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* **Corresponding author**.

saigoutham248@gmail.com

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Optimal Location of EV Charging Stations in the Distribution System Considering GWO Algorithm

Sai Goutham Golive[1]*, B Paramasivam[2], J Ravindra[3]

1 Research Scholar, Department of Electrical & Electronics Engineering, Annamalai University, Chidambaram, Tamil Nadu, India
2 Associate Professor, Department of Electrical & Electronics Engineering, Annamalai University, Chidambaram, Tamil Nadu, India
3 Assistant Professor, Department of Electrical & Electronics Engineering, Bapatla Engineering College, Andhra Pradesh, India

Abstract

Objectives: The transition from conventional vehicles to electric vehicles (EVs) has been significantly influenced by the current scarcity of fossil fuels and the environmental concerns surrounding greenhouse gas emissions. The exploration of the optimal location of electric vehicle charging stations has been prompted by the electrification of the transportation system and the increasing demand for EVs. **Methods:** One of the main challenges is the detrimental impact of improper positioning of charging stations on the power distribution network. The Grey Wolf Optimization (GWO) approach is used to determine the effective Charging Stations (CS) locations to minimize the losses, which is the major objective of the proposed technique. An IEEE 33 bus system is used to implement the suggested technique. **Findings:** The proposed method finds the suitable deployments for EVCS within the distribution system, which is of utmost importance due to the constraints imposed by limited battery capacity and prolonged charging periods. This article proposes the optimal location for EVCS to minimize losses inside the distribution network. **Novelty:** The effectiveness of the proposed GWO is evaluated by comparing it with the PSO optimal algorithm. Finally, a comparison of system voltage and nominal voltage is presented and the probability comparison of EV location with the base case and the proposed algorithms is presented.

Keywords: Electric Vehicle Charging Station; Distribution System; GWO; System and Nominal Voltage

1 Introduction

The electrification of the transportation sector has been brought in by the growth of battery technology advancements, which have been driven by concerns over environmental pollution and the increasing demand for energy. This development marks a significant turning point in the field. Based on research conducted by Business Intelligence and Strategy (BIS), it has been projected that the EV market is expected to witness significant growth over the forecast period from 2019 to 2030, with a Compound Annual Growth Rate (CAGR) of 43.13% [1]. But, grid operators have enormous potential and problems with rising charging demand due to the proliferation of EVs and the fast expansion of EV markets in the transportation industry. Minimizing operational risk when deploying vast amounts of EVs requires optimal planning and supervision of the current distribution networks. The improper use of EVs in the distribution network, on the other hand, may have a negative impact in terms of voltage deviations that are outside of allowed limits, increases in power loss, and a reduction in power quality [2]. The increasing importance of strategic EVCS planning is evident based on the aforementioned reasons. The examination of the impact of EVs on the power grid becomes imperative as the demand for electricity escalates with their integration. According to existing literature, the incorporation of EVs into a distribution network system resulted in a notable impact on peak demand. Specifically, the addition of a mere 10% of EVs led to a substantial increase of 17.9% in peak demand. Furthermore, when the proportion of EVs was raised to 20%, the peak demand experienced a more significant surge, escalating by 35.8%. These findings highlight the substantial influence that the integration of EVs can have on the overall demand profile of a distribution network system [3].

The planning of infrastructure is an essential component in the transition to sustainable transportation, and one of the most important aspects of this transition is the design of the ideal placement for EVCS. The ideal positioning of EVCS may be accomplished by a variety of approaches, each of which has its own objectives. Using EVs as a spinning reserve to meet peak demand and enhance system efficiency is one way to optimize the location of charging stations. Consequently, EVs have the potential to assist in the reduction of expenses and the optimization of essential characteristics such as voltage deviation and loss [4]. There is a significant impact on the generating and transmission networks caused by the large current carried by the distribution branches of the system during the charging of electric vehicles. Multiple factors, including charging procedures, vehicles density at particular stations, and other similar metrics, determine the extent to which they impact the distribution system [5].

