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Hybrid Dandelion Optimizer-based Multi-Objective Photovoltaic Power Penetration Maximisation in Reconfigurable Distribution Networks

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Abstract: Many industrial and commercial sectors have concentrated on sustainable practises to mitigate global warming. Integrating renewable energy (RE) into electrical systems reduces greenhouse gas (GHG) emissions from traditional power plants and improves low-voltage (LV)-based radial distribution networks (RDNs). LV-RDNs' high r/x ratio branches prevent high RE penetrations. They have substantial distribution losses and low voltage profiles. Hence, maximising photovoltaic (PV) power penetration in LV-RDNs reduces energy sector GHG emissions, distribution losses, and voltage profile. Regardless of PV penetration, changing the feeder configuration improves performance because PV power generation is intermittent. This paper offers a hybrid dandelion optimizer (HDO) using loss sensitivity factors (LSFs) for hourly optimal network reconfiguration (HONR) to maximise PV penetration and reduce GHG emissions, losses, and voltage profile. Simulation findings on IEEE 33-bus LV-RDN showed the superiority of the suggested methodology and motivated real-time adaption by improving performance. Three case studies are simulated: only PV unit allocation, simultaneous PV unit allocation, and variable loading profiles and PV penetration. In comparison to literature, the proposed HDO-based ONR increased PV penetration from 49.91% to 82.02%, reduced GHG emissions during peak loading conditions from 8.0221e+6 lb/h to 1.4786e+6 lb/h, and reduced distribution energy losses from 1837.07 kW/day from 2669.812 kW/day.

Keywords: Loss sensitivity factors, photovoltaic power penetration, Low-voltage radial distribution networks, Dandelion optimizer, Network reconfiguration.

1. Introduction

Global warming is one of the primary issues across the world, and thus many industries and business sectors have been focused on different sustainable practises for mitigating its consequences [1]. Integration of renewable energy (RE) is one of these promising methodologies in the electrical sector, not only for reducing greenhouse gas (GHG) emissions from conventional power plants but also for improving the performance of low-voltage (LV)-based radial distribution networks (RDNs) [2]. However, LV-RDNs cannot host high RE penetrations due to their configuration and high r/x ratio branches. In addition, they suffer from high distribution losses and low voltage profiles [3]. Thus, maximising photovoltaic (PV) power penetration in LV-RDNs can not only reduce GHG emissions in the energy sector but also reduce distribution losses and improve the voltage profile in LV-RDNs. Since PV power is intermittent in nature, it is necessary to simultaneously alter the network configuration of the feeder to improve overall performance, irrespective of PV penetration levels [4].

Many researchers are focused on the optimal allocation of RE-based distribution generation (DG) in LV-RDNs, considering GHG reduction, loss reduction, voltage profile improvement, and voltage stability margin enhancement. Initially, many analytical approaches have been introduced for solving the RE-based DG allocation problem in

RDNs [5]. These methods produce accurate and fast results. Such methods work for simple systems with few state variables. However, analytical methods are computationally inefficient for big, complicated systems. In this regard, meta-heuristic approaches (MHAs) have recently attracted many researchers [6, 7]. MHAs, which are capable of obtaining effective, precise, and ideal answers, are referred to as intelligent procedures. The most recent and charming meta-heuristic search approaches use the hypothesis that technology evolved from artificial intelligence. Also, these techniques are the most advantageous for resolving challenging issues in a variety of fields. [8].

In [9], an improved multi-objective elephant herding optimisation (IMOEHO) is proposed for optimal location and sizes of multiple DGs considering multi-objective optimisation with loss, voltage profile, and VSI. In [10], the RE-based DG allocation problem has been solved using the water cycle algorithm (WCA) for the reduction of GHG emissions, distribution losses, and voltage deviation, as well as maximising the voltage stability index (VSI). In [11], an improved decomposition-based evolutionary algorithm (I-DBEA) is developed for optimally integrating DGs considering multi-objective optimisation with loss, voltage profile, and VSI. In [12], a hybrid oppositional sine-cosine muted differential evolution algorithm (O-SCMDEA) is developed for solving the DG allocation problem for optimising multi-objective functions using loss, voltage profile, and VSI. In [13], a Pareto-based multi-objective sine-cosine algorithm (MOSCA) and the strength pareto evolutionary algorithm 2 (SPEA2) are proposed for optimising loss, VSI, and energy loss costs while solving the DG allocation problem.

From these works, it can be seen that the optimal allocation of RE-based DGs can improve the performance of LV-RDNs significantly. However, these works are not focused on the maximisation of RE penetration by utilising optimal network reconfiguration (ONR) simultaneously. In the literature, many researchers have worked on simultaneous approaches focusing on these benefits explicitly, but the improved RE penetration level can be seen implicitly.

In [14], evolutionary programming (EP), particle swarm optimisation (PSO), the firefly algorithm (FA), and the gravitational search algorithm (GSA) are used for solving simultaneous DG allocation and ONR by aiming at loss reduction. The comparative study has shown FA superiority with its global indices. In [15], power loss and VSI are optimised using the adaptive shuffled frogs leaping algorithm (ASFLA) while determining the ONR and DGs locations and sizes simultaneously. In [16], the stochastic fractal search algorithm (SFSA) along with loss sensitivity factors are used for loss reduction by optimising the DGs and reconfiguring them simultaneously. In [17], the chaotic search group algorithm (CSGA) is proposed for optimising the distribution losses by solving the DG allocation and ONR problems simultaneously. Similarly, quasi-oppositional chaotic neural network algorithm (QOCNNA) [18], symbiotic organism search (SOS) [19], non-dominated sorting stochastic fractal search (NSSFS) [20], quasi-oppositional chaotic symbiotic organism search (QOCSOS) [21], improved symbiotic organism search (ISOS) [22], and search group algorithm (SGA) [23] are such recent effective MHAs on simultaneous allocation of DGs and ONR problems by aiming multi-objectives.

