SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

MSAPSO-based Optimal Placement of EV Charging Stations and Capacitors in IEEE-34 Distribution System

Sandip S. Yeole[1*], Dr. Prakash G. Burade[2]

[1] Electrical and Electronics Engineering, School of Engineering and Technology, Sandip University, Nashik, India.
E-mail: sandipyeole91@gmail.com
[2] Electrical and Electronics Engineering, School of Engineering and Technology, Sandip University, Nashik, India.
E-mail: prakash.burade@sandipuniversity.edu.in
*Corresponding Author: Sandip S. Yeole, sandipyeole91@gmail.com

Abstract
The quick growth in the use of electric vehicles (EVs) has increased the need for public charging facilities as well as the operation complexities associated with electricity distribution systems. Poorly located public charging stations (PCSs) will add up feeder loading, active power loss, voltage fluctuation, and cost of investment. In this paper, a new two level process referred to as Public Charging Station Owner Index-Multi-Stage Adaptive Particle Swarm Optimization (PCSOI-MSAPSO) is developed for the optimal placement of public charging stations for electric vehicles and shunt capacitors. In the first step of the new model, the newly introduced Public Charging Station Owner Index (PCSOI) which considers both Land Value Index (LVI) and Electric Vehicle Population Index (EVPI) to come up with economically viable locations will reduce the optimization problem scope. The second step involves the new MSAPSO approach that finds out the best amongst the various charging stations and capacitors simultaneously to minimize active power loss under distribution system operating conditions. Unlike PSO, The proposed algorithm makes use of adaptive inertia weight, elite learning, adaptive exploration and exploitation, mutation and diversity maintenance to enhance convergence while preventing premature convergence. The proposed methodology is tested on the updated IEEE 34 bus radial distribution network with the use of Backward Forward Sweep (BFS) power flow calculation algorithm. The results of the simulations founded that that the proposed algorithm lowers the active power losses from 40.145 kW to 37.575 kW (approximately 6.40%), lowers the reactive power losses, enhances the minimum bus voltage and ensures stable convergence by achieving a best fitness of 0.43148. The proposed PCSOI-MSAPSO framework is a reliable and useful decision-making tool for EV charging infrastructure design and can be extended to larger smart distribution grids with renewable energy sources and V2G applications.

Keywords: Electric vehicles, Public charging stations, Multistage Adaptive particle Swarm Optimization (MSAPSO), Capacitor, Public charging station owner Index (PCSOI), Distribution system, Active power loss, IEEE 34-bus system.

1. Introduction

One such approach to reduce the GHG emissions, decrease the dependence on fossil fuels, and promote sustainable mobility is the quick adoption of electric vehicles (EVs). In order to do that, governments and automobile manufacturers use economic and regulatory measures as well as build infrastructure to support the deployment of electric vehicles [1], [2]. With an increasing number of EVs, it is important to provide convenient access to public charging stations (PCSs) which will be needed in the future [1], [2].

An increase in the penetration level of EVs creates new problems in terms of operation of the electrical distribution network. An increased load on feeders, transformers, voltage deviation, losses of energy, and peak load may be experienced due to high charging demands without proper planning of PCS installation [3]. Nevertheless, with coordinated charging and vehicle-to-grid technology, the flexibility of the network may increase; however, it highly depends on the geographic placement of charging infrastructure [4-6].

Charging station planning can be defined as a sophisticated process comprising of both engineering and economical aspects. Distribution system operators would like to achieve the lowest losses, better voltage profile, and efficient network operation, but EV charging station planners are interested in finding locations with minimal cost of land acquisition and high charging needs [7-8]. Hence, the real-world planning approaches should consider both aspects.

The various optimization platforms including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Differential Evolution (DE), etc can be applicable for planning of EV charging stations. Among these optimization algorithms, the PSO approach has received much popularity due to its easy implementation and fast convergence. However, traditional PSO is usually characterized by premature convergence, lack of swarm diversity, and stagnation at local optimal solutions.

In order to overcome these deficiencies, this paper suggests a two-step method called Public Charging Station Owner Index-Multistage Adaptive Particle Swarm Optimization (PCSOI-MSAPSO) algorithm for the joint planning of public EV charging station and shunt capacitor installations in radial distribution networks. In particular, the PCSOI index, which is based on the LVI and EVPI indices, finds economical locations in the first step and narrows down the search space. In the second step, the MSAPSO algorithm, on the other hand, optimizes the locations of the charging stations and shunt capacitors so that the active power loss is minimized without violating any of the operational constraints. The investigation on the proposed framework is tested on IEEE 34-bus test system.

2. Literature Survey

The development of optimal plans for the installation of charging stations for electric vehicles (EVCSs) has attracted considerable interest among researchers due to the increasing use of electric mobility. The rise in the number of EVs leads to improved loading of feeders, voltage deviations, power losses, loading of transformers, and peak load.

At first, there was an emphasis on the performance enhancement of distribution networks by the optimal placement of charging stations. Sensitivity techniques were used for identifying the most appropriate buses on the basis of voltage sensitivity factors and power flows [9]. In the further studies, the location of charging stations was considered as a power loss minimization problem by applying population-based evolutionary algorithms [10]. The multi-objective models were proposed to decrease active power losses, improve voltage profiles, minimize operational cost of distribution network, and consider coordination between charging stations and DG [11]. Genetic Algorithm (GA) based methods were also developed for locating the charging stations [12].

Moreover, the issue of economic factors has been included into the planning of charging infrastructure taking into account the issues of cost of installation, cost of operation, use of space, cost of grid connection, and demand response plans [13]. Additionally, the issue of charging infrastructure planning has been linked to the issue of distributed energy resources by implementing optimization technique such as Ant Colony Optimization (ACO) [14] for minimizing the cost of operation. The other transportation related issues like traffic density, accessibility of road, movement behavior, and charging demand have been taken into account for improving the accessibility of charging facilities [15].

The more recent works have used multi-objective optimization framework where both the issues of technical and economics have been considered such as loss minimization, infrastructure cost, waiting time, accessibility, and reliability [16-17]. Adapted Particle Swarm Optimization (APSO) has proven better convergence with dynamic parameter update and voltage regulation [18], on the other hand photovoltaic assisted charging infrastructure has been studied [19]. Mixed integer programming has been applied for maximizing the serviceability of charging facility in the network [20]

However, recent studies have given increasing attention to integrated planning of charging stations, distributed generation, capacitor locations, and V2G to achieve voltage regulation, network loss reduction, and flexibility [21]. Additionally, efficient use of modern metaheuristics such as the Grasshopper Optimization Algorithm (GOA), Grey Wolf Optimizer (GWO), and many others has been demonstrated for the simultaneous optimal allocation of DG units, shunt capacitors, and EV charging stations [22-25]. Despite the superiority of these methods alongwith traditional optimization methods, the performance of these methods still relies on parameter settings, diversity of the search, and balancing exploration-exploitation capabilities.

3. Research gap

The literature indicates that considerable research has been conducted on the present study using various optimization techniques such as GA, PSO, APSO, GWO, ACO, GOA, and hybrid metaheuristic algorithms. Existing studies mainly focus on minimizing power losses, improving voltage profiles, reducing installation costs, enhancing charging accessibility, or integrating renewable energy and vehicle-to-grid (V2G) technologies.

However, several research gaps remain. First, most studies optimize charging station locations based primarily on electrical network performance, while limited attention has been given to investor-oriented factors such as land acquisition cost and local EV population density, both of which strongly influence the economic viability and utilization of public charging stations. Second, many optimization approaches search the entire distribution network without first identifying economically feasible candidate locations, thereby increasing the search space and computational burden. Third, conventional PSO and several of its variants still suffering the premature convergences and reduced swarm diversities when solving complex, nonlinear optimization problems. Finally, the coordinated optimization of public EV charging stations together with shunt capacitor placement has received comparatively limited attention despite its potential to reduce feeder losses and improve voltage regulation.

To overcome these limits, this work proposes a two-stage planning framework. The first stage employs a Public Charging Station Owner Index (PCSOI), developed from the Land Value Index (LVI) and Electric Vehicle Population Index (EVPI), to identify economically attractive candidate buses and reduce the optimization search space. The second stage applies the proposed Multi-Stage Adaptive Particle Swarm Optimization (MSAPSO) algorithm to simultaneously determine the optimal locations of public EV charging stations and shunt capacitors. By integrating economic site screening with adaptive swarm intelligence, the proposed framework improves convergence characteristics while enhancing both electrical and economic performance.

