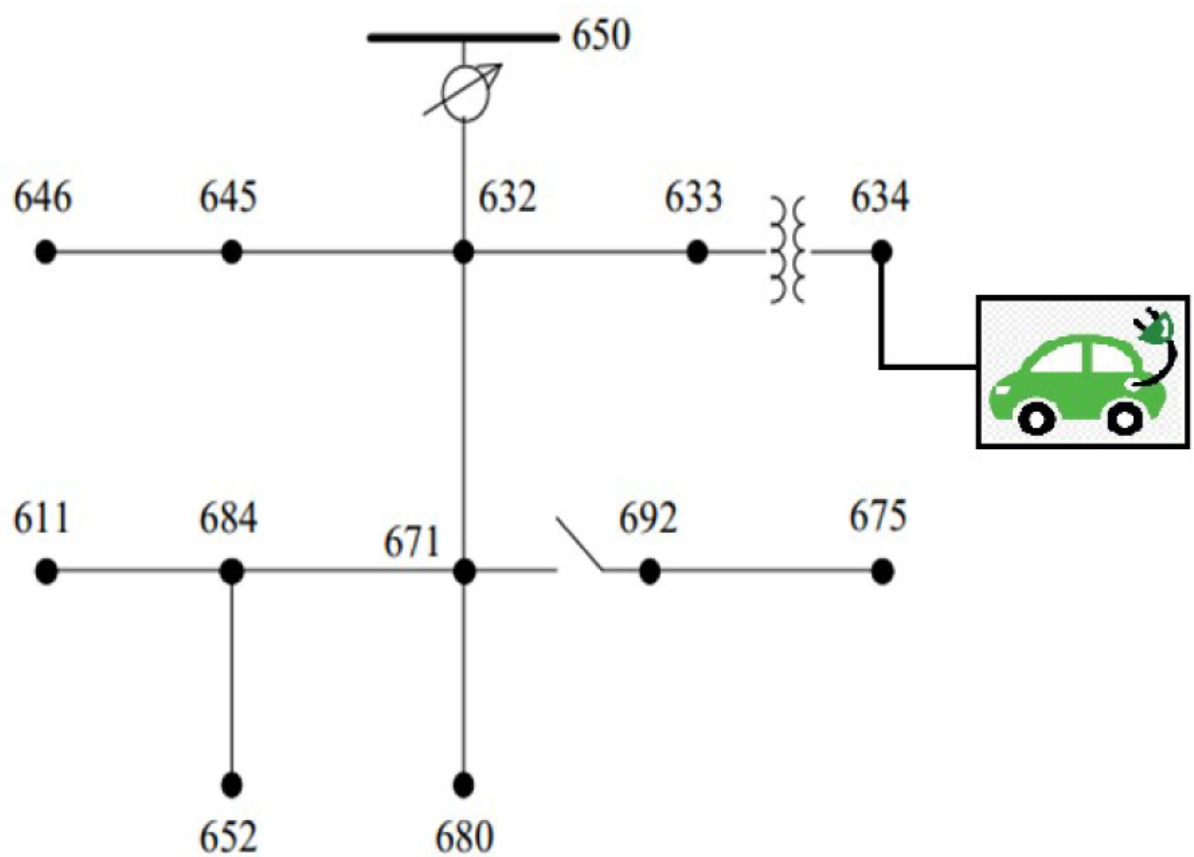


Fig. 4 Modified IEEE 13-Bus Network

Table 3 Cases Studied

Sr. No	Case	Description
A	No EV Integration	IEEE 13 Bus Network without any EV Integration
B	Uncoordinated Charging	Unoptimized charging of EVs with only G2V (Grid to Vehicle)
C	Coordinated Charging-Discharging	Genetic Algorithm optimized charging and discharging

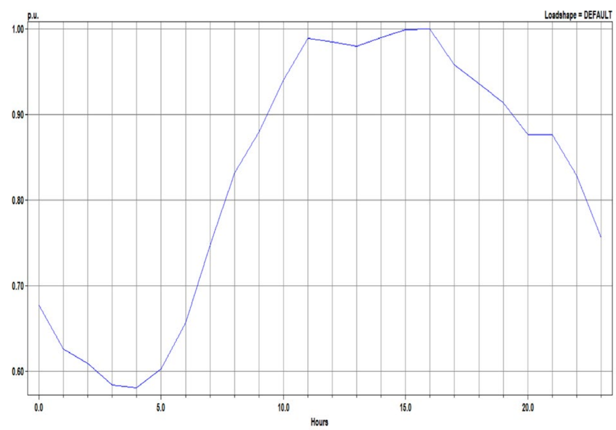


Fig. 5 Default Load Profile

benefits, reduced cost of electricity, and also lower greenhouse gas emissions.