In the above-reviewed works, MHAs for allocating DGs and ONR at the same time have a number of problems. Many works are solved by applying directly the basic MHAs as they were introduced [10, 13–14, 16, 19, 23]. Some works are proposed improvements or modifications to the MHAs [9, 11, 12, 15, 17, 18, 20–22]. In this context, many basic MHAs may produce poor answers and get trapped at a local optimum due to either exploration or exploitation phases, particularly for large search spaces. Hence, according to the no-free-launch (NFL) theorem [24, 25], there is no single MHA that can solve all types of optimisation problems. This is the basic motivation to introduce new and hybrid MHAs such as improved Coot optimisation (ICOOT) [26], hybrid rapidly-exploring random tree star-PSO (RRT*PSO) [27], a-star chaotic PSO (ACPSO) [28], hybrid firefly algorithm-modified chaotic particle swarm optimisation (HFAMCPSO) [29], and quarter orbit particle swarm optimisation (QOPSO) [30] for improving the convergence characteristics and accurate results. Particularly for the complex, multi-objective, multi-variable, multi-constrained simultaneous ONR and DGs allocation problem, it is important to ensure global optimum for maintaining reliability and security in the electrical grid.

On the other hand, these works completely ignore the variability of RE due to their intermittency. In this connection, this paper introduces hourly optimal network reconfiguration (HONR) for handling PV penetration effectively in LV-RDNs. Also, a new MHA, the dandelion optimizer (DO) [31], has been introduced by inspiring long-distance wind-powered flight with three stages of dandelion seed. Recently, in [32], DO is used effectively in electrical engineering for

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solving automatic voltage regulation (AVR) and frequency control via automatic generation control (AGC) in multi-area power systems. In [33], the parameters involved in the mathematical modelling of proton exchange membrane fuel cells (PEMFCs) are optimally determined using DO.

Self-adaption of parameters, good exploration and exploitation characteristics, and the ability to avoid local optimum traps have been the major abilities of DO that have been observed while solving complex multi-objective optimisation problems. By combining these factors, this paper adapts DO for solving the HDNR problem by aiming multiple benefits at LV-RDNs. In order to reduce the computational effort and convergence time, the search space for DO is predetermined by using loss sensitivity factors (LSFs). The proposed hybrid DO with LSFs (HDO) is aimed for maximum PV penetration, low GHG emissions, reduced losses, and an improved voltage profile.

The paper continues: Section 2 covers theoretical notions and models. HONR multi-objective optimisation is discussed in section 3. Section 4 presents the HDO with the LSFs' mathematical relations. Section 5 examines IEEE 33-bus LV-RDN simulations for varied PV penetration levels and hourly load profiles. Section 6 summarises this paper's main contribution and research findings.

2. Theoretical concepts and modelling

This section explains the mathematical modelling of PV penetration and hourly network loading profile are explained.

2.1 Photovoltaic penetration

In specific, annual energy served by PV systems in a distribution network is known as PV penetration [33]. In this work, PV penetration is defined with respect to hourly network load profile and hourly PV generation.

$$PV_{pen} = \left(\sum_{h=1}^{24} \frac{P_{pv(h)}}{P_{d(h)}}\right) \times 100\% \tag{1}$$

$$P_{pv(h)} = \sum_{k=1}^{npv} P_{pv,k(h)} \tag{2}$$

$$P_{d(h)} = P_{loss(h)} + \sum_{k=1}^{nbus} P_{ld,k(h)} \tag{3}$$

According to the basic rules of how a PV system works, its output depends on the weather,

$$P_{pv(h)} = PV_c\left(\frac{G_{(h)}}{G_{(r)}}\right)\left\{1 + \vartheta_{pv}\left(\left[T_{a(h)} + \left(\frac{T_N - 20}{0.8}\right)\right] - T_{(r)}\right)\right\}\alpha_{loss}\beta_{in} \tag{4}$$

2.2 Modeling of network loading profile

The network loading condition may not be always constant. By having PV system integration, the net effective loading at a bus and overall network loading profile is defined as,

$$P_{ld,k(h)} = \gamma_{(h)} P_{ld,k} - P_{pv,k(h)},\ \forall k = 1{:}npv \tag{5}$$

For all other buses (i.e., except PV locations), the real and reactive power loadings are defined by,

$$P_{ld,k(h)} = \gamma_{(h)} \bar{P}_{ld,k},\ \forall k = 1{:}nbus\ \&\ \neq 1{:}npv \tag{6}$$

$$Q_{ld,k(h)} = \gamma_{(h)} \bar{Q}_{ld,k},\ \forall k = 1{:}nbus\ \&\ \neq 1{:}npv \tag{7}$$

3. Problem formulation

This section provides the proposed multi-objective function with planning and operational constraints while maximizing PV penetration along with ONR problem.

