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ORIGINAL RESEARCH ARTICLE

Optimized planning framework of solar photovoltaic based generation with EV charging station in a rural distribution network considering uncertainties

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ABSTRACT

To address the adverse impacts due to rapid growth of electric vehicles (EVs), a robust planning framework is developed in this paper for optimal deployment of EV charging stations and solar energy resources in the distribution network. Uncertainty modeling of EV is done using probability density function considering stochastic parameters extracted from real National Household Travel Survey (NHTS)datasheet. Considering solar irradiance as the uncertainty parameter, a practical Photovoltaic (PV) model is developed using beta probability function. To solve the problem of optimal allocation of EV charging stations and PV in the distribution network, proposed Teaching Learning Based Optimization algorithm is used. The problem is formulated to minimize the power loss reduction index and the voltage deviation index while considering system constraints. Here this proposed approach is tested to Indian 28 bus rural distribution network and standard IEEE 69 bus system in MATLAB. Also to assess the efficiency of the proposed technique, it is compared with three different algorithms, i.e., Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) in terms of convergence characteristics and computational time. The system indices, i.e., voltage profile, line loss, voltage stability and the penetration level of EV charging station are improved after simultaneously optimally deploying EV charging station and PV units both in rural and standard 69 bus distribution networks. Different case studies were conducted and it was observed that deployment of EV charging station in the network leads to deterioration of voltage profile, voltage stability and line loss. The simulation outcome further reveals that the addition of PV panels concurrently with EV charging stations enhances the system performances and the penetration level of EV charging station in the network.

Keywords: electric vehicle; photo voltaic; National Household Travel Survey; voltage stability index; Teaching Learning Based Optimization Algorithm

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1. Introduction

Conventional Internal Combustion Engine vehicle emits the greenhouse gas mainly CO_2 which causes global warming effect[1]. Hence the transportation sector is slowly getting transformed from conventional to EV. EVs are eco-friendly in nature which are developed to reduce the dependency on fossil fuel and to limit the greenhouse gas emission. Due to growing popularity of EV, there is an increase in load demand in the distribution sector of the power system. This causes various technical issues such as poor voltage profile, voltage stability and higher value of power loss[2]. EVs draw power from grid for charging the vehicles and the grid demand is fulfilled mostly by thermal power stations which are in turn the main cause of environmental pollution. Hence to meet the surplus demand due to EV charging, to reduce greenhouse gas emission and to reduce the dependence on fossil fuels, the renewable sources should be jointly allocated with EV charging station in the radial distribution system[3]. However, most of the renewable energy sources are uncertain and intermittent in nature which may lead to issues such as over voltage, increased line loss, etc. Therefore, for safe and reliable operation of power system it becomes essential to integrate EV charging station and renewable energy source in the distribution system with proper planning and analysis. Considering this fact in the present research work PV renewable source and electric vehicle charging station is jointly allocated in the distribution network.

This paper[4] presents different optimal power flow formulations designed to find the maximum number of plug-in electric vehicles that can be simultaneously charging for a given power system operating condition. The impacts i.e., voltage profile of the system and penetration level of EV charging station is analyzed without considering important system parameters such as total line loss and voltage stability. In some previous research works[5,6], the planning of network is done with EV considering minimization of system loss, maximization of voltage profile, nevertheless renewable energy sources such as PV were not considered in the planning model. In this paper[7], different types of realistic charging models of EVs are developed and they are optimally integrated in distribution network using Grey Wolf Optimization (GWO) algorithm. The impacts of optimal integration EVs are analyzed without considering any renewable PV sources in the network. In some of the recent works[8,9], the simultaneous deployment of EVs and PV is done, but uncertainties of EV and PV are not considered which makes the analysis less practical. Uncertainties of EV like trip distance, trip end time, battery capacity, etc are essential for real and practical modelling. Similarly uncertainty parameter of PV such as solar irradiance, temperature, etc. needs to be taken into account for developing real and practical framework.

The consequences of different types of static EV models are studied and analysed in terms of active and reactive power loss and voltage deviation[10,11]. But dynamic modelling which considers hourly variation of EV should be taken into account for developing realistic planning model. EVs were integrated in the distribution system considering a deterministic approach[12]. However, as battery capacity, arrival time, trip distance, etc. are various uncertain parameters a probabilistic approach should be considered to develop a practical EV load model[13].In this paper[14], the electric vehicle charging station and Distributed Generators are simultaneously located using Harries Hawk Optimization method by minimizing power loss, voltage deviation and maximizing the voltage stability index. Here the authors consider the deterministic model of EV charging station and Distributed Generators instead of their probabilistic modeling which is more practical in nature. For simultaneous deployment of EV charging station and renewable source in the distribution network, the capacity and location of both should be fixed properly and carefully so that all the parameters such as voltage profile, voltage stability should be within the limits. If the size or location of EV charging stations and renewable sources are not suitable in the planning framework, then it will hamper various technical parameters such as line loss, voltage profile and voltage stability[15]. In this paper[16], it evaluates the potential benefits of the connection of photovoltaic generation with electric vehicles charging stations in commercial building considering voltage quality issues. It doesn’t utilize any optimization algorithms for integration.

Soft computing methods are very helpful now-a-days to solve nonlinear problem by satisfying equality and inequality constraints. Soft computing technique solves the problem with less computational time whereas traditional mathematical method takes more time[17,18].

To optimally integrate EV charging stations and renewable source, different researchers utilized various optimization algorithms like GA algorithm[19], PSO algorithm[20], DE algorithm[21]. The proposed model of the ideal site for an EV charging station is solved using the GA technique[22,23]. For the placement of EV Charging station, Particle Swarm Optimization (PSO) algorithm is adopted and the optimization problem is formulated by taking power loss as objective function[24,25]. The authors suggest another nature inspired algorithm i.e., Differential Evolution (DE) algorithm[26] for finding the optimal location of charging station and renewable energy sources by considering power loss and voltage profile as objective function. Parameters like crossover probability and mutation probability for GA algorithm, acceleration factors and weight updates for PSO algorithm, crossover and mutation parameters for DE algorithm need to be defined initially. So, these mentioned soft computing methods have some disadvantages like lots of parameter which needs to be tuned, poor convergence rate, excessive computational time, etc.[27] Hence these methods are more complex for solving the optimization problem. This study[28] proposes an effective deterministic methodology to maximize the accommodation of EVs and percentage power loss reduction in radial distribution networks. Instead of multiobjective function, here single objective function i.e., only minimization of total loss is considered.

In this paper, due to the above drawbacks of soft computing methods, the Teaching-Learning Based Optimization (TLBO) method is used for obtaining the optimal location and capacity of EV charging stations and PV. TLBO algorithm is a nature inspired algorithm considering the teaching learning process between the students and teachers in a classroom[29]. This algorithm requires fewer parameters to be tuned as compared to other algorithms. This proposed technique only requires the population size and maximum number of iterations for execution. For simplicity of this algorithm, it is easy to implement for optimization problem and the obtained solutions are accurate and better.

To make the planning framework accurate, in the present research work all the realistic uncertain parameters of EV such as trip miles, trip end time, state of charge, battery capacity and charging level are considered to develop probabilistic EV model. These data are extracted from real NHTS datasheet consisting of travel survey data of Americans[30]. Similarly, the stochastic parameter of PV like solar irradiance is considered for developing the probabilistic hourly output power curve of PV.

In this paper, the optimization problem is formulated using the objective function of minimization of power loss reduction index and voltage fluctuation index by satisfying various system constraints such as demand-supply constraints, voltage constraints, capacity of EV charging station and PV constraints. The power flow is done by backward forward sweep algorithm in MATLAB software (version 2018a) and here 28 bus Indian rural network and IEEE 69 bus are chosen as the test network. For thorough analysis of the distribution network, the technical performances such as voltage profile, line loss, voltage stability values are evaluated and studied for the network considering the integration of EV charging station with PV. This parameter is computed on 24 h average for analyzing and comparing the results more accurately. Further the penetration level of EV charging station for safe and secure system is also evaluated. To proof the efficacy of the proposed TLBO algorithm, the results are compared with three different optimization algorithms such as GA[19], PSO[20] and DE[21] in terms of convergence characteristics value and statistics values. The present research work will enable the planning engineers of the distribution companies to accurately design the system considering the electric vehicle charging station. The major contributions of the present work paper are as follows:

- Stochastic modelling of EV charging station is done utilizing the real NHTS datasheet considering various uncertainty parameters such as trip mileage, trip end time, state of charge, battery capacity using probability density function. Also, uncertainty modelling of PV module is done using beta probability density function considering stochastic parameters such as solar irradiance, temperature, etc.

- A robust optimized planning model is developed considering various objective functions such as minimization of Power Loss Reduction Index (PLRI) and Voltage Deviation Index. Further the voltage stability of the network is also calculated with deployment of EV charging station and PV in the network. While developing the planning framework the security constraints such as demand-supply constraints, voltage constraints, capacity of PV and EV charging station constraints are considered.

