Received: October 5, 2023. Revised: November 9, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

White Shark Optimization for Efficient Conservation Voltage Reduction in Photovoltaic-Enriched Distribution Grids with Smart Inverters and Network Reconfiguration

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Abstract: This research paper addresses the limitations inherent in conventional volt-VAR control (VVC) mechanisms, such as on-load tap changers (OLTC) and voltage and capacitor banks (CBs), when applied to the implementation of efficient conservation voltage reduction (CVR) strategies within active distribution networks. In this paper, we present a cost-effective strategy that synergizes the rapid-response capabilities of PV smart inverters with traditional VVC mechanisms to enhance CVR operations. This study delves into the optimal coordination between photovoltaic smart inverters and conventional VVC systems for effective CVR operations. The investigation takes into account the implications of distribution network reconfiguration (DNR) on the overall operational costs, encompassing grid power procurement, emissions, losses, and switching expenses related to OLTC, CB, and remote controlled switches (RCS). To attain the optimal solution, we leverage the recent advancements of the white shark optimization (WSO) technique, meticulously validating its performance through extensive trials conducted on the 119-bus distribution system. The empirical results vividly showcase the substantial advantages of integrating VVC devices and smart inverters, particularly in scenarios characterized by fluctuating load conditions. Notably, the synergistic approach achieves a remarkable 6.51% reduction in energy consumption. Additionally, active and reactive power loss reductions of up to 33.67% and 28.55%, respectively, underscore the potency of the proposed strategy.

Keywords: Smart inverter, Volt/Var control, Conservation voltage reduction, Power loss reduction, Optimization.

1. Introduction

Conservation voltage reduction (CVR) has emerged as a promising strategy to enhance energy efficiency and minimize power losses in active distribution networks [1, 2]. However, the efficacy of traditional volt-VAR control (VVC) devices, such as on-load tap changers (OLTC) and voltage and capacitor banks, has been hampered by their slow response and inability to handle sudden voltage fluctuations [2]. These disturbances often arise from intermittent photovoltaic (PV) power generation. Additionally, the distribution network reconfiguration (DNR) technique has proven effective in reducing losses, balancing loads, and enabling service restoration [3]. To address these limitations, this paper proposes a cost-effective approach that integrates PV smart inverters with traditional VVC devices and leverages DNR to enhance CVR operations.

1.1 Literature survey

In recent literature, various approaches were presented to address different objectives in distribution systems through volt-var optimization (VVO). In [4], volt-var control systems are investigated to integrate renewable energy into intelligent distribution networks. Similarly, [5] had employed PSO to optimally allocate reactive resources in the distribution system, aiming to reduce peak demand, power losses, and improve power factor. The impact of CVR operation on battery energy storage system allocation and VVC devices was studied in [6] through a two-stage coordinated optimization solved by a hybrid solver. Meanwhile, [7] had adopted a model predictive-based voltage control to investigate the interactions between CVR and DG placement for minimizing load consumption while maintaining voltage within acceptable limits. Topology-aided integrated voltage regulation has been proposed in [8] to improve CVR in three-phase active electric distribution networks with high spatio-temporal load variability. A multi-stage coordinated CVR methodology was proposed in [9], incorporating inverter-based DG and soft open point devices for day-ahead scheduling and real-time dispatch. However, the impact of DNR (Distribution Network Reconfiguration) had not been explored in the cited literature [4-9]. In [10], the modified grey wolf optimization (MGWO) algorithm was adopted for optimal DNR operation to minimize power loss and node voltage deviation. A Grey Wolf Optimization (GWO) based coordinated operation of traditional VVC devices, DNR, and a photovoltaic smart inverter (PVSI) was proposed in [11] to maximize energy savings. Finally, [12] utilized a whale optimization for CVR savings and loss minimization in active distribution networks to achieve energy savings.

