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Review article

Optimal location of electric vehicle charging station and its impact on distribution network: A review

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ABSTRACT

At present, the limited existence of fossil fuels and the environmental issues over greenhouse gas emissions have been directly affected to the transition from conventional vehicles to electric vehicles (EVs). In fact, the electrification of transportation system and the growing demand of EVs have prompted recent researchers to investigate the optimal location of electric vehicle charging stations (EVCSs). However, there are numerous challenges would face when implementing EVs at large scale. For instance, underdeveloped EVCSs infrastructure, optimal EVCS locations, and charge scheduling in EVCSs. In addition, the most fundamental EV questions, such as EV cost and range, could be partly answered only by a well-developed EVCS infrastructure. According to the literature, the researchers have been followed different types of approaches, objective functions, constraints for problem formulation. Moreover, according to the approaches, objective functions, constraints, EV load modeling, uncertainty, vehicle to grid strategy, integration of distributed generation, charging types, optimization techniques, and sensitivity analysis are reviewed for the recent research articles. Furthermore, optimization techniques for optimal solution are also reviewed in this article. In addition, the EV load impact on the distribution network, environmental impacts and economic impact are discussed.

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1. Introduction

Over the recent decade, the demand on Electrical Vehicles (EVs) have been accelerate significantly due to the rapid decrease in CO_2 emissions (Parker et al., 2021) and the operating costs compared to the internal combustion engines(ICE) (Zhou et al., 2021). According to research, EVs could reduce CO_2 emissions by 28% by 2030 (Adnan et al., 2018). However, there are two prime challenges which could affect to the general community when transferring to EVs, such as the high cost of EVs and the lack of charging facilities. The different industries and governments over the world is expected to reach the EVs market to USD 974,102.5 million by 2027 growing at a healthy compound annual growth rate in the forecast period of 2020 to 2027 (Electric vehicle, 2020). One of the most critical issues addressed by the authors in this study is the lack of infrastructure for charging EVs. The number of EVs are exponentially increasing worldwide, posing a new challenge to the distribution network infrastructure and distribution network operators (DNO). In fact, excessive electrical power requirements due to EVs integration, bus voltages, power loss, stability, harmonic distortion, voltage mismatch, and power efficiency could be negatively affected to the distribution network. Furthermore, the more addition of EVs require more reliable electric vehicle charging station (EVCS) systems with less EV charging time. As a result, fast charging in the EVCSs is viable for charging an EV's battery in 20-30 min Zeb et al. (2020). Beside from the drawbacks of fast charging in the EVCS, it has detrimental effects on the distribution system that could be mitigated by accurate EVCS planning (Steen and Tuan, 2017).

In addition, the optimal location of EVCSs and the impact of EVs load on the distribution system have become more prominent research topics (Lam et al., 2014) in the last decade. Therefore, the DNO approach, EVs users approach, and EVCS owner approach are reviewed for the placement of EVCS in this paper by the authors. Specially, several researches have already been published on the positioning of EVCSs by the DNO approach such as minimizing bus voltage, minimizing total power loss, and maximizing the reliability of the distribution system. The other researchers have found the EVCS investor approaches for the EVCS placement, while limited number of researches have considered the EV user's strategy for the EVCS placement.

1.1. Literature survey

Fig. 1 represents a survey which investigated the number of publicly available slow and fast charging stations among 13 prime countries 2020 (Publicly available, 2021). According to this figure, the EVCSs market is expected to reach \$103.6 billion by 2028, with the compound annual growth rate (CAGR) of 26.4% between 2021 and 2028. Further, this market is forecasted to increase by 31.1% CAGR from 2021 to 11.6 million units by 2028 (Electric vehicle, 2021). The charging station development cost, active power loss cost, reactive power loss cost and voltage deviation cost are utilized as indicators of charging station optimal location and the results are obtained by balanced mayfly algorithm (Chen et al., 2021b). Literature (Moradi et al., 2015) proposes power loss, voltage profile and EVs charging costs as objective function for the problem formulation for finding the optimal location of charging station and renewable energy sources which is solved by differential evolution algorithm.

In Liu et al. (2013), authors suggested the objectives as investment costs, operation costs, maintenance costs, and network loss costs for problem formulation which was gained by the modified primal–dual interior-point algorithm for optimal location of EVCS. The authors in Mainul Islam et al. (2018) proposed a multi objective optimization problem by transportation energy loss cost, station build-up cost and sub-station energy loss cost for the placement of FCSs, which was solved by the binary lighting search algorithm. Further, the authors in Pal et al. (2021), initially have proposed a multi objective optimization problem by energy loss, voltage deviation, EV population and land cost, whereas the uncertain variable of EV are controlled by 2 m point estimation method (2 m PEM) efficiently and optimization problem have obtained by Harris hawks optimization (HHO) algorithm. In addition, Gampa et al. (2020) proposed a two-stage fuzzy approach for optimal location of distributed generations (DGs), shunt capacitors (SCs) and charging stations. In first approach, a multi objective optimization problem was deployed to place the DGs and SCs and, in the second approach, a multi-objective optimization problem utilized power loss and voltage profile. Ultimately the proposed problems was solved by grasshopper optimization algorithm (GOA).

The authors in El-Zonkoly and Dos Santos Coelho (2015) have identified the optimal location of parking lots by considering, the power loss cost, power from the grid cost, power from the

Nomenclature

ABC	Artificial bee colony
B&B	Branch and Bound
BLSA	Binary Lighting Search Algorithm
BMA	Balanced Mayfly Algorithm
BN	Bayesian Network
CAIDI	Customer Average Interruption Duration Index
CRO	Chemical Reaction Optimization
CSO	Cat Swarm Optimization
CSO	Charging Station Owner
DE	Differential Evolution
DER	Distributed Renewable Energy Resources
DG	Distributed Generation
DNO	Distribution Network Operator
EHDG	Enhanced Heuristic Descent Gradient
EV	Electric vehicle
EVCS	Electric Vehicle Charging Station
FA	Firefly Algorithm
FCS	Fast Charging Station
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
GOA	Grasshopper Optimization Algorithm
GWO	Gray Wolf Optimization
HHO	Harris Hawks Optimization
ICE	Internal Combustion Engine
IHPSO	Improved Hybrid Particle Swarm Optimization
IP	Integer Programming
LGDG	Lazy Greedy with Direct Gain
LGEG	Lazy Greedy with Effective Gain
LP	Linear Programming
MCS	Monte Carlo Simulation
MPGA	Multi-Population Genetic Algorithm
NSGA	Non-Dominated Sorting Genetic Algorithm
PSO	Particle Swarm Optimization
QBLSA	Quantum Binary Lighting Search Algorithm
QGDA	Gaussian Mutational Dragonfly Algorithm
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SFL-TLBO	Shuffled Frog Leap-Teaching Learning Based Optimization
TLBO	Teaching–Learning Based Optimization
TSR	Trip Success Ratio
V2G	Vehicle to Grid

distributed renewable energy resources (DER) cost and the garage charging/ discharging cost. In fact, the Artificial bee colony (ABC) algorithm and firefly algorithm (FA) was used to obtain the optimization problem. Further the station development cost, specific energy consumption of EVs user cost, network power loss cost and maximum voltage deviation are proposed for multi-objective optimization problem. In addition, this problem solved by novel hybrid shuffled frog leap-teaching learning based optimization (SFL-TLBO) algorithm in Battapothula et al. (2019a). Furthermore, an improved shark smell optimization algorithm is used to obtain the optimal location and size of the electrical energy storage system in the microgrid (Tian et al., 2021). In Feng et al. (2021), Many variables influence the load on EVCSs, including weather, the number of EVs on the road, and power costs. An approach for EVCS load forecasting based on a multivariable residual correction gray model and a long short-term memory network.

In Zhu et al. (2016), the genetic algorithm (GA) technique is deployed to solve the proposed model of optimal location for EVCS, including two objective functions such as the construction cost of EVCS and charging station access cost. The Authors have dedicated the optimal location of the charging station toward the sustainable cities in Luo and Qiu (2020) and proposed the multi-objective functions for the optimization problem. Moreover, the annual time opportunity cost, traveling cost, construction cost, and operating cost are considered as objective functions and solved by GA. In Xiang et al. (2016), the authors have suggested the traveling cost, investment cost for EVCSs, the operation cost of the substations and power loss cost as economic factors for economic modeling. In fact, the proposed economic model for charging station placement is solved by GA. The Power loss minimization with demand response at load side is the objective to place the CS and problem answered by GA (Pazouki et al., 2013).

A mixed-integer nonlinear problem (MINLP) is formulated in Sadeghi-Barzani et al. (2014) by considering the CS equipment cost, land cost, cs electrification cost, electric grid loss cost, and EV loss cost for charging and the MINLP optimization problem was obtained by GA. In Mohsenzadeh et al. (2018), the authors have investigated the optimal location of parking lots by maximizing the revenue of parking lots and have considered the power loss cost, reliability cost, voltage improvement cost, and parking lot cost as the decision function, whereas the GA has been deployed the optimal results. Moreover, a mixed-integer programming model has been developed to formulate the problem for maximizing the overall plug-in EVs flows in the network and the GA has used to solve the proposed problem (Wang et al., 2018). In Battapothula et al. (2019b), the authors formulated a multi-objective mixed integer non-linear problem (MINLP) with FCS development cost, cost of specific energy consumption of EVs, electrical network power loss cost, DGs cost and voltage deviation. In this study, the formulated problem for the placement of FCSs and DGs in the distribution network was solved by non-dominated sorting genetic algorithm II (NSGA-II) and the proposed technique is evaluated by the 118-bus distribution system. In addition, the land cost, station equipment cost, operating and maintenance cost, real power loss cost and voltage profile improvement are proposed as objective functions for the placement of CS by authors in Awasthi et al. (2017) and the proposed problem answered by an advanced version of GA and PSO algorithm.

