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Enhancing Power System Efficiency and Profitability through Nodal Pricing and Arithmetic Optimization

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Abstract - Electricity trading has become more competitive due to recent sector reforms. Technology, environmental concerns, and small-scale power production have driven distributed generation (DG) sources. Distribution networks and local customers link smaller, more diversified DG sources. They decrease power losses, system costs, voltage, power quality, and infrastructure investments. DG reduces greenhouse gas emissions and improves power system integration, reliability, and efficiency. DG integration into the existing electricity system has presented management and planning issues. DG reduces losses and improves system performance, but poor installation may increase losses, voltage concerns, and costs. Optimizing distribution network usage maximizes DG. Power market deregulation increased competitiveness and efficiency. Transmission line congestion persists. Generation rescheduling, load shedding, and FACTS devices may reduce congestion and assure power supply. Power generation and distribution are private in a deregulated power market, but transmission is monopolized. Transmission Open Access (TOA) lets non-owners utilize the system. Nodal pricing was used to determine the appropriate distributed generation (DG) distribution for profit maximization, loss minimization, and voltage improvement to address voltage rise. The work improved arithmetic optimization for DG allocation. The thesis demonstrated how nodal pricing might boost power system economic efficiency and operator profit. DG location optimizes system performance and losses. This thesis indicates that nodal pricing-based DG allocation and increased arithmetic optimization are beneficial. Profits, system losses, and voltage stability increase. The results assist power system designers, operators, and regulators arrange DGs in their networks. The algorithm needs further testing and improvement under real-world conditions. To complete and apply the concept, further study should incorporate renewable energy integration, system reliability, and environmental impact.

***Key Words*:** FACTS, DG, distribution network, algorithm

1. INTRODUCTION

In recent years, the electricity industry has experienced significant changes that have increased competition in energy trading. Factors such as technological advancements, environmental concerns, and the growth of small-scale power generation have led to the rise of distributed generation (DG) sources. DG sources are smaller and more diverse than conventional sources, connected to distribution networks and local consumers. They offer benefits such as reduced power losses, lower system costs, improved voltage and power quality, and the avoidance of infrastructure investments. Additionally, DG can help reduce greenhouse gas emissions and improve power system integration, reliability, and efficiency. The integration of DG into the traditional power system has introduced opportunities and challenges for its management and planning. While DG can reduce losses and improve system performance, improper installation may lead to increased losses, voltage issues, and higher costs. To make the most of DG, the distribution network should optimize its utilization. Deregulation in the power sector has brought significant changes to the power market, introducing competition and improving efficiency. However, congestion on transmission lines remains a challenge. To address this, approaches like generation rescheduling, load shedding, and the use of Flexible AC Transmission Systems (FACTS) devices can alleviate congestion and ensure reliable power supply.In a deregulated power market, private entities compete in power production and distribution, while transmission remains a monopoly. However, Transmission Open Access (TOA) allows non-owners to use the transmission system.

Efficient operation and management of power distribution systems are crucial due to the increasing incorporation of renewable energy sources and growing electricity demand. Nodal price minimization and optimal power flow are essential objectives, and various optimization methods, including arithmetic optimization algorithms, have been proposed. The research aims to enhance these methods and develop an improved algorithm tailored for radial distribution systems, considering factors like nodal price minimization, power loss reduction, voltage profile enhancement, convergence speed, and scalability. The outcomes of this research can contribute to optimizing power systems, reducing costs, improving system stability, and facilitating the integration of renewable energy sources. The radial distribution system plays a crucial role in delivering electricity to consumers, but high nodal prices can pose financial challenges for power generators and consumers. This problem statement aims to develop an optimization algorithm to minimize nodal prices and ensure efficient operation of the radial distribution system. Existing optimization techniques have been ineffective in solving this problem efficiently. This study proposes a novel algorithm that combines the strengths of existing techniques and introduces new features to enhance efficiency. The goal is to minimize nodal prices, alleviate financial challenges, and improve the overall efficiency of the radial distribution system. The proposed algorithm has implications for the energy industry by providing a cost-effective solution. The research objectives include simulating load flow analysis, modeling DG placement, developing a novel optimization algorithm, and comparing it with existing methods for price reduction.