The Table 2 shows the modelled EV capacity for a single EV, which is taken from the Tata Tiago EV specifications having a Rated Charging Power of 3.3 kW for standard charging and a Battery Capacity of 24 kWh [23].

Cases

The daily load flow is computed for each case, with a time period of 24 h with an interval of 1 h. The cases considered in the research are listed in Table 3.

Results and Discussion

The analysis is performed in MATLAB and OpenDSS through COM interface to obtain the test bus results. The conventional loads on the bus 634 follow the default load shape as depicted in the Fig. 5.

IEEE 13 Bus System without EV Fleet

This case is run without any EV integration. The active power and neutral current profiles observed after running

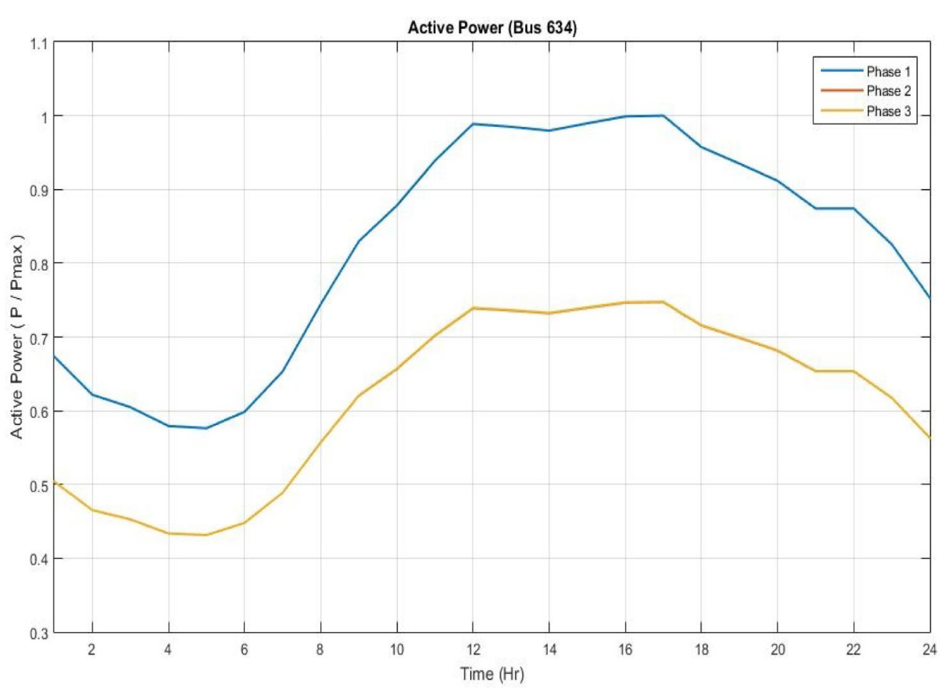


Fig. 6 Active Power Profile – No EV Integration

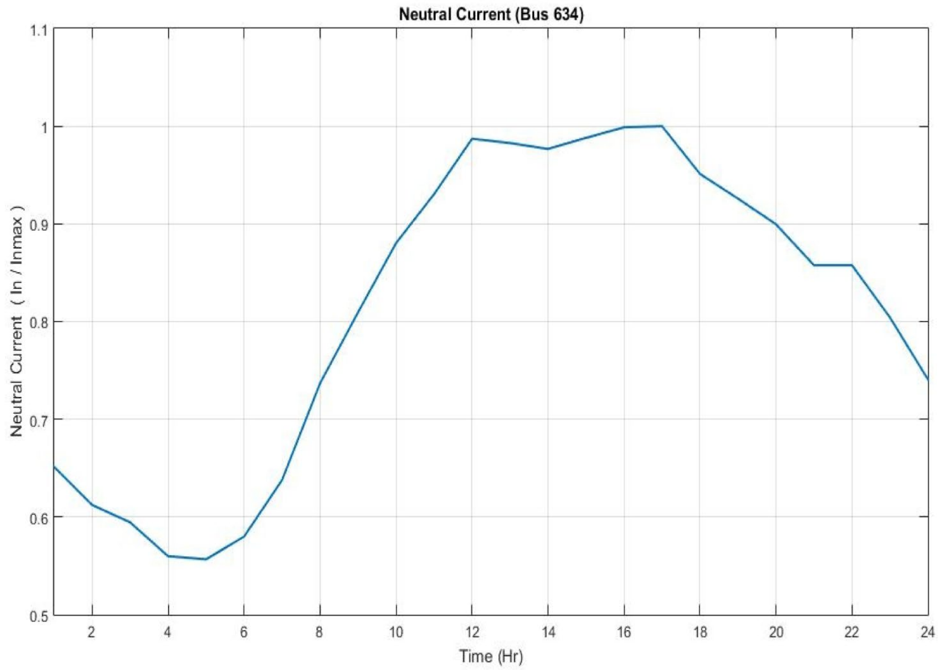


Fig. 7 Neutral Current Profile – No EV Integration

Table 4 Observed Parameters – No EV Integration

Parameters	Phase		
	1	2	3
Maximum Demand (kW)	162.55	121.46	121.54
Minimum Demand (kW)	93.67	70.12	70.13
Average Demand (kW)	133.91	100.12	100.17
Max Neutral current (A)	19.89		

load flow, for bus 634 are shown in Figs. 6 and 7. The Table 4 depicts the various parameters observed for this scenario. This case establishes the basis for our study, supplying the baseline values of power consumption and neutral current in the unbalanced distribution network that we seek to optimize with EVs.

Uncoordinated Charging

In this case it is assumed that each EV starts charging as soon as it arrives. The charging is continuous at the rated charge power (3.3 kW) and the end time of charging (t_{end}^{n}) of n^{th} EV is determined as depicted in Eq. (20).

