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Optimal Scheduling of EVs in Radial Distribution System using Optimization Techniques

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***Abstract*– The rapid increase in electric load penetration causes several other concerns which include increment of active power losses, generation demand mismatch in the network, voltage profile degradation and decreased voltage stability margin. In future that the expected transport will rely on Electric Vehicles (EVs) due to their sustainability emissions.Therefore the issues mention earlier proper amalgamation of electric vehicle charging stations (EVCS) at appropriate locations is essential.Mean while new challenges will emerge to the power grid on the connection of an EVCS. Thus the network requires power injection like distributed generation (DG) sources are integrated with EVCS to lessen the impact of EV charging load. In this study charging stations are mutual with DG units enhances the drive to use EVs. This paper proposes optimization techniques to examine the fitting nodes for DGs and EVCS in a unprejudiced distribution system using meta heuristic algorithm like Grey Wolf Optimizer (GWO) .The proposed methodology is verified on the IEEE-33 bus and 69 bus systems in MATLAB software.**

Keywords - Electric Vehicle, Charging stations, Radial distribution system, Distributed Generation (DG), Power loss reduction, Voltage Profile Improvement, Grey Wolf Optimization (GWO), Cuckoo Search Algorithm (CSA), Harmony Search Algorithm (HSA), Particle Swarm Optimization (PSO).

1. Introduction

A balanced distribution system is an important structure of power system which inter connects the high voltage transmission system to low voltage consume service mains. It is mandatory to maintain power quality for proper functioning of appliances, machines etc., to perform that the system losses should be minimized; voltage profile must be within constraint limits. The total losses in the distribution system are about 5-13% of the total generated power based on the statistics. Mean while the considerable increase in temperature and broad release of carbon footprint due to excessive usage of conventional vehicles impose a bad effect on the ecology. So a substitute form of transportation an electric field, i.e. battery based transport is needed to overwhelm the pollution effects engender by the traditional mode of transportation.

Furthermore, the charged EVs [1] using traditional power sources, the goal of utilization of EVs is not accomplished. In electrical distribution system the influence of EVs is examined using various EV scenarios and charging management methodologies. EVCS [2] integration in to the distribution system enhances the overall load of the network. These EVs ascendancy the formation of EVCS in a distribution system can be analyzed by properly modeling EVCS in a distribution system as there is charging procedures influence on the load profile.

The placement of EVCS at optimal location in the IEEE 33bus and 69 bus radial networks has been discussed based on the uncertainties regarding to the quantity of EVs to be charged. GWO [3] has been employed to handle the above issues. The bus with maximum quantity of EVs in the distribution system to be treated as EVCS after optimal allocation of DG in the distribution system.

The techniques which are the recent trend for the optimal placement of DG based on Artificial Intelligence, such techniques are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Harmony Search Algorithm (HSA), Cuckoo Search Algorithm (CSA), Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO) etc.

Finally the contribution of this study is summarized as follows:

- Objective functions are calculated using a faster and effective search based load flow method.

- The impact of EV penetration [4] on the reliability of the distribution system is explored.
- DG [5] units are duly introduced in to the distribution system to deplete the active power losses, enhancing both the voltage profile and the voltage stability index.
- Combination of DG units with EVCS to augment the consistency of distribution network.
- The simulation results achieved on testing on IEEE 33bus and 69 bus standard test networks to demonstrate the efficiency and performance of the proposed GWO technique. The above findings are compared to those obtained with other existing methods like CSA [6], HSA [7] and PSO [8].

In order to complete the contributions mentioned above is done as follows: Mathematical formulation of the problem and objective functions is given in section-2. Section-3 formulates and basic concepts of reliability parameters are explained along with the proposed optimization methodology .In section-4 the essential findings, discussions and comparison of methodologies are contained. Concluding remarks are given in section-5.

2. Problem Formulation

This section deals with DG allocation for balanced distribution system. To do that the objective functions, DG limits, Voltage limits and the load flow solution method is to be stated.

2.1 Objective function:

The objective function for the balanced system is defined as

$$\min (P_{loss}) = \sum_{k=1}^{N_{br}} I_k{}^2 R_k \quad (1)$$

Where, k is the bus number, I_k is the branch current, R_k is the branch resistance and N_{br} is the number of branches.

