Optimal Placement of Dynamic Voltage Restorer in Distribution System using Water Cycle Algorithm Techniques for Power Quality Enhancement

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Abstract - The increasing integration of sensitive loads and Renewable Energy Sources (RES) into modern distribution networks has intensified power quality issues such as voltage deviations and excessive distribution losses. This study addresses these challenges using a Dynamic Voltage Restorer (DVR). It is anticipated that optimal placement and sizing of the DVR within the distribution corridor, utilizing a metaheuristic optimization method, will significantly enhance voltage stability and reduce power losses. The proposed metaheuristic approach—based on the Water Cycle Algorithm (WCA)—was tested and benchmarked against the Firefly Algorithm (FFA) on an IEEE 69-bus radial distribution system within a MATLAB/Simulink environment. Simulation results confirmed the superiority of the WCA over FFA by optimally placing and sizing the DVR at Bus 66 with a capacity of 298.45 kVA, compared to the FFA's placement at Bus 65 with 284.26 kVA. The WCA achieved a reduction in active and reactive power losses by 41.78% and 27.45%, respectively, and improved voltage deviation by 16.35%. In contrast, the FFA achieved reductions of 26.46% in active power loss, 13.65% in reactive power loss, and 10.28% in voltage deviation.

Keywords: Dynamic Voltage Restorer (DVR), Metaheuristic Optimization, Water Cycle Algorithm (WCA), IEEE 69-Bus Distribution System, Power Quality Enhancement

I. INTRODUCTION

The delivery of quality and reliable electrical power to customers in a cost-effective manner remains a central objective for utility providers. However, the modern distribution system is increasingly challenged by the proliferation of sensitive electronic loads and renewable energy sources (RES), which introduce significant power quality issues. These include voltage sags, swells, flickers, harmonics, and excessive distribution losses, all of which contribute to reduced efficiency, instability, and the potential for cascading system failures [3].

To address these challenges, global research efforts have intensified, particularly in optimizing the stability, transfer capability, and reliability of distribution networks [11] [14]. In this context, Custom Power Devices (CPDs) have emerged as promising solutions for improving power quality and ensuring stable operation under dynamic conditions. CPDs are evolving, power-electronics-based technologies designed to enhance the performance of existing distribution infrastructure under stress conditions such as faults, load imbalances, and power disturbances.

Common examples of CPDs include:

- Dynamic Voltage Restorer (DVR) – for voltage sag mitigation and voltage profile improvement

- Distribution Static Compensator (D-STATCOM) – for dynamic reactive power support and voltage regulation
- Unified Power Quality Conditioner (UPQC) – for simultaneous compensation of voltage and current disturbances
- Solid-State Transfer Switch (SSTS) – for fast transfer between power sources during faults
- Active Power Filter (APF) – for harmonic mitigation and power factor correction

These devices collectively contribute to improved power dispatch, voltage stability, and reduction in power quality problems, especially in sensitive or heavily loaded distribution systems.

A. Definition And Operation Of Dynamic Voltage Restorer (DVR)

The Dynamic Voltage Restorer (DVR) is a series-connected CPD primarily used to mitigate voltage sags and swells in distribution networks. It is installed at the Point of Common Coupling (PCC) between the distribution feeder and the sensitive load, where it injects a compensating voltage in series with the feeder to maintain a stable voltage at the load terminal.

A typical DVR consists of:

- A Voltage Source Inverter (VSI)
- An energy storage device (e.g., capacitor or battery)
- Injection transformers
- LC filters for harmonic suppression
- A control unit for dynamic response

Its main functional roles include:

- Bus Voltage Regulation
- Apparent Power Flow Control
- Power Quality Improvement

Operating Principle: The DVR monitors the supply voltage in real time. Upon detection of a disturbance, its control unit sends signals to the inverter to produce a synchronously phased voltage. This voltage is injected in series via the injection transformer to restore the voltage seen by the load.

$$\mathbf{V}_{inj} = \mathbf{V}_{ref} - \mathbf{V}_{supply}$$

Where;

- V_{ref}: is the nominal desired voltage (usually 1.0 pu)
- $\mathbf{V}_{supply}$: is the actual supply-side voltage during disturbance
- V_{inj}= is the voltage injected by the DVR

Because of these capabilities, DVRs are highly suitable for deployment in distribution systems with high penetration of sensitive loads and distributed energy resources.

As a D-FACTS device, the DVR’s performance can be enhanced by tuning its parameters using metaheuristic optimization algorithms. These include Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Firefly Algorithms (FFA). However, these algorithms often face challenges like premature convergence or difficulty escaping local minima.

B. Motivation and Objective

To address these challenges, this paper explores the application of a metaheuristic optimization strategy—specifically the Water Cycle Algorithm (WCA)—a nature-inspired method that mimics the natural water cycle process—for determining the optimal placement and sizing of a DVR in a large-scale distribution network. WCA has demonstrated superior global search capabilities, fast convergence, and fewer parameter dependencies compared to traditional methods (Abusief et al., 2014; Khan et al., 2015; Patel et al., 2015; Quaia, 2018).