The optimal site for EVCS installation has been determined in this work using the IEEE 33 bus distribution scheme. Each charging station is distributed among three distinct areas to ensure that electric vehicles have access to charge in a designated space. Optimal placement of EVCS has been achieved by the use of soft computing approaches such as Symbiotic Organism Search (SOS) and PSO [6]. Optimal locations for electric vehicle charging stations (EVCSs) have recently been the subject of study because to the increasing demand for EVs and the electrification of transportation systems. On the other hand, widespread adoption of EVs presents a number of challenges, such as inappropriately planned EVCS sites, inadequate EVCS infrastructure, and EVCS charge scheduling [7]. Methods for incorporating micro grids into distribution networks for the purpose of installing electric car charging stations with varying capacity are detailed in this study. Micro grids that run on EVs have their economic feasibility studied in relation to operating costs, losses, and emissions. Therefore, this study also evaluates the system dependability as a result of EV operation, as the unpredictable behaviors of EVs generate some degree of uncertainty. Case studies and simulations are conducted using a 69-bus distribution system [8]. In order to determine the best location and size for EVCSs, this study presents an optimization framework based on uncertainty-based optimization techniques, which include robust optimization and scenario approach. By lowering power losses and providing services to energy markets, the suggested model hopes to reap the financial benefits for the operator of the power distribution system, all while taking use of the flexibility provided by EVCSs [9].

Many approaches for solving the problem of EVCS optimization have been proposed. CSs must be allocated on the route between source and destination. The problem of the optimized flow capture is mainly described as a problem of mixed integrated programming (MIP), in order to maximize EV flow over every feasible route via the EV network. There may be restrictions based on either route or demand, or both. The FLRM extension [10] is an expansion of the flow interceptor model, such that traffic flow is optimized due to a restricted number of installations. On the other hand, the FLRM may allocate several refill stations depending on the request and the maximum distance to be permitted. Since then, a number of different mathematical models of FLRMs have been developed. [11,12]. Models that can capture flow however, have several inconvenient: inflexibility: (i) all the information needed to simulate realistic EV networks is not easy to capture; (ii) high complexity: As the number of EVs in the network expands, so does the level of complexity in the model easing, the number of tour operators available or of CSs available is increasing; and (iii) centrality: the model ignores the problem of decentralization.

Node-serving models aim, however, either to increase demand or to reduce travel distance to certain refueling areas in order to maximize the EVCS coverage (nodes). Vasant, et.al, [13] devised an algorithm for three CS levels in an EV network. In response to demand in each area, the algorithm is established in order to reduce the gap between the CS nodes. Models that serve nodes in a network have been well-performed in handling EVCS allocation at urban areas, which need a wide range of limitations and requirements for each node in the electrical network. On the other side, the EV network must be fully modelled to specify all limitations and create a feasible yet practical solution.

Mathematical techniques of programming were primarily used for the literature to deal with EVCS allocation. The difficulty of computing such models nevertheless increases with the growing number of restrictions and/or options. It thus becomes difficult to determine the optimal choice. To identify global (near-optimal) solutions with minimal computing expense, however, metaheuristic algorithms are used. As a consequence, metaheuristic algorithms are more adaptable when modelling real circumstances in an EV network. The topic of EVCS allocation optimization was identified by Vazifeh et al[(14)] as a Non-Deterministic Polynome Hard Time Problem. The area was split into little square cells to address the problem of NP-Hard. To address the optimization problem, the genetic algorithm (GA). Other than the GA meta-heuristic, there have been several literary analyses that make use of swarm intelligence algorithms[(15,16)] which took into account the cost of energy and the limitations of the battery while constructing a CS infrastructure using the Gravitational Search (GSA) and PSO algorithms. It has relied heavily on big data and survey results to evaluate EVCS demand. A major flaw in the current approaches is that they do not account for demand uncertainty[(17,18)].