4. Contributions

- The work contribution to the proposed methodology as follows:
- Firstly, a planning procedure of two stages has been developed to solve the problem of optimal allocation of public EV charging stations and shunt capacitors. In this procedure, the economically viable candidate buses are determined using the Public Charging Station Owner Index (PCSOI), followed by technical optimization using the proposed MSAPSO technique.
- Secondly, a new PCSOI model has been introduced using the concepts of LVI and EVPI. The developed PCSOI model emphasizes the choice of sites taking into account the economic aspect of land acquisition cost and charging demand.
- MSAPSO Algorithm is introduced for the enhancement of traditional PSO approach through the use of adaptive inertia weighting, adaptive learning parameters, elitist learning, adaptive mutation, opposition based learning, velocity constriction, and random exploration.
- Concurrent optimal allocation of charging station and capacitor is carried out in order to minimize the active power losses in the distribution system while ensuring enhanced voltage regulation and reactive power compensation.
- The introduced technique has been applied to the IEEE 34 bus distribution system which shows enhanced results as compared to the traditional PSO algorithm through minimized active power losses, enhanced voltage regulation and fitness values along with rapid convergence rate.

5. Problem Formulation

The suggested planing approach considers the economical and technological factors in order to find the optimum places for installing public charging stations (PCSs) and shunt capacitors within the radial distribution network. The planning procedure is divided into two steps.

At the first step, an index called Public Charging Station Owner Index (PCSOI) is created in order to select candidate buses based on both Land Value Index (LVI) and Electric Vehicle Population Index (EVPI). LVI denotes the relative amount of investment needed to buy the lands while EVPI stands for the predicted charging demands. As a result, candidate buses with relatively lower cost of lands and relatively higher number of EVs are selected.

The buses selected through this process will then be fed into the proposed Multi-stage Adaptive Particle Swarm Optimization (MSAPSO) where optimization for both placement of EV charging stations and shunt capacitors takes place concurrently. The optimization process aims to minimize the total active power losses while meeting all the constraints set.

The proposed methodology is applied to the modified IEEE 34 bus distribution system illustrated in figure 1 below. The overall optimization process can be seen from figure 2 below. The mathematical model of the objective function and constraints is discussed in the following sub-sections.

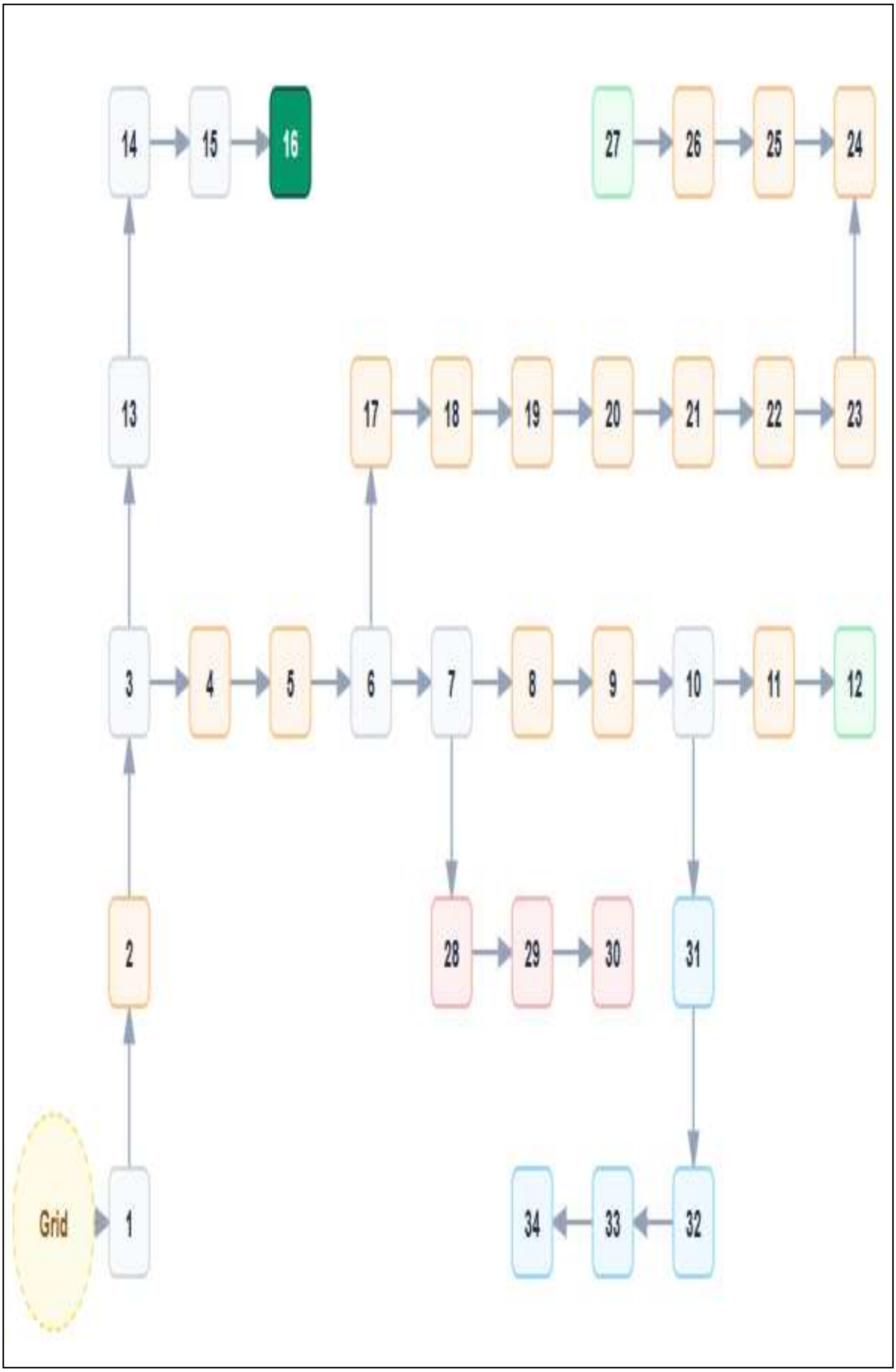

Figure 1: Radial IEEE-34 bus distribution system

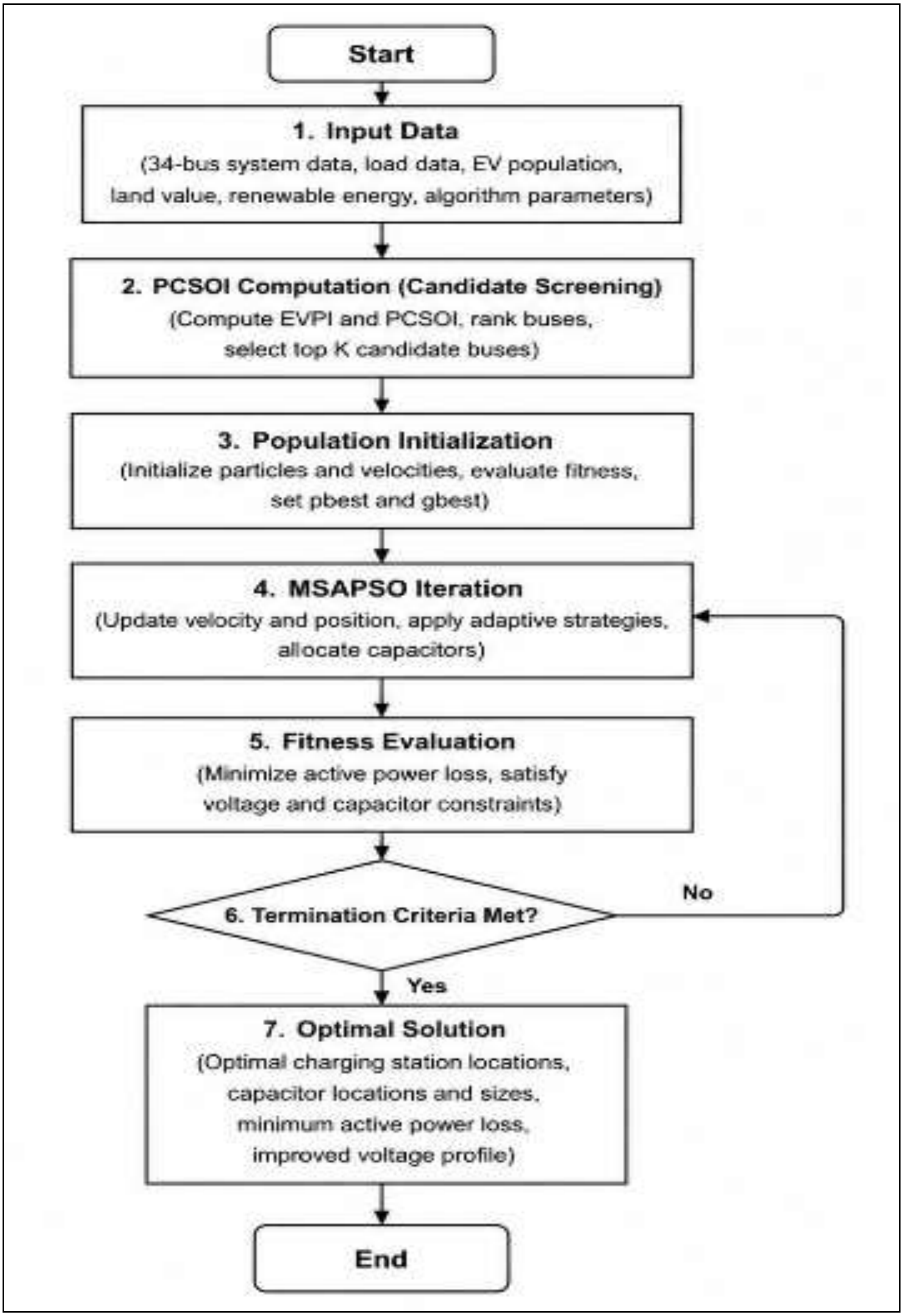

Figure 2: Flowchart showing the MSA-Particle Swarm Optimization algorithm.