$$t_{end}{}^{n} = t_a{}^{n} + t_c{}^{n} \tag{20}$$

Where, t_a^{n} is the time of arrival of n^{th} EV determined probabilistically as given in Eq. (7) and t_c^{n} is the time required by n^{th} EV to get fully charged as given in Eq. (11). The state of n^{th} EV at time t, x^{t}_{n} for this case, where only charging is taking place is described below –

$$x^{t}{}_{n} = 0/-1 \; when \; t \in \left[t_a, t_{end}\right] \tag{21}$$

$$x^{t}{}_{n} = 0 \; when \; t \notin \left[t_a, t_{end}\right] \tag{22}$$

In this scenario, each EV behaves as only a load, as depicted in (21), that can only charge or consume power from the network at a fixed rate (rated charge power). The active power and neutral current profiles at bus 634 for this case are presented in Figs. 8 and 9 respectively. The Table 5 shows the parameters observed for this case.

It can be seen from the graphs that the peak load and neutral current drawn have increased in this case due to the uncoordinated nature of charging. The Table 6 shows the comparison between the Case A (without EV Fleet) and uncoordinated charging case. Uncoordinated EV charging can significantly impact the electric grid by causing overloads, voltage fluctuations, and increased peak demand. This may result in inefficient energy use and higher operational cost.

The EV load on the grid is increasing rapidly and such uncoordinated charging can prove fatal for the stability of the power system. Therefore, there is a need for developing a coordinated charging-discharging strategy for this rapidly increasing special load on the system, such that its dispatchable characteristics can be used to the fullest for increasing the reliability of the power network.

