Application of CVR in Advanced Distribution Management System using Firefly Optimization

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Abstract: The Conservation Voltage Reduction (CVR) technique is a globally deployed method aimed at reducing voltage levels to conserve energy and reduce costs in electrical distribution systems. CVR achieves this by lowering voltages, which in turn impact the impedance, current, and power consumption of ZIP loads. This paper presents an optimized CVR approach utilizing heuristic optimization algorithms, specifically targeting smart grid-enabled distribution systems to minimize power loss and operational costs. The Advanced Distribution Management System (ADMS) manages Volt/VAR control in the proposed scheme to efficiently operate the distribution grid. When high levels of voltage reduction are necessary, capacitor banks are deployed to maintain voltage within acceptable limits by injecting reactive power. The effectiveness of the proposed CVR technique is evaluated using the IEEE 13-node test system, an unbalanced distribution system. MATLAB interfaces with OpenDSS software to simulate system performance. Some heuristic optimization techniques are explored to determine optimal locations for on-load tap changers (OLTC), automatic voltage regulators (AVR), and capacitor banks (CBs). We integrate the CVR methodology with various optimization algorithms to find an optimized voltage profile and minimize power loss at various CVR factors. The paper thoroughly discusses the efficacy of one these optimization techniques, Firefly Optimization, in improving voltage profiles and reducing power loss, as demonstrated by the simulation results.

Keywords: advance distribution management systems; conservation voltage reduction (CVR); firefly optimization; OpenDSS; smart grid; Volt-VAR Control (VVC)

1. Introduction

The faster development of science and technology leads to a rapid increase in energy demand. As science and technology advance, the demand for energy increases rapidly. There are primarily two methods for reducing this rising energy demand. The first one focuses on increasing the production of energy from conventional or unconventional sources. Utilizing conservation voltage reduction (CVR), the conventional distribution network is transformed into an intelligent, trustworthy, and safe distribution network[1].

During the 1980s and 1990s, many utilities implemented CVR technology to lower yearly energy usage and demand for power[2]. In 1973, the American Electric Power System and the New York Public Service Commission implemented CVR for the first time[3]. According to the utilities' observations on the performance of the CVR pilot projects, an accurate load pattern is critical for the CVR deployment. CVR adoption was not feasible on a broad scale throughout these decades because of low efficiency, inaccurate load modeling, and manual management. However, with the enactment of new energy regulatory frameworks and the advancement of smart grids, interest in CVR has been growing recently.

The authors provide significant perspectives on the management of renewable energy, techno-economic factors, and inventive approaches to energy saving in buildings. Their work underscores the significance of promoting sustainable energy practices and legislation[4–8].

All distribution feeders in the US have recently been equipped with CVR technology, which has reduced annual energy consumption by about 3.04%[9]. Other nations have also extensively researched CVR technology. By decreasing the voltage by 1%, Australia and Ireland were able to save 2.5% and 1.7% of energy, respectively[10,11]. We need an accurate load model to assess the efficacy of the CVR. This article examines the end-user load model's effect on the CVR in considerable detail.

Distribution networks employ voltage regulators (VR) and online tap changers (OLTC) to modify the voltage level. They

both function in the same way. OLTCs, which are added after the substation, have an impact on the network voltage overall, whereas VRs only control the voltage in a particular area of the network. VRs are frequently used in the long-radial distribution network in order to preserve the far-end voltage profile.

In smart distribution networks, voltage regulation, also known as voltage and VAR regulation, is a crucial procedure. Ensuring proper coordination between various devices is crucial as various sectors strive to automate specific aspects of their systems. For instance, a utility company might want to increase voltage levels using On-line Tap-Changer (OLTC) transformers, but it's important to think about how that will affect customers. The literature has proposed various techniques to perform voltage control in distribution networks.

1.1. Definition of CVR

The American National Standards Institute (ANSI) Standard C84.1 specifies that the voltage at the distribution transformer secondary terminals should be within 120 volts ±5%, meaning it should range between 114 Volts and 126 volts. Conservation Voltage Reduction (CVR) operates on the principle that it is feasible and cost-effective to maintain the voltage within the lower half of this acceptable range (114 to 120 volts) without adversely affecting consumer appliances. The effectiveness of CVR can be evaluated by utilizing the conservation voltage regulation factor, which is precisely described as follows:

$$CVR\ factor = \frac{Percentage\ change\ in\ quantity}{Percentage\ change\ in\ voltage} \qquad (1)$$

Figure 1 shows the voltage profiles along a feeder supplying the loads in a typical passive distribution network. It reveals that the consumer nearest to the power supply experiences the least voltage drop, while the last and farthest consumer experiences the largest voltage drop.
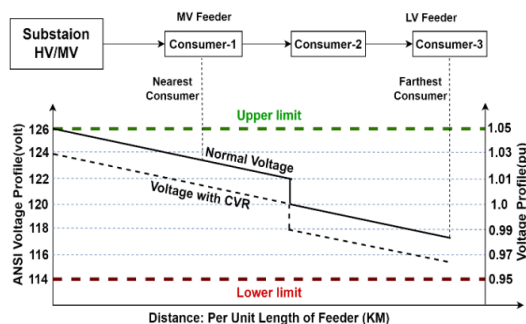

Fig. 1: Voltage distribution along the length of the feeder

1.2. Voltage regulator (VR) & On-line tap-changer (OLTC) control

For grids using renewable energy sources, a technique for voltage control taking tap-changer transformers into account is given in[12]. The optimization challenges aim to decrease the quantity of tap-switching operations while reducing the voltage deviation. According to a comparative analysis, the suggested regulated approach performs better at regulating voltage in distribution networks than the traditional unregulated technique[13]. The American National Standards Institute (ANSI) Standard C84.1 specifies that the voltage at the distribution transformer secondary terminals should be within 120 Volts ±5%, meaning it should range between 114 Volts and 126 Volts. Conservation Voltage Reduction (CVR) operates on the principle that it is feasible and cost-effective to maintain the voltage within the lower half of this acceptable range (114 to 120 Volts) without adversely affecting consumer appliances. The effectiveness of CVR can be assessed using the conservation voltage regulation factor, which is defined as follows:

1.3. Capacitor bank control

For on-load tap-changing transformers and capacitor banks, a brand-new zone-based multi-step scheduling method is suggested. To reduce voltage variation, the regulator was managed by the grid[14]. In reference[15], the author proposed a novel two-step technique for distributing dynamic reactive power in distribution networks. The first step of implementation uses the Genetic Niche Algorithm to optimize a number of devices consisting of OLTCs and capacitor banks (CBs). After this step, the Artificial Bee Colony (ABCO) method is then used to build day-ahead plans for OLTC and CB[15]. However, distribution networks that incorporate capacitor banks and on-load tap-changers have proposed techniques for managing voltage. It is evident that regulating the devices simultaneously lowers power loss and enhances the voltage profile[16].

The papers that were cited look at different optimization techniques for reconfiguring distribution networks to make them more efficient, cut down on energy losses, and improve system performance when renewable energy sources and changing loads are present. They have applied methods like evolutionary algorithms, particle swarm optimization, fuzzy logic, and stochastic optimization to address multi-objective objectives such as loss minimization, voltage stability enhancement, and power quality improvement. These paper integrate capacitor placement and network reconfiguration strategies, taking into account factors such as wind power integration and distributed generation. Additionally, the work focuses on addressing challenges such as load variability, local renewable generation, and power quality disturbances. These studies contribute to the advancement of understanding and implementing effective reconfiguration methods for modern distribution systems aiming for optimal performance and sustainability. Table 1 provides a literature review for this section of the paper.

Table 1: Summary of existing literature using optimization features

Ref.	Loss reduction	Voltage profile	On line tap changer	Capacitor placement/switching	Load model	Optimization method
17)	✓					Genetic algorithm
18)	✓	✓				AMPSO algorithm
19)	✓			✓	✓	Mixed integer nonlinear programming algorithm
20)	✓		✓			Differential evolution
21)	✓			✓		Ant colony algorithm
22)	✓	✓				Fuzzy based method
23)	✓	✓				Harmony search algorithm
24)	✓	✓				Adapative PSO+Fuzzy
25)	✓				✓	Genetic algorithm
26)	✓		✓	✓		Ant colony algorithm
27)	✓		✓	✓		Adaptive Genetic algorithm
28)	✓		✓	✓	✓	BE+Discrete genetic algorithm
29)	✓		✓	✓		Modified PSO algorithm
Proposed	✓	✓	✓	✓	✓	Firefly optimization, PSO, IWO, Artificial bee colony

This research enhances the advantages of smart grid-enabled CVR in terms of cost, energy savings, and voltage mitigation range by presenting sophisticated VVC algorithms.

This work provides valuable insights for enhancing energy efficiency and cost-effectiveness in modern distribution networks.

1.4. Key novel contributions

The proposed distribution system technique aims to achieve technical benefits of CVR at the same time improving the voltage profile and minimizing line losses.

We have applied novel metaheuristic approaches to determine the optimal position of OLTC taps and switching steps in the CB's positions, taking into account different CVR factors to achieve minimum power losses at optimal cost.

The solutions to the above different heuristic approaches have been compared in different cases and scenarios using the IEEE-13 bus radial unbalanced distribution system.

1.5. Layout of the Paper

In Section 2, the conversation voltage reduction for the smart-grid is displayed. Section 3 discusses how to formulate the Volt/VAR optimization problem. In this section, the optimal setting of various controllers (OLTC/AVR taps and steps of CBs) has been determined for the desired time. Section 4 discusses the methodology and various optimization techniques used in the proposed paper. We show in this paper that Firefly optimization, a different heuristic method, can be used to get the best results at the lowest cost while using CVR technology at the tap positions of the OLTC and AVR and the

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switching positions of the capacitor bank. Section 5 explains the experimental model and simulation results. Section 6 presents the conclusion and future scope of the present study.

2. Smart Grid-Enabled CVR

Reducing the supply voltage to a value of 0.95 to 1.0 per unit is the primary objective of the CVR, which is the lower half of the permissible range. This study has suggested a CVR plan that supports the smart grid. The circuit shown in Figure 2 has smart grid-enabled components, including a distribution management system, power optimization, smart voltage optimization controllers, AMI, and ICT.

The method proposed in this work that combines the CVR server with the voltage/VAR control and optimization (VVC&O) processor, and connects it to the advanced DMS server via the IEC61850. The ADMS application validates the voltage stability across the entire distribution network while continuously monitoring the CVR server. With these concepts, we can maximize energy efficiency for the circuit's consumers. An accurate load model is a fundamental prerequisite for CVR server support. The AMI data serves as the basis for the real-time evaluation of the CVR effect. The impact of the CVR is evaluated with the use of the following CVR factors[30,31]:

The energy saving CVR factor (kWh)…

$$CVR_{fE} = \frac{\Delta E / E_{mean}}{\Delta V / V_{mean}} = \frac{E_{aft} - E_{pre} / E_{mean}}{V_{aft} - V_{pre} / V_{mean}} \qquad (2)$$

The active power demand CVR factor (KW)…

$$CVR_{fP} = \frac{\Delta P / P_{mean}}{\Delta V / V_{mean}} = \frac{P_{aft} - P_{pre} / P_{mean}}{V_{aft} - V_{pre} / V_{mean}} \qquad (3)$$

