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Hybrid War Strategy Optimization with Power Loss Index for Optimal VAr Compensation in Distribution Feeders with Industrial Load Growth

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Abstract: Many countries have benefited from industrialisation and there is a growing global demand for power. For a power system to operate steadily, securely, and dependably, infrastructure must be upgraded and supply and demand must be balanced. In particular, reactive power (VAr) compensation is crucial for balancing the demand for reactive power from industries and, as a result, to ensure a sufficient voltage profile and voltage stability in low-voltage distribution lines. This study suggests the use of switched and fixed capacitors for dynamic volt-var controllers to handle heavy industrial loads. The voltage stability improvement, cost reduction, and loss reduction are the three goals of the multi-objective function. a new, straightforward meta-heuristic for war strategy optimisation (WSO) that combines the power loss index (PLI) to narrow the search space and boost the computing effectiveness. For various industrial load growth scenarios, simulations were performed on IEEE 33-bus low-voltage distribution feeder. A comparative study was also conducted using and compared with WOS (i.e., without reduced search space with PLIs) and whale optimization algorithm (WOA). In terms of global optima, the PLI-WSO findings are superior. In basic 33-bus feeder, having 84.78% VAr compensation results in a 34.39 % loss reduction and 33.23 % cost reduction in a 33-bus feeder, whereas having maximum 16% of industrial load growth in 10 years, the losses and costs are increased by 24.41 times to the base case, respectively. However, by having optimal VAr compensation, the losses and cost savings are resulted for 8.627% and 8.404%, respectively. Different load increase scenarios showed a similar type of overall benefit, demonstrating the scalability of the suggested methodology for real-time larger systems.

Keywords: Electrical distribution system, Loss reduction, Voltage stability enhancement, Reactive power compensation, War strategy optimization.

1. Introduction

In power system operation and control, reactive power management errors can harm the stability, efficiency, and dependability of a power system. Inadequate reactive power management causes voltage instability, power factor penalties, higher losses, equipment overload, lower transmission capacity, voltage collapse and blackouts, equipment damage, and poor system performance [1].

Low-voltage distribution feeders must install reactive power compensation devices, such as capacitor banks (CBs), shunt reactors, static var compensator (SVC), synchronous condensers, static compensators (STATCOM), unified power flow controller (UPFC), thyristor-controlled reactors (TCR) and thyristor-switched capacitors (TSC), automatic voltage regulators (AVRs), power factor correction (PFC) panels, and on-load load tap changers (OLTC) etc., to avoid these consequences. Proper control and management are crucial for stable, reliable, and efficient power systems [2]. However, CBs have several benefits in electrical distribution systems (EDSs), such as higher capacity, voltage management, lower losses, better power quality, and cost savings. CBs are vital assets for utilities and consumers alike in maintaining a dependable and effective power distribution network because of these advantages.

Multiple techno-economic-environmental goals have been targeted in the literature by researchers interested in the best possible integration of CBs into EDSs [3]. Their locations (discrete variables) and sizes (discrete/continuous variables) were identified as significant search factors in the optimal CB allocation (OACB) problem. In addition, the bus voltage magnitudes and compensation levels are considered as key restrictions. Thus, meta-heuristic algorithms (MHAs), rather than numerical or traditional procedures, are the most common solution techniques suggested in the literature [4] since they are excellent tools for tackling difficult real-world optimisation issues because of their key benefits, including their capacity to handle complex search spaces, global exploration capabilities, flexibility, robustness, and application to a wide range of optimisation problems [5].