The IEEE 69-bus radial distribution system, with its large scale and deep voltage drops in remote buses, is selected to validate the method’s effectiveness. The performance of the proposed WCA-based DVR allocation is compared with that of the Firefly Algorithm (FFA), which has shown competitive results in earlier studies [14] and is chosen here as a credible benchmark.

C. Paper Organization

The remainder of this paper is organized as follows: **Section II** outlines the system description and test case configuration. **Section III** presents the mathematical formulation of the optimization problem. **Section IV** describes the Water Cycle Algorithm. **Section V** discusses the simulation results and performance comparisons. **Section VI** provides the conclusion and outlines recommendations for future work, subsequently followed by the references section.

The selection of this system in the present study is based on its scale, diversity of load points, and the presence of critical voltage constraints. These attributes provide a robust and realistic platform to assess the scalability and accuracy of the proposed optimization method.

II. PROBLEM FORMULATION

A. Problem Statement

The increasing integration of sensitive loads and distributed energy resources (DERs), such as photovoltaic panels and wind turbines, in modern distribution networks has introduced significant power quality challenges. These include voltage sags, swells, and elevated system losses, all of which negatively impact network reliability and customer satisfaction. Addressing these issues requires effective mitigation strategies that ensure voltage stability and minimize power losses.

Among the solutions proposed in literature, Custom Power Devices (CPDs)—particularly the Dynamic Voltage Restorer (DVR)—have shown strong potential in mitigating voltage disturbances. The DVR operates by injecting a compensating voltage in series with the supply line, thereby stabilizing voltage levels at critical buses. However, for the DVR to function optimally, it must be strategically placed and appropriately sized. This task translates into a constrained nonlinear optimization problem.

Traditional methods for solving such problems have included deterministic techniques and early heuristic algorithms such as Genetic Algorithms (GA) and Simulated Annealing (SA). While useful, these approaches often suffer from premature convergence and poor global search capabilities, particularly in large and complex systems such as the IEEE 69-bus network.

To overcome these limitations, metaheuristic algorithms have been introduced. For instance [14], applied the Firefly Algorithm (FFA) to DVR placement and sizing and reported notable improvements in loss minimization and voltage stability. However, the FFA is limited by reduced exploration capability and a high computational cost due to excessive objective function evaluations.

This study proposes the use of the Water Cycle Algorithm (WCA)—a nature-inspired metaheuristic that simulates the flow of water through rivers and streams into the sea. WCA is known for its balanced search behavior, faster convergence, and reduced need for parameter tuning. It is applied in this work to jointly optimize the location and size of the DVR, with the goal of minimizing active power losses and voltage deviation.

Based on this background, the optimization problem is formulated as a multi-objective function subject to system constraints, which is detailed in the next subsection.

B. Mathematical Formulation of the Optimization Problem

The DVR placement and sizing problem in a distribution system is formulated as a multi-objective constrained optimization problem**,** aimed at minimizing both active power losses (P_{loss}) and voltage deviation (V_{dev}) in the radial distribution system.

1. Objective Function

The total objective function is expressed as a weighted sum of the two key performance metrics;

$$F = \psi f_{1+}\beta f_2 \quad \dots\dots\dots\dots (1)$$

$$\boldsymbol{f}(\boldsymbol{X}_i) = \psi \cdot \frac{\boldsymbol{P}_{loss}}{\boldsymbol{P}_{loss,\ base}} + \beta \cdot \quad (2)$$

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Where;

- F = Overall fitness function
- ψ = Weighting coefficients for power loss.
- β = Weighting coefficients for voltage deviation.
- $f_1 = \frac{\boldsymbol{P}_{loss}}{\boldsymbol{P}_{loss,\ base}}$
- $f_2 = \frac{\boldsymbol{V}_{dev}}{\boldsymbol{V}_{dev,\ base}}$
- P_{loss} = Total active power loss after DVR placement
- $P_{loss,\ base}$ = Active power loss in the base (uncompensated) system
- V_{dev} = Total voltage deviation after DVR placement

- $V_{dev,\ base}$ = Voltage deviation in the base system

The values of ψ and β were assigned equal values (i.e., 0.5 each) after normalization to ensure balanced treatment of both objectives. This approach is commonly adopted in multi-objective optimization problems involving power systems and has been shown to yield stable and unbiased convergence results [14].

The first part of the objective function represents the power loss minimization component obtained by normalizing the P_{loss} with its original value as expressed

$$f_1 = \frac{\boldsymbol{P_{loss}}}{\boldsymbol{P_{loss,\ base}}} \quad (3)$$

2. Active Power Loss Calculation

The active power loss (P_{loss}) in the network is given by;

$$\mathbf{P}_{\text{loss}} = \sum_{i=1}^{n} I_i^2\, R_i \quad (4)$$

Where;

- I_i = Current through the i[th] branch
- R_i = Resistance of the i[th] branch
- n = Total number of branches

The minimization of P_{loss} helps improve the overall energy efficiency and reduces network heating.