The cost saving CVR factor ($)…

$$CVR_{fC} = \frac{\Delta C / C_{mean}}{\Delta V / V_{mean}} = \frac{C_{aft} - C_{pre} / C_{mean}}{V_{aft} - V_{pre} / V_{mean}} \qquad (4)$$

Where, $\%\Delta V$ is the percentage (%) deviation in the voltage, $\%\Delta E$ is the percentage change in energy saving, $\%\Delta P$ is the percentage change in active power, $\%\Delta C$ is the reduction in cost saving percentage.

$$\%\Delta V = \frac{V_{aft} - V_{pre}}{V_{mean}} \times 100\% = \frac{\Delta V}{V_{mean}} \times 100\% \qquad (5)$$

$$\%\Delta E = \frac{E_{aft} - E_{pre}}{E_{mean}} \times 100\% = \frac{\Delta E}{E_{mean}} \times 100\% \qquad (6)$$

$$\%\Delta P = \frac{P_{aft} - P_{pre}}{P_{mean}} \times 100\% = \frac{\Delta P}{P_{mean}} \times 100\% \qquad (7)$$

$$\%\Delta C = \frac{C_{aft} - C_{pre}}{C_{mean}} \times 100\% = \frac{\Delta C}{C_{mean}} \times 100\% \qquad (8)$$
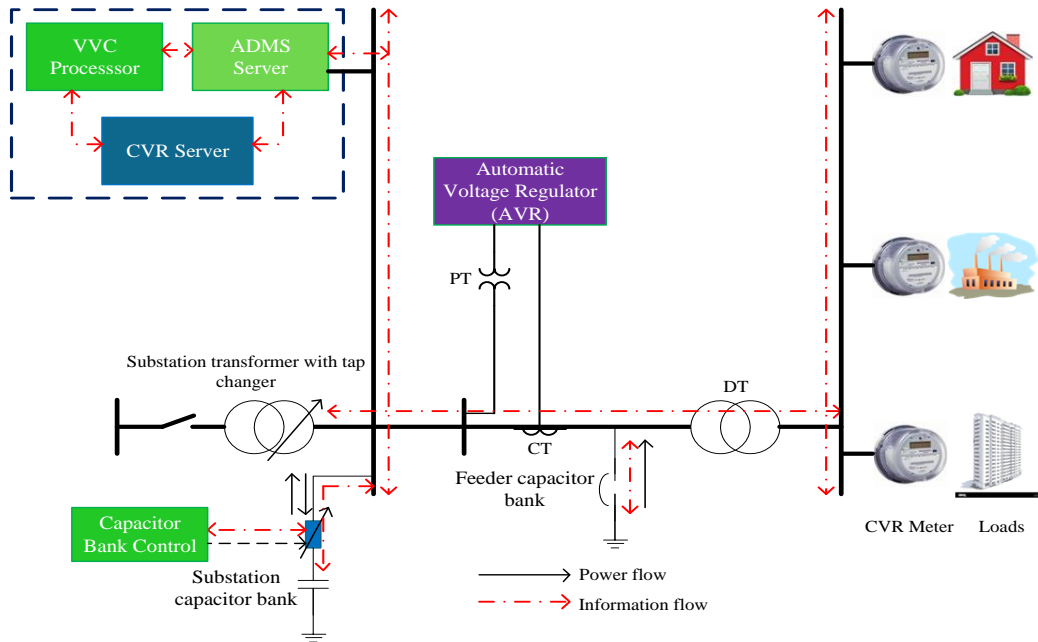

Fig. 2: Architecture of Smart-Grid VVO Framework

3. Volt/VAR optimization problem formulation

We have used the CVR optimization technique. We have established the ideal configuration for the controllers (OLTC/AVR taps and CB steps) for the intended duration. To minimize the node voltage deviation, we implement the CVR. The expected CVR voltage in the node voltage deviation is not subject to negotiation with system regulatory standards.

We prefer a multi-objective formulation to minimize the voltage deviation and losses, as illustrated below.

3.1. Objectives

Voltage deviation and system losses are expressed mathematically using system variables as shown below
a) Objective Function (f_1)
The first objective function f_1 for the above representation is based on the expected CVR voltage and minimizing the total squared voltage variation of each node across all phases and nodes. The source node at each hour is left out to save the most energy.

$$f_1 = \left\{ \sum_{a,b,c} \sum_i^{N-1} \left(V_{i,t} - V_{CVR,t}\right)_{a,b,c}^2 \right\} \qquad (9)$$

Where, $V_{i,t}$ is the per unit node voltage at i^{th} bus at time (t) in hours and $V_{CVR,t}$ is the desired per unit CVR voltage at time (t) in hours and N is the number of the nodes with phase a, b, c respectively.
b) Second Objective Function (f_2)
To accomplish this goal, we must minimize the total losses for all phases at each hour, as follows:

$$f_2 = \left\{ \sum_{a,b,c} \left(\sqrt{\left(P_{a,b,c}^{l,t}\right)^2 - \left(Q_{a,b,c}^{l,t}\right)^2} \right) \right\} \qquad (10)$$

Where, $P^{l,t}$ and $Q^{l,t}$ are the active and reactive power losses respectively at hour, t.

$$f = min\{w_1 \times f_1 + w_2 \times f_2\} \qquad (11)$$

Where w_1 and w_2 represent the weightage factor of the objective function, with values of 62.0 and 0.12 respectively.

3.2. Control variables(X)

The optimization problem contains the following control variables.
a) OLTC & AVR tap position (Tap_{oltc} & Tap_{avr});
b) CBs reactive power (Q_{CB}^j);

$$X = [Tap_{oltc}, Tap_{avr}, Q_{CB}^j] \qquad (12)$$

Subjects to the preceding operational limitations.