2.2 Constraints

The constraints are

2.2.1 Voltage Constraints

$$0.95 \leq V_k(pu) \leq 1.05 \quad (2)$$

2.2.2 DG limits

$$60 \leq P_{DG} \leq 3000 \quad (3)$$

2.2.3 Power balance constraints

$$P^{sub} + \sum_{k=1}^{N_{bus}} P_{DG}(k) = \sum_{j=1}^{N_{br}} P^j{}_{loss}(k, k+1) + \sum_{k=1}^{N_{bus}} P_{D,k} + P^k{}_{EVCS} \quad (4)$$

$$Q^{sub} + \sum_{k=1}^{N_{bus}} Q_{DG}(k) = \sum_{j=1}^{N_{br}} Q^j{}_{loss}(k, k+1) + \sum_{k=1}^{N_{bus}} Q_{D,k} \quad (5)$$

Where, P^{sub} and Q^{sub} are the real and reactive power supplied by electric substation respectively, $P_{D,k}$ and $Q_{D,k}$ are the total real and reactive power injected by DGs at k^{th} bus, $P^j{}_{loss}$ and $Q^j{}_{loss}$ represents the real and reactive power loss in the j^{th} branch, $P^k{}_{EVCS}$ is charging station load at the k^{th}bus and N_{bus} denotes the number of buses in the distribution network respectively.

2.3 Load flow solution:

J.H Teng [9] proposed a new load flow method of analysis for radial distribution system. Matrices called BIBC and BCBV has been developed which describes relationship of bus injection to branch current and branch currents to bus voltage is written as

$$[B] = [BIBC]\,[I] \quad (6)$$

$$[\Delta V] = [BCBV]\,[B] \quad (7)$$

Combining (6) and (7) we get

$$[\Delta V] = [BCBV]\,[BIBC]\,[I] \quad (8)$$

$$[\Delta V] = [DLF]\,[I] \quad (9)$$

The load flow solution of the distribution system is obtained by solving below equations (10), (11) and (12) iteratively.

$$[I_k] = \left(\frac{P_k + jQ_k}{V_k}\right)^* \quad (10)$$

$$[\Delta V_{k+1}] = [DLF]\,[I_k] \quad (11)$$

$$[\Delta V_{k+1}] = [V_\circ] - [\Delta V_{k+1}] \quad (12)$$

2.4 Index Vector Method

It is used to find the optimal location of DG. IV [10] value of each bus is calculated as

$$IV(k) = \frac{1}{V_k{}^2} + \frac{I_q(i)}{I_p(i)} + \frac{Q_{eff}(k)}{Q_{total}} \quad (13)$$

Where, V_k is the voltage at k^{th} bus. $I_q(i)$, $I_p(i)$ are the imaginary and real current values of the i^{th} branch. $Q_{eff}(k)$ is the reactive load of the k^{th} bus. Q_{total} is the total reactive load of the system.

Steps:

i. Perform load flow analysis for the given system.
ii. Calculate IV values for each bus.
iii. Normalize voltage values as $V_k/0.95$.
iv. Arrange the IV values in descending order.
v. Buses with high IV values and normalized voltage <1.01 is suitable for optimal location.

3. Proposed Method

GWO is a new novel inspired meta-heuristic algorithm based on the mimics' leadership hierarchy and hunting mechanism of grey wolves in nature developed Mirjalili[11]. Four types of grey wolves such as alpha (α), beta (β), delta (δ) and omega (ω) are employed for simulating the leadership hierarchy.

Further the three key steps of hunting pointed for prey encircling prey and attacking the prey are implemented.

3.1 Mathematical Modeling/formulation of GWO

The following are the major steps in mathematical formulation.

3.1.1 Social hierarchy of GWO

Considering the wolves α, β, δ in the algorithm α is considered to be the solution of best fit; followed by β and δ as the second and third best solutions fit respectively. The 'ω' wolves follow α, β, and δ and the hunting in GWO algorithm is guided by these three wolves.