C. Inherent Power Loss Calculation

The Inherent Power Loss $\mathbf{P_{loss,\ base}}$ also refered to as (P_{loss}^0) is given by in the optimized Distribution Network (DN) as;

$$P_{loss}^0 = \sum_{i=1}^{n_l} R_i \left\{ \frac{P_i^2 + Q_i^2}{V_i^2} \right\} \quad (5)$$

$$for\ i = 1,2, \dots, n_l) \quad (6)$$

Where;

- P_i *is* the active power at the i[th] bus
- P_{loss} is the minimized active power loss
- Q_i is the reactive power at the i^{th} bus
- R_i is the i^{th} branch resistance.

1. Reactive Power Loss Calculation

The Reactive power loss (Q_{loss}) in the network is calculated using the standard power loss formula;

$$\boldsymbol{Q}_{loss} = \sum_{i=1}^{nb} I_i^2 X_i \quad (7)$$

Where;

- $\mathbf{Q_{loss}}$ = Total reactive power loss (kVAr)
- $\mathbf{I_i}$ = Current magnitude through the ^{ith} branch (A)
- $\mathbf{X_i}$ = Reactance of the i[th] branch (Ω)
- **Nb** = Total number of branches in the distribution network

The current values are obtained from load flow analysis (using the forward-backward sweep method).

In the second part of the objective function, f_2 models the component of the total voltage deviation, which when minimized, Voltage Profile (VP) improves. It is similarly obtained by normalizing its minimized value, V_{dev} with its initial value. It is mathematically expressed as:

$$f_2 = \frac{\boldsymbol{V_{dev}}}{\boldsymbol{V_{dev,\ base}}} \quad (8)$$

Where;

- $\mathbf{V_{dev}}$: Total voltage deviation after DVR placement
- $\mathbf{V_{dev,\ base}}$: Total voltage deviation in the base (uncompensated) system.

2. Voltage Deviation Calculation

The total inherent voltage deviation $\boldsymbol{V_{dev}}$, also referred to as "$\Delta \boldsymbol{V_{total}^0}$" This type of index is frequently used in voltage optimization studies [8][14] is given by;

$$\Delta V_{total}^0 = \sum_{j=1}^{n_b} \left| V_{ref,j} - V_j \right| \quad for = 12, \dots n_b \quad (9)$$

Where;

- $V_{ref,j}$ is the nominal voltage magnitude of load bus j
- $\mathbf{V_j}$ is the voltage magnitude at bus j obtained from power flow results after Dynamic Voltage Restorer (DVR) installation.

- n_l and n_b are the total number of lines (branches) and buses in the Distribution Network (DN), respectively.
- ψ and β are the weighting coefficients of the P_{loss} and V_{dev} minimization components of the objective function, and equal priority is given to both objectives (ψ=0.5, β=0.5) respectively.

Since, there are different objectives to be satisfied simultaneously, after normalizing all the terms of the objectives, the weighing coefficients the weighting coefficients ψ and β were assigned equal values (i.e., 0.5 each) after normalization to ensure balanced treatment of both objectives. This approach is commonly adopted in multi-objective optimization problems involving power systems and has been shown to yield stable and unbiased convergence results [14].

3. Constraints

The proposed DVR's optimal placement in the Distribution Network (DN) is solved by considering the following constraints: -

i. **Voltage limit:** the bus voltage magnitudes are constrained within lower and upper limits as in

$$V_{ij}^{min} \leq V_{ij} \leq V_{ij}^{max}, i = 1, 2, \dots, n_b \qquad (10)$$

Where;

- $\boldsymbol{V}_{ij}^{max}$ is the bus voltage maximum limit, and
- $\boldsymbol{V}_{ij}^{min}$ is the bus voltage minimum limit.

ii. **Maximum permissible line current carrying capacity:** to avoid exceeding the current capacity of the branches, the current in the ij^{th} branch, I_{ij} is limited to a maximum and minimum permissible current.

$$I_{ij}^{min} \leq I_{ij} \leq I_{ij}^{max}, i \neq j \qquad (11)$$

Where;

- i is the sending end bus.
- j is the receiving end bus.
- $\boldsymbol{I}_{ij}^{min}$ is the minimum current in the ij^{th} branch, and
- $\boldsymbol{I}_{ij}^{max}$ is the maximum current in the ij^{th} branch.

4. DVR Sizing Limits

The apparent power rating of the DVR is constrained within practical installation limits:

$$S_{min}^{DVR} \leq S_{DVR} \leq S_{max}^{DVR} \qquad (12)$$

Where;

- S_{DVR} = Apparent power rating of the DVR
- Typical limits may range from 50 kVA to 500 kVA, depending on network capacity and cost considerations

D. Test Systems Description

The network used for this study is the IEEE 69-bus test system, which consists of 69 buses and 68 branches according to Zu et al., 2018. The system operates at a nominal voltage level of 12.66 kV and is configured in a radial topology. It has a total active load demand of 3.802 MW and a reactive load demand of 2.694 MVAR.

In its uncompensated base state, the system exhibits an inherent active power loss of 224.89 kW. The inherent voltage deviation, computed as the sum of the absolute deviations of all bus voltages from the nominal 1.0 pu reference, was determined to be 1.9320 pu. These baseline metrics serve as reference points for evaluating the performance improvement resulting from DVR deployment and metaheuristic optimization.