3.3. Constraints

a) Transformers/Regulator constraints: Limit of tap value and relationship to tap position for the OLTC transformer and AVRs.

$$p.u. \leq Tap_{oltc} \leq 1.1 \, p.u. \qquad (13)$$
$$p.u. \leq Tap_{avr} \leq 1.1 \, p.u. \qquad (14)$$
$$Tap_{oltc,c} = \left\{ 1 \pm \left(\frac{\Delta V_{inc}}{100} \right) \times \right.$$

$$\left. Tap_{oltc} \right\}, Tap_{oltc} \epsilon \{Tap_{oltc}^{min} \dots 0 \dots Tap_{oltc}^{max}\} \qquad (15)$$
$$Tap_{avr,c} = \left\{ 1 \pm \left(\frac{\Delta V_{inc}}{100} \right) \times \right.$$
$$\left. Tap_{avr} \right\}, Tap_{avr} \epsilon \{Tap_{avr}^{min} \dots 0 \dots Tap_{avr}^{max}\} \qquad (16)$$

Where ΔV_{inc} increment in voltage at each step and Tap_{oltc} & Tap_{avr} is tap position from $-16(Tap^{min})$ to $+16(Tap^{max})$.
b) CB constraints: Equation (17) determines the reactive power supplied by the jth capacitor bank (Q_{CB}^j), and equation (17) specifies the relationship that the capacitor bank's daily switching operation should follow.

$$Q_{CB}^j = Sw_{CB}^j \times \Delta Q_{CB}^j, Sw_{CB}^j = \{0,1,2, \dots Sw_{CB}^{j,max}\} \qquad (17)$$
$$N_{sw,d}^i \leq N_{sw,max}^i \qquad (18)$$

Where, ΔQ_{CB}^j, Sw_{CB}^j, $Sw_{CB}^{j,max}$, $N_{sw,d}^i$ and $N_{sw,max}^i$ are the reactive power variation in per step, the switching step number, available max frequency of switching steps, number of switching operations per day, and maximum switching operation permitted per day at j^{th} CB, respectfully.

4. Methodology

Set the Volt/VAR controls to their optimal configuration to optimize energy savings and reduce peak power consumption while using the CVR. The previous section modeled voltage control devices, such as capacitor banks and AVRs. We analyze the CVR under various voltage loading conditions using MATLAB and OpenDSS tools. Figure 4 illustrates the utilization of the Component Object Model (COM) to enhance communication between OpenDSS and MATLAB. The problem is divided into two parts: the first part deals with managing the voltage/VAR control, while the second part sets up the capacitor bank control to reduce losses during CVR operation.

4.1. Volt-VAR Controller (VVC)

Regcontrol, or regulator controllers, are used by the CVR, whereas Capcontrol manages capacitor banks. These controllers are integrated with OpenDSS. We coordinate the OpenDSS control loops in CVR and VVC using the MATLAB interface[32–36].

4.2. Capacitor Bank Control

As seen in Figure 3, capacitor bank controllers have control devices like voltage transformers, current transformers, or some sort of cap control. The capacitor control is frequently situated on the demand end of the line that is wired to the circuit breakers. During the controlled capacitor test, samples of voltage and current are passed via the CTs and VTs. It then decides whether the capacitors should be switched on or off and the number of steps needed depending on the sort of

control criteria used, such as kVar, power factor, voltage, current, or time of day on the controlled devices.
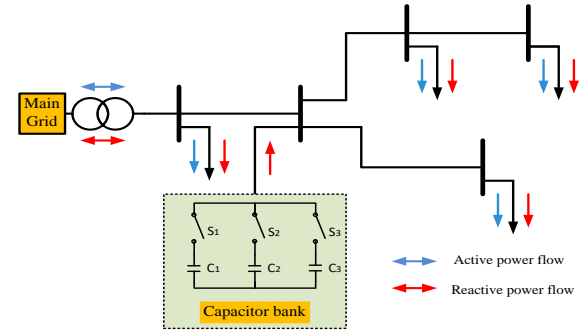

Fig. 3: Capacitor Bank control

The CB module switches should be turned on when the measured line voltage is less than 0.95pu and greater than 1.05pu.
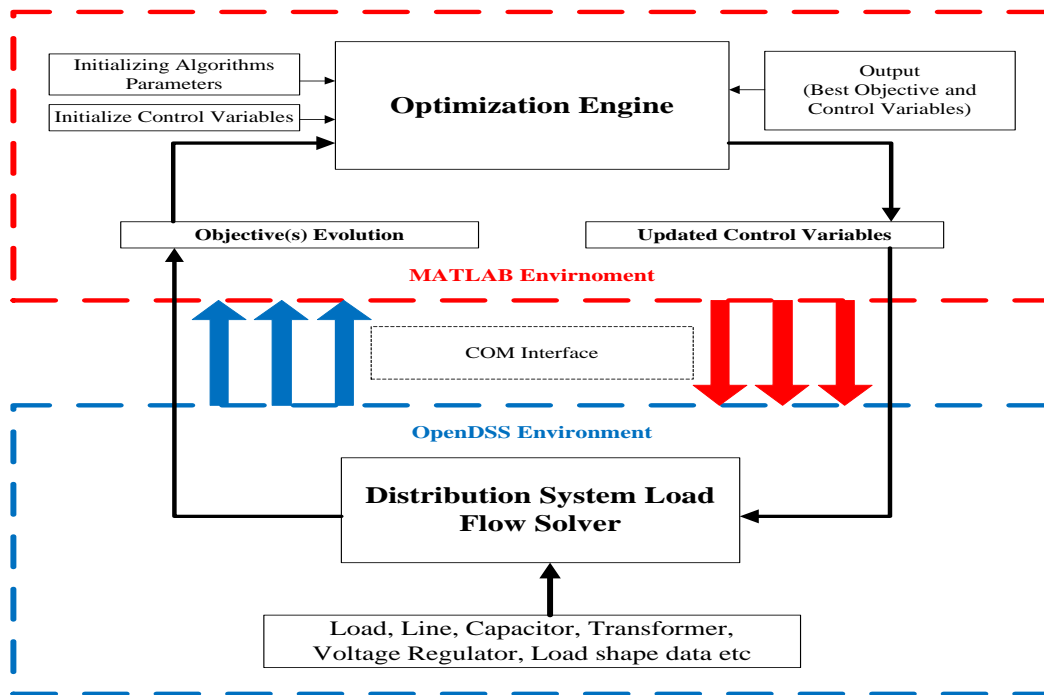