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2. Literature Review

A cuckoo search optimization-based strategy is a sought-after approach to determine where to place static shunt capacitors across regional distribution networks. The goal function helps to enhance the voltage profile of the system and lower operating costs in a variety of load conditions. The proposed technique can also be used to optimize the placement and values of fixed and switching capacitors in distribution networks subject to a wide range of loading conditions. First, using the power loss index, the buses with the highest potential to put capacitors are identified. That approach, however, hasn't worked out that well because power loss indices don't always point to the right location. At that point, the suggested approach determines the best size and placement and makes the final choice for the best position among the buses nominated with the fewest possible effective locations and the fewest possible injected VARs. The approach's overall correctness and dependability have been verified and tested on radial distribution systems of various sizes, complexity levels, and topologies. It has been determined that the results produced by the suggested approach outperform those of current heuristic algorithms. Integrating DGs and CBs (capacitor banks) into distribution networks has been shown to boost system performance. According to a study, there has been a rise in interest in incorporating DG units into power transmission networks. By taking into account DG capacity restrictions, the optimal DG placement (ODGP) technique provides the ideal locations and DG sizes to improve the functioning and management of electrical distribution networks. Several models and methods have been proposed as answers to the ODGP issue. Both the customer load categories and the feeder failure rate were modeled in the study. The system's energy loss and risk level were greatly decreased over the planning period when the best location for both the DG and capacitor was discovered.

The amount of research on the financial and technical advantages of implementing DG in transmission networks is still minimal, with the majority of studies concentrating on its advantages in the distribution sector, such as enhancing voltage profile and lowering power loss. By identifying the best location/position and DG size in both the Day-ahead Energy Market (DEM) and the Real-time Energy Market (REM), this study tries to close this gap. The continual rise in energy demand on the distribution system, whether brought on by the natural expansion of a service area or by the stimulation of the energy market, presents a substantial problem for planning engineers. Increased costs are frequently paid to build new substations or increase the capacity of existing substations as a result of the system's increasing load. Based on scholarly investigations, the distribution networks experience power losses ranging from 5 to 13 percent of the overall electricity generated, thereby contributing significantly to the cost of electricity. The optimization of voltage stability and reduction of power loss are critical components of power systems, as they are essential in mitigating potential transmission line contingencies, minimizing financial losses for utility companies, and preventing power system failures. Optimizing the distribution grid through the integration of distributed generation (DG), capacitors, and other related components is a promising strategy to enhance the efficiency of the power system. The allocation of Distributed Generation (DG) is expected to result in significant technical benefits including load balancing, reduction in power losses, voltage stability improvement, and reduction of congestion in a power system. This paper suggests a new approach for optimizing the operation of private distributed generation (DG) units within the context of distribution networks. The main idea of the approach is to incentivize private units by offering them surplus profit of the Distribution System Operators (DSOs) derived from reduction of power loss and greenhouse gas (GHG) emissions.

The optimization problem is formulated as a mixed-integer non-linear programming (MINLP) problem with a focus on maximizing the DG owners' profit, which includes not only the selling price of the generated power but also the surplus profit offered by the DSOs. Various optimization techniques have been employed to determine the optimal location and capacity of DG units. These include the Fireworks Algorithm, Grey Wolf Optimizer, and Hybrid PSO. Nodal pricing mechanisms have been discussed as well as multi-objective optimization techniques. This thesis investigates the best location for distributed generation (DG) considering power/energy loss reduction, voltage stability improvement, and enhanced voltage profile. Existing methodologies and their respective planning criteria are outlined and discussed. The Water Cycle Algorithm (WCA) is proposed as a novel optimization technique inspired by the natural water cycle. WCA has shown promising results in terms of accuracy and convergence rate, and it requires minimal parameter tuning. Several research papers are referenced, highlighting the optimization of DG placement and its impact on nodal pricing, power loss reduction, congestion problems, reliability improvement, and power quality enhancement. Different algorithms and methodologies are mentioned, such as Particle Swarm Optimization (PSO), Q-Learning technique, evolutionary dragonfly algorithm, and nodal pricing methods