In [6], artificial rabbit optimisation (ARO) was employed to handle power quality issues and to minimise distribution losses in photovoltaic (PVs) systems integrated with EDSs using reactive power control via passive power filters (PPFs). In [7], an integer genetic algorithm (IGA) was proposed for determining the optimal number of switched CBs (SCBs), their locations, and sizes for energy loss reduction by considering the variable load profile in the Vietnam distribution system. In [8], the annual net savings and voltage stability were optimised simultaneously by solving the OACB problem using a non-dominated sorting genetic algorithm-2 (NSGA-II) with fuzzy sets on 33-bus and Portuguese 94-bus radial EDSs. In [9], master-slave optimisation was proposed for reactive power compensation in radial and meshed EDSs considering load variations. The grid structure, variable active and reactive demand curves, economic analysis, net present value, energy losses, CB procurement, installation, and operation are considered. The master stage uses a discrete generalised normal distribution optimisation (GNDO) algorithm. For the discrete optimisation problem of the OACB problem in EDSs for cost reduction and voltage profile enhancement, mixed-integer linear programming was introduced in [10]. The magnitude of the voltage, which is sensitivity-dependent, was considered when choosing the candidate buses in this formulation. In addition, the linear dependence of the voltage profile on the reactive load was demonstrated. In [11], an imperialist competitive algorithm (ICA) was introduced for the OACB problem along with PVs, with the aim of reducing losses in 33-bus and Jaipur City’s 130-bus EDSs. Furthermore, the effectiveness of ICA was verified using ETAP software. In [12], a dynamic Aquila optimiser algorithm (DAOA) was proposed for loss reduction and loading margin enhancement via the optimal integration of distribution generation (DG) and STATCOM considering multiple loading conditions. In [13] artificial neural networks (ANN) were employed to optimally allocate series CBs for voltage profile improvement and loss reduction. In [14], the adaptive firefly algorithm (AFA) was utilised for reactive power compensation via distribution SVCs (D-SVCs) and CBs. Loss reduction and voltage stability enhancement were considered the major objectives. In [15], multi-objective thermal exchange optimisation (MOTEO) and multi-objective Lichtenberg algorithm (MOLA) were proposed for CBs and DGs allocation in EDSs, considering the objectives of loss, root mean square voltage index (RMSVI), and voltage stability index (VSI). In [16], an improved grey wolf optimisation method (IGWO) and tabu search (TS) were hybridised to solve the series CB allocation problem in EDS by considering the loss minimisation. In [17], the techno-economic-environment operation of EDS was optimised by reducing the cost of DGs, CBs, substation power, greenhouse gas (GHG) emissions, and loss reduction. The multi-objective OACB and DG allocation problems are solved by considering voltage dependency. A new evolutionary algorithm that hybridises GA-differential evolution-particle swarm optimisation (GA-DE-PSO) is proposed to enhance the computational aspects. In [18], an improved sand cat swarm optimisation algorithm (ISCSO) was proposed for DGs and shunt CBs allocation, focusing on loss reduction and voltage deviation. In [19], the weighted index using the loss sensitivity factor (LSF) and loss sensitivity indices (LSI) were employed with an enhanced crow search algorithm (ECSA) for optimal location and sizes of CBs in a two-stage optimisation approach. In [20], GA and PSO were used for the OACB problem in a 132 kV Manipur transmission system for voltage profile improvement and loss reduction. The simulations were validated using MATLAB and ETAP software. Further, moth–flame optimization (MFO) [21], hybrid PSO-GSA [22], chaotic whale optimization algorithm (CWOA) [23], honey badger algorithm (HBA) [24], improved flower pollination algorithm (IFPA) [25], and water cycle algorithm (WCA) [26] are some recent meta-heuristic approaches adapted for OACB problems.

However, most of these algorithms do not ensure reproducibility or global optimality. Additionally, they struggle with a broad search space, slow rate of convergence, sensitivity to initial solutions, parameter adjustment, and premature convergence.

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Thus, advancements in the exploration and exploitation stages as well as the introduction of new algorithms have driven researchers to hybridise [27]. Meta-heuristic algorithms continue to be useful tools for resolving challenging optimization issues despite these disadvantages, and they have been effectively used in a number of different fields.

Recently, a novel stochastic optimisation technique called war strategy optimisation (WSO) [28], motivated by classical military tactics, has been adapted to solve the OACB problem. With the use of two tactics and an adjustable weighting system based on rank, the army positions are changed. Compared to the reviewed works, the following are the major contributions of this study.