Fig. 4: Interface OpenDSS with MATLAB via (COM)

4.3. Optimization Technique

Because there is no global optimal solution, the traditional gradient search-based methodologies may fail to solve the aforementioned optimization problem. Other researchers have experimented with a variety of heuristic optimization strategies, including particle swarm optimization (PSO)[37,38], artificial bee colony optimization(ABCO)[39–41], and invasive weed optimization (IWO)[42,43]. In this study, that Firefly optimization, a different heuristic method, can be used to get the best results at the lowest cost while using CVR technology at the tap positions of OLTC and AVR and the switching positions of capacitor banks[27,44].

4.4. Proposed Firefly Algorithm

This algorithm's optimization mechanism draws inspiration

from the natural brightness phenomenon of fireflies[44,45]. This algorithm's optimization mechanism draws inspiration from the natural brightness phenomenon of fireflies. The characteristics of the fireflies are as follows[46]:

The unisex nature of the fireflies attracts them to each other. Fireflies' brightness directly relates to their attractiveness, meaning that fireflies with less brightness will attract those with more brightness. These values also increase as the distance increases.

The firefly's brightness determines the objective function value.

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (19)$$

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma r_{ij}^2}(X_j^t - X_i^t) + \alpha_t \in_i^t \qquad (20)$$

$$0 \leq \alpha_t \leq 1 \qquad (21)$$

Where, $\beta(r)$ is the variation of attractiveness with distance (r), β_0 is the attractive at zero distance, X_i^{t+1} is the position update at X_i^t, α_t is the randomization parameter, $\in_i^t$ is the vector at time t containing random numbers selected from a uniform distribution.
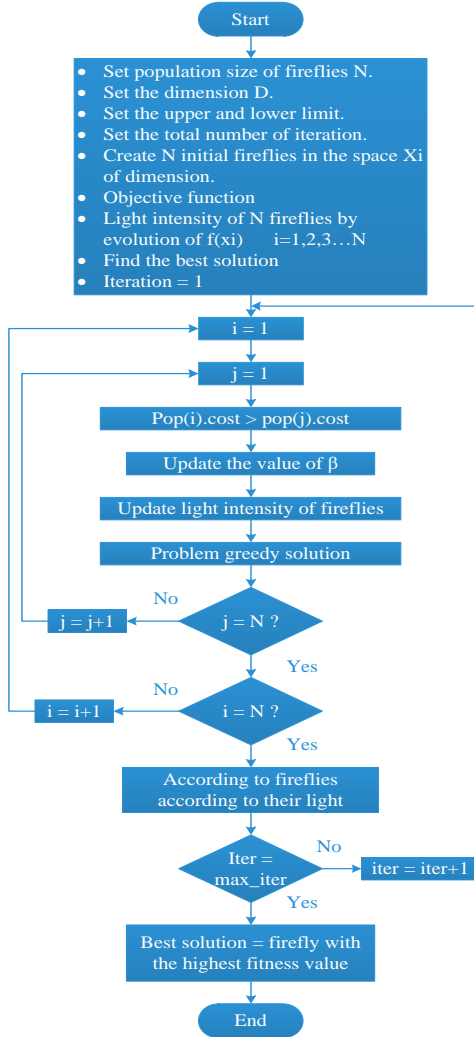

Fig. 5: Flow chart for proposed firefly optimization

Algorithm 2 Steps for implementing firefly optimization technique

```
1. Input: the radial distribution
system data {loads, lines, power
demand at each bus}.
2. Input: Firefly parameters and light
absorption coefficient.
3. Set the upper and lower limit and
population size.
4. Randomly place the N fireflies in
the dimensional search space Xi, {i =
1, 2, 3,…N}, where Xi =[Xi1,Xi2,Xi3,…Xid]
```

```
5. Input the objective function and
calculate light intensity of all N
firefliesf(Xi).
6. Set the stopping criteria (Total
number of iteration).
7. Start two loops i from 1 to total
population size.
8. Compare the iᵗʰ position pop(i).cost
to jᵗʰ position pop(j).cost.
9. If the position of pop(i).cost
greater than jᵗʰ position pop(j).cost.
10. Update the value of beta using
equation (20) and have the firefly j
towards firefly I using equation (21).
11. Update light intensity of
fireflies at new position and then
perform greedy solution.
12. Check the stopping criteria else
go to step 8.
13. Rank the fireflies based on their
brightness or fitness and identify the
current best.
14. Check the stopping criteria if yes
then go to 15 else go to 6.
15. Output: Firefly with the highest
brightness value is the global optimum
solution.
```