3.1 Multi-objective function

Distribution loss reduction, minimization of GHG emission, and improvement in voltage profile is focused and mathematically given by:

$$P_{loss} = \sum_{k=1}^{(nbr+ntl)} I_{k(ij)}^2 r_{k(ij)} \tag{8}$$

$$AVDI = \frac{1}{nbus}\sqrt{\sum_{i=1}^{nbus}(1 - |V_i|)^2} \tag{9}$$

$$GHG_e = (k_c + k_n + k_s)\left(\sum_{n=1}^{nbus} P_{ld,k} + P_{loss}\right) \tag{10}$$

$$MOF = min(P_{loss} + AVDI + GHG_e) + \frac{1}{PV_{pen}} \tag{11}$$

3.2 Planning and operational constraints

In this paper, number of PV locations and their penetration levels are the major search variables. However, voltage magnitudes of all buses should be maintained with in specified limits, and the size of PV system should not be more than total real power demand of the network at any time. In addition, active and reactive power balance, network radial constraints are considered as defined by,

$$V_{min} \leq |V_i| \leq V_{max},\ i = 1{:}nb \tag{12}$$

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$$I_{k(ij)} \leq I_{k(max)}, k = 1\colon nbr + ntl \quad (13)$$

$$PV_c \leq \sum_{k=1}^{nbus} P_{ld,k(h)} \quad (14)$$

$$P_{pv(h)} \leq P_{d(h)} \quad (15)$$

$$P_{grid(h)} + P_{pv(h)} = P_{d(h)} + P_{loss(h)} \quad (16)$$

$$Q_{grid(h)} = Q_{d(h)} + Q_{loss(h)} \quad (17)$$

$$ntl + nbr = nbus - 1 \quad (18)$$

$$|\bar{A}| \neq 0 \quad (19)$$

4. Solution methodology

In this section, LSFs and DO based hybrid approach is explained for solving the optimal allocation of DGs problem, HONR problem either individually or simultaneously.

4.1 Dandelion optimizer

This section describes the dandelion optimizer (DO)'s operators and mathematical model. In the DO, there are just two varieties of dandelions: core (CD) and assistance (AD), and they seed differently. Mutation seeding avoids local optimum. Ultimately, dandelions are chosen to reproduce. To summarise, the DO includes normal sowing, mutation sowing, and a selection strategy.

Normal sowing**:** Because the CD grows on adequate land, the DA states that it can generate more seeds than the assistant. Sowing produces seeds dependent on the dandelion population's fitness scores. Assuming $s_{n,max}$ and $s_{n,min}$ are as the maximum and minimum number of seeds, respectively, the number of seeds s_n for each dandelion d_i is given by,

$$s_n = \begin{cases} s_{n,max}\left[\frac{f_{max}-f(d_i)+\epsilon}{f_{max}-f_{min}+\epsilon}\right] & s_n > s_{n,min} \\ s_{n,min} & s_n \leq s_{n,min} \end{cases} \quad (20)$$

where ϵ is the machine epsilon to avoid a denominator of zero, $f_{max} = max\{f(d_i)\}$ and $f_{min} = min\{f(d_i)\}$, respectively.

From (20), for the minimization problem, the dandelion with a lower fitness value will sow more seeds, while the one with a large fitness value will sow less but not less than the minimum.

The CD is the fittest dandelion in DA and it is given by:

$$D_{CD} = min\{f(d_i)\} \quad (21)$$

The radius of the ADs and the CDs are calculated differently. Except for CD, the sowing radius of ADs is calculated by:

$$r_{ad(k)} = \begin{cases} u_{lim} - l_{\mathrm{lim}} & k = 1 \\ \varphi r_{ad(k-1)} + (\|D_{CD}\|_\infty - \|d_i\|_\infty) & else \end{cases} \quad (22)$$

where u_{lim} and l_{lim} are the upper and lower limits, respectively; k is the iteration number.

Eq. (22) initialises the planting radius of the ADs to the diameter of the search space. After that, we use the infinite norm to determine how far the current helper dandelion is from the CD. Based on the above, we included the AD's sowing radius from the previous generation and a weight factor φ, to dynamically adjust the previous generation's effect on the present sowing radius in order to reduce convergence and improve the efficiency of global search. The weight factor φ is given by,

$$\varphi = 1 - \frac{f_{e(k)}}{f_{e(max)}} \quad (23)$$

where $f_{e(k)}$ is function evaluations at iteration k and $f_{e(max)}$ is total function evaluations. The sowing radius of the previous generation had less and less influence on the present sowing radius when φ decreased from large to small.

But, for the CD, there is an additional method of calculating the sowing radius that is constructed as follows and is changed depending on the CD in the previous generation.

$$r_{cd(k)} = \begin{cases} u_{lim} - l_{\mathrm{lim}} & k = 1 \\ r_{ad(k-1)} \times r_k & g = 1 \\ r_{ad(k-1)} \times e_k & g \neq 1 \end{cases} \quad (24)$$

where $r_{ad(k)}$ is the sowing radius of CDs The r_{ad} for the CD is also set to the diameter of the search space at the start of the procedure. r_k and e_k are the withering and growth factors, respectively, while g represents the growth trend, as determined by:

$$g = \frac{f(cd)_k + \epsilon}{f(cd)_{k-1} + \epsilon} \quad (25)$$

The location is not suitable for sowing when $g = 1$, as the DO does not provide a better solution. As a result, we must restrict the sowing radius, and the withering factor r_k is developed to take this into account. Naturally, r_k cannot be too small; its value should be between [0.9, 1). The growth factor e_k is suggested as a result; of course, e cannot be too large; the value should be in the range of [1, 1.1]. On the other hand, when $g \neq 1$, the algorithm finds a better solution than the previous generation, the location is suitable for sowing, and the sowing radius should be increased, which can speed up the convergence rate.

***Mutation sowing*:** Sowing in a different way, called "mutation sowing," is proposed for the CD as a way to avoid falling into the local optima trap and keep the diversity of the population. It is said to be:

$$D'_{CD} = D_{CD} \times [1 - Levy()] \tag{26}$$

where $Levy()$ is the Levy distribution based random number calculated by a parameter 1.5.

