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Energy Optimization in Smart Grids Using Whale Optimization Algorithm and Fuzzification

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Abstract

Regarding the significance of energy distribution smart grids and the operation of smart grids, this paper presents a novel method to reduce power loss in these grids. The proposed method determines the injected reactive power and tap of an on-load tap changer (OLTC) optimally using an optimization algorithm. Loss reduction, voltage profile improvement, costs caused by reactive power injection by the capacitor in the grid, conservation voltage reduction (CVR), and transformer loss are considered as objective functions. The new Whale Optimization Algorithm (WOA) is employed as the Volt/VAR Optimization (VVO) algorithm in this paper. The algorithm inspired by the hunting behavior of humpback whales has a high convergence speed, fewer parameters to adjust, and a balance between exploitation and exploration phases. In addition to the above advantages, the WOA has accurate convergence and an effective variety of solutions. The suggested method is applied to the standard IEEE 33-bus system. According to the optimization results, the operating conditions of the distribution smart grid has been improved and the loss has been significantly reduced. Furthermore, the WOA provides better performance in solving the given optimization problem.

Keywords: Smart grid, whale optimization algorithm, energy losses, voltage-var optimization, capacitor placement.

1. INTRODUCTION

In recent years, many electric power companies have upgraded and improved the operation of their distribution networks using smart grid technologies such as Energy Management System (EMS), Distribution

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Management System (DMS), and System Automation (SA). Some companies have enhanced the accuracy of their network by utilizing technologies provided by such smart grid components, such as advanced metering infrastructure (AMI). The United States and several European countries have proposed the concept of smart grids to achieve the goal of making power systems safer, more reliable, more flexible, more environmentally friendly, more controllable, and more efficient [1]. The term "smart grid" refers to the modernization of power grids, which includes the integration of various technologies such as distributed generation (DG), controllable loads, communication systems, and storage devices in both islanded and grid-connected operation modes [2]. In [3], with the optimal placement of distributed resources and rearrangement of the distribution network, the suggested method randomly aims to reduce network costs and increase the profits of owners of distributed resources, as well as reduction of network losses. In reference [4], the method of the optimal distribution of scattered resources and rearrangement of the network aims to reduce network costs and network losses, as well as reducing unmet loads. The smart grid upgrades the present network to a participatory, responsive, and organized network. Based on the documents of the strategic expansion of European electricity networks in the future, the smart grid is an electrical network that can integrate the actions of all related users, generators, customers, and those that do both, to provide secure, economical, and sustainable electricity supply [5]. High emission levels, high power loss, poor power quality, and low reliability are the main challenges to tackle in these systems. Distributed energy resources are small-scale sources, controllable loads or energy storage devices that are a proper solution to deal with these challenges. They are normally smaller in scale than relative power plants and may include photovoltaic (PV) panels, wind turbines (WTs), energy storage (ES) devices, combined heat and power (CHP) diesel generators, and controllable loads [6].

With rising energy costs as well as electricity prices in many countries, distribution companies must increasingly look for optimal methods to minimize power loss based on distributed power and control circuit topologies in a smart grid. Voltage and reactive power control in the distribution system is an important issue in terms of reliability. Today, the distribution system is highly loaded and a significant voltage drop occurs during peak times in the feeders, leading to the violation of the allowable voltage limits. Moreover, increasing the penetration level of renewable DGs has resulted in a high injection of active power, which can increase the voltage in some conditions [7]. Volt-VAR optimization (VVO) is one of the well-known energy distribution network optimization methods commonly used by power companies. The VVO is an advanced optimization method that optimizes the voltage or reactive power (VAR) of a distribution network based on the load voltage profile of a default compact feeder. One solution to store energy is to adjust and reduce the CVR, which attempts to bring the customer's voltage levels to the lower range of the ANSI spectrum, 114-126 V, so that energy consumption is reduced without expecting a change in consumption status of customers [8]. Volt-VAR control actuators, such as LTCs and VRs, can be classified as Volt-VAR control components and are well-coordinated as VVO and CVR objectives [9]. In smart grids, bilateral electricity and data exchange between the power grid and consumers are normally used to create an extensive and automated energy distribution network [2].

One of the methods to reduce losses is to use capacitors in the distribution system. Thus, the location and size of capacitors should be determined optimally in the distribution system, which can be founded by using optimization algorithms [10].