According to Reddy and Selvajyothi (2020a), a power loss of an unbalanced radial distribution system has suggested as an objective function for the placement of EVCS and the formulated optimization problem was solved by the PSO algorithm. In Reddy and Selvajyothi (2020b), the annual average construction cost of EVCS, the annual operating cost of EVCSs and the cost of charging have selected as the objective functions for the optimal location of EVCSs, which was solved by the PSO algorithm. Similarly, EVCS and DER are placed as an optimal location in the radial distribution system, power loss is considered as an objective function for optimization problems and solved by the PSO algorithm (Gupta and Narayanankutty, 2020). In Amini et al. (2017), the authors have observed the land cost, bus attraction for EVs, reliability of distribution network, and power loss cost with DERs which was

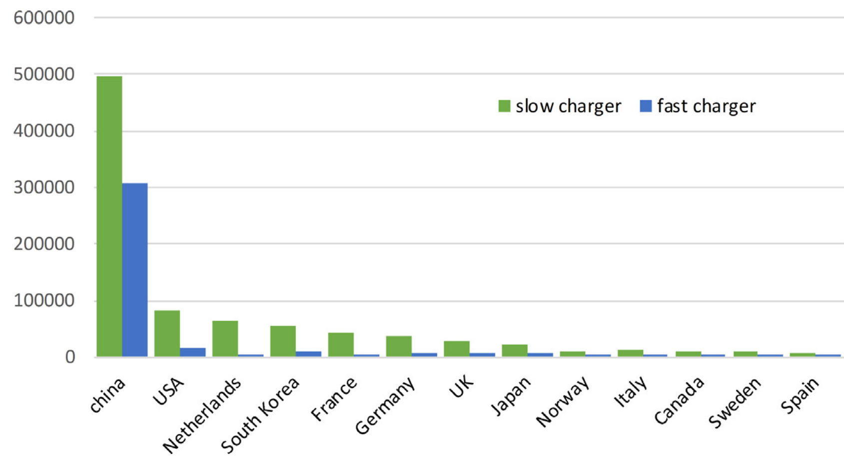

Fig. 1. Number of available charging station in 2020.

proposed as the objective for EVs parking lots placement and optimization problem was obtained by GA and PSO algorithm. Further, PSO solved the optimal location and sizing of the EVCS problem by minimizing the grid power loss and the bus voltage deviation integrating the solar power generation (Pashajavid and Golkar, 2013). The study in Eid (2020) minimizes the power loss and maximizes the distribution system's stability for the placement of EVCS, while the optimization problem was gained by APSO. With regards to Zhang et al. (2016), the investment cost of CS, operation and maintenance costs, electricity cost for battery charging, electricity cost for traveling to charge the battery, time cost for driving, waiting time cost and charging time cost was utilized as the objective for problem formulation, and the integrated planning problem solved by PSO algorithm. Furthermore, in Sa'adati et al. (2021) the authors proposed the model to minimize the investment costs of FCSs, DERs, distribution network expansion, and the cost of energy losses of the distribution system and the proposed mixed integer linear problem have been solved by the capacitated flow refueling location model and capacitated deviation flow refueling location model.

1.2. Shortcoming

Regarding the previous studies, the EVCS placement problem formulation and its solution techniques consists of shortcomings (**Sh**) as follows:

- **Sh1**: Most of the researchers have considered one or two approaches for the placement of charging stations where it is not recommended for the real-world problem. The problem formulation for optimal locations of CSs are equally important for the CS owner, distribution network operator, and EV users.
- **Sh2**: Fluctuations of CS load on the distribution system due to uncertainty in EV users' behavior are not considered for the EV load modeling.
- **Sh3**: Demand-side management (DSM) and vehicle to grid (V2G) scheme have been ignored problem formulating of optimal CS locations.
- **Sh4**: Integration of renewable energy sources are not considered with problem formulation of EVCS placement.
- **Sh5**: The charging schedules with problem formulation of EVCS optimal location is not considered by the authors.
- **Sh6**: Most of the authors have placed the charging station (especially fast charging) by considering the cost functions while ignoring the impact of the charging station.

1.3. Contributions

The main purpose of this paper is to review different problem formulations proposed by researchers to determine the optimal location of CSs and identify the best solution by the various solution techniques. The major contributions could be summarized as follows.

1. An overview and comparative analysis of different problem formulation approaches of EVCSs placement adopted by researchers are provided. Every approach consists of different objective functions to place the EVCSs. Therefore all approaches have been reviewed in this paper to place the EVCSs (addressing **Sh1**).
2. The objective functions and constraints for the problem formulation to determine the EVCS optimal locations are reviewed in this paper. After the problem formulation, the solution techniques are reviewed in this paper for the optimal solution of the problem (addressing **Sh1**).
3. The review of EV load integration impact at existing distribution networks is also discussed in this study (addressing **Sh6**).

In addition, this paper is organized as follows: In Section 2, three different approaches for placement of charging stations, problem formulations, objective functions, equality/ inequality constraints with proper citations are presented. In Section 3, different types of solution techniques for a single objective and multi-objective problem are reviewed while in Section 4, EV load impacts are investigated. Moreover, the summary and discussion are presented in Section 5 whereas the future research directions are concluded in Section 6, and Section 7 presents the conclusion of the review paper.

2. Review of problem formulation

The generalized framework for optimal location of charging stations is represented in Fig. 2. According to the literature, the authors have been concluded that the investors of charging stations require to place the CSs to minimize the installation cost and maximize the profit by charging the EVs. On the other hand, the EVs drivers intend to place the CSs to minimize the traveling cost, charging time, waiting time, charging, access cost, etc, while the distribution network operator desire to place the CSs to minimize the impact at distribution system parameter. Therefore, three approaches have been reviewed in this paper for the optimal placement of EVCSs as shown in Fig. 3. All types of approaches with their possible combinations are illustrated in the Table 1 (Hashemian et al., 2020).

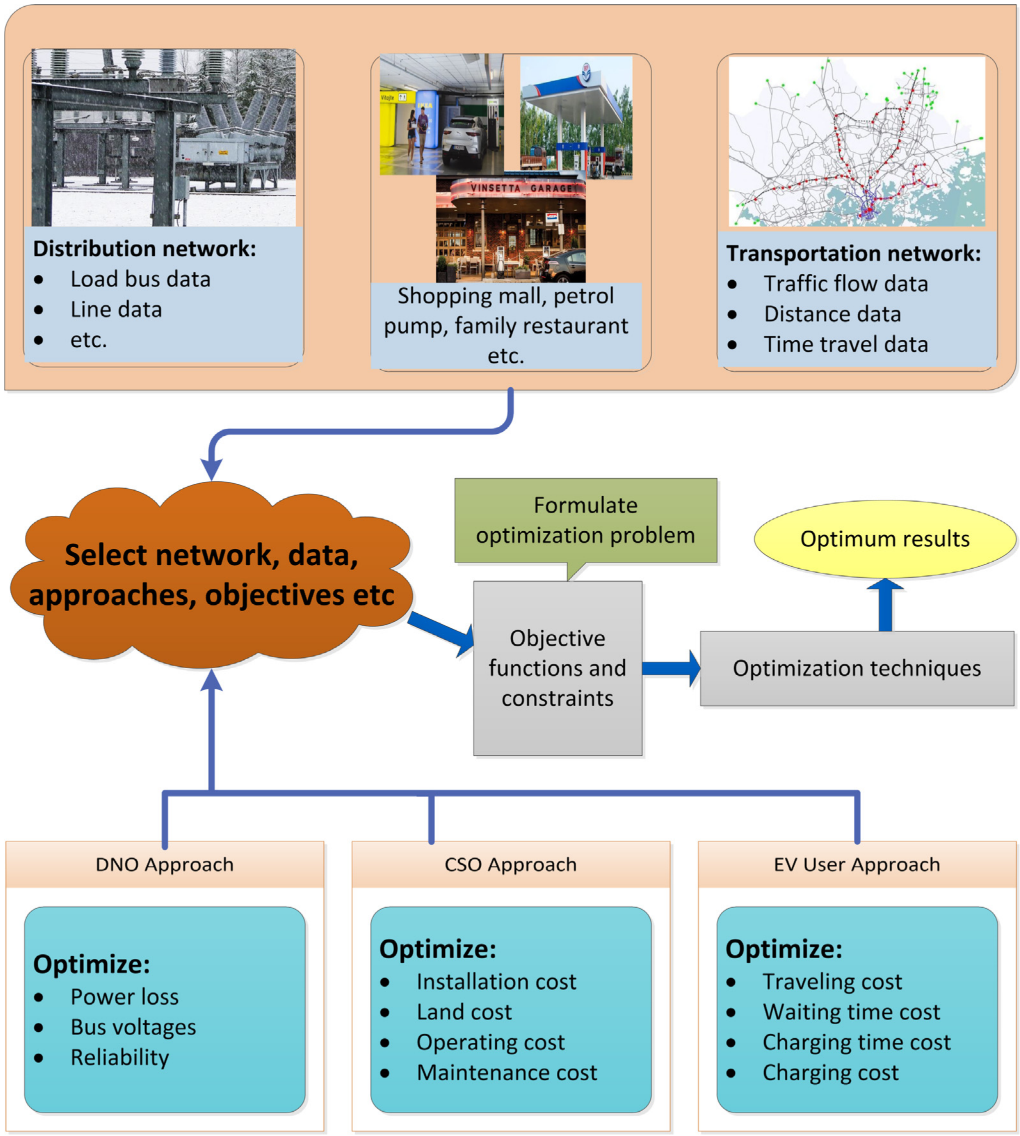

Fig. 2. Framework of FCS placement.

Table 1
Different approaches and their references in literature for placement of EVCS.

Approaches for optimal location of EVCS	References
DNO approach	Gampa et al. (2020), Reddy and Selvajyothi (2020a,b), Gupta and Narayanankutty (2020), Pashajavid and Golkar (2013), Su et al. (2013) and Aljanad et al. (2018)
CSO approach	Xi et al. (2013), Wang et al. (2018), Faridpak et al. (2019) and Lam et al. (2014)
EV user approach	Yi et al. (2019) and Othman et al. (2020)
DNO and CSO mixed approach	Shukla et al. (2019), Zeb et al. (2020), Chen et al. (2021b), Moradi et al. (2015), Liu et al. (2013), Pal et al. (2021), El-Zonkoly and Dos Santos Coelho (2015), Battapothula et al. (2019a), Mohsenzadeh et al. (2018), Awasthi et al. (2017), Deb et al. (2020), Zhang et al. (2018), Mozafar et al. (2017), Moradijoz et al. (2018), Deb et al. (2019) and Faddel et al. (2018)
CSO and EV user mixed approach	Zhu et al. (2016), Luo and Qiu (2020), Ren et al. (2019), Tian et al. (2018), Zhu et al. (2018), Kong et al. (2019), Rahman et al. (2013), Alhazmi et al. (2017) and Ma and Zhang (2018)
EV user and DNO mixed approach	Pazouki et al. (2013)
DNO, CSO and EV user mixed approach	Mainul Islam et al. (2018), Xiang et al. (2016), Sadeghi-Barzani et al. (2014), Battapothula et al. (2019b), Amini et al. (2017), Zhang et al. (2016), Hashemian et al. (2020), Simorgh et al. (2018), Hosseini and Sarder (2019), Zhang et al. (2020), Neyestani et al. (2015), Moradijoz et al. (2013), Luo et al. (2017), Deb et al. (2021) and Jiang et al. (2018)

