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RESEARCH ARTICLE

Optimal Distributed Generation Allocation in Practical Distribution System in the Presence of Plug-in Electric Vehicles

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ABSTRACT

Due to the rising interest in sustainable transportation efforts, the adoption rate of plug-in electric vehicles (PEVs) in the transportation sector has grown significantly. However, a rise in PEVs will create an additional load demand on the electrical distribution system (EDS), which leads to increased system power loss and bus voltage deviation. Hence, the additional load must be balanced through auxiliary generation units known as distributed generation (DG) which can be integrated into EDS that minimize system power loss and bus voltage deviation. In the present study, Harris hawk's optimization technique has been implemented for optimal DG allocation in the presence of PEVs. To crisscross the feasibility of the technique, a daily load curve has been considered with various load demand patterns in a day of 24 h. The optimization technique has been implemented and tested on practical 28 – bus EDS which is in Kakdwip, West Bengal, India.

Index Terms— Distributed generation, distribution system, Harris hawk's optimization, plug-in electric vehicles, power loss minimization

I. INTRODUCTION

Currently, the world is facing various economic and environmental issues due to the increased demand for electrical energy. It was noticed that in the past few decades, due to urbanization and industrialization, this demand has been increasing in rapid phase. Since conventional power-generating stations utilize fossil fuels, greenhouse gas (GHG) is emitted causing harmful effects on the environment. However, demand for electrical energy is escalating gradually. Hence, auxiliary generation through distributed generation (DG) is one of the viable solutions for escalating electric demand. It is noticed that the appropriate allocation (location and size) of DG into the existing electric distribution system (EDS) will minimize system power loss and bus voltage deviation. However, inappropriate DG allocation will have an adverse impact on EDS. Hence, optimal DG allocation is a complex combinatorial optimization problem. Various reviews on DG allocation methods and techniques have been presented in [1–3].

Several authors used various techniques for solving DG allocation problems in EDS for power loss minimization as a major objective. Ackermann et al. have reviewed the significance and concern to give a general definition of distributed power production in competitive energy markets [4]. In the past few decades, several researchers have used various techniques to solve DG allocation problems. Initially, researchers have implemented analytical methods for solving DG allocation problems in EDS. In [5], researchers used rules of thumb also known as a golden rule or 2/3rd rule for DG allocation in an EDS. Hung et al. have implemented an analytical expression using the exact loss formula for single DG allocation and quick loss calculation in EDS [6]. Aman et al. have implemented a novel index method considering the system power stability index for DG allocation in EDS [7]. Hung et al. have implemented an analytical expression using Elgerd's loss formula for the allocation of both dispatchable and non-dispatchable renewable DG with various power factor operations [8]. Viral et al. have implemented a self-correction algorithm with reduced search space for enhancing computational speed to allocate multiple DG [9]. Ghosh et al. have developed a simple conventional search method for evaluating the cost of losses and DG [10].

In [11], researchers have used the Kalman filter algorithm and power loss sensitivity index for identifying DG size and location, respectively. In the past few years, researchers are implementing heuristic or meta-heuristic algorithms for DG allocation in distribution systems. In [12], researchers have used an artificial bee colony algorithm for DG allocation in variable loading conditions.

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In [13], a bacterial foraging optimization algorithm has been used to solve DG allocation problem by considering techno-economic benefits. Sultana and Roy have implemented an oppositional krill herd algorithm for allocation of various energy sources in EDS [14]. In [15], researchers have used a bat algorithm for allocation of solar photovoltaic arrays in distribution system. Sultana et al. have used grey wolf optimizer (GWO) for multiple DG the allocation in distribution systems for loss minimization [16]. In [17], researchers have used flower pollination algorithm for allocation of different types of DGs in standard distribution systems. In [18], researchers have implemented symbiotic organisms search algorithm for power loss minimization through DG allocation. In [19], researchers have implemented ant lion optimization for the allocation of different types of DGs in standard distribution systems. Tanvar et al. evaluated techno-economic benefits of DG allocation in distribution systems using a combinational method of analytical and particle swarm optimization [20]. In [21], researchers have used whale optimization algorithm for the allocation of different types of DGs and evaluated the system reliability in standard distribution systems.

In recent years, researchers have shifted from single algorithm to combination of two or more algorithms to exchange qualities of algorithms for obtaining optimal results. In [22], researchers have implemented a combinational technique that consists of genetic algorithm and particle swarm optimization for power loss minimization through multiple DG allocation. A genetic-based tabu search technique has been implemented for renewable DG allocation in EDS [23]. Jamian et al. have implemented evolutionary particle swarm optimization which is based on ranking procedure for DG allocation [24]. Sanjay et al. have implemented hybrid GWO for multiple DG allocation in standard distribution systems [25]. In [26], researcher has implemented water cycle algorithm for solar- and wind-based generation system allocation in practical distribution systems considering power loss minimization as main objective. Venkatareddy et al. have implemented Jaya optimization algorithm for the allocation of mixed solar and wind energy source in EDS for loss minimization [27]. Several researchers have considered load on distribution systems is varying from 50% to 160%, which is linear variation. However, in practical, scenario distribution system with different loads residential, commercial, and agricultural has stochastic load variation. Hence, in the present study, stochastic nature of daily load curve of practical distribution system has been considered for more realistic feasibility of DG allocation in the presence of plug-in electric vehicles (PEVs).

