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An Application of Hybrid Sine Cosine Optimization for Developing Sustainable Agriculture Distribution Feeders with Optimal Photovoltaic Systems

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Abstract: The growing threat of global warming necessitates immediate demand for the adoption of sustainable methods in all sectors, including agriculture. Most agricultural practices require quality and reliable power sources to maximise productivity. In this regard, this work proposes the efficient integration of photovoltaic systems (PVs) with agriculture distribution feeders (ADF) with multiple objectives. The main goals of this study are to maximise efficiency, energy loss cost and reduce greenhouse gas (GHG) emissions while working within various operational and planning restrictions. The ideal position and size of PVs for a specified ADF must account for both continuous and discrete variables, which is why this study introduces hybrid sine cosine optimization (HSCO). HSCO is designed to achieve both efficient search characteristics and a quick convergence rate by embedding the linear search route features of the particle swarm optimisation (PSO) and adaptive convergence factor (ACF), respectively. HSCO's effectiveness of the HSCO is demonstrated by tackling the challenge of optimal PV integration in a real-time 28-bus ADF and IEEE 33-bus feeder for different situations. The 28-bus feeder reduces cost and loss by 45.5%, 47.518%, and 48.3% for light, normal, and heavy loads. However, 33-bus optimum PV systems cut losses by 64.94% compared to basic scenario and better than existing literature works. A comparative analysis of the computational aspects of the proposed HSCO with basic sine cosine optimization (SCO), particle swarm optimization (PSO), northern goshawk optimization (NGO) and artificial rabbits optimization (ARO) is also presented. Notably, with global optima and reduced computational time, HSCO outperformed than other algorithms. Furthermore, ADF was observed with a loss reduction, good efficiency and significant reduction in GHG emissions with appropriate PVs integration. These figures are encouraging in terms of adapting the proposed methodology for real-time applications.

Keywords: Agriculture distribution feeder, Real power loss, Greenhouse gas emission, Optimization, Particle swarm optimization, Sine cosine optimization.

1. Introduction

The paris agreement on climate change is difficult to implement as global carbon emissions increase [1]. Developing global warming mitigation strategies requires an understanding of carbon emission parameters. Global warming and the possible disruption of the global carbon cycle make environmental degradation a key concern that is rapidly gaining global government attention [2]. Climate change is one of the biggest problems in humanity. Extreme weather, wildlife extinction, and food scarcity are unprecedented risks to growth and human existence due to greenhouse gas (GHGs) emissions, especially CO_2 [3]. The analysis in [4] focused on solar energy utilisation and its impact on CO_2 reduction in the United States. It also emphasised approaches for increasing solar energy utilisation, notably in the energy sector, to reduce GHG emissions. Photovoltaic systems (PVs) are one such technology that has the capacity to scale from the large-scale grid level to the small-scale consumer level [5].

Many researchers in the literature have focused on integrating renewable energy sources (RESs) as distribution generation (DG) in electrical distribution systems (EDSs), not only for technical-economic benefits but also for environmental goals [6]. However, optimal location, size, their operating power factor plays a key role in achieving the desired benefits for these sources in EDSs [7]. According to a comprehensive review [8], meta-heuristics have been widely used to solve the optimal allocation of RE-based DGs in EDSs. Some of the most recent studies are discussed in this section.