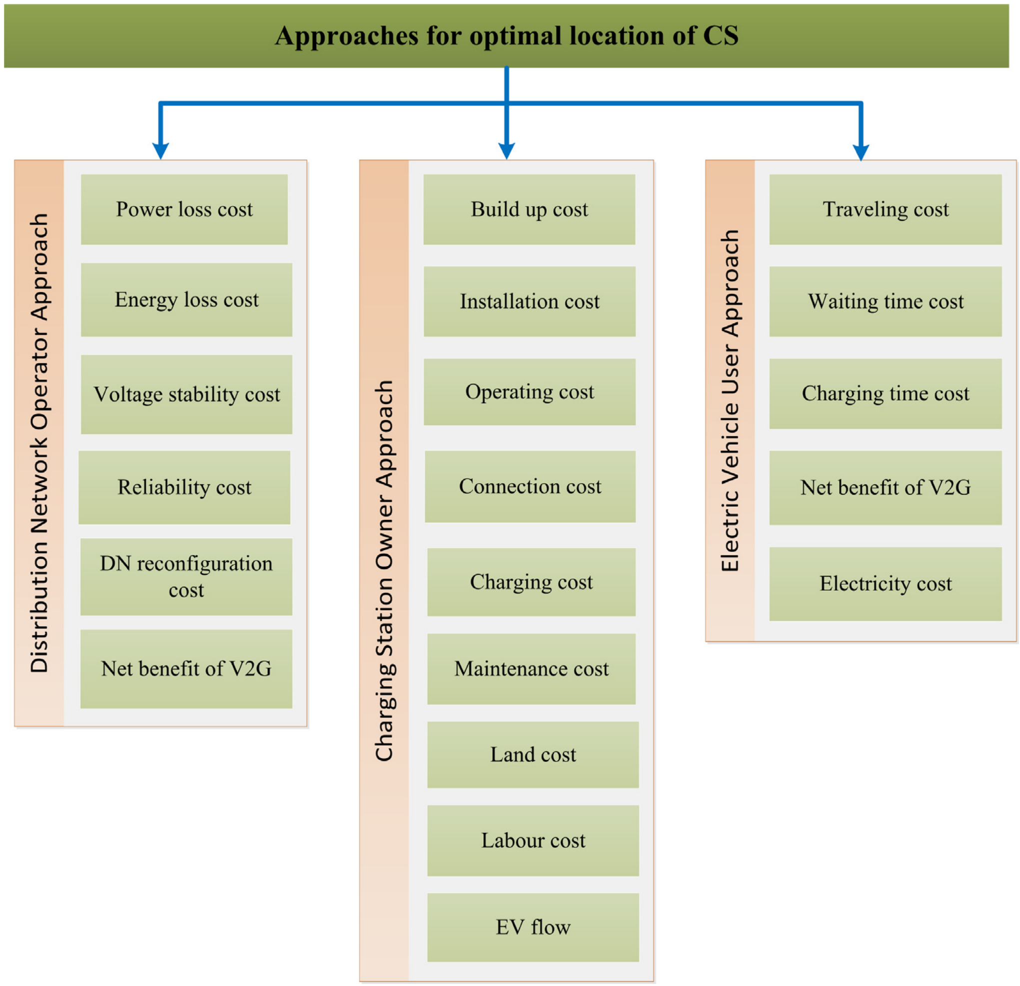

Fig. 3. Approaches of problem formulation for placement of EVCS.

2.1. Distribution network operator approach

The distribution networks (DN) are responsible for providing the electric power for every connected electric loads in residential, commercial, and industrial areas. In fact, the location of the new loads would affect the parameters of DN. Therefore, active power loss cost (Shukla et al., 2019; Zeb et al., 2020; Chen et al., 2021b; Pal et al., 2021; Gampa et al., 2020; Battapothula et al., 2019a; Xiang et al., 2016; Deb et al., 2020), reactive power loss cost, voltage deviation cost (Chen et al., 2021b; Pal et al., 2021; Battapothula et al., 2019a; Awasthi et al., 2017; Mozafar et al., 2017; Deb et al., 2019), reliability cost (Amini et al., 2017; Deb et al., 2019) and stability cost (Ponnam and Swarnasri, 2020) of the distribution system are optimized to the placement of EVCSs under the DNO approach.

2.2. Charging stations owner approach

Total costs related to the installation of EVCS is paid by charging station owner (CSO) to gain the maximum revenue from the EVCS through EVs charging. Therefore, the CSO are searching for CS locations with maximum revenues and minimum investments. Hence, the investment cost (Faridpak et al., 2019; Moradijoz et al., 2018; Tian et al., 2018; Simorgh et al., 2018), installation cost (Chen et al., 2021b; Battapothula et al., 2019a; Deb et al., 2019; Kong et al., 2019), operating cost (Zhang et al., 2016; Deb et al., 2019; Kong et al., 2019), maintenance cost, road construction cost and land cost (Chen et al., 2021b; Pal et al., 2021; Awasthi et al., 2017) are considered under the CSO approach for the optimal CS location.

2.3. Electric vehicle users approach

The placement of EVCS affects the EV user charging behavior. In Yi et al. (2019), access cost, traveling cost for charging from demand point to EVCS, waiting time cost (Zhang et al., 2016; Tian et al., 2018), and charging time cost have been considered as an objective function for the placement of EVCS under the EV drivers approach.

However, when accessing the optimal location of EVCS, more than one approach should be considered with real-world data for an accurate result. The authors typically use only one or two approaches and ignore others as shown in Table 2, which is not considered a promising approach in the real problem formulation. In reality, the problem formulation of EVCS placement in any dedicated area is extremely complex when identifying the accurate location of EVCS. Identification of objective functions and constraints for the problem formulation are important research work for the placement of charging stations.

2.4. Objective function

This subsection provides an outline of the various objective functions that were utilized when formulating the EVCS placement planning problem.

Table 2
Analysis of EVCS placement problem formulation and solution techniques using DN operator, CS owner and EV user approaches.

Objective function	Year	Solution techniques	Approaches			EVs load modeling	DGs integration	Uncertainty	V2G scheme	Types of charging	Sensitivity analysis
			DNO	CSO	EV users						
CS development cost, active and reactive power loss cost, voltage deviation cost (Chen et al., 2021b)	2021	BMA	Y	Y	N	N	N	N	N	L3	N
CS installation cost, operating cost, penalty cost, traveling cost (Deb et al., 2021)	2021	CSO,TLBO	Y	Y	Y	N	N	N	N	L2,L3	N
Investment cost, installing devices cost, power loss cost (Tadayon-Roody et al., 2021)	2021	GA	Y	Y	N	N	N	Y	N	L3	N
Power loss cost, charging zone center deviation (Bitencourt et al., 2021)	2021	BAT	Y	N	Y	Y	N	Y	N	L3	N
Construction cost, travel distance cost, waiting time cost (Li et al., 2021)	2021	MPGA,k-mean	N	Y	Y	Y	N	Y	N	L2,L3	N
Power loss cost, cumulative voltage deviation (Sengupta and Datta, 2021)	2021	INBPSO	Y	N	N	N	Y	N	N	L3	Y
Real and reactive power loss cost (Rajesh and Shajin, 2021)	2021	QGDA	Y	N	N	N	N	N	N	–	Y
Maximum profit, optimal voltage, minimum fluctuations in load, maximum charging satisfaction of the EV (Liu et al., 2021)	2021	IHPSO	Y	N	N	N	N	N	N	L3	N
Energy loss cost, voltage deviation cost, EV population and land cost (Pal et al., 2021)	2021	HHO	Y	Y	N	Y	N	Y	Y	L2,L3	Y
Power loss cost (Reddy and Selvajyothi, 2020b)	2020	PSO	Y	N	N	N	N	N	N	L3	N
Power loss cost (Gupta and Narayanankutty, 2020)	2020	PSO	Y	N	N	N	Y	N	N	–	N
Distribution power loss cost and voltage deviation cost (Gampa et al., 2020)	2020	Fuzzy GOA	Y	N	N	Y	Y	N	N	L3	N
EVCSs cost, voltage stability, reliability and power loss (VRP) (Deb et al., 2020)	2020	CSO, TLBO	Y	Y	N	N	N	N	N	L3	N
Active power losses cost (Reddy and Selvajyothi, 2020a)	2020	PSO	Y	N	N	N	Y	N	N	L3	N
Installation, chargers, waiting time, travel in TN, purchasing active and reactive power costs (Hashemian et al., 2020)	2020	GAMS	Y	Y	Y	N	N	N	N	L3	N
Annual time opportunity cost, traveling cost, construction cost and operating cost (Luo and Qiu, 2020)	2020	GA	N	Y	Y	Y	N	Y	N	L3	N
Traveling cost (Othman et al., 2020)	2020	EHDG	N	N	Y	N	N	N	N	L3	N
Charging Likelihood, Charging Willingness of Drivers, Charging Demand, Distance Reduction (Zhang et al., 2020)	2020	LGDG, LGEG	Y	Y	Y	N	N	N	N	L3	N
Installation and power loss cost (Zeb et al., 2020)	2020	PSO	Y	Y	N	Y	Y	Y	N	L1,L2,L3	N
Benefit of DSO and EVCS (Hadian et al., 2020)	2020	MOPSO	Y	Y	N	Y	N	Y	N	L2	N
Development cost, cost of specific energy consumption of EVs, electrical network power loss cost (Battapothula et al., 2019b)	2019	NSGA-II	Y	Y	Y	N	Y	N	N	L3	N
Construction cost, operation cost and wastage cost in the process of user charging (Ren et al., 2019)	2019	GA	N	Y	Y	N	N	N	N	L3	N
Power loss cost and EV flow (Shukla et al., 2019)	2019	GWO	Y	Y	N	Y	N	Y	N	L3	Y

(*continued on next page*)

Table 2 (*continued*).

Objective function	Year	Solution techniques	Approaches			EVs load modeling	DGs integration	Uncertainty	V2G scheme	Types of charging	Sensitivity analysis
			DNO	CSO	EV users						
Environmental, economic, technical and social criterion cost (Hosseini and Sarder, 2019)	2019	BN	Y	Y	Y	Y	N	Y	N	L3	Y
Costs of CS, DN expansion, voltage regulation and protection device upgrade (Cui et al., 2019)	2019	Convexification	Y	Y	N	N	N	N	N	L3	Y
User Charging Convenience cost, User Charging Cost and User Charging Time cost (Yi et al., 2019)	2019	Artificial Immune	N	N	Y	Y	N	Y	N	L3	N
Cost of EVCS (Faridpak et al., 2019)	2019	LP	N	Y	N	Y	N	Y	N	L3	N
Construction and operational cost (Kong et al., 2019)	2019	Simulation	N	Y	Y	Y	N	Y	N	L2	N
Station development cost, EV user cost, power loss cost and Maximum voltage deviation (Battapothula et al., 2019a)	2019	Hybrid SFL-TLBO	Y	Y	Y	N	Y	N	N	L3	N
Installation, operation, voltage profile, reliability and power loss costs (Deb et al., 2019)	2019	Hybrid CSO-TLBO	Y	Y	N	N	N	N	N	L2,L3	N
Power loss cost, reliability cost, voltage improvement cost and parking lot cost (Mohsenzadeh et al., 2018)	2018	GA	Y	Y	N	N	N	N	N	L2,L3	N
Waiting time cost, traveling time cost and investment cost (Tian et al., 2018)	2018	SCE-UA	N	Y	Y	Y	N	Y	N	L2	N
Investment cost, connection cost, active power loss cost, demand response cost (Simorgh et al., 2018)	2018	PSO	Y	Y	Y	N	N	N	N	L3	N
For EVCS installing cost and management cost. For users charging cost, station access cost and waiting cost (Zhu et al., 2018)	2018	CPLEX	N	Y	Y	N	N	N	N	–	N
Investment cost, the penalty for unsatisfied charging demands and power distribution network cost (Zhang et al., 2018)	2018	B&B	Y	Y	N	N	N	N	N	L3	Y
Loss reduction benefit, Revenue of V2G and EV charging cost (Moradijoz et al., 2018)	2018	–	Y	Y	N	N	N	N	Y	L3	N
Charging cost, charging waiting time, charging travel time, power loss voltage deviation (Jiang et al., 2018)	2018	MAS simulation	Y	Y	Y	N	N	N	N	L3	N
Number of charging stations (Xie et al., 2018)	2018	MCS,IP	N	Y	Y	Y	Y	Y	Y	L3	Y
Plug-in EVs flows (Wang et al., 2018)	2018	HA,GA	N	Y	N	N	N	N	N	L3	N
Voltage deviation, power loss, thermal effect (Aljanad et al., 2018)	2018	QBLSA	N	Y	N	N	N	N	N	L3	N
Transportation energy loss cost, Station build-up cost and Sub-station energy loss cost (Mainul Islam et al., 2018)	2018	BLSA	Y	Y	Y	N	N	N	N	L3	N
Waiting time cost and operating cost of CS (Ma and Zhang, 2018)	2018	Exhaustion method	N	Y	Y	Y	N	N	N	L3	N
Total profit, voltage deviation cost and power loss cost (Faddel et al., 2018)	2018	NSGA-II	Y	Y	N	Y	N	N	N	PL	Y
Power loss, voltage fluctuations and power purchased from the grid (Mozafar et al., 2017)	2017	GA,PSO	Y	Y	N	Y	N	Y	N	L1	N