5.1 Total Public Charging Stations (PCSs)

Estimation of the total number of public EV charging stations needed to meet the demand is the first phase of planning process. In this estimation, practical considerations such as the population of EVs, charging time, time station operates, charger capacity,charging efficiency, and load factor are considered. The required number of charging stations will evaluated by [23]:

$$N_{PCS} = \left\lceil \frac{pr * N_{EV} * Ch_t}{st * q * C_{PCS} * lf} \right\rceil \quad (1)$$

where Ppr represents the needed power, NEV represents the amount of electric vehicles, st represents the duration of daily operation of PCS in 24 hours, CPCS represents the capacity, q represents the efficiency, lf represents the load factor of charging, and Cht represents the average charging time.
The approximate cost NPCS identifies the number of charging stations to be assigned through the proposed PCSOI-MSAPSO framework.

5.2 Public Charging Station Owner Index (PCSOI)

A critical factor that will determine the economic success of a public charging station is its installation cost and projected usage. As such, a pre-optimization process of evaluating potential candidates is conducted prior to using the PCSOI.
The PCSOI combines two investor-oriented indicators:

- Land Value Index (LVI), representing the relative land acquisition cost.
- Electric Vehicle Population Index (EVPI), representing the potential charging demand.

Places having low land costs and high number of EVs receive more preference since they require less investment and provide more utilization.
Contrary to the location problem of charging stations where all the buses are considered simultaneously, the proposed PCSOI approach first identifies the economic buses, hence reducing the number of buses that would be optimized.
The identified economic buses serve as inputs for the MSAPSO optimization technique to determine the optimal locations of EV charging stations and shunt capacitors to minimize losses in the power distribution system subject to some constraints.
Mathematical formulation of LVI, EVPI and PCSOI approaches are presented in the subsequent sub-sections.

5.3 Land Value Index (LVI)

One of the significant economic aspects that impact the feasibility of public electric vehicle (EV) charging station projects is land acquisition cost. Land values differ greatly depending on whether the land is located in urban or semi-urban areas.
In this study, every bus of the modified IEEE 34-bus distribution system is initially considered as a potential charging station location. The adopted network together with the corresponding electrical, EV population and land-value data are shown in fig. 1 and table 1, respectively.
To enable comparison among candidate locations, the land value at each bus is normalized using the Land Value Index (LVI),

$$\mathbf{LVI_i^{BS}} = \frac{\mathbf{LV_i^{BS}}}{\mathbf{max\{LV_i^{BS}\}}} \qquad \textbf{(2)}$$

where, LV_i is the land value at i^{th} node, BS is the total bus in the system.

Table 1: The line, load and EV data for IEEE-34 system [25-26]

Node No.	Load (kW)	Load (kVAR)	EVs Population	From node	To node	R (ohm)	X (ohm)
1	0	0	0	1	2	0.117	0.048
2	230	142.5	10	2	3	0.1072	0.044
3	0	0	90	3	4	0.1644	0.0456
4	230	142.5	20	4	5	0.1495	0.0415
5	230	142.5	30	5	6	0.1495	0.0415
6	0	0	40	6	7	0.3144	0.054
7	0	0	40	7	8	0.2096	0.036
8	230	142.5	40	8	9	0.3144	0.054
9	230	142.5	50	9	10	0.2096	0.036
10	0	0	50	10	11	0.131	0.0225
11	230	142.5	50	11	12	0.1048	0.018
12	137	84	60	3	13	0.1572	0.027
13	72	45	60	13	14	0.2096	0.036
14	72	45	90	14	15	0.1048	0.018
15	72	45	90	15	16	0.0524	0.009
16	13.5	7.5	130	6	17	0.1794	0.0498
17	230	142.5	170	17	18	0.1644	0.0456
18	230	142.5	150	18	19	0.2079	0.0473
19	230	142.5	180	19	20	0.189	0.043
20	230	142.5	30	20	21	0.189	0.043
21	230	142.5	20	21	22	0.262	0.045
22	230	142.5	20	22	23	0.262	0.045
23	230	142.5	10	23	24	0.3144	0.054

24	230	142.5	10	24	25	0.2096	0.036
25	230	142.5	10	25	26	0.131	0.0225
26	230	142.5	10	26	27	0.1048	0.018
27	137	85	20	7	28	0.1572	0.027
28	75	48	30	28	29	0.1572	0.027
29	75	48	30	29	30	0.1572	0.027
30	75	48	20	10	31	0.1572	0.027
31	57	34.5	20	31	32	0.2096	0.036
32	57	34.5	20	32	33	0.1572	0.027
33	57	34.5	10	33	34	0.1048	0.018
34	57	34.5	10	34	1	0.117	0.048

Lower LVI values indicate lower land acquisition costs and therefore more attractive locations from an investor's perspective. The LVI constitutes the first component of the proposed Public Charging Station Owner Index (PCSOI).

5.4 Electric Vehicle Population Index (EVPI)

The use and profitability of the public charging facility would be determined to a large extent by the density of electric vehicles in the area. The places having more electric vehicles would experience more demand for charging services and economic profitability.

Thus, Electric Vehicle Population Index (EVPI) would be described as the normalization of the electric vehicle population at each bus as

$$\mathbf{EVPI_i^{BS}} = \frac{\mathbf{EVP_i^{BS}}}{\mathbf{max\{EVP_i^{BS}\}}} \qquad \mathbf{(3)}$$

where, EVP_i is the EV population at ith bus.

A higher EVPI value indicates a greater EV charging demand. The EVPI is subsequently combined with the LVI to formulate the proposed Public Charging Station Owner Index (PCSOI).

To identify economically feasible charging station locations, the normalized LVI and EVPI are combined to form the Public Charging Station Owner Index (PCSOI),

$$\mathbf{PCSOI_i^{BS}} = \mathbf{w_1} \times \mathbf{LVI_i^{BS}} - \mathbf{w_2} \times \mathbf{EVPI_i^{BS}} \qquad \mathbf{(4)}$$

where, w_1 and w_2 are parameters written to adjust the priority in decision among the EV flow and land value. The PCSOI performs a preliminary screening of all buses and significantly reduces the optimization search space by retaining only economically attractive candidate locations. Buses with higher PCSOI values correspond to lower land costs and higher charging demand, making them more suitable for public charging station installation. The computed LVI, EVPI and PCSOI values together with the corresponding rankings are presented in table 2, from which the candidate buses are selected for the subsequent MSAPSO optimization stage.