In [9], the water cycle algorithm (WCA) was utilised for solving different types of DGs integration problems in 33-bus and 69-bus EDSs considering multiple objectives, including loss minimisation, voltage profile improvement, voltage stability enhancement, cost of power generation, and GHG emission reduction. In [10], the archimedes optimisation algorithm (AOA) was introduced to solve PVs integration in EDS to reduce grid-dependency by maximising the PV capacity, distribution loss reduction, and consequently, minimisation of GHG emissions. In [11], the honey badger algorithm (HBA) was proposed to solve the simultaneous allocation of DGs and optimal network reconfiguration (ONR) considering EV load penetration. The analysis focuses on technical and environmental objectives. In [12], a hybrid dandelion optimiser (HDO) with loss sensitivity factors was developed for the ONR problem to maximise the PV penetration, loss reduction, voltage improvement, and GHG reduction. In [13-14], artificial rabbit optimisation (ARO) was used to optimally allocate PVs along with power quality devices for loss reduction and harmonic reduction in EDSs. In [15], northern goshawk optimisation (NGO) was adapted to solve different types of DGs allocation in EDSs considering techno-environmental benefits. In [16], an improved harris hawks optimiser (IHHO) for single and multiple technical objectives was used while solving the DG allocation problem. In [17], techno-economic benefits in EDSs were optimised by integrating RE-based DGs using the shark optimisation algorithm (SOA). In [18], the honey badger algorithm (HBA) was implemented for loss reduction in EDSs to solve RE-based DGs. In [19], the loss, voltage stability, cost of DG power, and GHG emissions were optimised while solving the DG allocation problem in EDSs using multi-objective because of the cosine algorithm (MOSCA). In [20], a transient search algorithm (TSA) was employed for DG allocation with the aim of loss, voltage deviation, and voltage stability. In [21], a new oppositional hybrid sine-cosine muted differential evolution algorithm (O-SCMDEA) was developed to avoid local traps in SCA and applied for solving DG allocation by focusing only on technical objectives. In [22], an improved decomposition-based evolutionary algorithm (I-DBEA) based DG allocation was solved for technical objectives by considering the power factor of DG as a controllable variable. In [23], an enhanced artificial ecosystem-based optimisation (EAEO) with a dynamically decreasing phase-balancing operator and SCA was proposed for DG allocation. In [24], a future search algorithm (FSA) was employed to reduce loss, enhance voltage stability, and reduce GHG emissions by optimally integrating PVs and electric vehicle (EV) fleets. In [25], optimal integration of PVs for loss reduction is analysed on a real-time bahir dar distribution feeder using modified particle swarm optimization (MPSO).

The above-mentioned articles were highly focused on maximising technological benefits in solving the RE-based DGs allocation in EDS. Only a few studies have concentrated on the economic and environmental benefits. The majority of the studies, on the other hand, have simulated IEEE standard test systems but have not considered practical distribution feeders. Furthermore, as demonstrated in [26], SCA is a well-proven metaheuristic with strong computational efficiency and convergence characteristics with hybridisation or enhanced variations. In contrast to prior works, this study’s significant contribution is as follows:

1) To prevent significant reliance on the main grid, optimal integration of solar photovoltaic systems (SPVs) in farm feeders is recommended, taking into account several techno-economic-environmental objectives.
2) Because the energy requirements of agricultural feeders vary according to the season, the sizes of SPVs are adjusted to be adequate for all seasons.
3) The proposed multi-objective problem with multi-equal and unequal constraints must be solved for multiple variables; therefore, a hybrid sine cosine algorithm (HSCA) [27] with particle swarm optimisation (PSO) linear search path behaviour and adaptive convergence factor (ACF) is used.
4) The effectiveness of the proposed methodology was evaluated using a 28-bus Indian real-time agricultural feeder.
5) The computing efficiency of the proposed HSCA is compared to that of the basic SCA, NGO, PSO,

and ARO.

The remainder of this paper is structured as follows: Section 2 describes the mathematical modelling of an agricultural feeder with several types of associated loads. The proposed multi-objective optimisation problem is presented in section 3. Section 4 examines the HSCA using mathematical relationships. The simulation results for a 28-bus farm feeder are presented in section 5. Section 6 presents the conclusions of this study.

2. Modelling of agriculture feeder

Electric motors are critical in contemporary agriculture as they power equipment such as water pumps, conveyor belts, and augers. These are essential for irrigation systems, crop handling, and cargo transportation. Electric fencing is used to keep animals in check, and crops are protected from animal damage. To maximise farming operations, modern tractors and farm machines are outfitted with electric components. Electric grain dryers minimise the moisture content, whereas electric heaters and feeding systems are used in poultry equipment. In greenhouses, electric systems regulate the temperature, humidity, lighting, and watering. Milking machines employ electric motors to automate the milking process, and grain-handling equipment uses electric motors. Pest control devices reduce the need for chemical pesticides, whereas electric fertiliser spreaders dispense nutrients and soil supplements. Heat lamps kept young animals warm during chily weather. Solar-powered equipment lowers the energy costs and has a lower environmental impact. Weather monitoring stations provide real-time data that can be used to inform decisions. In the proposed modelling, battery charge, fluorescent lamps, fluorescent lighting, air conditioner, resistance space heater, pumps, fans other motors, incandescent lamps, compact fluorescent lamps, small industrial motors and large industrial motors are considered. As per the voltage-dependent load modelling [28], the real and reactive power consumption by these loads is dependent on voltage magnitude of its associated bus. Mathematically,