Main Points

- The complex combinatorial problem of distributed generation allocation in the presence of plug-in electric vehicles has been solved using Harris hawk's optimization technique.
- The technique has been implemented and tested on practical distribution system.
- To crisscross the practicality of the technique, daily load curve has been considered with various load demand patterns in a day of 24 h.
- The present study will serve as a source for researchers and distribution network operators.

Concerns about emissions of greenhouse gas have prompted a trend toward zero-emission PEVs, which are likely to play a vital role in transforming the road transportation system. In [28], researchers have solved dynamic economic dispatch problem with PEVs charging pattern in daily load demand of 24 h using a multi-objective biogeography-based optimization. Yang et al. implemented teaching a learning-based optimization for solving similar optimization problem considering multiple PEVs integration [29]. In [30], researchers have presented relationship between penetration of PEVs and load demand increase in distribution system and solved this through effective load modeling technique. Injeti et al. have implemented a bio-inspired optimization algorithm for solving DG allocation in the presence of PEVs problem considering stochastic load demand pattern [31]. In [32, 33], researchers have discussed the impact and prospects of PEV charging pattern and energy source allocation on grid. An investigation of the barriers to the adoption of electric vehicles and vehicle-to-grid technology in India has been presented in [34]. However, it is observed from the literature that very few researchers have considered the impact of PEVs integration and DG allocation with various charging conditions.

In the present study, charging behavior of PEVs is considered for two different scenarios which are based on probability distribution of charging time. These two scenarios are evaluated through certain count of PEVs and later integrated into the load pattern of a day of the distribution system. The impact of PEVs charging behavior is evaluated. Since integration of PEVs creates additional demand on the system and deteriorates its performance, optimal DG allocation must be carried out. In the present study, a novel Harris hawk's optimization (HHO) technique has been implemented to solve the optimal DG allocation in the presence of the PEVs.

The present article is structured as a formulation of mathematical model illustrated in section II; implementation of HHO technique for optimal DG allocation in the presence of PEVs in section III analysis of system for various charging patterns of PEVs without DG allocation, section IV presents simulation results attained after optimal DG allocation using HHO, and section V presents conclusion and future directions of the current study.

II. PROBLEM FORMULATION

The practical influence of PEVs charging behavior and DG allocation into distribution system must be evaluated appropriately to avoid deterioration of power quality and system reliability.

A. Objective Function

The major objective of the current optimization problem is to minimize daily active power in the distribution system. The daily active power loss can be curtailed by minimizing active power loss index (APLI). Here, APLI is considered as the ration of daily active power loss of the system with and without DG allocation which is given as $P_{daily\ loss}^{DG}$ and $P_{daily\ loss}$, respectively.

$$OF = min\left\{APLI\right\} \tag{1}$$

$$APLI = \frac{P_{daily\ loss}^{DG}}{P_{daily\ loss}} = \frac{\sum_{t=1}^{24} P_{t,loss}^{DG}}{\sum_{t}^{24} P_{t,loss}} \tag{2}$$

where $P_{t,loss}^{DG}$ and $P_{t,loss}$ are the t^{th} hour active power loss of the system with and without DG allocation, respectively.

The power loss and voltage profile as noticed from the literature are contradictory in nature; due to this reason, in the present study, voltage deviation index (VDI) has been evaluated to check the feasibility of the technique.

$$VDI = min\sum_{t=1}^{24}\left\{\frac{V_1 - V_{t,j}}{V_1}\right\} \quad \forall j = 2,..,N_{bus} \; and \; V_1 = 1.05 \; p.u. \tag{3}$$

where $V_{t,j}$ is the bus voltage at j^{th} bus at t^{th} hour.

B. System Constraints

1) Equality Constraints

System equality constraints refer to balance of active and reactive powers.

$$P_{t,sub} + P_{t,DG} = P_{t,PEV} + P_{t,demand} + P_{t,loss} \tag{4}$$

$$Q_{t,sub} = Q_{t,demand} + Q_{t,loss} \tag{5}$$

where $P_{t,sub}$ and $Q_{t,sub}$ are the active and reactive power from the substation at t^{th} hour; $P_{t,loss}$ and $Q_{t,loss}$ are the active and reactive power loss of the system at t^{th} hour; $P_{t,demand}$ and $Q_{t,demand}$ are the active and reactive power demand at t^{th} hour; $P_{t,DG}$ power generated from DG at t^{th} hour; $P_{t,PEV}$ active load demand of PEV at t^{th} hour.