Table 2: LVI of 34 bus system and bus order based on PCSOI for IEEE-34 Bus system

C-1				C-2				C-3			
Bus No.	LVI	Bus Order	PCSOI	Bus No.	LVI	Bus Order	PCSOI	Bus No.	LVI	Bus Order	PCSOI
1	Inf	19	-0.933	1	Inf	17	-0.700	1	Inf	18	-0.516
2	0.833	17	-0.700	2	0.050	18	-0.516	2	0.500	15	-0.450
3	Inf	18	-0.516	3	Inf	19	-0.333	3	0.666	19	-0.333
4	0.050	13	-0.233	4	0.500	9	-0.183	4	Inf	17	-0.250
5	0.666	10	-0.200	5	0.033	5	-0.116	5	Inf	28	-0.116
6	0.166	28	-0.116	6	0.333	31	-0.050	6	0.333	21	-0.050
7	0.833	30	-0.083	7	0.833	2	0	7	0.833	32	-0.050
8	0.666	4	-0.050	8	0.666	6	0.183	8	0.666	25	0.016
9	0.333	32	-0.050	9	0.066	28	0.183	9	0.666	3	0.166
10	0.050	6	0.016	10	0.500	29	0.233	10	0.500	6	0.183
11	Inf	24	0.033	11	Inf	30	0.233	11	Inf	29	0.233
12	0.666	9	0.083	12	0.666	10	0.250	12	0.666	30	0.233
13	0.066	29	0.233	13	0.666	34	0.283	13	0.666	10	0.250
14	1	31	0.233	14	1	15	0.333	14	1	34	0.283
15	0.833	34	0.283	15	0.833	20	0.350	15	0.050	20	0.350
16	Inf	15	0.333	16	Inf	13	0.366	16	Inf	13	0.366

17	0.050	20	0.350	17	0.050	4	0.400	17	0.500	31	0.400
18	0.333	12	0.416	18	0.333	32	0.400	18	0.333	9	0.416
19	0.066	8	0.466	19	0.666	12	0.416	19	0.666	12	0.416
20	0.500	5	0.516	20	0.500	8	0.466	20	0.500	2	0.450
21	0.666	21	0.566	21	0.666	21	0.566	21	0.050	8	0.466
22	Inf	14	0.600	22	Inf	14	0.600	22	Inf	14	0.600
23	0.833	26	0.616	23	0.833	26	0.616	23	0.833	26	0.616
24	0.083	33	0.616	24	0.833	33	0.616	24	0.833	33	0.616
25	1	7	0.633	25	1	7	0.633	25	0.066	7	0.633
26	0.666	27	0.683	26	0.666	27	0.683	26	0.666	27	0.683
27	0.833	2	0.783	27	0.833	23	0.783	27	0.833	23	0.783
28	0.033	23	0.783	28	0.333	24	0.783	28	0.033	24	0.783
29	0.333	25	0.950	29	0.333	25	0.950	29	0.333	1	Inf
30	0.016	1	Inf	30	0.333	1	Inf	30	0.333	4	Inf
31	0.333	3	Inf	31	0.050	3	Inf	31	0.500	5	Inf
32	0.050	11	Inf	32	0.500	11	Inf	32	0.050	11	Inf
33	0.666	16	Inf	33	0.666	16	Inf	33	0.666	16	Inf
34	0.333	22	Inf	34	0.333	22	Inf	34	0.333	22	Inf

*5.5*Objective Function

After identifying the candidate buses using the PCSOI, the proposed MSAPSO algorithm determines the optimal locations of public EV charging stations and shunt capacitors by minimizing the total active power loss of the distribution network while satisfying all operating constraints.

The optimization objective is

$$\mathbf{f = min\left(\sum_{j=1}^{N} P_{loss,j}\right)} \qquad \mathbf{(5)}$$

where, $P_{loss,j}$ is electrical loss in j^{th} line for IEEE-34 network.

The optimization is performed subject to the following constraints:

- Bus voltage

$$\mathbf{V^{min} < V_i < V^{max}} \qquad i=1,2.....N_B \qquad \mathbf{(6)}$$

where V^{min} and V^{max} are the lower and upper node voltage, V_i is the i^{th} node voltage, N_B is the total number of buses in the network.

- Branch current

$$\mathbf{I^{min} < I_j < I^{max}} \qquad j = 1,2....N \qquad \mathbf{(7)}$$

where I^{min} and I^{max} are the lower and upper line current, I_j is the line current. N is the total number of distribution lines.

- Reactive power

$$\mathbf{Q^{lower} < Q_i < Q^{upper}} \qquad i = 1,2...N_B \qquad \mathbf{(8)}$$

where Q^{lower} and Q^{upper} are the lower and upper node reactive power.

- Charging station allocation

$$\mathbf{PCS_i \in \Omega_{PCS}}, \qquad PCS_i \neq PCS_j, \qquad i \neq j \qquad \mathbf{(9)}$$

where Ω_{PCS} denotes the candidate bus set obtained from PCSOI, and PCS_i represents the location of the i^{th} charging station.

- Capacitor allocation

$$\mathbf{CAP_i \in \Omega_{CAP}}, \qquad CAP_i \neq CAP_j, \qquad i \neq j \qquad \mathbf{(10)}$$

where Ω_{CAP} denotes the capacitor candidate bus set, and CAP_i represents the location of the i^{th} capacitor bank. The feeder topology is maintained as radial throughout the optimization process.

*5.6*Distributed renewable energy source (DRES) configuration

To provide realistic operating conditions, three distributed renewable energy sources (DRESs) are incorporated into the modified IEEE 34-bus distribution system. Their locations and capacities are adopted from the modified IEEE 34-bus benchmark reported in the literature and remain fixed throughout the optimization process.

Since the primary objective of this work is the simultaneous optimal placement of public EV charging stations and shunt capacitors, the DRES units are not treated as optimization variables. Instead, they provide renewable generation support during the optimization. The adopted DRES locations and capacities are listed in table 3.

Table 3: Location of DRESs with capacity

Types of source	Node number	Capacity of DRES (kW)
DRES1	21	450
DRES2	6	265
DRES3	12	265

6. Solution Technique by Proposed MSAPSO (Multistage Adaptive Particle Swarm Optimization) Algorithm

6.1 MSAPSO Overview

Particle Swarm Optimization (PSO), developed by Kennedy and Eberhart in 1995, is one of the most extensively used swarm intelligence algorithms for solving nonlinear optimization problems due to its easy application, fast convergence, and less control parameters [24]. Particle Swarm Optimization has been effectively implemented for optimal power flow, capacitors allocation, distributed generation, renewable energy resources, and EV charging stations planning within the electrical power systems due to the capacity to solve efficiently non-convex optimization problems [25-32].

In the classical PSO algorithm, each particle illustrates a potential solution which adjusts its position through learning based on the experience of the particle itself (Personal Best, Pbest values) and the best solution discovered by the swarm (Global Best, Gbest values). While classical PSO algorithm performs satisfactorily in many engineering problems, the performance of classical PSO in highly nonlinear and multimodal optimization problems decreases due to the problems of premature convergence, loss of swarm diversity, and falling into local optima. The above drawbacks appear even more in the charging stations planning problems as the problem's domain is discrete and highly complex.

However, a number of better performing versions like Adaptive Particle Swarm Optimization (APSO), Modified Particle Swarm Optimization (MPSO), Chaotic Particle Swarm Optimization (CPSO), and Particle Swarm Optimization with hybrid algorithms have also been developed to improve convergence by adaptive inertia weight and learning rate. However, most methods still depend upon the relationship between Pbest and Gbest,

which may reduce population diversity during the later optimization stages and limit the probability of locating the global optimum.

The paper presents an MSAPSO technique to solve the joint problem of placing public EV charging stations along with the placement of shunt capacitors in radial power distribution systems. In the new approach, each particle represents the feasible combination of charging station and capacitor placement among the candidates selected using the proposed PCSOI. The search space is greatly reduced because only the economically viable buses are chosen for placing the charging stations..

Unlike conventional PSO, the proposed MSAPSO incorporates multiple adaptive search mechanisms that improve both exploration and exploitation throughout the optimization process. The principal enhancements include:

- adaptive inertia weight,
- adaptive learning coefficients,
- elite learning strategy,
- constriction-factor-based velocity regulation,
- adaptive random exploration,
- adaptive mutation,
- local neighborhood refinement, and
- early convergence detection.

A comparison between commonly used optimization algorithms is presented in table 4, while the principal differences between the proposed MSAPSO and existing PSO variants are summarized in table 5.