$$\bar{P}_{d(i)} = \gamma_{lc} P_{d(i)} \left(\frac{|V_{(i)}|}{|V_{(s/s)}|}\right)^{\alpha_p} \quad (1)$$

$$\bar{Q}_{d(i)} = \gamma_{lc} Q_{d(i)} \left(\frac{|V_{(i)}|}{|V_{(s/s)}|}\right)^{\beta_q} \quad (2)$$

The power coefficients (α_p and β_q) along with their composition factor (γ_{lc}) in the proposed load modelling are given in Table 2.

Table 1. Proposed load composition and their power coefficients as per load modelling [28]

Load component	α_p	β_q	$\gamma_{lc}(\%)$
Battery charge	2.59	4.06	5
Fluorescent lamps	2.07	3.21	10
Fluorescent lighting	1.00	3.00	5
Air conditioner	0.50	2.50	10
Resistance space heater	2.00	0.00	15
Pumps, fans other motors	0.08	1.60	10
Incandescent lamps	1.54	0.00	5
Compact fluorescent lamps	1.00	0.35	5
Small industrial motors	0.10	0.60	15
Large industrial motors	0.05	0.50	20

3. Problem formulation

In this work, minimization of grid-dependency of the agriculture feeder, energy loss cost and GHG emission are proposed considering different load profiles based on spring, summer, autumn and winter seasons. The proposed multi-objective function mathematically given by:

$$F = \sum_s \left\{ \left(\frac{P_{SPV}}{\bar{P}_{D(s)} LF_{(s)}} \right) + C_{loss} P_{loss(s)} + GHG_{(s)} \right\} \quad (3)$$

The total net-effective loading after integrating SPVs, real power loss and GHG emission are given by:

$$\bar{P}_{D(s)} = \sum_{i=1}^{nbus} \bar{P}_{d(i)} - \sum_{i=1}^{npv} P_{SPV(i)} \quad (4)$$

$$P_{loss(s)} = \sum_{br=1}^{nbr} I_{br}^2 r_{br} \quad (5)$$

$$GHG_{(s)} = (CO_2 + NO_x + SO_2)\left(\bar{P}_{D(s)} + P_{loss(s)}\right) \quad (6)$$

The following are the constraints to be satisfied while solving the Eq. (3).

$$|V_{(i),min}| \leq |V_{(i)}| \leq |V_{(i),max}| \quad (7)$$

$$\sum_{i=1}^{nbus} \bar{P}_{d(i)} = \sum_{i=1}^{npv} P_{SPV(i)} \quad (8)$$

4. Solution methodology

This section explains the concepts of HSCA and its application procedure to solve the proposed objective function. At first, the basic SCA is explained and later, the proposed modifications to develop HSCA are elaborated mathematically.

4.1 Sine cosine optimization

The sine-cosine algorithm (SCA) is a metaheuristic optimization algorithm inspired by the trigonometric functions sine and cosine [26]. It is used to solve optimization problems by finding the best solution. The quick rundown of the algorithm is provided as follows:

Initialization: Begin by populating a population of potential solutions, which is commonly represented as a set of candidate solution vectors.

Function Objective: Using an objective function that must be optimized, assess the fitness of each solution in the population. The problem to be solved is defined by the objective function.

The main loop: Repeat steps (a)-(b) for a set number of iterations or until a convergence condition is met:

(a) Using sine and cosine functions, update the positions of the solutions in the population. This is the origin of the algorithm's name.
(b) Determine the fitness of the revised solutions.
(c) Compare the fitness of the revised solutions to the fitness of the present solutions and choose the best of the best.