5. Simulation results and analysis

In this study, an IEEE benchmark 13-node system has been considered. The system comprises of one voltage regulator and two capacitor banks as the main control element. Here, we have examined the deviation in voltages using a voltage-dependent ZIP-type load model for different load zones , as shown in Figure 6[4]. The test system utilizes the ZIP constant-load charging model for industrial, business, and residential load zones using appropriate ZIP factors in the load model[16]. The test system comprises an on-load tap changer (OLTC) and four single-phase switched shunt capacitor banks (CBs). Nodes 650 and 651connect the OLTC, which provides approximately ±16 taps with a step increment of 0.00625 per step. At nodes 675a, 675b, 675c, and 611c, we have installed four single-phase shunt capacitor banks, each with a capacity of 200 kVAR and step variations ranging from 0 to 4. For each of the four shunt CBs (cap1(a), cap1(b), cap1(c), and cap2), the maximum kVAR rating is 50 kVAR.
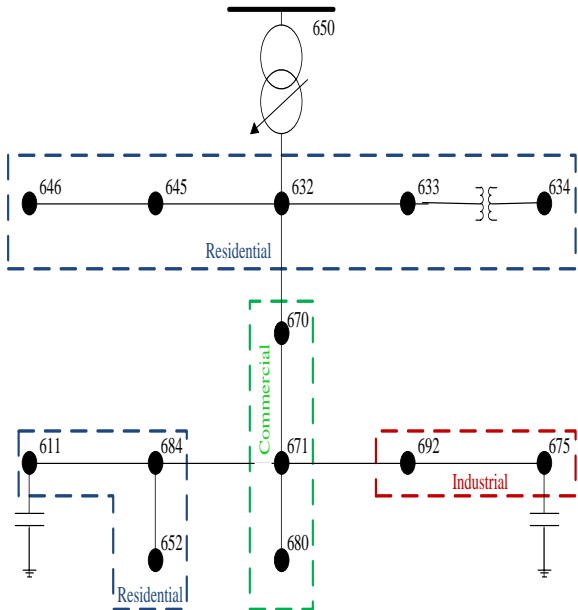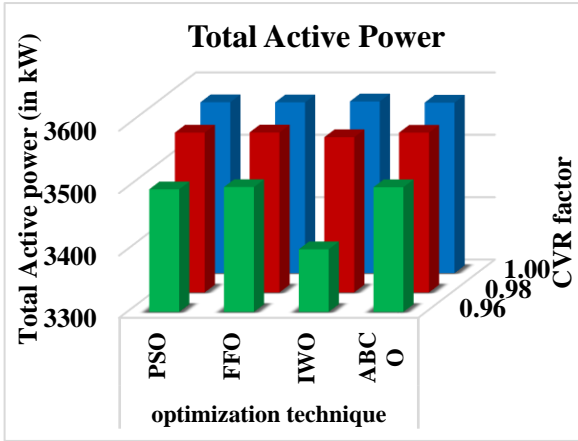
Fig. 6: IEEE 13 node distribution test feeder

Fig. 7: Reduction in Active Power Demand due to CVR

Table 2: Phase-wise voltage profile using different optimization techniques at 1.00 CVR

Voltage (pu)	Phase	Optimization Technique			
		PSO	FFO	IWO	ABCO
Vmin	1st	0.9822	0.9829	0.9748	0.9838
	2nd	0.9838	0.9825	0.9999	0.9828
	3rd	0.9775	0.9767	0.9702	0.9750
Vmax	1st	1.0558	1.0528	1.0518	1.0536
	2nd	1.0279	1.0271	1.0472	1.0274
	3rd	1.0686	1.0691	1.0655	1.0676

Table 3: Phase-wise voltage profile using different optimization techniques at 0.98 CVR

Voltage (pu)	Phase	Optimization Technique			
		PSO	FFO	IWO	ABCO
Vmin	1st	0.9633	0.9628	0.9586	0.9649
	2nd	0.9606	0.9620	0.9465	0.9614
	3rd	0.9562	0.9561	0.9443	0.9545
Vmax	1st	1.0364	1.0342	1.0411	1.0361
	2nd	1.0060	1.0074	1.0000	1.0068
	3rd	1.0503	1.0509	1.0524	1.0494

Table 4: Phase-wise voltage profile using different optimization techniques at 0.96 CVR

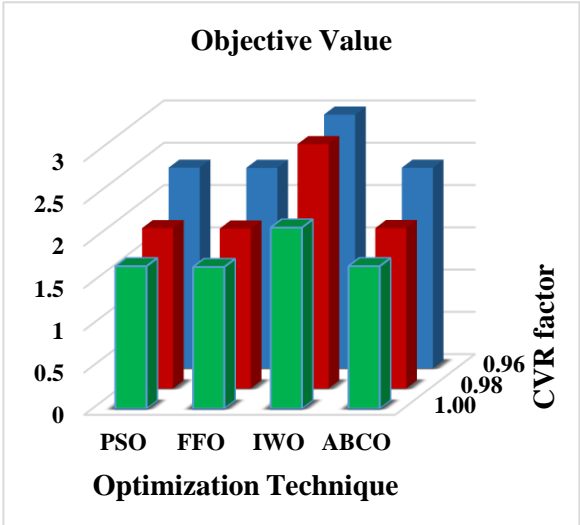| Voltage (pu)	Phase	Optimization Technique			
		PSO	FFO	IWO	ABCO
Vmin	1st	0.9398	0.9411	0.9126	0.9408
	2nd	0.9423	0.9417	0.944	0.9431
	3rd	0.9423	0.9347	0.9256	0.9344
Vmax	1st	1.0127	1.0136	1.0000	1.0133
	2nd	1.0000	1.0000	1.0000	1.0000
	3rd	1.0296	1.0302	1.0208	1.0298