In order to summarize the previous information, the distribution of EVCS is an extremely challenging problem for the electric vehicles industry. The most common solutions in the literature are flow collector models. The issues with these methods are: inflexibility, excessive complexity and centralism. It has been far more flexible and have been capable of simulating a genuine EV network scenario. Nevertheless, none of these models understood EV demand's ambiguities. Several methods have been studied in the literature for calculating the EV demand. There is much importance to go for optimal location of EVCS which is presented in this article.

The proposed article contributes for the following objectives:

1. To analyze the impact of improper location of EVCS in distribution system.
2. To identify the best CS location using PSO and comparison of system and nominal voltages with base case.
3. To identify the best CS location using GWO and comparison of system and nominal voltages with base case.
4. The probability test comparison of base case with PSO and GWO for the optimal location of EVCS.

The rest of the paper is organized as, the Methodology is presented in section II, followed with Results and Discussion in section III and concludes in section IV.

2 Methodology

The research focuses on an enhanced distribution system of IEEE-33 bus[(19)]. The system initially comprised of 12.66 kV and 100 MVA with many fixed loads and the primary power supply was linked via the base load of 3.715MW, having a base loss of 0.203MW. The system does not utilize distributed generation (DG) tools. The proposed distribution system is shown in Figure 1. The planning framework for charging stations involves the identification of the most optimal position for the EVCS. The identification of strong buses for the location of EVCS is typically done using the loss sensitivity factor (LSF) approach. The utilization of loss sensitivity parameters is crucial in determining optimal sites for the installation of EVCS within the Distribution System (DS). The reduction of the search area is made possible by estimating the locations of these critical nodes.

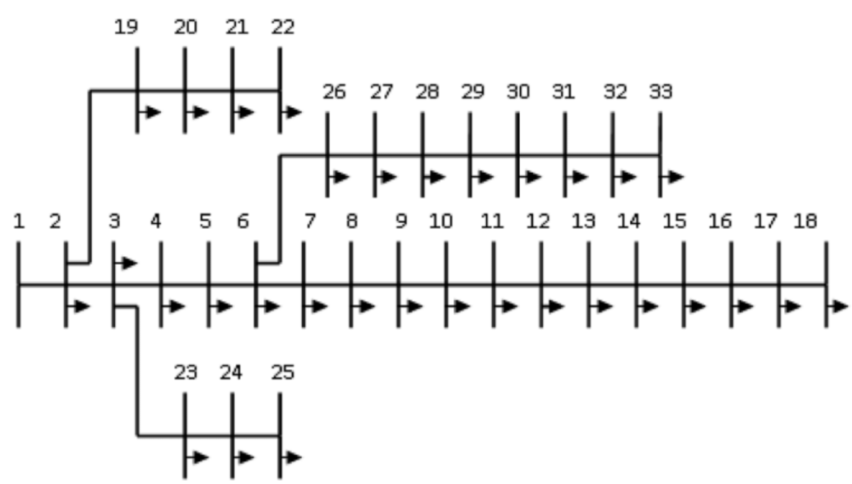

Fig 1. Proposed IEEE 33 Bus System

Metaheuristic algorithms are search processes that aim to find a satisfying solution to optimization problems that are complex and difficult to solve. Identifying a near-optimal solution with incomplete or partial data is crucial in this real-world setting with limited resources. The introduction of metaheuristics to deal with such optimization problems is one of the most momentous developments in operations research over the last two decades. Exploration and exploitation are the two optimization processes that are used by meta-heuristic algorithms in typical situations[(20,21)]. Exploration refers to a search that is conducted on a global scale inside the search space, while searching on a local scale is referred to as exploitation. Inevitably exploration and exploitation are incompatible with one another. The most challenging obstacle is definitely going to be figuring out a means to provide stability to them. In the proposed method for determining the most effective location for EVCS, some of the search algorithms that are offered include PSO and GWO.