3.1.2Grey wolves encircling prey

While hunting grey wolves' foremost encircling prey the encircling position is presented in ref [12] and represented as follows.

$$\vec{K} = |\vec{C} \cdot \vec{P_k}(it) - \vec{P}(it)| \quad (14)$$

$$\vec{P}(it+1) = \vec{P_k}(it) - \vec{D} \cdot \vec{K} \quad (15)$$

Where it is current iteration, $\vec{P}$ and $\vec{P_k}$ denote the position vector of a grey wolf and the prey respectively. $\vec{C}$ and $\vec{D}$ be a sign of coefficient vectors and are intended by the following equations.

$$\vec{D} = 2 \cdot \vec{a} r_1 - \vec{a} \quad (16)$$

$$\vec{C} = 2 \cdot r_2 \quad (17)$$

$$\vec{a} = 2(1 - \frac{it}{max-iter}) \quad (18)$$

Here r_1 and r_2 are random numbers between 0 and 1. $\vec{a}$ Component is decreased linearly from 2 to 0 over the course of the iterations.

3.1.3 Hunting Prey

Mathematically to simulate the hunting behavior of grey wolves, assume that α, β and δ have better information concerning about the potential position of the prey. So the first three best solutions set on so far are saved for compelled to update their positions according to their best positions. In Ref[13] the following formulas were developed in this view.

$$\vec{K_\alpha} = |\vec{C_1} \cdot \vec{P_\alpha} - \vec{P}| \quad (19)$$

$$\vec{K_\beta} = |\vec{C_2} \cdot \vec{P_\beta} - \vec{P}| \quad (20)$$

$$\vec{K_\delta} = |\vec{C_3} \cdot \vec{P_\delta} - \vec{P}| \quad (21)$$

$$\vec{P_1} = \vec{P_\alpha} - \vec{D_1} \cdot (\vec{K_\alpha}) \quad (22)$$

$$\vec{P_2} = \vec{P_\beta} - \vec{D_2} \cdot (\vec{K_\beta}) \quad (23)$$

$$\vec{P_3} = \vec{P_\delta} - \vec{D_3} \cdot (\vec{K_\delta}) \quad (24)$$

$$\vec{P}(it+1) = \frac{\vec{P_1}+\vec{P_2}+\vec{P_3}}{3} \quad (25)$$

The exploration and exploitation abilities of the GWO's are represented by searching and attacking of grey wolves for prey respectively.

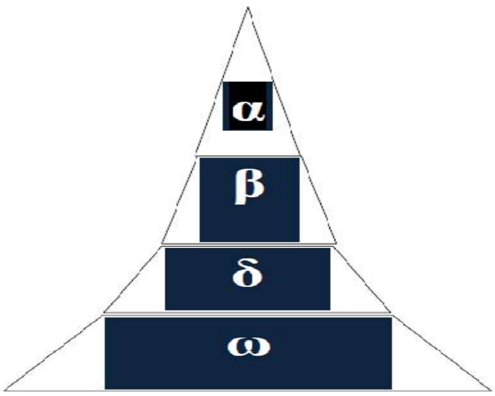

Figure 1The hierarchy level from top down

3.2 GWO applied to Optimization

i. Read line data and load data for the given system.
ii. Calculate the best location for placement of DG using Index vector method.
iii. Initialize the parameters of population size, max-iterations, DG limits.
iv. Generate a random population within the DG limits.
v. Calculate the power losses for the randomly initialized population.
vi. Best solution of the current iteration is noted.
vii. Generate a new set of population by using GWO algorithm of equations (14) to (25).
viii. Check these values are within the limits and if violated replace them with bound values.
ix. Calculate losses and if the new value is better than previous value then replaces it with new value else go back to step vii.
x. After iterations reached to the maximum value then print the results.

