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Improvement of Distribution Network Performance by Optimally Allocating EV Charging Station

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Abstract. With zero emissions to the environment, electric vehicles (EVs) are the most environmentally friendly mode of transportation. The placement of EV charging stations (EVCS) in the Radial Distribution Network (RDN) is necessary to satisfy the demand of charging in various places while minimizing power loss on the power system networks. In the distribution system, distributed generation (DG) not only reduces power loss but also enhances power quality. To fully utilize the benefits of DG, it is necessary to find the optimal location and size in the distribution system. In this work, the ideal installation of EVCS has been consistently demonstrated in the IEEE 33 bus distribution network. In order to provide widespread charging facilities, the RDN has been split into three regions, and it has been established that each area has one charging station placed. The main purpose is to minimize the Active Power Loss and Voltage Deviation Index (VDI) to maintain a healthy power system network. Adding DG to the appropriate EV Station is obtained through optimization. This problem has been formulated as a problem of optimization for finding the best location to install EVCS in the IEEE 33 bus RDN by using the Symbiotic Organisms Search (SOS) algorithm. The obtained results have been validated and compared using the Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA).

1 Introduction

The main factors influencing the popularity of electric vehicles are environmental degradation and the crisis of fossil fuels [1]. The photovoltaic (PV) energized EV technology has been verified to reduce greenhouse gas emissions by 47% to 78%, and the rate of interest and feed-in rate for Power generation may be utilized as policy-making elements to build limited carbon transportation networks [2]. The current situation's availability of electric vehicles causes a significant increase in the entire necessity for electrical power. Power generation must be enhanced in the same proportion in order to resolve this issue [3]. EVCS is a prerequisite for EV users in addition to charging their vehicles. Infrastructure for charging EVs must be established for widespread adoption [4]. The distance between an EV customer's

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home and the closest charging station must be taken into account by the planner as it impacts how rapidly the battery can be recharged. Therefore, a charging station should be installed in an area with a high density of EV ownership or use. This will minimize the EV customer's daily travel expenses [5]. As a result, it's necessary to carefully add DG and distribute EVCS to the distribution network so that active power loss and VDI may be reduced to a minimum and the voltage profile is acceptable.

In [6], it is observed that the distribution system is significantly impacted when the EV charging station's position is determined using the GWO and WOA. An EV optimal charging model is developed in [7] for the change of load characteristics. In [8], the presented approach accurately identifies the best position and the capacity of one or more voltage-controlled DG(s) for minimizing power loss. In [9] use the new optimization technique known as accelerated PSO for the positioning and size of DG concerns and maintained systems power loss in the distribution system. The authors in [10], provide a unique method for analyzing the dependability of radial distribution networks that may be utilized to cut down on maintenance durations and component failure rates. On the basis of this, a technique for calculating the maximum capacity of DG integration in a distribution system is suggested. In [11]–[14], the researchers ensured that EVCS was implemented correctly by utilizing a variety of soft computing techniques. In [15], the prototype was assembled and successfully tested to charge a PHEV vehicle. This can justify both conventional and instant charging.

The key priority of the proposed work is to reduce active power loss and VDI in order to locate DG and EVCS optimally within the IEEE 33 bus distribution network. To make EVCS widely available to consumers, the distribution network is split into three sections. After G2V and V2G configuration analysis, the charging stations are put in optimal areas to minimize active power loss and VDI with DG while maintaining a strong power system network. The GWO, WOA and SOS method has been used to resolve the issue, which has been presented as an optimization problem. A secure and robust power system network has also been definite.

2 Problem Formulation

2.1 *Minimization of Active Power Loss:*

DG has been incorporated system for reducing power loss. The optimization and sizing of DG units for a single objective problem were executed for this research project in order to minimize the active power loss.

Assuming the l^{th} branch of the distribution network. Here Z^l, R^l, X^l, and $I^l$is the impedance, resistance, reactance, and current passing through the l^{th} branch.