***Selection strategy*:** In the DA, it is required that the optimal location from the last iteration is always kept for the next one. So that there is still a lot of variety, the remaining places are chosen using a disruptive selection operator. Here's how to figure out the selection probability p_i for location D_i:

$$p_i = F_i / \left(\sum_{n=1}^{nsd} F_n\right) \tag{27}$$

$$F_i = \left|F_i - F_{avg}\right| \tag{28}$$

where F_i and F_{avg} are the fitness of MOF and mean fitness of all population's fitness in iteration k, respectively, nsd is the total number of seeds.

This method's selection probabilities can provide good and bad seeds greater opportunities to be picked for the following iteration while eliminating middling fitness values. This strategy preserves population variety and improves global searches.

4.2 Loss sensitivity factors

Loss sensitivity factors (LSFs) can be used to identify potential candidate locations to influence the distribution losses. By knowing such candidate locations, the computational effectors in finding optimal locations can be reduced significantly and thus, it is possible to attain global optima by excluding local minima trap in optimization process. Mathematically, LSFs can be defined by,

$$LSF_i = \frac{\partial P_{loss}}{\partial \tilde{P}_{d,i}} = \left(2 \times P_{eff,k} \times r_{k(ij)}\right) / |V_i|^2 \tag{29}$$

The locations which are having high LSFs are more suitable for PV penetrations in the network. From Eq. (1), the total PV penetration level in a day PV_{pen} can be maximized by simultaneously increasing $P_{pv(h)}$ and decreasing $P_{loss(h)}$. According to Eq. (4), by maximizing the PV capacity, maximum PV penetration can be attainable. Thus, optimal allocation of PV-based DGs allocation problem is solved first using proposed HDO along with LSFs considering peak loading conditions. Later, ONR is solved for reducing the distribution losses. In this way, this hybrid approach can ensure maximum PV penetration without violating the operational constants of LV-RDNs effectively.

5. Simulation results

Simulations are performed on the IEEE 33-bus, which has 33 buses, 32 branches, and 5 tie-lines. The line data and bus date of the network are taken from [34]. It has a total real and reactive power loading of 3715 kW and 2300 kVAr, respectively. The LSFs for this loading condition were evaluated.

By performing load flow, it is observed that the total distribution losses are 202.677 kW and 135.141 kVAr, respectively. The lowest voltage is registered at bus-18 as 0.9131 p.u. and the AVDI is evaluated as 0.0104, respectively. The total GHG emission is estimated at 8.0221e+6 lb/h. To figure out how well the proposed HDO works with computers, three kinds of case studies are done. Case (1) is solved for only the optimal allocation of PV units considering multiple objectives as defined in Eq. (11) with the constraints from Eqs. (12)–(17). In Case (2), simultaneous allocation of PV units and ONR is solved considering the MOF defined in Eq. (11) and all constraints defined in Eqs. (12)–(19) are applicable. All these three case studies are compared with the literature and describe the results obtained by HDO.

5.1 Optimal allocation of photovoltaic units

In this case, only PV units are optimised using the proposed methodology. At first, the best candidate locations are determined using LSFs. The top 20 locations are used for search space. The optimal locations determined by HDO are buses 14, 24, and 29, and correspondingly, the sizes are 800 kW, 1063 kW, and 1150 kW, respectively. Thus, the total PV capacity is 3013 kW, which is 81.1036 percent of the total load. It is observed that the total distribution losses are decreased to 72.2587 kW and 50.3921 kVAr, respectively. The lowest voltage is registered at bus-33 as 0.9686 p.u. and the AVDI is evaluated as 0.0044, respectively. The total GHG emission is estimated at 1.7639 E+6 lb/h. In comparison to the base case, the losses are reduced by 64.94% and GHG emissions are reduced by 78.01%.

Table 1. Only PV units' allocation

Method	Open Switches	PV (kW)/ bus #	P_{loss} (kW)	$P_{loss\ (red)}$ (%)	PV_{Pen} (%)
Base	33, 34, 35, 36, 37	-	202.677	-	-
QOCNNA [18]	33, 34, 35, 36, 37	705/ 14, 570.2/ 25, 953.8/ 30	75.424	62.79	60
MOSCA [13]	33, 34, 35, 36, 37	609.8/ 33, 629.3/ 13, 1159.4/ 6	78.4	61.32	64.55
ASFLA [15]	33, 34, 35, 36, 37	1209.4/ 12, 993.6/ 29, 545.7/ 24	66.87	67.01	73.99
SOS [19]	33, 34, 35, 36, 37	768.7/ 14, 1085.1/ 24, 1053.6/ 30	71.47	64.74	78.26
SFA [16]	33, 34, 35, 36, 37	754/ 14, 1099.4/ 24, 1071.4/ 30	71.47	64.74	78.73
QOCSOS [21]	33, 34, 35, 36, 37	754/ 14, 1099.4/ 24, 1071.4/ 30	71.457	64.74	78.73
O-SCMDEA [12]	33, 34, 35, 36, 37	1048.3/ 30, 805.2/ 13, 1093.6/ 24	72.778	64.09	79.33
HDO	**33, 34, 35, 36, 37**	**800/ 14, 1063/ 24, 1150/ 29**	**72.2587**	**64.94**	**81.1036**
IMOEHO [9]	33, 34, 35, 36, 37	1057/ 14, 1054/ 24, 1741/ 30	95.003	53.13	103.69
IDBEA [11]	33, 34, 35, 36, 37	1098/ 13, 1097/ 24, 1715/ 30	94.851	53.21	105.33