Most of the VVO methods, which have been studied by different companies, are centralized or the scenarios are performed on a daily basis [11]. Authors in [12] utilize the EPSO evolutionary algorithm to control the day-ahead operational planning, which runs every hour for voltage control purposes. This algorithm should be implemented as a software module suitable for microgrid operation that runs every hour so that it provides the control operations required to maintain the voltage profile within an allowable range. The papers [9 and 13] deal with the decentralized VVO method, which operates the Volt-VAR control components (VVCC) within the substation and feeder using a local control and the particle swarm optimization (PSO) algorithm. The advantage of a decentralized method to a centralized method is that it does not encounter the high volume of information sent from AMI to the support office and from VVO to VVCCs in the distribution network substations, and, in this paper, we have presented a decentralized, practical VVO method that can be well-coordinated with the distributed power and control topology in microgrids [13]. Since the VVO subsets may conflict with each other (for example, minimizing losses can increase the voltage, while the CVR tries to reduce the terminal point voltage) in some operating conditions, the fuzzy method is used in [9] to facilitate weighting of each subset of the VVO's objective function.

The present paper employs the WOA for its optimization algorithm and uses the fuzzification method to accurately determine the weighting coefficients of each subset of the VVO's objective function.

The paper is arranged in five sections. After the Introduction section and listing the nomenclature, Section 2 provides the topology, main objectives, constraints, and characteristics of the optimization algorithm. Section 3 first introduces the case study and then it describes various operation scenarios, and finally, Section 4 concludes the paper.

2. SMART GRID-COMPATIBLE VVO

2.1. Structure of the VVO Network

Fig. 1 shows the proposed VVO in a distribution feeder sample [8]. As illustrated in Fig. 1, the data of AMI can be sent to the VVO instrument at any quasi-real-time period (that is, every 15 minutes) (see Fig. 1, the AMI flow path). The VVO tool that includes an algorithm capable of gathering the required AMI data solves optimization problems. It is based on network constraints and gives control commands to Volt-VAR control components such as CBs, LTCs, and

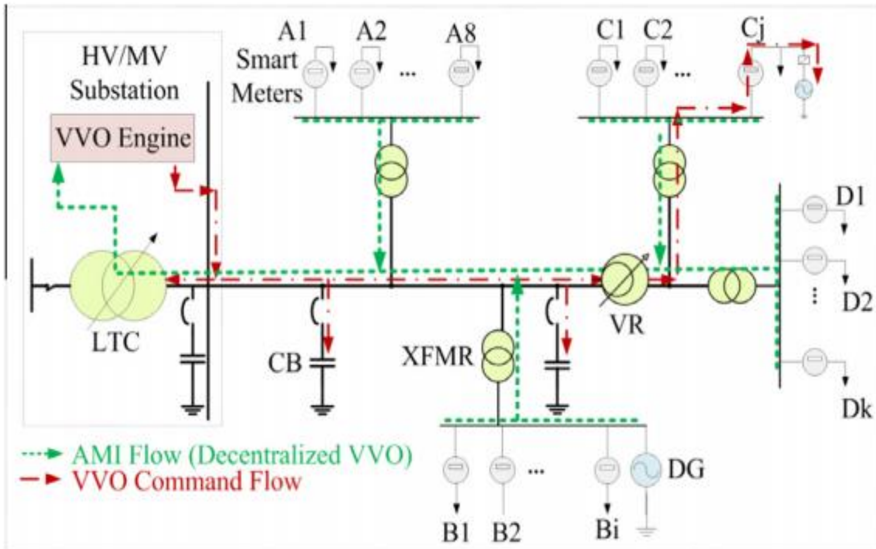

Fig. 1. Structure of the proposed VVO in a distribution network.

VRs located at the substation along with the downstream feeder nodes.

The information required by the VVO tool includes the following: active power, reactive power, voltage, current, and power factor (PF). In addition, the optimization parameters include VR and LTC tap steps as well as the size and number of capacitor bank units. As explained, the objective function has the ability to minimize several important operating costs, including network losses, replaceable parallel capacitor, voltage deviation, and VR and CVR loss costs. Finally, control decisions such as the optimal location and size of the capacitor banks, the number of capacitor banks, and the VR and CVR tap steps are determined via the VVO tool and sent to the relevant Volt-VAR control components.

The VVO sends optimization results to VVCCs as a control command to reconfigure the distribution network based on the new optimal settings (refer to the power flow path in Fig. 1). This topology is aligned with the controlled structure and distributed command of microgrids such that the VVO is located in the medium voltage (MV) substation and can receive local AMI and global specifications from DMS/SCADA.