Table 4: General Comparison of optimization algorithms

Feature	PSOs	GPA	ACO
Number of control parameters	Minor	Intermediate	Significant
Complexity of Computational	Minor	Intermediate	Intermediate–High
Speed of Convergence	Fast	Moderate	Moderate

Feature	PSOs	GPA	ACO
Memory requirement	Minor	Intermediate	Significant
Suitability for continuous optimization	Excellent	Good	Good
Ease of implementation	Excellent	Moderate	Moderate

Table 5: Comparison of existing PSOs and proposed PSO algorithm

Feature	Conventional PSOs	Adaptive PSOs	**Proposed PSO (MSAPSO)**
Adaptive inertia	✓	✓	✓
Adaptive learning coefficients	✗	✓	✓
Elite learning	✗	✗	✓
Random exploration	✗	✗	✓
Adaptive mutation	✗	Partial	✓
Early convergence detection	✗	✗	✓

To enhance convergence performance, the proposed algorithm introduces an additional Elite Best (Ebest) learning component together with adaptive random exploration into the velocity updating process. Consequently, the particle velocity is updated as

$$\mathbf{v_i^{t+1} = K[wv_i^t + c_1r_1(Pbest_i - x_i^t) + c_2r_2(Gbest - x_i^t) + c_3r_3(Ebest - x_i^t) + c_4R_i]} \qquad \textbf{(11)}$$

where

- v_i^{t+1} denotes the updated velocity of the ith particle
- v_i^t denotes the current velocity,
- w denotes the weight of inertia
- c1, c2, c2, c3, c3, and c4 denote the cognitive and social acceleration coefficients
- r1, r2, and r3 denote uniformly distributed random numbers within the interval [0,1]
- $Pbest_i$ represents the personal best position of the particle,
- Gbest represents the best global solution identified by the swarm,
- Ebest denotes the Elite best solution or particle obtained by the swarm,
- x_i^t is the current particle position
- K represents the constriction factor and
- R_i denotes the adaptive random exploration vector

Compared with conventional PSO, the additional Elite Best and adaptive exploration terms enable the swarm to preserve diversity during the early optimization stages while improving local refinement near convergence. As a result, the probability of premature convergence is significantly reduced.
The particle position is subsequently updated using

$$\mathbf{x_i^{t+1} = x_i^t + v_i^{t+1}} \qquad \textbf{(12)}$$

where

- x_i^{t+1} represents the revised position of the i^{th} search entity,
- x_i^t denotes the current search entity position,
- v_i^{t+1} is the revised particle speed obtained from eq. (11).

Following each position update, the candidate charging station and capacitor locations are evaluated using the objective function developed in chapter 5 through backward-forward sweep load-flow analysis. The obtained fitness value is then used to update the Pbest, Gbest, and Ebest solutions until the stopping condition is fulfilled.

6.2 Generation of Population

The optimization is commenced through the initialization of a swarm with feasible solutions for allocation of the charging stations. In contrast to the standard PSO in which the initialization takes place in the whole solution space with random positioning of the particles, MSAPSO initializes particles from the set of selected

buses using PCSOI. This preliminary screening considerably reduces the search space while preserving economically attractive locations.
Each particle consists of a position vector representing the selected charging station locations and a corresponding velocity vector governing particle movement during optimization. Assuming that N_{PCS} charging stations are to be installed, the particle position is expressed as

$$X_i = [x_{i1}, x_{i2}, \ldots, x_{iNPCS}] \tag{13}$$

where

- X_i denotes the position vector of the i_{th} particle,
- x_{ij} represents the selected candidate bus for the j_{th} charging station, and
- N_{PCS} is the total number of public charging stations to be allocated.

Similarly, the corresponding velocity vector is given by

$$Vi = [v_{i1}, v_{i2}, \ldots, v_{iNPCS}] \tag{14}$$

where

- V_i denotes the velocity vector of the i_{th} particle, and
- v_{ij} represents the search velocity associated with the j_{th} charging station location.

After initialization, every particle is evaluated using the objective function developed in chapter 5 through the Backward–Forward Sweep (BFS) load-flow analysis. The resulting fitness values are used to update the personal best (Pbest) and global best (Gbest) solutions. In addition, the proposed MSAPSO forms an elite particle set by selecting the highest-performing particles during initialization. The mean position of these elite particles is stored as the Elite Best (Ebest) and is subsequently incorporated into the velocity update equation to enhance swarm cooperation and reduce premature convergence.
The overall optimization procedure employed in the proposed PCSOI-MSAPSO framework is summarized in figure 2, where the initialized swarm is subsequently processed through adaptive exploration, elite learning, adaptive exploitation, and convergence refinement until the optimal charging station configuration is obtained.
The overall implementation procedure of the proposed MSAPSO is summarized in figure 2. Initially, candidate buses are selected using the proposed PCSOI, after which the swarm is randomly initialized without duplicate charging station locations. The fitness of each particle is estimated using the Backward-Forward Sweep load-flow algorithm to determine the initial Pbest, Gbest, and Ebest solutions. The initialized swarm then proceeds through the adaptive exploration, elite learning, and adaptive exploitation stages until the stopping criterion is satisfied and the optimal charging station and capacitor allocation is obtained.

6.3 Adaptive exploration

Adaptive exploration phase allows the swarm to efficiently explore the search space in the initial stages of the optimization process without converging prematurely. While the traditional PSO algorithm uses fixed values for the control parameters, the proposed MSAPSO algorithm modifies the inertia weight dynamically to find the balance between exploration and exploitation.
The inertia weight is changed based on

$$w(t) = w_{max} - (t/T)*(w_{max} - w_{min}) \tag{15}$$

where
•w represents the inertia weight,
•wmax represents the initial inertia weight,
•wmin represents the final inertia weight,
•t is the present iteration,
•T is the maximum iteration number.
The value of inertia weight will increase the range of area in which the particles will look for solutions at the early stage of search, while lower values of inertia weight help the particles search the nearby solutions at the later stage. The quality of particle will be calculated using the objective function, described in equation (5):

$$\text{Fitness} = f(x) \tag{16}$$

where f(x) = Objective function of active power loss minimization given in eq. (5)

In such way, the diversification of swarms can be ensured at an early stage of search process.

6.4 E-learning strategy for Elite Learning

In conventional PSO, updating the swarm occurs through the global best only. This leads to premature convergence in case the global best gets stuck into a local optimum. To enhance the reliability of convergence, MSAPSO incorporates an Elite Learning Strategy where several high quality particles are employed to lead the swarm. The number of elite particles is calculated as follows:

$$Ne = \max(2, \alpha N) \tag{17}$$

where

•Ne is the number of elite particles,

•N is the population size of the swarm, and

•α is the elite ratio.

The elite-best solution is given by the average position of elite particles,

$$Ebest = 1/Ne \sum x_{elite,i} \quad i = 1 \ldots Ne \tag{18}$$

where

- Ebest represents the Elite Best position,
- $x_{elite,i}$ denotes the position vector of the i^{th} elite particle.

In contrast to the traditional global best approach, the new elitist learning algorithm leverages the accumulated wisdom of multiple high-performance particles, thus enhancing search reliability, maintaining diversity, and lowering the risk of premature convergence. The elite-best solution is incorporated into the velocity update equation 11, enabling every particle to learn simultaneously from its personal best, the global best, and the elite-best solutions.

6.5 Adaptive Exploitation

After promising regions have been identified through adaptive exploration and elite learning, the proposed MSAPSO gradually shifts toward local exploitation to improve solution accuracy.
The adaptive cognitive and social learning coefficients are updated as

$$c1 = c1,max - (c1,max - c1,min)t/T \tag{19}$$

$$c2 = c2,max + (c2,max - c2,min)t/T \tag{20}$$

where

- c1 denotes the adaptive cognitive learning coefficient,
- c2 denotes the adaptive social learning coefficient,
- c1,max and c1,min are the maximum and minimum cognitive coefficients,
- c2,max and c2,min are the maximum and minimum social coefficients,
- t represents the current iteration,
- T denotes the maximum number of iterations.

To improve convergence stability, a constriction factor is introduced,

$$K = 2/\{2 - \phi - \mathrm{sqrt}(\phi^2 - 4\phi)\} \tag{21}$$

where

ϕ=c1+c2+c3 and c3 represents the elite learning coefficient introduced in the proposed MSAPSO algorithm.

The updated particle velocity therefore becomes

$$v_i^{t+1} = K[wv_i^t + c_1r_1(Pbest_i - x_i^t) + c_2r_2(Gbest - x_i^t) + c_3r_3(Ebest - x_i^t) + c_4R] \tag{22}$$

where R denotes the adaptive random exploration component and c_4 is the adaptive random exploration coefficient.

To further enhance local refinement, the particle velocity is slightly reduced during the final optimization stage,

$$v_i^{t+1}=0.8*v_i^{t+1} \tag{23}$$

This adaptive exploitation strategy accelerates convergence while maintaining solution stability and preventing oscillatory particle movement near the optimum.

6.6Computational complexity

The computational complexity of the proposed method PCSOI-MSAPSO framework depends on the particular swarm size, the number of optimization iterations, and the computational effort required for the Backward-Forward Sweep (BFS) load-flow analysis. The total computational complexity for the case of N particles and up to T iterations will be given by

$$O(N\times T\times LF) \tag{24}$$

where LF is the computational complexity cost for one bfs load flow calculation.

As compared with the traditional PSO approach, the present approach involves PCSOI to eliminate uneconomic buses prior to optimization. This step greatly decreases the search space which results in less computational burden and faster convergence of the algorithm. In addition, being a particle-based algorithm, MSAPSO allows independent fitness computation of the algorithm which can be implemented in parallel fashion in multicore computers.

Table 6 and Table 7 illustrate the distribution system and MSAPSO parameters utilized in all simulations and figure 2 represents the whole implementation process flowchart of the developed optimization approach.