Separating the impedance Z^l real and imaginary components provide,

$$Z^l = R^l + jX^l \tag{1}$$

Thus, S^l is determined by the entire apparent power loss,

$$S^l = (I^l)^2 \times Z^l \tag{2}$$

The procedures needed to determine the network's overall load,

$$t^{LOAD} = \sum_{lS=1}^{NlS} p_{EX}^{lS} + p_{EVCS}^{lS} \tag{3}$$

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Where, t^{LOAD} = network's overall load,

NlS = Overall bus count in the network,

p_{EX}^{lS} = The load that is existing on the lS^{th} bus,

p_{EVCS}^{lS}= The charging station that is linked to the extra load caused by EVs at the lS^{th} bus.

p_{EVCS}^{lS} may also be improved as,

$p_{EVCS}^{lS} = \left(n_{EV}^{g2v} \times c_{Char}\right) - \left(n_{EV}^{v2g} \times c_{DCh}\right)$,

If $lS \in$ charging stations position.

= 0, if $lS \notin$ charging stations position. (4)

Where, n_{EV}^{g2v}= The entire EVs count connected to the charging station in G2V.

n_{EV}^{v2g}= The entire EVs count connected to the charging station in V2G.

c_{Char}= The charging rate for EVs.

c_{DCh} = The discharging rate for EVs.

On that specific bus, the EVCS will be installed as a link for the additional load for the charging stations. The number of bus serves as a significant determining factor for optimization in this work (the lS ∈ position of the charging station).

As a result, the components of active and reactive power loss are differentiated from the overall apparent power loss.

$$p_{Loss^l} = R^l * \frac{(p_l^2+q_l^2)}{|v^{l2}|} \tag{5}$$

$$q_{Loss^l} = X^l * \frac{(p_l^2+q_l^2)}{|v^{l2}|} \tag{6}$$

Where, p_{Loss^l} , q_{Loss^l} represented the active and reactive power loss elements in l^{th} branch respectively. p_l^2, q_l^2 represents active and reactive power flows from l^{th} bus.

The entire active power loss, p_{Loss} in the radial distribution network is calculated by,

$$p_{Loss} = \sum_{l=1}^{nl} p_{Loss}{}^{l} \tag{7}$$

Where, nl = The entire branch's number.

2.2 Voltage Deviation Index (VDI)

By using the voltage deviation index (VDI), the bus's voltage quality is evaluated. In order to provide a more regulated bus voltage profile along the RDN, bus VDI must be decreased. The suggested ideal EVCS and DG allocation uses bus VDI as an objective function [16].

$VDI = \sum_{l=1}^{N_{Bus}} (V^l V^{ref})^2$

(8) V^l = Bus voltage in the l^{th}branch.

V^{ref} = The reference voltage in the l^{th}branch.

N_{Bus} = the no. of buses in the distribution network.

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This is how, the objective function is represented,

$$min\ (F_1) = min\ [(w \times p_{Loss}) + \{(1-w) \times VDI\}] \tag{9}$$

Where, w is a weightage value.

2.3 Constraints

2.2.1 Constraints For Voltage Limit:

The voltage through each node should always be kept within the permissible range at any given moment.

$$V^{min} \leq V^{lS} \leq V^{max}, \text{ for } lS = 1 \text{ to } NlS \tag{10}$$

Where, V^{min}= The lowest voltage's limit.

V^{max}= The maximum voltage limit.

V^{lS}= Bus voltage in the lS^{th} bus.

2.2.2 Constraints on Current Flowing Limit:

The output of flowing current (I^l) from each branch should be lower than its maximum rated capacity (I^{max}),

$$I^l \leq I^{max}, \text{ for } l = 1 \text{ to } nl \tag{11}$$

Where, I^l= The flowing current through the l^{th} branch.

I^{max}= Maximum allowable current flow limit.

nl = Number of overall branches.