The single-line diagram of the IEEE 69-bus distribution system is illustrated in Figure 1.

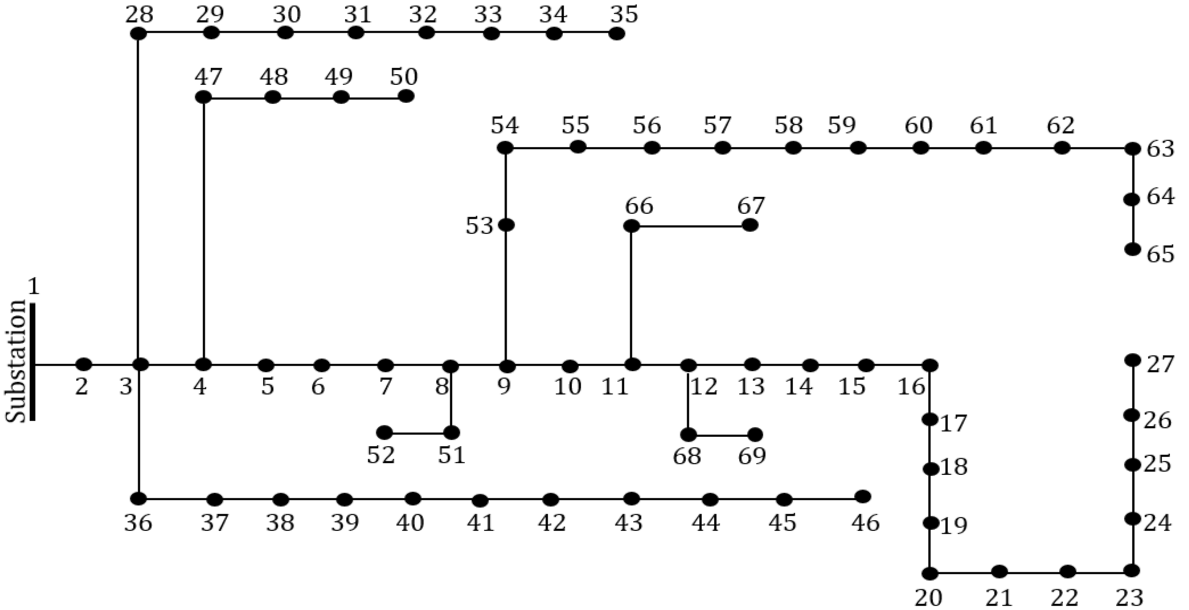

Figure 1: Single line diagram of 69-bus test system (Zu, et al., 2018).

III. OPTIMIZATION TECHNIQUE: WATER CYCLE ALGORITHM

The Water Cycle Algorithm (WCA), introduced by Eskandar [6], is a population-based metaheuristic inspired by the natural hydrological cycle—mimicking the flow of water from streams to rivers and finally into the sea. This method simulates the cooperative search behavior of water droplets to locate optimal solutions across complex and multidimensional search spaces [6]. The algorithm has been effectively applied in power systems for problems such as power flow optimization, distributed generation (DG) allocation, microgrid control, and dynamic voltage restorer (DVR) placement [1][10] [12].

A. Advantages of WCA

Compared to traditional heuristics, WCA offers multiple advantages:

- It provides a balanced exploration and exploitation mechanism that improves global convergence rates.
- It is known to avoid premature convergence, a common issue in algorithms like Genetic Algorithm (GA) and Simulated Annealing (SA).
- It is simple to configure due to its low parameter dependency and relatively intuitive structure (Thongsan & Chatchanayuenyong, 2023; [10]
- It has demonstrated superior performance in DVR and FACTS optimization compared to conventional methods [1] [12].

B. Mathematical Representation of Solution Search

Let $\boldsymbol{X}_i \in \mathbf{R}^d$ the position of the ith solution (raindrop) in a ddd-dimensional solution space. The best solution in the population is called the sea**,** and is denoted $\mathbf{X}_{sea}$. A set of elite solutions, $\boldsymbol{X}^r_{river}$, represent rivers, and the remaining are streams**,** $\boldsymbol{X}^s_{stream}$.

1. Movement of Streams Toward Rivers

The movement of a stream $\boldsymbol{X}^s_{stream}$ toward its assigned river $\boldsymbol{X}^r_{river}$ is defined by:

$$\boldsymbol{X}^{s,\ new}_{stream} = \boldsymbol{X}^{s,\ current}_{stream} + r_1 \cdot C \cdot (\boldsymbol{X}^r_{river} - \boldsymbol{X}^{s,\ current}_{stream}) \quad (13)$$

Where;

- $r_1 \in [0, 1]$ is a random number ensuring exploration.
- $C \in (0, 1)$ is a learning coefficient (typically 2).
- $\boldsymbol{X}_{stream}^{s,\ new}$ is the updated stream position.