1.2 Metaheuristic approaches

The Several metaheuristic approaches aimed to find solutions that were either near-ideal, suboptimal, or acceptable, differing from exact methods that guarantee the discovery of the best choice but lack a guarantee for optimality. In [13], the extended stochastic coati optimizer (ESCO) was introduced as an expansion of the Coati optimization algorithm (COA), utilizing an increased number of searches and references, along with a stochastic process for search selection. The swarm magnetic optimizer (SMO), outlined in [14], modeled the behavior of magnets and adopted a push-pull mechanism as a novel search. [15] introduced the walk-spread algorithm (WSA), which combined direction-based and neighborhood searches. The four directed search algorithm (FDSA), presented in [16], was a directed search-based metaheuristic with four sequentially executed searches. In [17], the Squirrel search optimizer (SSO) was applied to economic load dispatch (ELD) problems, mimicking squirrel foraging behavior. In [18] presented the krill herd optimization (KHO) model, considering goals of increasing krill density and reaching sustenance. The shell game optimization (SGO) in [19] simulated the rules of a game to design an algorithm for optimization problems in various scientific fields, based on guessing the ball's position under three shells. In [20]. Whale optimization algorithm (WOA) employed for allocation of distributed generators improve energy efficiency. The white shark optimization (WSO) algorithm, designed to emulate the hunting behaviors of white sharks, including prey tracking and capture [21], was employed for the first time by the authors to solve the challenging power system MINLP optimization problem.

Overall, the literature showcased various optimization algorithms and methodologies applied to volt-var optimization and distribution system operation to achieve different objectives, such as energy savings, loss minimization, and voltage profile control. However, some areas, like the impact of DNR, needed further exploration. Moreover, aforementioned survey, focused on power loss and power demand reduction only, but operating cost analysis in CVR operation has not been performed.

1.3 Contribution of present work

This paper makes several key contributions:

- Introduces a cost-effective strategy that combines high-speed voltage regulation tools, particularly PV smart inverters, with conventional VVC devices to improve CVR operation.
- Explores the optimal synchronization of photovoltaic smart inverters and traditional VVC devices in CVR operation.
- Examines the influence of distribution network reconfiguration (DNR) on overall system costs.
- The white shark optimization (WSO) algorithm has been utilized for the first time to optimize a nonlinear mixed-integer programming power system operation problem.

To the best of the authors' knowledge, no previous reports have suggested a cost-effective approach that integrates fast-acting voltage regulation devices, specifically PV smart inverters, with traditional VVC devices to enhance CVR operation.

1.4 Structure of paper

The structure of this paper is outlined as follows: In section 2, the mathematical formulation of the research objective is presented. Section 3 elaborates on the solution approach, encompassing an overview of the white shark optimization (WSO) and the application of the WSO technique aimed at minimizing the total annual operation cost. Section 4 offers a summary of the conclusions and discussions. The closing section 5 covers the conclusion.

2. Problem formulation

The main goal of this study is to minimize the total annual operation cost (TAOC), which includes power purchased from the grid, emission cost, loss cost, and switching cost of OLTC, CB, and remote controlled switches (RCSs) as given in Eq. (1)

$$TAOC = \frac{\sum_{t=1}^{T}\begin{bmatrix} C_{grid}^{t}\left(\sum_{i=1}^{n} P_{i,cons}^{t}\right) + C_{loss}\left(\sum_{m=1}^{nbr} P_{m,loss}^{t}\right) \\ +C^{tap}\left|tap^{t} - tap^{t-1}\right| \\ +\sum_{i\in\Omega_{cap}} C^{cap}\left|CB_{i}^{t} - CB_{i}^{t-1}\right| \\ \sum_{i\in\Omega_{SW}} C^{SW}\left|SW_{i}^{t} - SW_{i}^{t-1}\right| + C_{CO_2}P_{grid}^{t} \end{bmatrix}\times}{365} \quad (1)$$

Subjected to the following constraints Eqs. (2-10)

- Active and reactive power flow constraints

$$P_{grid}^{t} - \sum_{m=1}^{nbr} P_{m,loss}^{t} - \sum_{i=1}^{nd} P_{i,cons}^{t} + \sum_{i\in\Omega_{PV}} P_{i,PV}^{t} = 0 \quad (2)$$

$$Q_{grid}^{t} - \sum_{m=1}^{nd} Q_{m,loss}^{t} - \sum_{i=1}^{nd} Q_{i,cons}^{t} + \sum_{i\in\Omega_{cap}} Q_{i,cap}^{t} + \sum_{i\in\Omega_{PV}} Q_{i,PV}^{t} = 0 \quad (3)$$

- Active ($P_{i,cons}^{t}$) and reactive ($Q_{i,cons}^{t}$) power consumption by voltage dependent loads

$$P_{i,cons}^{t} = P_{i,cons}^{n,t}\left(\frac{V_i^t}{V_i^{n,t}}\right)^{k_i^p} \quad (4)$$

$$Q_{i,cons}^{t} = Q_{i,cons}^{n,t}\left(\frac{V_i^t}{V_i^{n,t}}\right)^{k_i^q} \quad (5)$$