Table 2. Simultaneous ONR and PV units' allocation

Method	Open Switches	PV (kW)/ bus #	P_{loss} (kW)	$P_{loss\ (red)}$ (%)	PV_{Pen} (%)
Base	33, 34, 35, 36, 37	-	202.677	-	-
FA [14]	7, 10, 28, 32, 34	556/ 31, 680/ 32, 618/ 33	73.4	63.8	49.91
ASFLA [15]	14, 24, 26, 33, 35	609.3/ 13, 271.2/ 25, 893.5/ 31	49.51	75.57	47.75
ISOS [22]	7, 9, 14, 28, 30	469/ 12,1020/ 25, 739/ 33	54.479	73.12	59.97
CSGA [17]	7, 9, 14, 28, 30	469.7/ 12, 1021.3/ 25, 738/ 33	54.48	73.12	60
QOCNNA [18]	7, 9, 14, 27, 30	482.2/ 12, 1015.3/ 25, 731.5/ 33	54.69	73.01	60
SGA [23]	7, 9, 14, 26, 31	436.5/ 11, 1177.8/ 29, 614.7/ 18	56.14	72.30	60
SFA [16]	7, 9, 14, 27, 30	775.3/ 22, 1285.8/ 25, 735.6/ 33	53.01	73.85	75.26
QOCSOS [21]	10, 28, 31, 33, 34	870.8/ 7, 711.8/ 18, 1227.4/ 25	51.539	74.57	75.64
SOS [19]	6, 11, 28, 31, 34	793.2/ 8, 669/ 18, 1402.9/ 25	52.88	73.91	77.12
NSSFS [20]	11, 28, 31, 33, 34	958.3/ 17, 1278.5/ 25, 752.8/ 7	50.718	74.98	80.47
HDO	**10, 28, 31, 33, 34**	**799.64/ 7, 950/ 17, 1296.67/ 25**	**53.2144**	**73.74**	**82.0188**

The results of HDO are compared with the literature and given in Table 1. In comparison to the proposed HDO and O-SCMDEA [12], the loss reduction is higher in ASFLA [15], SPEA2 [13], SOS [19], SFA [16], and QOCSOS [21], but their PV penetration levels are low. On the other hand, the results of HDO are better than QOCNNA [18], MOSCA [13], ASFLA [15], SPEA2 [13], SOS [19], SFA [16], QOCSOS [21], and O-SCMDEA [12] not only in terms of PV penetration but also in terms of losses.

On the other hand, the PV total capacity is oversized for the network load or failed to satisfy the constraint defined in Eq. (14) in IMOEHO [9] and IDBEA [10], which resulted in higher PV penetration of 103.69 % and 105.33 %, respectively.

5.2 Simultaneous allocation of PV units and optimal network reconfiguration

In this case study, the network performance is optimised by simultaneously allocating PV units and ONR resources. The best PV sizes at buses 7, 17, and 25 are 799.64 kW, 950 kW, and 1296.67 kW, respectively. The optimal braches and tie-lines opened under ONR are 10, 28, 31, 33, and 34, respectively. It is observed that the total distribution losses reduced to 53.2144 kW and 41.5498 kVAr, respectively. The lowest voltage is registered at bus-31 as 0.9777 p.u. and the AVDI is evaluated as 0.0022, respectively. The total GHG emission is estimated at 1.4786e+6 lb/h. In comparison to the base case, the losses are reduced by 64.94% and the GHG emissions are reduced by 81.57%.

The ONR obtained by the proposed HDO is higher PV penetration in comparison to FA [14], ASFLA [15], ISOS [22], CSGA [17], QOCNNA [18], SGA [23], SFA [16], QOCSOS [21], SOS [19], and NSSFS [20], but losses are compromised due to the simultaneous priority for reduction in GHG emissions and higher PV penetration.

The comparisons of the voltage profiles for three cases are given in Fig. 1. In comparison to base case, and PV, the simultaneous approach results for more smooth voltage profile in the network. The convergence characteristics of HDO while solving PV allocation and simultaneous PV allocation and ONR problems are given in Fig. 2.

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Table 3. Network performance under variable PV penetration with HONR

Hr	PV_{pen} (%)	Before			After		
		P_{loss} (kW)	AVDI	GHG×10^6 (lb/hr)	P_{loss} (kW)	AVDI	GHG×10^6 (lb/hr)
1	0	120.209	0.0080	6.202	88.765	0.0059	6.1381
2	0	106.082	0.0075	5.831	78.482	0.0055	5.7747
3	0	101.591	0.0073	5.708	75.206	0.0054	5.6539
4	0	97.206	0.0072	5.585	72.005	0.0053	5.5332
5	0	94.627	0.0071	5.511	70.120	0.0052	5.4609
6	0	88.756	0.0069	5.339	65.826	0.0051	5.2924
7	3.51	77.884	0.0064	4.935	57.205	0.0047	4.8924
8	28.42	54.765	0.0048	3.315	35.332	0.0034	3.2749
9	50.92	61.016	0.0041	2.301	34.508	0.0026	2.2466
10	66.38	64.231	0.0032	1.122	34.125	0.0017	1.0606
11	76.19	75.630	0.0031	0.710	39.929	0.0014	0.6372
12	81.10	83.205	0.0031	0.574	43.921	0.0014	0.4931
13	79.91	84.014	0.0033	0.790	44.291	0.0015	0.7091
14	73.83	83.622	0.0038	1.463	44.398	0.0021	1.3826
15	62.52	75.793	0.0042	2.109	41.460	0.0025	2.0382
16	46.49	79.337	0.0053	3.351	47.446	0.0035	3.2856
17	23.91	100.999	0.0070	5.053	68.666	0.0050	4.9871
18	0	140.593	0.0086	6.701	103.551	0.0064	6.6248
19	0	148.155	0.0089	6.876	109.020	0.0065	6.7957
20	0	192.341	0.0101	7.818	140.826	0.0074	7.7129
21	0	202.677	0.0104	8.022	148.230	0.0076	7.9106
22	0	192.341	0.0101	7.818	140.826	0.0074	7.7129
23	0	187.289	0.0100	7.717	137.202	0.0074	7.6141
24	0	157.450	0.0091	7.085	115.732	0.0067	6.9997
Total		**2669.812**	**0.0066**	**111.936**	**1837.07**	**0.0047**	**110.231**