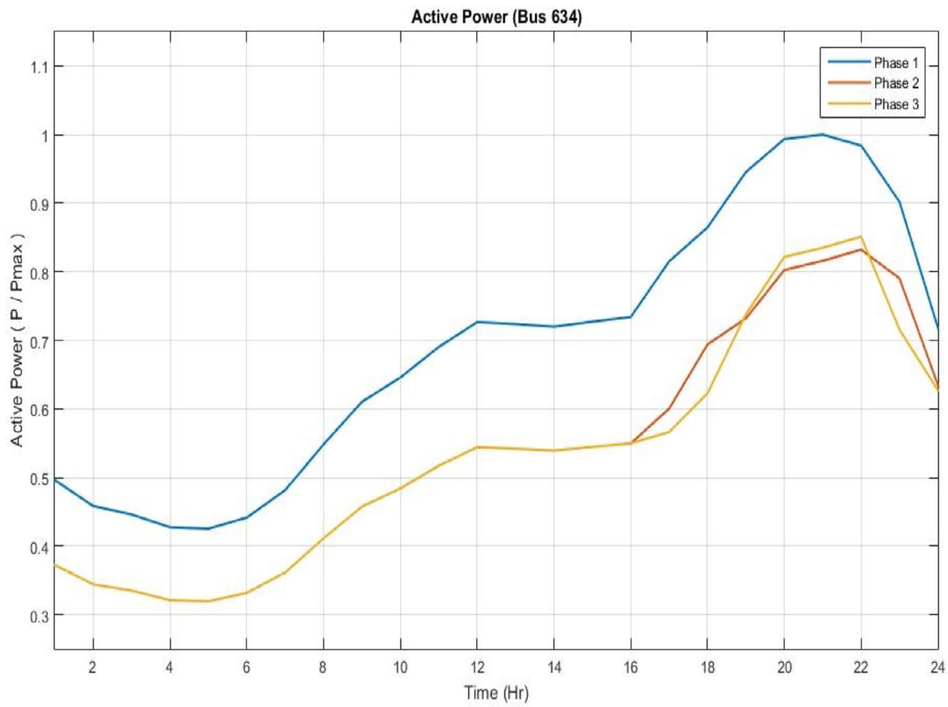


Fig. 8 Active Power Profile – Uncoordinated Charging

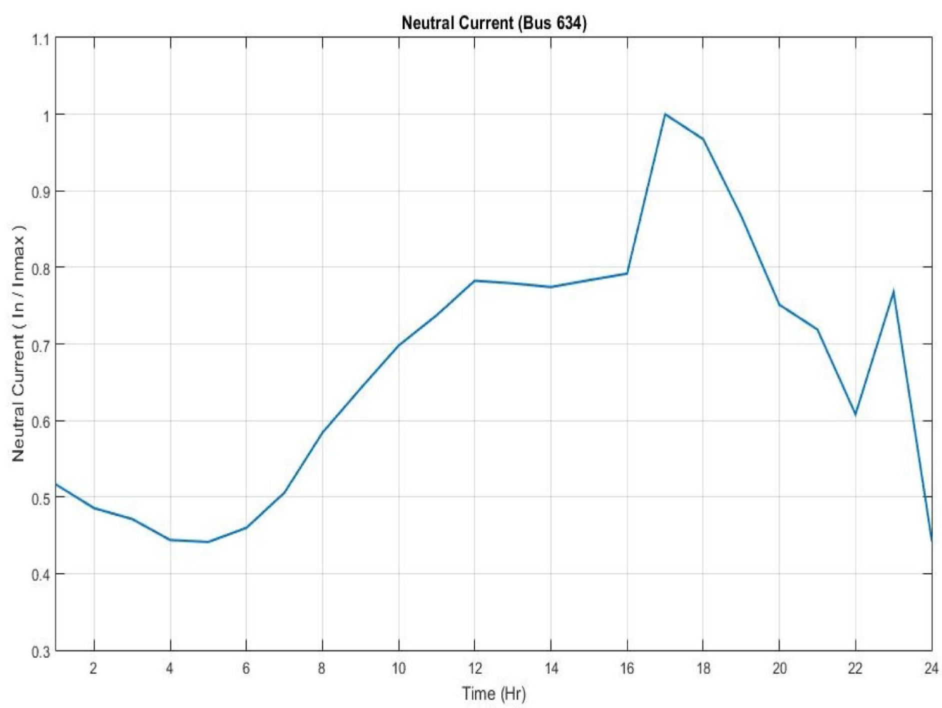


Fig. 9 Neutral Current Profile – Uncoordinated Charging

Coordinated Charging Discharging

In this case, we have optimized the charging and discharging of EVs using GA in MATLAB. This approach for optimization is very useful when dealing with stochastic environment due to its inherent adaptability which allows to handle the complexity introduced by such variables and iteratively refine the strategies, converging towards an optimal or near-optimal solution.

The EV fleet behaves as a load as well as a power source according to the duty cycle computed from the optimization. This method proves beneficial in managing the dynamic and uncertain nature of factors such as grid demand, user preferences etc. in the context of EVs. Our decision variable is the

Table 5 Observed Parameters – Uncoordinated Charging

Parameters	Phase		
	1	2	3
Maximum Demand (kW)	222.47	185.16	189.35
Minimum Demand (kW)	94.61	71.07	71.06
Average Demand (kW)	153.18	119.36	118.21
Max Neutral current (A)	25.10		

charging-discharging matrix of the EV fleet for 24 h which is of the order of (24 X 75 = 1800 variables), that is 600 variables per phase. The fitness function and the constraints for GA are given in the Eq. (14) and Eqs. (15) to (18) respectively. The implementation of optimization through GA is carried out as per the following –

- Parent Selection is done using Roulette Wheel Selection.
- Crossover – Two rows are entirely exchanged among two randomly selected parents.
- Mutation – This operation is adjusted to ensure that the final generated offspring follow the constraints.