2.1 PSO Optimal Algorithm

PSO is the computer technique for refining the problem by attempting to provide a potential solution in a coherent computer science measure. It solves a problem, utilizing the basic math- based location and speed method to create a population of potential solutions called particles. The motion of each particle relies on its locally best-known site[(22)]. However, the movements are frequently directed to the best-known places in the search space.

The swarm may thus move in the correct direction. The flow chart for PSO optimal algorithm is shown in Figure 2.

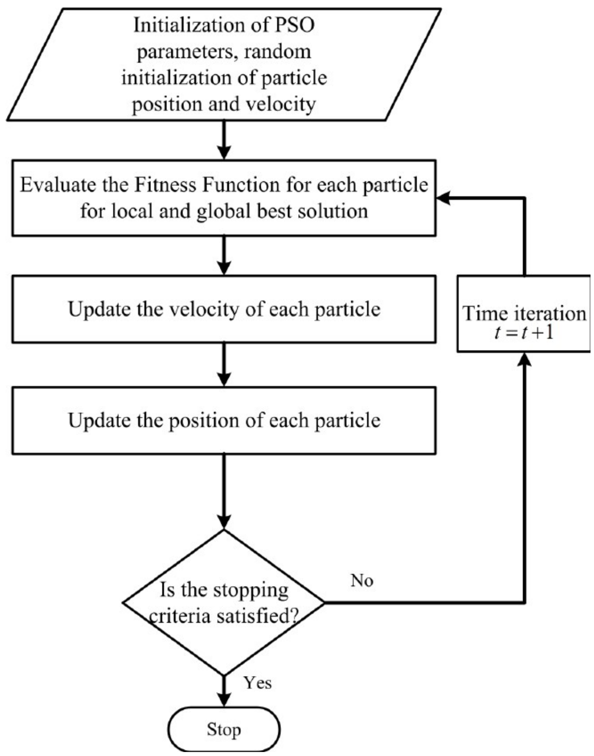

Fig 2. PSO Flow Chart

2.2 Grey Wolf Optimization Algorithm (GWO)

It imitates the management pyramid and also chasing procedure of Gray wolves in attribute recommended through four various sorts of Gray wolves including alpha, omega, delta and also beta are actually hired for replicating the management power structure. Alpha is actually taken as the fittest remedy while making GWO. Beta as well as delta are actually the 3rd and also 2nd absolute best options and also continuing to be wolves are actually thought about to become omega. Grey wolves search the victim through bordering its own intended and also the hemming in actions is actually designed due to the succeeding formulas:

$$D = C.X(t) - X_P(t) \tag{1}$$

$$(t+1) = X_P(t) - A.D \tag{2}$$

Where

D, A, C = Coefficient Vectors Xp = Position Vector

X = Initial Postion

t = Current Iteration

Below is an equation for determining A and C.