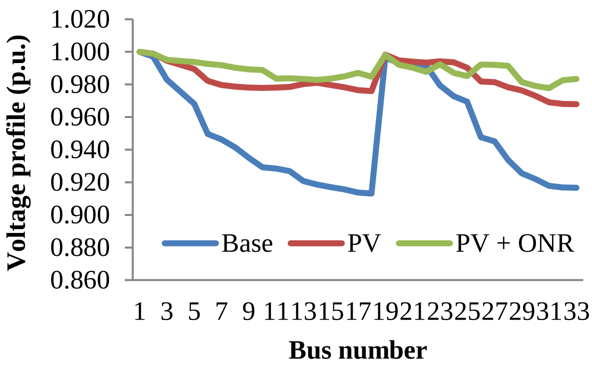

Figure.1 Voltage profile for different scenarios

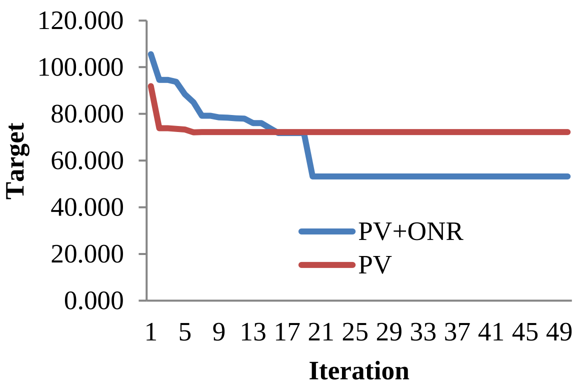

Figure.2 Convergence characteristics of HDO

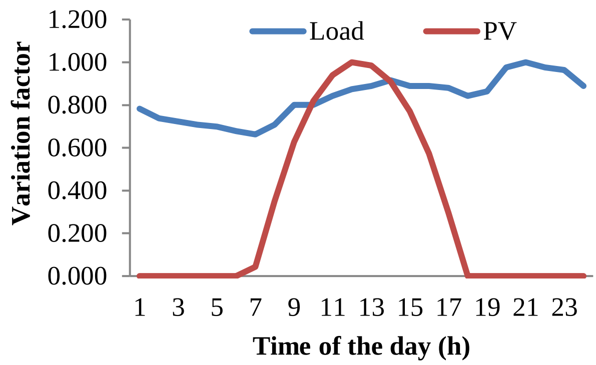

Figure.3 Hourly network loading profile and PV power

5.3 Hourly optimal network reconfiguration

The works described in [9–23] have considered peak loading conditions and determined maximum PV penetration levels. However, in real-time, the peak loading conditions may take place around 7 p.m. to 10 p.m., but the maximum PV generation may take place during midday, i.e., around 11 a.m. to 2 p.m. Thus, the results discussed in Case (1) and Case (2) may not be satisfactory for a real-time scenario. In flip to all these literature works, Case (3) presents the HONR for maximising overall network performance under variable loading conditions and PV penetration levels [35], as given in Fig. 3.

Considering the best PV locations and sizes in the network as obtained in Case (2), their generation levels are adjusted in accordance with the hourly variation factor. Also, the hourly loading condition at each bus is adjusted to the variation factors. The network performance HONR is given in Table 3 for before and after scenarios. Before ONR, all the tie-lines are open, and the PV penetration and loads are adjusted as per Eqs. (5)–(7). The variation in real and reactive power losses, the minimum voltage profile, the AVDI, and GHG emission are tabulated in Table 3.

By having optimal reconfiguration, the total energy losses are reduced to 1837.07 kW from 2669.812 kW. The AVDI is reduced to 0.0047 from 0.0066, and GHG emissions are reduced to 110.231106 lb/day from 111.936 lb/day. Since the GHG emission is mainly dependent on PV penetration, which is unchanged in both cases, the variation in GHG emission is almost negligible. However, there is a significant reduction in energy loss of 31.19%. This scenario indicates the need for HONR for variable loading conditions in modern electrical grids.

6. Conclusion

This research presents a unique hybrid method for simultaneously addressing the optimum allocation of PV units and the optimal network reconfiguration using loss sensitivity factors (LSFs) and the dandelion optimizer (DO) (ONR). The multi-objective function is designed to maximise PV penetration while reducing losses, improving voltage profiles, reducing GHG emissions, and maintaining network operating conditions. Using an IEEE 33-bus network, simulations are run for three different case studies and compared to the literature. The proposed methodology reduces the overall energy losses from 2669.812 kW to 1837.07 kW. The AVDI is decreased from 0.0066 to 0.0047, and the daily GHG emissions are decreased from 111.936 to 110.231×10^6 lb/hr. The variance in GHG emissions is essentially nonexistent because it is mostly dependent on PV penetration, which is unchanged in both scenarios. The energy loss has been significantly reduced by 31.19 %, though. This situation highlights the requirement for HONR in modern electrical grids under changeable loading situations.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, writing-original draft preparation, Srinivasarao Thumati; software, writing—review and editing, Madhusudana Rao Ranga; validation, Veera Reddy Aduru and Veera Vasantha Rao Battula; investigation and formal analysis, Sravanthi Kantamaneni.