2) Inequality Constraints

The following are the inequality constraints:

$$0.95 \le V_{t,j} \le 1.05 \tag{6}$$

$$P_{min}^{DG} \le P_t^{DG} \le P_{max}^{DG} \tag{7}$$

$$Q_{min}^{DG} \le Q_t^{DG} \le Q_{max}^{DG} \tag{8}$$

III. METHODOLOGY

A. Harris Hawks' Optimization

Heidari et al. proposed a novel population-based optimization technique known as HHO. It is a nature-inspired optimization technique. The optimization technique is inspired by the hunting behavior of predatory birds which are found in the USA, especially the southern portion of Arizona lives in steady communities called Harris' hawk (Parabuteo unicinctus). These birds possess a unique cooperative behavior of foraging with other members of the family living in a similar group. However, other birds will normally discover and attacks the prey, alone. This bird desert predator demonstrates advanced team hunting abilities in tracking, surrounding (encircling), flushing out, and finally attacking the prospective prey. During the non-breeding season, these birds are smart enough to offer dinner parties for several individuals. In the raptor realm, these birds are known as genuinely cooperative predators. The team mission of these birds starts at morning twilight. These birds often sit on power poles and giant trees within their territory. The strategic moves of these birds are well-planned because they know their family team. To catch a prey, Harris' hawks use one of the seven killing strategy known as surprise pounce. During the hunt, these hawks use this intelligent strategy to detect and attack the fleeing rabbit beyond the cover from various directions and converges simultaneously. The assault may be accomplished quickly by catching the astonished victim in a few seconds, but depending on the prey's fleeing ability and habits, the seven kills may entail repeated, short-length, fast dives nearby the prey over many minutes. Harris' hawks can exhibit a range of pursuit methods depending on the complexity and a prey's fleeing habits. When the best hawk (leader) stoops at the prey and becomes disoriented, the hunt is resumed by other team members. The escaping rabbit can be confused through these alternating hunt resume behaviors. The main advantage of such cooperative tactics is that the birds can pursue the detected rabbit to exhaustion, which cannot reestablish its defensive abilities by baffling the predators. In general, among other hawks, one effective and skillful hawk will quickly catch the exhausted rabbit and shares it with the others. The main behavior of Harris' hawks can be observed from nature. The major phases of HHO are exploratory and exploitative. These phases are inspired by the different attacking strategies of Harris' hawks which are exploring a prey and surprise pounce [35].

1) Exploration Phase

In general, Harris' hawks have powerful eyes to identify and chase prey. However, sometimes, it is not easy to identify the prey. Hence, the hawks must wait and examine the desert area to identify a prey which may take several hours. In the present optimization, the candidate solutions are the hawks and the best candidate solution in every move will be taken as near optimum or intended prey. The hawks randomly sit in some locations and follow two strategies to identify a prey. In HHO, for each perching strategy, there will be an equal chance q is considered. First strategy is based on distance between position of the rabbit and other family members and the second strategy is based on perch on tall trees randomly inside the home region. These two strategies are formulated as follows:

$$Y(t+1) = \begin{cases} Y_{rand}(t) - r_1 * \left|Y_{rand}(t) - 2 * r_2 * Y(t)\right| & q \ge 0.5 \\ \left(Y_{rabbit}(t) - Y_m(t)\right) - r_3 * \left(lb + r_4 * (ub - lb)\right) & q < 0.5 \end{cases} \tag{9}$$

where $Y_m(t)$ and $Y(t+1)$ are the hawks' position vector for the present and subsequent iteration t; $r_1, r_2, r_3, r_4,$ and q are random numbers updated in every iteration between 0 and 1; $Y_{rand}(t)$ is current population randomly chosen hawk; $Y_{rabbit}(t)$ is the prey or rabbit position; $lb and ub$ are lower and upper limits of variables; $Y_m(t)$ is the hawks' current population average position.

$$Y_m(t) = \frac{1}{N}\sum_{i=1}^{N} Y_i(t) \tag{10}$$

where $Y_i(t)$ specifies each hawk position in iteration t; N indicates overall hawks.

2) Transition from Exploration to Exploitation

The HHO algorithm transitions from exploration to exploitation and then switches between different exploitative actions depending on the prey's fleeing energy. During the escape activity, a prey's energy level drops significantly. The prey's energy to escape is modeled as:

$$E = 2 * \left(1 - \frac{t}{T}\right) * E_0 \tag{11}$$

where E is the prey's escaping energy; T is the maximum iteration number; t is the current iteration; and E_0 is prey's initial escaping energy. The value of E_0 varies from $-1 \text{ to} +1$ for two different scenarios of rabbit escaping energy. If E_0 value is decreasing from $0 \text{ to} -1$, the rabbit is physically declining. The rabbit will strengthen when E_0 value is increasing from $0 \text{ to} +1$. When the prey's fleeing strength is less than one, HHO will improve the local search for the finest choices in the vicinity.

