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Review of Power Loss and Voltage Improvement Optimization Algorithms in Electricity Distribution Network

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Abstract: *The The optimization of electricity distribution networks is crucial for enhancing efficiency, reducing power losses, and improving voltage profiles. Distribution systems, typically radial in structure, face various challenges such as voltage drops and losses due to long transmission distances and low-voltage networks. These challenges require comprehensive solutions that integrate optimization algorithms to ensure cost-effective, reliable, and efficient power delivery. Various algorithms have been developed over the past decade to address the challenges associated with \ optimal DG placement, minimizing power losses, and enhancing voltage profiles. This critical review examines and evaluates the major algorithms used in these areas, including classical optimization methods, heuristic techniques, metaheuristic approaches, and hybrid algorithms. Metaheuritics (GA, PSO, DE) effectively handle non-linear, multi-objective DG optimization problem. Hybrid algorithms combine techniques strengths, enhancing search processes. Algorithm choice depends on network specific requirement. Each method is analyzed regarding its computational complexity, convergence behavior, and real-world applicability.*

Keywords: *Classical optimization, Heuristic optimization techniques, Metaheuristic optimisation, Hybrid algorithms, Distribution systems.*

INTRODUCTION

Electricity distribution networks are vital for transmitting electrical energy from substations to consumers. However, they are subject to inefficiencies due to power losses and voltage instability.

Power losses typically result from the inherent resistance in conductors, while voltage fluctuations are influenced by load imbalances and system configurations. With the rapid integration of Distributed Generators (DGs), optimizing the placement and sizing of these units is essential to enhance system efficiency. Various optimization algorithms have been developed to address these issues, with the primary objectives of minimizing power losses and improving voltage profiles.

Power losses are commonly categorized as technical and non-technical losses. Technical losses stem from energy dissipation in electrical components such as transformers and conductors (Jafari and Vahidinasab, 2019), while non-technical losses relate to theft, metering errors, and other administrative issues (Kumar and Sharma, 2020). The technical losses in particular can account for up to 13% of the total power generated in some distribution systems (Parihar *et al.,* 2018). These losses increase operational costs and reduce overall efficiency, necessitating the implementation of loss-reduction strategies. The majority of losses in distribution systems are I^2R losses (where I is the current and R is the resistance of conductors), which are directly proportional to the square of the current and the resistance of the lines (Vasquez *et al.,* 2016; Reddy *et al.,* 2016). This relationship indicates that one effective way to reduce power losses is to minimize the current flowing through the distribution network by employing proper optimization techniques, such as load balancing and capacitor placement. Technical losses account for the bulk of energy wastage and are a key target for optimization strategies. Voltage profiles refer to the voltage levels measured at different points within a distribution network. Poor voltage profiles occur when voltage levels deviate from the nominal values, leading to inefficient equipment operation and potential instability. Voltage drops are especially common in radial distribution networks, which have long lines with high impedance (Baghaee *et al.,* 2018). Maintaining a stable voltage profile within the acceptable range is essential for reliable and efficient power delivery (Farahani *et al.,* 2020). The acceptable voltage range is typically regulated by utility companies and is usually within ±5% of the nominal voltage (Kansal and Swarup, 2011). Improving the voltage profile is critical not only for reducing losses but also for ensuring the proper operation of customer equipment. Poor voltage profiles can lead to equipment failure, reduced operational life of devices, and customer dissatisfaction. Therefore, various optimization algorithms have been developed to address voltage profile issues and enhance overall system performance (Ameli *et al.,* 2021).

The introduction of Distributed Generators (DGs) has shown significant potential for reducing power losses. Properly sized and located DGs reduce the amount of current flowing through long distribution lines, thus minimizing I^2R losses (Zhang *et al.,* 2017). Capacitor banks are another solution to improve reactive power compensation, reducing the reactive power flows and thereby lowering technical losses (Shekari and Mohammadi, 2018). With the rising integration of DGs such as renewable energy sources, they have become a pivotal component in modern electrical distribution networks. Proper placement and sizing of DGs are crucial to achieving key objectives such as minimizing power losses, improving voltage profiles, and enhancing overall system reliability. The placement problem, however, involves solving complex nonlinear optimization problems that must consider multiple variables and constraints such as network topology, load demand, and generation limits.