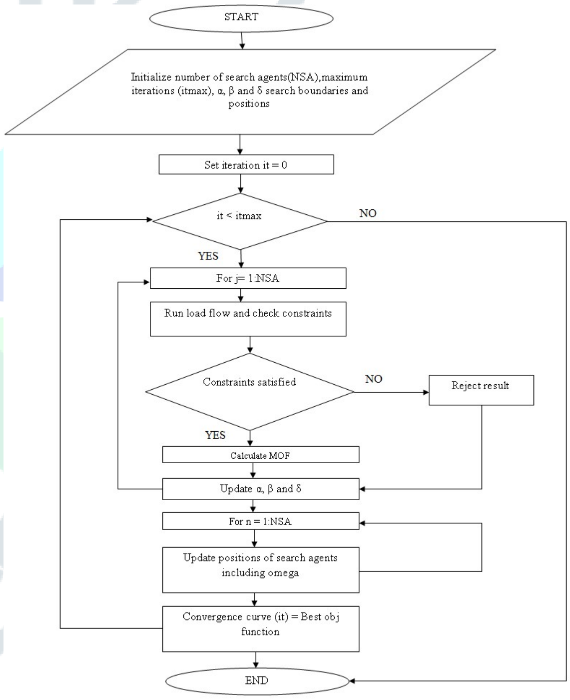

Figure 2.FLow chart of GWO algorithm

3.4 Optimal Scheduling of EVs in the distribution system

The different scenarios are addressed to work for validating the methodology. The scenarios are given below:

1. Balanced IEEE radial distribution network with existing loads only.
2. Addition of one DG in radial distribution network.
3. Simultaneous allocation of multi DGs

The following EVs allotted for charging EVs at charging stations [14] with desired state of charge (SoC) and charging time slot.

3.4.1 State of Charge (SoC)

State of Charge (SoC) [15] is the level of charge of an electric battery relative to its capacity. The units of SoC are percentage points (0% = empty, 100%=full).

$$SoC = \frac{Nominal\ Capacity(A-h)}{Rated\ Capacity(A-h)} \quad (26)$$

3.4.2 Formulation of number of EVs

$$N(j) = \frac{I_{br}(j)}{SoC*T(j)*I_{rated(EV)}} \quad (27)$$

$$N_{opt} = max(N(j)) \quad (28)$$

Where, N_{opt} is optimal number of EVs, $I_{br}(j)$ is the branch current flowing form j^{th} node to $(j+1)^{th}$ load. $T(j)$ is step down transformer ratio, $I_{rated(EV)}$ is EV rated current.

We know that the branch current is directly proportional to N_{opt}, then based on current division rule the different rated N_{opt} EVs are determined.

$$N_{opt} \propto I_{Nbr}(j = opt_{bus}) \quad (29)$$

$$I_{div} = I_{Nbr}(j = opt_{bus}) * \frac{Z_{opp}}{Z_T} \quad (30)$$

Where, Z_{opp} is the EVs opposite branch impedance, Z_T is total equivalent impedances of all EVs.

$$N_{opt}(i) = N_{opt} * \frac{Z_{ev}^{opp}(i)}{Z_T} \quad (31)$$

4. Simulation Results

GWO is applied on the IEEE balanced 33bus and 69bus systems for optimal sizing of DG.

4.1 33bus and 69bus test systems

The network data for 33bus system is taken from[13] consists of 32 branches and 5 tie lines. The total active power and reactive power load on the system is 3.715MW and 2.3MVAR. The losses of the system for base configuration are 202.665KW, 135.1327KVAR with minimum voltage of 0.9131pu at bus 18. And the 69bus system with active power loads 3.80MW and reactive power loads 2.69MVAR which include losses obtained as 224.92KW, 102.13KVAR with minimum voltage of 0.9092pu at bus 65.(Base Voltage =12.66KV and Base MVA = 100MVA)

The tested EVs ratings are as follows:
Integrated EVs are employed with SoC of 0.8 & 0.5 with a common charging slot of 7.5hrs.