3) Exploitation Phase

The Harris' hawks conduct the surprise pounce in this phase by attacking the target prey discovered in the previous phase. Prey, on the other hand, frequently attempts to flee from harmful circumstances. As a result, different pursuing techniques emerge in real-world settings. The HHO proposed four different ways to mimic the attacking stage based on prey fleeing behaviors and pursuit strategies of Harris' hawks. Preys are continually trying to get away from dangerous circumstances. Assume r is the probability of a prey successfully escaping $(r < 0.5)$ or unable to escape $(r \geq 0.5)$ before a surprise pounce. Irrespective of prey's trails, the hawks will engage in a harsh or soft besiege to capture it. Prey encircle is performed from various directions, softly or hardly, depending on the prey's residual energy. The prey's escaping energy (E) is utilized to simulate this strategy and allow the HHO to switch flip between the processes of soft and hard besiege. The hard besiege happens when $|E| < 0.5$ and soft besiege occurs when $|E| \geq 0.5$.

a) Soft Besiege

Soft besiege will be performed by the hawks when the rabbit is failed to escape after trying some misleading random jumps with enough energy (i.e., $r \geq 0.5 \, and |E| \geq 0.5$). The following rules mimic this behavior:

$$Y(t+1) = \Delta Y(t) - E * \left| J * Y_{rabbit}(t) - Y(t) \right| \tag{12}$$

$$\Delta Y(t) = Y_{rabbit}(t) - Y(t) \tag{13}$$

$$J = 2 * (1 - r_5) \tag{14}$$

where $\Delta Y(t)$ is the variation of rabbit position vector at iteration t; J is rabbit jump strength during escaping procedure; r_5 is random number between 0 and 1. The nature of rabbit moment is simulated randomly in each iteration when J value changes.

b) Hard Besiege

Hard besiege will be performed by the hawks when the rabbit has exhausted and has less energy to escape (i.e., $r \geq 0.5 \, and |E| < 0.5$). The hawks finally execute the surprise pounce by encircling the prey. The present locations are updated using the following equation:

$$Y(t+1) = Y_{rabbit}(t) - \left| \Delta X(t) \right| * E \tag{15}$$

c) Soft Besiege with Progressive Rapid Dives

Before the surprise pounce, a soft besiege is planned, but the rabbit can effectively escape with enough energy (i.e., $r < 0.5 \, and |E| \geq 0.5$). This process is further intelligent than the earlier case. In competitive circumstances when hawks wish to grab the prey, they use the skill of choosing the best possible dive.

$$A = Y_{rabbit}(t) - E * \left| J * Y_{rabbit}(t) - Y(t) \right| \tag{16}$$

Earlier dive results will be compared with current movement possible results to identify good dive among two. If it is not satisfactory (when hawks find that the rabbit is performing more misleading movements), hawks start to execute irregular, sudden, and quick dives when advancing the rabbit. For diving, hawks chose levy flight (LF) patterns as follows:

$$Z = A + LF(D) \times S \tag{17}$$

where LF is levy flight function [36]; D is problem dimension; S is $1 \times D$ sized random generated vector.

As a result, the ultimate approach for updating hawk locations during the soft besiege phase can be achieved via (18) shown below.

$$Y(t+1) = \begin{cases} A & if\, F(A) < F(Y(t)) \\ Z & if\, F(Z) < F(Y(t)) \end{cases} \tag{18}$$

Only the better location of A or Z will be chosen as the next spot in each phase. This approach is used by all search agents.

d) Hard Besiege with Progressive Rapid Dives

Before the surprise pounce, a hard besiege is planned to catch and kill the prey. The rabbit is not having sufficient energy to escape (i.e., $r < 0.5 \, and |E| < 0.5$). In this scenario, hawks will try to reduce the gap between them and escape prey.

As a result, the ultimate approach for updating hawk locations during the hard besiege phase can be achieved via (18). However, A and Z will be updated as follows:

$$A = Y_{rabbit}(t) - E * \left| J * Y_{rabbit}(t) - Y_m(t) \right| \tag{19}$$

$$Z = A + LF(D) \times S \tag{20}$$

B. Implementation of Harris Hawks' Optimization for Optimal Distributed Generation Allocation in the Presence of Plug-in Electric Vehicles

The sequence of steps involved to employ present optimization technique for optimal DG allocation in the presence of PEVs is given as follows:

Step 1: Initialize the algorithm parameter values (N and T are population size and maximum number of iterations, respectively) as per the requirement.

Step 2: Input the bus and line data for the load flow study program [37].

Step 3: Assign the lower and upper limit for variables (DG locations and sizes).

Step 4: With above lower and upper limits generate a solution set of random variables (search hawks).

Step 5: Using the direct approach method for load flow, evaluate the objective function for different set of randomly generated variables using equation (1).

Step 6: Identify the optimal value of the objective function through identification of best hawk position using equation (9).

Step 7: In every step, for each hawk, the values of E, E_0 and J have to be updated using (11).