Several techniques have been developed to enhance voltage profiles, with DG integration being one of the most effective. DGs provide localized generation, which reduces the current drawn from the substation and mitigates voltage drops along distribution feeders (Hashemi *et al.,* 2020). Additionally, voltage regulators, such as on-load tap changers and capacitor banks, are employed to adjust voltage levels dynamically (El-Fergany, 2018).

This review explores the evolution of algorithms used to optimize DG placement. The review is structured into sections covering classical optimization methods, heuristic techniques, metaheuristic approaches, and hybrid algorithms. The strengths and limitations of these algorithms are discussed, focusing on their effectiveness in reducing power losses and improving voltage profiles in electrical distribution systems.

MATERIALS AND METHODS

2. Optimization Algorithms for Power Loss Reduction and Voltage Profile Improvement

The various optimisation algorithms that have been employed for the optimisation of DG placements, power loss reduction and voltage profile improvement are:

2.1 Classical Optimization Methods

Classical optimization techniques, including Linear Programming (LP), Nonlinear Programming (NLP), Mixed-Integer Programming (MIP), and Quadratic Programming (QP), provide deterministic solutions for power system optimization problems (Reddy *et al.,* 2016).

2.1.1. Linear Programming (LP)

Linear Programming (LP) is one of the most well-established optimization techniques, used for problems where both the objective function and constraints are linear. In the context of distribution networks, LP has been employed to optimize power flows, minimize losses, and improve voltage profiles, especially in small to medium-sized systems (Amini *et al.,* 2016). LP's effectiveness stems from its simplicity and ease of application in well-structured problems (Ghosh and Shankar, 2017). However, LP is limited when dealing with nonlinear relationships common in power systems (Amini *et al.,* 2016), such as those found in the modeling of reactive power flows and voltage variations. Despite this limitation, LP has been successfully applied in scenarios where linear approximations are valid. LP can be applied to minimize power losses by optimizing the dispatch of DGs and reactive power compensation devices. For instance, LP-based models have been used to determine the optimal sizing and placement of capacitor banks, which improve voltage profiles and reduce I^2R losses in distribution lines (El-Fergany, 2018). Additionally, LP models are useful for allocating DGs in locations that can enhance voltage stability and reduce power losses (Amini *et al.,* 2016).

2.1.2 Nonlinear Programming (NLP)

NLP is used when the objective function or constraints of the optimization problem are nonlinear (Shekari and Mohammadi, 2018; Momoh, El-Hawary, and Adapa, 1999). Power systems are inherently nonlinear due to the relationship between voltage, current, and impedance, making NLP a more appropriate choice for optimizing larger, more complex systems than LP. NLP techniques have been applied to minimize power losses by considering the nonlinear nature of voltage drops in radial distribution networks (Prakash and Khatod, 2016). By incorporating voltage constraints and system losses into the optimization model, NLP provides a more accurate solution than LP for improving voltage profiles (Prakash and Khatod, 2016). NLP is also used in optimal power flow (OPF) problems, where the goal is to minimize power losses while maintaining voltage levels within specified limits (Zhang *et al.,* 2017). However, NLP methods can be computationally intensive, especially for large-scale systems with multiple nonlinear constraints. Shekari and Mohammadi (2018) applied NLP to optimize DG placement for minimizing power losses and voltage deviations. The study demonstrated the effectiveness of NLP in solving complex DG placement problems. However, NLP methods often struggle with convergence issues and may require significant computational resources.

2.1.3 Mixed-Integer Programming (MIP)

Mixed-Integer Programming (MIP) is an extension of LP and NLP where some decision variables are restricted to integer values (Reddy *et al.,* 2016). This is particularly useful for problems where decisions are binary (e.g., whether or not to install a device) or where the number of units of equipment is discrete. MIP has been widely used for the optimal placement of DGs and capacitors in distribution networks to reduce power losses and improve voltage profiles. The placement problem often requires binary decisions, such as determining the exact locations for DGs or capacitor banks (Sahoo and Prasad, 2017).

MIP models are especially effective in handling discrete optimization problems like these, ensuring that the solution is practical and implementable in real-world systems. MIP's strength lies in its ability to handle both continuous and discrete variables, making it ideal for mixed-variable optimization problems in power systems. However, MIP suffers from scalability issues, as the computational complexity increases exponentially with the size of the problem (El-Ela *et al.,* 2019). Reddy *et al.* (2016) used MIP for minimizing active power losses and improving voltage profiles, demonstrating the algorithm's effectiveness in small to medium-sized networks. However, MIP's computational complexity increases exponentially with system size, making it less suitable for large networks.