2.2. Objective Function and Constraints of the VVO

The objective function of the VVO, in general, can be represented as (1):

$$MinO.F = \alpha \times \sum_{l=1}^{l=L} S_{LOSS,l} + \beta \times \frac{1}{2} \times \sum_{i=1}^{i=I} |V_{base} - V_i| \qquad (1)$$

where

$$S_{LOSS,l} = \left(P_{LOSS,l}^2 + Q_{LOSS,l}^2\right)^{0.5} \qquad (2)$$

The current injection model can be as (3). The power flow is in the form of the backward-forward sweep (BFS) method and can be obtained using (3)-(6):

$$I_{i,t}^{k} = \left(\frac{S_{i,t}}{V_{i,t}^{k}}\right)^{*} = \left(\frac{P_{i,t} + jQ_{i,t}}{V_{i,t}^{k}}\right) \quad (3)$$

$$[B] = [BIBC][I] \quad (4)$$

$$\left[V^{k+1}\right] = \left[V^{0}\right] + \left[\nabla V^{k+1}\right] \quad (5)$$

The required constraints of the proposed VVO are described as follows.

$$[BCBV][B] = [BCBV][BIBC]\left[I^{K}\right] = [DLF]\left[I^{K}\right] \quad (6)$$

Bus voltage magnitude:

$$V_{i,t}^{\min} \le V_{i,t} \le V_{i,t}^{\max} \rightarrow 0.95PU \le V_{i,t} \le 1.05PU \quad (7)$$

The active power output of each feeder:

$$P_{i,t}^{\min} \le P_{i,t} \le P_{i,t}^{\max} \quad (8)$$

The reactive power output of each feeder:

$$Q_{i,t}^{\min} \le Q_{i,t} \le Q_{i,t}^{\max} \quad (9)$$

Active power balance based on power flow:

$$\forall t \in T : P_{i,t} = P_{Gi,t} - P_{Loadi,t} \quad (10)$$

Reactive power balance based on power flow:

$$\forall t \in T : Q_{i,t} = Q_{Gi,t} - Q_{Loadi,t} + Q_{c,t}^{i} \quad (11)$$

Active power of the DG:

$$P_{DGi,t}^{\min} \le P_{DGi,t} \le P_{DGi,t}^{\max} \quad (12)$$

Reactive power of the DG:

$$Q_{DGi,t}^{\min} \le Q_{DGi,t} \le Q_{DGi,t}^{\max} \quad (13)$$

Thermal limits of the feeder:

$$S_{l,t} \le S_{l,t}^{\max} \quad (14)$$

LTC/VR constraints of the transformer:

$$1 + tap_{tr,t} \frac{\Delta V_{tr,t}}{100} = \text{Turn ratio of the OLTC/VR} \quad (15)$$

where

$$tap_{tr,t} \in \left\{-tap_{tr,t}^{\max}, \ldots, -1, 0, 1, \ldots, tap_{tr,t}^{\max}\right\} \quad (16)$$

LTC and VR, in this study, are set to have 33 taps (the first tap is zero). Therefore, $\Delta V_{tr,t} = \%0.3125$.

Thirty-two tap steps from 0.95 to 1.05 p.u. (based on the ANSI stnadard). For instance, for a full turn ration:

$$\frac{0.1}{32} = 0.003125 \text{ or equally } 03125\%$$

$$\rho_{tr,t} = 1 + 16(0.003125) = 105$$

Capacitor bank (CB) constraints:

$$Q_{c,t}^{i} = \beta_{c,t}^{i} \Delta q_{c,t}^{i}, \beta_{c,t}^{i} = \left\{0, 1, 2, \ldots, \beta_{c,t}^{\max}\right\} \quad (17)$$

where $Q_{c,t}^{i}$ is the capacity of the CB, $\Delta q_{c,t}$ denotes the VAR amount of each CB, and $\beta_{c,t}^{i}$ shows the integer number of CB units.

Maximum compensation by the CB:

$$\sum_{i=1}^{I} Q_{c,t}^{i} \le \sum_{i=1}^{I} Q_{L,t}^{i} \quad (18)$$

where, *i* is the feeder number and *L* shows the number of the last feeder.

When the operator tends to consider VR and CVR losses, the objective function of the final VO can be presented as (19):

$$
\begin{aligned}
&Min O.F = \\
&\alpha \times \sum_{l=1}^{l=L} S_{LOSS,l} + \beta \times \frac{1}{2} \times \sum_{i=1}^{i=I} \left| V_{base} - V_i \right|^2 \qquad (19) \\
&+\gamma \times \sum_{e=1}^{e=E} \left| V_{END} - V_{CVR} \right| + \delta \times \left(P_{Trans} - VR \right)
\end{aligned}
$$

As one can observe, each subset of the VVO's objective function includes a weighting coefficient, which obtained using (20):

$$
\begin{cases}
\alpha = C_{loss} \times \alpha_{fuzzy} \\
\beta = C_{dev} \times \beta_{fuzzy} \\
\gamma = C_{CVR} \times \gamma_{fuzzy} \\
\delta = C_{VR} \times \delta_{fuzzy}
\end{cases} \qquad (20)
$$

To determine the fuzzy coefficients, the fuzzification method has been used in this paper. In this method, the network operator must first determine the minimum and maximum values for each VVO objective subset according to the technical/economic operation scenarios of the network. Then, if the optimized values of a subset are less/greater than the minimum desired value, the fuzzy weight will be equal to one/zero. If the optimized value is between minimum and maximum, a number between zero and one will be determined based on the algorithm presented in (21) for example for the weight loss coefficient.