1) For the first time, a WSO was proposed for solving the OACB problem considering multiple objectives.
2) To avoid premature convergence, the proposed work hybridised the basic WSO with power loss indexes (PLIs).
3) The proposed approach ensures global optima by reducing the search space with predetermined candidate locations ranked according to PLIs in the first stage.
4) Later, WSO is used to deduce optimal locations for a reduced search space along with the sizes of CBs.
5) Simulations are performed on IEEE 33-bus test system, and the results of WSO are compared with the literature.
6) Further, the reproducibility of the PSI-WSO is quantified and compared with WOS (i.e., without reduced search space with PLIs) and whale optimization algorithm (WOA).

The remainder of this paper is structured as follows: the mathematical formulation of the load flow study and the corresponding PLIs to solve the OACB problem are introduced in section 2; the multi-objective optimisation problem is proposed in section 3; the WSO concept and its mathematical relations are introduced in section 4; the simulation results are explained in section 5; and the conclusion is provided by a thorough discussion of the main findings of the research in section 6.

2. Most economic power factor

By improving operating power factor (*p.f.*), the feeder's maximum kVA consumption can decrease significantly and consequently, economic savings annually. However, improving the *p.f.* requires investment in *p.f.* correction equipment such as CBs. Thus, the net annual saving is the maximum demand charge savings minus *p.f.* correction equipment expenditure. To maximise net annual savings, the *p.f.* should be adjusted to the most economical value.

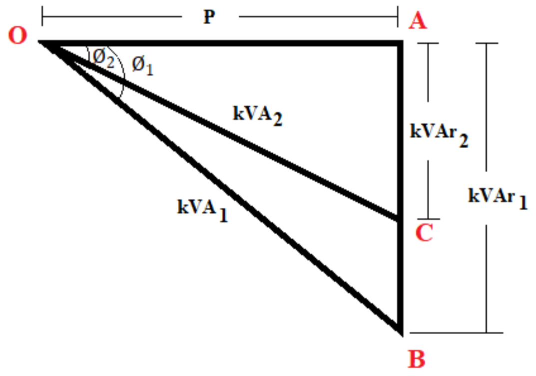

Figure. 1 Power triangle with corrected power factor

Distribution feeder with a peak load of P kW and a *p.f.* of $cos(\emptyset_1)$ is charged Rs × per kVA of the maximum demand per year. The feeder can increase the power factor to $cos(\emptyset_2)$ by adding *p.f.* correction equipment.

Let c_1 be the rate of energy per maximum kVA demand/ year and c_2 be the cost of CB per kVAr/year. The power triangle at the original *p.f.* $cos(\emptyset_1)$ is OAB, whereas the improved triangle is OAC, as shown in Fig. 1.

Annual saving in maximum kVA demand charges is given by:

$$S_d = c_1 \times P \times (sec\emptyset_1 - sec\emptyset_2) \tag{1}$$

$$C_{cb} = c_2 \times P \times (tan\emptyset_1 - tan\emptyset_2) \tag{2}$$

$$S_{annual} = S_d - C_{cb} \tag{3}$$

Only $\emptyset_2$ is variable in Eq. (3), and all other parameters are fixed. Therefore, if the differentiation of the foregoing expression with respect to $\emptyset_2$is zero, the net annual saving will be at its maximum and that $cos\emptyset_2$ is equal to most economic *p.f.* (pf_{ec}).

$$pf_{ec} = \frac{d}{d\emptyset_2}(S_{annual}) = 0 \tag{4}$$

$$pf_{ec} = cos\emptyset_2 = \sqrt{1 - (c_2/c_1)^2} \tag{5}$$

In order to achieve most economic power factor as defined in Eq. (5), the required $kVAr_2$ support by CBs needs to be optimized without compromising in feeder's operating conditions.

3. Industrial load growth modelling

In electrical industry, the load growth is estimated for specific years in relation to the base case load of a particular year. Mathematically [29],

$$\bar{P}_{d,i} = P_{d(0),i} \times (1 + \rho_{in})^n \times V_i^{\alpha_{id}} \quad (6)$$

$$\bar{Q}_{d,i} = Q_{d(0),i} \times (1 + \rho_{in})^n \times V_i^{\beta_{id}} \quad (7)$$

where $\bar{P}_{d,i}$ and $\bar{Q}_{d,i}$ are the active and reactive power demands of bus-i by considering industrial load, respectively; $P_{d(0),i}$ and $Q_{d(0),i}$ are the active and reactive power loads of bus-i at a particular year or base loads, respectively; ρ_{in} is the industry load growth rate, n is the number of years for load estimation to be done, α_{id} and β_{id} are the exponents for real and reactive power loads, respectively, V_i is the voltage magnitude of bus-i.