TABLE-I. EV MODEL RATINGS

Ratings	EV model-1	EV model-2
Voltage	480V	480V
Energy	40KWH	25KWH
Charging time	7.5hrs	3.5hrs
EVCS charging current	22.22A (for 7.5hrs charging)	14.167A (for 7.5hrs charging)

A. IEEE33-bus test system

TABLE-II. SIMULATION RESULTS WITH TYPE_2 DG(33-bus system)

	Base case	With type_2 DG with pf =0.8			
		PSO	CSA	HSA	GWO
Active Power loss(KW)	202.665	62.108	62.611	62.611	61.593
Reactive Power loss(KVAR)	135.132	48.870	48.870	48.870	48.840
DG sizing(MVA) and location	-	2.875 (25)	2.875 (25)	2.8756 (25)	2.7883 (25)
V_{min}(pu)	0.9131 (18)	0.9642 (18)	0.9642 (18)	0.9642 (18)	0.9644 (18)
Computation time(secs)	0.659	15.75	29.835	15.577	15.099
EVCS	30 | 24	26 | 30	26 | 30	26 | 30	26 | 31

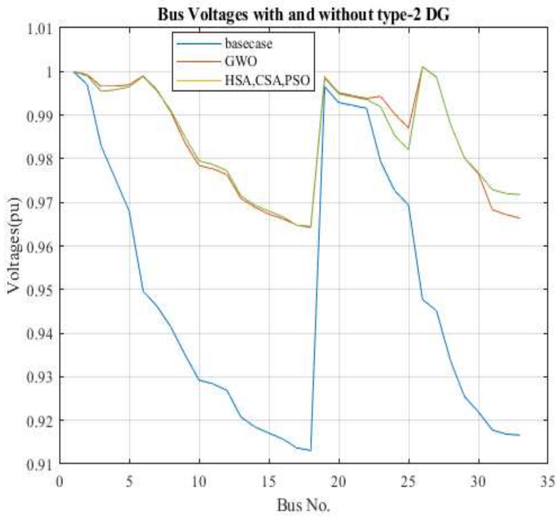

Figure 3 Voltage profile of 33-bus system with and without type_2 DG

In 33bus test system the voltage profile with type_2 DG with minimum voltage of 0.9644pu at bus 18 is shown in figure 3.

TABLE-III. OPTIMALNUMBER OF EVs ALLOCATION AT EACH EVCS(with and without type_2DG)

Optimal no. of EVS allocation	EVCS1				EVCS2				Total real power losses after EVs placement(KW)
	SoC=0.8		SoC=0.5		SoC=0.8		SoC=0.5		
Basecase	39	53	62	84	28	39	46	62	213.664
PSO	176	240	281	385	39	53	62	84	73.575
CSA	176	240	281	385	39	53	62	84	73.575
HSA	109	307	175	491	24	68	38	108	73.576
GWO	170	233	273	372	39	53	62	84	72.568

TABLE-IV. SIMULATION RESULTS WITH TYPE_1 DG(33-bus system)

	With type_1 DG with pf =1			
	PSO	CSA	HSA	GWO
Active Power loss(KW)	105.814	105.814	105.814	105.814
Reactive Power loss(KVAR)	75.55	75.55	75.55	75.55
DG sizing(MW) and location	2.3771 (25)	2.3771 (25)	2.3771 (25)	2.3771 (25)
V_{min}(pu)	0.949(18)	0.949(18)	0.949(18)	0.949(18)
Computation time(secs)	16.577	29.238	15.916	15.728
EVCS	26 30	26 30	26 30	26 30

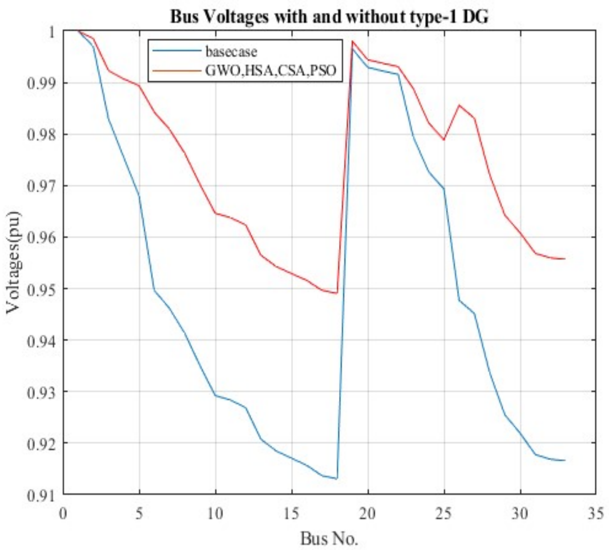

Figure 4.Voltage profile of 33-bus system with and without type_1 DG

In 33bus test system the voltage profile with type_1 DG with minimum voltage of 0.949pu at bus 18 is shown in figure 4.