Notations

$P_{pv(h)}$	Hourly PV generation
$P_{d(h)}$	Hourly network load
$P_{pv,k(h)}$	Hourly PV generation at bus-*k*
$P_{ld,k(h)}$	Hourly network load at bus-*k*
$P_{loss(h)}$	Hourly distribution losses
npv	Number of PV systems
$nbus$	Number of buses
h	Hour number
PV_c	Capacity of PV system
$G_{(h)}$	Hourly radiance on PV module
$G_{(r)}$	Reference radiance
$T_{a(h)}$	Ambient temperature at hour-*h*
NOCT	Nominal operating cell temperature
$T_{(r)}$	Reference temperature
α_{loss}	Correction factor for different losses
β_{in}	Inverter efficiency
$\gamma_{(h)}$	Hourly load scaling factor at hour-*h*
$Q_{ld,k(h)}$	Reactive power load at hour-*h*
$\bar{P}_{ld,k}$	Peak real power loading of bus-*k*
$\bar{Q}_{ld,k}$	Peak reactive power loading of bus-*k*
P_{loss}	Distribution losses
$AVDI$	Average voltage deviation index
GHG_e	GHG emission [10]
$P_{grid(h)}$	Real power import at hour-*h*
$Q_{grid(h)}$	Reactive power import at hour-*h*
$Q_{loss(h)}$	Reactive power loss at hour *h*
$\lvert\bar{A}\rvert$	Det of element-node incident matrix
$I_{k(ij)}$	Current flow in branch-*k*
nbr	Number of braches/lines
ntl	number of tie-lines
k_c	Coefficient of CO_2 emission
k_n	Coefficient of NO_x emission
k_s	Coefficient of SO_2 emission
MOF	Multi-objective function
LSF_i	Loss sensitivity factor of bus-*i*,
$P_{eff,k}$	Effective loading of bus-*k* after integrating PV systems in the network,
$r_{k(ij)}$	Resistance of branch *k*,
$\lvert V_i\rvert$	Voltage magnitude of bus-*i*

References

[1] A. F. Ghoniem, "Needs, resources and climate change: Clean and efficient conversion technologies", *Progress in Energy and Combustion Science*, Vol. 37, No. 1, pp. 15-51, 2011.

[2] D. J. Arent, A. Wise, and R. Gelman, "The status and prospects of renewable energy for combating global warming", *Energy Economics*, Vol. 33, No. 4, pp. 584-593, 2011.

[3] J. P. Painuly, "Barriers to renewable energy penetration; a framework for analysis", *Renewable Energy*, Vol. 24, No. 1, pp. 73-89, 2001.

[4] Badran, S. Mekhilef, H. Mokhlis, and W. Dahalan, "Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies", *Renewable and Sustainable Energy Reviews*, Vol. 73, pp. 854-867, 2017.

[5] A. Ehsan and Q. Yang, "Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques", *Applied Energy*, Vol. 210, pp. 44-59, 2018.

[6] Z. Abdmouleh, A. Gastli, L. B. Brahim, M. Haouari, and N. A. A. Emadi, "Review of optimization techniques applied for the integration of distributed generation from renewable energy sources", *Renewable Energy*, Vol. 113, pp. 266-280, 2017.

[7] S. K. Dash, S. Mishra, L. R. Pati, P. K. Satpathy, "Optimal Allocation of Distributed Generators Using Metaheuristic Algorithms—An Up-to-Date Bibliographic Review", In: *Proc. Green Technology for Smart City and Society (GTSCS 2020)*, Odisha, India, pp. 553-561, 2021.

[8] K. Hussain, M. N. M. Salleh, S. Cheng, and Y. Shi, "Metaheuristic research: a comprehensive survey", *Artificial Intelligence Review*, Vol. 52, pp. 2191-2233, 2019.

[9] N. K. Meena, S. Parashar, A. Swarnkar, N. Gupta, and K. R. Niazi, "Improved elephant herding optimization for multiobjective DER accommodation in distribution systems", *IEEE Transactions on Industrial Informatics*, Vol. 14, No. 3, pp. 1029-1039, 2017.

[10] A. A. Abou, E. Ela, R. A. E. Sehiemy, and A. S. Abbas, "Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm", *IEEE Systems Journal*, Vol. 12, No. 4, pp. 3629-3636, 2018.

[11] A. Ali, M. U. Keerio, and J. A. Laghari, "Optimal site and size of distributed generation allocation in radial distribution network using multi-objective optimization", *Journal of Modern Power Systems and Clean Energy*, Vol. 9, No. 2, pp. 404-415, 2020.

[12] S. K. Dash, S. Mishra, A. Y. Abdelaziz, M. L. Alghaythi, and A. Allehyani, "Optimal Allocation of Distributed Generators in Active Distribution Networks Using a New Oppositional Hybrid Sine Cosine Muted Differential Evolution Algorithm", *Energies*, Vol. 15, No. 6, p. 2267, 2022.

[13] U. Raut and S. Mishra, "A new Pareto multi-objective sine cosine algorithm for performance enhancement of radial distribution network by optimal allocation of distributed generators", *Evolutionary Intelligence*, Vol. 14, No. 4, pp. 1635-1656, 2021.

[14] Badran, H. Mokhlis, S. Mekhilef, and W. Dahalan, "Multi-Objective network reconfiguration with optimal DG output using meta-heuristic search algorithms", *Arabian Journal for Science and Engineering*, Vol. 43, pp. 2673-2686, 2018.