2.1.4 Quadratic Programming (QP)

Quadratic Programming (QP) is a type of optimization where the objective function is quadratic, and the constraints are linear (Conejo *et al.,* 2002). This method is particularly useful for problems involving quadratic cost functions, such as those used in the modelling of energy losses in distribution networks. QP has been employed in optimal power flow problems, where the objective is to minimize the quadratic cost of power losses while maintaining voltage levels within permissible ranges (Baghaee *et al.,* 2018). The quadratic nature of the objective function in these problems accurately reflects the relationship between power flows and losses, making QP an effective tool for improving both power losses and voltage profiles. However, like other classical methods, QP is limited in its application to linear constraints and may not be suitable for more complex, nonlinear systems (Sinha *et al.,* 2016).

2.1.5 Dynamic Programming (DP)

Dynamic Programming is a technique that solves complex problems by breaking them down into simpler sub problems, solving each sub problem, and combining the solutions. In power distribution networks, DP is used to optimize decisions over time, such as optimal switching sequences for network reconfiguration and load management (Bellman, 1957). It is particularly useful in scenarios where the optimization problem involves a series of decisions, such as determining the best configuration of the network under changing load conditions (Sarfi *et al.,* 1994).

2.1.6 Lagrangian Relaxation (LR)

Lagrangian Relaxation is a classical optimization technique used to solve constrained optimization problems by relaxing some of the constraints using Lagrange multipliers. In the context of power distribution, LR has been applied to OPF and other related problems where the objective is to minimize losses while satisfying a set of constraints such as power balance, voltage limits, and line flow limits (Batidzirai *et al.,* 2006). LR is particularly useful in large-scale optimization problems, such as optimal reactive power dispatch and capacitor placement.

2.1.7 Gradient Descent Methods

Gradient Descent is an iterative optimization algorithm used to find the minimum of a function by moving in the direction of the steepest descent (negative gradient) from the current point. In power distribution systems, gradient descent methods are used to optimize load flows, reduce losses, and improve voltage profiles by iteratively adjusting network parameters (Sun, 1986).

These methods are efficient for solving OPF problems and can be used in conjunction with other techniques to achieve better performance in large networks (Carpentier, 1962).

2.2 Heuristic and Metaheuristic Algorithms

Heuristic and metaheuristic optimization techniques emerged in the late 1970s to address the limitations of traditional methods like Linear Programming (LP), Nonlinear Programming (NLP), and Dynamic Programming (DP) (Rao and Keesari, 2018). A heuristic is designed to solve problems more quickly when conventional methods are too slow or inefficient. In contrast, a metaheuristic is a higher-level approach that generates or selects heuristics to provide sufficiently good solutions to optimization problems (Attea *et al.,* 2021). These techniques were developed to manage challenges such as nonlinearity, multi-objective optimization, and uncertainty (Fayaed *et al.,* 2013). Metaheuristics are broadly categorized into two types: population-based and neighborhood-based algorithms (Kumor and Yadav, 2022). Population-based algorithms include evolutionary computation and swarm intelligence approaches, which are known for their flexibility and ability to find global solutions more efficiently. These techniques rely on an initial population of solutions, which are randomly generated, and they evolve towards a global solution using probabilistic methods. Examples of evolutionary computation methods include Genetic Algorithm (GA), Differential Evolution (DE), Genetic Programming (GP), Evolutionary Programming (EP), and Evolutionary Strategies (ES) (Du & Swamy, 2016). Swarm intelligence-based methods consist of algorithms like Ant Colony Optimization (ACO), Harmony Search (HS), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Bat Algorithm (BA), Honey Bee Mating Optimization (HBMO), and Shuffled Frog Leaping Algorithm (SFLA). On the other hand, neighbourhood-based algorithms, such as Simulated Annealing (SA) and Tabu Search (TS), focus on exploring the neighbourhood of the current solution to find improvements (Kumar & Yadav, 2021). These metaheuristic methods provide robust solutions to complex optimization problems, adapting to various system constraints and requirements. The applications of heuristic and Metaheuristic algorithms for power loss reduction and voltage profile improvement are discussed herein:

2.2.1 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are widely used for optimizing distribution networks due to their ability to find near-optimal solutions for complex, multi-objective problems (Araujo and Tsuzuki, 2015). GAs is especially effective in solving non-linear optimization problems such as reactive power compensation, network reconfiguration, and capacitor placement, which are common techniques for reducing power losses and improving voltage profiles (Sinha *et al.,* 2016). By evolving a population of possible solutions through crossover, mutation, and selection, GAs can explore a vast search space and identify optimal network configurations (Mistry and Roy, 2015). It has been applied for determining the optimal placement and sizing of distributed generators (DGs), leading to reduced power losses and enhanced voltage stability. Reddy *et al.* (2016) demonstrated the use of GA to reduce losses and improve voltage profiles by optimal capacitor placement.