- Bus voltage magnitude (V_i^t) limits

$$V^{min} \le V_i^t \le V^{max} \quad (6)$$

- OLTC Transformer tap (tap^t) limits

$$V^t = 1 + tp^t\frac{\Delta V_{step}}{100} \quad (7)$$

here, $tp^t \in \{tp^{min,t}, \ldots\ldots, -1,0,1, \ldots\ldots tp^{max,t}\}$

- Switched capacitor bank's ($Q_{i,cap}^t$) limits

$$Q_{i,cap}^{t} = cbp_i^t \Delta q_i^{cap}; i \in \Omega_{cap} \quad (8)$$

Where, $cbp_i^t \in \{0,1, \ldots\ldots cbp_i^{max}\}$

- Reactive power limit of smart inverter

$$\left|Q_{i,PV}^{t}\right| \le \sqrt{S_{pv,i}^{2} - \left[P_{pv,i}^{t}\right]^{2}} \quad (9)$$

- Maintenance of radial structure constraint for DNR

$$\sum_{ij=1}^{nbr} sw_{ij} = nd - 1 \quad (10)$$

2.1 Decision variables

The solution vector, denoted as per Eq. (11), embodies the optimal combination of OLTC transformer tap position, shunt capacitor banks step position, status of remote controlled switches, and reactive power from PV smart inverters. This vector serves as the solution to the CVR problem, effectively addressing the goal of achieving cost-effective power distribution.

$$Y = \left[tp^t, cbs_i^t, sw_i^h, Q_{i,PV}^t\right] \quad (11)$$

3. Solution approach

This research aims to investigate the optimal coordination of PV smart inverters and traditional VVC devices for efficient CVR operation while considering the impact of distribution network reconfiguration on the total operation cost. The total operation cost includes power purchased from the grid, emission cost, loss cost, and the switching cost of OLTC, CB, and reclosers. To achieve the optimal solution, we employ the white shark optimization (WSO) technique, a powerful algorithm capable of handling complex optimization problems.

3.1 Overview of white shark optimization (WSO)

This section provides a detailed explanation of the mathematical frameworks employed in the proposed white shark optimization (WSO) technique for addressing the optimal power flow (OPF) challenge. These models are designed to emulate the

Received: October 5, 2023. Revised: November 9, 2023.

hunting behaviors of white sharks, encompassing aspects such as prey tracking and capture.

1. WSO Initialization: Illustrated in the subsequent 2-dimensional matrix, an assembly of n WSO instances within a d-dimensional search domain is depicted, where each shark's position signifies a proposed resolution for these issues [21].

$$y = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_d^1 \\ y_1^2 & y_2^2 & \cdots & y_d^2 \\ \vdots & \vdots & \vdots & \vdots \\ y_1^n & y_2^n & \cdots & y_d^n \end{bmatrix} \tag{12}$$

Here, y signifies the collective spatial positions of the sharks within the exploration area, while d indicates the count of decision variables associated with a specific task.

2. Velocity of Approach to Prey: The speed at which a white shark advances towards its target is determined by detecting disturbances in the water waves caused by the prey's movement, as depicted in Eq. (13).

$$\vartheta_{k+1}^i = \mu\left[\vartheta_k^i + m_1\left(y_{best_k} - y_k^i\right) \times k_1 + m_2\left(y_{best}^{\vartheta_k^i} - y_k^i\right) \times k_2\right] \tag{13}$$

For indices i = 1, 2, ..., n representing the range of size n, the updated velocity vector of the shark at position i is labeled as ϑ_{k+1}^i. Here, ϑ_k^i signifies the vector associated with the ith shark's position optimization, as detailed by the formulation presented in Eq. (14).

$$\vartheta = [n \times rand(1,n)] + 1 \tag{14}$$

Here, rand(1, n) denotes a set of randomly generated values distributed within the range of [0, 1].

$$m_1 = m_{max} + (m_{max} - m_{min}) \times e^{-(4k/K)^2} \tag{15}$$

$$m_2 = m_{max} + (m_{max} - m_{min}) \times e^{-(4k/K)^2} \tag{16}$$

Here, considering the present iteration as 'k', the maximum iterations as 'K', and utilizing 'mmin' and 'mmax' to represent the initial and adjusted velocities for white shark movement, a comprehensive analysis established that the optimal values for 'mmin' and 'mmax' are determined to be 0.5 and 1.5, respectively.

$$\mu = \frac{2}{\left|2-\tau-\sqrt{\tau^2-4\tau}\right|} \tag{17}$$

The acceleration factor, denoted as τ, has been identified through extensive research [18] to have a value of 4.125.

