Multi-Objective Optimal Allocation of Electric Vehicle Charging Stations in Radial Distribution System Using Teaching Learning Based Optimization

Ponnam Venkata K Babu*‡, K. Swarnasri**

* Department of EEE, Research Scholar, Acharya Nagarjuna University, Guntur, AP, India

** Department of EEE, RVR & JC College of Engineering, Chowdavaram, Guntur, AP, India

(kishore.ponnam@gmail.com, swarnasrik@gmail.com)

‡ Corresponding Author; Ponnam Venkata K Babu, Department of EEE, Research Scholar, Acharya Nagarjuna University, Guntur, AP, India. Tel: +91 9494414529, kishore.ponnam@gmail.com

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Abstract- In recent times, the adoption rate of Electric Vehicles (EVs) in the transportation sector has been increased significantly across the world towards sustainability. On the other side, the increasing EV load penetration in an electric power sector can cause for the generation-demand imbalance, real power loss increment, poor voltage profile, and consequently voltage stability margin decrement. To mitigate the impact of increasing EV load penetration on radial distribution systems (RDS), it is essential to integrate EV Charging Stations (CSs) at appropriate locations. In this paper, the teaching-learning based optimization (TLBO) algorithm is applied to determine the optimal locations of EV-CSs considering the objectives minimization of real power loss and average voltage deviation index and maximization of voltage stability index. The simulation studies are performed on standard IEEE 33-bus and 69-bus test systems. The results have highlighted the need for optimal allocation of EV-CSs for maintaining the system performance as better as possible even under increased loading conditions due to EV-CSs. Also, TLBO has shown its ability over other heuristic algorithms namely particle swarm optimization (PSO), ant lion optimizer (ALO),flower pollination algorithm (FPA) and cuckoo search algorithm (CSA) by providing the optimal value consistently in solving the complex non-linear multi-objective optimization problem.

Keywords Electric vehicles, charging stations, optimal allocation, multi-objective optimization, TLBO algorithm, radial distribution system.

1. Introduction

In view of increasing carbon footprints due to conventional energy (CE) generation sources and petroleum-based transportation, sustainable measures such as integration of renewable energy sources (RES) in the energy sector and adoption of electric vehicles (EVs) for transportation have been focused significantly across the world. According to global EV outlook 2019, International Energy Agency (IEA), the E-mobility is expanding at a rapid pace. In 2018, the global electric car fleet was exceeded 5.1 million and the growth was almost double as compared with 2017 statistics. Under this scenario, it is essential to provide the required infrastructure such as charging stations (CSs), parking lots (PLs), battery swapping stations (BSSs), energy storage systems (ESSs) and energy balance using RES etc in the existing electric distribution networks (EDN) and also performance evaluation for better reliable and secured operation. The performance improvement of EDN is handled effectively via optimally allocating renewable based distribution generation (DG) in the past 2 decades. In [1], voltage stability factors (VSFs) and Flower Pollination Algorithm (FPA) are proposed to optimally allocate solar photovoltaic distribution generation (DG) considering loss minimization and voltage stability maximization. In [2], the implementation and effect of renewable energy on the power grid using Grid LAB-D program.A study of four different cases for different proportions of renewable energy sources is analyzed on slightly modified IEEE 13 Node Test Feeder. In [3], Proposed a method for improving the quality of power when EV is using as a power storage device for suppressing PV fluctuations. In [4], the implementation of a PSO-based MPPT algorithm to a photovoltaic power generation system functioning under dynamic conditions is proposed to optimize and build an intelligent controller relative to a traditional one. In [5], Firefly Algorithm (FA), and Adaptive Acceleration Particle Swarm Optimization (AAPSO) techniques based Proportional-Integral (PI) controller proposed to study the stability analysis of Photo Voltaic Systems connected to grid. In [6], the amount of renewable energy can be used in public transport vehicles and the size of the photovoltaic system must be installed to charge the Exchangeable battery systems is investigated efficiently.

In [7], a comprehensive review on optimal siting of EV charging infrastructure is presented and classified as (i) transportation-network based model, (ii) distribution-network based model, and (iii) transportation-distribution-networks based models. An example of a transportation-network model optimal location of EV-CSs can be found in [8], which formulated as Route-Node-Coverage (RNC) problem considering the driving range of EV. The simulations performed on Sioux-Falls network and southern Sweden highway. Similarly in [9], the location of EV-CSs are planned in cites of Vasteras, Sweden based on traffic flow rate and land-use classification data using Geographic Information System (GIS) and the optimization problem is solved using Mixed Integer Linear Programming (MILP) for maximizing the profits with new CSs. In [10], considering highway features (the flow of vehicles with related indicators), the infrastructures (the number of sockets and the charging station power), and driver behavior (range anxiety), the required EV infrastructure and locations are determined for the Italian transportation network. In [11], the location of CSs and their sizes are determined using service risk using improved whale optimization algorithm (IWOA). Further, a comprehensive review of the transportation-network based model can also be found in [12]. Notably, the transportation-network based model is not suite for the realization of EV-CSs impact on the performance of distribution networks and energy balance in grid operation and control. These factors can realize in distribution-network based model, but not suit for realizing the EV owners' driving-range anxiety.