2. Movement of Rivers Toward the Sea

Similarly, a river $\boldsymbol{X}_{river}^{r}$ moves toward the sea $\mathbf{X}_{sea}$ as:

$$\boldsymbol{X}_{river}^{r,\ new} = \boldsymbol{X}_{river}^{r,\ current} + r_2 \cdot C \cdot (\boldsymbol{X}_{\boldsymbol{sea}} - \boldsymbol{X}_{river}^{r,\ current}) \quad (14)$$

Where $\mathbf{r_2} \in [0,1]$ is another random factor for stochastic behavior.

3. Position Evaluation and Replacement

Each new candidate solution $\mathbf{X}_i$ is evaluated using the fitness function $\boldsymbol{f}(\boldsymbol{X}_i)$**.** If the updated position offers better fitness, it replaces the previous one. Otherwise, it may be discarded or replaced through an evaporation and precipitation mechanism**,** which reinitializes stagnant solutions:

$$If\ no\ improvement\ for\ T\ iterations,\ then\ X_i \leftarrow Random\ Position$$

Where **T** is the stagnation threshold (typically 5–10 iterations).

4. Convergence Criterion

The algorithm stops when one of the following is met:

- A maximum number of iterations $\mathbf{N}_{max}$
- The fitness of the sea does not improve beyond a threshold ε

C. Algorithm Summary

1. **Initialize** population $\{\boldsymbol{X}_i\}$ of size N
2. **Evaluate** fitness of each solution using $f(\boldsymbol{X})$
3. **Assign** sea, rivers, and streams based on fitness
4. **Update positions** of streams → rivers and rivers → sea using the above equations
5. **Apply evaporation** if stagnation occurs
6. **Repeat** until convergence criterion is met

D. Pseudocode Overview

1. Initialize population (raindrops)
2. Evaluate fitness using objective function
3. Identify sea (best), rivers (next-best), and streams (rest)
4. While not converged:
   a. Move streams toward rivers
   b. Move rivers toward sea
   c. Evaluate new positions
   d. Evaporate worst if stagnant
   e. Update sea if a better solution is found
5. Return sea as optimal DVR configuration

E. Application in This Study

In this study, each solution $\boldsymbol{X}_i$ represents a vector:

$$\boldsymbol{X}_i = [\boldsymbol{Bus}_{DVR}, \boldsymbol{S}_{DVR}] \quad (15)$$

Where;

- $\boldsymbol{Bus}_{DVR} \in \{1, 2, \ldots, 69\}$ is the location of the DVR
- $\boldsymbol{S}_{DVR} \in [\boldsymbol{S}_{min}, \boldsymbol{S}_{max}]$is the DVR rating in kVA

Fitness is computed using the normalized multi-objective function:

$$\boldsymbol{f}(\boldsymbol{X}_i) = \psi \cdot \frac{\boldsymbol{P}_{loss}}{\boldsymbol{P}_{loss,\ base}} + \beta \cdot \frac{\boldsymbol{V}_{dev}}{\boldsymbol{V}_{\boldsymbol{dev,base}}} \quad (16)$$

The WCA ensures a globally competitive search for the best location and size of DVR while satisfying power system constraints.

IV. SIMULATION RESULTS

This section presents the results of the simulation carried out in MATLAB environment for the sake of establishing the performance of the proposed technique in optimally placing and sizing the DVR for the target objectives.

A. Optimized Voltage Profile in IEEE 69-Bus System

Figure 2 presents a graphical comparison of the voltage profiles for the IEEE 69-bus system before and after DVR optimization. The base case without DVR compensation (Red curve) reveals several buses with voltages dropping below the acceptable threshold. In contrast, the optimized case using the Water Cycle Algorithm (Blue curve) shows a clear improvement, particularly at the most remote buses (Bus 60–69), where the voltage rose from a minimum of **0.9062 pu to 0.9695 pu**. This highlights the effectiveness of WCA in voltage profile enhancement when the DVR is placed at **Bus 66**.