(*continued on next page*)

Table 2 (*continued*).

Objective function	Year	Solution techniques	Approaches			EVs load modeling	DGs integration	Uncertainty	V2G scheme	Types of charging	Sensitivity analysis
			DNO	CSO	EV users						
Land cost, bus attraction of EVs, reliability, power loss cost (Amini et al., 2017)	2017	GA,PSO	Y	Y	Y	Y	Y	Y	N	L1,L3	N
Charging station coverage (Alhazmi et al., 2017)	2017	TSR	N	Y	Y	Y	N	Y	N	L3	N
Service provider profit, distribution network disturbance, Luo et al. (2017)	2017	BN	Y	Y	Y	Y	N	N	N	L1,L2,L3	N
Land cost, station equipment, operating and maintenance cost, real power loss, reactive power loss and voltage profile (Awasthi et al., 2017)	2017	Hybrid of GA & PSO	Y	Y	N	N	N	N	N	L1	N
Construction cost and access cost (Zhu et al., 2016)	2016	GA	N	Y	Y	N	N	N	N	–	N
Investment cost, operating and maintenance cost, EV owner profit, DN Operator profit (Kazemi et al., 2016)	2016	GA,LP	Y	Y	Y	Y	N	Y	Y	PL	N
Traveling cost, investment cost, the operation cost of the substations and power loss cost (Xiang et al., 2016)	2016	GA	Y	Y	Y	Y	N	Y	N	L2	N
Investment, operation, electricity and time costs (Zhang et al., 2016)	2016	PSO	Y	Y	Y	Y	N	Y	N	L3	Y
Profit of parking lots, power loss cost, voltage deviation and network reliability (Neyestani et al., 2015)	2015	–	Y	Y	Y	Y	Y	Y	N	L2	N
Power loss, voltage profile and EVs charging costs (Moradi et al., 2015)	2015	DE	Y	Y	N	Y	Y	Y	N	L2	N
Power loss, power from the grid, power from DER and garage charging/discharging cost costs (El-Zonkoly and Dos Santos Coelho, 2015)	2015	ABC, FA	Y	Y	N	N	Y	N	N	L1	N
Construction cost (Lam et al., 2014)	2014	CRO	N	Y	N	N	N	N	N	L3	N
Station development, Station electrification, grid loss and EV loss costs (Sadeghi-Barzani et al., 2014)	2014	GA	Y	Y	Y	N	N	N	N	L3	N
Distribution energy loss cost (Su et al., 2013)	2013	GA	Y	N	N	Y	N	Y	N	L2,L3	N
Grid power loss cost and bus voltage deviation cost (Pashajavid and Golkar, 2013)	2013	PSO	Y	N	N	Y	Y	Y	N	–	N
EVs flow (Xi et al., 2013)	2013	LP	N	Y	N	Y	N	Y	N	L1,L2	N
Power loss cost with DR (Pazouki et al., 2013)	2013	GA	Y	N	Y	N	N	N	N	L3	N
Revenue cost, capital cost, cost of purchased energy, reliability cost and power loss cost (Moradijoz et al., 2013)	2013	GA	Y	Y	Y	N	N	N	Y	L2	N
Voltage sensitivity (Rahman et al., 2013)	2013	Simulation	Y	N	N	N	N	N	N	L1	N

2.4.1. Cost

The cost has been considered as an analytical function in several research studies. As could be seen in Fig. 4, the cost functions can be formulated by using several factors and different approaches as mentioned earlier. The infrastructure cost is a one-time investment associated with the building of EVCSs and it could be further subdivided into land cost, building cost, charger cost, and labor cost. Further, the annual cost of electricity deployed to provide charging service is known as the operating cost. The additional expense paid by EV drivers when moving from the point of charging demand to the EVCS point is known as access cost. The cost of waiting in an EVCS due to the charging availability is known as the waiting time cost. The development cost of CS is defined in Eq. (1) as an objective functions proposed in several research papers (Sadeghi-Barzani et al., 2014; Chen et al., 2021b; Mainul Islam et al., 2018; Battapothula et al., 2019a; Deb et al., 2019; Kong et al., 2019) for the placement of EVCS.

$$DC_i = C_{int} + 25 \times C_{lan} \times S_i + PC \times C_{con} \times (S_i - 1) \tag{1}$$

where C_{int} is an initial cost of EVCS, C_{lan} is a land cost, S_i represents the number of connectors at ith EVCS, and C_{con} is a connector cost.

The traveling cost from charging demand point to EVCS are the prominent cost which was observed by researchers for the

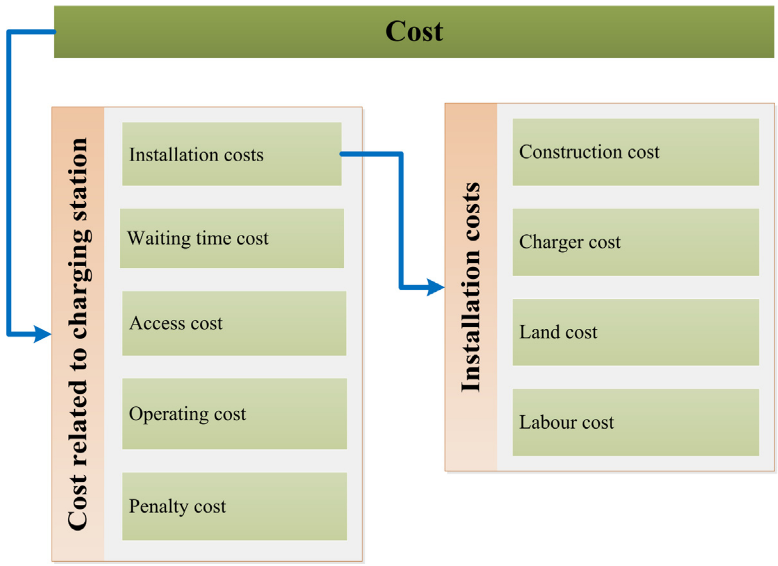

Fig. 4. Cost classification of the objective function for optimal placement of EVCS.

placement of EVCS. According to Eq. (2), the objective function of EV user cost are expressed as below (Battapothula et al., 2019b).

$$EVUC = \sum_{j=1}^{NFCS} \sum_{z=1}^{NZONE} d(z,j) \times SEC \times \sum_{h=1}^{24} CPEV(h) \times NEV(z) \times EP \quad (2)$$

where, $NFCS$ and $NZONE$ are the total numbers of fast-charging stations and the number of zone in the study area respectively, while $d(z,j)$ are the distance from possible charging station location to zone locations, $CPEV(h)$ is the probabilistic set of EV charging in h hours, and SEC is the specific energy consumption of EV.

Further, the annual electricity cost of the fast charging station for optimal placement of FCS is calculated as Eq. (3) which has been formulated by the authors in (Zhang et al., 2016).

$$C_E = \sum_{s\in S} \sum_{i_F=1}^{I_F} \sum_{j\in J_{i_F}} \left(D_s \times \frac{\left(SOC_j^d - SOC_j^a\right) \times B_j}{\eta} \times EC \right) \quad (3)$$

where, D_s is the total number of days, SOC_j^d and SOC_j^a are the departure and arrival SOC respectively, while B_j is the battery capacity of j_{th} PEV, and EC is the cost of electricity per unit in $.

2.4.2. Net benefit

The charging stations could serve as a point of connection between EVs and the power grid. In addition, the V2G allows EVs to provide power to the grid through EVCSs during peak hours. For the planning of V2G-enabled EVCSs, net profit is contributed as the objective function as illustrated in Fig. 5.

The monetary profit earned by EVCSs by purchasing electricity from EV owners instead of the grid at a lower price during peak demand hours is a prime benefit of discharging. EVs support the grid by serving as temporary energy storage by discharging (V2G scheme). In addition, the lower load demand and lower power price at night, charging EVs are more cost-effective. The EVCSs could earn money by providing daytime charging at a better price than night charging. Moreover, the revenue generated in Eq. (4) by EVCSs by supplying electricity to the grid at peak demand hours is a benefit of providing power from the upstream grid (Moradijoz et al., 2013).

$$r(i) = Pr_p \times P_{park}(i) \times t_{dis}(i) \quad (4)$$

where $r(i)$ is the gained total revenue from ith charging station, $t_{dis}(i)$ is total time in which EV battery discharging through V2G facility, Pr_p is the electricity market price at peak hours.

Further, the benefit of improved reliability and voltage profile refers to revenue generated by EVCSs with improved reliability indices and voltage profile as a result of the V2G scheme's implementation given in Eq. (5) (Moradijoz et al., 2013).

$$C_{NS}(j) = \left[\sum_{b=1}^{Nl} C_{inj} \times y_b \times L_b \times \left(\sum_{res=1}^{Nres} P_{res} \times t_{res} + \sum_{rep=1}^{Nrep} P_{rep} \right) \times t_{rep} \right] + C_{equipj} \quad (5)$$

where Nl is the total lines in the network, C_{inj} is the rate of energy not supplied at load j, y_b is the failure rate of branch b, L_b is the length of branch b, $Nres$ is the total nodes which are isolated during the fault, $Nrep$ is the total nodes which are isolated during the fault repair, P_{res} is the loads not supplied during fault, t_{res} is the duration of the fault location, P_{rep} is the loads not supplied during fault repair, t_{rep} is the fault repair time, and C_{equipj} is the energy not supplied cost based on failure in equipment except for branches j.