In the transportation-distribution-network model, both the factors can be addressed. In [13], using a superimposed road-distribution network of Guwahati City, India, optimal allocation of EV-CSs problem is solved using hybrid chicken swarm optimization (CSO) and teaching-learning-based optimization (TLBO). The objective function is formulated considering economic factors and grid operational factors. In [14], the number of CSs, duration of their planning period, total cost (investment, operating and maintenance) CSs and network operating constraints like bus voltages and branch current limits are considered to determine the optimal allocation of EV-CSs and the objective function is solved using PSO algorithm. In [15], considering transportation/ routing cost of EVs and distribution system performance, optimal allocation of freight EV-CSs problem is addressed. In [16], the problem of optimal location of fast CSs is solved considering candidate locations with economy of operation at the upper layer and impact of CSs on drivers, EV power loss, traffic condition, grid operation at the lower layer. In [17], a multi-objective grey wolf optimizer (MOGWO) algorithm is proposed to solve the problem of EV fast CSs locations in 123-bus distribution system considering grid and transportation network constraints. In [18], the optimal location of EV parking lots (PLs) is presented considering traffic-flow, EV charging behavior, and distribution network constraints.

In this work, as similar to the distribution-network based model, the optimal allocation of EV-CSs in radial distribution network is presented. Here some of such works are reviewed and presented. In [19], a hybrid approach using particle swarm optimization (PSO) and sequential quadratic programming (SQP) is proposed to identify EV aggregator-CSs in the radial distribution system. The objective function is formulated to minimize the operating cost of system load, EV load, and losses. Considering transformer aging and distribution losses [20] and also battery charging monetary cost [21], the impact of EV charging on the distribution network is analyzed. In [22], the impact of EV load penetration in Latin American is presented. And the study determines the 23 fast CSs location optimally for serving the 10% penetration of EV load without compromising the grid operational codes such as voltage profile, harmonic distortion. In [23], a real-time low-voltage residential distribution network of Bhubaneswar electrical division, CESU, Odisha, India consisting of 107 buses is considered for allocating the EV-CSs. According to transformer ratings, the feasibility of number EVs are determined. Using the Salp swarm algorithm (SSA), the charging cost is minimized by satisfying grid technical limits under conventional (dump) and smart charging modes are presented and the results highlighted the fact that the voltage profile variation due to EV loads is higher in the secondary distribution feeders than compared with primary distribution feeder. Further the reader can be found a comprehensive review of CS placement problem using nature-inspired algorithms (NIA) in [24]. The work also presented the performance of different stand-alone algorithms such as DE, PSO, CSO, TLBO and GA and compared with hybrid algorithms namely CSO-TLBO, GA-PSO. The simulation results highlighted the supremacy of hybrid algorithms in solving the CSs allocation problem. Similarly, the impact of EV load on distribution networks under conventional charging mode and smart charging mode is presented in [25]. Different charging scenarios and case studies recommended the smart charging mode to minimize the operational cost at peak-demand and to maintain grid reliability and security factors. At this point, it can be said that the increased EV load on the distribution system should be adequately planned to enhance technical and economic benefits and consequently to improve the adoption rate of EV technologies in developing countries like India.

The public EV-CSs should design for multiple facilities such as AC slow chargers (ACCs), DC rapid charges (DCCs) and AC and DC integrated chargers (ADCs) [7]. They should also design with multiple charging ports (CPs) for multiple types of EVs to achieve the economic goals and to increase the EV adoption rate. According to the EV model, the power rating can change. For an instant, Tesla Model X power rating is 13 kW, BMW i3 needs 44 kW, Chevrolet VOLT needs 2.2 kW and CHANG AN YIDONG needs 3.75 kW [19]. Moreover, different types of AC and DC EV models and their power demand specifications can be found in [10]. Hence, the total power demand of EV-CSs is mainly dependent on the number of CPs and their type. On the other side, the dispersed EV demand for a CS can estimate using either a spatial-temporal probabilistic model or a rough probabilistic model for better reliable operation of the network [26].In this work, depending upon type of the EV model and number of CPs, the power demand of EV-CSs is determined.

In light of the above works, the optimal allocation of EV-CSs in the distribution network using TLBO algorithm [27] was proposed for attaining technical benefits. The efficiency of TLBO is compared with particle swarm optimization (PSO) [28], ant lion optimizer (ALO) [29] and flower pollination algorithm (FPA) [30], cuckoo search algorithm (CSA) [31]. The simulations are performed on standard IEEE 33-bus and 69-bus test systems.

2. Problem Formulation

To mitigate the impact of increased EV load on distribution system performance, the size and location of CSs should be optimized. Backward/Forward (BW/FW LF) technique [32] is used for solving the load flow problem of the radial distribution system (RDS). The multi objectives of this study are: to minimize real power losses, improve voltage profile and enhance voltage stability.