3. Methodology

3.1 Problem Formulation

Total power system cost determines distribution network (DN) nodal pricing. Power Supply Point (PSP) is where producing and transmission meet. Power flows determine a "reference bus" for PSP nodal pricing. The PSP's active power price in US dollars per megawatt hour equals the grid-supplied energy price. When the distribution network is not crowded, the following formulae may calculate active and reactive power nodal prices.

$$C_i^a = \lambda + \lambda \cdot \rho_{Pi=\lambda}\left(1 + \rho_{Pi)}\right) \quad (1)$$

$$C_i^r = \lambda \cdot \rho_{Qi} \quad (2)$$

Bus nodal expenses will decrease if DG lowers DN inefficiencies and delays, and vice versa. Let $C_i^a(no_{DG})$ and $C_i^r(no_{DG})$ represent the nodal price for active and reactive power without distributed generation (DG) at Bus-i, in US$/MWh and US$/MVArh respectively. When DG is included, $Pi(no_{DG})$ represents the active power of the DG. The power requirement at $Bus - i$ is QDi (MVAr) and PDi (MW), and the cost of grid-supplied electricity at the Power Supply Point (PSP) is λ (US$/MWh). The power bill $P_{elect}^{no_{DG}}$ including DG can be obtained in the time domain Δt.

$P_{elect}^{no\_DG} = \sum_{i=1}^{n}\{C_i^n(no\_DG) \times P_{Di} \times \Delta t + C_i^r(no_{DG}) \times Q_{Di} \times \Delta t + \lambda \times P_i(no\_DG) \times \Delta t\}$ (3)

Loss cost is computed using energy price at the power supply point since loss is not tied to any specific place (i.e. λ). Let C_i^r and C_i^n denote the nodal price of reactive and active power with the inclusion of distributed generation (DG), in US$/MVArh and US$/MWh respectively. $P_l(DG)$ represents the active power dissipation in MW when DG is included. P_{DGi} and Q_{DGi} represent the active and reactive power supplied by DG in MW and MVAr at $Bus - i$, while C(DG) represents the cost of DG's energy supply in US$/MWh. The cost of P_{elect}^{DG}, including DG, for each time period Δt can be calculated as follows:

$P_{elect}^{DG} = [\{C_i^a(DG) \times (P_{Di} - P_{DGi}) \times \Delta t + C_i^r(DG) \times (Q_{Di} - Q_{DGi}) \times \Delta t\} + \{C(DG) \times P_{DGi} \times \Delta t\} + \lambda \times P_L(DG) \times \Delta t]$
(4)

In the presence of a distributed generation (DG) at a particular bus, the DG is treated as a negative load at that bus. When a single DG is placed, the active power (P_{DGi}) and reactive power (Q_{DGi}) are assumed to be zero at all buses except the bus where the DG is located. Additionally, at all other buses except for those with DG placements, both P_{DGi} and Q_{DGi} are set to zero.

$P_{DGi} = 0\,; Q_{DGi} = 0,$ Expected DG buses positioned by $\forall$ buses (5)

How effectively DG operates depends on how much money it saves on power bills [35]. Thus, the issue is:

Maximize $(P_{elect}^{no\_DG} - P_{elect}^{DG})$
(6)

For

$V_{0,i} \leq V_{max},$
$\forall$ secondary side of the transformers (7)

$V_{end,i}|\,max\ load, no\ DG \geq V_{min},$ $\forall$ feeder end node
(8)

$V_{DG}|\,min$ load, max $DG \leq V_{max}$
(9)

$V_{DG}|$ min load, max DG $\leq V_{0,i}$
(10)