3. Advancing towards optimal prey location: Within this context, the approach for updating the position, as outlined in Eq. (18), was adopted to elucidate how white sharks navigate towards their prey.

$$y_{k+1}^i = \begin{cases} y_k^i \cdot \neg \oplus y_0 + u \cdot a + l \cdot b; rand < m\vartheta \\ y_k^i + \vartheta_k^i / f;\ rand \geq m\vartheta \end{cases} \tag{18}$$

Eqs. (18) and (19) establish 'a' and 'b' as binary vectors, individually.

$$a = sgn\left(y_k^i - u\right) > 0 \tag{19}$$

$$b = sgn\left(y_k^i - 1\right) < 0 \tag{20}$$

$$y_0 = \oplus\ (a, b) \tag{21}$$

The outcome of a bitwise XOR operation is represented by the symbol ⊕. The frequency of the undulating motion exhibited by a white shark, along with the number of instances it engages in targeting its prey, are delineated by Eqs. (22) and (23) correspondingly.

$$f = f_{min} + \frac{f_{max} - f_{min}}{f_{max} + f_{min}} \tag{22}$$

$$m\vartheta = \frac{1}{\left(a_0 + e^{(k/2-k)/a_1}\right)} \tag{23}$$

The constants a0 and a1, employed to regulate the balance between exploration and exploitation, are indicative of specific positions.

4. Advancing Toward the Optimal Shark's Position: Sharks possess the ability to maintain a strategic stance ahead of the most advantageous fellow shark that is in proximity to the target. Eq. (24) elucidates the representation of this phenomenon.

$$y'^i_{k+1} = y_{best_k} + r_1 \overrightarrow{D_y} sgn(r_2 - 0.5) r_3 < S_s \tag{24}$$

The refined location of the shark, denoted as y'^i_{k+1}, is determined. The function sgn(r_2 - 0.5) is employed to adjust the search trajectory by generating either 1 or -1. Here, r1, r2, and r3 correspond to randomly generated numbers within the interval [0, 1]. The value of $\overrightarrow{D_y}$, serving as the length for both the target and the shark, is defined in Eq. (25). Additionally, the

Received: October 5, 2023. Revised: November 9, 2023.

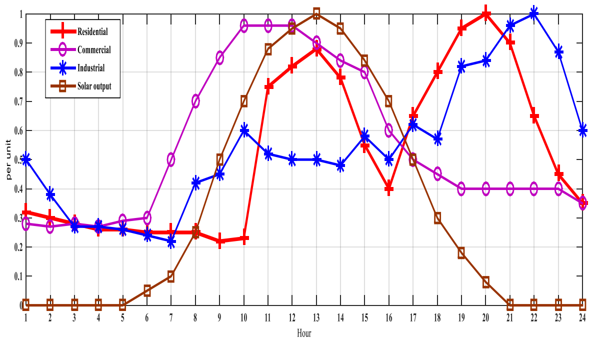

Figure. 1 Different loads and PV generation in per unit

parameter S_s, suggested to encapsulate the potency of white sharks, is expressed in Eq. (26).

$$\overrightarrow{D_y} = \left|rand \times sgn\left(y_{best_k} - y_k^i\right)\right| \tag{25}$$

$$S_s = \left|1 - e^{(-a_2 \times k/k)}\right| \tag{26}$$

Utilizing a2 as a positional factor to govern the balance between exploration and exploitation.

5. Fish schooling dynamics: The subsequent equation has been introduced to characterize the collective behavior resembling a fish school that is displayed by white sharks.

$$y_{k+1}^i = \frac{y_k^i + y'^{i}_{k+1}}{2 \times rand} \tag{27}$$

Incorporating a uniformly distributed random number within the interval [0, 1], represented as 'rand'. As substantiated by Eq. (26), the sharks adeptly fine-tune their positions, guided by the optimal shark that has successfully reached the vicinity of the target. The ultimate destination of the sharks converges ideally around the prey within the exploration region.