2.2.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is another popular algorithm that has been applied to reduce power losses and improve voltage stability. PSO is based on the social behaviour of birds flocking or fish schooling and is known for its fast convergence speed (Baran and Wu, 2013). In the context of power distribution, PSO has been successfully employed in network reconfiguration, optimal placement of Distributed Generation (DG), and reactive power compensation to minimize losses and enhance voltage profiles (Mokhlis *et al.,* 2010). Ghosh and Shankar (2017) applied PSO to a radial distribution network and achieved significant improvements in both power loss reduction and voltage regulation.

Similarly, Farahani *et al.,* (2020) used PSO for voltage profile enhancement in large-scale distribution systems. Zhang *et al.* (2017) also applied PSO to optimize DG placement, reducing power losses and enhancing voltage profiles in a distribution network. While PSO has proven effective, its performance can be highly sensitive to the selection of parameters, and it may converge prematurely if not properly tuned.

2.2.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) has also been applied to distribution network optimization. ACO mimics the foraging behaviour of ants to find optimal paths in graphs. In the case of distribution networks, ACO has been used for network reconfiguration and capacitor placement, leading to reduced power losses and improved voltage profiles (Zhu, 2015). ACO is particularly useful in scenarios where the search space is discrete and where network constraints are present. Kumar and Sharma (2020) utilized ACO to optimize the placement of DG units in distribution networks, resulting in reduced power losses and voltage profile enhancement.

2.2.4. Simulated Annealing (SA)

Simulated Annealing mimics the annealing process in metallurgy, where materials are heated and cooled to alter their physical properties. SA is known for its robustness in escaping local minima. SA is a probabilistic optimization technique that accepts worse solutions with a certain probability, which helps to avoid local minima. El-Ela et al. (2019) demonstrated the application of SA in optimizing DG placement to minimize power losses in distribution networks. SA's ability to escape local optima makes it valuable for complex systems, but it requires careful tuning of its cooling schedule to ensure convergence. El-Ela *et al.* (2019) applied SA to optimize DG placement in distribution networks, showing its efficacy in reducing losses and maintaining voltage stability.

2.2.5. Differential Evolution (DE)

Differential Evolution (DE) is a robust, population-based optimization method used in power system optimization. Jafari and Vahidinasab (2019) successfully applied DE to minimize power losses through optimal DG placement, showing that it is highly effective in large-scale networks. DE's ability to handle nonlinearity makes it an excellent choice for real-world applications. Several studies have demonstrated the effectiveness of DE in minimizing power losses through optimal DG placement and sizing. For example, Mistry and Roy (2015) applied DE to a radial distribution network, optimizing the placement and sizing of DGs to minimize power losses. Their results showed that DE outperformed traditional optimization methods, providing significant reductions in power losses while maintaining acceptable voltage levels throughout the network. Similarly, Abu-Mouti and El-Hawary (2011) used DE to optimize the location and size of DGs in a 69-bus radial distribution system, achieving reductions in both active and reactive power losses.

The basic approach in these studies involves setting up an objective function that minimizes power losses subject to constraints such as voltage limits, power balance, and DG capacity limits. DE evolves an initial population of randomly generated candidate solutions (comprising different DG locations and sizes), and through iterative improvements, it converges to an optimal or near-optimal solution that satisfies the system constraints. Gandhi and Allamsetty (2017) applied DE to optimize DG placement in a 33-bus distribution system, aiming to improve the voltage profile. Their results demonstrated that DE was capable of improving the voltage profile significantly, with voltage levels at all buses maintained within acceptable limits. In comparison to traditional techniques, DE provided superior results due to its ability to explore a wider solution space and avoid local minima.

2.2.6 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is inspired by the foraging behaviour of ants. Kumar and Sharma (2020) applied ACO to solve the DG placement problem, demonstrating its ability to minimize power losses and enhance voltage profiles. ACO is particularly effective in handling discrete problems but requires significant computational resources for larger networks. ACO is a population-based algorithm, where the solution is constructed incrementally through probabilistic transitions based on the pheromone levels and heuristic information.