$$
\begin{aligned}
&if: \alpha_{fuzzy} \le S_{LOSS,\min} \rightarrow \alpha_{fuzzy} = 1 \\
&elseif: \alpha_{fuzzy} \succ S_{LOSS,\min} \,\&\, \alpha_{fuzzy} \prec S_{LOSS,\max} \\
&\rightarrow \alpha_{fuzzy} = \frac{\left| \alpha_{fuzzy} - S_{LOSS,\min} \right|}{S_{LOSS,\max} - S_{LOSS,\min}} \qquad (21) \\
&else: \alpha_{fuzzy} \ge S_{LOSS,\max} \rightarrow \alpha_{fuzzy} = 0
\end{aligned}
$$

Therefore, by fuzzification of fuzzy coefficients, the VVO's objective function reaches the desired value according to the network operating conditions.

2.3. Whale Optimization Algorithm

This paper presents a smart grid-compatible energy optimization and conservation tool using the AMI data. This section describes the whale optimization algorithm (WOA), which is based on the imitation of the humpback whale hunting method, as the optimization algorithm of the proposed VVO tool. The advantages of the WOA are high convergence speed, a fewer number of parameters, and providing a balance between exploitation and exploration. The multi-objective WOA, in addition to the abovementioned merits, provides accurate convergence, accurate Pareto fronts, and an effective variety of solutions [12].

According to the mentioned needs, the WOA has been used in this paper. The WOA can support the solution of continuous linear/nonlinear optimization problems with either continuous or discrete variables. According to [12], the WOA is a meta-heuristic method that was developed in 2016 inspired by the life of humpback whales. This

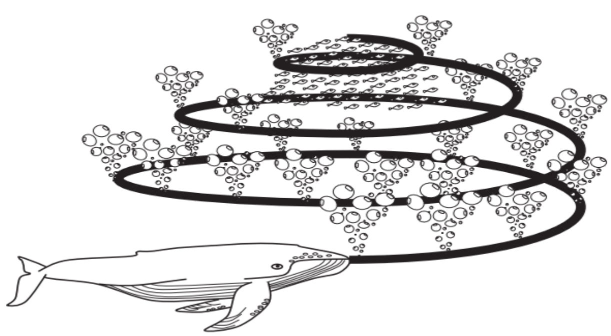

Fig. 2. Bubble-net feeding behavior of humpback whales.

method employs the bubble creating attack strategy to hunt prey. Fig. 2 shows the foraging behavior of this animal, which is called the bubble net feeding method [14].

The following is a mathematical model of the WOA resulting from the encircling the prey using spiral bubbles, feeding maneuvers, and search for prey.

2.3.1. Encircling the Prey

The humpback whale identifies the prey and surrounds it. It then updates its position relative to the optimal solution on the iterative path from start to maximum iteration according to the following equations.

$$\vec{D} = \left| \vec{C} . \vec{X}^{*}(t) - \vec{X}(t) \right| \tag{22}$$

$$\vec{X}(t+1) = \vec{X}^{*}(t) - \vec{A}\vec{D} \tag{23}$$

where *t* represents the current iteration, A and C are coefficient vectors, X^{*} is the position vector of the best solution obtained so far, and X shows the location vector of the object.

Vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{24}$$

$$\vec{C} = 2.\vec{r} \tag{25}$$

where, $\vec{a}$ is the linear vector decreasing from 2 to 0 during the iteration period (in both exploration and exploitation phases), and $\vec{r}$ is a random vector in the range [0, 1].

2.3.2. Bubble-Net Attacking Method (Exploitation Phase)

Two methods are designed as follows:

A) Reduction of the encircling mechanism

This technique is used by linearly reducing the value of *a* from 2 to 0. The random value of A is in the range [-1, 1].

B) Spiral position update

The spiral equation is used to update the position between the whale and the prey, that is a spiral motion:

$$\vec{X}(t+1) = \vec{D}^{'}.e^{bl}.\cos(2\pi l) + \vec{X}^{*}(t) \tag{26}$$

where, 1 is a random number between [-1, 1], *b* is a constant logarithmic form, and $D^{'} = \left| \overline{X^{*}(t)} - \vec{X}(t) \right|$ expresses the distance between whale *i* and the best solution obtained so far.

$$\vec{X}(t+1) = \begin{cases} \vec{X}^{*}(t) - \vec{A}.\vec{D} & if \;\; p < 0.5 \\ \vec{D}.e^{bl}.cos(2l) + (\vec{X}^{*})(t) & if \;\; p > 0.5 \end{cases} \tag{27}$$

2.3.3. Search for prey (exploration phase)

The vector $\vec{A}$ can be used for exploration in the search for prey. The vector also has values greater than one or less than minus one. Exploration follows two conditions:

The exploration of the WOA algorithm is augmented by $|\vec{A}| > 1$,avoiding local optima to find the global optimal.