The real power losses are determined by summation of all branches losses in the system and are given in (1).

$$f_1 = P_{loss} = \sum_{k=1}^{nl} \frac{r_{ij}\left(P_j^2+Q_j^2\right)}{V_i^2} \tag{1}$$

The average voltage deviation index (AVDI) is defined in terms of all bus voltage magnitudes are deviation w.r.t. ideal voltage magnitude 1.0 p.u. and is given in (2).

$$f_2 = AVDI = \frac{1}{nb}\sum_{i=1}^{nb}|1-V_i| \tag{2}$$

As defined in [33], the voltage stability index (VSI) of a receiving end bus of a branch can be determined using voltage magnitude of sending end bus, real and reactive power loads at receiving end bus and its resistance and reactance as in (3).

$$f_3 = VSI_j = \left[|V_i|^4 - 4\left(P_j x_{ij} - Q_j r_{ij}\right) - 4\left(P_j r_{ij} + Q_j x_{ij}\right)|V_i|^2\right] \tag{3}$$

For stable operation, VSIj should be greater than 0. Among all the buses, the minimum value of VSI can be treated as the overall stability of the system.

Hence, the overall objective function is formulated to minimize power losses, voltage deviation index and to maximize voltage stability index. Mathematically, expressed as given in (4).

$$OOF = min\left(w_1 f_1 + w_2 f_2 + w_3\left(\frac{1}{f_3}\right)\right) \tag{4}$$

The proposed multi-objective function given in (4) is minimized by having the node voltage (Vi), and branch flow (|Si|) operational constraints, and CS design constraints such as number of CPs and number of CSs, which are given in (5) – (8).

$$V_{\min} \le V_i \le V_{\max} \qquad i = 1,2,...nb \tag{5}$$

$$|S_l| \le |S_{l,\max}| \qquad l = 1,2,...nbl \tag{6}$$

$$nCP_{\min} \le nCP \le nCP_{\max} \tag{7}$$

$$nCS_{\min} \le nCS \le nCS_{\max} \tag{8}$$

The load flow algorithm is extended to determine the function values specified in OOF and the TLBO algorithm shall take care of the lower and upper limits specified in (5) – (8), while minimizing the OOF.

3. Teaching -Learning Based Optimization

3.1 Overview

The Teaching-Learning-Based Optimization (TLBO) algorithm is introduced by R. V. Rao et. al (2011) [34] using the influence of a teacher on learners. As compared with similar type of nature-inspired algorithms namely artificial bee colony (ABC), differential evaluation (DE), evolutionary programming (EP), and PSO, TLBO is characterized by less computational effort and high consistency in providing the global solution for continuous nonlinear optimization problems. Basically the TLBO simulates the traditional teaching-learning process in a classroom. In the assumptions, the learning may take place in two phases like (i) through teacher (known as teacher phase) and (ii) interaction with co-learners/classmates (known as learner phase). In similar to the population based algorithms, in TLBO, the number of students or group of students considered as population, the number of subjects as design variables of the optimization problem, the best solution among all population is treated as teacher and results of the learners as the fitness function. In this section, the basic operations involved in teacher phase and learner phase are explained briefly.

➢ *Teacher phase*

In this phase, the students learn from the teacher and teacher keeps an effort to increase the mean of results of the students by conveying knowledge among them. Let Sn (n = 1… l) is the number of learners (population) and Sm (m = 1… s) is the number of subjects (design variables in the optimization problem). Consider the sequential teaching-learning process (iteration) and at any sequence k, the mean result of a subject 's' as M(s, k). In the entire learners, the best learner who secured best mean result in all the subjects is treated as teacher in that iteration and denoted as Xtotal-kbest,k. In general, the teacher puts his maximum effort to increase the knowledge level of all the students, but the rate of learning depends on the quality of the teacher as well as learners in that class. This fact is expressed in (9) as the difference between the best learner and mean of the remaining class.

$$DM_{s,k} = r_k\left(X_{s,kbest,k} - T_F M_{s,k}\right) \tag{9}$$

where Xs,kbest,k is the result of best learner (or teacher) in the subject 's'; rk is uniformly distributed random number between [0, 1]; TF is the teaching quality factor, which is the root cause for improving or change the mean result of the entire class in that subject Ms,k; The value of TF can be either 1 or 2 and it decided randomly with equal probability as defined in (10).

$$T_F = round\left[1 + rand\left(0,1\right)\left\{2-1\right\}\right] \tag{10}$$

Note here, TF is not an input parameter and can be generated in the process of TLBO algorithm using (10). Using difference mean defined in (9), the current solution is updated in teaching phase as given in (11).

$$X'_{l,s,k} = X_{l,s,k} + DM_{s,k} \tag{11}$$

All the updated X'l,s,k values are accepted and carry forward for the next cycle/iteration as input, if they produce better function value else, remain same.

➢ *Learning phase*

This phase simulates the cooperative learning process in which student can also gain new knowledge by interacting with other classmates, particularly from those who have better knowledge than him/her. This phenomenon is modelled here with brief explanatory.