$V_{min} \leq V_i \leq V_{max}$ (11)

Eqs. (7)–(11)'s voltage restrictions will address any LTC controlled feeder's voltage growth issue. LTC modulation is unaffected by power quality or active/reactive power flow, although large networks may control each feeder individually. The DG central hub's voltage increase affects the power source's voltage [36]. Current paper nomenclatures are explained here. In the system with n buses, Δt represents the time duration (hours). Voltage at a specific time is denoted as $V_{0,i}$ for $bus - i$. V_{max} is the maximum voltage limit, $V_{end,i}|max\ load, no\ DG$ is the end voltage of highly loaded feeders without DG. V_{min} is the minimum voltage, and $V_{DG}|max\ load, max\ DG$ is the voltage at the location of the DG with maximum loading and generation. V_i refers to the voltage at any $bus - i$.

3.2 Simulation Network

Fig. 3.1 shows a simulated network with 69 buses in a rural Indian location. The system is simulated for time-invariant and time-variant demands. Time-varying load curves describe the latter kind. According to the National Thermal Power Corporation of India's annual report [37], the unit cost of electricity, 'k', is 44.5 US dollars per megawatt-hour. The current network evaluates and shows the proposed method for locating and sizing scattered generating systems to optimize voltage restrictions and loading conditions.

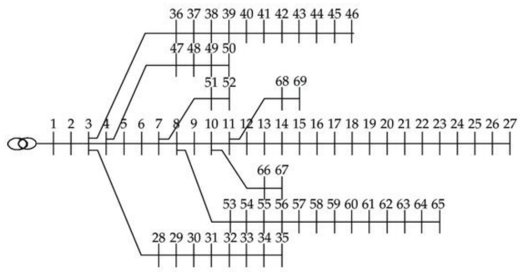

Figure Error! No text of specified style in document.**-1:** The IEEE 69 bus radial distribution.

3.3 Proposed Optimization Scheme

The optimization approach under examination determines the best location and dimensions of a distributed generation (DG) unit inside a distribution network, taking voltage limits into account. Random DG location and size will provide an initial population vector for the method. Next, the network will implement each population of the starting vector and evaluate voltage limitations. Population vectors meeting voltage requirements will be selected. Each vector's goal function will be calculated next. Optimal population vectors have the best objective function. The convergence criteria will end the optimization process and display the results. The survivors will breed the next generation. Optimizing distributed generation (DG) unit location and capacity reduces losses and improves voltage stability while taking into consideration network constraints.

3.4 Improved AOA

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Mathematical algorithms optimize computer arithmetic processes. These methods reduce the number of arithmetic operations needed to solve a problem or compute. Optimization or enhancement techniques in population-based algorithms start with a pool of randomly generated candidate solutions. Random solutions and optimization rounds increase the likelihood of finding the global optimum solution [38]. Despite metaheuristic algorithm variations, population-based optimization approaches have two main stages: exploration and exploitation. "Former" refers to an algorithm's search agents' complete investigation of the search space to avoid local solutions. Exploration improves solution correctness. The AOA uses division (D "÷"), multiplication (M "×"), addition (A "+"), and subtraction (S "−") to explore (diversify) and exploit (intensify). Subsequent sections explain these processes. Population-based meta-heuristics solve optimization issues without derivative computations.

3.4.1 Initialization phase

Each iteration of the AOA approach selects the best-obtained answer among the candidate solutions. Optimization begins with a stochastic assembly of possible solutions (X), as shown in Matrix (12).

$$X = \begin{bmatrix} X_{1,1} & \cdots & \cdots & X_{1,j} & X_{1,n-1} & X_n \\ X_{2,1} & \cdots & \cdots & X_{2,j} & \cdots & X_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{P-1,1} & \cdots & \cdots & X_{P-1,j} & \cdots & X_{P-1,n} \\ X_{P,1} & \cdots & \cdots & X_{P,j} & X_{P,n-1} & X_{P,n} \end{bmatrix}$$

(12)