If a parking lot is located in a distribution system, it could be utilized as an alternate source to restore power for a fraction of the loads that have failed and therefore the distribution system will be improved. The benefit of increased reliability for each year DISCO could be calculated by the Eq. (6) as given in Moradijoz et al. (2013).

$$DC_{NS}(j) = C_{NS}(j) - C_{NSV2G}(j) \quad (6)$$

where $C_{NS}(j)$ is the energy not supplied cost without V2G, and $C_{NSV2G}(j)$ is the energy not supplied cost with V2G.

2.4.3. Other objective functions

Power loss, distance, covered trip, and power supply moment balance index are also considered as objective functions by the researchers when dealing with charging stations placement planning problems, in addition to the above mentioned objective functions. Moreover, the installation of an EVCS adds to the load on the current network. An increment in load would result in a greater loss of electricity. Hence, EVCSs must be strategically

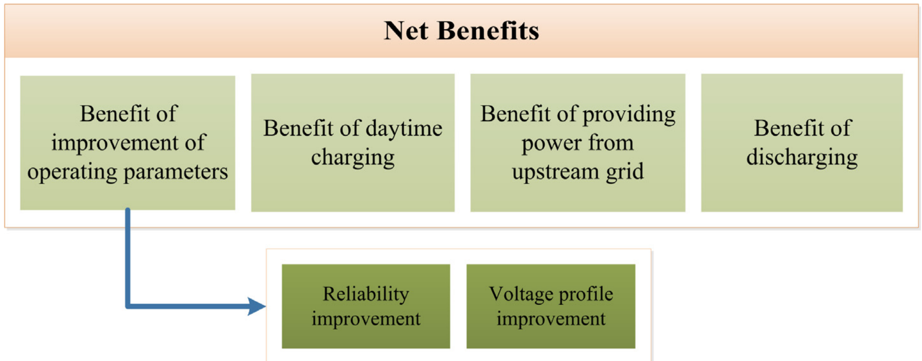

Fig. 5. Benefit review of the implementation of V2G in the placement of EVCS.

located in the distribution network to reduce power loss. In addition, the power loss cost, voltage deviation cost are the main considerations for the placement of EVCS under DNO approach. Therefore, most of the researchers have included power loss cost (Shukla et al., 2019; Zeb et al., 2020; Chen et al., 2021b; Moradi et al., 2015; Pal et al., 2021; Gampa et al., 2020; El-Zonkoly and Dos Santos Coelho, 2015; Battapothula et al., 2019a; Xiang et al., 2016) as the objective function in Eq. (7) and voltage deviation cost (Xiang et al., 2016; Zhang et al., 2016; Faridpak et al., 2019; Moradijoz et al., 2018; Tian et al., 2018) as objective function in Eq. (8).

The Gauss–Siedel method, Newton–Raphson method and Fast-Decoupled method, backward forward sweep algorithm, direct approach based algorithm are utilized for the power flow analysis (Garces, 2016; Kawambwa et al., 2021; Sereeter et al., 2017; Rupa and Ganesh, 2014). Many works of literature have used backward forward sweep algorithm and its improved version (Petridis et al., 2021) for power flow analysis due to its various advantages.

$$P_{loss}^{c} = E_c \sum_{i=1}^{Nb} \sum_{j=1}^{Nb} G_{ij}(V_i^2 - V_j^2 - 2V_iV_j cos(\theta_{ij})) \tag{7}$$

where, E_c is the electricity cost in \$, Nb is the number of bus, G_{ij} is the conductance of line between i^th bus to j^th bus, V_i is the ith bus voltage, θ_{ij} is the load angle difference, UD^t is the voltage deviation at time t, U_{bu}^t is the voltage of bu^{th} bus at time t.

$$UD^t = \sum_{t=1}^{24} \sum_{bu=1}^{N_{bu}} abs(1 - U_{bu}^t) \tag{8}$$

The power supply moment balance is an indicator that determines the deviation and the degree of power supply dispersion. Further, a higher value of this index indicates less power supply fluctuation, less power loss, and improved system reliability. Therefore, when formulating the charging infrastructure planning problem, the minimization of the power supply moment balance index must be considered.

2.5. Constraints

The charging station location planning problem is performed under a set of equality and inequality constraints as illustrated in Fig. 6. The voltage limits at each bus, current flow limits, and thermal limit must all be accomplished after EVCSs are installed in the distribution network. It is also necessary to determine the minimum and maximum number of EVCSs that will be installed. Furthermore, EVCSs should not be installed closely. The distance restriction takes into account the distances between EVCSs.

Voltage constraints: the authors applied an inequality limit of voltage at buses which is given in Eq. (9). Where V^min and V^max are the minimum and maximum value of voltage limits respectively at j^th bus (Awasthi et al., 2017; Chen et al., 2021b).

$$V_j^{min} < V_j < V_j^{max} \tag{9}$$

Active and reactive power constraints: active and reactive power at distribution system should be balanced (Awasthi et al., 2017; Chen et al., 2021b; Deb et al., 2021, 2019) therefore an equality constraints of the power is formulated by the researchers as determined in Eqs. (10) and (11). Where P_{gi} and Q_{gi} are the active and reactive power obtained from the grid respectively, P_{di} and Q_{di} are the total active and reactive power demand of distribution system respectively, while V_i and V_j are the voltages of i_{th} and j_{th} bus respectively, Y_{ij} is the admittance of line from ith bus to jth bus.

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N} V_jY_{ij}cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{10}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N} V_jY_{ij}cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{11}$$

Power inequality constraints: A limit is imposed on the minimum and maximum value of the real and reactive power (Awasthi et al., 2017; Chen et al., 2021b; Deb et al., 2019) on the ith bus as given in Eqs. (12) and (13).

$$P_{gi}^{min} \leqslant P_{gi} \leqslant P_{gi}^{max} \tag{12}$$

$$Q_{gi}^{min} \leqslant Q_{gi} \leqslant Q_{gi}^{max} \tag{13}$$

Branch current constraints: the current in every branch of distribution network should be followed maximum limit (Pal et al., 2021) as expressed in Eq. (14).

$$I_{br} < I_{br}^{max} \tag{14}$$

SOC of battery: to keep battery health of EV the maximum and minimum SOC should be maintained (Pal et al., 2021) during charging and discharging as given in Eq. (15).

$$25\% \leqslant SOC \leqslant 90\% \tag{15}$$

3. Review of the techniques to solve the optimal location problem of EVCS

Optimization techniques are deployed to minimize or maximize the cost function of the formulated optimization problem. There are many optimization techniques available that could

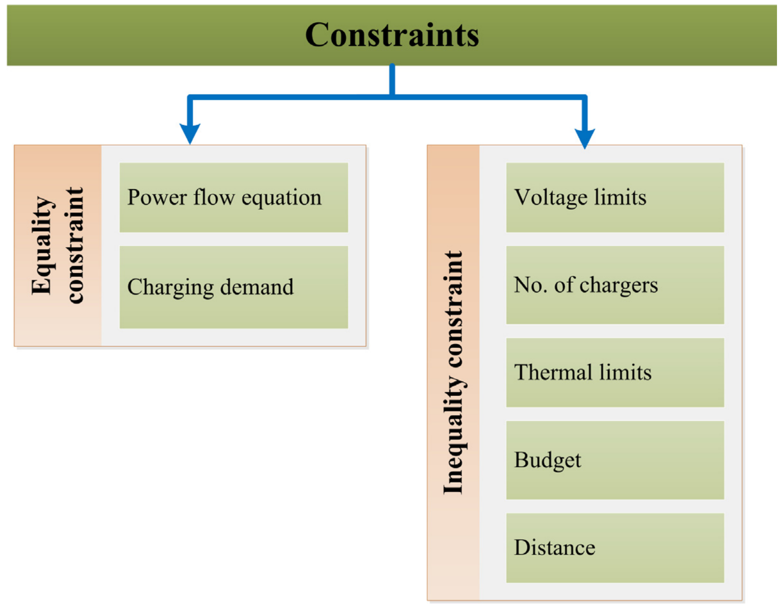

Fig. 6. Constraints for problem formulation of EVCS placement.

optimize the cost function as shown in Fig. 7. In particular, the formulated optimization problems for the placement of EVCS can be a single objective or multi-objective, linear or nonlinear, convex or concave. According to the used variables, the formulated problem can be continuous, integer, discrete, and combination. Therefore, the right selection of optimization techniques for the particular problem is a critical decision. In this paper, the authors give a short review of some optimization techniques for the optimal location of EVCS. In addition, classical and advanced optimization are the two main categories of optimization techniques.

Classical optimization techniques are useful in finding the optimum solution or unconstrained maxima or minima of continuous and differentiable. Further, the classical methods have a limited scope in practical applications as some of them involve objective functions which are not continuous and/or differentiable.

Advance optimization techniques multi-modality, dimensionality, and differentiability are connected with the optimization of large-scale problems, where the classical techniques fail to solve such large-scale problems. Most of the classical techniques require gradient information and hence it is not suitable to solve non-differentiable functions with such techniques. Moreover, classical techniques often fail to solve optimization problems that have many local optima. However, advanced optimization techniques overcome these issues to solve the optimization problem.

3.1. Single objective optimization techniques

The solution of single-objective optimization problem is simple against the solution of multi-objective problem. therefore, classical and advanced optimization algorithms are used to solve the single objective optimization problems.

3.1.1. Genetic algorithm

As the name implies, genetic algorithms (GA) mimic the genetic aspect of candidate populations to improve existing set selection. To apply a GA to a problem, careful design choices must be created to adapt the algorithm to the problem. In fact, the ability of the algorithm to find the right result is directly influenced by the gene-encoding system, its cross-over process, and fitness functions. A large pool of diverse data is also needed to ensure that the algorithm does not get stuck in local minima. This is usually accomplished by selecting genes for a crossover at random, which results in a slower convergence rate while ensuring exploration. When increasing the population size improves the solution of the GA, it also dramatically increases the computation time, even if the improvement in the solution is minor. In Xiang et al. (2016), traveling cost, investment cost for EVCSs, the operation cost of the substations and power loss cost are the objective functions to formulate the problem for placement of EVCS and problem solved by GA. Eventually, in Sadeghi-Barzani et al. (2014) an MINLP is formulated which is solved by GA.

3.1.2. Simulated annealing

The name and inspiration from the annealing process in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. In the simulated annealing method, each point of the search space is compared to a state of some physical system, and the function to be minimized is interpreted as the internal energy of the system in that state. Therefore, the goal is to bring the system, from an arbitrary initial state to a state with the minimum possible energy (Eren et al., 2017).

3.1.3. Particle swarm optimization

Particle Swarm Optimization (PSO) is another common and efficient algorithm that optimizes performance by real number randomness and global communication among particles. The swarm of possible solutions (particles) scour the search space for the right solutions, constantly exchanging and reviewing the personal and global bests. In fact, each particle flies in a path vector derived from its personal best and global best at the start of each iteration, ultimately converging into the global optima. Recently, some improvements to the original PSO were made to enhance computing time and provide more precise solutions, IPSO. In Reddy and Selvajyothi (2020b), EVCS and DER are placed at an optimal RDS location, power loss is considered as an objective function for the optimization problem and solved by the PSO algorithm.