Let consider two students randomly Sp and Sq and their updated solutions at the end of teaching phase as $X'_{total,p,k} \neq X'_{total,q,k}$. By interacting both, their knowledge levels are updated as (12) in the maximization problem.

$$X''_{p,s,k} = X'_{p,s,k} + r_k\left(X'_{p,s,k} - X'_{q,s,k}\right) \quad \text{if } X'_{total,p,k} > X'_{total,q,k} \tag{12a}$$

$$X''_{p,s,k} = X'_{p,s,k} + r_k\left(X'_{q,s,k} - X'_{p,s,k}\right) \quad \text{if } X'_{total,p,k} < X'_{total,q,k} \tag{12b}$$

Note here (12) can be reversed for minimization problem and the accepted values can carry forward to the next cycle, if updated values produce the better solution, else remain the same.

➢ *Application of TLBO for solving the OOF*

In this section, the sequential steps involved in solving the problem of optimal allocation of EVCSs using TLBO algorithm are given.

St 1) Define either maximization or minimization objective function subjected to equal and inequal constraints of the design variables.

St 2) Initialize the population size equal to number of learners and design variables equal to the number of CSs, their sizes in kW and location range in the network (from bus – to bus) for each CS.

St 3) Using BW/FW load flow, evaluate the initial population and determine overall function values (OOF) using (4).

St 4) Set iteration count k=1 and identify the best population/learner which has given best OOF and treat that learner as a teacher. Also, determine the mean of all the population.

St 5) Update the existing solutions using equations (9) – (11) and carry forward all accepted solutions if they result for a better solution than the current teacher.

St 6) Using (12) modify the solutions obtained in step (5) and carry forward all accepted solutions if they result for a better solution than the current teacher.

St 7) Save the current best teacher and repeat steps (4) to (6) until iteration count reaches to its maximum.

St 8) At the end, print the best solution/teacher as the optimal solution and plot the saved best teacher record of all iterations as convergence characteristics and stop.

4. Results and Discussions

The proposed optimization algorithm has been evaluated using the MATLAB program, which is implemented in a PC having Intel Core i5-4210U processor, up to 1.7 GHz and 8 GB of RAM memory. The simulations are performed on IEEE standard 33-bus and 69-bus RDS test systems. The data for the test systems are taken from [35].

In addition to the EV models (Chevrolet VOLT, CHANG AN YIDONG, Tesla Model X and BMW i3) given in Table 1, AC/DC Level-2 type charging ports (CPs) are also considered in CS design. According to SAE J1772 standard, this type of CPs can suit for both Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), which has a maximum power rating of 7 kW [36].The design features of CPs such as types of EVs which can charge at a time in a particular CS and their power ratings in kW, the minimum and maximum number of CPs for different types of EVs and correspondingly the minimum and maximum power rating of CS. The details are given in Table 1. For an instant, if all the CSs are designed for only minimum CPs as given in Table 1, the power rating of 1 CS is 975 kW. Similarly, for maximum number CPs, the demand may increase to 1675.5 kW.

Table 1. Design features of EV-CSs for the simulation

EV Type	EV power rating (kW)	No. of CPs		Rating of CS (kW)	
		Min	Max	Min	Max
Chevrolet VOLT	2.2	25	35	55	77
CHANG AN YIDONG	3.75	20	30	75	112.5
Tesla Model X	13	15	25	195	325
BMW i3	44	10	20	440	880
SAE J1772 Standard	7	30	40	210	280
Total power rating of CS (kW)				975	1674.5

4.1 33-Bus Test System

The 33-bus system is operating at 12.66 kV, and it has real and reactive power loads of 3715 kW and 2300 kVAr respectively. By performing load flow, it has been observed that the real and reactive power losses as 210.9897 kW and 143.027 kVAr respectively and the minimum voltage 0.9038 p.u. at bus-18. Also, the minimum VSI of the network is observed as 0.6661 at bus-18 [34]. This simulation is treated as Case-A in the further sections.

In this test system, it is assumed to integrate totally 3 CSs considered 1 in each sub-feeder optimally. By imposing a total power demand of 2925 kW (975 kW×3) for 3 CSs with the minimum number of CPs at all CSs as given in Table 1, the new loading condition of the test system is determined. According to this, the real power load is increased from 3715 kW to 6640 kW, (which is 1.7873 times more than Case-A) and the corresponding test system performance is given in Table 2. Due to increased EV-CS load, the real losses (Ploss, F1) are increased to 576.1705 kW from 210.9897 kW (which is 72.606 % raise to the Case-A), the average voltage deviation index (AVDI, F2) is increased to 0.0108from 0.0041, the stability index (VSImin, F3) is decreased to 0.4984 from 0.6661 and the minimum voltage at bus-18 is decreased to 0.8408 p.u. from 0.9038 p.u. This simulation is treated as Case-B in the further sections.