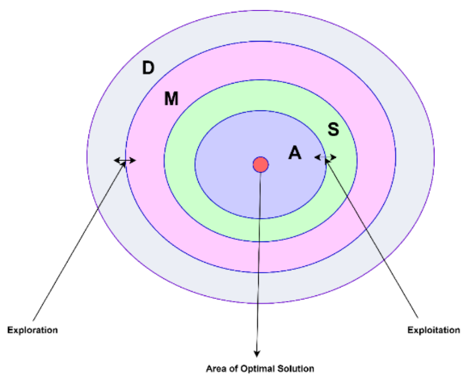

Figure Error! No text of specified style in document.**-2:** Arithmetic operator hierarchy (descending order of dominance)

The AOA should choose an exploration or exploitation phase before starting operations. The Math Optimizer Accelerated (MOA) function is a coefficient from Eq. (13) used in subsequent search phases. Given the above,

$$MOA(C_{Iter}) = Min + C_{Iter} \times \left(\frac{Max-Min}{M_{Iter}}\right) \quad (13)$$

The notation $MOA(C_{Iter})$ represents the function's value at the t^{th} iteration, determined by Eq. (13). The current iteration is denoted by C_{Iter} , ranging from 1 to the maximum number of iterations M_{Iter}. The terms Min and Max refer to the minimum and maximum values of the accelerated function, respectively.

3.4.2 Exploration Phase

This section describes the exploratory behavior of the AOA algorithm. The use of the Division (D) or Multiplication (M) operators in mathematical computations introduces high-distributed values or judgments, which contribute to the exploratory search mechanism based on arithmetic operators. However, the $D\ and\ M$ operators face challenges in effectively reaching the objective due to their significant dispersion, unlike the $S\ and\ A$ operators. To illustrate the impact of distribution values of different operators, a function employing four mathematical operations is utilized, demonstrating how the exploration search identifies an optimal solution after multiple iterations. In the context of optimization, the exploration operators $D\ and\ M$ are employed to facilitate the exploitation phase by enhancing communication between them. The AOA algorithm employs two main search methods, the Division (D) search strategy and Multiplication search strategy, represented by Equation (14). These methods randomly explore multiple regions within the search area to improve the solution. The exploration search phase, using $D\ or\ M$, is conditioned by the Math Optimizer Accelerated (MOA) function (Equation 13), with the requirement that $r_l > MOA$, where r_l is a random number. The subsequent operator, denoted as "M," remains unacknowledged until the initial operator "D" completes its operation as per Equation (14). If the second operator (M) is unavailable, it is replaced by the variable D (with r_2 as a stochastic variable) for executing the current operation. To expand the range of diversification and explore alternative areas in the search space, a stochastic scaling coefficient is incorporated for each element, following the principles of arithmetic operators. The study proposes position updating equations for the exploratory sections.

$$X_{i,j}(C_{Iter}+1) = \begin{cases} best(X_j) \div (MOP+\in) \times \left((UB_j - LB_j) \times \mu + LB_j\right), & r2 \\ best(X_j) \times MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right) \end{cases}$$

< 0.5 otherwise (14)

In this context, $X_i(C_{Iter})$ represents the i^{th} position in the current ideal solution, while $X_{i,j}(C_{Iter})$ represents the j^{th} position at the present iteration. $X_i(C_{Iter}+1)$ denotes the i^{th} solution in the next iteration. ϵ is a small numerical value, and UB_j and LB_j indicate the upper and lower bounds for the j^{th} position. The control parameter μ, fixed at 0.5, modifies the search process.

$$MOP(C_{Iter}) = 1 - \frac{C_{Iter}^{\frac{1}{\alpha}}}{M_{Iter}^{\frac{1}{\alpha}}}$$
(15)

In the given context, the Math Optimizer Probability (MOP) coefficient is denoted as C_{Iter} for the current iteration. M_{Iter} represents the maximum number of iterations, and $MOP(C_{Iter})$ indicates the function value at the t^{th} iteration. In this study, the sensitivity parameter α, which determines the exploitation precision across iterations, remains fixed at 5.