2.2.3 Constraints for Load Balancing:

The substation's delivered power needs to be sufficient for the entire demand and the loss.

$$p_{subst} = \sum_{lS=1}^{NlS} p_{lS} + p_{Loss} \tag{12}$$

Where, p_{subst}= the substation's power supply.

p_{lS} = Load on the lS^{th} bus.

NlS = The system's total number of buses.

p_{Loss}= The overall active power loss

2.2.4 Thermal Limit Constraints:

The thermal limit across each branch should not reach the maximum permissible limit.

$$S_l <= S_{l(\max)}, \forall l \tag{13}$$

Where, S_l = The l^{th} branch's apparent power.

$S_{l(\max)}$= The l^{th} branch's maximum apparent power limit.

2.2.5 DG Constraints:

The bus's Active and reactive equality constraints are,

$$p^{DG,l} = p_{Loss} + \sum p^{D,l} \tag{14}$$

$$q^{DG,l} = q_{Loss} + \sum q^{D,l} \tag{15}$$

Where, $p^{DG,l}$= The DG's bus l active power injection.

$q^{DG,l}$ = The DG's bus l reactive power injection.

$\sum p^{D,l}$ = The overall active power at bus l.

$\sum q^{D,l}$ = The overall reactive power at bus l.

2.2.5.1 DG Position:

Bus 1 has been considered as the slack bus in IEEE 33 bus distributed system. The DG position should lie within acceptable bus limit.

$$(DG)_i \in (Area)_i \tag{16}$$

Where, $(DG)_i$, $(Area)_i$ denotes the position of DG and area of 33 bus.

2.2.5.2 Constraints of DG Capacity:

In this work, 30% DG penetration has been estimated to satisfy the network's peak demand.

$$0 \leq p^{DG,l} \leq 0.3 \sum_{i=1}^{n} p_{LOAD}(i) \tag{17}$$

Where, $p_{LOAD}(i)$ denotes the total active power of the network.

3 Optimization Tool

The Grey Wolf Optimizer (GWO), a new meta-heuristic method inspired by grey wolves (Canis lupus). The GWO algorithm imitates the natural leadership structure and hunting strategy of grey wolves [18].

Whale Optimization Algorithm (WOA), is a unique meta-heuristic optimization algorithm inspired by nature that imitates the social behavior of humpback whales. The bubble-net searching strategy served as the basis for the algorithm [19].

Dieu T.T. Do and Jaehong Lee proposed a modified symbiotic organisms search algorithm in 2017 [20]. Engineering design and numerical optimization problems are solved with the use of SOS, a novel, strong, and reliable metaheuristic technique. The symbiotic interaction techniques that organisms utilize to exist and spread through the environment are simulated by SOS. Mutualism, commensalism, and parasitism are the main three prevalent symbiotic interactions in the environment. Mutualism is a term used to describe a symbiotic relationship whereby two different species benefit from each other. Commensalism is a type of symbiotic interaction in which one species benefit while the other is unaffected. Parasitism is a symbiotic interaction in which one species benefit and the other is purposefully harmed [21]. The optimal position for EVCS was determined in this work using the SOS algorithm.

Fig. 1 depicts the proposed flow chart for locating the appropriate location for DG and EVCS. In this paper, the search agent specifies the location of undefined branches where DG and EVCS will be linked. The objective function and the different constraints are computed using the backward forward sweep load flow method for distribution networks. The SOS

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algorithm is being used to modify the position of the DG and EVCS.