Termination: The method finishes when it achieves the given ending criterion (e.g., a maximum number of iterations or a good solution is found), and the best answer obtained throughout the process is returned as the optimal solution.

Update using the sine-cosine function: The positions of solutions in the SCA algorithm are updated using sine and cosine functions. The equations for updating a solution's position are as follows:

$$x_{i(k+1)} = \begin{cases} x_{i(k)} + r_1 sin(r_2)\left|r_3 F_{i(k)} - x_{i(k)}\right| & r_4 < 0.5 \\ x_{i(k)} + r_1 cos(r_2)\left|r_3 F_{i(k)} - x_{i(k)}\right| & r_4 \geq 0.5 \end{cases} \quad (9)$$

Here, r_1 is a balancing factor decreased from *a* to 0, as defined by,

$$r_1 = a\left(1 - \frac{k}{k_{max}}\right) \quad (10)$$

where $r_2 \in [0,\ 2\pi]$, is a random variable, r_3 is uniformly distributed random number, r_4 is used to alter the search path, $F_{i(k)}$ is the objective function of current iteration, $x_{i(k+1)}$ and $x_{i(k)}$ are the search variable position in the next and current iteration, respectively; k and k_{max} are the current and maximum number of iterations, respectively.

The sine and cosine functions add exploration and exploitation components to the algorithm, allowing it to successfully explore the solution space while converging toward global optima.

4.2 Proposed hybrid sine cosine optimization

The basic SCA search path is nonlinear because of the presence of absolute value and trigonometric function terms in the position updating equations, making it challenging to limit the method search direction for complex optimisation problems. The search path does not aim for the global best path. In multi-parameter optimisation and severely ill-conditioned situations, the solution may only be a local optimum, as discussed in section 4.1.

The PSO method uses a linear search path. This study enhances Eq. (10) by incorporating a linear path into SCA, inspired by PSO. Compared to basic SCA, the new search route maintains random sine and cosine parameter selection, dual path characteristics, alters the convergence factor definition, and cancels the absolute value. The original SCA search path has only one ideal value Pi, which is insufficient for complex situations. Knowledge and information about prior searches and results can lead to accurate iterations using empirical parameters [27]. Therefore, empirical parameters are added to the search path to improve the accuracy as given below:

$$x_{i(k+1)} = r_1 x_{i(k)} + c_1 sin(r_2)\left|r_3 F_{i,best(k)} - x_{i(k)}\right| + c_2 sin(r_2)\left|r_3 E_{i,best(k)} - x_{i(k)}\right|, r_3 < 0.5 \quad (11)$$

$$x_{i(k+1)} = r_1 x_{i(k)} + c_1 cos(r_2)\left|r_3 F_{i,best(k)} - x_{i(k)}\right| + c_2 cos(r_2)\left|r_3 E_{i,best(k)} - x_{i(k)}\right|, r_3 > 0.5 \quad (12)$$

Furthermore, the definition of the relevant parameters was altered in this study. It is critical to define a convergence factor that performs well in the optimisation procedure.

$$r_1 = a_{max} - (a_{max} - a_{min})\frac{k}{k_{max}} \quad (13)$$

A larger convergence factor at the start of the iteration improves the global search. The convergence factor may rapidly decrease as the number of iterations increases. A smaller value and slow declining speed improved the algorithm

Table 2. Real-time 28-bus feeder performance without PV systems

Loading	P_d (kW)	Q_d (kVAr)	P_{ls} (kW)	Q_{ls} (kVAr)	V_{min} (p.u.)	V_{min} bus #	GHG (lb/h)
Normal	1008.03	994.06	120.560	80.816	0.8843	26	2310.97
Light	525.24	526.56	30.137	20.201	0.9423	26	1137.22
Heavy	1450.07	1407.91	273.347	183.244	0.8254	26	3528.97

Table 3. Real-time 28-bus feeder performance with PV systems by HSCO

Loading	PVs		P_{ls} (kW)	Q_{ls} (kVAr)	V_{min} (p.u.)/ Bus #	GHG (lb/h)
	Locations	Sizes				
Normal	22, 12, 18	413.19, 318.19, 213	63.272	41.955	0.9458/ 28	2193.663
Light	4, 22, 14	171.84, 279.71, 48.87	16.424	10.796	0.9738/ 21	1109.141
Heavy	6, 22, 14	801.11, 407.62, 288.07	141.44	94.05	0.9251/ 26	3258.872