- The EV charging station and PV module are jointly allocated in the Radial Distribution System at optimal location with optimal size utilizing proposed TLBO algorithm. Also, the effectiveness of this proposed algorithm is studied and its efficacy is established by comparing it with other known optimization algorithms.
- Different case studies are conducted considering placement of only EV charging station in the distribution network, placement of PV panels and EV charging station concurrently as well as a thorough comparative performance analysis is done in terms of various technical parameters such as EV penetration level, line loss, voltage profile, voltage stability.

2. Uncertainty modelling of EV charging stations and PV

In this section the modeling of EV charging station and PV is discussed as follows:

2.1. EV modelling

A set of trustworthy and real data is needed to predict EV charging station load profiles. The NHTS statistics are taken into consideration as dependable and beneficial in figuring out the behavior of different automobile owners[30]. The Federal Highway Administration (FHWA) of the United States conducts the National Household Travel Survey (NHTS) 2017 to gather information on Americans' travel habits[31]. All 50 states and the District of Columbia are represented by 129,696 households in the NHTS 2017, which also includes information on trip origin and destination, trip time, purposes of trip and mode of transportation (U.S. DOT 2017)[30]. The datasheet represents everyday journeys over a period of 24 h, and that they have been accrued for journeys of all functions and lengths, and to all regions of the country, each city and rural. Each household, person, and vehicle with inside the 2017 NHTS datasheet has a completely unique ID number. These functions are used to evaluate distinct parameters for predicting power density functions for arrival time, and trip mileage of EVs, which are mentioned with inside the following paragraph. In this survey data, the four most popular vehicle classes—passenger cars, pickup trucks, sport utility vehicles, and vans are taken into account.

Before modelling the daily charging EV load at-home charging station, several random factors that may affect EV charging load must be taken into account. In this present work, uncertain factors such as trip mileage, charging start time, charging level and battery capacity of a single EV are considered. By extracting these stochastic factors from NHTS datasheet, initial State of Charge (SoC), energy consumption, charging duration and power demand of a single vehicle can be determined. After quantifying all these parameters, 24 h EV load curve can be developed.

2.1.1. Daily travel distance

Due to a paucity of trip statistics, it is assumed that EVs have driving characteristics equal to those of traditional vehicles, which have the same daily trip characteristics. In general, it is found that the dissemination of day by day driving distance is of log-normal type, with zero likelihood of event of all negative distances, and a "tail" expanding to limitlessness for positive distance. For the prediction of the SoC and the behavior of every day mileage of each vehicle, the Probability Density Functions (PDFs) are quantified as follows[31]:

$$f_d = \frac{1}{x_d \sigma_d \sqrt{2\pi}} exp\left[-\frac{(\ln d - \mu_d)^2}{2\sigma_d^2}\right] \tag{1}$$

where X_d = daily trip distance of EV. μ_d = mean value of EV, σ_d = standard deviation of EV.

Figure 1 demonstrates that the majority of daily driving lengths lie between 10 and 70 miles. The likelihood of daily trip distances exceeding 100 miles is rather low. Additionally, it is shown that the daily trip distances follow logarithmic normal distribution.

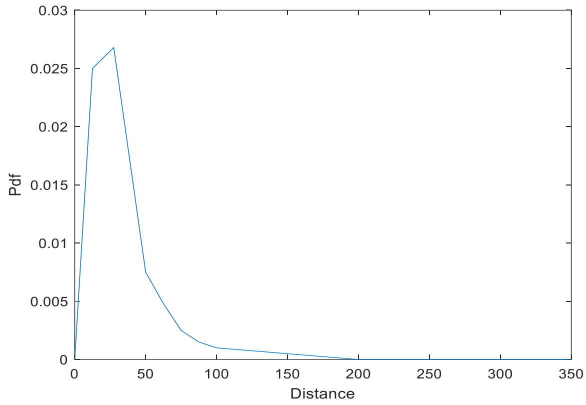

Figure 1. Probability density function of EV daily distance travelled.

Figure 2 shows the percentage of EVs arrival time at different hours of the day. The maximum EVs arrive at home for charging in between 6 pm to 8 pm.

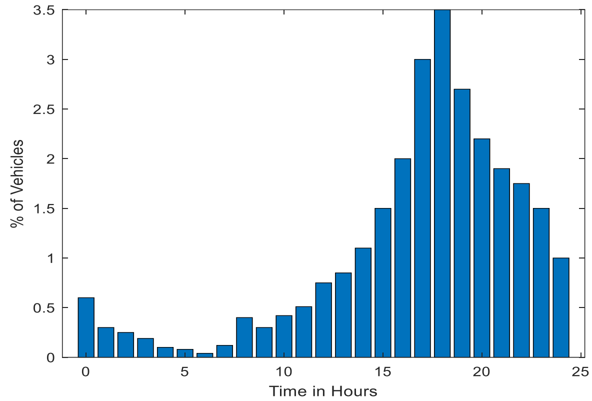

Figure 2. Percentage of vehicles verses arriving time.

2.1.2. State of charge

The amount of charge left in the car after all journeys are completed is known as the state of charge (SoC). The SoC of a car can be calculated using the distance travelled and the EV's all-electric range. The percentage of the overall charge used to represent SoC. Assuming an EV-x is completely charged and travels 'x' miles on electricity[32], the following equation determines the SoC of a vehicle travelling 'd' miles:

$$SoC = \begin{cases} \left(1 - \dfrac{d}{x}\right) * 100, d \leq x \\ 0, d > x \end{cases} \tag{2}$$

where *d*= distance travelled by each vehicle.

In this paper, the maximum and minimum values of SoC are taken to be 0.90 (representing 90%) and 0.20 (representing 20%), respectively. Here the distance is taken i.e., calculated from Equation (2).

2.1.3. Charge start time

In the present work, EV proprietors begin charging at the time when they wrap up their trip and get back to the charging stations. On the basis of this supposition, it is inferred that the start of EV charging is thought to begin at the finish of the previous journey, designated here as t_{start}. Calculations for the charging start time's probabilistic nature include the following[31]:

$$f_c(t_{start}) = \begin{cases} \dfrac{1}{\sigma_c\sqrt{2\pi}} e^{\left(-\frac{(t_{start}-\mu_c)^2}{2\sigma_c^2}\right)}, (\mu_c - 12) \le t_{start} \le 24 \\ \dfrac{1}{\sigma_c\sqrt{2\pi}} e^{\left(-\frac{(t_{start+24}-\mu_c)^2}{2\sigma_c^2}\right)}, 0 \le t_{start} \le (\mu_c - 12) \end{cases} \tag{3}$$

where μ_c = mean value of charge start time, σ_c = standard deviation of charge start time.

Figure 3 depicts that the probability distribution of the EV charging start time and also it shows that the pattern of this distribution is of normal type. Moreover, it is observed that the beginning time of charging of EVs at 8 pm is the highest one during 24 h period.

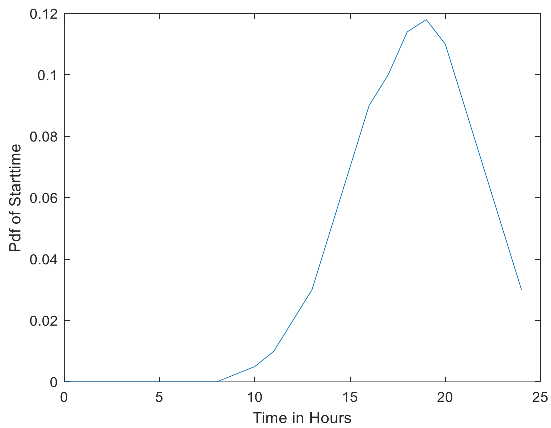

Figure 3. PDF of start time of charging.

2.1.4. Power demand

In this research work, initial battery SOC and charging begin time are assumed as two independent variables. At power level P_j at time instant 't', the probability of power for EV charging can be expressed as $\varphi(P_j, t)$ where φ is the PDF,$(1 \le t \le 24)$[33].

$$\varphi(P_j, t) = f_c(t_{start}) * h(SoC_j)(j = 1,2,3, \ldots, n_c) \tag{4}$$

where, $\mathrm{h(SoC_j)}$ is the PDF of initial SoC.

The overall estimated power demand P_n can be quantified using the following formula.

$$P_n = \sum_{i=1}^{n} \sum_{j=1}^{n_c} P_{ij} * \varphi(P_{ij}, t) \tag{5}$$

where the number of EV and the number of hourly intervals are n and n_c respectively.