3.2 Implementation of WSO on CVR problem

In this research endeavor, we harnessed the potential of the WSO algorithm to address the intricate optimization challenge encapsulated by equations ranging from Eq. (1) to Eq. (10). The algorithm's execution commenced by initializing a dynamic assembly of white shark agents through (1), meticulously adhering to specified constraints (2)-(10).

4. Outcomes and discussions

The performance evaluation of the WSO algorithm was conducted on a 119 bus distribution system using the MATLAB platform. The system's intricate details concerning line data and load data

Table 1. Comparison of different cases in terms of energy demand, consumption and losses

Cases		Case 1	Case 2
Energy Demand (MVAh)		370.04	347.27
Energy Demand savings	MVAh	----	22.76
	%	----	6.15
Active energy Loss(MWh)		6.76	4.48
Active energy loss savings	MWh	----	2.28
	%	----	33.67
reactive energy Loss(MVARh)		4.76	3.40
Reactive energy loss savings	MVARh	----	1.36
	%	----	28.55
Active energy cons. (MWh)		289.60	281.23
Active energy consumption savings	MWh	----	8.37
	%	----	2.89
Reactive energy cons. (MVARh)		217.03	193.99
Reactive energy consumption savings	MVARh	----	23.04
	%	----	11.81
Overall minimum voltage (pu)		0.95	0.95
Overall maximum voltage (pu)		1.043	1

were acquired from [11]. Notably, the system's capabilities were enhanced by incorporating an OLTC transformer between the substation and node 1, enabling precise voltage adjustments with a change of 0.625% for each tap adjustment [11].

Furthermore, to exercise control over reactive power, four CBs were strategically positioned at buses 39, 48, 108, and 110, providing a controllable range of 0 to 300 kVAR. The CBs operate through three switching steps, with each step causing a 100 kVAR change in reactive power. Additionally, the system was bolstered by the integration of four smart inverters designated for PV energy generation. Each inverter, boasting a capacity of 1000 kVA, was interconnected with buses 18, 49, 83, and 108, respectively. Cost parameters are taken from [22]-[24]. Fig. 1 offers comprehensive insights into

Received: October 5, 2023. Revised: November 9, 2023.

diverse load types, encompassing industrial, residential, and commercial loads, along with the per unit values of PV active power generation throughout a 24-hour timeframe.

4.1 Different cases

In order to assess the significance of the combined operation of control devices in reducing energy demand, four distinct scenarios were examined for 119 bus test system. The objective of these investigations was to understand the impact and effectiveness of employing control devices in tandem.

- Case 1: Enabled OLTC, CB devices with CVR operation only
- Case 2: Enabled OLTC, CB, smart inverter with CVR and DNR operations

Table 1 presents the simulation outcomes for the 119 bus systems across two distinct scenarios. The table encompasses essential energy-related metrics, including energy demand, losses, and consumption for each case. Meanwhile, Table 2 provides a breakdown of the number of operations executed by OLTC and CBs throughout the day in the various scenarios. Additionally, Table 3 offers insights into the status of opened remote controlled switches (RCS) within the 119 bus test system for the different cases.

Case 1: Enabled OLTC, CB devices with CVR operation only

In this particular scenario, the CVR operation was carried out by controlling the OLTC and CBs. According to the data presented in Table 2, the total energy demand was measured at 370.04 MVAh, with active and reactive energy losses recorded as 6.76 MWh and 4.76 MVARh, respectively. Moreover, the consumption of active and reactive energy was documented as 289.6 MWh and 217.03 MVARh, respectively. Table 3 provides information about the total number of tap position adjustments made by the OLTC and the steps taken by the CBs in the different cases. Notably, in case 1, a total of 27 OLTC operations were conducted, while the number of capacitor bank operations reached 19. Throughout the day, the minimum and maximum voltages recorded were 0.95 pu and 1.043 pu, respectively, indicating that the CVR operation effectively managed to keep the voltage within permissible limits.