Table 4. Comparison of HSCO for normal loading with other algorithms

Algorithm	Best	Worst	Mean	Median	SD	Time (min)
PSO	63.551	63.909	63.738	63.743	0.242	2.234
NGO	63.695	64.348	63.769	63.878	0.740	2.253
ARO	63.371	65.130	**63.516**	63.823	0.268	2.155
SCO	63.272	64.102	63.517	63.638	0.318	**2.127**
HSCO	**63.253**	**63.751**	63.594	**63.518**	**0.136**	2.128

optimisation.

5. Simulation results

The simulations were executed on a computer system equipped with a 2.3 GHz, 64-bit Intel Core i3-2410M CPU, and 4 GB of RAM. In order to comprehensively analyze the feeder performance, three distinct case studies were conducted for each feeder, encompassing normal load, light load, and heavy load scenarios. Each case study was simulated employing various optimization algorithms, including basic SCO [26], HSCO [27], particle swarm optimization (PSO) [28], northern goshawk optimization (NGO) [29], and artificial rabbits optimization (ARO) [30]. To assess the economic implications, the cost of loss was considered at a rate of 168 USD per kilowatt-hour (kWh).

5.1 Real-time 28-bus agriculture feeder

The determination of net effective loading for each bus, as outlined in section 2, takes into account the operating voltage of the feeder, which is set at 11 kV. As previously mentioned, three distinct case studies have been conducted, each with two sub-scenarios: one without PV systems and the other with PV systems. The results obtained from these case studies for scenario 1 can be found in Table 1, while the results for scenario 2 are presented in Table 2. Moreover, a comparative analysis of the convergence features of SCO, PSO, NGO, ARO, and HSCO is conducted over 50 independent runs. The statistical analyses of these simuations are given in Table 3.

5.1.1. Case 1

In this particular scenario, the feeder is assumed to operate under normal load conditions, with a total demand of 1008.03 kW for real power and 994.06 kVAr for reactive power. After conducting a load flow analysis, the resulting real power losses are determined to be 120.56 kW, while the reactive power losses amount to 80.82 kVAr. Since the feeder is connected to the main grid, the corresponding greenhouse gas (GHG) emissions are calculated to be 2310.968e+03 lb/MWh. Notably, the lowest voltage magnitude is observed at bus-26, measuring 0.8843 p.u.

To improve the performance of the feeder, the integration of three PV systems is optimized using the hybrid sine cosine optimization (HSCO) technique. The optimal locations for these PV systems are determined to be at buses 22, 12, and 18. The corresponding sizes of the PV systems are 413.19 kW, 318.19 kW, and 213 kW, respectively. As a result of this optimal integration, the real power losses are reduced to 63.272 kW, while the reactive power losses are reduced to 41.955 kVAr. Furthermore, the minimum voltage magnitude is raised to 0.9458 p.u at bus-28. Additionally, the integration of PV systems leads to a significant reduction in GHG emissions, which are now measured at 2193.663 lb/MWh.

5.1.2. Case 2

In this given scenario, the feeder is assumed to be operating under light load conditions, at 0.5 times the normal load. Consequently, the total demand for real power and reactive power in the feeder is calculated to be 525.24 kW and 526.56 kVAr, respectively. Upon conducting a load flow analysis, the resulting real power losses are determined to be 30.14 kW, with reactive power losses amounting to 20.2 kVAr. As the feeder is connected to the main grid, the corresponding greenhouse gas (GHG) emissions are estimated to be 1137.22e+03 lb/h. Notably, the lowest voltage magnitude is observed at bus-26, measuring 0.9422 p.u.