A < 1: The best solution is selected to update the current search agent position.

3. VVO CASE STUDY RESULTS AND ANALYSIS

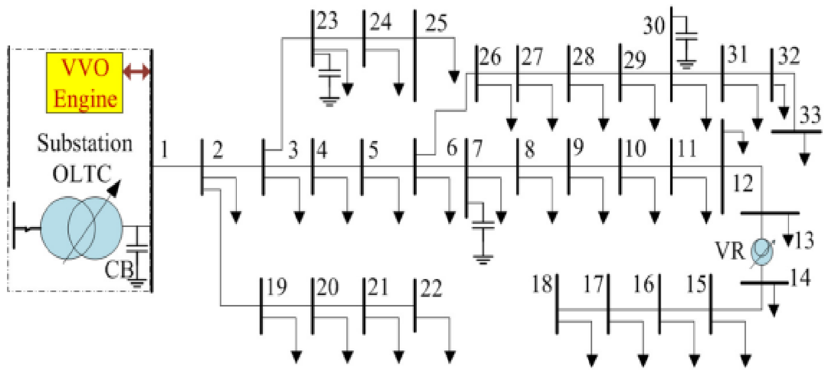

Fig.3. Single-line diagram of the 33-bus test distribution feeder.

Table 1. ***Average load data of the 33-bus distribution feeder.***

Node No.	Active Power (KW)	Reactive Power (KVAR)	Node No.	Active Power (KW)	Reactive Power (KVAR)
1	100	60	17	60	20
2	100	60	18	90	40
3	90	40	19	90	40
4	120	80	20	90	40
5	60	30	21	90	40
6	60	20	22	90	40
7	200	100	23	90	50
8	200	100	24	420	200
9	60	20	25	420	200
10	60	20	26	60	25
11	45	30	27	60	25
12	60	35	28	60	20
13	60	35	29	120	70
14	120	80	30	200	100
15	60	10	31	150	70
16	60	20	32	210	100
			33	60	40

Table 2. ***ZIP coefficients.***

ZIP coefficients	Z	I	P
Active power	0.418	0.135	0.447
Reactive power	0.515	0.023	0.462

Table 3. ***Comparison of results before and after capacitor placement.***

Location of capacitors	Bus 1	Bus 7	Bus 23	Bus 30
Capacitor size	25 kvar	300 kvar	25 kvar	300 kvar
Tap size	0.95	1.25		
Active losses	Before installing the capacitor: 150.4648 KW	After installing the capacitor: 130.699	Reduction rate: %13.1365	
Reactive losses	Before installing the capacitor: 100.1157 kvar	After installing the capacitor: 86.7465 KW	Reduction rate: %13.3537	
Minimum voltage (pu)	Before installing the capacitor: 0.96193	After installing the capacitor: 0.9689		
Maximum voltage (pu)	Before installing the capacitor: 1.04	After installing the capacitor: 1.04		
Voltage adjustment	% 0.032449			
Annual cost ($)	Before installing the capacitor: 24525.7581	After installing the capacitor: 21303.9353	Annual reserve: 3221.8228	

3.1. Simulation

A 33-bus experimental distribution system [12] has been utilized to test the proposed VVO tool. Fig. 3 shows the single-line diagram of the system under study [9].

The network consists of 33 buses with 33 terminal points, i.e. smart meters. Power is supplied from an HV/MV substation to a radial distribution network. Four shunt capacitor banks, the locations of which are optimally determined by the algorithm, are placed in the system. The range of capacity of capacitive banks is from 25 to 300 kVar. Moreover, an OLTC is placed in the HV/MV substation and a VR is on the bus 13, both of which are in the 32nd tap. The average active/reactive power loads of the case study are shown in Table 1.

In order to accurately model the loads, this paper uses the ZIP coefficients listed in Table 2 [9].

The outputs taken from the smart meters every 15 minutes are the active power of the nodes, the reactive power of the nodes, node voltages, branch currents, and power factors of the nodes. The VVO tool is designed and programmed in MATLAB software and the current path of the distribution load is carried out through BFS with 100 sweeps. The maximum and minimum values of the apparent power loss desired, $(S_{LOSS,min}, S_{LOSS,max})$, are considered by the operator as 0.35 and 0.1 p.u., respectively. In addition, the maximum and minimum voltage values required, $(V_{dev,min}, V_{dev,max})$, are 10 and 0.1. The maximum and minimum values of CVR are set 0.01 and 0.001, respectively, and for VR losses, the maximum and minimum settings are 0.05 and 0.005 p.u., respectively. For the scenario with weighting coefficients, the loss cost is defined based on the electricity price (0.12 $/kWh). The cost of voltage deviation is assumed to be eight times higher than the loss cost. Furthermore, the loss costs of VR and CVR are assumed to be ten times higher than the voltage deviation cost based on the operating needs of the distribution network.