The Fig. 10 shows the function cost plot for GA implementation with respect to iteration number. The active power and neutral current profiles are shown in Figs. 11 and 12 respectively. The Table 7 shows the various parameters observed for this case. Coordinated EV charging offers several benefits such as—Grid Stability; Voltage Regulation; Peak Demand Reduction; Enhanced Efficiency; Cost Savings and Improved Demand Response and Renewable Integration Opportunities.

It can be observed from the results obtained below that optimized EV integration has resulted in flattening the load profile and decreasing the maximum neutral current drawn at the test bus (634) and there is also an improvement in the voltage profile of the test feeder.

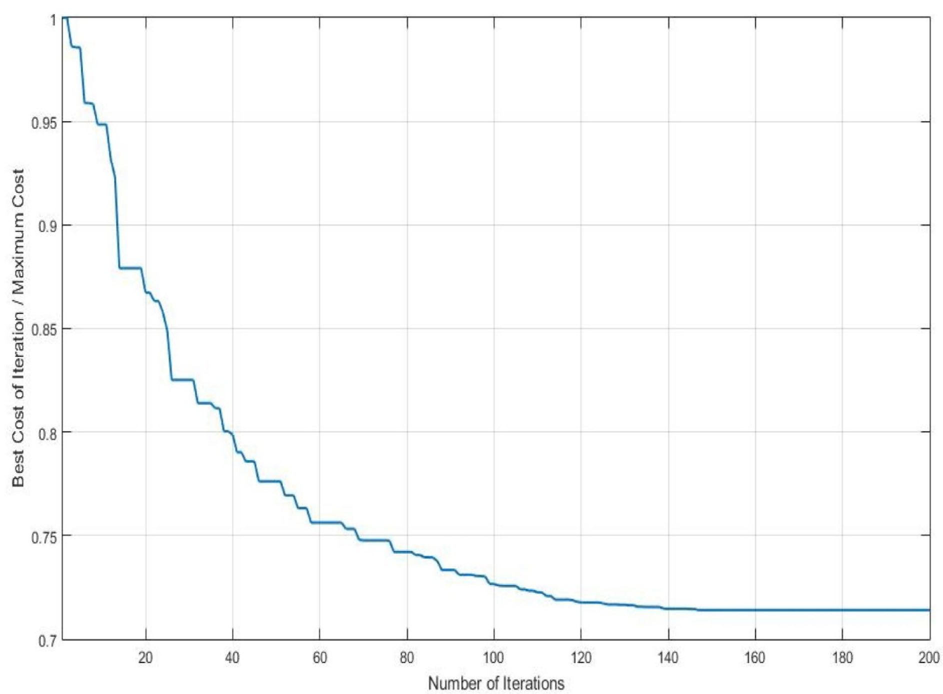
The Table 8 shows the comparison between the uncoordinated charging case and the coordinated charging-discharging case.

The observations that can be made for the coordinated charging-discharging case are as follows –

Table 6 Comparison of Parameters of Case B from Case A

	Phase	Maximum Demand	Average Demand	Max Neutral current
Un coordinated Charging	1	↑36.9%	↑14.4%	↑26.2%
	2	↑52.4%	↑19.2%	
	3	↑55.8%	↑18.0%	