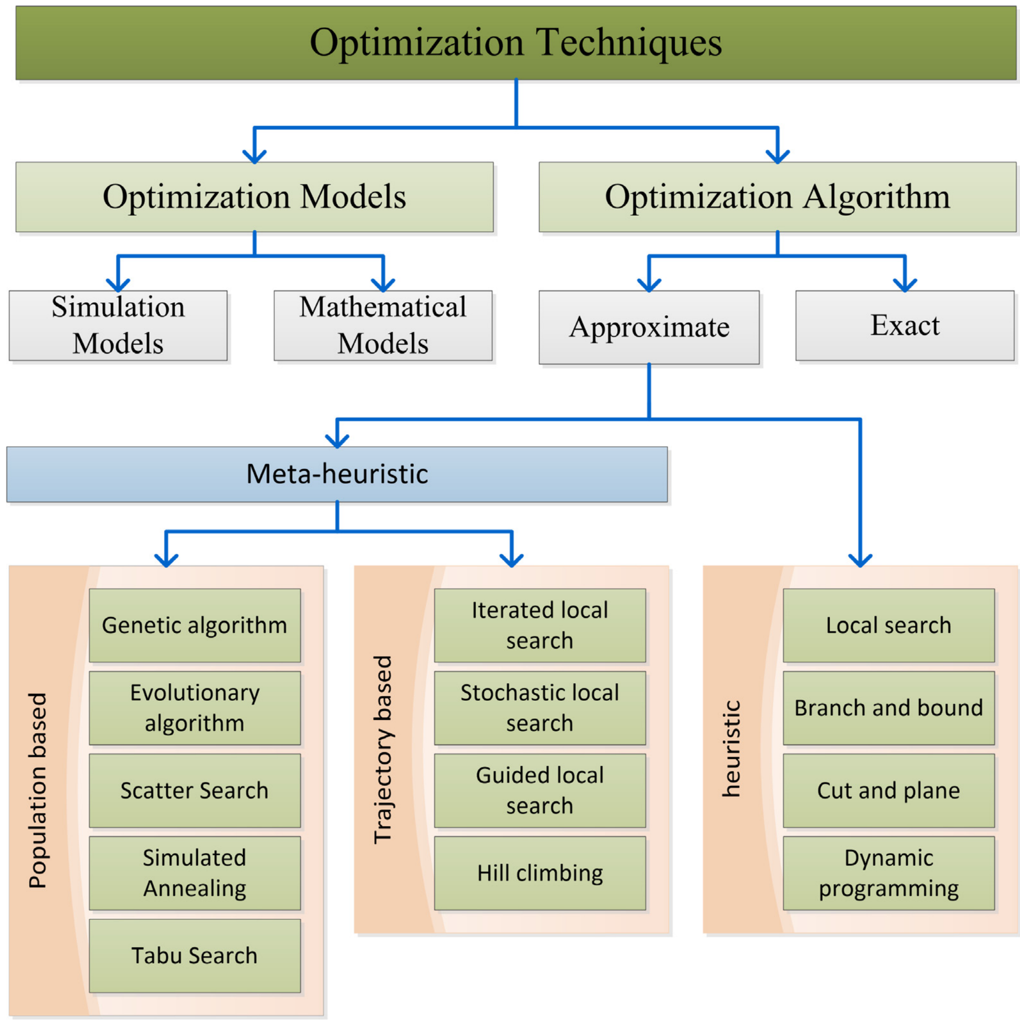

Fig. 7. Classification of optimization techniques.

3.1.4. Teaching–learning based optimization algorithm

The teaching–learning based optimization (TLBO) algorithm is a teaching–learning process inspired algorithm based on the effect of the influence of a teacher on the output of learners in a class. Further, the algorithm describes two basic modes of the learning: (i) through teacher known as teacher phase) and (ii) through interaction with the other learners (known as the learner phase). a hybrid CSO and TLBO algorithm are used for optimal location of EVCS in which three objective functions include EVCS cost, cost of voltage deviation, reliability of the system, power loss, and the other one accessibility of EVCSs index.

3.1.5. Gray wolf optimization

Mirjalili et al. (2014) is the creator of gray wolf optimization (GWO). The natural habit and hunting technique of gray wolves inspire the author. Moreover, gray wolves have a different leadership structure within their packs. The alpha wolf is the leader of the group members. Gray wolves are at second position in the following category. They make lives easier for alphas. They are referred to as beta wolves. Delta wolves are valued less than alpha and beta wolves. Their goal is to submit to alpha and beta wolves while still maintaining influence over omega wolves. The omegas are the wolves with the lowest importance since they must obey the leadership gray wolves.

3.1.6. Artificial bee colony algorithm

The artificial bee colony (ABC) algorithm was created by simulating the behaviors of real bees when it comes to seeking food sources, such as nectar, and sharing the knowledge with the other bees in the hive. In particular, the ABC is made up of three different types of bees: employed bees, onlooker bees, and scout bees. By flying around in a multi-dimensional search space that represents the solution space, each of them plays a different role in the process. In El-Zonkoly and Dos Santos Coelho (2015), ABC algorithm and FA, approaches are used to find the optimal parking lots in the distribution system by minimizing the power loss cost, power from grid cost, power from DER cost, and garage charging/discharging cost.

3.2. Multi-objective optimization techniques

There are two basic approaches for multi-objective optimization techniques: a **posteriori** vs a **priori**. In a priori approach, multi-objective optimization problem is changed to a single-objective one by aggregating the objectives. Further, a set of weights specifies how significant the objectives are and how often given by a problem domain expert. However, one of the primary disadvantages of such approaches is that an algorithm must be run multiple times to identify the Pareto optimum set. Furthermore, expert consultation is required, and some particular Pareto optimum fronts cannot be identified by this method (Mirjalili et al., 2017).

The posterior techniques derive from the ability to maintain multi-objective formulations of multi-objective problems and

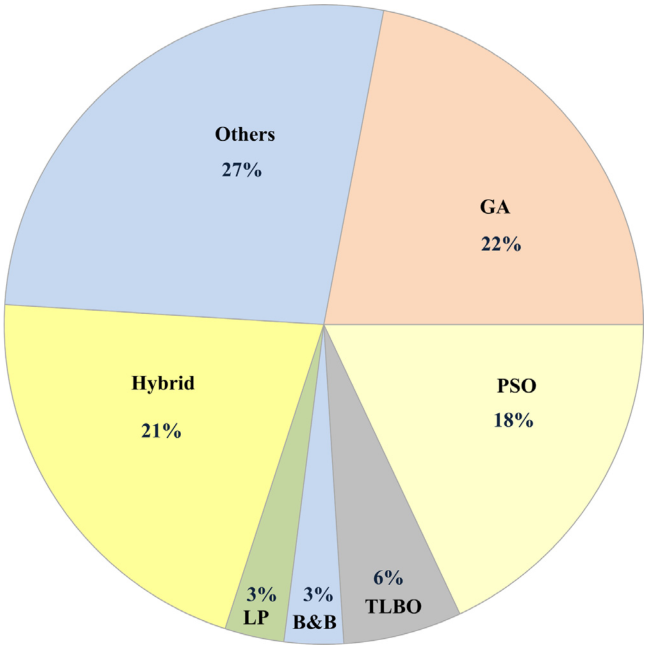

Fig. 8. Optimization techniques analysis in literature.

identify the Pareto optimum set in a single run. Another advantage is that these methods may be used to determine any type of Pareto front. However, they require a greater computing cost and the simultaneous pursuit of several objectives (Mirjalili et al., 2017).

3.2.1. Non-dominated sorting genetic algorithm-II

Non-dominated sorting genetic algorithm II (NSGA-II) is an efficient meta-heuristic multi-objective genetic algorithm that is commonly deployed to solve multi-objective optimization problems in applications such as facility distribution, supply network architecture, and congested facility location. The NSGA-II divides the population into several non-dominated chromosome fronts, where every set's chromosomes are ranked according to their diversity. In addition, the multi-objective function is formulated by considering EVCS development cost, cost of specific energy consumption of EVs, electrical network power loss cost, DER power generation cost and maximum voltage deviation for placement of EVCS and DER in the distribution network and solved by NSGA-II (Battapothula et al., 2019b).

3.2.2. Multi-objective colliding optimization algorithm

Colliding bodies optimization (CBO) is a population-based evolutionary method that mimics the rules of object collision (Kaveh and Mahdavi, 2014). The CBO has investigated positive results for a wide range of constrained and unconstrained benchmark functions, as well as engineering single-objective problems. This algorithm formulation is simple as it consumes no memory and requires no parameter tuning. Recently, a simplified multi-objective CBO (Kaveh and Mahdavi, 2019) technique based on non-dominated sorting was developed for optimizing the building material prices of reinforced concrete structural components and carbon dioxide emissions.

3.2.3. Multi-objective ant lion optimizer

A new meta-heuristic multi-objective ant lion optimization (MOALO) algorithm proposed by Mirjalili et al. (2017) to solve the multi-objective problem. Further, it mimics the natural interactions of ants and antlions. Antlions are a type of predatory bug that belongs to the Myrmeleontidae family that feeds on ants. Moreover, antlions excavate trenches in the sand and hide beneath the sand to await their preferred food, which they subsequently consume with their massive jaws. To understand the complete mathematical modeling of MOALO algorithm, it is important to understand first the modeling of single objective ALO which was proposed in Mirjalili (2015). The GA, PSO, and hybrid algorithms have been widely utilized in literature to address optimization problems, as could be seen in Fig. 8.

4. Review analysis of EVs load impact

Fig. 9 shows how the effects of EV integration could be categorized. The first category is the effect of EV load on distribution network parameters, followed by the environmental and economic impacts. Fig. 9 also represents the positive and negative impacts of EV load integration on the distribution network, with details on each form of impact is expressed below.

4.1. Impact of EVs load on distribution system

The current distribution system faces numerous problems as EV charging infrastructure expands. In recent years, these issues have been carefully assessed. EV impact analysis is primarily defined in the current literature to assess the effects of EVs on electricity generation adequacy, transformer aging, and distribution system power efficiency. In fact, it is possible that EV charging during peak load hours would increase peak load demand, requiring the expansion of generation capability. Furthermore, increased EV load demand would overload substation and service transformers, shortening their lifespan. Moreover, EV charging can cause voltage drops, power unbalances, and voltage/current harmonics, among other power quality issues.

4.1.1. Negative impacts

Impact on the power quality of the distribution system. Power quality refers to a power grid network's ability to provide a reliable and clean power supply with a sinusoidal waveform and noise-free voltage and current harmonics. In particular, harmonics and voltage sag/swelling are two typical power quality issues. When connecting to the grid, EV chargers are the components that cause these issues. According to IEEE standard 519, the total harmonics distortion (THD) value for up to 69 kV power networks should be less than 5% to preserve power quality. According to this study, the harmonic disturbances would be higher when the EV chargers are connected to the grid and distribution network. The THD is around 4.82 percent for single EVs attached to the device, 12.35 percent for three EVs, and 19.69 percent for five EVs with different configurations (Karmaker et al., 2019; Ahmed et al., 2021).