3.4.3 Exploitation Phase

The exploitation approach of AOA uses arithmetic operations: addition (A) and subtraction (S). These operations yield high-density outcomes and facilitate the exploitation phase in mathematical calculations. Unlike other operators, S and A converge rapidly towards the target due to their low dispersion. After multiple iterations, the exploitation search algorithm successfully identifies a near-optimal solution. In the optimization phase, S and A operators enhance exploitation by improving communication between them. The search phase executes S or A for exploitation, ensuring $r_1 \leq MOA(C_{Iter})$ (Equation 13). AOA employs Subtraction (S) and Addition (A) operators to explore dense regions and enhance the solution. The search strategies are formulated in Equation (16).

4 $$X_{i,j}(C_{Iter}+1) = \begin{cases} best(X_j) - MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right), \\ best(X_j) + MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right) \end{cases}$$
r3 < 0.5 otherwise (16)

This phase implements an exhaustive search approach, utilizing the entire search space. The second operator (A) remains inactive until the completion of the first operator (S), following the rule in Equation (16). If the first operator (S) is unavailable, it is replaced by the second operator (A) to achieve the current objective. The partitions used in this phase are similar to those in the previous phase. However, the exploitation search operators (S and A) aim to avoid the local search area. This allows for exploratory search strategies to discover the optimal solution while maintaining a diverse range of potential solutions. To ensure consistent exploration, stochastic values are generated for each iteration. This search segment is particularly beneficial in later iterations when encountering stagnation in local optima. The positions of search solutions in a 2-dimensional search space are modified using the parameters $D, M, S, and\ A$. The ultimate position may fall within a statistical range defined by the placements of $D, M, S, and\ A$. Other factors include approximating the position of suboptimal solutions using D, M, S, A, and probabilistic adjustments to nearby alternative solutions.

3.4.4 Improvement in AOA

Numerical calculations have improved significantly due to position update-based arithmetic optimization methods. Position updates. The position update step changes arithmetic expressions or solutions, allowing for the investigation of alternative operands and operations. These modified placements are then fitness-tested. The method improves speed and efficiency by repeatedly updating its location. This method lets the algorithm overcome local optima and find better arithmetic setups by exploring the search space. Position updates in arithmetic optimization methods enhance numerical calculations over time.

4 $$X_{i,j}(C_{Iter}+1) = X_{i,j}(C_{Iter}+1) - g\sum_{i=j}^{n} \frac{x_i - best(X_j)}{r_{ij}} \quad if\ r < 0.5 \qquad (17)$$

The formula for g balances exploration and exploitation. $If\ r < 0.5$, equation (17) updates the location, otherwise (14) does.

5 $$g = g_{max} - t\frac{g_{max} - g_{min}}{T}$$
(18)

The parameter g is represented by g_{max} and g_{min}, which respectively denote its maximum and minimum values. The variable t represents the current iteration, while T represents the maximum iteration. The maximum g_{max} in the IAOA system is equal to 1, while the minimum g_{min} is equal to 0.000001. The Improve arithmetic optimization algorithm (AOA) begins by generating a set of arbitrary candidate solutions. During the iterative process, the operators $D, M, S, and\ A$ are used to determine potential positions for the nearly optimal solution. Each solution adjusts its positions based on the identified optimal solution. The MOA parameter is incrementally increased from $0.2\ to\ 0.9$ in a linear fashion to balance exploration and exploitation. The solution candidates aim to deviate from the near-optimal solution when $r_1 > MOA$ and converge towards it when $r_1 < MOA$. Once the desired goal is reached, the AOA algorithm terminates. The suggested AOA is described without numbering. It is presented in Algorithm 3.1, which provides the pseudo-code.