2.2. PV modelling

A PV panel transforms solar energy into electrical form based on the radiation that strikes the panel's surface. Since solar irradiance affects solar cells' performance, it is crucial to take into account this variable's behaviour while modelling a PV unit. Using the stochastic parameter i.e., solar irradiance (s^t), the uncertainty modelling of PV is stated using beta probability density function[34]. Mathematically it is represented as follows:

$$f_{pd}^t(s^t) = \begin{cases} \dfrac{\Gamma(c+d)}{\Gamma(c)\Gamma(d)} (s^t)^{c-1}(1 - s^t)^{d-1}, & if 0 \le s^t \le 1 c, d > 0 \\ 0, & otherwise \end{cases} \tag{6}$$

$$c = \frac{\mu \times d}{1-\mu} d = (1-\mu) \times \left(\frac{\mu(1+\mu)}{\sigma^2} - 1\right) \quad (7)$$

The following equation represents the maximum power output $P_0(s^t)$of a deployed PV array at a particular ‘t’

$$P_0(s^t) = N_{\text{mod}} \times FLF \times V \times I \quad (8)$$

$$FLF = \frac{V_{MPP} \times I_{MPP}}{V_O \times I_S}, \qquad V = V_O - K_V \times T_C \quad (9)$$

$$I = s^t[I_S + K_I \times (T_C + 25)], T_C = T + s^t(\frac{T_0 - 20}{0.8}) \quad (10)$$

where N_{mod} is the number of PV modules, V & I are voltage and current of a PV module respectively, V_{MPP} & I_{MPP} the maximum power point voltage and current, V_0 represents open circuit voltage, I_S represents short circuit current, T_C is the temperature of a PV cell, K_I & K_V temperature coefficient of current and voltage respectively.

Each hour is broken into a number of states to increase accuracy. The solar output $P(s)_h$ for each hour is assessed as follows:

$$P(s)_h = \sum_{i=1}^{N_S} P_o(s^t) \times f_{pd}^t(s^t) \quad (11)$$

where N_S represents number of states in an hour[34].

Using Equation (11), the power of solar irradiance states for each hour is estimated. Thus by employing this probabilistic solar irradiance model, PV output curve is generated which is integrated to the distribution system. To develop the hourly stochastic power curve of PV, historical datasheet consisting of five year data of solar irradiance is considered in this work. This historical datasheet is the collection of solar irradiance data of the place Durgapur in the state of West Bengal (Latitude 23.5204 °N, Longitude 87.3119 °E)[35].

3. Voltage stability

One crucial system performance metric is the voltage stability. To secure system voltage stability, the voltage on each bus should be within the permissible range. Assessing the impacts of distribution system merging with EV charging stations and PV modules entails examining and discussing the following parameter.

Voltage stability index

For stable operation and improving the voltage stability, the voltage stability index (VSI) should be maximized i.e., SI(n_i)>0[36]. Mathematically voltage stability index is represented as follows[36]:

$$SI(n_i) = |V_{mi}|^4 - 4[P_{ni}(ni)R_{ni} + Q_{ni}(ni)X_{ni}]|V_{mi}|^2 - 4[P_{ni}(ni)R_{ni} + Q_{ni}(ni)X_{ni}]^2 \quad (12)$$

As shown in **Figure 4**, $P_{ni}(ni)$ represents the total active power fed through bus n_i. Whereas the total reactive power load through bus n_i is represented by $Q_{ni}(ni)$. R_{ni} and X_{ni} are the resistance and reactance of the branch i.

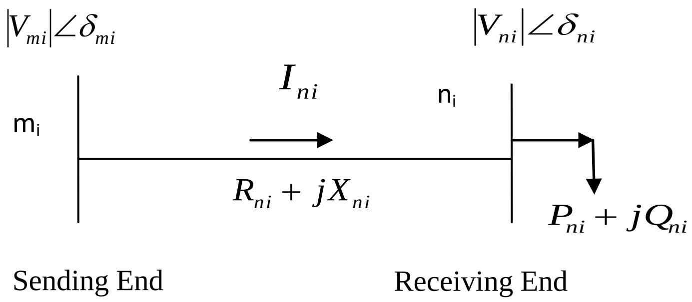

Figure 4. A Representative branch of a radial distribution system.

4. Objective functions and constraints

In this section, different objective functions are explained for solving the optimization problem by satisfying different types of equal and unequal constraints as follows:

4.1. Objective functions

For solving the optimization problem of finding out the position and sizing of both EV charging stations and PV units in the distribution network, here two objective functions are considered as follows. These objective functions should be minimized.

4.1.1. Power loss reduction index (PLRI)

The real power loss is a major performance parameter for planning of distribution network. Here the first objective function is power loss reduction index which is defined as the ratio of real power loss of the system with EV charging station or PV or both and the system without EV charging station or PV[37].To solve the optimization problem, this index should be minimized and it is quantified as follows:

$$PLRI = \frac{P_{Loss_{wEV/PV}}}{P_{Loss_{woEV/PV}}} \tag{13}$$

where $P_{Loss_{wEV/PV}}$= Real Power Loss of the system with devices, $\mathrm{P}_{\mathrm{Loss}_{\mathrm{woEV/PV}}}$= Real Power Loss of the system without devices.

4.1.2. Voltage deviation index (VDI)

Another important aspect of the system is the voltage profile deviation from the rated voltage (1 p.u). This deviation index should be minimized at each bus of the system and maintained within the range at the demand site[38].Accordingly, this fluctuation index may vary with the value of voltage profile. This index value should be minimized for solving the problem. Mathematically the second objective function is represented as follows:

$$VDI = \sum_{ni=1}^{n_n} |1 - V_{ni}| \tag{14}$$

4.2. Constraints

The objective functions should be minimized subject to various equality and inequality constraints discussed as follows.

4.2.1. Demand-supply constraints

The power balance equation is updated by adding PV and EV in the bus. Mathematically it is represented as follows:

$$\sum_{i=1}^{n_n} PG_i - P_{Loss} = P_d \tag{15}$$

$$\sum_{i=1}^{n_n} QG_i - Q_{Loss} = Q_d \tag{16}$$

where PG_i and QG_i are total active and reactive powers injected at i^{th} bus respectively. P_{Loss} and Q_{Loss} are the active and reactive power losses at the i^{th} bus. Similarly, P_d and Q_d are the active and reactive power demands at the i^{th} bus respectively.

4.2.2. Voltage constraints

The magnitude of each voltage should be within the minimum and maximum limit.

$$V_{\min} \leq V_i \leq V_{\max} \tag{17}$$

4.2.3. PV capacity

The PV output power should be within the maximum and minimum capacity as follows:

$$PV_{\min} \leq PV_i \leq PV_{\max} \tag{18}$$

4.2.4. EV charging station capacity

The active and reactive power of EV charging station should be kept within the range as follows:

$$P_{\min}^{EV} \leq P_1^{EV} \leq P_{\max}^{EV} \tag{19}$$

5. Problem formulation

In this present work, the integration of uncertain EV charging station and uncertain PV unit in the distribution network is done optimally by proposed TLBO optimization algorithm. The input parameters to this problem are line data and load data of 28-bus and 69-bus test system, probabilistic EV model, probabilistic PV model. The output parameters of this problem are optimal size and location of EV charging station and PV.

Multi-objective function is formulated considering following objectives as follows.

1) Minimization of PLRI
2) Minimization of VDI

Mathematically this multi objective function is represented as follows,

$$MinF_T = \tau PLRI + \beta VDI \tag{20}$$

The values of coefficients are τ=0.5, β=0.5. These two objective functions have equal weights means they have same importance for minimization of objective function value.

6. Methodology

In this research work, the EV charging stations with PV units are deployed optimally by proposed TLBO algorithm. Due to fewer tuning parameters and less time taken for convergence, the proposed TLBO method is applied for the present research work.

6.1. Teaching learning based optimization algorithm

Here the proposed TLBO algorithm is a nature inspired population based algorithm which has the main principle of teaching-learning process of a class[39]. In a classroom, the teacher gives maximum effort on education of all the learners of a class. So the learners gain knowledge from the best learner of the classroom i.e., the teacher. Then the learners interact with themselves to further modify and improve their gained knowledge. The result of the class depends upon the results of the students. For this algorithm, the students of the class and the total subjects taught in the class are considered as the population and the variables of the optimization problem respectively. This algorithm is performed in two phases i.e., teacher phase and learner phase.