Case 2: Enabled VVC devices, Smart inverter and DNR

In this particular case, the CVR operation was conducted by coordinating the OLTC, CBs, smart inverter, and DNR (distributed network reconfiguration). Based on the data presented in Table 1, significant reductions were observed across various energy-related metrics compared to case 1. Notably, the total energy demand exhibited a noteworthy decrease, reaching 347.27 MVAh (a reduction of 6.15%). Additionally, the active and reactive energy losses were substantially reduced to 4.48 MWh (a reduction of 33.67%) and 3.40 MVARh (a reduction of 28.55%), respectively. Moreover, the consumption of active and reactive energy displayed substantial reductions, amounting to 281.23 MWh (a decrease of 2.89%) and 193.99 MVARh (a decrease of 11.81%), respectively. These reductions can be attributed to the collective influence of the OLTC, CBs, smart inverter, and DNR, which worked in tandem to optimize energy usage. Analyzing Table 3, it is evident that in case 2, the number of OLTC operations was recorded as 16, while the total number of capacitor bank operations reached 15. Furthermore, Fig. 2 illustrates the variation of reactive power from the smart inverter throughout the day. Table 3 presents the set of opened RCS (remote controlled switches) over the course of a day, with a total number of switching operations (TNS) amounting to

Table 2. Number of operations of OLTC and CBs over a day in different cases

cases	OLTC	CB# 39	CB# 48	CB# 108	CB# 110	TCB
case 1	27	5	8	3	3	19
case 2	16	5	2	4	4	15

Table 3. Opened RCS of 119 bus test system for case 2

Hour duration	Opened RCS	NS
Initial	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	0
1-7	21, 25, 48, 32, 45, 40, 60, 37, 126, 76, 71, 73, 130, 82, 109	26
7-14	23, 25, 50, 32, 45, 40, 60, 37, 95, 76, 71, 73, 130, 107, 109	8
14 – 18	23, 25, 50, 121, 45, 40, 60, 125, 95, 76, 71, 73, 130, 107, 109	4
18-24	23, 25, 50, 121, 45, 40, 60, 125, 95, 76, 71, 73, 130, 131, 109	2
total number of switches (TNS)		40

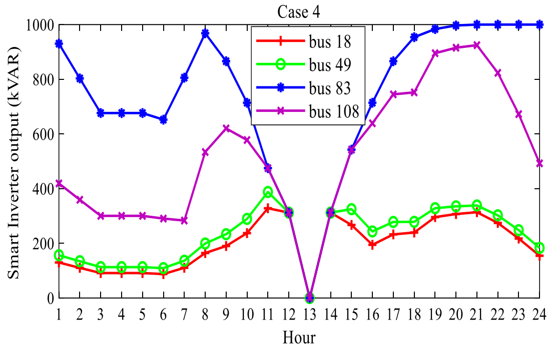

Figure. 2 Smart i
nverter output for 119 bus system for case 2

Table 4. cost analysis for different cases

cases	Case 1	Case 2
E_{con} (k$)	8456.2	8211.82
E_{loss} (k$)	493.4	327.259
E_{emis} (k$)	2316.46	2223.2
OLTC (k$)	197.1	116.8
CB (k$)	69.35	54.75
RCS (k$)	0	14.6
Total Cost (k$)	11532.5	10948.4
Cost in Savings (k$)	----	584.081

40. Throughout the day, the minimum and maximum voltages observed were 0.95 pu and 0.9996 pu, respectively, demonstrating the effectiveness of the VVC devices, smart inverter, and DNR in maintaining the voltage profile within permissible limits. This application, which involved the integration of VVC devices, smart inverter, and DNR, not only succeeded in maintaining the voltage profile but also had a more substantial impact on reducing energy consumption and losses within the system compared to other cases.

4.2 Cost analysis

Table 4 presents a comprehensive overview of various cost parameters for different cases over the course of a year. These parameters include energy consumption (E_{con}), energy losses (E_{loss}), CO_2 emissions from the grid (E_{emis}) [22], switching cost of traditional devices such as OLTC and CB [23], and remote controlled switches (RCS) [24]. The data reveals noteworthy cost savings achieved through the integrated approach. Specifically, in case 2, significant savings of k$ 584.081 were observed. These results underscore the remarkable advantages of combining PV smart inverters with traditional VVC devices for CVR operation.