Similarly for the maximum number of CPs in each CS, the load can increase on the network by 1674.5 kW and 5023.5 kW for 3 CSs (which is 2.3522 times more). The corresponding system performance is given in Table 2. The losses are increased to 1024.3908 kW (which is 285.517 % raise to the Case-A and 78.1021% raise to the Case-B), voltage deviation index raised to 0.0187 and stability index decreased to 0.3854 and the minimum voltage at bus-18 reaches to 0.7888 p.u. This simulation is treated as Case-C in the further sections.

Hence, the objective of optimal allocation of EV-CSs is to improve the test system performance for the above mentioned increased EV loading condition. The parameters of TLBO are as follows: the number of unknown variables in the search space is 3 (for 3 EV locations), the number of population is 50, and number of maximum iteration are50.

The impact of optimal EV-CSs with minimum number of CPs at best locations (bus-2, 19 and 25) is given in Table 2. The real losses are decreased to 295.6474 kW from 576.1705 kW, the average voltage deviation index is decreased to 0.0047 from 0.0108, the voltage stability index is improved to 0.6499 from 0.4984 and the minimum voltage at bus-18 is increased to 0.8982 p.u from 0.8408 p.u. By observing the results, the losses are decreased by 48.6875% as compared to Case-B. The results of this case are considered as Case-D.

Similarly, the results of EV-CSs with the maximum number of CPs at the best locations (bus-2, 19 and 25) are given in Table 2. The real losses are decreased to 390.6266 kW from 1024.3908 kW, the average voltage deviation index is decreased to 0.0053 from 0.0187, the voltage stability index is improved to 0.6381 from 0.3854 and the minimum voltage at bus-18 is increased to 0.8941 p.u from 0.7888 p.u.

By observing the results, the losses are decreased by 61.8674% as compared to Case-C. The results of this case are considered as Case-E. The voltage profile and VSI profile for different cases are given in Fig.1 and Fig.2 respectively.

Table 2. Performance of 33-bus test system with EV-CSs at optimal locations

Case	Algorithm	EV Locations	F_1, P_{loss}	F_2, AVDI	F_3, VSI_{min}	V_{min} (p.u)
A	-	-	210.9897	0.0041	0.6661	0.9038
B	-	-	576.1705	0.0108	0.4984	0.8408
D	TLBO	2/ 19/ 25	295.6474	0.0047	0.6499	0.8982
	ALO [29]	2/ 19/ 25	295.6474	0.0047	0.6499	0.8982
	FPA [30]	2/ 19/ 25	295.6474	0.0047	0.6499	0.8982
	CSA [31]	2/ 19/ 25	295.6474	0.0047	0.6499	0.8982
	PSO [28]	2/ 19/ 25	295.6474	0.0047	0.6499	0.8982
C	-	-	1024.3908	0.0187	0.3854	0.7888
E	TLBO	2/ 19/ 25	390.6266	0.0053	0.6381	0.8941
	PSO [28]	2/ 19/ 25	390.6266	0.0053	0.6381	0.8941
	ALO [29]	2/ 19/ 25	390.6266	0.0053	0.6381	0.8941
	FPA [30]	2/ 19/ 25	390.6266	0.0053	0.6381	0.8941
	CSA [31]	2/ 19/ 25	390.6266	0.0053	0.6381	0.8941

The statistics for convergence characteristics of different algorithms are given in Table 3. Since the power ratings of CSs are not variable in the optimization process and hence all the considered algorithms are finally resulted for only one combination of best locations. By observing the mean values of OOF, the TLBO has outperformed than ALO, FPA, CSA and PSO in both the cases with best mean. The convergence characteristics of these algorithms for Case-D are only given in Fig.3.

Table 3. Convergence characteristics of different algorithms in 33-bus system

Case	OF value	Algorithm				
		TLBO	FPA	ALO	CSA	PSO
D	Minimum	297.191	297.191	297.191	297.191	297.191
	Maximum	311.834	354.210	330.382	311.834	375.157
	Average	**297.776**	298.331	297.855	298.655	298.750
E	Minimum	392.199	392.199	392.199	392.199	392.199
	Maximum	588.340	524.620	720.255	760.514	583.209
	Average	**397.824**	402.090	403.256	412.038	403.812

4.2 69-Bus Test System

The 69-bus test system is operating at 12.66 kV, and it has total real power load of 3801.4 kW and reactive power load of 2693.6 kVAr respectively. The load flow results for real power loss of 224.8807 kW and reactive power loss of 102.1094 kVAr respectively. Also, the minimum voltage of 0.9092 p.u. is observed at bus-65. This operating condition is treated as Case-A in further sections.

As similar to 33-bus test system simulations, in this test system also, 3 EV-CSs are considered (1 in each sub-feeder) to integrate at optimal locations with different CPs. By imposing a total power demand of 2925 kW for 3 CSs with minimum CPs, the test loading condition is increased from 3801.4 kW to 6726.4 kW (1.7695 times to Case-A). Due to increased EV load, the real losses are increased to 613.4994 kW from 224.8807 kW (which is 72.81 % raise to the Case-A), the average voltage deviation index is increased to 0.004 from 0.0014, the stability index is decreased to 0.5114from 0.6823 and the minimum voltage at bus-65 is decreased to 0.8462 p.u. from 0.9092 p.u. This operating condition is treated as Case-B in further sections.