6.1.1. Teacher phase

During this phase, the teacher helps students to enhance their knowledge so that the result of the class is improved. But depending upon the teaching skills of teachers and potentials of students present in the class, learners will gain the knowledge[27]. Suppose the total number of subjects and total number students in the class are represented by 'm' and 'n' respectively and the population is represented by k = 1, 2, 3, ..., n and the process of sequential teaching–learning method is represented by 'i'. The mean results for a particular subject of all the students i.e., learners are expressed by M_{ji} whereas j = 1, 2, ..., m. By considering the results of all the subjects, the teacher of the class recognizes for the result of best learner and it is expressed as $X_{total-kbest,i}$ & $X_{jkbesti}$ for all subjects and for a particular subject 'j' respectively. This above process of teacher phase is expressed mathematically as follows[34]:

$$Difference\_mean_{jki} = r_i\left(X_{jkbesti} - T_F M_{ji}\right) \tag{21}$$

where T_F is known as the teaching factor and its value is randomly decided and r_i is the random number in the range [0,1].

$$T_F = round[1 + rand(0,1)\{2-1\}] \tag{22}$$

As per the algorithm, the solution is revised as follows:

$$X'_{jki} = X_{jki} + Difference\_mean_{jki} \tag{23}$$

where X_{jki} is the outcome of the class's students taking into account all the disciplines and the new value of learners is X'_{jki}.

This will be permitted if it gives a better value. All function values accepted at the end of the teacher phase are saved and utilised as input during the next phase of proposed algorithm.

6.1.2. Learner phase

In this phase, the learners i.e., students of the class gain their knowledge and also enhance their learning through mutual interaction among themselves. This learning process can be demonstrated as follows. Randomly two different learners, i.e., P and Q are chosen such that

$$X'_{total-P_j} \neq X'_{total-Q_j} \tag{24}$$

where $X'_{total-P_j}$ and $X'_{total-Q_j}$ are updated values of $X_{total-P_j}$ and $X_{total-Q_j}$ respectively at the end of teacher phase.

If $X'_{total-P_j} < X'_{total-Q_j}$,

$$X''_{jpi} = X'_{jpi} + r_i(X'_{jQi} - X'_{jpi}) \tag{25}$$

If $X'_{total-Q_j} < X'_{total-P_j}$,

$$X''_{jpi} = X'_{jpi} + r_i(X'_{jPi} - X'_{jQi}) \tag{26}$$

The value of X''_{jpi} is approved if it has better value otherwise rejected. The proposed TLBO algorithm consisting of teacher phase and learning phase as discussed above is demonstrated in the flowchart i.e., in **Figure 5**.

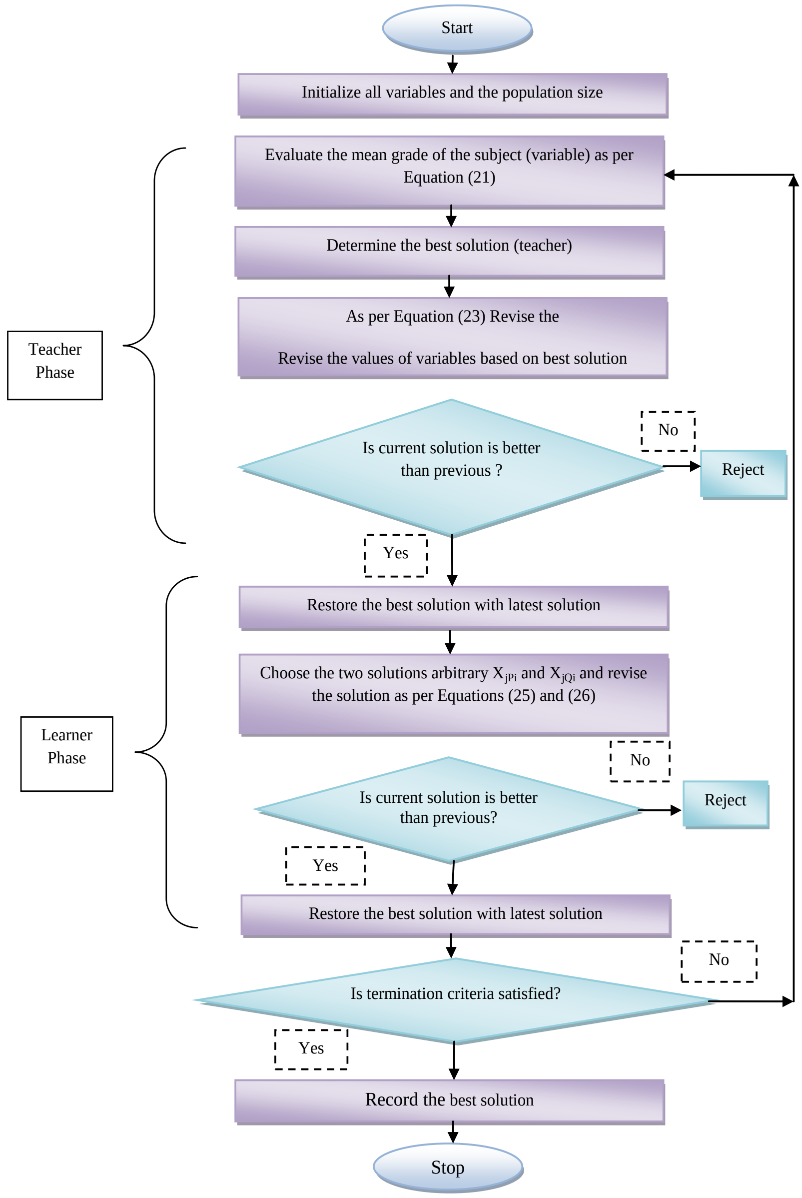

Figure 5. Flowchart of proposed TLBO algorithm

6.2. Implementation of TLBO for installation of EV charging stations and solar panels in the distribution network

For optimal deployment of EV charging stations and PV unit, the TLBO technique is applied by initializing number of population, number of iterations, number of design variables (size & location of EV charging station and PV) and limits of design variables. EV charging stations and PV units are randomly placed with different capacity within their limits. Then these randomly generated control variables contain a vector which describes the results of a particular student and it also describes a solution for the optimal EV charging stations with PV units deployment problems. Each set of matrix P_{EVi} & P_{PVi} describes a possible solution of location and capacity of EV charging station & PV respectively and is given by,

$$P_{EVi} = [loc_{i,1}, loc_{i,2}, \ldots, loc_{i,N_D}, EV_{i,1}, EV_{i,2}, \ldots, EV_{i,N_D}] \tag{27}$$

$$P_{PVi} = [loc_{i,1}, loc_{i,2}, \ldots, loc_{i,N_D}, PV_{i,1}, PV_{i,2}, \ldots, PV_{i,N_D}] \tag{28}$$

where EV_i & PV_i are the initial size of installed EV charging stations and PV units. N_D represents number of EV/PV installed. Initial solution of P_{EV}&P_{PV} are generated according to the population size (N_P), which is given by:

$$P_{EV} = [P_{EV,1}, P_{EV,2}, \ldots, P_{EV,i}, \ldots, P_{EV,N_P}] \quad (29)$$

$$P_{PV} = [P_{PV,1}, P_{PV,2}, \ldots, P_{PV,i}, \ldots, P_{PV,N_P}] \quad (30)$$

Then the load flow is done by forward-backward sweep method and these solution matrices are updated by teacher phase and learner phase as discussed above. After the termination criteria have been checked, the best solutions for capacity and location of EV charging stations and PV units are printed. In **Figure 6**, the proposed methodology considered in this paper is explained in the flowchart.