To enhance the feeder's performance, the optimal integration of three PV systems is achieved using the hybrid sine cosine optimization (HSCO) technique. Through this optimization process, the optimal locations for the PV systems are determined to be at buses 4, 22, and 14. The corresponding sizes of these PV systems are 171.84 kW, 279.71 kW, and 48.87 kW, respectively. As a result of this optimal integration, the real power losses are reduced to 16.424 kW, while the reactive power losses are reduced to 10.796 kVAr. Furthermore, the minimum voltage magnitude is raised to 0.9738 p.u at bus-21. Additionally, the integration of PV systems leads to a significant reduction in GHG emissions, which are now measured at 1109.141 lb/MWh. These outcomes highlight the effectiveness of the proposed HSCO methodology in improving the feeder's performance while contributing to a reduction in environmental impact.

5.1.3. Case 3

In this given scenario, the feeder is assumed to be operating under heavy load conditions, at 1.5 times the normal load. Consequently, the total demand for real power and reactive power in the feeder is calculated to be 1450.07 kW and 1407.91 kVAr, respectively. Upon conducting a load flow analysis, the resulting real power losses are determined to be 273.35 kW, with reactive power losses amounting to 183.244 kVAr. As the feeder is connected to the main grid, the corresponding greenhouse gas (GHG) emissions are estimated to be 3528.973e+03 lb/h. Notably, the lowest voltage magnitude is observed at bus-26, measuring 0.8253 p.u.

To enhance the performance of the feeder, the optimal integration of three PV systems is achieved using the hybrid sine cosine optimization (HSCO) technique. Through this optimization process, the optimal locations for the PV systems are determined to be at buses 6, 22, and 14. The corresponding sizes of these PV systems are 801.11 kW, 407.62 kW, and 288.07 kW, respectively. As a result of this optimal integration, the real power losses are reduced to 141.44 kW, while the reactive power losses are reduced to 94.05 kVAr. Furthermore, the minimum voltage magnitude is raised to 0.9251 p.u at bus-26. Additionally, the integration of PV systems leads to a significant reduction in GHG emissions, which are now measured at 3258.872 lb/MWh.

Moreover, a comparative analysis of the convergence features of SCO, PSO, NGO, ARO, and HSCO is conducted over 50 independent runs. In Table 3, a comparison of performance metrics for different algorithms are presented. The algorithms evaluated in the table are PSO, NGO, ARO, SCO, and HSCO. The performance metrics measured include the best, worst, mean, median, and standard deviation (SD) of the results obtained using each algorithm, as well as the time taken in minutes.

In terms of the best performance metric, PSO achieves a value of 63.551, indicating that it produced the best result among all the algorithms. On the other hand, ARO has the worst performance with a value of 65.130, suggesting that it generated the poorest result. When considering the mean performance, PSO has the lowest value of 63.738, indicating that, on average, it performs better than the other algorithms. However, it is worth noting that the differences in mean values among the algorithms are relatively small. The median values provide an additional measure of central tendency. In this case, PSO and HSCO have the same value of 63.743, implying that they both have the same middle value in their distribution of results. The standard deviation (SD) measures the variability or spread of the results. Lower SD values indicate less variability and more consistent performance. In this table, HSCO has the lowest SD value of 0.136, suggesting that it produces the most consistent results compared to the other algorithms. Lastly, the table includes the time taken by each algorithm to complete its calculations. All the algorithms have similar time values, ranging from 2.127 minutes to 2.253 minutes.

From the statistical results, including best and minimum worst, median, and standard deviation (SD) values, indicate that HSCO outperforms the other algorithms. However, ARO also exhibits competitive results, with a lower mean and average computational time.

The voltage profiles of the feeder without PV systems and with HSCO-based PV systems are presented in Figs. 1 and 2, respectively. Additionally, Fig. 3 illustrates the convergence characteristics of all algorithms when solving PV allocation for normal loading conditions. From all loading conditions, heavy loading condition has poor

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Table 5. Comparison of literature works on IEEE 33-bus Feeder