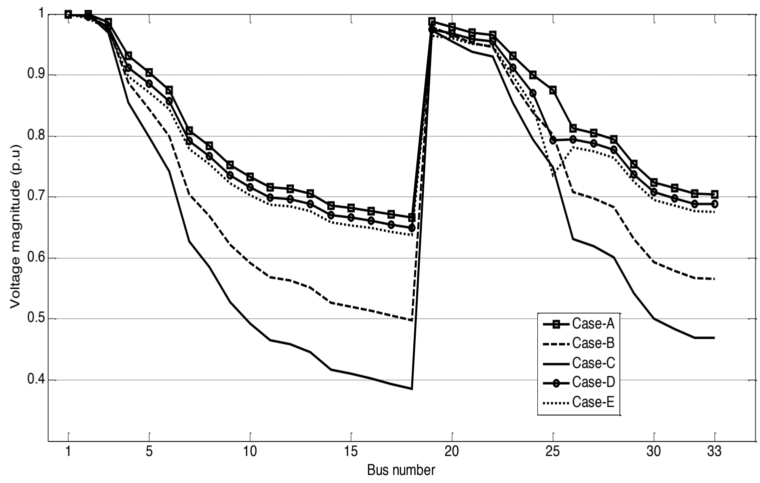

Fig. 1. Voltage profile for different cases in 33-bus system

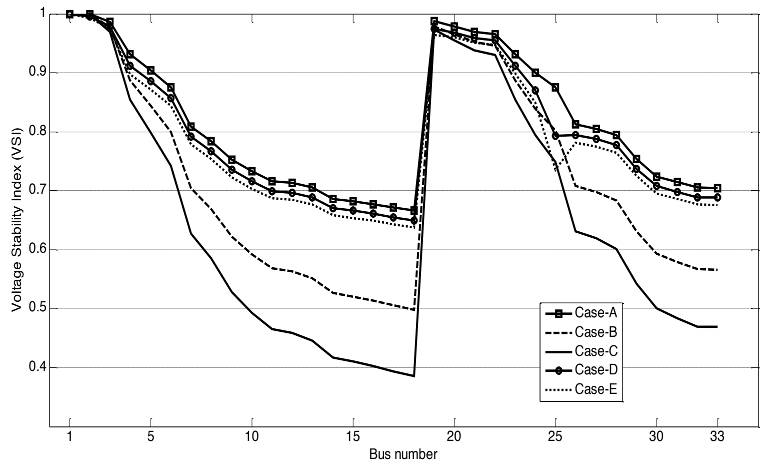

Fig. 2. Voltage stability index (VSI) for different cases in 33-bus system

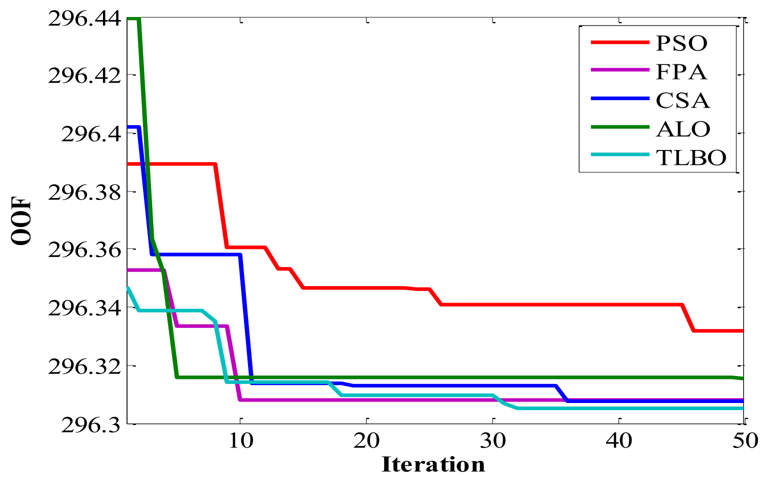

Fig. 3. Convergence characteristics of different algorithms for Case-D in 33-bus system

Similarly by imposing a total power demand of 5023.5 kW for 3 CSs with maximum CPs, the test loading condition is increased from 3801.4 kW to 8824.9 kW (2.3215 times to Case-A). Due to increased EV load, the real losses are increased to 1108.6 kW from 224.8807 kW (which is 292.97 % raise to the Case-A and 172.81% raise to Case-B), the average voltage deviation index is increased to 0.0072 from 0.0014, the stability index is decreased to 0.3949 from 0.6823 and the minimum voltage at bus-65 is decreased to 0.7935 p.u. from 0.9092 p.u. This operating condition is treated as Case-C in further sections.