Impact on the voltage. This section discusses the effects of PEV integration on voltage change, which affects the efficiency of the power delivered to consumers. When EV load is added to the existing distribution system, the voltage drop at buses is related to charging. With regards to literature, in certain places, the voltage drop reported is less than 96 percent of the nominal voltage. As a result, system enhancements are required. In [73], various charging rates show a voltage deviation of 12.7 percent to 43.3 percent from rated voltage with 20 percent and 80 percent PEV penetration (Deb et al., 2018).

Impact on power loss. When considering the future demand generated by gradual PEV grid integration, power system losses

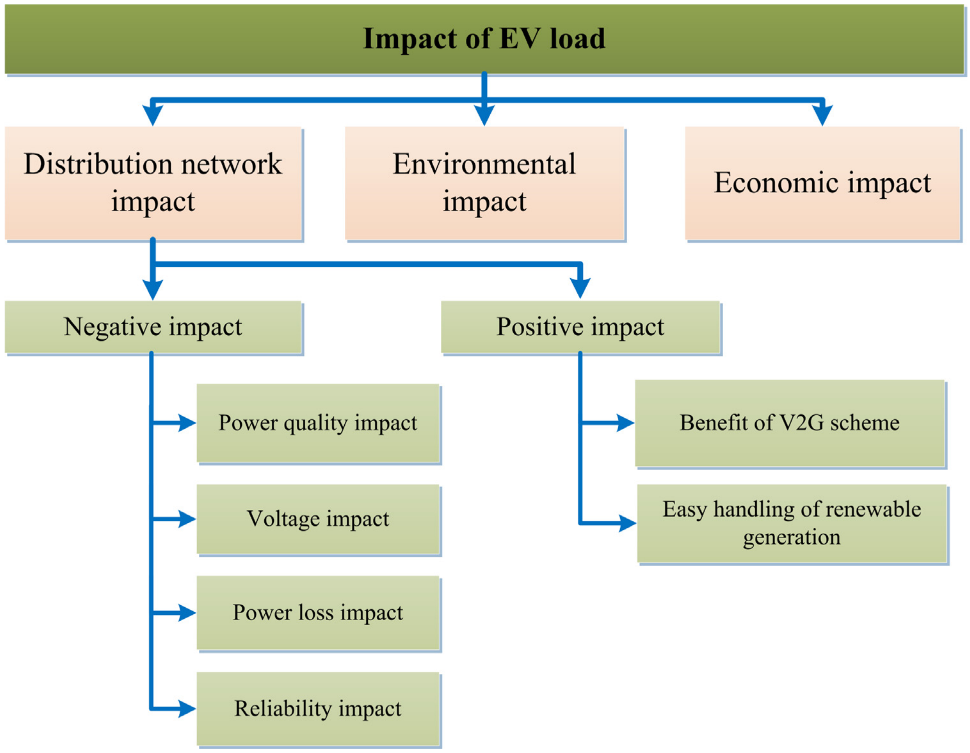

Fig. 9. EV load impact classification.

become a major concern. According to Ref. Dharmakeerthi et al. (2011), energy losses in off-peak charging could increase by up to 40 percent, for 62 percent of PEV market penetration. According to the researchers, network power losses increased significantly as PEV penetration is increasing (Deb et al., 2018). The increment of power loss could be minimized up to certain limits by applying the optimal location of EVCS process.

Impact on the reliability of distribution network. The reliability analysis of the distribution network has been a challenging area of research in recent years. Specifically, the distribution network's reliability indices are calculated by statistical data on failure rate, repair rate, average outage duration, and the number of consumers (Deb et al., 2020). Furthermore, the bus reliability index is a metric used to assess the reliability and vulnerability of each distribution network bus. In fact, the stability of the entire distribution network is measured by system reliability indices. Customer and energy-oriented reliability indices are subsets of system reliability indices. Customer-oriented reliability indexes are primly named SAIFI, SAIDI, and CAIDI. SAIFI is defined as the number of times a system customer experiences interruption during a particular period, while the average interruption period per customer served is specified by SAIDI. In addition, SAIDI depends on the duration of the failure as well as the number of customers (Deb et al., 2018).

4.1.2. Positive impacts

Benefit of V2G scheme. The V2G deployment of EVCSs has several advantages, including lower costs for EV users, lower costs for EVCS operators, and smoother EVCS load curves. In fact, the key contribution of the V2G scheme is the transferring of vehicle battery energy to the grid at peak hours and the charging of the battery at off-peak hours. Further, the revenue generated by V2G power is determined by the form of electricity demand to which sold demand. For markets that only pay for electricity, such as peak power, revenue is the product of price and energy dispatched. In addition, V2G capacity would provide a portion of peak power, reducing the grid's requirement to purchase electricity on the wholesale market. As a result, cost savings could be formulated in Moradijoz et al. (2013) by providing loads of V2G power rather than purchasing power from the wholesale market.

Easy handling of renewable generation. Due to the intermittency of renewable energy generation, power providers are dealing with difficulties when integrating huge amounts of renewable energy supplies into their grids. However, the EV charger's fast-responding control electronic interface, together with the battery storage, reveals a practical solution for source intermittency. The study's most positive customer is that when EV participated in primary frequency control, the system was capable of handling wind integration up to 59 percent of total grid generation ability. On the other hand, it is possible to utilize certain solar energy for charging the EV. Moreover, it measures the energy requirements of a mid-sized sport utility vehicle based on a regular driving range of 40 miles, which is common in North America. In addition, the energy demand for all-electric mode driving and frequent charging is estimated to be 15–17 kWh. With respect to the normal average solar radiation year-round in Alberta, Canada, the derived panel sizes are 20 m^2 and 78 m^2 for the best and worst day solar radiation, respectively.

4.2. Environment impact of EVs integration with grid

Instead of using gasoline based on conventional technology, the power demand of EVCS for EVs is served by a distribution network, which limits carbon emissions. Moreover, the large-scale integration of green energy systems to charge an EV battery world further reduce pollutant emissions. Generally, all-electric cars emit an average of 4450 pounds of CO_2 equivalent each year as well-to-wheel emissions are also considered (Chen et al., 2021a). On the other hand, conventional diesel engines could emit more than twice as much annually. In addition, the amount of well-to-wheel pollution your EV produces is primarily determined by the location and the most widely used energy sources for electricity.

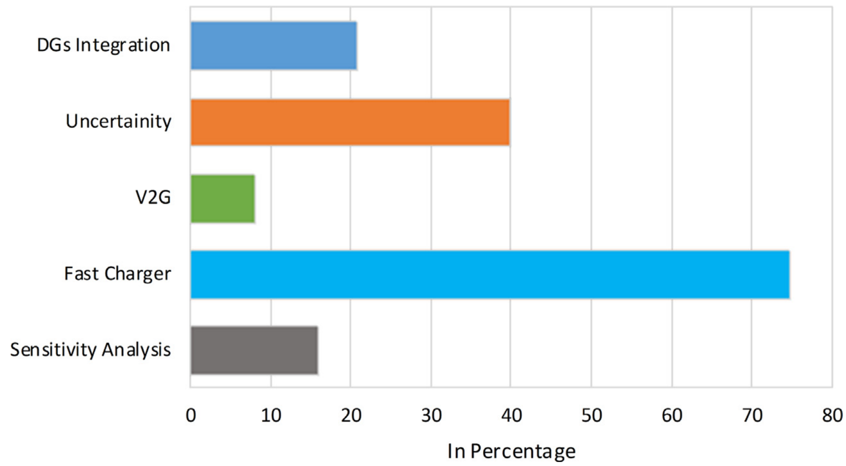

Fig. 10. Analysis of DGs integration, uncertainty, V2G, fast charger, sensitivity analysis in literature.

4.3. Economic impact of EVCS load

The economic impacts of EVs could be seen from two perspectives: the EV owner and the utility provider. In particular, the cost of an EV is also high as compared to an ICE vehicle. On the other hand, because of the higher efficiency of electric motors, EVs consume less fuel and low maintenance costs than ICE vehicles. In addition, the average ICE vehicle's efficiency ranges from 15% to 18%, while the efficiency of EV fluctuates from 60% to 70%. The EV owner would benefit from the V2G concept if it transfers the battery's stored energy to the distribution network. According to research (Dharmakeerthi et al., 2011), EV fleets will save fundamental power system costs between USD 200–300 per vehicle per year.

5. Summary and discussions

It has been found that different optimization approaches were utilized to determine the best solution for EVCSs placement. Table 3 offers a comparative overview of different optimization approaches defined in EVCS placement problems in this context. Furthermore, various researchers have considered different approaches for optimal location EVCS. These methods are dependent on the choice of objective functions, constraints, solution mechanisms. According to Fig. 10, the available literature primarily defines that different approaches determine the problem formulation of optimal location of EVCS. In fact, these approaches are the DNO approach, CSO approach, EV user approach and combination of given approaches. According to the literature, 15.2% of the study is focused on the DNO approach deployed to position, while 6.52% of the study was focused on the CSO approach for EVCS placement. Previous studies were focused on EV user approach has a proportion of 4.35% and the combination of DNO with CSO has 32.6%, CSO with EV user consist of 15.22%, EV user with DNO is 2.17% whereas the combination of three is 26.1% considered for problem formulation of EVCS placement as shown in Fig. 10. According to Table 2, researchers use a variety of techniques to address the issue of EVCS placement. The two prime techniques used by researchers for problem-solving are GA and PSO. The other techniques of the authors to solve the problem could be introduced as ACO, ABC, TLBO, LP, greedy algorithm, GWO, GOA, branch and bound, and a detailed analysis is given in Table 4. Further, the Literature survey of voltage, power quality, power loss, reliability impact of the distribution system is also analyzed in this study. In addition, the past studies provide a review of the DGs integration, uncertainty, V2G scheme, rapid charger, and sensitivity analysis. Therefore, the percentage of all evaluated factors for every observed paper that is reviewed for charging station location is illustrated in Fig. 11.

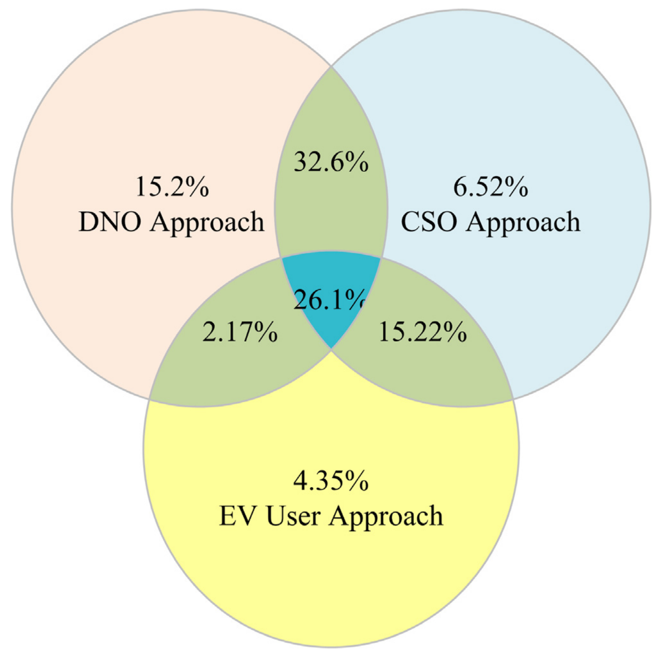

Fig. 11. Analysis of different approaches.