Fig. 10 Function Cost Plot – GA



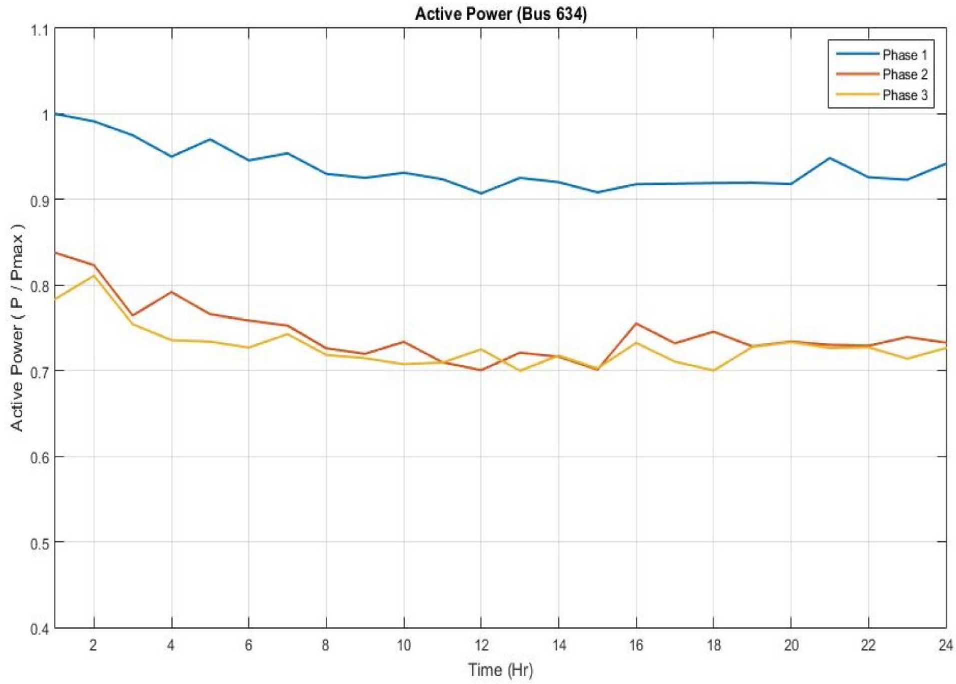


Fig. 11 Active Power Profile – Coordinated Charging-Discharging

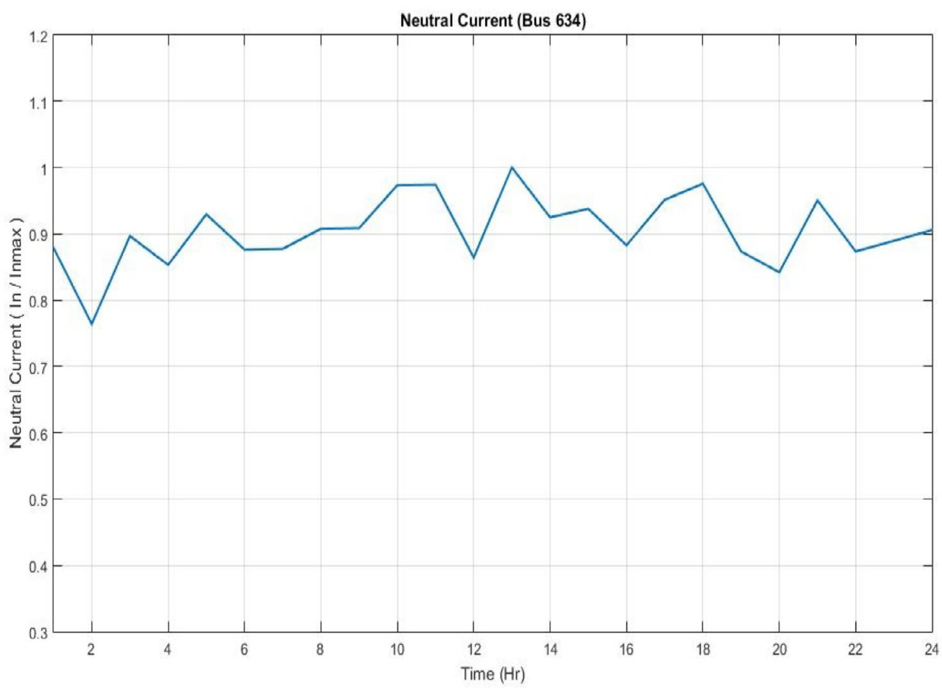


Fig. 12 Neutral Current Profile – Coordinated Charging-Discharging

- The peak load on the test bus reduces for all the three phases (by 27.3% for phase 1, by 26.8% for phase 2 and by 30.7% for phase 3) as can be observed in Table 8.
- There is also a decrease in unbalancing of the system as depicted by the reduction in the value of maximum neutral current drawn on the test bus (reduced by 28.2%).