Reference	PVs		P_{ls} (kW)	Q_{ls} (kVAr)	V_{min} (p.u.)/ Bus #
	Locations	Sizes (kW)			
I-DBEA [22]	13, 24, 30	1098, 1097, 1715	94.8514	-	0.965/ -
MOSCA [19]	33, 13, 6,	609.8, 629.3, 1159.4	78.4	-	0.9689/ -
IHHO [16]	14, 24, 30	775.54, 1080.83, 1066.69	72.79	-	-
TSO [20]	14, 24, 30	771.54, 1103.65, 1064.57	72.79	-	-
ARO [13]	30, 13, 24	1053.585, 802.441, 1089.637	72.7865	50.6519	-
EAEO [23]	13, 24, 30	801.8, 1091.31, 1053.6	72.7837	-	-
ARO [14]	14, 24, 30	759.06, 1075.7, 1069.27	71.464	49.376	0.969/33
Proposed	14, 24, 30	759.12, 1076.07, 1069.32	71.464	49.376	0.969/33
WCA [9]	14, 24, 29	854.6, 1101.7, 1181	71.052	-	0.973/ 33
WSO [17]	13, 24, 30	790, 1070, 1080	69.4808	-	0.9726/33

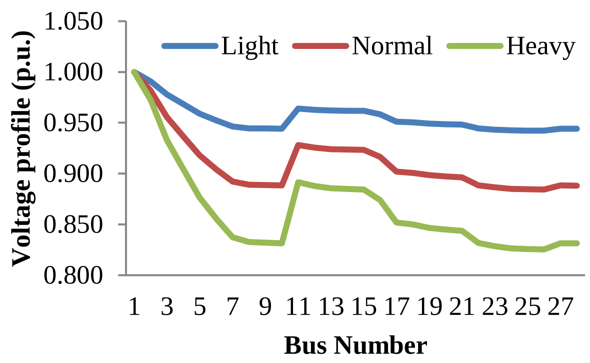

Figure. 1 Voltage profile without PVs

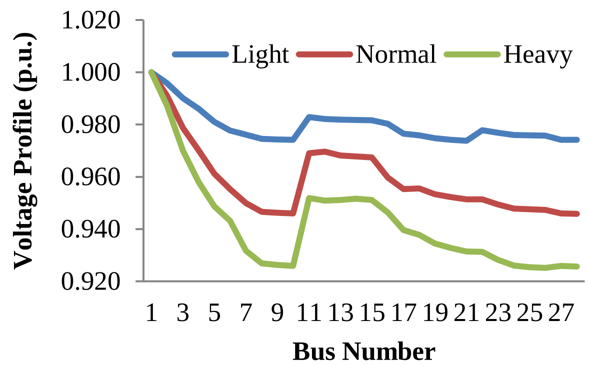

Figure. 2 Voltage profile with PVs by HSCO

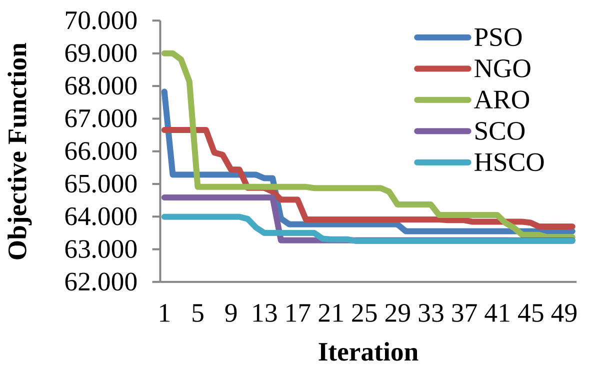

Figure. 3 Convergence characteristics

voltage profile however, it has been improved significantly with PV systems.

As observed in Fig. 1, the feeder experiences low voltage magnitudes of around 0.845 p.u under heavy loading conditions. However, in Fig. 2, the voltage profile is significantly improved, with values exceeding 0.925 p.u. These findings demonstrate the effectiveness of the proposed HSCO methodology in optimizing PV integration, improving the feeder's voltage profile, and reducing GHG emissions.

5.2 Comparative study

The comparative study is performed with IEEE 33-bus test system. In this particular feeder, the loads are representative of the standard test system data. The feeder operates at a voltage of 12.66 kV and exhibits total demands of 3.715 MW for real power and 2.3 MVAr for reactive power. After conducting a load flow analysis, the resulting real power losses are determined to be 202.68 kW, while the reactive power losses amount to 135.141 kVAr. Notably, the minimum voltage magnitude is observed at bus-18, measuring 0.9131 p.u.