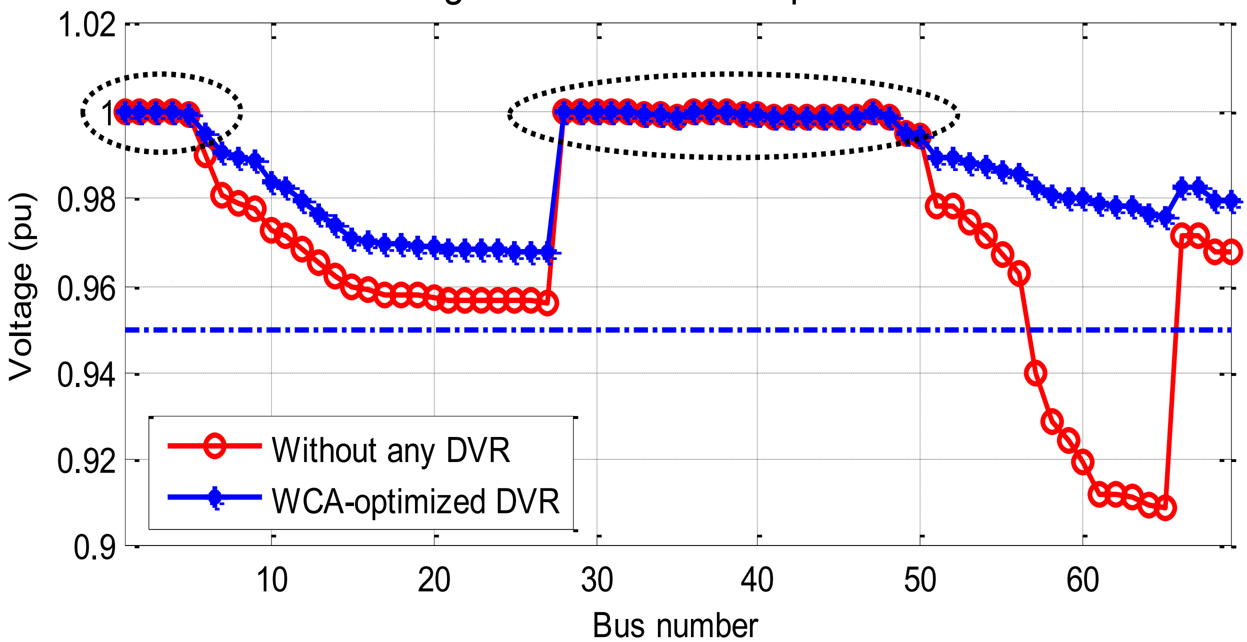

Figure 2: Optimized IEEE 69-bus test system voltage profile.

B. Active Power Loss in IEEE 69-bus system

The impact on active power loss is illustrated in Figure 3. The base case without DVR (Red bar) shows a total active power loss of **224.98 kW**, while the system with the WCA-optimized DVR placement (Blue bar) records a reduced loss of **191.07 kW**, corresponding to a **15.07% reduction**. This validates the energy-saving potential of the DVR when optimally sized and allocated.

C. Reactive Power Loss in 69-bus system

Figure 4 shows the comparative analysis of reactive power loss. The system without DVR compensation (Red bar) incurs a total reactive power loss of **102.18 kVAR**, whereas the WCA-optimized DVR configuration (Blue bar) reduces this to **63.35 kVAR**, achieving a **38.00% reduction** in reactive losses. These results were calculated using the standard power loss expression provided earlier (see Equation 7).

D. Optimized IEEE 69-bus System

In this scenario, a relatively bigger distribution network is considered. The WCA is used to determine optimal location and size of the DVR in the IEEE 69-bus system. The size of the DVR is optimally found to be **298.45 kVA** located close to bus 66 (as shown in Figure 5).