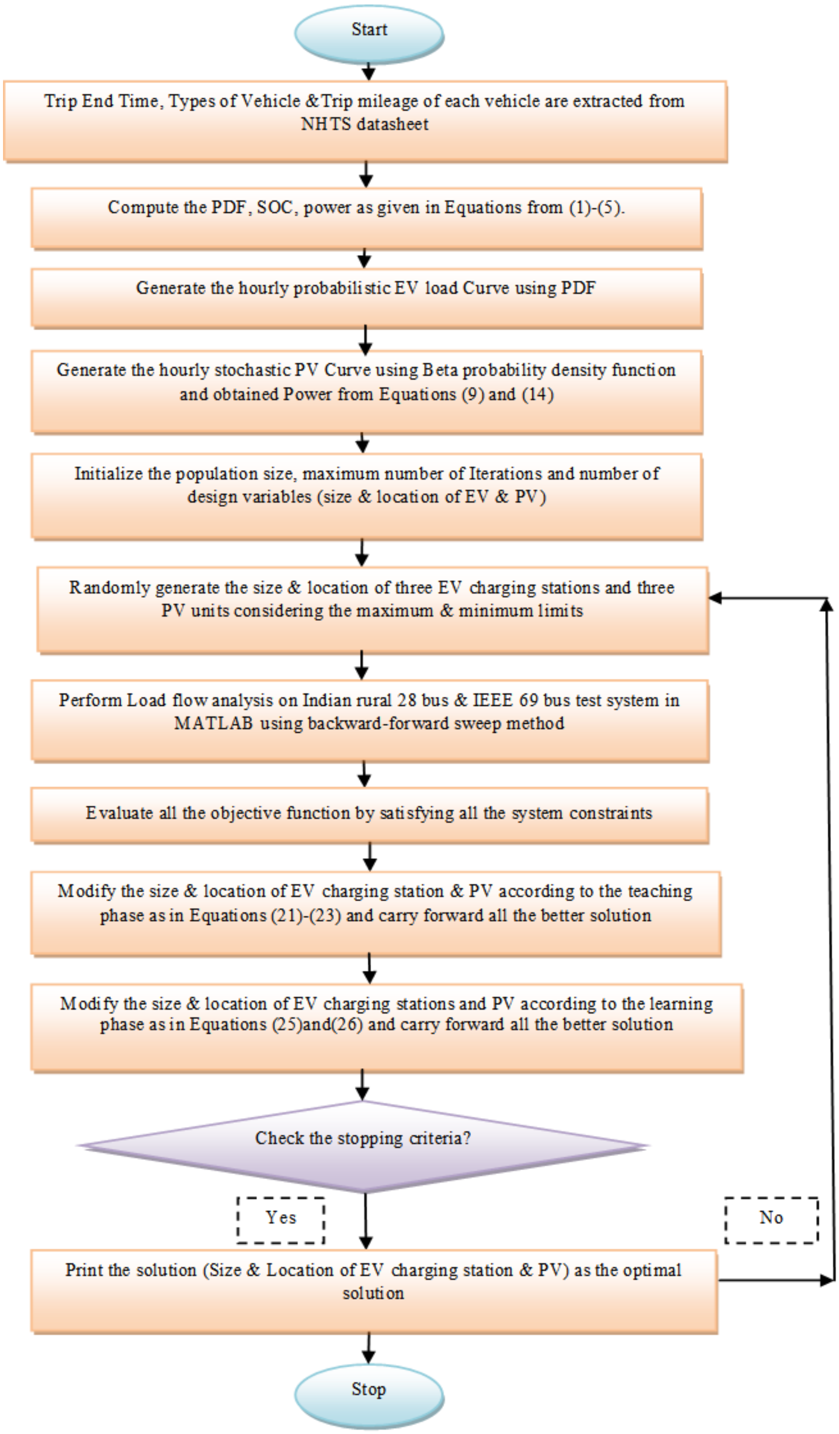

Figure 6. Flowchart of proposed methodology adopted in this paper.

7. Results and discussion

MATLAB software (version R2018a) is used to implement the above process of allocation of EV charging stations and PV unit. After uncertainty modelling of EV charging station, the probabilistic load curve of EV charging station is generated for 24 h as shown in **Figure 7**. PV unit is simultaneously and optimally allocated in the system. PV output power curve which is developed as discussed in Section 2.2, is shown in **Figure 8**[34].

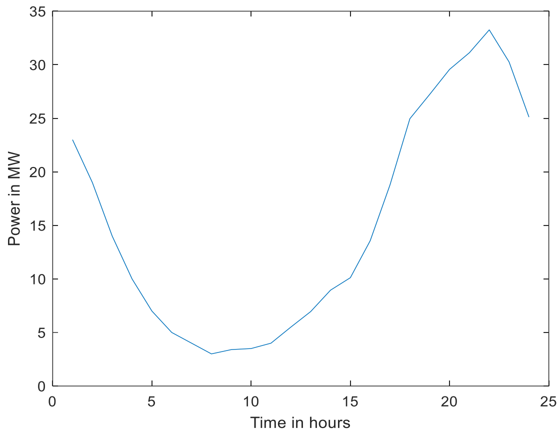

Figure 7. Hourly probabilistic EV load curve.

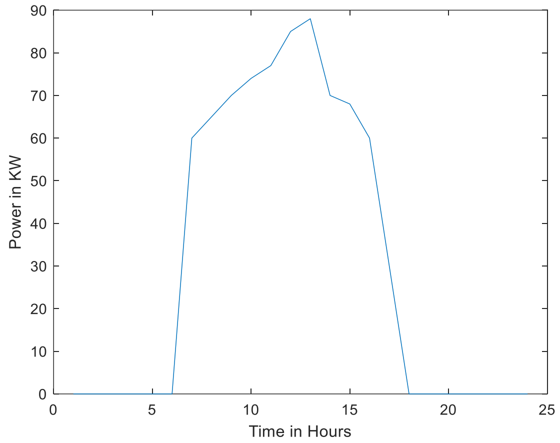

Figure 8. PV Output power curve for 24 h.

The planning framework in the present work allocates simultaneously three EV charging stations and three PV panels in a distribution network using the proposed TLBO technique. The size of population and iteration counts are initialized as 50 and 100 respectively. Four variables: EV charging station capacity, locations, PV unit size and locations are considered in the present work. The minimum and maximum values for EV charging stations are 4 MW and 33 MW as shown in **Figure 7**, while the lower and upper values for PV units are 0.1 MW and 1.8 MW respectively as shown in **Figure 8**[34] as taken into account.

Selection of parameters for execution of TLBO:

Since the results of the proposed optimization method are sensitive to the choice of parameters, so sufficient attention should be given while selecting the parameters for the algorithm. Here the parameters for the proposed technique are population size and maximum number of iterations. The program is run for 100 times i.e., maximum number of iterations. For each iteration, the optimal solutions are obtained. It is observed that after 30 number of iterations, the optimal solutions are converged. Moreover, if the iterations counts are increased more than 100, then there is no significant improvement in optimal solutions rather it consumes more computational time. Similarly here the problem is solved for varying the size of population from 10 to 100 and at the size of 50 the best solutions are obtained. After the size of 50, no significant changes in best solutions are found out, so the size of population is considered as 50 in this paper by solving with the proposed TLBO technique.

To analyze the system performance by allocating EV charging stations and PV units in distribution network, three cases are considered as follows:

Case I: Base Case

Case II: System with EV charging stations

Case III: System with EV charging stations and PV units

The two test systems i.e., 28 bus rural Indian system and IEEE 69 bus system are used to analyze and discuss the effects.

7.1. Rural 28 bus system

In this paper, for analysing and comparing the results, first test system is taken as standard 28 bus rural Indian test system. It consists of 28 buses and 27 branches as in **Figure 9** and the total load of this system are 829.88 kW as real power and 828.07 kVaras reactive power. 11 kV & 1 MVA are considered as base voltage and base MVA respectively[40]. The radial distribution load flow is done by forward-backward sweep method and the line loss, voltage values at each bus are quantified. The total loss of this system without any devices is quantified after the load flow as 68.85 kW as real loss and 46.07 kVaras reactive loss. In this test system optimal allocation of EV charging stations and PV units are obtained for all the three cases considering minimization of objective functions. All the equality and inequality constraints as explained in Equations (15)–(19) are satisfied. With the obtained results the parameters such as voltage profile, real power loss and voltage stability index are evaluated for all the three cases.

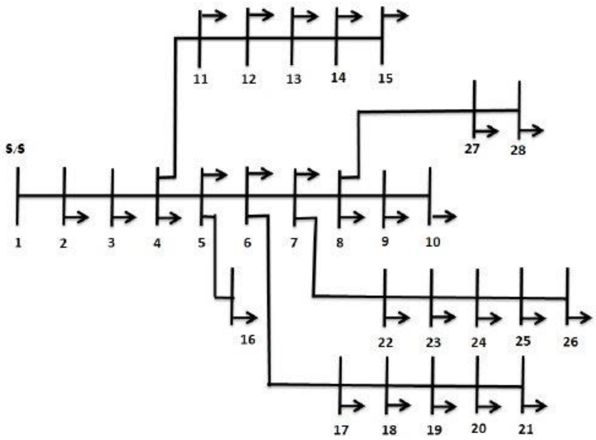

Figure 9. Single line diagram of Indian 28 bus rural distribution test system.

In **Table 1**, the optimal location and size of EV charging stations and PV units are shown for different cases of the network. It reveals that for case II considering all the security constraints, the obtained optimal capacity of EV charging station is 4.33 MW which is 13% penetration in the network. In this paper, this penetration level is quantified as percentage of EV charging station penetrated to the system relative to the peak load as shown in **Figure 7**. After integrating PV unit at optimal location with EV charging station, the capacity of EV charging station rises to 5.1 MW that is 16% penetration in the distribution network. Hence the capacity of charging station is increased so more no. of EVs can be penetrated in the network for charging in Case III than that of Case II.

Table 1. Optimal size & location of EV charging station & PV unit using TLBO in the 28-Bus system for different cases.

Cases	**EV charging station**		**PV**	
	Size (MW)	**Location**	**Size (MW)**	**Location**
Case II	2.11, 1.35, 0.87	2, 4, 14	-	-
Case III	2.32, 1.01, 1.76	3, 12, 4	1.14, 0.85, 0.92	11, 26, 28

From **Table 2**, it is observed that the real power loss increases after the integration of EV charging station in the network, so PLRI value increases with the presence of EV charging station. The total line loss increases from base case value of 68.86 kW to 120.54 kW which is almost 68%. But in Case III, the line loss value diminishes by 23% from Case II. As in Case I, there is no EV charging station and PV in the system, the ratio remains as 1. But in Case II, the loss of the system with EV charging station at optimal places increases so this value increases to 1.7452. In Case III, due to the optimal placement of PV and EV charging station, this value decreases to 1.3988.