By implementing the hybrid sine cosine optimization (HSCO) technique, the optimal locations for photovoltaic (PV) systems are determined to be at buses 14, 24, and 30. The corresponding sizes of these PV systems are 759.12 kW, 1076.07 kW, and 1069.32 kW, respectively.

Through the optimal integration achieved, the real power losses have been effectively reduced to 71.464 kW, while the reactive power losses have been minimized to 49.376 kVAr. Additionally, the minimum voltage magnitude is observed at bus-33, measuring 0.969 per unit (p.u.).

The results obtained from the HSCO technique have been compiled and presented in Table 4, allowing for a comprehensive comparison with the findings reported in existing literature. In contrast to previous works such as I-DBEA [22], MOSCA [19], IHHO [16], TSO [20], ARO [13], EAEO [23], and

ARO [14], the proposed HSCO approach showcases superior performance with significantly reduced losses. However, it is important to acknowledge that the results achieved by WCA [9] and WSO [17] surpass those of HSCO, indicating the potential for further research and exploration in the development of new and improved variants or novel meta-heuristic algorithms. The notable success of the HSCO technique highlights its efficacy in optimizing the integration process, but it also encourages the pursuit of future investigations to enhance its capabilities even further.

6. Conclusion

The present study proposes the efficient integration of photovoltaic systems (PVs) with agriculture distribution feeders (ADF) to achieve multiple objectives. The primary goals of this research are to enhance efficiency, minimize energy loss costs, and reduce greenhouse gas (GHG) emissions while adhering to operational and planning constraints. The determination of the optimal size and placement of PVs within a given ADF entails considering both continuous and discrete variables. Thus, this study introduces the hybrid sine cosine optimization (HSCO) technique, which combines the favourable search characteristics of particle swarm optimization (PSO) with the adaptive convergence factor (ACF) to ensure rapid convergence. The effectiveness of HSCO is demonstrated by applying it to the challenge of optimal PV integration in a real-time 28-bus ADF and an IEEE 33-bus feeder under various scenarios. In 28-bus feeder, the cost and loss are reduced by 45.5%, 47.518%, and 48.3% for light, normal and heavy loaded conditions, respectively. On the other hand, in 33-bus, the optimal PV systems are caused to reduce losses by 64.94% compared to base case. Additionally, a comparative analysis of the computational aspects of HSCO is conducted, considering basic SCO, PSO, NGO, and ARO algorithms. Notably, HSCO outperforms the other algorithms by achieving global optima while significantly reducing computational time.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization by K Bhavana and V Rajeswari; methodology, review, and formal analysis by K Lalitha and J Vijayanand; software and original draft preparation by Srinivasarao Thumati.

Notations

$P_{d(i)}$	Real power loading of a bus-*i* at nominal voltage magnitude,
$Q_{d(i)}$	Reactive power loading of a bus-*i* at nominal voltage magnitude,
$\bar{P}_{d(i)}$	Real power loading of a bus-*i* at specified voltage magnitude,
$\bar{Q}_{d(i)}$	Reactive power loading of a bus-*i* at specified voltage magnitude
α_p	Real power coefficients as per voltage-dependent load modeling
β_q	Reactive power coefficients as per voltage-dependent load modeling
γ_{lc}	Type of load composition in the total net-effective loading
$\lvert V_{(i)}\rvert$	Voltage magnitudes of bus-*i*
$\lvert V_{(s/s)}\rvert$	Voltage magnitudes substation bus
P_{SPV}	Total capacity of SPV systems
s	Season
$\bar{P}_{D(s)}$	Maximum real power demand of the feeder in as specified season
$LF_{(s)}$	Load factor in as specified season
C_{loss}	Cost of loss
$P_{loss(s)}$	Real power loss in a season
$GHG_{(s)}$	GHG emission in a season
$nbus$	Number of buses
nbr	Number of branches
npv	Number SPV systems
I_{br}	Current flow in a branch
r_{br}	Resistance of branch-*br*
$\lvert V_{(i),min}\rvert$	Minimum limits of bus voltage magnitudes
$\lvert V_{(i),max}\rvert$	Maximum limits of bus voltage magnitudes

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