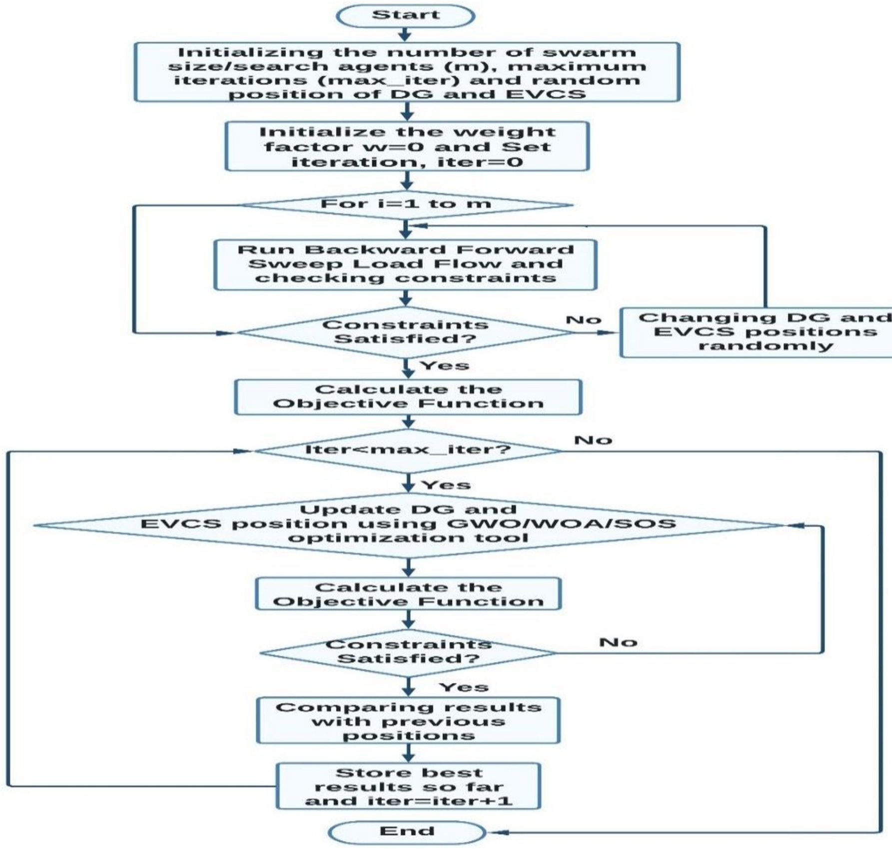

Fig. 1. Flow chart for optimal positioning of DG and EVCS by implementing GWO/WOA/SOS optimization technique.

4 Results and Discussion

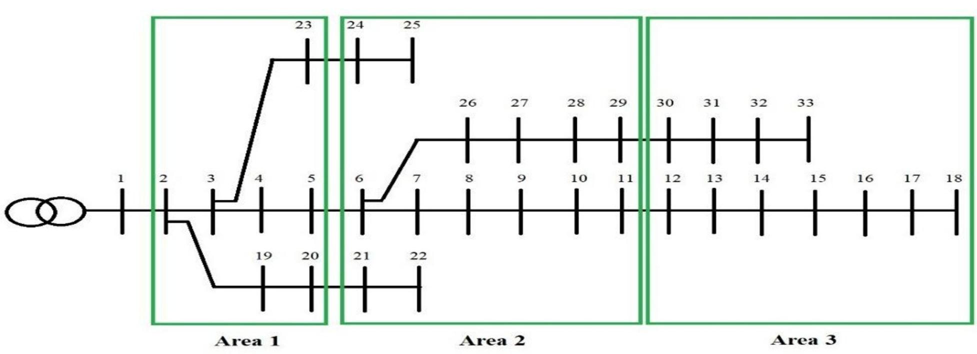

Fig.2. Area Splitting in IEEE 33 Bus RDN

VDI and active power loss, as well as other power system parameters, have been calculated using IEEE 33 bus RDN data and the distribution network's backward forward sweep load flow algorithm [22]. In the G2V working mode, the charging rate is 19 kW [11] and the discharging rate in V2G working mode is 8 kW [17] respectively. It is assumed in this article that 20% of EVs can function in V2G mode. To provide EVCS additional accessibility, Fig. 2 shows the distribution network separated into three sections. In this work, the active power loss and VDI as a multi-objective function were minimized when installing the EVCS into three distinct regions utilizing GWO, WOA and SOS optimization tools. By assuming the following three possibilities, the problem is instantly fixed: 15, 25, and 35 EVs are connected to the charging port at that time. In the worst-case situation, there can never be more than 35 EVs in the network at once.