The algorithm is well-suited for discrete optimization problems and has been adapted for continuous optimization tasks, including DG placement and sizing in power systems. Prakash and Lakshminarayana (2007) applied ACO to optimize DG placement in a radial distribution system, minimizing power losses while ensuring voltage stability. Their results showed that ACO could effectively identify the optimal locations and sizes of DGs, leading to significant reductions in power losses compared to conventional methods. Similarly, Moradi and Abedini (2012) applied an ACO-based algorithm to a 33-bus distribution system, achieving substantial improvements in power loss reduction and voltage profile enhancement. In another study by Kaur and Kamboj (2018), ACO was used to improve the voltage profile in a distribution network by optimizing the placement and sizing of DG units. The results indicated that ACO could significantly enhance the voltage profile, with voltage levels maintained within acceptable limits across all buses. Similarly, Amin *et al.* (2013) applied ACO to a 69-bus distribution system, showing that ACO was capable of optimizing DG placement for both power loss reduction and voltage profile improvement. In multi-objective optimization, ACO can be adapted by introducing multiple objective functions, or by using a weighted sum approach to combine different objectives into a single scalar function. For example, Niknam *et al.* (2011) proposed a multi-objective ACO algorithm for DG placement in distribution networks, optimizing both power loss reduction and voltage stability. Their approach showed that ACO could efficiently find a set of Pareto-optimal solutions, allowing system operators to choose the best trade-offs between competing objectives.

2.2.7 Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) is another bio-inspired algorithm based on the foraging behavior of honey bees. Yahia *et al.* (2020) used ABC to optimize DG placement in distribution networks, showing promising results in terms of reducing power losses and improving voltage profiles. However, ABC can suffer from slow convergence in complex networks. The ABC algorithm has been applied successfully to optimize DG placement and sizing for power loss minimization. Typically, an objective function is defined to minimize active power losses, subject to system constraints such as voltage limits, power balance, and DG capacity limits. The algorithm's ability to balance exploration and exploitation makes it well-suited for finding global optima in large, complex solution spaces. In a study by Roy and Sultana (2016), the ABC algorithm was applied to minimize power losses by optimizing the placement and sizing of DG units in a radial distribution network. The results showed that ABC could achieve significant reductions in power losses compared to traditional methods, providing near-optimal solutions with fewer computational resources. The study highlighted ABC's effectiveness in dealing with the non-linearity of the power flow equations and its robustness in finding optimal DG configurations. In another study, Rao and Ravindra (2014) applied ABC to a 33-bus radial distribution system to optimize DG placement and sizing for power loss minimization. The results demonstrated that ABC could reduce active power losses significantly while maintaining voltage levels within acceptable limits. Additionally, the ABC-based approach outperformed other metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), in terms of both solution quality and computational efficiency.

2.2.8 Hybrid Heuristic Algorithms

Hybrid approaches, combining two or more heuristic techniques, have shown promise in addressing the complexities of distribution network optimization. For instance, Hashemi, Ramezani, and Mahdavi (2020) proposed a hybrid Differential Evolution (DE) and PSO algorithm for optimal DG placement, achieving superior performance in loss minimization and voltage profile improvement compared to single-method approaches. Another study by Jafari and Vahidinasab (2019) combined GA and PSO, yielding excellent results in minimizing power losses in radial networks.

One other popular hybrid approach used for power loss minimization is the combination of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The PSO-GA hybrid algorithm integrates the strong exploration capabilities of PSO with the powerful exploitation and crossover capabilities of GA. In this combination, PSO explores the global search space, while GA enhances local search by applying selection, crossover, and mutation operators. Moradi and Abedini (2012) presented the hybrid of PSO-GA algorithm applied to a 33-bus radial distribution system to optimize DG placement and sizing. The results showed that the hybrid approach outperformed both standalone PSO and GA in terms of power loss reduction and convergence speed. The hybrid algorithm effectively reduced active power losses by identifying the optimal DG locations and sizes, with the combination of PSO and GA providing a balance between exploration and exploitation. Another hybrid approach that has been used for power loss minimization is the combination of Genetic Algorithm (GA) and Artificial Bee Colony (ABC) algorithm. This hybrid technique utilizes the global search capabilities of ABC, which mimics the foraging behavior of honey bees, and combines it with GA's efficient search operators. The GA-ABC hybrid enhances the search process by balancing local refinement (GA) with global exploration (ABC). Abdelaziz *et al.* (2014) applied the GA-ABC hybrid algorithm to minimize power losses in a distribution network with DG units. The results demonstrated that the hybrid algorithm achieved superior performance compared to standalone GA and ABC, with a significant reduction in power losses and improved convergence efficiency. This hybrid approach allowed for better handling of the non-linear, multi-modal nature of the power loss minimization problem.