3.2. Operation Scenarios

To investigate the effects of different subsets of the VVO's objective function, six exploitation scenarios are presented in this section.

Scenario 1: The VVO is performed without fuzzification and without minimizing the operation cost of the CB.

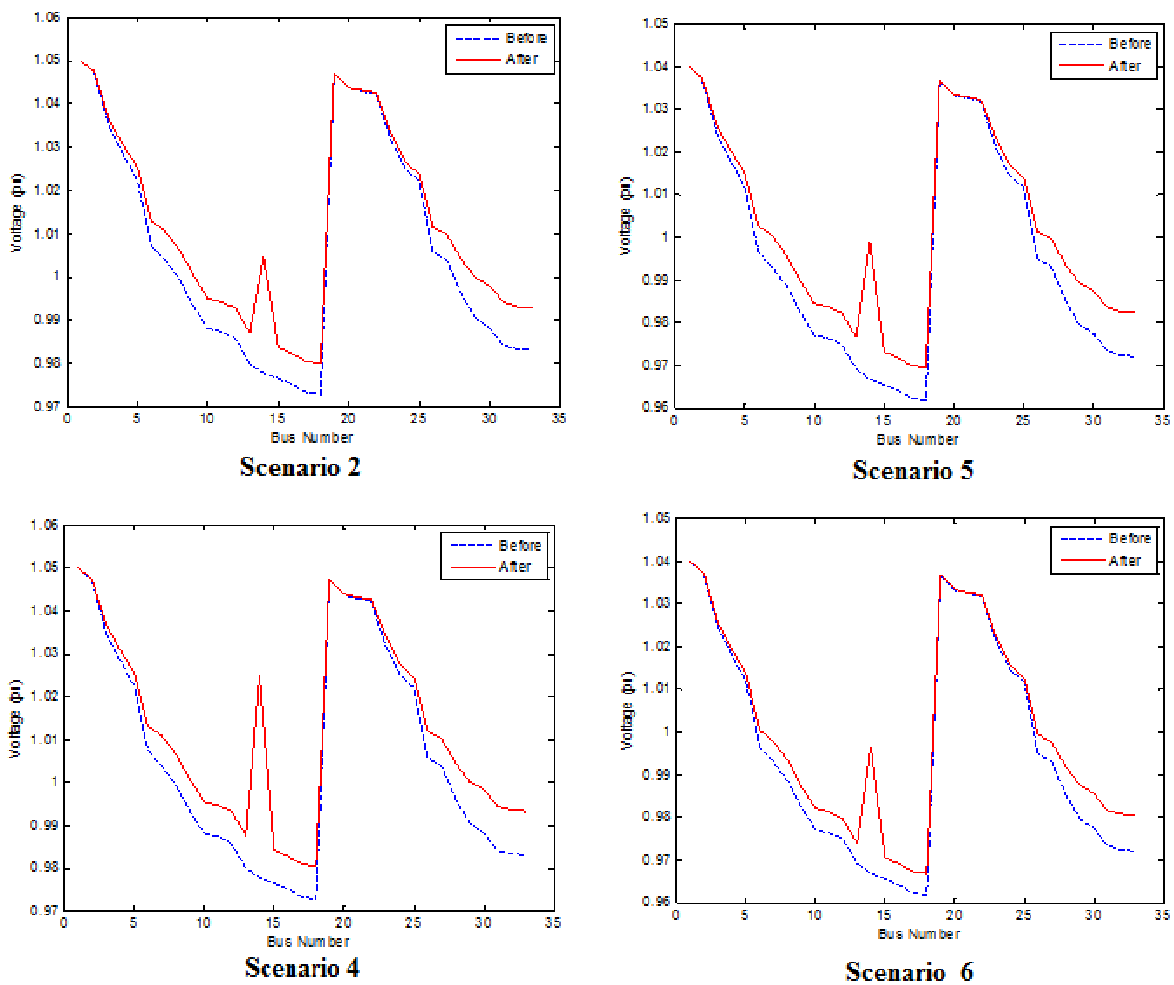

Fig. 4. Distributed feeder node voltages in different scenarios.