TABLE-V.OPTIMALNUMBER OF EVs ALLOCATION AT EACH EVCS (with and type_1 DG)

Optimal no. of EVS allocation	EVCS1				EVCS2				Total real power losses after EVs placement(KW)
	SoC=0.8		SoC=0.5		SoC=0.8		SoC=0.5		
PSO	145	199	232	318	39	53	62	84	116.774
CSA	145	199	232	318	39	53	62	84	116.774
HSA	90	254	144	406	24	68	38	108	116.78
GWO	134	210	214	336	36	56	57	89	116.78

B.IEEE 69-bus test system

TABLE-VI.SIMULATION RESULTS WITH TYPE_2 DG (69-bus system)

	Base case	With type_2 DG with pf =0.8			
		PSO	CSA	HSA	GWO
Active Power loss(KW)	224.954	23.267	23.267	23.267	23.267
Reactive Power loss(KVAR)	102.145	14.423	14.423	14.423	14.423
DG sizing(MVA) and location	-	0.7159 (60)	0.7159 (60)	0.7159 (60)	0.7159 (60)
V_{min}(pu)	0.9092 (65)	0.9725 (27)	0.9725 (27)	0.9725 (27)	0.9725 (27)
Computation time(secs)	0.1844	33.5853	58.336	31.283	29.066
EVCS	61 49	61 49	61 49	61 49	61 49

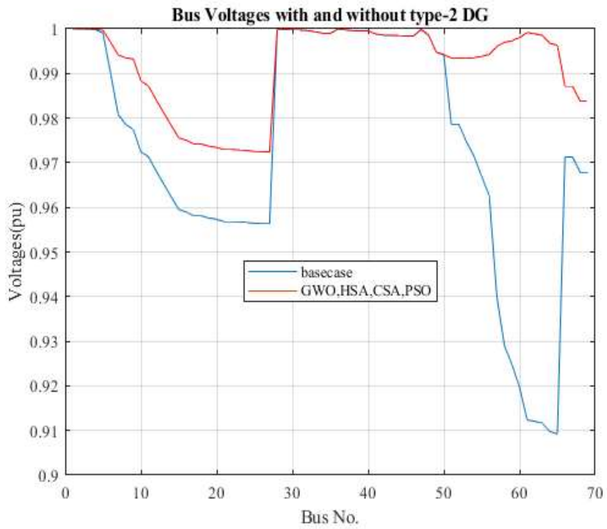

Figure 5.Voltage profile of 69-bus system with and without type_2 DG

In 69bus test system the voltage profile with type_2 DG with minimum voltage of 0.9725pu at bus 27 is shown in figure 5.

TABLE-VII.OPTIMALNUMBER OF EVs ALLOCATION AT EACH EVCS(with and without type_2DG)

Optimal no. of EVS allocation	EVCS1				EVCS2				Total real power losses after EVs placement(KW)
	SoC=0.8		SoC=0.5		SoC=0.8		SoC=0.5		
Basecase	93	128	150	204	29	39	46	43	34.2909
PSO	44	60	70	96	29	39	46	43	34.2909
CSA	44	60	70	96	29	39	46	43	34.2909
HSA	44	60	70	96	29	39	46	43	34.2909
GWO	44	60	70	96	29	39	46	43	34.2909

TABLE-VIII. SIMULATION RESULTS WITH TYPE_1 DG (69-bus system)

	With type_1 DG with pf =1							
	PSO		CSA		HSA		GWO	
Active Power loss(KW)	83.2105		83.2105		83.2105		83.2105	
Reactive Power loss(KVAR)	40.5309		40.5309		40.5309		40.5309	
DG sizing(MW) and location	1.088 (60)		1.088 (60)		1.088 (60)		1.088 (60)	
V_{min}(pu)	0.9683 (27)		0.9683 (27)		0.9683 (27)		0.9683 (27)	
Computation time(secs)	35.6154		35.6154		35.6154		35.6154	
EVCS	61	49	61	49	61	49	61	49