Similarly VDI value for base case is 0.8140. But if EV charging station is allocated in the network with optimal capacity and location, this index value increases to 1.2681 as the voltage profile deviates more from the rated voltage profile in Case II. This value reduces to 0.9203 in Case III after EV charging stations and PV units are simultaneously allocated at the optimal position with optimal capacity.

Table 2. Objective function values of the 28-Bus system for different cases.

Cases	**PLRI**	**VDI**
Case I	1.0000	0.8140
Case II (TLBO)	1.7452	1.2681
Case III (TLBO)	1.3988	0.9203

The average hourly bus voltage profile graph is demonstrated for all three cases in **Figure 10**. It is observed that the minimum voltage of value 0.919 p.u for Case I i.e., base case occurs at bus number 9. For Case II, after optimally locating EV charging stations at bus no. 2, 4 and 14 with optimal size 2.11 MW, 1.35 MW and 0.87 MW respectively, it is also observed that more voltage drop occurs and the minimum voltage reduces to the value of 0.8012 p.u from the base value. For Case III where the EV charging stations along with PV modules are optimally incorporated in the radial distribution system, the minimum bus voltage profile improves to the value 0.9085 p.u.

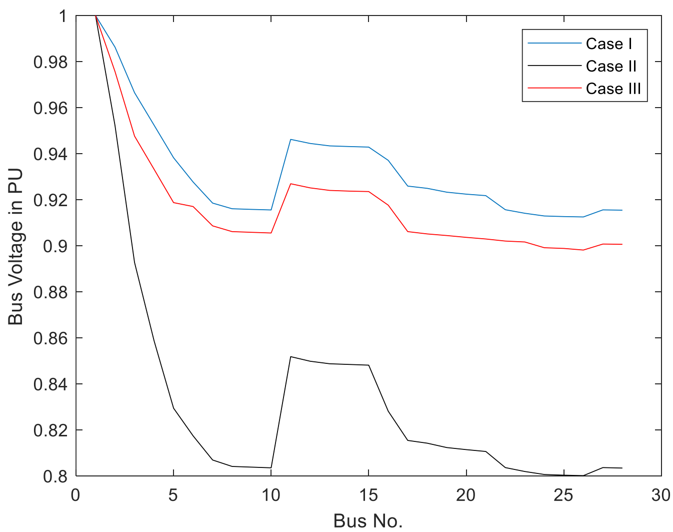

Figure 10. Voltage profile of Indian rural 28 bus system for different cases.

Figure 11 shows the VSI value at each bus of the Indian rural 28 bus system for different cases. It is observed that the lowest VSI is 0.705 at the bus number 12 for base case. As this index is a major index to predict the voltage collapse in the power system, so small change in VSI value will affect the power system. For Case II by optimally adding EV charging stations to the network, the VSI value diminishes to 0.577. This index value is improved to the value 0.663 by optimally placing both EV charging stations and PV modules in the distribution network.

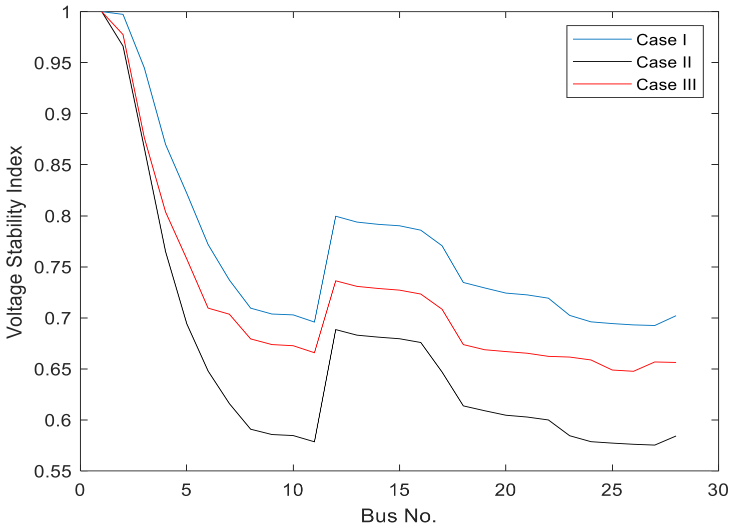

Figure 11. VSI value at different bus no. of rural 28 bus system for different cases.

7.2. IEEE 69 bus system

In this paper, for analysing and comparing the results, second standard IEEE 69 bus test system is taken which has 69 nodes and 73 branches[41]. The single line diagram of IEEE 69 bus system represented in **Figure 12** has the total load of this system is 3.80 MW as real power and 2.69 MVaras reactive power and base voltage of 12.66 kV and 1 MVA as base. The radial distribution load flow is done by forward-backward sweep method[42]. Then the total real power loss of the system is 224 KW, and the total reactive loss of the system is 110 KVar. EV charging stations are injected in this test system at three different locations with different capacity using TLBO optimisation method.

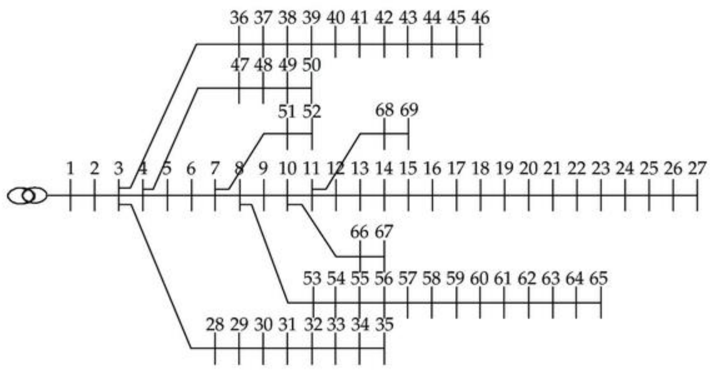

Figure 12. Single line diagram of IEEE 69 bus distribution test system.

The optimal location and size of EV charging stations and PV units after integration in the 69 bus system are listed for different cases in **Table 3**. It reveals that for Case II, the total obtained capacity of EV charging stations is 5.93 MW which is nearly 18% penetration of peak EV load curve. After integrating PV unit at optimal locations the capacity of EV charging station rises to 7.02 MW that is approximately 22% penetration level. Hence more EV charging stations can be penetrated in the distribution network by jointly assigning PV unit.

Table 3. Optimal size & location of EV charging station & PV Unit using TLBO in the 69-Bus system for different cases.

Cases	EV charging station		PV	
	Size (MW)	Location	Size (MW)	Location
Case II	2.27, 1.89, 1.74	2, 31, 49	-	-
Case III	2.61, 1.93, 2.46	3, 9, 38	1.06, 0.28, 1.76	25, 55, 63

The objective function values i.e., PLRI and VDI values for 69-bus test system are shown in **Table 4**. The real power loss in the system without any device remains 224 kW, but after integrating EV charging station in the system, this value becomes 319.02 kW that is 45% of base value. However, having both EV charging station and PV in the system, the loss decreases to 288.72 kW which is 11% less than that of Case II. In Case I, there is no device in the system, the ratio remains as 1. But in Case II, the loss of the system with EV charging stations at optimal places increases hence this index increases to 1.4251. In Case III, due to the presence of PV and EV charging stations at optimal places with optimal size, this value decreases to 1.2858.

Table 4. Performance analysis of the 69-Bus system for different cases.

Cases	PLRI	VDI
Case I	1.0000	0.2198
Case II	1.4251	0.5124
Case III	1.2858	0.3936

The VDI value for base case is 0.2198 if EV charging stations are allocated in the network at optimal location with optimum capacity, this index value increases to 0.5124 as the voltage profile deviates more from the rated voltage profile in Case II. This value reduces to 0.3936 in Case III after EV charging stations and PV unit are simultaneously deployed.

Figure 13 shows the voltage profile graph of IEEE 69 bus distribution system for three different cases. It is observed that minimum voltage level i.e., 0.92 p.u. occurs at the bus number 64 for base case scenario. After integrating EV charging stations, the voltage profile for each bus is observed. As the demand of electricity rises due to EV charging, the voltage profile falls as compared to the base case and the minimum voltage becomes 0.85 p.u.