Fig. 8: Comparison of objective values across Optimization techniques for different CVR factors
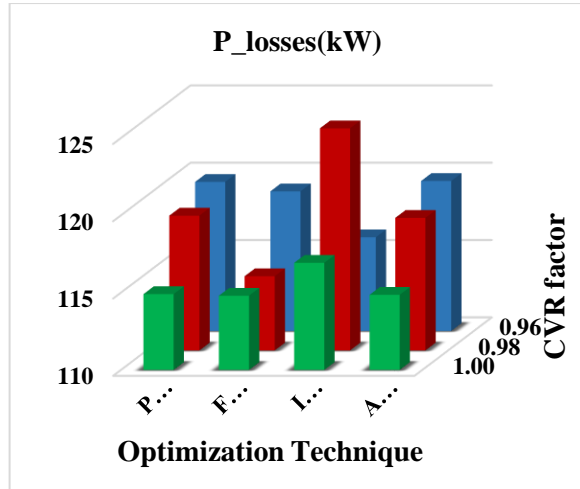
Fig. 9: Impact of CVR factors on Active power losses for optimization techniques
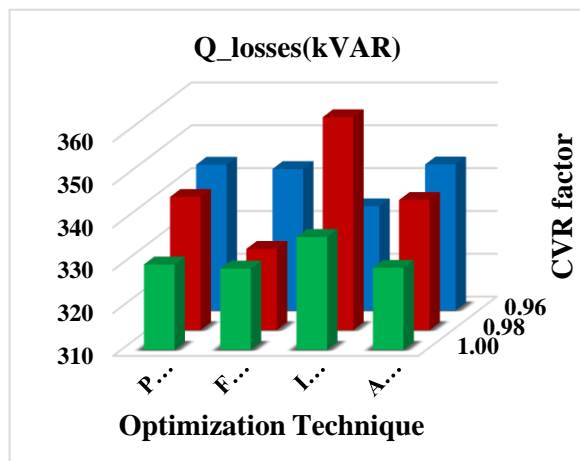

Fig. 10: Impact of CVR factors on Reactive power losses for optimization techniques

The simulation environment utilizes multiple platforms, including OpenDSS for load flow analysis and MATLAB for optimization and control strategies. The study comprises of evaluating the performance of given system at three different CVR factors 1.0, 0.98 and 0.96. Various metaheuristic optimization techniques are applied for calculating the optimal OLTC's tap positions and CBs switching positions. These tap positions and switching position are further used in

a mathematical expression to determine the performance of the system.

The primary purpose of applying CVR technique is to reap the benefits in terms of reduction in total active power consumption of the system as depicted in Figure 7. The analysis of the system is performed at three different CVR levels (1.00, 0.98, and 0.96) and four distinct optimization techniques Particle Swarm Optimization (PSO), Firefly Optimization (FFO), Invasive Weed Optimization (IWO), and Artificial Bee Colony Optimization (ABCO). The other key metrics that are observed in this study include the overall objective function, voltage profiles (minimum and maximum voltages), active power losses (P_losses), and reactive power losses (Q_losses).

At a CVR level of 1.00, Firefly Optimization achieved the lowest objective function value of 1.6754, outperforming Particle Swarm Optimization (1.6852), Invasive Weed Optimization (2.1425), and Artificial bee colony optimization (1.6857) as shown in Figure 9. It also minimized active power losses (114.8 kW) and reactive power losses (328.97 kVAR) as shown in Figure 10, while maintaining higher minimum voltage levels (0.9829, 0.9825, 0.9767) and stable maximum voltage levels as shown in Table 2.

For a CVR level of 0.98, Firefly Optimization achieved an objective function value of 1.8913, marginally better than Particle Swarm Optimization (1.8963) and Artificial bee colony optimization (1.897), and significantly better than Invasive Weed Optimization (2.8892) as shown in Figure 9. Active power losses were 114.8 kW, with Q_losses of 328.97 kVAR as shown in Figure 10. Firefly Optimization maintained stable minimum voltages across phases, ensuring voltage stability and efficiency as shown in Table 3.