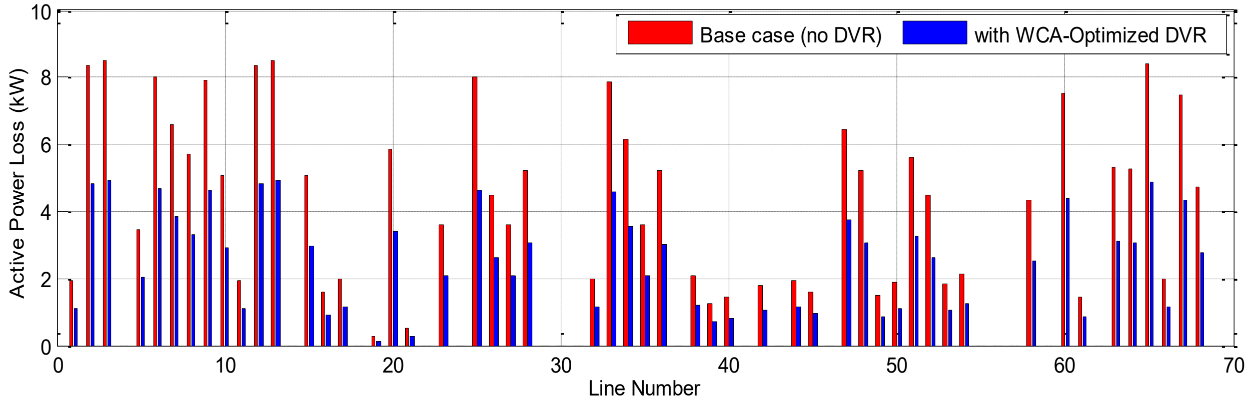

Figure 3: Active Power Loss in IEEE 69-bus system

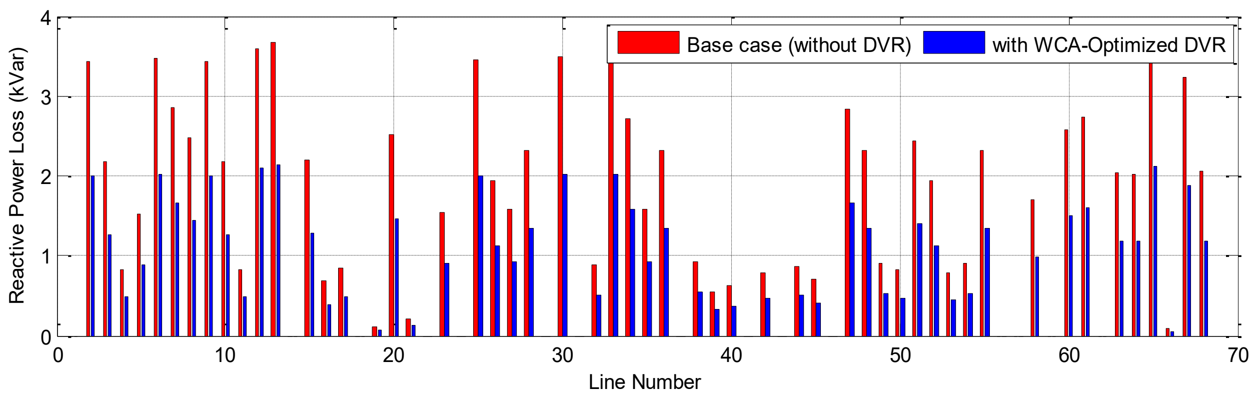

Figure 4: Reactive Power Loss in 69-bus system

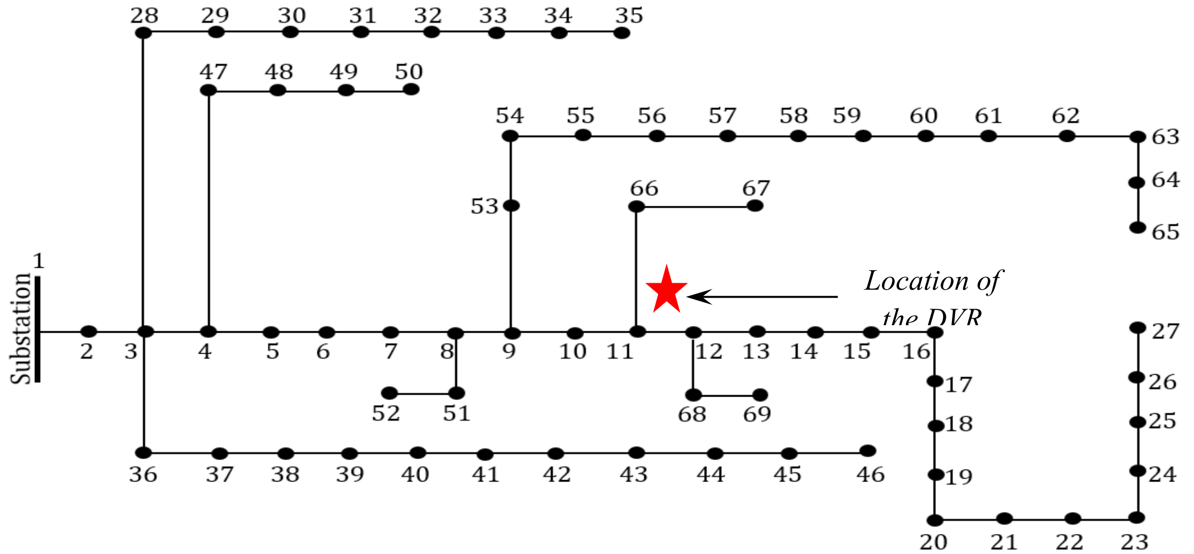

Figure 5: Single line diagram of optimized IEEE 69-bus test system

The location of the DVR is justified by the remote placement of **Bus 66**, which lies near the end of the distribution feeder and experiences significant voltage drops. By strategically placing the DVR at this location, the system records a reduction in active power loss of **15.07%** from its total inherent loss of 224.98 kW. Furthermore, the voltage deviation is improved by **16.36%** compared to the initial deviation value of **1.9320 pu**, as summarized in **Table 1**.

***Table 1: Summary of Optimized IEEE 69-Bus Test System (*Performance Metrics)**

Parameters	**Initial**	**With DVR Optimally Deployed**	Improvement
DVR location	NA	Bus 66	NA
DG Size (*kVAR*)	NA	298.45	NA
P_{loss} (*kW*)	224.9804	191.07	15.073%
Q_{loss}*(KVAR)*	102.18	63.35	38.001%
V_{dev} *(pu)*	0.2140	0.179	16.355%
Min. Voltage (*pu)*	0.9062	0.9695	6.985%

Overall, the simulation results demonstrate that the application of the Water Cycle Algorithm leads to significant improvements in power quality and energy efficiency through optimal DVR deployment.

V. COMPARATIVE ANALYSIS WITH FIREFLY ALGORITHM

To ascertain the superiority of the proposed WCA-based optimal deployment of the DVR, its performance is compared with those obtained using Firefly Algorithm (FFA) Optimization. The comparative analysis is carried out on the IEEE 69-bus system as shown in Figure 6.

The superiority of the WCA over the FFA is largely due to the higher number of objective function evaluations in the latter. In addition, the WCA performs fewer computations since it can evaluate the objective function using the fixed user-defined parameters.