Table 1. Optimal Location of DG and EVCS Along with the Active Power Loss and VDI.

Optimization Tool Applied	No. of EVs	Allocation	Best Positions			Active power loss in kW	VDI (p.u)
SOS	15	EVCS Location	2	21	33	213.32	0.1338
		DG Location	4	26	14		
		DG Size (kW)	34.96	12.87	27.42		
	25	EVCS Location	19	22	30	217.34	0.1368
		DG Location	3	7	32		
		DG Size (kW)	19.98	7.32	51.76		
	35	EVCS Location	19	21	33	225.86	0.1416
		DG Location	4	7	32		
		DG Size (kW)	34.82	34.02	62.22		
GWO	15	EVCS Location	2	21	33	213.32	0.1338
		DG Location	4	26	14		
		DG Size (kW)	34.96	12.87	27.42		
	25	EVCS Location	19	22	30	217.34	0.1368
		DG Location	3	7	32		
		DG Size (kW)	19.98	7.32	51.76		
	35	EVCS Location	19	21	33	225.86	0.1416
		DG Location	4	7	32		
		DG Size (kW)	34.82	34.02	62.22		
WOA	15	EVCS Location	2	21	33	213.32	0.1338
		DG Location	4	26	14		
		DG Size (kW)	34.96	12.87	27.42		
	25	EVCS Location	19	22	30	217.34	0.1368
		DG Location	3	7	32		
		DG Size (kW)	19.98	7.32	51.76		
	25	EVCS Location	19	21	33	225.86	0.1416
		DG Location	4	7	32		
		DG Size (kW)	34.82	34.02	62.22		

The nominal loads are connected at different nodes in accordance with the IEEE 33 bus RDN. Installation of the EVCS takes place at the node that accommodates the increased demand provided by EV charging. Depending on the number of EVs and the rate of charging and discharging, the load that has to be connected in V2G and G2V configurations ranges widely. For this work, an Intel Core i5 processor at 2.20 GHz and 8 GB of RAM is used, along with the programming language MATLAB R2019b, which is installed on the system.

By using the GWO, WOA and SOS optimization approaches, table 1 displays the best positions for allocating DG and EVCS, active power loss, and VDI for various EV penetration levels. It has been observed that the optimal position of installing DG and EVCS has been identified and has been validated by using various optimization techniques. It has been ensured that active power loss and VDI has been minimized simultaneously for obtaining an efficient and reliable network for installing DG and EVCS. The obtained results have been validated for various EV penetration and using SOS optimization tool and compared with GWO and WOA optimization techniques. It has been observed that the position of attained location of EVCS and DG remains similar which is feasible from a practical perspective