At a CVR level of 0.96, Firefly Optimization delivered an objective function value of 2.3702, slightly better than Artificial bee colony optimization (2.3718) and Particle Swarm Optimization (2.3723), while outperforming Invasive Weed Optimization (3.0246) as shown in Figure 9. Active and reactive power losses were competitive at 119.03 kW and 343.01 as shown in Figure 10 kVAR, respectively, and voltage stability was maintained with superior minimum voltage levels as shown in Table 4.
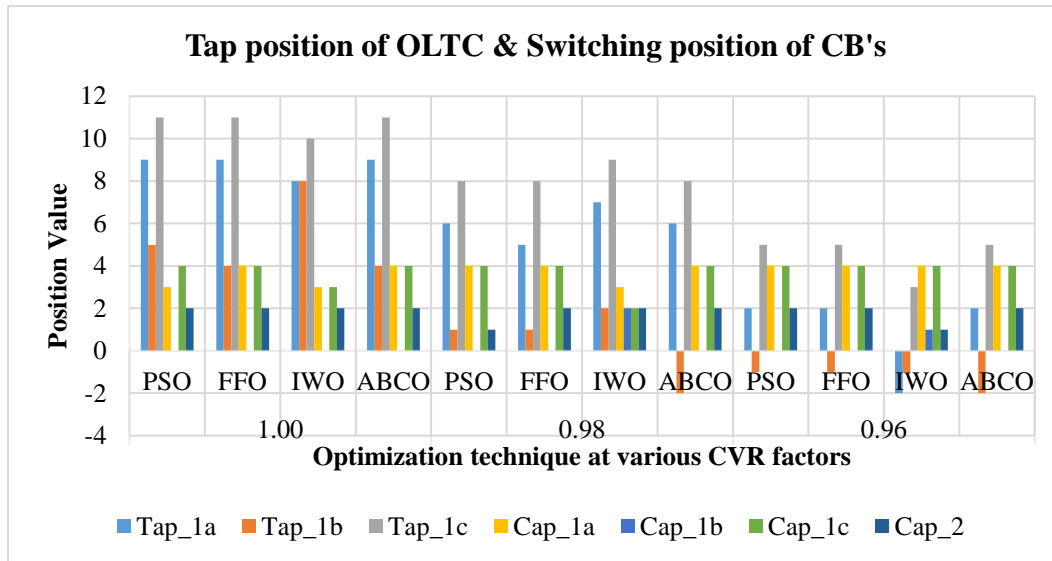
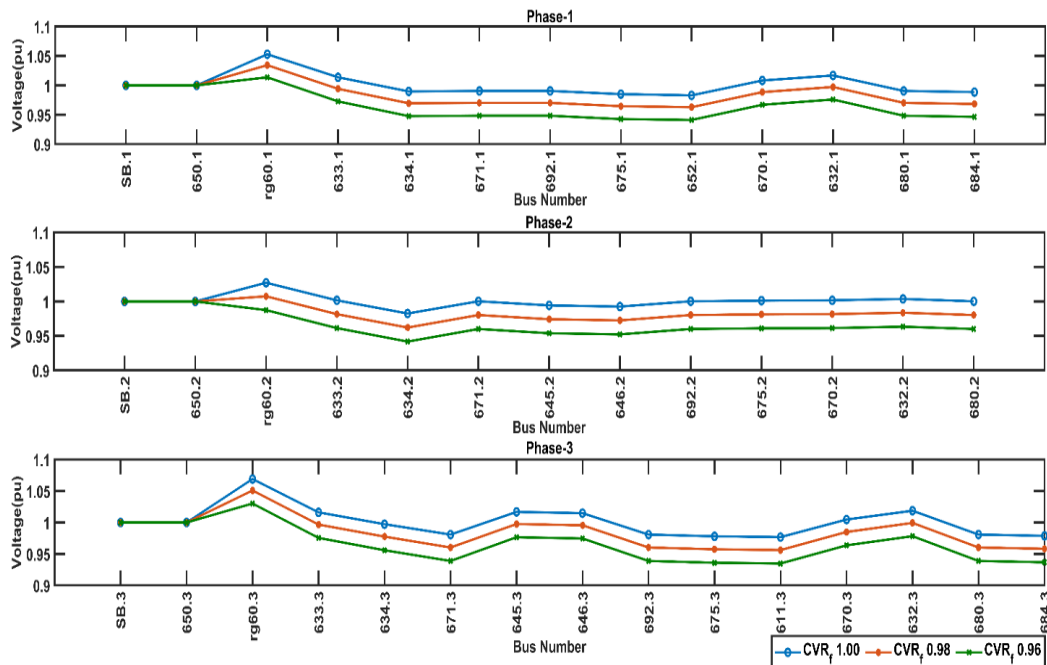**Fig. 11**: Tap position of OLTC/AVR & switching steps of CBs

Fig. 12: Voltage profile at different CVR factors using firefly optimization

The values of optimal tap positions and CB switches are shown in Figure 11 for all cases under study. From the above results it is evident that Firefly Optimization consistently achieved the lowest objective function values, minimized power losses, and ensured voltage stability. Its ability to balance exploration and exploitation effectively allows it to outperform the other algorithms in CVR optimization tasks. Figure 12 presents voltage profiles (pu) for three phases across various bus numbers under CVR factors 1.00, 0.98, and 0.96, optimized using the firefly algorithm. It highlights the impact of conservation voltage reduction on voltage regulation. The profiles demonstrate the effectiveness of the optimization technique in maintaining voltage within acceptable limits while achieving energy savings through CVR implementation.

6. Conclusion

This study analyses the implementation of a smart grid enabled CVR scheme and compares results obtained through four metaheuristic algorithms Firefly Optimization, Particle Swarm Optimization, Invasive Weed Optimization, and Artificial bee colony optimization at three distinct (CVR) levels in power distribution networks. Results demonstrate

Firefly Optimization's consistent superiority in minimizing the objective function, maintaining voltage stability, and reducing power losses.

At a CVR level of 1.00, Firefly Optimization delivered the best performance, achieving the lowest objective function value and minimizing power losses while maintaining stable voltage profiles. At a CVR level of 0.98, it outperformed other methods by ensuring lower power losses and higher voltage stability. Even at a CVR level of 0.96, Firefly Optimization remained competitive, showcasing its robustness under challenging conditions.

Firefly Optimization's strength lies in its balance between exploration and exploitation, enabling it to locate optimal solutions efficiently under operational constraints. While Particle Swarm Optimization and Artificial bee colony optimization performed reasonably well under some conditions, their results lacked the consistency of Firefly Optimization. Invasive Weed Optimization displayed limitations, particularly in voltage stability and power loss reduction.

The findings emphasize Firefly Optimization's potential as a reliable tool for improving energy efficiency, reducing losses, and maintaining voltage stability in power distribution networks. Its robustness across varying CVR levels further highlights its applicability to broader optimization challenges.

In conclusion, out of the four algorithms Firefly Optimization is the most effective algorithm for CVR-based optimization tasks, delivering consistently superior results compared to Particle Swarm Optimization, Invasive Weed Optimization, and Artificial bee colony optimization. Future work could explore hybrid frameworks incorporating Firefly Optimization or its real-time implementation to enhance practical outcomes further.

Nomenclature

CVR   Conservation voltage reduction

CBs   Capacitor banks

OLTC   On-load tap-changing

VVO   Volt-VAR optimization

ADMS   Advanced distribution management system

VVC   Volt-VAR control

AVR   Automatic voltage regulator

LDC   Line drop compensation

ABCO   Artificial bee colony optimization

PSO   Particle swarm optimization

IWO   Invasive weed optimization

FFO   Firefly optimization

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Appendix

Quantity	Value
Maximum number of Iterations	$max_{It} = 50$
Number of Fireflies	$n_{pop} = 50$
Light Absorption coefficient	$\gamma = 1$
Attraction Coefficient Base Value	$\beta = 2$
Mutation Coefficient	$\alpha = 0.2$
Mutation Coefficient Damping Ratio	$\alpha_{damp} = 0.98$