Table 6: System Parameters

Parameters	Magnitude	Unit
Quantity of EV (N_{EV})	1625	-
Charging time (Ch_t)	0.33	hours
Charger capacity (C_{PCS})	460	kW
Charger service time (st)	17.5	hours
Average power of EV (p)	96	kW
Charger load factor (lf)	0.90	-
Charger efficiency (q)	0.90	-

Table 7: MASPSO Parameters

Parameters	Value
Swarm size	30
Maximum iterations	100
Inertia weight	0.9 to 0.4
Cognitive coefficient (c1)	2
Social coefficient (c2)	2
Velocity limit(Vm)	±20% of search range
Number of runs	30

7. Results and Discussions

The suggested PCSOI-MSAPSO framework was implemented for verification on the modified IEEE 34-bus radial distribution network. In the modified feeder network, the real-world scenario has been taken into account which includes load demand, electric vehicle population, land price index, sites of charging stations, and renewable energy resources. All simulation results have been obtained from MATLAB R2023a with the Backward-forward sweep (BFS) load flow model. Convergence time of the proposed MSAPSO was 6 seconds. The main difference between the existing approach to planning charging stations and the developed approach is that the optimal placement for public electric vehicles' charging stations and shunt capacitors is found simultaneously to reduce the active power losses.

7.1 Obtained Results of Public Charging Station Owner Index (PCSOI)

The base load flow study was initially carried out in order to determine the reference operating point of the modified IEEE 34 bus distribution system. This feeder had an active power loss of 40.145 kW, reactive power loss of 11.804 kVAr, and minimum bus voltage of 0.98908 p.u. These results provide the yardstick with which the optimization methodology is to be evaluated.

Because the modified IEEE 34 bus feeder system was used, the absolute loss values are different from that of the benchmark system.

7.2 Convergence Characteristics of the Proposed MSAPSO

Figure 3 shows the convergence characteristics of the proposed MSAPSO algorithm. There is no oscillation or premature convergence as the fitness value is decreasing smoothly from about 0.562 to 0.431. It can be seen that fast convergence is attained in the initial iterations after which there is a smooth convergence towards the global optimum. This kind of convergence proves that the proposed search method effectively balances exploration and exploitation, thus leading to faster convergence.

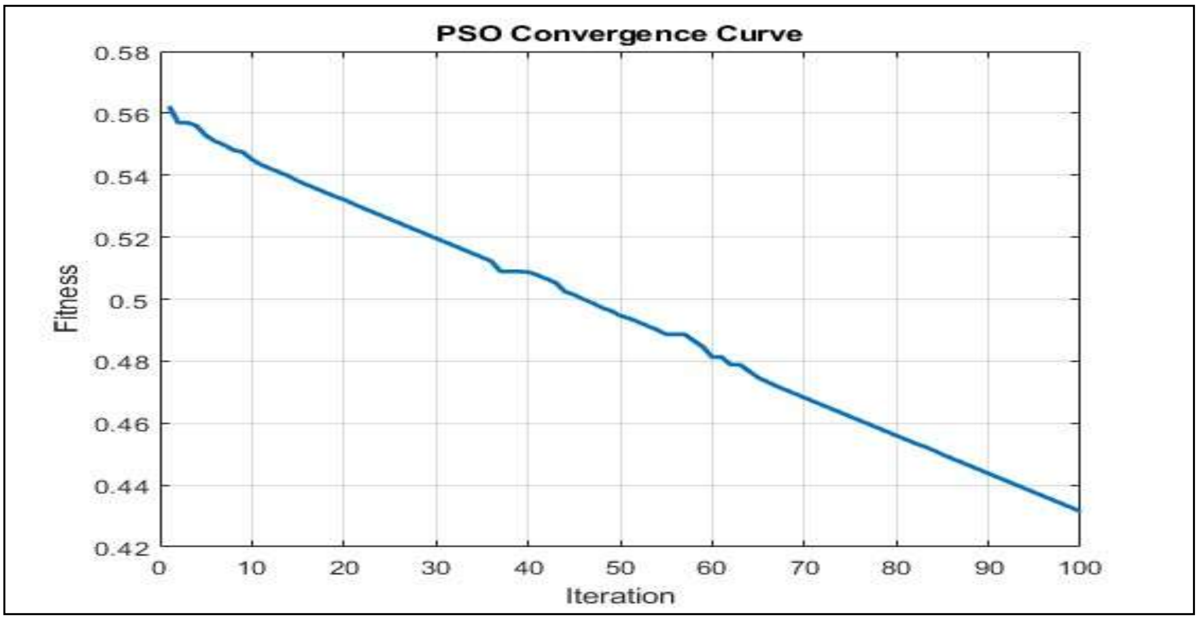

Figure 3: Convergence behavior of proposed MSA-PSO algorithm throughout the optimization process.

7.3 Optimal Allocation of EV Charging Stations and Capacitors

Optimal charging station sites for public EVs from the suggested MSAPSO algorithm were obtained at Buses 4, 13, and 15, while the optimal sites for shunt capacitor placement were found at Buses 25 and 26.
The suggested sites meet the candidate selection criteria that have been carried out through the proposed PCSOI algorithm and minimize active power losses with consideration of the operational constraints of the distribution system. The bus sites chosen for charging stations are those with high land prices and larger numbers of EVs, while the bus sites for shunt capacitors are those which give adequate reactive power support to the overloaded feeders.

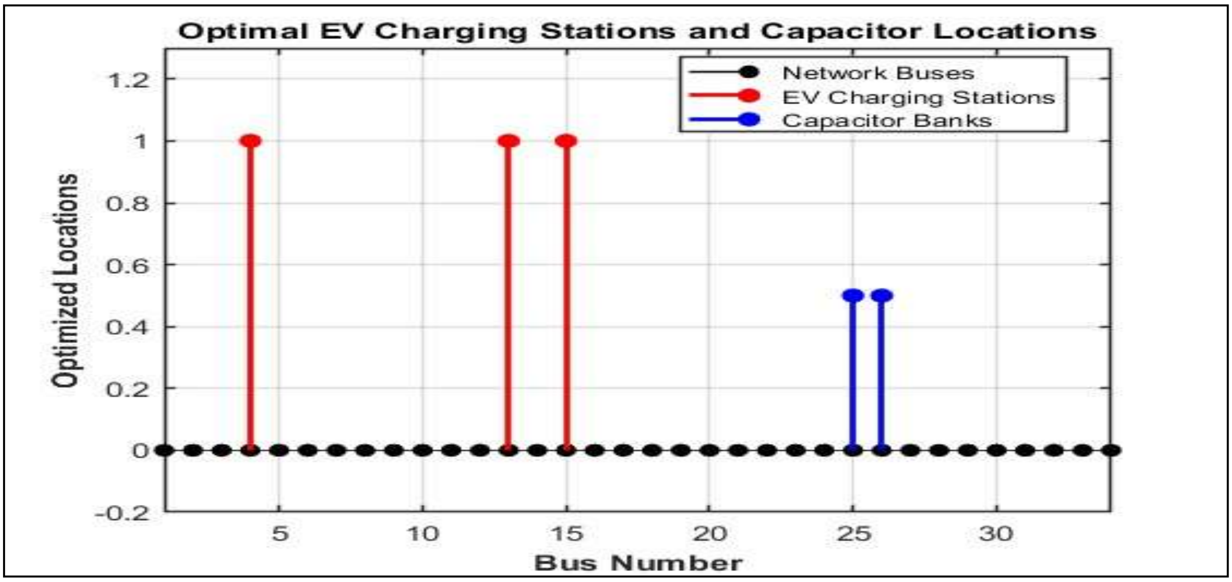

Figure 4: Final locations selected by the proposed optimization algorithm.

7.4 Voltage Profile Improvement

Figure 5 compares the voltage profile of the distribution network before and after optimization. The optimized voltage profile consistently remains above the corresponding base-case profile throughout most of the feeder, particularly at heavily loaded buses where voltage drops are comparatively larger.