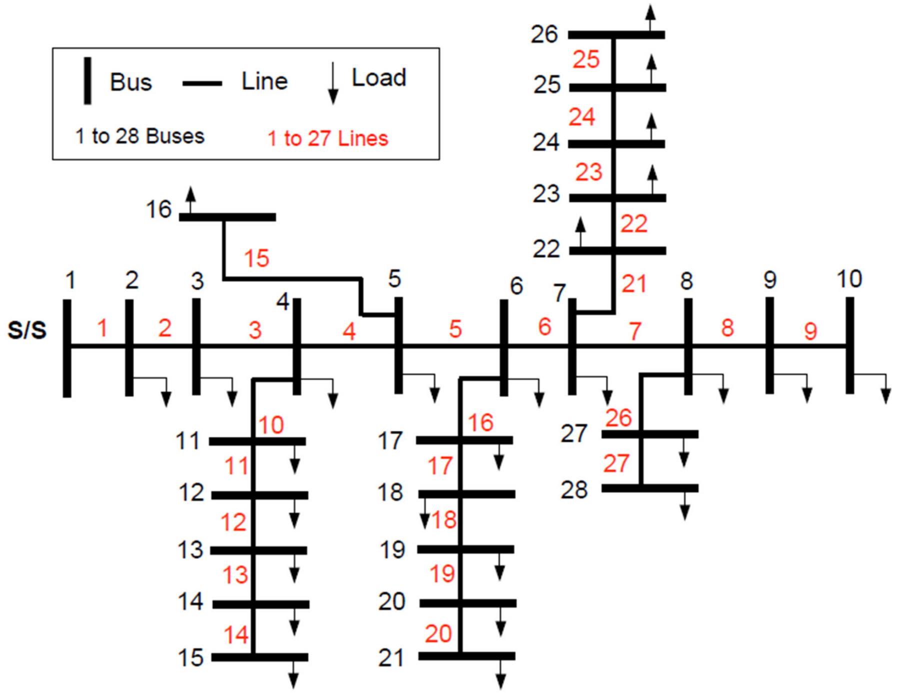

Fig. 1. Single line diagram of 28 – bus system.

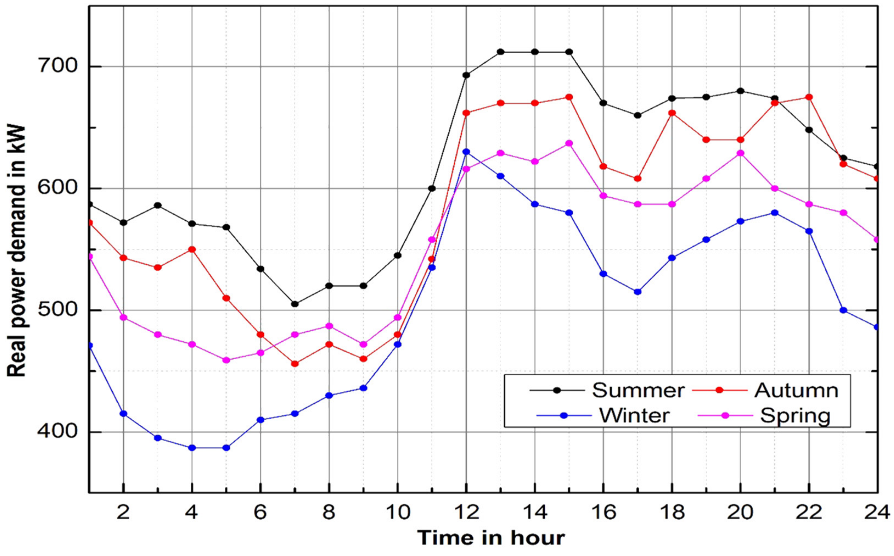

Fig. 2. Daily load demand pattern of 28 – bus system

Step 8: If $E \geq 1$, update the hawks position using , else go to next step.

Step 9: If $E \geq 0.5$, proceed to next step, else jump to step 11.

Step 10: If $r \geq 0.5$, update the hawks position using (12), else update using the equation (18) and jump to step 12.

Step 11: If $r < 0.5$, update the hawks position using (18), else update using the equation (18) and jump to step 13.

Step 12: If $E < 0.5$, update the hawks position using (16), proceed to next step, else jump to step 13.

Step 13: Check for the stopping criteria or maximum number iterations. If yes, display the values of DG location and size, else go to step 4 and repeat.

IV. RESULTS AND DISCUSSION

A practical 28 – bus distribution system which is in Kakdwip, West Bengal, India, has been considered for the analysis of the present optimization technique. The single-line diagram of the distribution