6. The challenges faced and future research directions

Electric vehicle charging station research is vital, yet it is still in its early phases. EVs, for example, now account for a smaller proportion of all vehicles in the globe. Furthermore, due to the early stage of development, data on electric vehicles and charging stations is limited. Secondly, technology in the field of electric vehicles and charging stations is constantly evolving. Furthermore, the country that is more reliant on fossil fuels lacks the confidence to embrace the EV. These are the primary research challenges. On the other hand, future research directions related to this review paper include optimal placement and sizing of charging stations for coupled distribution and transportation networks, optimal placement of EVCS with renewable energy sources, consideration of V2G for EVCS placement, integration of EVCS loads for power management problems in the grid, and

Table 3
Review of the objective function and constraints considering different approaches for placement of EVCS.

Attributes		References	DNO approach	CSO approach	EV user approach
Objective functions	Power loss	Shukla et al. (2019), Zeb et al. (2020), Chen et al. (2021b), Moradi et al. (2015), Pal et al. (2021), Gampa et al. (2020), El-Zonkoly and Dos Santos Coelho (2015), Battapothula et al. (2019a), Xiang et al. (2016), Deb et al. (2020), Pazouki et al. (2013), Sadeghi-Barzani et al. (2014), Mohsenzadeh et al. (2018), Battapothula et al. (2019b), Awasthi et al. (2017), Reddy and Selvajyothi (2020a,b), Gupta and Narayanankutty (2020), Amini et al. (2017), Pashajavid and Golkar (2013), Hashemian et al. (2020), Su et al. (2013), Zhang et al. (2018), Mozafar et al. (2017), Deb et al. (2019), Simorgh et al. (2018), Neyestani et al. (2015), Moradijoz et al. (2013), Faddel et al. (2018) and Jiang et al. (2018)	Y	N	N
	Voltage deviation	Chen et al. (2021b), Moradi et al. (2015), Pal et al. (2021), Battapothula et al. (2019a), Awasthi et al. (2017), Mozafar et al. (2017), Deb et al. (2019), Rahman et al. (2013), Deb et al. (2021), Faddel et al. (2018) and Jiang et al. (2018)	Y	N	N
	Investment cost	Xiang et al. (2016), Zhang et al. (2016), Faridpak et al. (2019), Moradijoz et al. (2018), Tian et al. (2018), Simorgh et al. (2018) and Moradijoz et al. (2013)	N	Y	N
	Installation cost	Chen et al. (2021b), Mainul Islam et al. (2018), Battapothula et al. (2019a), Sadeghi-Barzani et al. (2014), Deb et al. (2019), Kong et al. (2019), Deb et al. (2021) and Lam et al. (2014)	N	Y	N
	Connection cost	Simorgh et al. (2018)	N	Y	N
	Traveling cost	Xiang et al. (2016), Sadeghi-Barzani et al. (2014), Tian et al. (2018), Zhang et al. (2020), Othman et al. (2020), Deb et al. (2021) and Jiang et al. (2018)	N	N	Y
	Charging cost	Moradi et al. (2015), Zhang et al. (2016) and Moradijoz et al. (2018)	N	Y	Y
	Transportation cost	Mainul Islam et al. (2018)	N	N	Y
	Waiting time cost	Zhang et al. (2016), Tian et al. (2018), Ma and Zhang (2018) and Jiang et al. (2018)	N	N	Y
	Operating cost	Xiang et al. (2016), Awasthi et al. (2017), Zhang et al. (2016), Deb et al. (2019), Kong et al. (2019), Ma and Zhang (2018) and Deb et al. (2021)	N	Y	N
	Maintenance cost	Awasthi et al. (2017)	Y	Y	N
	Reliability cost	Amini et al. (2017), Deb et al. (2019) and Moradijoz et al. (2013)	Y	N	N
	Land cost	Chen et al. (2021b), Pal et al. (2021), Awasthi et al. (2017) and Amini et al. (2017)	N	Y	N
	Net benefit of V2G	Xi et al. (2013) and Moradijoz et al. (2018)	N	Y	Y
	EV flow	Pal et al. (2021) and Wang et al. (2018)	N	Y	N
Constraints	Thermal limit	Shukla et al. (2019), Zeb et al. (2020), Chen et al. (2021b), Battapothula et al. (2019b), Su et al. (2013) and Deb et al. (2020)	Y	N	N
	Distance	Kong et al. (2019) and Simorgh et al. (2018)	N	N	Y
	Voltage limit	Shukla et al. (2019), Zeb et al. (2020), Chen et al. (2021b), Battapothula et al. (2019b) and Su et al. (2013)	Y	N	N
	Number of chargers	Zeb et al. (2020), Pal et al. (2021) and Simorgh et al. (2018)	Y	Y	N
	Power flow equation	Shukla et al. (2019), Chen et al. (2021b), Battapothula et al. (2019b), Pashajavid and Golkar (2013), Su et al. (2013), Deb et al. (2020) and Deb et al. (2021)	Y	N	N
	Charging demand	Pashajavid and Golkar (2013) and Simorgh et al. (2018)	Y	N	N

forecasting of EVCS load. The following are the possible research directions in this area.

6.1. Integration of renewable energy with EVCS placement

The literature has already proved the advantages of integrating renewable energy, the capacity of solar energy and wind energy generation could be increased by using EV load in the grid. Due to the intermittency of renewable energy generation, power providers are facing difficulties when integrating vast amounts of renewable energy supplies into their grids. However, the EV charger's fast-responding control electronic interface, together with its battery storage, could control such source intermittency.

6.2. Multi-objective problem formulation using different approaches

The current research on charging infrastructure planning indicates that the challenge has a wide range of behaviors. Certain shortcomings have been found with the problem formulation. Multi-objective functions such as running costs, construction costs, durability indexes, waiting time costs, and so forth must be included in the problem formulation. When defining the targets, reliability indexes such as average system interruption period, system average interruption duration, and system average interruption frequency index should be inserted. In addition, the intermittent parameters should be included for EV flow, TN, and EV load demand.

6.3. Techniques to solve the problem of EVCS placement

It has been observed that the majority of researchers have utilized GA and PSO to solve the problem of EVCS positioning. However, for a better approach to the EVCS problem, other techniques such as gray wolf optimization, teaching–learning based optimization, grasshopper optimization, spider monkey optimization, game theory, artificial intelligence, machine learning could be added.

6.4. Future technologies related to charging station

Vehicle to grid is a crucial component of EV charging energy management, allowing for two-way energy exchange between the vehicle and the grid. V2G allows energy stored in an EV to be supplied back into the grid during peak demand periods, reducing strain on the grid. Furthermore, Wireless EV charging might provide the impetus for widespread adoption of electric vehicles. Vehicles may automatically charge while parked at designated pick-up/drop-off areas using a high-powered wireless EV charging system. Moreover, Charging vans, portable chargers, and temporary chargers are examples of mobile charging, where

Table 4
Review analysis of optimization techniques for the placement EVCS problem.

Techniques	References where techniques is used	Origin of techniques	Benefits	Challenges
Genetic algorithm (GA)	Sadeghi-Barzani et al. (2014), Ren et al. (2019), Mohsenzadeh et al. (2018), Su et al. (2013), Xiang et al. (2016), Wang et al. (2018), Awasthi et al. (2017), Zhu et al. (2016), Luo and Qiu (2020), Pazouki et al. (2013), Ren et al. (2019) and Moradijoz et al. (2013)	Natural process of evolution of new offspring from a set of the randomly generated population by the process of selection, crossover, and mutation.	Easy to implement; more suitable for placement problems.	Takes a long time to solve the placement and sizing problem.
Particle swarm optimization (PSO)	Zhang et al. (2016), Pashajavid and Golkar (2013), Simorgh et al. (2018), Amini et al. (2017), Reddy and Selvajyothi (2020a), Zeb et al. (2020), Mozafar et al. (2017), Reddy and Selvajyothi (2020b), Gupta and Narayanankutty (2020) and Awasthi et al. (2017)	Optimization algorithm inspired by the natural phenomenon of bird flocking.	Simple computation and the ability to find near-optimal solution.	Premature convergence; higher possibility to get stuck in local optima.
Gray wolf optimization (GWO)	Shukla et al. (2019)	GWO mimics the leadership hierarchy and hunting mechanism of gray wolves in nature.	Tackle unconstrained as well as constrained and multi-objective problems.	Low solving accuracy, bad local searching ability and slow convergence rate.
Teaching–learning based optimization (TLBO)	Battapothula et al. (2019a), Deb et al. (2020) and Deb et al. (2019)	Based on the effect of the influence of a teacher on the output of learners in a class.	Not requiring any parameter of the algorithm for its operation.	Computation time is more and more space is required.
Branch and bound (B&B)	Zhang et al. (2018)	The set of candidate solutions is thought of as forming a rooted tree with the full set at the root.	Generally, it will inspect fewer sub problems and thus saves computation time.	Normally it will require more storage.
Artificial bee colony (ABC)	El-Zonkoly and Dos Santos Coelho (2015)	It was inspired by the intelligent foraging behavior of honey bees.	Simplicity and proper exploration ability.	It suffers from improper exploitation in solving complicated problems.
Linear programming (LP)	Xi et al. (2013) and Faridpak et al. (2019)	–	Simplicity; solves many diverse combinations of problems.	Only works with linear variables; it cannot potentially solve stochastic problems.
CPLEX optimization software package	Zhu et al. (2018)	It was inspired by the intelligent foraging behavior of honey bees.	Efficiently solves linear, convex, or non-convex constrained problems.	Difficulty in modifying optimization routines.

the chargers themselves are "on the go" and do not require infrastructure expenditures.

7. Conclusion

The location of the electric vehicle charging station might affect the distribution network's parameters, as well as the investor's attitude due to investment and profit. Furthermore, the position of EVCS influences the EV user's decision to charge. Therefore, research articles on optimal locations for charging stations are examined under three approaches: distribution network operator, charging station owner, and electric vehicle user. In the literature, many papers have analyzed and evaluated the problem formulation, approaches, objective functions, and constraints to determine the best location for the charging stations. Moreover, this article addresses objective functions and constraints for problem formulation, EV load modeling, handling of uncertainty, integration of renewable energy sources, solution techniques, charging level, sensitivity analysis, used approaches, and V2G strategy. Furthermore, the authors addressed optimization strategies for tackling the given issue, and the authors obtained better results via the metaheuristics algorithm, as previously mentioned. Eventually, the impact of charging stations load on the distribution network is also analyzed in this review article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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