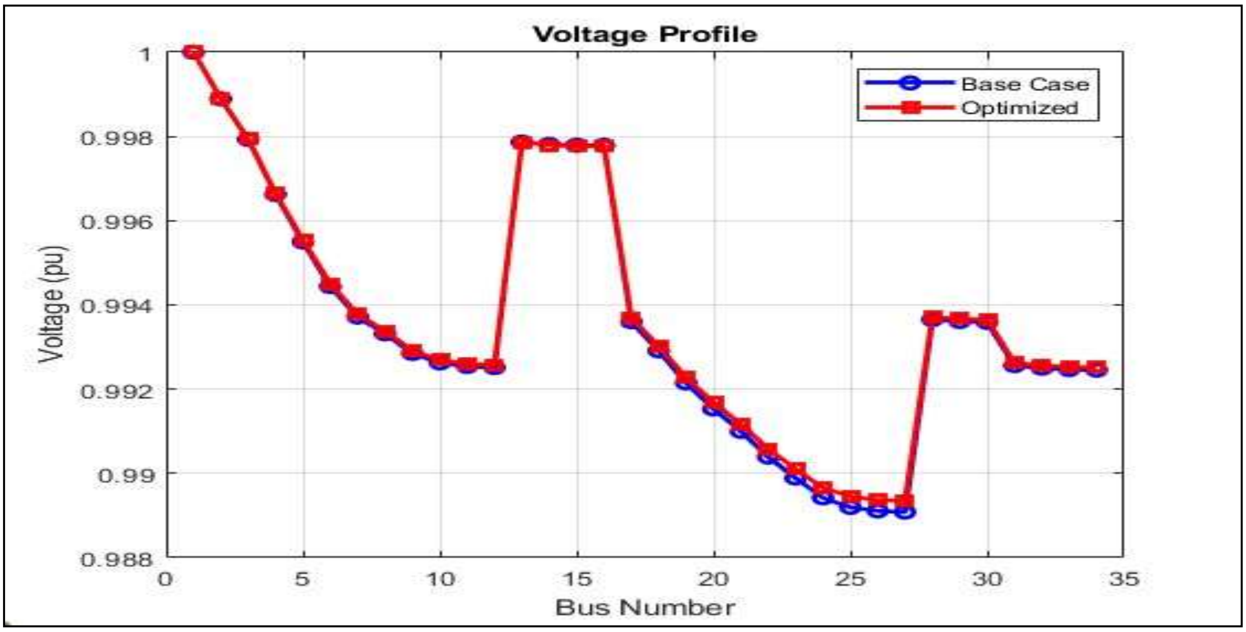

Figure 5: Voltage profile of the distribution network of base case and optimized case.

The minimum bus voltage improves from 0.98908 p.u. to 0.98935 p.u. representing an improvement of approximately 0.027%. Although the numerical improvement appears relatively small, it demonstrates that the proposed optimization simultaneously reduces feeder losses while maintaining acceptable voltage regulation despite the integration of public charging stations. The voltage improvement is mainly attributed to the optimal allocation of shunt capacitors, which inject reactive power locally and reduce the reactive current flowing through the feeder.

*7.5*Branch Power Loss Analysis

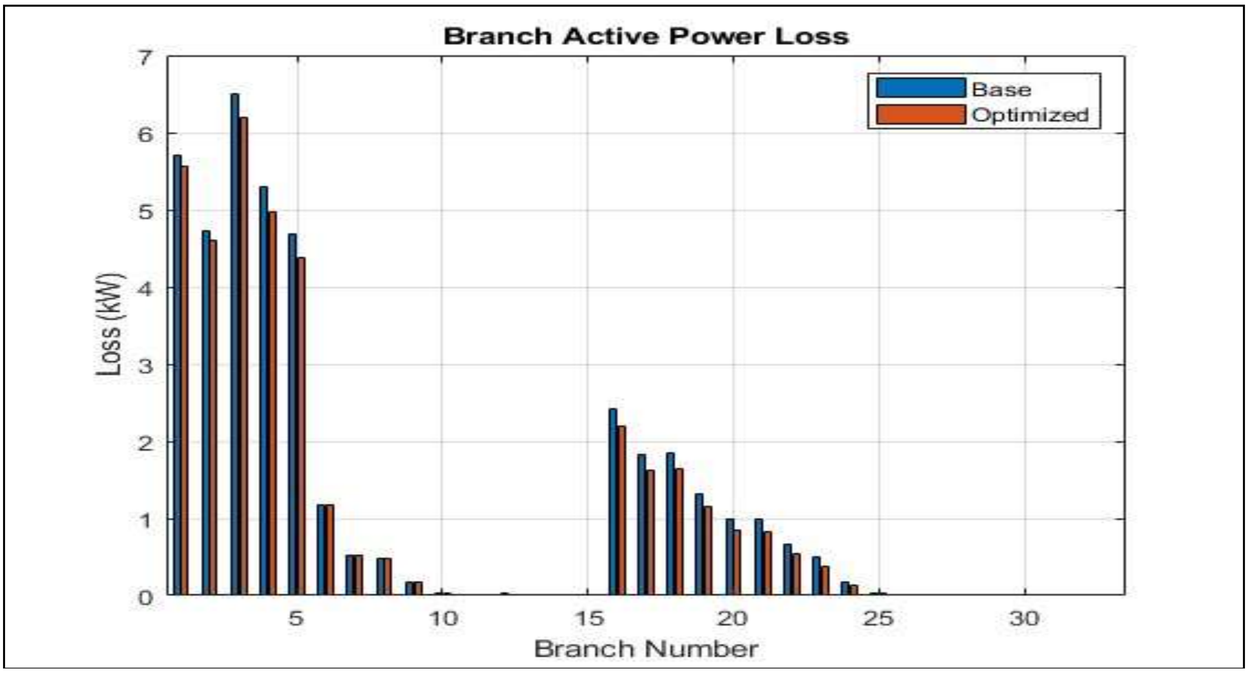

Figure 6: Branch-wise active power loss before and after optimization.

It is evident that the proposed MSAPSO framework reduces losses over almost all heavily loaded branches of the distribution system. This can be especially observed in the downstream parts of the feeders where the voltage drops and branch currents are relatively high.

As a result of reduction in branch current through the combination of charging stations and capacitors, there is an overall decrease in the I^2R losses of the system. Instead of considering only the total losses in the system, the benefits can be seen through branch-wise analysis.

7.6 Comparative Performance Analysis

The proposed model has the potential to reduce the active power loss to 37.575 kW from 40.145 kW; hence there is a reduction of about 6.40%. Reactive power loss is also reduced by about 5.71% from its previous value. This can be seen in Table 8 below.

Table 8: Overall performance obtained using the proposed MSAPSO algorithm.

Performance Index	Base System	Proposed MSAPSO
Active Power Loss (kW)	40.145	37.575
Reactive Power Loss (kVAr)	11.804	11.130
Minimum Voltage (p.u.)	0.98908	0.98935
Best Fitness	—	0.43148
EV Charging Stations	—	4, 13, 15
Capacitor Locations	—	25, 26

It can be seen that the optimal setup is able to maintain a satisfactory level of voltage profile at the same time as getting the minimum fitness value of 0.43148. Thus, the multi-stage optimization approach has been validated.

Table 9: Comparison with all existing PSOs

Method	Active Loss (kW)	Loss Reduction (%)	Fitness
Base	40.145	–	–
Conventional and adaptive PSOs	40.55 to 44.20	−1.00 to 4	0.46 to 0.56
MSA-PSO **(This work)**	37.58	6.40	0.431

The obtained results prove that the developed PCSOI-MSAPSO approach manages to achieve the balance between performance and cost efficiency through the optimal placement of both charging stations and capacitors.

Discussion

The better performance of the presented MSAPSO algorithm is explained by its adaptive search capability, which achieves a balance between the global and local searches during the entire optimization process. The inclusion of the elite learning mechanism ensures convergence stability and leads the swarm towards good solutions, whereas adaptive search capabilities prevent early convergence.

Simultaneous optimization of EV charging station and shunt capacitor location optimization yields reduced feeder currents resulting in low losses in both real and reactive power without compromising voltage performance. As a result, the developed model manages to attain 6.40% improvement in real power losses, stable convergence, and good reactive power management.

In conclusion, the acquired results indicate that the PCSOI-MSAPSO framework is an effective and practical tool for planning public charging stations, which satisfies not only technical considerations but also the site selection criteria from the investor's perspective.

8. Conclusion

In this paper, an optimal design of public EV charging stations in electrical distribution systems based on two-stage Public Charging Station Owner Index-Multi-Stage Adaptive Particle Swarm Optimization (PCSOI-MSAPSO) approach has been presented. The PCSOI approach was proposed by utilizing the combination of Land Value Index (LVI) and Electric Vehicle Population Index (EVPI), which will help in finding economically viable locations of public EV charging stations, thereby shrinking the optimization process. The second phase involved the application of MSAPSO algorithm for the simultaneous optimization of public EV charging station and shunt capacitor locations with respect to minimizing active power loss..

The proposed framework was applied on the modified IEEE 34-bus radial distribution network. It was analyzed through simulations that the proposed framework was successful in selecting technically viable and economic charging stations, while improving the performance of the network. In comparison to the base

model, there was a drop in active power loss from 40.145 kW to 37.575 kW (6.40% decrease) using the proposed model, while there was a decrease in reactive power loss, an improvement in minimum bus voltage, and the model achieved stability with best fitness value of 0.43148.
The proposed PCSOI-MSAPSO framework offers a practical decision-support tool for distribution network operators and charging infrastructure planners by simultaneously considering economic feasibility and electrical network performance.