$$A = 2a.r_1 - a \tag{3}$$

$$C = 2.r_2 \tag{4}$$

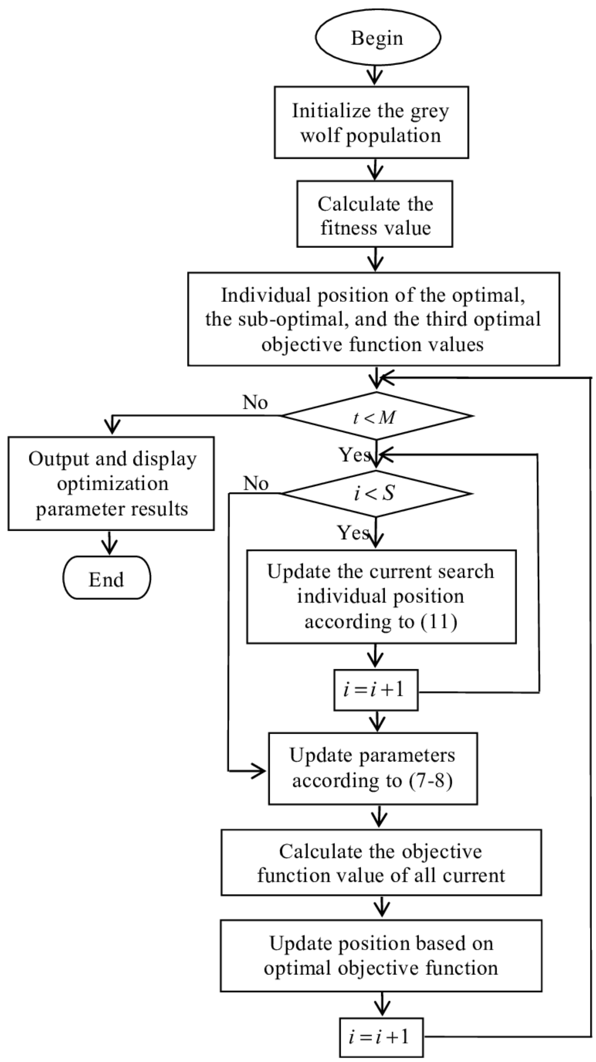

Fig 3. GWO Flow Chart

The process for the optimal position of GWO is shown in above Figure 3.

3 Result and Discussion

In this paper Optimal allocation of EVCS in the real time IEEE 33 bus distributions system is implemented using GWO optimal algorithm. The performance of the suggested algorithm is assessed in comparison to GWO optimal algorithm. The loss sensitivity factor in the real time IEEE 33 bus distributions system is shown in Figure 4.

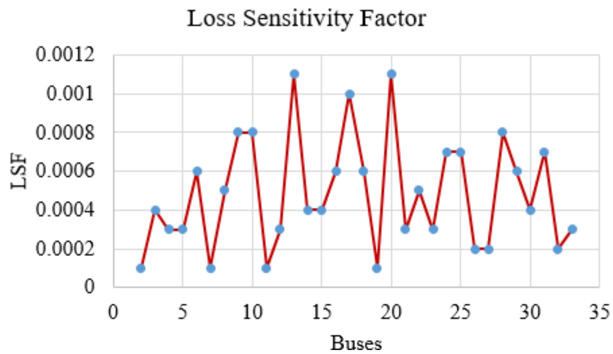

Fig 4. Loss Sensitivity Factor for IEEE 33 Bus

The system voltage and nominal voltage of IEEE 33 bus system with base case is shown in Figure 5.

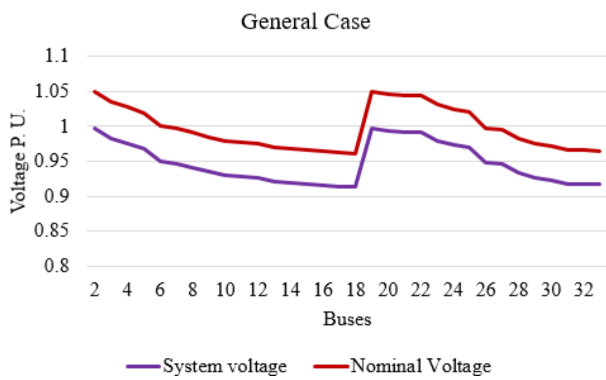

Fig 5. System Voltage and Nominal Voltage

Table 1. LSF approach for base case (conventional system)