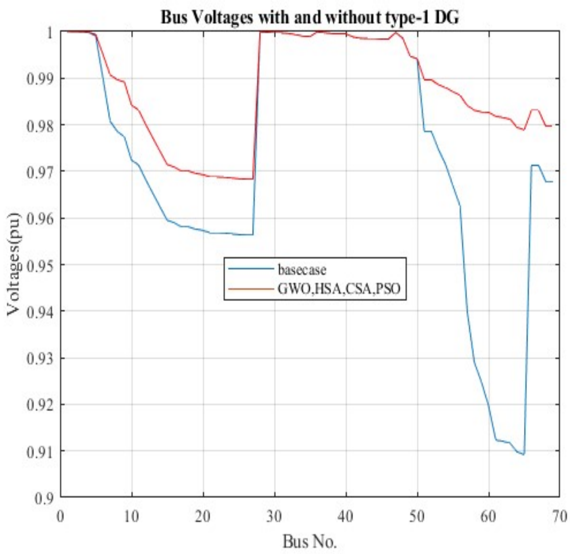

Figure 6.Voltage profile of 69-bus system with and without type_1 DG

In 69bus test system the voltage profile with type_1 DG with minimum voltage of 0.9683pu at bus 27 is shown in figure 6.

TABLE-IX.OPTIMALNUMBER OF EVs ALLOCATION AT EACH EVCS (with and type_1DG)

Optimal no. of EVS allocation	EVCS1				EVCS2				Total real power losses after EVs placement(KW)
	SoC=0.8		SoC=0.5		SoC=0.8		SoC=0.5		
PSO	61	96	98	154	26	42	42	67	94.2961
CSA	66	91	107	145	29	39	46	63	94.2961
HSA	66	91	107	145	29	39	46	63	94.2961
GWO	66	91	107	145	29	46	39	63	94.2961

C. Results and Discussion

The potency and efficacy of the generated solution based on GWO is compared in terms of optimal placement of DG units, simultaneously optimal number of EVs scheduled for charging at EVCS, optimal reduction in power loses and computational time with well known meta-heuristic algorithms such as HSA, CSA and PSO.

In this paper two different types of DGs are placed at optimal locations in both IEEE 33 and 69 bus systems are type_1 (injects only real power) and type_2 (injects both real and reactive power with pf=0.8). Simultaneously the EVCS shows optimal number of EVs scheduled for charging. Due to distinct nature of meta-heuristic algorithms (GWO,HSA,CSA & PSO) the optimal placement of type_2 DG, optimal reduction of losses in the system and optimal number of EVs scheduled are non-conventional, while placing type_1 DG at common optimal location they performed homogeneously and comes to an agreement. In IEEE 69 bus system as the loads are roughly different and after the allocation of single DG units of both type in alone, the optimal number of EVs and optimal reduction in power losses are round about in agreement.

The over-all performance of GWO optimization perspective is capable of solving the DG allocation problem, enhancement of voltage profile, optimal reduction in power losses is executed with better computation time compared with remaining algorithms(HSA,CSA & PSO) in MATLAB R2021a software.

5. Conclusion

Grey Wolf Optimization algorithm is implemented for the optimal sizing of DG in this paper. It is a novel nature inspired meta-heuristic algorithm based on the leadership hierarchy and hunting mechanism of grey wolves in nature. The Index Vector method is implemented to identify the optimal location of DG.

Voltage profile enhancement and optimal reduction in power losses in the distribution network are the objectives is being achieved. It is tested on IEEE balanced 33bus and 69 bus systems and is compared with other methods. It is observed that the power loss has been bringing down and voltage is enhanced compared to base case. The results indicate that GWO is competitive with other methods to solve optimization problems.

Simultaneously the EVCS are updated with optimal number EVs along with optimal sizing and allocation of DG in the standard IEEE 33bus, 69 bus systems of type_1 and type_2 DG units and emulated based on number of EVs integrated at EVCS, optimal loss reduction in the system, computation time for fast convergence.

The GWO algorithm govern over other algorithms in the aspects developed in above terms in both IEEE 33 and 69 bus radial distribution test networks.

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