Table 5. Relative study of different metaheuristic approaches

Metaheuristic approach	Minimum value ($\times10^3$ $)	Mean value ($\times10^3$ $)	Standard deviation ($\times10^3$)
SSO [17]	12203.67	13060.59	2298.10
KHA [18]	12072.68	13060.59	2196.75
SGO [19]	11961.18	12788.69	1941.59
WOA [20]	11563.89	12694.07	2283.33
GWO [10]	11234.75	12196.65	2138.92
WSO	10948.44	11743.30	1864.97

4.3 Performance of WSO algorithm and other algorithms

In the realm of metaheuristic algorithms, the white shark optimizer (WSO) emerges as a formidable solution, outperforming its counterparts—SSO [17], KHA [18], SGO [19], WOA [20], and GWO [10]—in addressing the complexities of case 2. WSO's remarkable convergence at k$10,948.44, accompanied by a mean standard deviation of k$1864.97 and a mean value of k$11,743.30, significantly surpasses the convergences achieved by SSO, KHA, SGO, WOA, and GWO at k$12,203.67, k$12,072.68, k$11,961.18, k$11,563.89, and k$11,234.75, respectively.

The substantial progress demonstrated by WSO, evident in its minimal value and tight standard deviation, underscores its efficiency in navigating the optimization landscape. This efficiency arises from its dynamic position updating, ensuring adaptability, with search agents continuously refining their positions based on the best-so-far solutions. Crucially, WSO strikes a balance between exploration and exploitation, a key factor in optimization success. By allowing search agents to explore new areas while exploiting promising ones, WSO mitigates the risk of getting stuck in local minima and excels in discovering global optimal solutions.

5. Conclusion

In conclusion, this research provides valuable insights into the effective collaboration between PV smart inverters and traditional VVC devices, highlighting their essential contribution to improving voltage regulation and energy efficiency in active distribution networks. Through rigorous testing on 119-bus distribution systems, our proposed algorithm's effectiveness becomes evident, revealing that combining traditional VVC devices and smart

Received: October 5, 2023. Revised: November 9, 2023.

inverters in CVR operations yields substantial cost savings. Moreover, accounting for the impact of distribution network reconfiguration further amplifies these financial advantages, demonstrating the economic viability of this integrated strategy. Notably, the synergistic approach achieves an impressive 6.51% reduction in energy consumption. Additionally, the strategy's prowess is emphasized by notable reductions of up to 33.67% in active power losses and 28.55% in reactive power losses, all while maintaining voltage within acceptable parameters. The financial gains are equally noteworthy, with significant cost reductions observed. Moreover, the white shark optimization (WSO) algorithm's superior performance over other metaheuristic methods reinforces its effectiveness in tackling the complex optimization demands posed by CVR operations. These findings hold significant implications for policymakers, utility companies, and researchers, shedding light on the advantages of integrating coordinated PV smart inverter and VVC strategies to achieve efficient CVR operations with cost optimization. The proposed approach not only promises the development of future sustainable distribution networks but also paves the way for cost-efficient solutions that align with the global shift towards a more sustainable energy landscape.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Ravindhar; methodology, Ravindhar; software, Ravindhar; validation, Ravindhar; formal analysis, Suresh; investigation, Suresh; resources, Suresh; data curation, Ravindhar; writing—original draft preparation, Ravindhar; writing—review and editing, Suresh; visualization, Mangu; supervision, Mangu.

Nomenclature

Index		
T	:	Index for hour
n/nbr	:	Total number of buses/branches
$\Omega_{cap}/\Omega_{PV}/\Omega_{sw}$		Set of capacitor banks (CBs) and PV mounted buses/ switches
parameters		
C_{grid}, C_{loss}		Cost of power purchased from grid, power loss cost
C^{tap}, C^{sw}, C_{CO2}		Cost of OLTC tap operations, switches, carbon emission
Δq_i^{cap}	:	capacitor bank step change at i^{th} bus
Variables		
$P_{m,loss}^t, Q_{m,loss}^t$	:	active and reactive power loss at t^{th} hour in m^{th} branch
P_{grid}^t, Q_{grid}^t	:	Active and reactive power taken from grid at t^{th} hour
$P_{i,con}^t, Q_{i,con}^t$	:	consumption of active and reactive power at t^{th} hour at i^{th} bus
$Q_{i,cap}^t$	:	Capacitor bank reactive power injection at t^{th} hour at i^{th} bus
$P_{i,PV}^t, Q_{i,PV}^t$	:	PV-smart inverter active power and reactive power at t^{th} hour at i^{th} bus
$S_{i,PV}$	:	Apparent power of PV smart inverter at i^{th} bus
V_i^t	:	voltage magnitude at t^{th} hour at i^{th} bus

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Received: October 5, 2023. Revised: November 9, 2023.

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