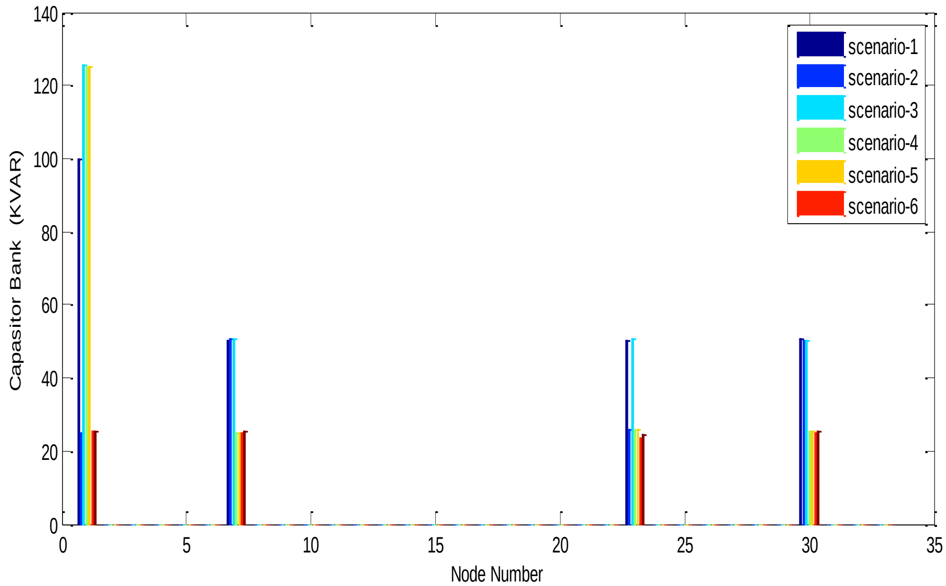

Fig. 5. Comparison of capacitors in different scenarios.

Scenario 2: The VVO is performed without fuzzification and with minimizing the operation cost of the CB.

Scenario 3: The VVO is performed without fuzzification but without minimizing the operating cost of the CB.

Scenario 4: The VVO is performed without fuzzification but with minimizing the operating cost of the CB.

Scenario 5: Minimizing VR, where CVR losses is added to the VVO and the VVO is performed without fuzzification.

Scenario 6: Minimizing VR, where CVR losses is added to the VVO and the VVO is performed with fuzzification using weighting coefficient calculations.

3.3. Results

The network bus voltages for different operating scenarios (scenarios 2, 4, 5, and 6) are shown in Fig. 4. Fig. 5 illustrates the kVar values of shunt capacitor banks, andFig. 6 shows the VR and LTC taps in all operating scenarios under-study, identified by the VVO tool. Fig. 7 illustrates the active power losses of Scenario 6, compared to a system without the VVO. Fig. 8 exhibits the voltage profile of the system nodes in Scenario 6 for all quasi-real-time periods. Fig. 9, the WOA convergence, shows the VVO tool for Scenario 6. At each simulation real-time interval (i.e. every 15 minutes), the VVO tool attempts to compensate for the system's reactive power to minimize distribution network losses. This is realized through replaceable shunt capacitive banks.

4. CONCLUSION

This paper presents a smart grid-compatible Volt-Var optimization tool using the WOA. To determine the weighting coefficient of each subset of the VVO’s objective function,

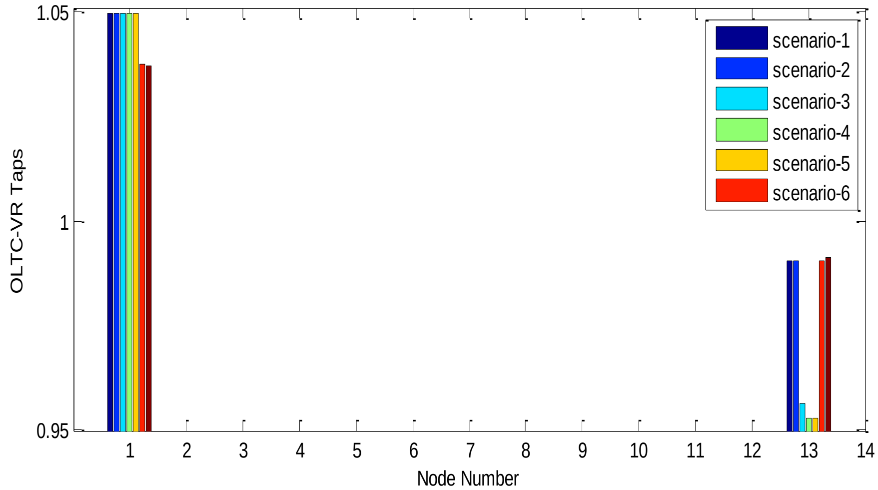

Fig. 6. Comparison of tap-changers in different scenarios.