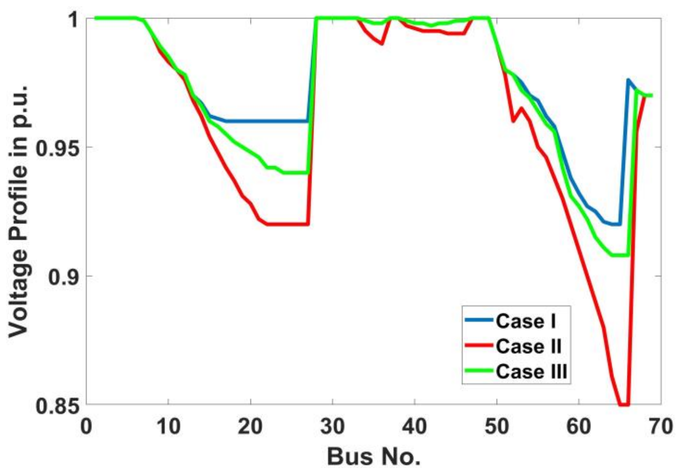

Figure 13. Voltage profile of IEEE 69 bus with different cases.

To enhance the voltage profile, diminish the excess demand due to EV and minimise the environmental pollution, the solar energy source is incorporated with the 69 bus system at bus number 25, 55, 63 with optimal size of 1.06 MW, 0.28 MW, 1.76 MW. Then it is noticed that for Case III the voltage profile improves and the minimum voltage increases to 0.91 p.u as compared to Case II.

Figure 14 shows the graph between bus numbers versus VSI value at each bus for IEEE 69 bus distribution system for three cases. It is observed that the bus number 60 has minimum VSI value i.e., 0.7014. For Case II by optimally adding EV charging stations to the network using TLBO algorithm, the VSI value diminishes to 0.586. This index value is improved to the value 0.648 by simultaneously deploying both EV charging stations and PV modules at the optimal location with optimal capacity using TLBO technique in the distribution network.

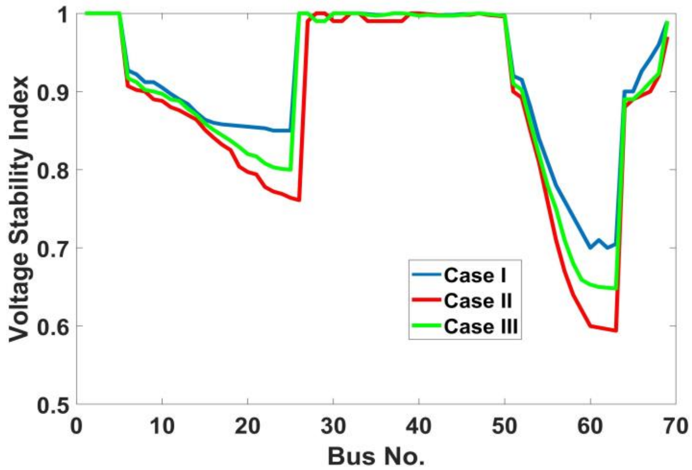

Figure 14. VSI value at different bus no. of IEEE 69 bus system for different cases.

To validate the effectualityof the proposed TLBO algorithm, three soft computing algorithms such as GA, PSO and DE are also applied for concurrent allocation of the EV charging stations and PV units.

7.3. Comparison of proposed algorithm with PSO, GA and DE

To proof the efficacy of proposed technique, the convergence characteristics and statistical values are compared among four algorithms i.e., TLBO, GA, PSO and DE. All algorithms are applied to find out the optimal placement and sizing of EV charging stations and PV units in the distribution network. To solve this optimization problem, the common parameters i.e., population size and number of iterations are taken as 50 and 100 respectively for all algorithms.

For GA technique, the parameters are considered as crossover probability 0.85 and mutation probability 0.01[22]. Similarly another nature inspired algorithm i.e., PSO algorithm is implemented by considering the parameters as; accelerating factors (c_1 & c_2) 0 & 2, updating factors (w_1 & w_2) 0.4 & 0.9[25]. Another heuristic optimization method i.e., DE algorithm[26] is applied by taking the parameters for this DE algorithm are considered as crossover 0.3 and mutation 0.45.

Convergence characteristics graph of TLBO algorithm with other algorithms for objective function for 69 bus system is illustrated in **Figure 15**. It is observed that the proposed TLBO algorithm converges faster with the lowest value of objective function than other three algorithms i.e., PSO algorithm, GA algorithm, and DE algorithm. Hence this algorithm is more effective for placing optimally EV charging stations and PV units in the IEEE 69 bus test network by minimizing the objective functions.

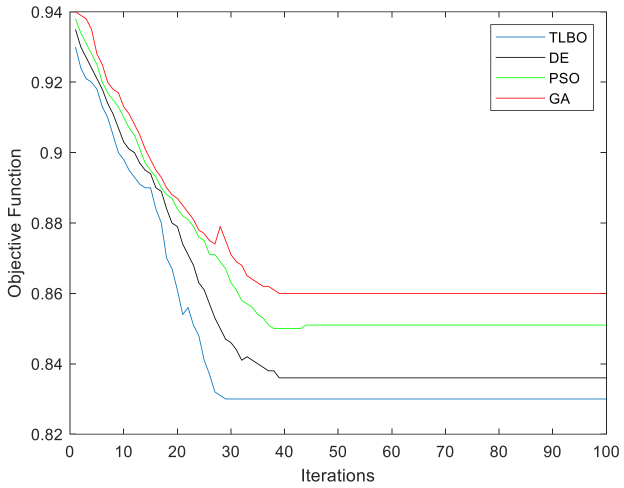

Figure 15. Convergence characteristics of different algorithms.

Table 5 shows the statistical value i.e., mean (μ) and standard deviation (σ) and the required computation time of operation for implementation of different optimization algorithms in the 69 bus test network. The lowest value of mean and standard deviation represents the better performance of optimization algorithm. It is observed that the proposed TLBO algorithm has the lowest value of mean and standard deviation than other three algorithms which reveals that TLBO algorithm is more effective. Moreover, another observation revealed that the proposed TLBO method required least time among all other algorithms for execution of optimization problem in the 69 bus test system.

Table 5. Comparison of TLBO algorithm with other algorithm.

Different parameters	**TLBO**	**GA**	**PSO**	**DE**
Mean (μ)	0.6085	0.6307	0.6231	0.6124
Standard deviation (σ)	0.0041	0.0052	0.0048	0.0043
Computation time (in Sec)	11.5623	15.9401	14.2137	12.9728

8. Conclusion

In this present work, the influence of EV charging station loads and solar energy sources on Indian 28 bus rural network and IEEE 69 bus system is rigorously examined in terms of the system indices such as voltage, voltage stability and power losses. To assess the effects on distribution network, both EV charging station along with PV is optimally incorporated in the radial distribution network using proposed TLBO algorithm. The device allocation is done considering minimization of PLRI and VDI by satisfying various system constraints i.e., demand supply constraint, voltage constraints and capacity of EV charging station & PV unit. In view of realistic aspects, a practical framework of EV charging station and PV in the distribution network is developed by considering uncertainty parameters such as trip miles, trip end time and vehicle types from real NHTS datasheet for EV charging station and solar irradiance for PV.

To analyze the system performance different case studies are conducted. In Case II where only EV charging stations are optimally deployed in the test networks, the result shows that there is deterioration of the line loss, voltage stability and voltage. However, there is a significant improvement in results in terms of voltage profile, stability and line loss in Case III, where both EV charging stations and PVs were jointly allocated in both the test networks. Therefore, it is concluded that concurrent optimal allocation of EV charging stations with solar PV based generation units using the proposed TLBO algorithm improves performance indices such as total line loss, voltage stability, and voltage profile for both the rural network as well as the IEEE standard system. Also it is observed from the above research work that the proposed TLBO algorithm is more effective than other optimization algorithms considering the convergence characteristics, statistical values and computation time of operation.