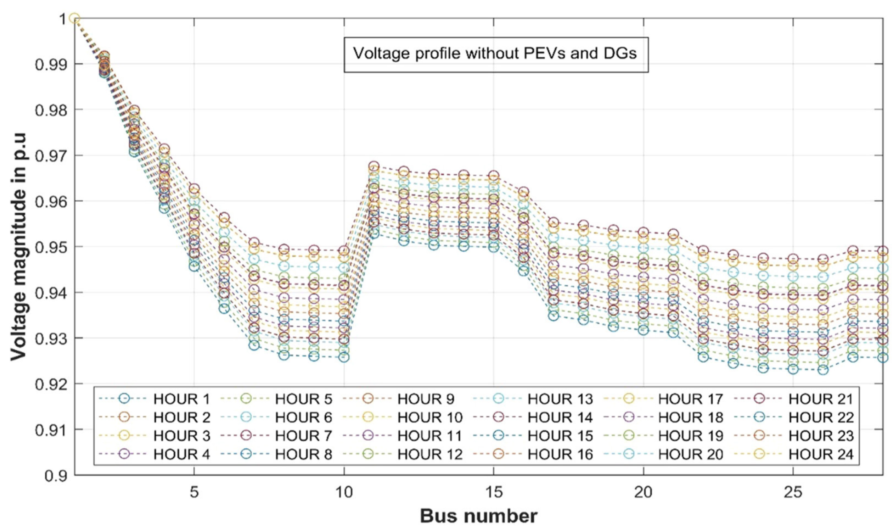

Fig. 3. Voltage profile of the system without PEVs and DGs. PEVs, plug-in electric vehicles; DG, distributed generations.

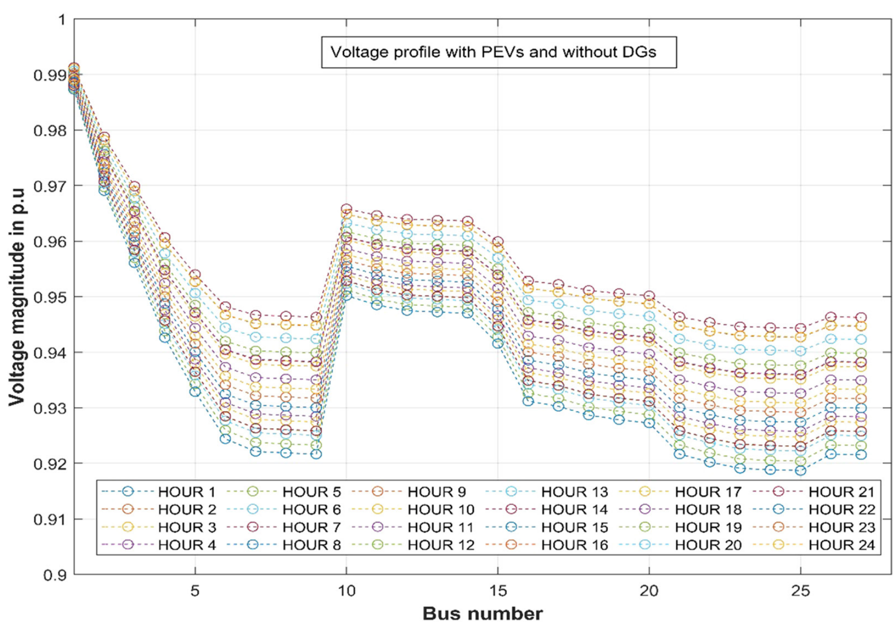

Fig. 4. Voltage profile of the system with PEVs and without DGs. PEVs, plug-in electric vehicles; DG, distributed generations.

system is illustrated in Fig. 1. The bus and line data of the system are taken from [38]. The seasonally varying load demand on the system is considered from [39]. However, for the present study, the daily load demand is considered as peak demand on the system during summer season for 24 hours as illustrated in Fig. 2. The present system has been assessed based on three different cases.

Case i: Actual system assessment without PEVs and DGs (base case);

Case ii: System assessment with PEVs and without DGs;

Case iii: System assessment with PEVs and DGs (optimal case).

A. Actual System Assessment without Plug-in Electric Vehicles and Distributed Generations (Base Case)

The present simulation has been implemented in MATLAB® version R2021b installed on laptop of Core i7 6500U CPU @ 2.5 GHz, 8GB RAM. A direct approach for distribution system load flow studies has been used for load flow analysis [37]. The total real and reactive power demand on the system is 761 kW and 776.41 kVAr, respectively. The network has maximum power demand of 947 kVA. The active power loss of the system is 68.81 kW. The voltage profile of the network without PEVs and DGs is illustrated in Fig. 3.

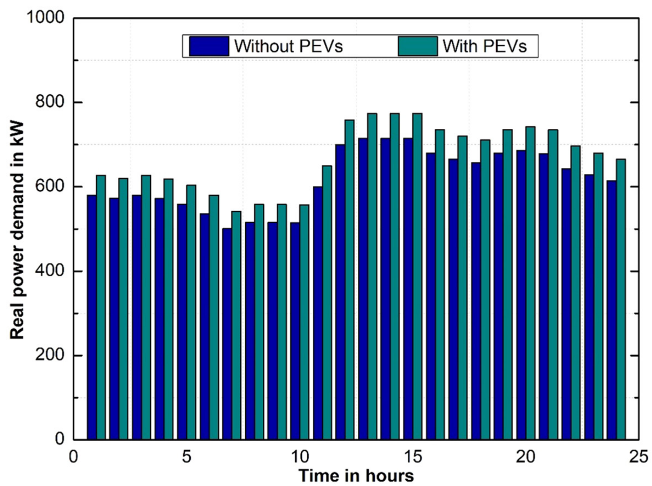

Fig. 5. Real power demand with and without PEVs. PEVs, plug-in electric vehicles.