4. Problem formulation

The proposed multi-objective function OF is formulated for loss reduction, voltage stability index (VSI) enhancement and net-savings maximization.

Objective function:

$$OF = \left\{c_1 \times P_{loss} - c_2 \times \sum_{k=1}^{ncb} kVAr_k\right\} + \frac{1}{VSI_q} \quad (8)$$

Subjected to:

$$\left(\sum_{k=1}^{ncb} kVAr_{cb,k}\right) \leq \left(\sum_{k=1}^{nbus} kVAr_{d,k}\right) \quad (9)$$

$$V_{p,min} \leq V_p \leq V_{max} \quad (10)$$

$$VSI_q = V_p^4 - 4\left(x_{pq}P_q - r_{pq}Q_q\right)^2 - 4\left(r_{pq}P_q + x_{pq}Q_q\right)V_p^2, \quad VSI_q \geq 0, q = 2{:}nbus \quad (11)$$

where VSI_q is the VSI of bus-q, r_{pq} and x_{pq} are the resistance and reactance of branch-pq, respectively; P_q and Q_q are the active and kVAr power loads of bus-q, respectively; $kVAr_{cb,k}$ and $kVAr_{d,k}$ are the reactive power compensation by CB and load demand at bus-k, respectively; P_{loss} is the active power loss in the feeder, ncb and $nbus$ are the number of CBs and number of buses in feeder, respectively.

5. Solution methodology

In this section, the proposed solution methodology using war strategy optimization (WSO) and power loss index (PLI) are explained briefly.

5.1 War strategy optimization

Ancient countries used armies and '*Vyuha*' to win wars, with emperors and unit commanders working together to achieve their objectives. The war strategy involves ongoing coordination and combat with a drum-based team. The King's goal is to defeat the opponent, while soldiers aim to defeat the other team and advance. All troops have equal chances of becoming kings or commanders in each trail. The present war strategy optimization (WSO) was modelled with two military plans, with the King and Commander's locations determining each soldier's position [28].

5.1.1. Attack strategy

Success determines the rank and weight, while the plan's winding down keeps the king, commander, and soldiers close to the goal.

$$x_{i(k+1)} = x_{i(k)} + 2\alpha(x_c - x_k) + r_i\left[w_i\left(x_k - x_{i(k)}\right)\right] \quad (12)$$

where x_c and x_k are the positions of commander and king, in the last iteration, respectively; $x_{i(k+1)}$ and $x_{i(k)}$ are the ith solder position at previous and present iteration, respectively; r_i and w_i are the random number and weighting factors, respectively.

The soldier's new location is outside the commander's position if $w_i > 1$, and then $w_i\left(x_k - x_{i(k)}\right)$ is outside the king's position. There is $w_i < 1$, between the soldier's present location and king's position. The soldier's current location is closer to the earlier incident. If $w_i = 0$, the end of the war is indicated when trends toward zero, at which point the soldier's updated position is very close to the commander's position.

Weight and Rank Updation: The king was ready to launch a huge assault on the enemy. The strongest sol was the king. The update of each search agent's position is influenced by their troops, commanders, and king ranks. Each soldier's rank is determined by Eq. (6), which has an impact on w_i. The ranks of soldiers indicate how close they are to the goal (fitness value). If the attack force (fitness) in the new position (F_{k+1}) is less than that in the previous position (F_k), then the soldier returns to the former position.

$$x_{i(k+1)} = x_{i(k+1)}(F_{k+1} \geq F_k) + x_{i(k)}(F_{k+1} < F_k) \quad (13)$$

$$R_i = R_{i(k+1)}(F_{k+1} \geq F_k) + R_i(F_{k+1} < F_k) \quad (14)$$

$$w_i = w_i(1 - R_i/k_{max})^{\propto} \quad (15)$$

where R_i is the rank of *i*th solder, k_{max} is the maximum number of iterations.