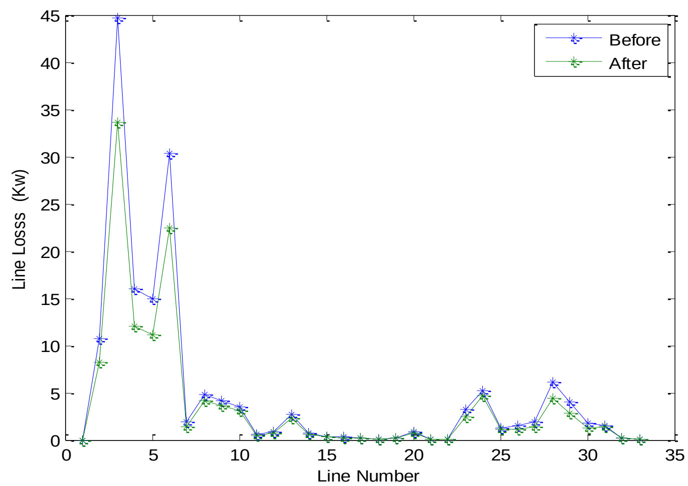

Fig. 7. Line losses.

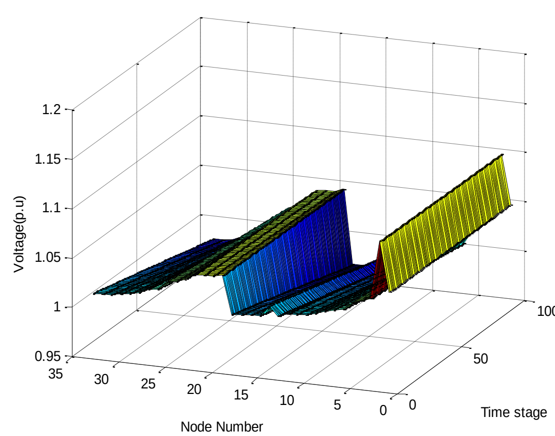

Fig. 8. Node voltages of Scenario 6 for 96 real-time quasi-periods.

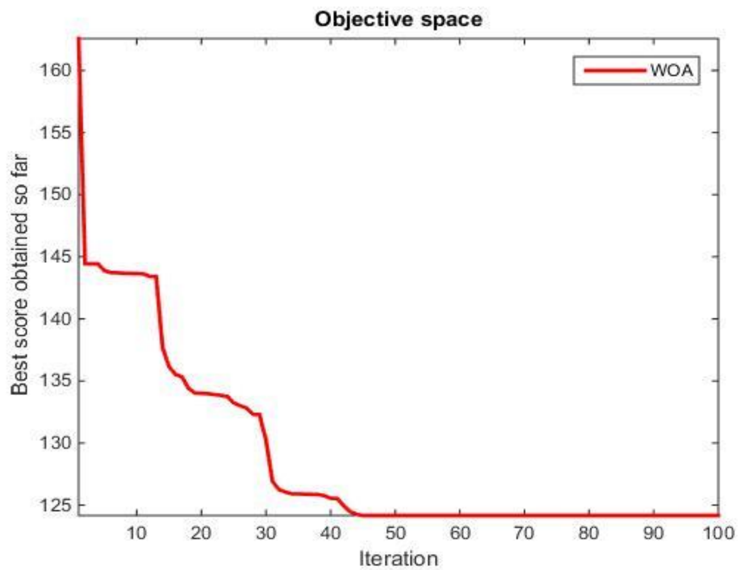

Fig. 9. The WOA convergence of the VVO tool in Scenario 6.

the fuzzification method is utilized in this algorithm and different scenarios are compared for a 33-bus test distribution feeder. The results highlight that employing the VVO tool, which uses the WOA and fuzzification;distribution networks are optimized according to the technical and economic requirements of the distribution network.

Nomenclature

$S^i_{l,t}$ apparent power loss (kVA)

$P_{loss,l,t}$ active power loss of feeder-l at time-t (kW)

$Q_{loss,l,t}$ reactive power loss of feeder-l at time-t (kVAR)

S complex power (kVA)

V voltage magnitude (V)

P active power (kW)

Q reactive power (kVAR)

C cost ($)

I current (A)

V_{base} base voltage of system (V)

$S_{l,t}$ power limit of feeder-l at time-t

V_{vel} velocity of particle is PSO

ρ off-nominal turn ratio of OLTC and VR

Tap tap unit

ΔV voltage change

$P_{Trans-VR}$ active power loss of VR

$\beta^i_{c,t}$ integer value for capacitor bank units

$\Delta q^i_{c,t}$ VAr value for each bank unit

$Q^i_{c,t}$ capacitor bank capacity

$\alpha, \beta, \gamma, \delta$ weighting factors

φ_1, φ_2 acceleration constants in WOA

r_1, r_2 random values (between 0 and 1)

Loss loss

dev deviation of voltage

[B] branch current matrix

[BIBC] bus-injection to branch-current matrix

[BCBV] branch-current to bus-voltage matrix

G, Load generator, load
X position of particle
Min, Max minimum, maximum
DG distributed generation
END last nodes of feeder
CVR conservation voltage reduction set
VR voltage regulator
Fuzzy Fuzzification factor
c,k capacitor bank, iteration
i, j indices for buses
I, J indices for the last buses
t, T time interval, last time interval
l, L feeder number, last feeder

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