TABLE I.
COMPARISON OF VARIOUS NETWORK PARAMETERS WITHOUT AND WITH PEVS LOAD

Network Parameter	Without PEVs	With PEVs
Daily real power demand of the system in kWh	18264	19951.5
Daily real power loss of the system in kWh	1243.44	1376.16
Minimum bus voltage in p.u.	0.9230 at 13th hour	0.9186 at 13th hour
Maximum bus voltage in p.u.	0.9917 at 9th hour	0.9912 at 7th hour

PEVs, plug-in electric vehicles.

B. System Assessment with Plug-in Electric Vehicles and without Distributed Generations

To assess the effect of PEVs addition on distribution system performance, it has been considered that each bus will have five PEVs (i.e., a total of $27 \times 5 = 135$ PEVs). However, the additional electric demand due to PEVs will be supplied by the slack bus.

TABLE II.
DAILY REAL POWER DEMAND AND LOSS ON THE SYSTEM FOR THREE DIFFERENT CASES

Time in Hour	System Without PEVs and DGs		System With PEVs and Without DGs		System With PEVs and DGs	
	Load in kW	Loss in kW	Load in kW	Loss in kW	Load in kW	Loss in kW
1	580	33.07	627.33	36.54	627.33	14.55
2	572.65	32.27	620	35.65	620	14.33
3	580	33.07	627	36.54	627	14.55
4	572	32.14	619	35.51	619	14.26
5	558	30.58	603.66	33.77	603.66	13.84
6	536	28.09	580	31.017	580	13.13
7	500.78	24.39	541.94	26.91	541.94	12.25
8	515.62	25.81	558	28.5	558	12.5
9	515.62	25.81	558	28.5	558	12.5
10	514.8	25.77	557.17	28.44	557.17	12.51
11	600	35.68	649.32	39.42	649.32	15.477
12	700	49.67	758.38	54.95	758.38	20.94
13	714.8	51.81	773.6	57.34	773.6	21.87
14	714.8	51.76	773.6	57.29	773.6	21.82
15	714.8	51.76	773.6	57.29	773.6	21.82
16	679.68	46.4	735.55	51.33	735.55	19.49
17	665.62	44.43	720.33	49.13	720.33	18.72
18	657.03	43.22	711	47.79	711	18.24
19	680	46.44	735.55	51.38	735.55	19.54
20	686	47.14	742.32	52.44	742.32	19.96
21	678.9	46.44	734.71	51.3	734.71	19.53
22	643	41.35	696.6	45.71	696.6	17.49
23	628.9	39.36	680	43.5	680	16.75
24	614.48	37.52	665.38	41.47	665.38	16.09

PEVs, plug-in electric vehicles; DG, distributed generations.

It has been considered that the penetration of low, medium, and pure battery-based PEVs are 45%, 25%, and 30%, with battery capacity of 15, 25, and 40 kWh, respectively [29]. It is also expected that the state of charge of home-returned PEVs is 50%. Hence, overall electric demand due to PEVs per bus per day is $5*(15\times0.45+25\times0.25+40\times0.30)*0.5=62.5\,kW$ and total demand for electric distribution system required per day is $62.5*27=1687.5\,kW$. The voltage profile of the network with PEVs and without DGs is illustrated in Fig. 4. The real power demand on the network without and with PEVs is illustrated in Fig. 5.

The comparison between various parameters of distribution system without and with PEVs load is presented in Table I. It can be observed that subsequent increase in the system real power demand after PEVs load integration. From Table I, it is noticed that due to the PEVs load demand of 1687.5 kW, the daily real power demand of distribution network is increased by 9%.

C. System Assessment with Plug-in Electric Vehicles and Distributed Generations (Optimal Case)

The actual real power demand on the electric distribution network has increased due to PEVs load. Hence, integration of DGs shares increased real power demand on the network. The DGs considered for allocation will inject only real power generation. For optimal DG allocation, HHO algorithm has been implemented. Table II presents the daily real power demand and loss on the system for three different cases. The voltage profile of the network with PEVs and DGs is illustrated in Fig. 6. Fig. 7 illustrates the daily real power loss variation