Notably, by having EV-CSs at best locations (bus-2, 28 and 47) in both the case B and C, the test system has retained almost similar performance as Case-A. The losses in Case-B with EV-CSs are decreased to 225.2186 kW from 613.4994, AVDI is decreased to 0.0014 from 0.004 and VSI is increases to 0.6822 from 0.51114. Also, the minimum voltage at bus-65 is raised to 0.9092 p.u from 0.8462 p.u. The voltage profile and VSI profile for different cases are given in Fig.4 and Fig.5 respectively. Similarly in Case-C with EV-CSs, the losses are decreased to 225.5766 kW from 1108.6266, AVDI is decreased to 0.0014 from 0.0072and VSI is increases to 0.6821 from 0.3949. Also, the minimum voltage at bus-65 is raised to 0.9092 p.u from 0.7935 p.u. The results of all cases are tabulated in Table 4. The convergence characteristics of different algorithms are given in Table 5 in terms minimum, maximum and average values of OOF. In similar to 33-bus test system, TLBOS has performed better than ALO, FPA, CSA and PSO in both the cases with best mean. The convergence characteristics of these algorithms for Case-E are only given in Fig.6.

The convergence characteristics of TLBO along with other heuristic algorithms are given in Fig.3 and Fig.6. Each algorithm is simulated for 10 times and correspondingly the minimum (best), maximum (worst) and average of the overall objective function (OOF) is given in Table 3 and Table 5. By observing the minimum values of TLBO in both the cases, it has shown superior characteristics of stability than other algorithms.

Table 4. Performance of 69-bus test system with EV-CSs at optimal locations

Case	Algorithm	EV Locations	F_1, Ploss	F_2, AVDI	F_3, VSI_{min}	V_{min} (p.u)
A	-	-	224.8807	0.0014	0.6823	0.9092
B	-	-	613.4994	0.004	0.5114	0.8462
D	TLBO	2/ 28/ 47	225.2186	0.0014	0.6822	0.9092
	ALO [29]	2/ 28/ 47	225.2186	0.0014	0.6822	0.9092
	FPA [30]	2/ 28/ 47	225.2186	0.0014	0.6822	0.9092
	CSA [31]	2/ 28/ 47	225.2186	0.0014	0.6822	0.9092
	PSO [28]	2/ 28/ 47	225.2186	0.0014	0.6822	0.9092
C	-	-	1108.6266	0.0072	0.3949	0.7935
E	TLBO	2/ 28/ 47	225.5766	0.0014	0.6821	0.9092
	PSO [28]	2/ 28/ 47	225.5766	0.0014	0.6821	0.9092
	ALO [29]	2/ 28/ 47	225.5766	0.0014	0.6821	0.9092
	FPA [30]	2/ 28/ 47	225.5766	0.0014	0.6821	0.9092
	CSA [31]	2/ 28/ 47	225.5766	0.0014	0.6821	0.9092

Table 5. Convergence characteristics of different algorithms in 69-bus system

Case	OF value	Algorithm				
		TLBO	FPA	ALO	CSA	PSO
D	Minimum	226.686	226.686	226.686	226.686	226.686
	Maximum	226.727	227.117	232.436	267.046	227.945
	Average	**226.687**	226.695	226.801	227.494	226.711
E	Minimum	227.044	227.044	227.044	227.044	227.044
	Maximum	235.630	263.223	319.490	252.343	245.235
	Average	**227.216**	227.768	228.893	227.550	227.408