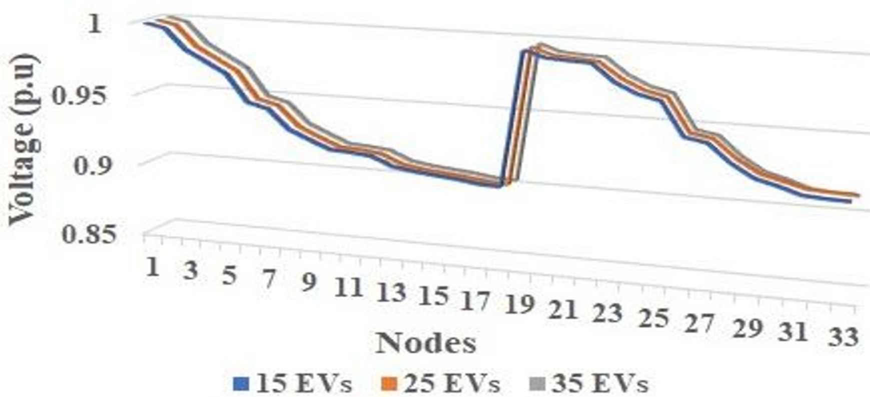

Fig. 3. Voltage Profile for Various EV Penetration

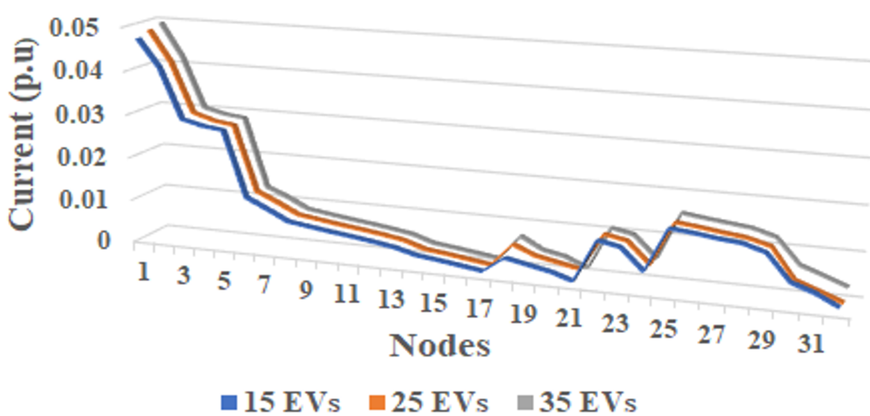

Fig. 4. Current Profile for Various EV Penetration

Using the SOS tool, the voltage and current profile for the various EV penetration rates is shown in Fig. 3 and 4. It has been observed that despite an increase in the number of EVs, the voltage and current profile changes just minimally.