9. Future scope

Future work will focus on incorporating stochastic EV charging behavior, renewable energy uncertainty, vehicle-to-grid (V2G) operation, dynamic electricity pricing, and multi-objective optimization, together with validation on larger and unbalanced real-world distribution networks

Declarations

- **Funding:** No funding was received to assist with the preparation of this manuscript.

- **Conflicts of interest/Competing interests:** The authors have no competing interests to declare that are relevant to the content of this article.

- **Availability of data and material:** Data can be provided as per the request

- **Code availability:** Not applicable to this research

- **Authors' contributions**

Sandip S Yeole contributed to the study conception and design. Material preparation, data collection and analysis were performed by Sandip S Yeole. The first draft of the manuscript was written by Sandip S Yeole. Prakash G. Burade helped in simulation and supervised the first draft of the manuscript.

- **Ethics approval:** There is no conflict of interest

- **Consent to participate:** Not applicable to this research

- **Consent for publication:** Not applicable to this research

References

1. F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. khan, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," Nov. 01, 2022, Elsevier Ltd. doi: 10.1016/j.egyr.2022.01.180.
2. F. Ahmad, A. Iqbal, I. Asharf, M. Marzband, and I. Khan, "Placement and Capacity of EV Charging Stations by Considering Uncertainties With Energy Management Strategies," in IEEE Transactions on Industry Applications, Institute of Electrical and Electronics Engineers Inc., May 2023, pp. 3865–3874. doi: 10.1109/TIA.2023.3253817.
3. M. Bilal, F. Ahmad, and M. Rizwan, "Techno-economic assessment of grid and renewable powered electric vehicle charging stations in India using a modified metaheuristic technique," Energy Convers Manag, vol. 284, May 2023, doi: 10.1016/j.enconman.2023.116995.
4. S. Pazouki, "Optimal Planning of PEVs Charging Stations and Demand Response Programs Considering Distribution and Traffic Networks," no. December, 2013,
doi: 10.1109/SGC.2013.6733806.
5. H. Simorgh, H. Doagou-Mojarrad, H. Razmi, and G. B. Gharehpetian, "Cost-based optimal siting and sizing of electric vehicle charging stations considering demand response programmes," IET Generation, Transmission and Distribution, vol. 12, no. 8, pp. 1712–1720, 2018, doi: 10.1049/iet-gtd.2017.1663.
6. G. Battapothula, C. Yammani, and S. Maheswarapu, "Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and DGs in distribution system," Journal of Modern Power Systems and Clean Energy, vol. 7, no. 4, pp. 923–934, 2019, doi: 10.1007/s40565-018-0493-2.
7. Z. Zhu, Z. Gao, J. Zheng, and H. Du, "Charging station location problem of plug-in electric vehicles," JTRG, vol. 52, pp. 11–22, 2016, doi: 10.1016/j.jtrangeo.2016.02.002.
8. P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," Appl Energy, vol. 125, pp. 289–299, 2014, doi: 10.1016/j.apenergy.2014.03.077.
9. G. Battapothula, C. Yammani, and S. Maheswarapu, "Multi-objective optimal planning of FCSs and DGs in distribution system with future EV load enhancement," IET Electrical Systems in Transportation, vol. 9, no. 3, pp. 128–139, 2019, doi: 10.1049/iet-est.2018.5066.

10. L. Yazdi, R. Ahadi, and B. Rezaee, "Optimal Electric Vehicle Charging Station Placing with Integration of Renewable Energy," Proceedings of 2019 15th Iran International Industrial Engineering Conference, IIIEC 2019, pp. 47–51, 2019, doi: 10.1109/IIIEC.2019.8720644.
11. R. Xie, W. Wei, M. E. Khodayar, J. Wang, and S. Mei, "Planning Fully Renewable Powered Charging Stations on Highways: A Data-Driven Robust Optimization Approach," IEEE Transactions on Transportation Electrification, vol. 4, no. 3, pp. 817–830, 2018, doi: 10.1109/TTE.2018.2849222.
12. B. Faridpak, H. F. Gharibeh, M. Farrokhifar, and D. Pozo, "Two-Step LP Approach for Optimal Placement and Operation of EV Charging Stations," Proceedings of 2019 IEEE PES Innovative Smart Grid Technologies Europe, ISGT-Europe 2019, pp. 1–5, 2019, doi: 10.1109/ISGTEurope.2019.8905469.
13. H. Zhang, S. J. Moura, Z. Hu, and Y. Song, "PEV fast-charging station siting and sizing on coupled transportation and power networks," IEEE Trans Smart Grid, vol. 9, no. 4, pp. 2595–2605, 2018, doi: 10.1109/TSG.2016.2614939.
14. K. Yenchamchalit, Y. Kongjeen, K. Bhumkittipich, and N. Mithulananthan, "Optimal Sizing and Location of the Charging Station for Plug-in Electric Vehicles Using the Particle Swarm Optimization Technique," iEECON 2018 - 6th International Electrical Engineering Congress, pp. 1–4, 2018, doi: 10.1109/IEECON.2018.8712336.
15. A. Dubey and S. Santoso, "Electric vehicle charging on residential distribution systems: impacts and mitigations," IEEE Access, vol. 3536, no. c, pp. 1–22, 2015, doi: 10.1109/ACCESS.2015.2476996.
16. S. Deb and K. Tammi, "Review of recent trends in charging infrastructure planning for electric vehicles," no. November 2017, pp. 1–26, 2018, doi: 10.1002/wene.306.
17. Z. Darabi, S. Member, and M. Ferdowsi, "Extracting Probability Distribution Functions Applicable for PHEVs Charging Load Profile," pp. 1–6, 2012.
18. A. Shukla, "Consumer Perspective based Placement of Electric Vehicle Charging Stations by Clustering Techniques".
19. S. Deb, S. Member, K. Tammi, X. Gao, K. Kalita, and P. Mahanta, "A hybrid multi-objective chicken swarm optimization and teaching learning based algorithm for charging station placement problem," IEEE Access, vol. 8, pp. 92573–92590, 2020, doi: 10.1109/ACCESS.2020.2994298.
20. M. Z. Zeb et al., "Optimal placement of electric vehicle charging stations in the active distribution network," IEEE Access, vol. 8, pp. 68124–68134, 2020, doi: 10.1109/ACCESS.2020.2984127.
21. M. M. Rahman, S. Barua, S. T. Zohora, K. Hasan, and T. Aziz, "Voltage Sensitivity Based Site Selection for PHEV Charging Station in Commercial Distribution System," pp. 1–6, 2013.
22. F. Ahmad, I. Ashraf, A. Iqbal, M. Marzband, and I. Khan, "A novel AI approach for optimal deployment of EV fast charging station and reliability analysis with solar based DGs in distribution network," Energy Reports, vol. 8, pp. 11646–11660, Nov. 2022, doi: 10.1016/j.egyr.2022.09.058.
23. T. Dias De Lima, J. F. Franco, F. Lezama, J. Soares, and Z. Vale, "Joint Optimal Allocation of Electric Vehicle Charging Stations and Renewable Energy Sources Including CO 2 Emissions," Energy Informatics, doi: 10.1186/s42162-021-00157-5.
24. M. Bilal, F. Ahmad, and M. Rizwan, "Techno-economic assessment of grid and renewable powered electric vehicle charging stations in India using a modified metaheuristic technique," Energy Convers Manag, vol. 284, May 2023, doi: 10.1016/j.enconman.2023.116995.
25. F. Ahmad et al, "Placement of electric vehicle charging stations in distribution network considering power loss, land cost, and electric vehicle population, Energy source, Part A: Recovery, utilization, and environmental effects, 2022, https://cmte.ieee.org/pes-testfeeders/resources/
26. Kennedy, J.; Eberhart, R., Particle Swarm Optimization, IEEE ICNN, 1995.
27. Shi, Y.; Eberhart, R., A Modified Particle Swarm Optimizer, IEEE ICEC, 1998.
28. Clerc, M.; Kennedy, J., The Particle Swarm-Explosion, Stability, and Convergence in a Multidimensional Complex Space, IEEE Transactions on Evolutionary Computation, 2002.
29. Yenchamchalit et al., 2018
30. D. Das, H. S. Nagi, and D. P. Kothari, Novel Method for Solving Radial Distribution Networks, IEE Proceedings-Generation, Transmission and Distribution, 1994.
31. W.H. Kersting, Distribution System Modeling and Analysis, CRC Press