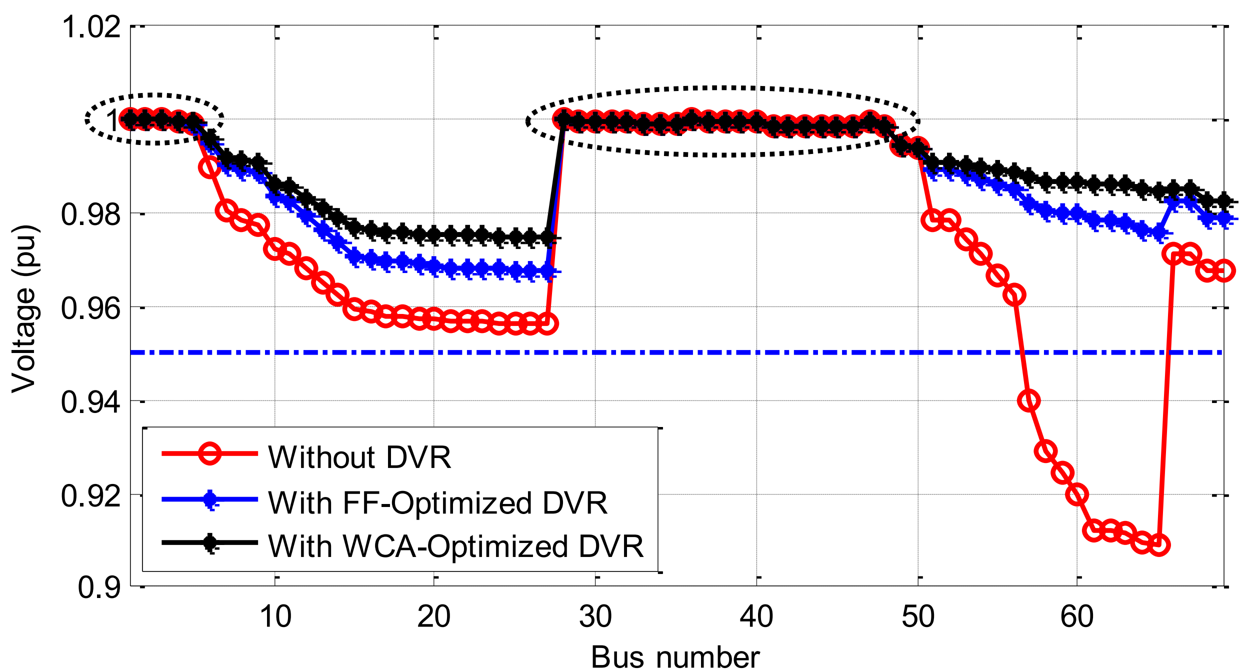

Figure 5: Voltage Profile of IEEE 69-bus System with FF-optimized and WCA-optimized DVR

Table 2: Summary of DVR Optimal placement in IEEE 69-bus system

Scenario	DVR Optimization		Voltage Deviation	Active Power Loss (kW)	Reactive Power Loss (kVAR)	Improvement Over voltage deviation	Active power Improvement over the base case	Reactive improvement Over the as case
	Location	Size (kVAR)						
Base case	-	-	0.214	224.98	144.06		--------	---------
FF-Optimized DVR	65	284.26	0.192	165.44	124.40	10.28%	26.46%	13.65%
WCA-Optimized DVR	66	298.45	0.179	130.98	104.56	16.35%	41.78%	27.45%

VI. CONCLUSION

This paper presented the application of the Water Cycle Algorithm (WCA) for the optimal placement and sizing of a Dynamic Voltage Restorer (DVR) in the IEEE 69-bus radial distribution system. The proposed approach aimed to minimize active power loss and voltage deviation while adhering to operational constraints. Simulation results demonstrated that placing the DVR at Bus 66 with a capacity of 298.45 kVA significantly enhanced the system's performance.

The WCA-optimized DVR configuration achieved a 15.07% reduction in active power loss, a 38.00% reduction in reactive power loss, and a 16.36% improvement in voltage deviation compared to the base case. These improvements affirm the WCA's effectiveness in addressing power quality issues in large-scale, complex distribution systems.

VII. RECOMMENDATION FOR FUTURE WORK

This study focused on enhancing power quality in radial distribution systems through the optimal placement and sizing of a Dynamic Voltage Restorer (DVR) using a recent metaheuristic technique—the Water Cycle Algorithm (WCA). The algorithm was selected due to its flexibility, scalability, and strong global search capabilities, which contributed to noticeable improvements in voltage stability and power loss reduction.

However, as observed in the comparative analysis between the Firefly Algorithm (FFA) and WCA for the IEEE 69-bus system, WCA, despite yielding better performance in terms of voltage deviation and loss minimization, produced a larger DVR size than its FFA counterpart. This highlights a potential limitation of WCA**:** it does not explicitly account for the cost implications associated with device sizing**.**

Therefore, it is recommended that future research explore:

- The integration of cost-aware objective functions to balance technical performance and economic feasibility.
- The application of more recent or hybrid metaheuristic algorithms (e.g., Grey Wolf Optimizer, Sine Cosine Algorithm, or hybrid PSO-WCA) that may yield more cost-efficient solutions.
- The development of multi-objective frameworks that simultaneously minimize power losses, voltage deviation, and DVR cost.
- Real-time and adaptive implementations for dynamic load environments.

These enhancements could improve the practical deployment of DVRs and broaden the applicability of metaheuristic approaches in modern smart grid contexts.

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