5.1.2. Defense strategy

The second strategy position update was made using the positions of the king, the army commander, and a random soldier. However, there has been no change in the update of the ranking and weight.

$$x_{i(k+1)} = x_{i(k)} + 2\alpha\left(x_k - x_{r(k)}\right) + r_i\left[w_i\left(x_c - x_{i(k)}\right)\right] \quad (16)$$

This battle strategy investigates more search space than the earlier method because it considers the position of a random soldier. When is high, the soldiers move quickly and update their locations. Troops update their positions in tiny stages for low values of w_i.

Replacement/relocation of weak soldiers: Find the least fit and weakest solder for each iteration. Authors have experimented with a wide range of approaches to transformation. Replace the weak soldier with a random soldier, it's one of the simplest things to accomplish.

$$x_{w(k+1)} = L_b + r_i(U_b - L_b) \quad (17)$$

The second strategy is to position the weaker soldier in the centre of the army in the battlefield, as depicted in Eq. (18). This algorithm is more likely to agree with the use of this technique.

$$x_{i(k+1)} = -(1 - r_i) + \left[x_{w(k)} - median(x_i)\right] + x_{i(k)} \quad (18)$$

The weights of the soldiers fluctuated over time. While an unfit soldier weighs more, a fit soldier weighs less. At the start of the battle, every soldier walks large and their weight varies. Soldiers take small measures to reach the goal and alter their weight as the battle draws to a close. Because the strategy is chosen at random, the soldiers follow the king at random. The exploration algorithms were improved by this method. After the battle, army forces locate the target area (an important search space). The King and Commander are close to the target, along with army forces. The troop moves toward the objective point incrementally, based on Eqs. (16) and (18). Therefore, this algorithm has exploitation potential.

5.2 Power loss index

The computing effectiveness of any metaheuristic algorithm is influenced by the search space boundary. A border that has been strategically decreased can effectively achieve this goal. To reduce the search space for CB sites, a power loss index (PLI) was adapted in this study [30]. By using CB integration, sites with a high PLI can dramatically reduce the loss. The loss reductions at each bus were determined by adjusting the total reactive load at each bus.

$$PLI_k = \frac{P_{lr(k)} - P_{lr,min(k=2:nbus)}}{P_{lr,max(k=2:nbus)} - P_{lr,min(k=2:nbus)}} \quad (19)$$

where PLI_k is the power loss index of bus-*k*, $P_{lr,min(k=2:nbus)}$ and $P_{lr,max(k=2:nbus)}$ are the minimum and maximum loss reductions among all other buses, respectively; $P_{lr(k)}$ is the loss reduction due to total VAr compensation by CB at bus-*k*.

These values were then adjusted to fall within the range [0, 1]. These numbers were used to calculate the minimum and maximum loss reductions.

6. Results and discussion

Simulations are performed on IEEE 33-bus low-voltage feeder. The cost of annual energy loss (c_1) is taken as 168 $/kWh. Further, the cost of CBs (c_2) is taken from [31]. For all algorithms, maximum number of iterations and population size is taken as 50 and 30, respectively.

6.1 Standard feeder without industrial load growth

The test system has a total of real and reactive power loading of 3.715 MW and 2.3 MVAr respectively. By having an operating voltage of 12.66 kV, it is suffering by a total of real and reactive power losses of 210.9983 kW and 143.0329 kVAr respectively. The lowest voltage magnitude of 0.9038 p.u is observed at bus-18 among all buses. The overall VSI of the feeder is determined as 0.6486. Further, the operating power factor of the substation is estimated as 0.849 lagging. Thus, the cost of total annual energy loss before VAr compensation by CBs is 35448 $/ year.

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6.1.1. Loss sensitivity factors

The search space for CBs location is first evaluated by determining the PLIs as defined in Eq. (19). By neutralising VAr loading of a bus at each run time, the load flow is repeated to determine new power loss $P_{lr(k)}$. Among all, bus-30 and bus-19 have maximum ($P_{lr,max(k=2:nbus)}$) and minimum ($P_{lr,min(k=2:nbus)}$) loss reductions when they compensated their VAr loading. From these, PLI_k for all buses are determined, ranked in descending order and finally top 15 ranked locations are used for deducing the optimal locations for CBs along with their sizes. Thus, the final search space for CBs in 33-bus feeder becomes buses 30, 32, 31, 14, 8, 29, 7, 25, 24, 33, 18, 13, 12, 11 and 4. Similarly, the minimum and maximum sizes of CBs are taken as 150 kVAr and 2300 kVAr (i.e., as equal to the total VAr loading of the feeder).