Algorithm Error! No text of specified style in document.**-1 Improved AOA**

Algorithm 1: The arithmetic optimization algorithm's (AOA) pseudo-code

1 Start the parameters of Arithmetic Optimization Algorithm α, µ.

2 Start the outcomes positions arbitrarily. (Outcomes: i = 1,2,...,N-1 ,N.)

3 While (C_Iter < M_Iter) do

4 For provided solution calculate the Fitness Function(FF)

5 Get the ideal solution

6 By applying equation (13), modify the math optimizer acceleration (MOA) value

```
By applying equation (15), modify the math optimizer probability (MOP) value
    For (i = 1 to Outcomes) do
        For (j = 1 to Locations) do
            Make a arbitrary range of values within [0, 1] (r1,r2, and r3)
            If r1 > MOA then
                Exploration phase
                If r2 > 0.5 then
                    (1) Employ the Division procedure (D "÷")
                    Update the i^thoutcome location by using the first rule in Eq. (17)
                Else
                    (2) Employ the Multiplication procedure (M "×")
                    Update the i^th outcome location using the second rule in Eq. (14).
                End if
            Else
                Exploitation phase
                If r3 > 0.5 then
                    (1) Employ the Subtraction procedure (S "-")
                    Update the i^th outcome location using the first rule in Eq. (16)
                Else
                    (2) Employ the Addition math operator (A "+")
                    Update the i^th outcome location using the second rule in Eq. (16).
                End If
            End If
        End For
    End For
    C_Iter= C_Iter+1
End While
Return the possible ideal outcome (y).
```

4. Results

IAOA algorithms efficiently size and place multiple DG units, as demonstrated through testing on a reconfigured IEEE-69 bus radial distribution system. The study involved five DG simulations to identify optimal DG distribution network sites. The Improved Arithmetic Optimization Algorithm effectively optimized DG placement, resulting in improved system voltage profile, reduced voltage deviations, dips, and unbalances, enhanced voltage stability, and improved power quality. DG installation also led to decreased active losses and increased energy efficiency, resulting in lower distribution system costs. The research provided valuable insights into voltage profile enhancement and loss reduction objectives in the distribution system. The convergence curve of the arithmetic optimization algorithm showed significant improvement, with fitness values approaching optimal solutions. These findings demonstrate the resilience and efficiency of the updated arithmetic optimization approach. Fig. 4.1 illustrates the convergence curve of DG deployment, indicating quicker convergence and faster stabilization of fitness with the enhanced algorithm. The balance between exploration and exploitation was achieved, resulting in a smoother convergence curve compared to the original method, which required more iterations for optimal results.

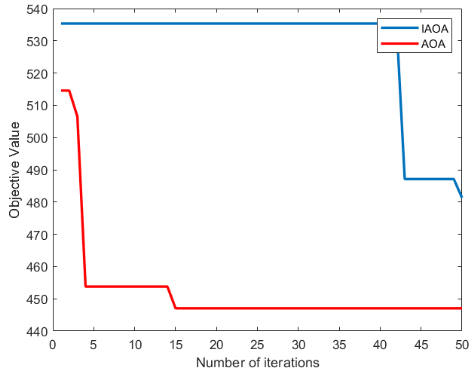

Figure Error! No text of specified style in document.**-3** Convergence curve for AOA and IAOA

The convergence curves show that the improved arithmetic method is faster and more efficient than the original approach. The upgraded algorithm's rapid convergence yields better solutions faster, making it a more effective optimization method. The arithmetic optimization algorithm's enhancements demonstrate its usefulness and ability to solve complex optimization problems.

1.1 Multiple DG Placement

The research on how to arrange several Distributed Generators (DGs) in a distribution network to maintain voltage profile and reduce losses yielded interesting results. To achieve the aims, the study identified the best distribution network locations for distributed generators (DGs).