Table 7 Observed Parameters – Coordinated Case

Parameters	Phase		
	1	2	3
Maximum Demand (kW)	161.84	135.58	131.25
Minimum Demand (kW)	146.81	113.38	113.28
Average Demand (kW)	151.66	120.36	117.89
Max Neutral current (A)	18.03		

- It should also be noted that the gap between the maximum and minimum load decreases (by 88.2% for phase 1, by 80.5% for phase 2 and by 84.8% for phase 3) thereby resulting in a flattened load profile, which was the main objective of the optimization.
- There is also an improvement in the voltage profile of the test bus as depicted in Fig. 13, which shows a comparison of voltage profiles for all the three cases viz. base case (in blue), uncoordinated charging (in red) and coordinated charging-discharging (in yellow).

It should be noted that most of the research work on EV integration in the grid is simulated on balanced distribution system and randomness of the EV fleet is not considered. However, a power distribution system is inherently unbalanced and EV fleet modelling is not deterministic. This research is a step into that direction.

Conclusion

In this paper, the impact of probabilistic EV fleet integration in the IEEE 13 bus distribution network has been considered. It was observed that uncoordinated charging results in rise of unbalance on the test feeder (bus 634) as depicted by the increased neutral current drawn and also the rise in the peak load. These changes are undesirable and can prove fatal for the stability and reliability of the power network. Genetic Algorithm based optimization model minimizes the fluctuations in the daily load and attain reduction in the peak demand of the system. With this proposed algorithm, it is observed that the peak demand and load fluctuations on the test bus reduce

Table 8 Comparison of Parameters of Case C from Case B

	Phase	Maximum Demand	Gap in Max & Min Demand	Max Neutral current
Coordinated Case	1	↓27.3%	↓88.2%	↓28.2%
	2	↓26.8%	↓80.5%	
	3	↓30.7%	↓84.8%	

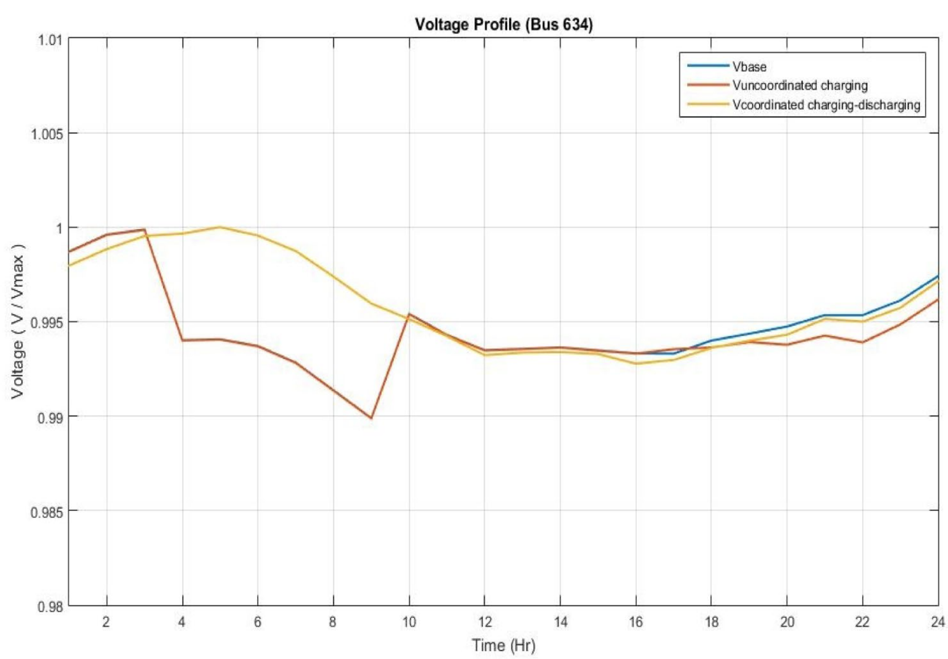


Fig. 13 Voltage Profile Comparison

along with the reduction in the neutral current drawn that aids in balancing the system. A flattened load profile is attained with appreciable reduction between the maximum and minimum power demand (over 80%) along with improved voltage profile. Therefore, this optimized charging-discharging strategy of EVs can be used for improving the power system performance when used along with an EV aggregator.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40866-024-00220-6.

Authors' Contribution Both authors contributed to write the main manuscript text and provided valuable suggestions to improve and consolidate the research work. Both authors reviewed the manuscript.

Funding This declaration is not applicable to our research.

Data Availability This declaration is not applicable to our research.

Declarations

Ethical Approval This declaration is not applicable to our study.

Competing Interests No competing interests for the authors.

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