6.1.2. Optimal locations and sizes of CBs

The optimal location and sizes of CBs are simultaneously determined by WSO using the search space as determined the search space using PLIs. The optimal results of WSO are as follows: optimal buses are 12, 30 and 24, correspondingly the sizes are 450 kW, 1050 kVAr and 450 kW, respectively. Thus, the total CB capacity is 1950 kVAr, which is equivalent to 84.78% VAr compensation.

By this VAr compensation, the feeder is now suffering by a total of real and reactive power losses of 138.4291 kW and 94.2646 kVAr respectively. The lowest voltage magnitude of 0.9306 p.u is observed at bus-18 among all buses. The overall VSI of the feeder is determined as 0.7304. Further, the operating power factor of the substation is estimated as 0.9934 lagging.

Thus, the cost of total annual energy loss after VAr compensation by CBs is 23256 $/ year. In addition, the cost of 1950 kVAr is 0.211 $/ kVAr-year [32] and correspondingly, total cost of CBs is 411.45 $/ year. Hence, the annual energy cost savings are equal to 11781 $/ year. In comparison to uncompensation case, it is equal to 33.23% reduction.

Further, the effectiveness of proposed LSF-WSO is compared with WSO (i.e., without having reduced search space by PLIs) and whale optimization algorithm (WOA). The results obtained by these approaches are listed in Table 1. Further, the results of NSGA-II [8] and ISCSO [18] are also compared in the same table. By observing, the results of LSF-WSO are better than all other compared works. The convergence characteristic of PLI-WSO, WSO and WOA are given in Fig. 1. Further, the improved voltage profile before and after VAr compensation can be observed in Fig. 2.

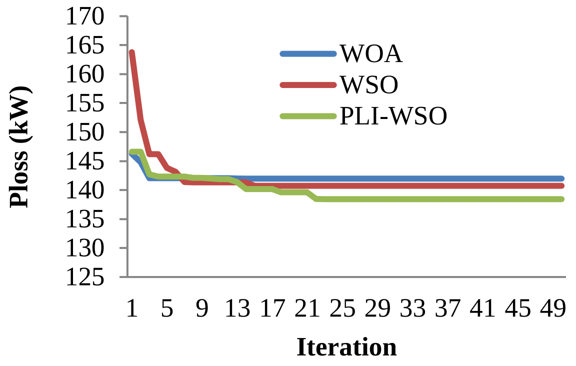

Figure. 1 Convergence characteristics for 33-bus feeder

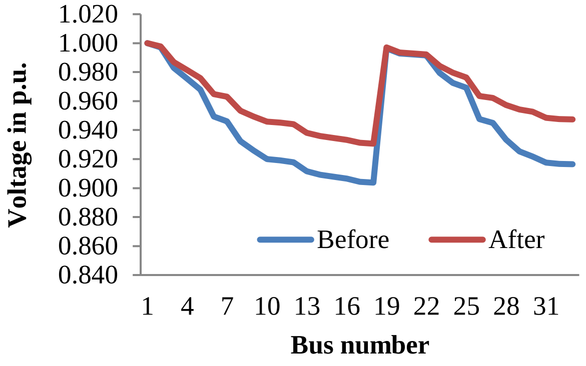

Figure. 2 Comparison of voltage profile of 33-bus feeder

Table 1. Comparison of results in 33-bus feeder

Reference	CB Locations/ Sizes in kVAr	P_{loss} (kW)
Base	-	210
NSGA-II [8]	6, 8, 30, 13 137, 359, 1035, 430	142.7004
ISCSO [18]	12, 29, 30 454.65, 485.11, 613.33	141.72
WOA	30, 16, 3 1050, 150, 1050	141.975
WSO	16, 30, 7 150, 900, 750	140.7368
PLI-WSO	12, 30, 24 450, 1050, 450	138.4291

6.2 With Industrial load growth

The exponents' for real and reactive power loads are taken as α_{id} and β_{id} [29]. The net-effective loading for different growth levels are given in Table 2. Correspondingly, the real and reactive power losses, minimum voltage profile and VSI are determined as given in Table 2. From this, it is clearly evident that the feeder performance is considerably decreased due to load growth without any compensation.