3. Comparison of Power Loss and Voltage Improvement Optimization Algorithms in Electricity Distribution Networks

Table-1 shows the comparison of power loss and voltage improvement optimization algorithms in electricity distribution networks. The table compares the methods, advantages, disadvantages of the various approaches.

Table-1 Comparison of power loss and voltage improvement optimization algorithms in electricity distribution networks

Algorithm	Advantages	Disadvantages	Reference
Ant Colony Optimization (ACO)	- Multi-objective optimization - Can find optimal placement and sizing of distributed generation	- May have slow convergence - High computational complexity	Kaur & Kamboj (2018); Kumar & Sharma (2020)
Genetic Algorithm (GA)	- Global optimization capability - Can handle complex constraints	- Premature convergence - Dependent on parameter tuning	Moradi & Abedini (2012); Mistry & Roy (2015); Roy & Sultana (2016)
Particle Swarm Optimization (PSO)	- Fast convergence - Easy to implement	- Sensitive to parameter settings	Mokhlis *et al.* (2010); Mistry & Roy (2015)

		- Can get stuck in local minima	
Artificial Bee Colony (ABC)	- Good balance between exploration and exploitation - Simple to implement	- Slow convergence in some cases - Requires careful parameter tuning	Rao & Ravindra (2014); Roy & Sultana (2016)
Differential Evolution (DE)	- Good for continuous optimization - Robust against getting trapped in local minima	- Can be computationally intensive - Not suitable for highly constrained problems	Mistry & Roy (2015)
Jaya Algorithm	- No algorithm-specific parameters - Simple and effective	- Requires modification for complex problems	Rao & Keesari (2018); Kumar & Yadav (2018)
Non-Linear Programming (NLP)	- Provides exact solutions for small-scale problems - Well-suited for voltage profile optimization	- Computationally expensive for large-scale systems - Difficult to handle multiple objectives	Shekari & Mohammadi (2016); Zhang *et al.* (2017)
Hybrid Algorithms (GA + PSO)	- Combines strengths of GA and PSO - Improved convergence speed	- Increased complexity - May require more computation time	Moradi & Abedinim (2012); Vasquez *et al.* (2016)
Mixed-Integer Programming (MIP)	- Exact solutions for discrete and continuous variables - Suitable for distributed generation siting	- Computationally expensive for large systems - Sensitive to problem formulation	Sahoo & Prasad (2017)
Quadratic Programming (QP)	- Efficient for convex problems - Well-suited for power loss minimization	- Limited to quadratic objective functions - May not handle non-linear constraints effectively	Sinha *et al.* (2016)

Table-2 shows the optimization algorithms for power loss minimization and voltage profile improvement in distribution networks, categorized by strongest, strong and weak in terms of specific problem and context

Table-2 Optimization algorithms for power loss minimization and voltage profile improvement in distribution networks

STRONGEST	STRONG	WEAK
1.Hybride algorithms (PSO-GA, DE-PSO, GA-ABC)	1.Anty colony optimization (ACO)	1.Linear Programming (LP)
2.Differential Evolution (DE**)**	2.Simulated annealing (SA)	2. Nonlinear programming (NLP)
3Genetic Algorithm (GA)		3. Dynamic Programming (DP) 4.Quadratic Programming

CONCLUSION

Optimization algorithms have evolved significantly, with heuristic, metaheuristic, and hybrid methods becoming the preferred tools for power loss minimization and voltage profile improvement in distribution networks. Metaheuristic algorithms such as GA, PSO, and DE have proven effective in handling the non-linearity and multi-objectivity of DG optimization problems. Hybrid algorithms further enhance the search process by combining the strengths of different techniques. While each algorithm has its strengths and limitations, the choice of optimization technique depends on the specific requirements of the distribution network, including computational efficiency, robustness, and the complexity of the problem.

CONFLICT OF INTEREST

There is no conflict of interest for this research work

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