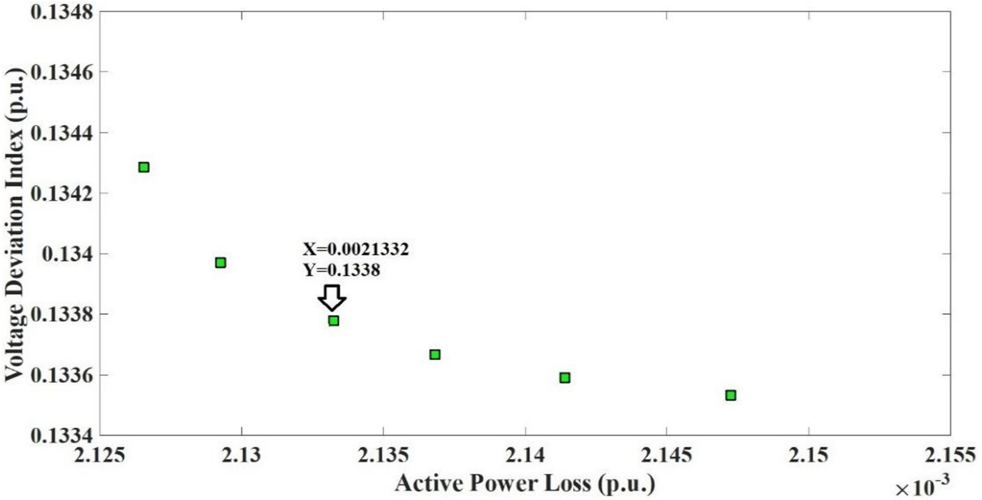

Fig. 5. Pareto Optimal Front for 15 EVs

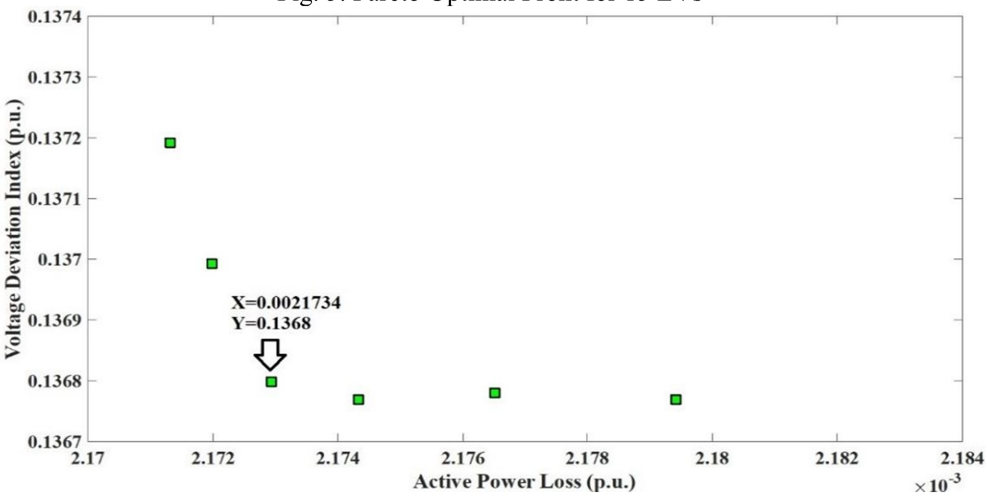

Fig. 6. Pareto Optimal Front for 25 EVs

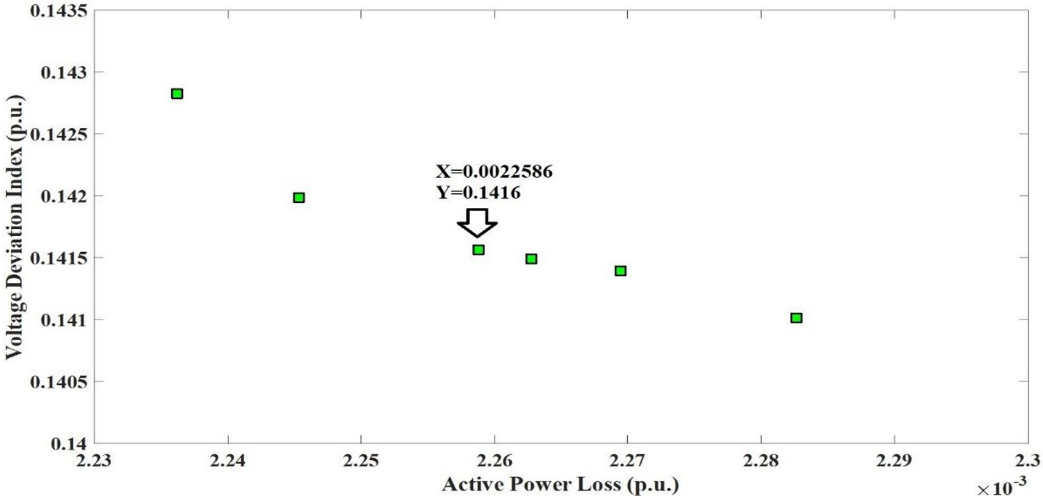

Fig. 7. Pareto Optimal Front for 35 EVs

For different levels of EV penetration, Fig. 5-Fig. 7 shows the pareto optimal front for simultaneously minimizing active power loss and VDI using the SOS optimization approach. For decreasing active power loss or VDI, the multi-objective function appears to be much more practical than the single-objective function since it provides a compromised outcome. For different numbers of EV penetrations, the pareto optimal front for concurrent reduction of active power loss and VDI in the IEEE 33 bus distribution network displays smoother characteristics.

5 Conclusion

The shortage of EVCS is the biggest barrier for preventing the widespread adoption of EV. In this work, Using GWO, WOA, and SOS optimization methods, it has been demonstrated that the ideal location for placing DG and EVCS has been determined and evaluated. For the purpose of obtaining an effective and dependable network for the installation of DG and EVCS, it has been assured that active power loss and VDI have been reduced simultaneously. The obtained results have been verified for various EV penetrations, and the placement of the EVCS has remained consistent, which is realistic. The allocation of DG and EVCS have a substantial influence on the power system parameters of RDN. Incorporating the DG and EVCS in the designated positions of IEEE 33 bus RDN maintains a healthy current and voltage profile in the network. The installation of DG and EVCS in RDN while providing wider access to EVCS considering active power loss is minimized is much more sensible from practical stand point.

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