Bus No.	Sysvolt1	Voltnom1	LSF	LSFd	EV
2	0.997	1.0495	0.0001	0.0011	0
3	0.983	1.0347	0.0004	0.0011	0
4	0.9755	1.0269	0.0003	0.001	0
5	0.9682	1.0191	0.0003	0.0008	0
6	0.9498	0.9998	0.0006	0.0008	1
7	0.9464	0.9962	0.0001	0.0008	1
8	0.9415	0.9911	0.0005	0.0007	1
9	0.9353	0.9845	0.0008	0.0007	1
10	0.9295	0.9784	0.0008	0.0007	1
11	0.9286	0.9775	0.0001	0.0006	1
12	0.9271	0.9759	0.0003	0.0006	1
13	0.921	0.9695	0.0011	0.0006	1
14	0.9188	0.9672	0.0004	0.0006	1
15	0.9174	0.9657	0.0004	0.0005	1
16	0.916	0.9642	0.0006	0.0005	1
17	0.914	0.9621	0.001	0.0004	1

Continued on next page

Table 1 continued

18	0.9134	0.9615	0.0006	0.0004	1
19	0.9965	1.049	0.0001	0.0004	0
20	0.9929	1.0452	0.0011	0.0004	0
21	0.9922	1.0445	0.0003	0.0003	0
22	0.9916	1.0438	0.0005	0.0003	0
23	0.9794	1.031	0.0003	0.0003	0
24	0.9727	1.0239	0.0007	0.0003	0
25	0.9694	1.0204	0.0007	0.0003	0
26	0.9479	0.9978	0.0002	0.0003	1
27	0.9454	0.9951	0.0002	0.0002	1
28	0.934	0.9831	0.0008	0.0002	1
29	0.9258	0.9745	0.0006	0.0002	1
30	0.9223	0.9708	0.0004	0.0001	1
31	0.9181	0.9664	0.0007	0.0001	1
32	0.9172	0.9654	0.0002	0.0001	1
33	0.9169	0.9651	0.0003	0.0001	1

The nominal voltage can be obtained by dividing the system voltage with 0.95, In the similar approach, it was obtained for PSO and GWO algorithms.

In the following graphs, it is observed that system and nominal voltage follows the constant trend. The PSO and GWO based system and nominal voltages are shown in Figures 6 and 7 respectively.

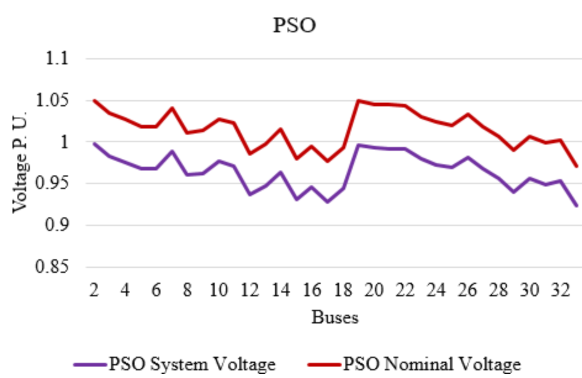

Fig 6. System Voltage and Nominal Voltage with PSO

From the graph (Figure 7) it is observed that GWO algorithm gives the better performance compared to PSO.

Buses that exhibit normalized values exceeding 1.01 are recognized as strong buses for positioning of EVCS whereas, buses exhibiting normalized values below 1.01 are considered as potential nodes that may require compensation. The determination of the order in which buses should be examined for the location of charging stations is influenced by Loss Sensitivity parameters. Additionally, the viability of a particular bus for positioning is determined by normalized voltage values, which influence the positioning of the buses. The probability of EV location in the IEEE 33 bus system is shown in Figure 8.

Here the bus 1 is selected as slack bus. In the above graph, the strong buses are represented by 1 and weak buses are represented by 0. It is observed that in the base case EV is located at 6,7,8,9,10,11,12,13,14,15,16,17,18,26,27,28,29,30,31,32,33 a total of 21 locations the EVs are placed. In the PSO case, EV is placed at 7,11,12,13,16,17,18,30,31,33, total at 10 locations. In the GWO case EV is placed at 8,9,12,13,15,16,17,18,26,31,32,33 total at 12 locations.