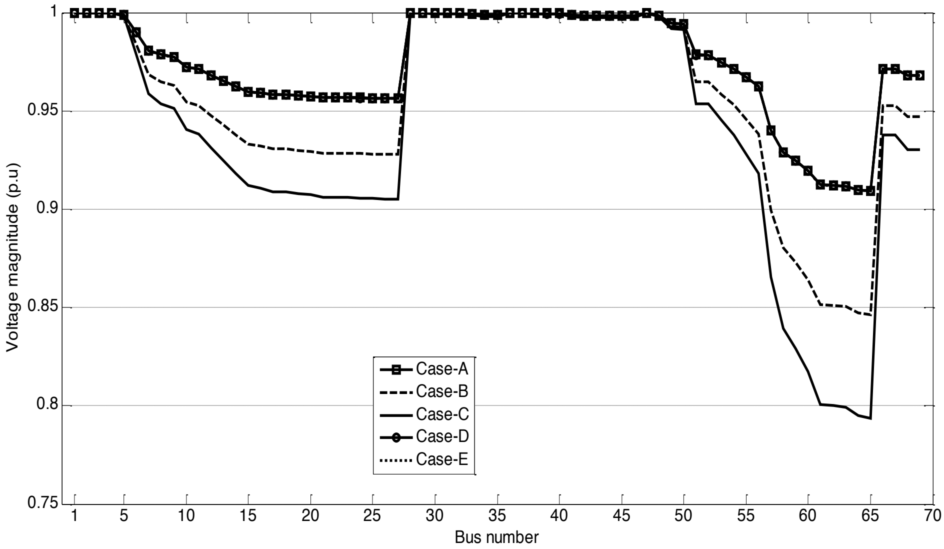

Fig. 4. Voltage profile for different cases in 69-bus system

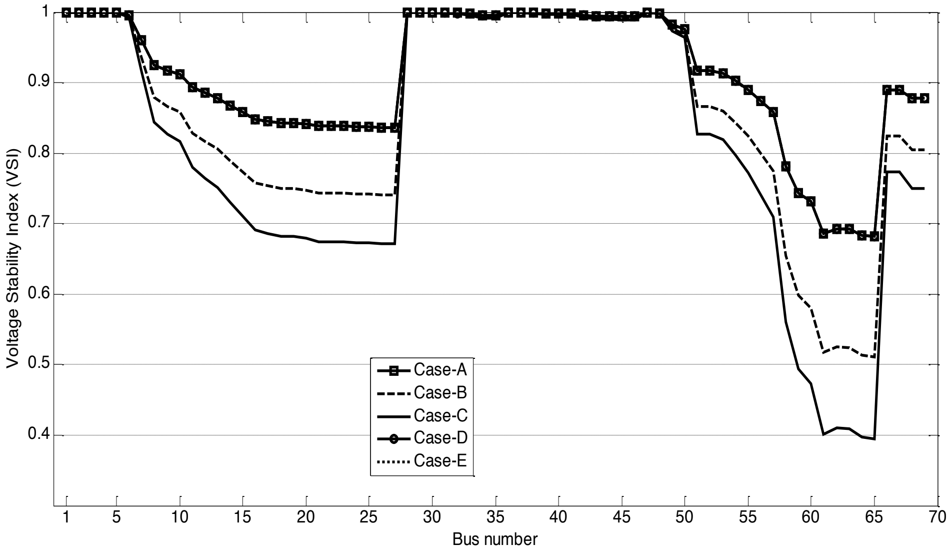

Fig. 5. Voltage stability index (VSI) for different cases in 69-bus system

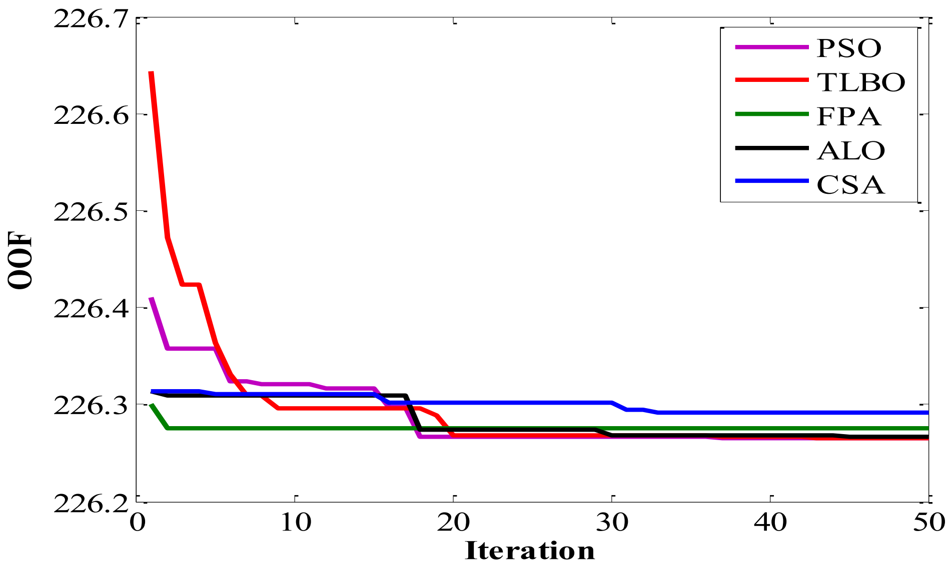

Fig. 6. The convergence characteristics of different algorithms for Case-E in 69-bus system

5. Conclusions

In this paper, a novel approach for allocating the EV-CSs with multiple features in EDS. In addition to the AC/DC Level-2 EV-CSs suitable for both BEVs and PHEVs, different EV models (Chevrolet VOLT, CHANG AN YIDONG, Tesla Model X and BMW i3) are taken into account while designing the CS with multiple CPs. The multi-objective function is formulated for achieving the minimum real power losses, improved voltage profile and enhanced voltage stability. The OF is optimized using TLBO, ALO, FPA, CSA and PSO algorithms. The simulation results presented on standard IEEE 33-bus and 69-bus test systems have highlighted the technical benefits which can achievable through the optimal allocation of EV-CSs even with increased EV loading conditions. Notably, the impact of EV-CSs at optimal location is not negligible in 33-bus system with 40.12% increased losses when EV-CSs are designed for minimum CPs and 85.89% increased losses maximum CPs when compared with standard test operating conditions, where as in 69-bus system, it is almost negligible. On the other side, the proposed TLBO optimization algorithm has proven its ability in solving the multi-objective non-linear complex problem by providing the global objective value consistently than ALO, FPA, CSA and PSO. In addition to the optimal allocation of EV-CS based on distribution system performance, optimal/smart charging feature of EVs can also system performance significantly [37], and considered as future scope of this research.

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