Table 2. Uncompensation feeder performance with industrial load growth

ρ_{in} (%)	Base (0)	5	10	13	16
Years (n)	0	2	5	8	10
$\bar{P}_{d,i}$ (kW)	3683.559	4057.598	5901.617	9649.383	15680.640
$\bar{Q}_{d,i}$ (kVAr)	1704.256	1824.963	2314.795	2874.239	2918.484
P_{loss}	167.870	203.466	433.208	1236.650	4266.491
Q_{loss}	113.588	137.703	293.557	840.934	2927.294
V_{min}	0.9153	0.9068	0.8651	0.7764	0.5908
VSI	0.7018	0.6763	0.5602	0.3634	0.1218
p.f.	0.9043	0.9083	0.9247	0.9464	0.9596

Table 3. Compensation feeder performance with industrial load growth

ρ_{in} (%)	Base (0)	5	10	13	16
Years (n)	0	2	5	8	10
CB locations	30, 13, 24	14, 30, 25	25, 30, 10	14, 7, 30	7, 29, 7
CB Sizes (kVAr)	1050, 450, 600	450, 1200, 300	600, 1650, 900	1500, 1650, 2700	300, 3000, 3000
$\bar{P}_{d,i}$ (kW)	3691.755	210.547	134.829	91.706	0.9352
$\bar{Q}_{d,i}$ (kVAr)	4066.625	556.034	165.548	112.552	0.9278
P_{loss}	5919.917	556.097	367.394	249.886	0.8913
Q_{loss}	9699.093	715.905	1104.365	756.067	0.8277
V_{min}	15778.323	883.401	3898.405	2682.217	0.6388
VSI	3691.755	210.547	134.829	91.706	0.9352
p.f.	4066.625	556.034	165.548	112.552	0.9278
Loss reduction ($)	19.682	18.636	15.192	10.697	8.627
Savings (%)	17.962	17.399	14.347	10.456	8.404

In Table 3, the feeder performance is optimized by using VAr compensation. For each load growth level, the optimized CB locations and their sizes are determined using PLI-WSO. Further, the improved performance in terms of reduced net-effective reactive loading, improved power factor, the real and reactive power losses, minimum voltage magnitude, VSI, total VAr compensation, and thus, the percentage of loss reduction and correspondingly, net annual savings are given. From these results, it can be evident that optimal VAr compensation improved the feeder performance at all load growth levels significantly.

7. Conclusion

For the optimal allocation of capacitor banks (OACB) problem, a recent study introduced war strategy optimisation (WSO), a stochastic optimisation method that is influenced by military tactics. First, it solved the OACB problem with multiple objectives using a WSO for the first time. The study used the basic WSO and power loss indices to avoid convergence. This hybrid approach ensured global optima by narrowing the search space using specified candidate locations ranked by PLIs in the initial stage, and the WSO was then used to establish optimal locations and capacitor bank sizes. Through simulations of IEEE 33-bus test system and comparisons with the literature, this approach was shown to be effective. The PLI-WSO approach was measured for reproducibility and compared with WSO (without reduced search space with PLIs) and the whale optimisation algorithm. PLI-WSO achieved better global optima than the others. In a simple 33-bus feeder, 84.78% VAr compensation reduces losses by 34.39% and costs by 33.23%. With a maximum industrial load growth of 16 %, losses and expenses climbed 24.41 times the base case. Optimising the VAr compensation reduced losses by 8.627% and costs by 8.404%. This strategy is scalable for real-time use in larger systems, as other load-rise scenarios show similar benefits.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization by M Devika Rani and KJ Jegadish Kumar; methodology, review, and formal analysis by V Sai Geetha Lakshmi and K Muthuvel; software and original draft preparation by M Devika Rani and P Muthu Kumar.

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