Author contributions

Conceptualization, ST, SN, SRG and PA; methodology, ST; software, ST; validation, ST, SN and SRG; formal analysis, ST and SRG; investigation, ST and SN; resources, SRG and PA; data curation, ST and PS; writing—original draft preparation, ST and SN; writing—review and editing, ST, SRG and PA; visualization, ST; supervision, SRG, PA and PS; project administration, ST and SRG; funding acquisition, ST and SN. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

References

1. International Energy Agency. *Global EV Outlook 2017*. International Energy Agency; 2017.
2. Pieltain Fernandez L, Gomez San Roman T, Cossent R, et al. Assessment of the impact of plug-in electric vehicles on distribution networks. *IEEE Transactions on Power Systems* 2011; 26(1): 206–213. doi: 10.1109/tpwrs.2010.2049133
3. Saber AY, Venayagamoorthy GK. Plug-in vehicles and renewable energy sources for cost and emission reductions. *IEEE Transactions on Industrial Electronics* 2011; 58(4): 1229–1238. doi: 10.1109/tie.2010.2047828
4. Ahmad F, Khalid M, Panigrahi BK. An enhanced approach to optimally place the solar powered electric vehicle charging station in distribution network. *Journal of Energy Storage* 2021; 42: 103090. doi: 10.1016/j.est.2021.103090
5. Ahmed R, Sreeram V, Mishra Y, Arif MD. A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renewable and Sustainable Energy Reviews* 2020; 124: 109792. doi: 10.1016/j.rser.2020.109792
6. Das UK, Tey KS, Seyedmahmoudian M, et al. Forecasting of photovoltaic power generation and model optimization: A review. *Renewable and Sustainable Energy Reviews* 2018; 81: 912–928. doi: 10.1016/j.rser.2017.08.017
7. Zárate-Miñano R, Flores Burgos A, Carrión M. Analysis of different modeling approaches for integration studies of plug-in electric vehicles. *International Journal of Electrical Power & Energy Systems* 2020; 114: 105398. doi: 10.1016/j.ijepes.2019.105398
8. Zhou B, Yang X, Yang D, et al. Probabilistic load flow algorithm of distribution networks with distributed generators and electric vehicles integration. *Energies* 2019; 12(22): 4234. doi: 10.3390/en12224234
9. Zakaria A, Ismail FB, Lipu MSH, Hannan MA. Uncertainty models for stochastic optimization in renewable energy applications. *Renewable Energy* 2020; 145: 1543–1571. doi: 10.1016/j.renene.2019.07.081
10. Kongjeen Y, Bhumkittipich K, Mithulananthan N, et al. A modified backward and forward sweep method for microgrid load flow analysis under different electric vehicle load mathematical models. *Electric Power Systems Research* 2019; 168: 46–54. doi: 10.1016/j.epsr.2018.10.031
11. Dharmakeerthi CH, Mithulananthan N, Saha TK. Impact of electric vehicle fast charging on power system voltage stability. *International Journal of Electrical Power & Energy Systems* 2014; 57: 241–249. doi: 10.1016/j.ijepes.2013.12.005
12. Lin S, He Z, Zang T, Qian Q. Impact of plug-in hybrid electric vehicles on distribution systems. In: Proceedings of 2010 International Conference on Power System Technology; 24–28 October 2010; Zhejiang, China.
13. Shafiee S, Fotuhi-Firuzabad M, Rastegar M. Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems. *IEEE Transactions on Smart Grid* 2013; 4(3): 1351–1360. doi: 10.1109/tsg.2013.2251483
14. Ponnam VKB, Swarnasri K. Multi-objective optimal allocation of electric vehicle charging stations and distributed generators in radial distribution systems using metaheuristic optimization algorithms. *Engineering, Technology & Applied Science Research* 2020; 10(3): 5837–5844. doi: 10.48084/etasr.3517
15. Deb S, Tammi K, Kalita K, Mahanta P. Impact of electric vehicle charging station load on distribution network. *Energies* 2018; 11(1): 178. doi: 10.3390/en11010178
16. Memon ZA, Said DM, Hassan MY, et al. Effective deterministic methodology for enhanced distribution network performance and plug-in electric vehicles. *Sustainability* 2023; 15(9): 7078. doi: 10.3390/su15097078
17. Ko M, Tiwari A, Mehnen J. A review of soft computing applications in supply chain management. *Applied Soft Computing* 2010; 10(3): 661–674. doi: 10.1016/j.asoc.2009.09.004
18. Burney SMA, Ali SM, Burney S. A survey of soft computing applications for decision making in supply chain

management. In: Proceedings of 2017 IEEE 3rd International Conference on Engineering Technologies and Social Sciences (ICETSS); 7–8 August 2017; Bangkok, Thailand.
19. Thirugnanam K, Ezhil Reena JTP, Singh M, Kumar P. Mathematical modeling of Li-ion battery using genetic algorithm approach for V2G applications. *IEEE Transactions on Energy Conversion* 2014; 29(2): 332–343. doi: 10.1109/tec.2014.2298460
20. Ishaque K, Salam Z. A deterministic particle swarm optimization maximum power point tracker for photovoltaic system under partial shading condition. *IEEE Transactions on Industrial Electronics* 2013; 60(8): 3195–3206. doi: 10.1109/TIE.2012.2200223
21. Storn R, Price K. Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization* 1997; 11: 341–359. doi: 10.1023/A:1008202821328
22. Moradi MH, Abedini M. A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. *International Journal of Electrical Power & Energy Systems* 2012; 34(1): 66–74. doi: 10.1016/j.ijepes.2011.08.023
23. Zhu ZH, Gao ZY, Zheng JF, Du HM. Charging station location problem of plug-in electric vehicles. *Journal of Transport Geography* 2016; 52: 11–22. doi: 10.1016/j.jtrangeo.2016.02.002
24. Xiang Y, Liu J, Li R, et al. Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates. *Applied Energy* 2016; 178: 647–659. doi: 10.1016/j.apenergy.2016.06.021
25. Pashajavid E, Golkar MA. Optimal placement and sizing of plug in electric vehicles charging stations within distribution networks with high penetration of photovoltaic panels. *Journal of Renewable and Sustainable Energy* 2013; 5(5): 053126. doi: 10.1063/1.4822257
26. Moradi MH, Abedini M, Tousi SMR, Hosseinian SM. Optimal siting and sizing of renewable energy sources and charging stations simultaneously based on Differential Evolution algorithm. *International Journal of Electrical Power & Energy Systems* 2015; 73: 1015–1024. doi: 10.1016/j.ijepes.2015.06.029
27. Rao RV, Savsani VJ, Vakharia DP. Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems. *Computer-Aided Design* 2011; 43(3): 303–315. doi: 10.1016/j.cad.2010.12.015
28. Wu X, Feng Q, Bai C, et al. A novel fast-charging stations locational planning model for electric bus transit system. *Energy* 2021; 224: 120106. doi: 10.1016/j.energy.2021.120106
29. National household travel survey. Available online: http://nhts.ornl.gov (accessed on 7 November 2023).
30. *2017 National Household Travel Survey Data Explorer User's Guide—Public Use Version*. Federal Highway Administration; 2018.
31. Ni X, Lo KL. A methodology to model daily charging load in the charging stations based on monte carlo simulation. In: Proceedings of 2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE); 4–7 October 2020; Kuching, Malaysia.
32. Darabi Z, Ferdowsi M. Extracting probability distribution functions applicable for PHEVs charging load profile. In: Proceedings of PES T&D; 7–10 May 2012; Orlando, FL, USA.
33. Qian K, Zhou C, Allan M, Yuan Y. Modeling of load demand due to EV battery charging in distribution systems. *IEEE Transactions on Power Systems* 2011; 26(2): 802–810. doi: 10.1109/tpwrs.2010.2057456
34. Roy Ghatak S, Sannigrahi S, Acharjee P. Optimised planning of distribution network with photovoltaic system, battery storage, and DSTATCOM. *IET Renewable Power Generation* 2018; 12(15): 1823–1832. doi: 10.1049/iet-rpg.2018.5088
35. Weather Archive Tokyo. Available online: https://www.meteoblue.com/en/weather/historyclimate/weatherarchive/durgapur_india_1272175,2017. (accessed on 14 November 2023).
36. Mohanty B, Tripathy S. A teaching learning based optimization technique for optimal location and size of DG in distribution network. *Journal of Electrical Systems and Information Technology* 2016; 3(1): 33–44. doi: 10.1016/j.jesit.2015.11.007
37. Mozafar MR, Moradi MH, Amini MH. A simultaneous approach for optimal allocation of renewable energy sources and electric vehicle charging stations in smart grids based on improved GA-PSO algorithm. *Sustainable Cities and Society* 2017; 32: 627–637. doi: 10.1016/j.scs.2017.05.007
38. Tan WS, Hassan MY, Rahman HA, et al. Multi-distributed generation planning using hybrid particle swarm optimisation-gravitational search algorithm including voltage rise issue. *IET Generation, Transmission & Distribution* 2013; 7(9): 929–942. doi: 10.1049/iet-gtd.2013.0050
39. Rao RV, Savsani VJ, Vakharia DP. Teaching–learning-based optimization: An optimization method for continuous non-linear large scale problems. *Information Sciences* 2012; 183(1): 1–15. doi: 10.1016/j.ins.2011.08.006
40. Singh RK, Goswami SK. Multi-objective optimization of distributed generation planning using impact indices and trade-off technique. *Electric Power Components and Systems* 2011; 39(11): 1175–1190. doi: 10.1080/15325008.2011.559189
41. Hamouda A, Zehar K. Efficient load flow method for radial distribution feeders. *Journal of Applied Sciences* 2006; 6(13): 2741–2748. doi: 10.3923/jas.2006.2741.2748
42. Bompard E, Carpaneto E, Chicco G, Napoli R. Convergence of the backward/forward sweep method for the

load-flow analysis of radial distribution systems. *International Journal of Electrical Power & Energy Systems* 2000; 22(7): 521–530. doi: 10.1016/S0142-0615(00)00009-0