[15] A. Onlam, D. Yodphet, R. Chatthaworn, C. Surawanitkun, A. Siritaratiwat, and P. Khunkitti, "Power loss minimization and voltage stability improvement in electrical distribution system via network reconfiguration and distributed generation placement using novel adaptive shuffled frogs leaping algorithm", *Energies*, Vol. 12, No. 3, p. 553, 2019.

[16] T. T. Tran, K. H. Truong, and D. N. Vo, "Stochastic fractal search algorithm for reconfiguration of distribution networks with distributed generations", *Ain Shams Engineering Journal*, Vol. 11, No. 2, pp. 389-407, 2020.

[17] T. H. Huy, T. V. Tran, D. N. Vo, and H. T. Nguyen, "An improved metaheuristic method for simultaneous network reconfiguration and distributed generation allocation", *Alexandria Engineering Journal*, Vol. 61, No. 10, pp. 8069-8088, 2022.

[18] T. V. Tran, B. H. Truong, T. P. Nguyen, T. A. Nguyen, T. L. Duong, and D. N. Vo, "Reconfiguration of distribution networks with distributed generations using an improved neural network algorithm", *IEEE Access*, Vol. 9, pp. 165618-165647, 2021.

[19] S. N. Quoc and D. V. Ngoc, "Symbiotic organism search algorithm for power loss minimization in radial distribution systems by

network reconfiguration and distributed generation placement", *Mathematical Problems in Engineering*, Vol. 2020, pp. 1-22, 2020.

[20] T. T. The, B. H. Truong, K. D. Tuan, D. V. Ngoc, "A nondominated sorting stochastic fractal search algorithm for multiobjective distribution network reconfiguration with distributed generations", *Mathematical Problems in Engineering*, Vol. 2021, pp. 1-20, 2021.

[21] M. T. N. Hoang, B. H. Truong, K. T. Hoang, K. D. Tuan, and D. V. Ngoc, "A quasioppositional-chaotic symbiotic organisms search algorithm for distribution network reconfiguration with distributed generations", *Mathematical Problems in Engineering*, Vol. 2021, pp. 1-13, 2021.

[22] T. H. Huy, "Enhancing Distribution System Performance via Distributed Generation Placement and Reconfiguration Based on Improved Symbiotic Organisms Search", *Journal of Control Science and Engineering*, Vol. 2023, pp. 1-10, 2023.

[23] B. H. Truong, P. M. Le, D. N. Vo, T. L. Duong, and T. T. Nguyen, "Optimal System Reconfiguration and Placement of Distributed Generations Using Search Group Algorithm", *International Journal on Electrical Engineering and Informatics*, Vol. 14, No. 2, pp. 411-425, 2022.

[24] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization", *IEEE Transactions on Evolutionary Computation*, Vol. 1, No. 1, pp. 67-82, 1997.

[25] T. Joyce and J. M. Herrmann, "A review of no free lunch theorems, and their implications for metaheuristic optimisation", *Nature-Inspired Algorithms and Applied Optimization*, pp. 27-51, 2018.

[26] J. A. Abdulsaheb and D. J. Kadhim, "Robot path planning in unknown environments with multi-objectives using an improved COOT optimization algorithm", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 5, pp. 548-565, 2022, doi: 10.22266/ijies2022.1031.48.

[27] A. A. Rasheed, A. S. Araji, and M. N. Abdullah, "Static and Dynamic Path Planning Algorithms Design for a Wheeled Mobile Robot Based on a Hybrid Technique", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 4, pp. 167-181, 2022, doi: 10.22266/ijies2022.0831.16.

[28] O. A. Wahhab and A. S. Araji, "Path planning and control strategy design for mobile robot based on hybrid swarm optimization algorithm", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 3, pp. 565-579, 2021, doi: 10.22266/ijies2021.0630.48.

[29] N. A. Zghair, and A. S. A. Araji, "Intelligent Hybrid Path Planning Algorithms for Autonomous Mobile Robots", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 5, pp. 309-325, 2022, doi: 10.22266/ijies2022.1031.28.

[30] Z. E. Kanoon, A. S. Araji, and M. N. Abdullah, "Enhancement of Cell Decomposition Path-Planning Algorithm for Autonomous Mobile Robot Based on an Intelligent Hybrid Optimization Method", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 3, pp. 161-175, 2022, doi: 10.22266/ijies2022.0630.14.

[31] S. Zhao, T. Zhang, S. Ma, and M. Chen, "Dandelion Optimizer: A nature-inspired metaheuristic algorithm for engineering applications", *Engineering Applications of Artificial Intelligence*, Vol. 114, p. 105075, 2022.

[32] T. Ali, S. A. Malik, A. Daraz, S. Aslam, and T. Alkhalifah, "Dandelion Optimizer-Based Combined Automatic Voltage Regulation and Load Frequency Control in a Multi-Area, Multi-Source Interconnected Power System with Nonlinearities", *Energies*, Vol. 15, No. 22, p. 8499, 2022.

[33] V. Sharma, S. M. Aziz, M. H. Haque, and T. Kauschke, "Effects of high solar photovoltaic penetration on distribution feeders and the economic impact", *Renewable and Sustainable Energy Reviews*, Vol. 131, p. 110021, 2020.

[34] M. M. Aman, G. B. Jasmon, A. H. Bakar, and H. Mokhlis, "Optimum network reconfiguration based on maximization of system loadability using continuation power flow theorem", *International Journal of Electrical Power & Energy Systems*, Vol. 54, pp. 123-133, 2014.

[35] S. H. Dolatabadi, M. Ghorbanian, P. Siano, and N. D. Hatziargyriou, "An enhanced IEEE 33 bus benchmark test system for distribution system studies", *IEEE Transactions on Power Systems*, Vol. 36, No. 3, pp. 2565-2572, 2020.