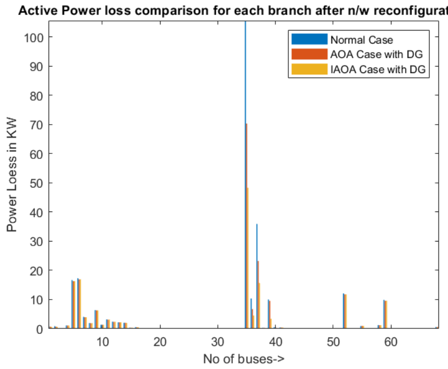

Figure Error! No text of specified style in document.**-4** Active Power Loss Comparison

Advanced optimization approaches showed that strategically placing several distributed generators (DGs) improved the voltage profile throughout the network. Voltage stability and power quality improved after reducing voltage deviations, dips, and unbalances. One DG simulates the system. After the network is rebuilt using IAOA, AOA, active power loss and voltage profile are addressed for each Bus in a single graph. Multiple DGs reduced system losses, improving energy efficiency and cost savings. The research examined several DGs' capacity and location modifications and did sensitivity analysis to test the suggested solution's resilience. The results show that the proposed methodology can achieve voltage profile enhancement and loss reduction objectives by optimally placing multiple DGs in distribution systems, providing valuable insights for distributed generation technology integration.

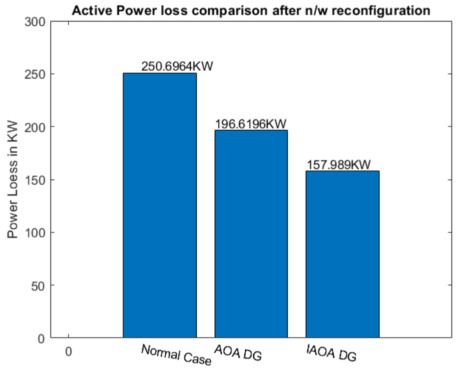

Figure Error! No text of specified style in document.**-5** Total Power Loss Comparison

Fig. 4.2 shows branch loss for 69 buses. Network design shows active power loss for normal, AOA, and IAOA. As shown in Fig. 4.1, the cost of running the system with the electrical grid and adding DG to every bus minimizes bus power loss. At buses 30-40, IAOA reduces active power loss by 55% and AOA by 30%. The method reduces power losses and boosts distribution system efficiency. Managing a larger electricity distribution network becomes more complicated. Addressing voltage profile issues and power losses requires DG unit installation. As seen in Fig. 4.3, AOA reduces power loss by 21.570%. IAOA reduces power loss 36.979%. IAOA may enhance the voltage profile by strategically adding DG units, keeping the power distribution network within acceptable voltage limits. Fig. 4.4 shows voltage profile.

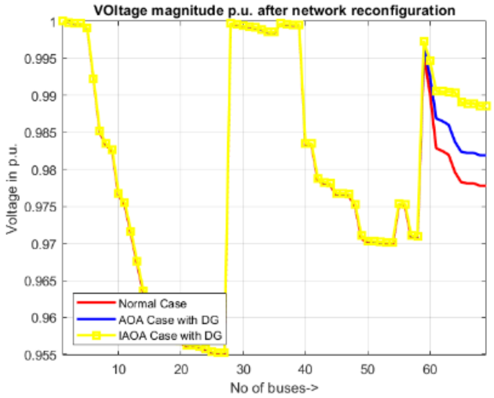

Figure Error! No text of specified style in document.**-6** Voltage Profile

5. CONCLUSIONS

This research studied the best distribution of distributed generation (DG) based on nodal pricing for profit maximization, loss minimization, and voltage enhancement to address voltage increase. The study enhanced arithmetic optimization to solve DG allocation problems. The thesis showed how nodal pricing might improve power system economic efficiency and profit for the system operator. Optimal DG placement reduces system losses and improves system performance. This thesis shows that nodal pricing-based DG allocation and the enhanced arithmetic optimization technique provide considerable advantages. Profits, system losses, and voltage stability improve. The findings help power system designers, operators, and regulators allocate DGs in their networks. However, further study is needed to evaluate and improve the algorithm in real-world circumstances. Future research should include renewable energy integration, system dependability, and environmental effect to make the suggested strategy completer and more applicable.

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