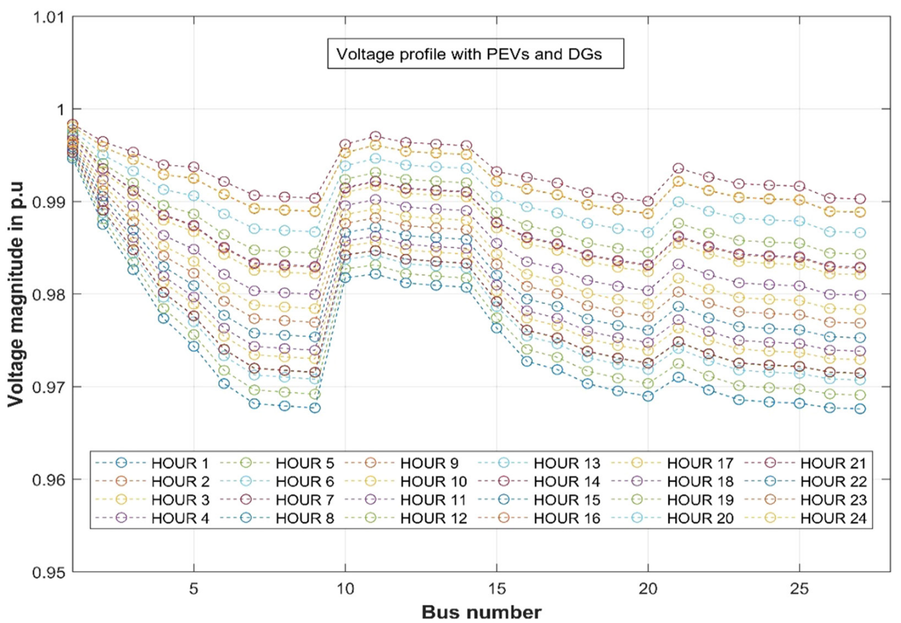

Fig. 6. Voltage profile of the system with PEVs and DGs. PEVs, plug-in electric vehicles; DG, distributed generations.

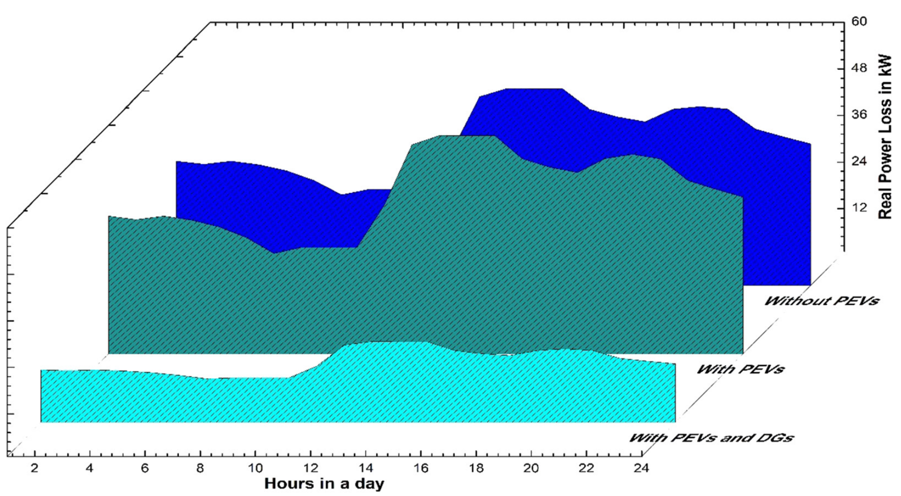

Fig. 7. Power loss reduction from base case to optimal case.

TABLE III.
OPTIMAL RESULTS OBTAINED AFTER DG INTEGRATION IN THE PRESENCE OF PEVS

Parameter	HHO
DG size in kW @ bus location	236 @ 5
	204 @ 11
	250 @ 21
Daily real power loss in kW	402.157
% Daily real power loss reduction	77.06
Minimum bus voltage in p.u.	0.9675 at 13th hour
Maximum bus voltage in p.u.	0.9983 at 7th hour

PEVs, plug-in electric vehicles; HHO, Harris hawks' optimization.

for different cases. It can be observed that the daily real power loss is increased after PEVs load and decreased when DGs are allocated appropriately in the network.

It is noticed from Table II that rise in load demand causes increase in power loss every hour for normal system and system with PEVs load. However, for system with PEVs and DGs, power loss has reduced.

Table III shows the optimal results obtained after DG allocation in the presence of PEVs. It is noticed from Table III that significant amount of power loss has been reduced from base case to optimal case of system using HHO algorithm. The minimum bus voltage has been increased from 0.9230 to 0.9675 at 13th hour. The power loss reduction from base case to optimal case can be noticed from Fig. 7.

V. CONCLUSION AND FUTURE DIRECTIONS

In the present article, a practical 28-bus Indian distribution system is considered for assessing the effect of PEVs along with DG allocation. The load pattern of daily real power demand for 24 hours is considered. The active power loss of the system is 68.81 kW. It can be observed that subsequent increase in the system real power demand after PEVs load integration is 1687.5 kW, and the daily real power demand of distribution network is increased by 9%. The objective function is framed to minimize the daily active power loss using repetitive direct approach for load flow analysis. Harris hawk's optimization algorithm is implemented to minimize the objective function. The superiority of HHO for solving the optimization problem of optimal DG allocation in practical distribution system in the presence of PEVs is discussed. It can be observed that the daily real power loss is increased after PEVs load and decreased when DGs are allocated appropriately in the network. The voltage profile of the network with PEVs and DGs has been improved. From the simulation results obtained, it is concluded that by using the HHO algorithm, the system performance is enhanced. The future direction of the work is considering PEVs simultaneously as a load and DG, with its charging and discharging habits considered during off and on peak hour demand. For further reduction of system losses and to enhance the performance, researchers can extend the vehicle to grid technology as one of the DGs to the already existing DGs.

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