From the above comparison of base case with PSO and GWO the further analysis can be carried in possible cases shown below

Case I : To analyze the performance of the system by considering only the strong buses suggested in the proposed system for the placement of EVCS in IEEE 33 bus system.

Case II: The analysis can also be carried out by considering only the weak buses, which is not the suggested method.

Case III: Further, the analysis can be carried out by considering both the strong and weak buses i.e the moderate case for the placement of EVCS and estimate the performance of the system.

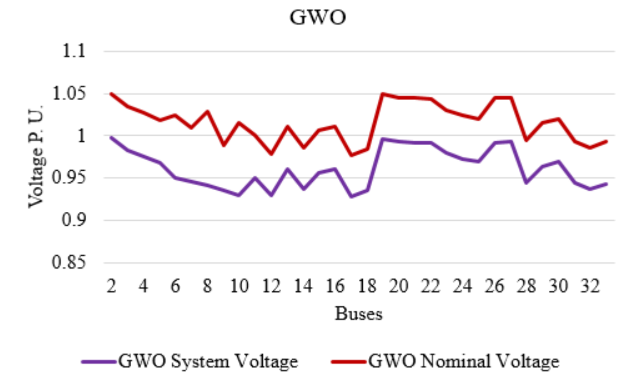

Fig 7. System Voltage and Nominal Voltage with GWO

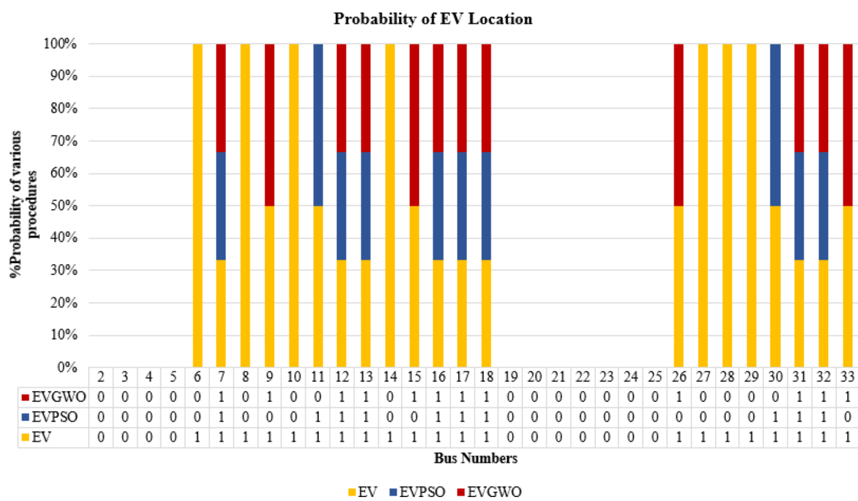

Fig 8. EV location in the IEEE 33 bus system

Table 2. Possible Cases for placement of EVCS in IEEE 33 bus system

Possible Cases	Strong Bus	Weak Bus	Moderate Bus
Case I	7,12,13,16,17,18,31,32	-	-
Case II	-	6,8,10,14,27,28,29	-
Case III	-	-	9,11,15,26,30,33

4 Conclusion

The distribution system's best location for EV charging stations is suggested in this article. The GWO approach is used to choose the best CS locations in order to minimize the losses. The proposed method is implemented in IEEE 33 bus system. The effectiveness of the proposed GWO is evaluated by comparing it with base case and PSO optimal algorithm. Finally, comparison of system voltage and nominal voltage is presented and probability of EV location is presented for the possible cases. The optimal location of the EVs is proposed for strong (7,12,13,16,17,18,31,32 i.e 8 buses), weak (6,8,10,14,27,28,29 i.e 7 buses) and moderate buses (9,11,15,26,30,33 i.e 6 buses) for an IEEE 33 bus system based on the comparison of base case, PSO and proposed GWO algorithms to minimize the losses. Further the research can be carried out by considering the simultaneous placement of EVCS and DGs for the placement over weak and strong buses in Distribution System.

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