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HYBRID TECHNIQUES FOR OPTIMAL REACTIVE POWER DISPATCH: A COMPREHENSIVE REVIEW

[1]Srikant Kalekar, [2]Prabhu, [3]Sharad Darshan

[1]Ph.D. Scholar, [2]Assistant Professor, [3]Assistant Professor
[1]Srinivas University, Karnataka, India
[2]B.M.S. College of Engineering, Bengaluru, India
[3]B.M.S. College of Engineering, Bengaluru, India

Abstract : Reactive power planning and optimization play a crucial role in maintaining voltage stability, reducing power losses, and achieving efficient and economic operation of modern power systems. As power grids become increasingly complex, traditional optimization techniques face challenges in handling the non-linear, multi-objective, and highly constrained nature of optimal reactive power dispatch (ORPD) problems. To address these complexities, hybrid metaheuristic algorithms have emerged as powerful tools, combining the strengths of individual optimization techniques to enhance exploration, exploitation, and convergence. This paper reviews the contributions of various hybrid approaches which are applied to standard IEEE test systems to optimize control variables, minimize transmission losses, improve voltage profiles, and manage reactive power resources under varying system conditions. Comparative analyses demonstrate the superiority of hybrid algorithms over traditional methods, highlighting their robustness and effectiveness in achieving superior solutions to complex ORPP challenges. This review consolidates key advancements, providing a foundation for future research in hybrid metaheuristic optimization for power system applications.

IndexTerms - Reactive power planning, Optimal reactive power dispatch, Optimization techniques, Hybrid optimization techniques and voltage stability.

I. INTRODUCTION

Optimal reactive power dispatch (ORPD) is a critical aspect of power system operations, ensuring voltage stability, minimizing power losses, and improving the overall efficiency of electric power networks. The ORPD problem involves the optimization of multiple objectives, such as reducing transmission power losses, enhancing voltage profiles by minimizing voltage deviations, and maintaining system constraints within permissible limits. This optimization is achieved through the tuning of specific control parameters, including generator bus voltages, transformer tap settings, and the placement and sizing of shunt capacitors. Achieving these objectives requires addressing the highly nonlinear, multi-objective, and constrained nature of the ORPD problem.
Traditionally, several classical optimization techniques have been employed to solve the ORPD problem, including linear programming (LP) [1], quadratic programming (QP) [2], interior point methods [3], Newton-Raphson approaches [4], and dynamic programming [5]. While these methods provided foundational approaches to solving ORPD, they suffered from significant limitations. These include high computational overhead due to numerous numerical iterations, difficulty in handling nonlinearity, and reliance on approximations that can compromise solution accuracy. Additionally, these methods often struggle with local optima and lack robustness in solving highly constrained, real-world problems.
In recent years, substantial progress has been made in the field of optimization techniques, particularly with the advent of metaheuristic algorithms. Unlike conventional optimization methods, metaheuristic approaches are highly versatile and capable of tackling complex, nonlinear, and multi-objective problems, making them especially suitable for addressing challenges in ORPD. Metaheuristic algorithms are inspired by natural phenomena, biological systems, and social behaviors, enabling them to explore and exploit the solution space effectively while adapting to the dynamic constraints of ORPD problems.
Several metaheuristic techniques have been applied to ORPD with notable success. For instance, particle swarm optimization (PSO) [6], inspired by the social behavior of bird flocking, has been extensively used due to its simplicity and ability to converge rapidly. Genetic algorithms (GA) [7], based on the principles of natural selection and evolution, have proven effective in exploring large search spaces and avoiding local optima. Other techniques, such as wind-driven optimization (WDO) [8], inspired by atmospheric motion dynamics, and bacteria foraging optimization (BFO) [9], modeled on the foraging behavior of bacteria, have shown strong performance in addressing specific ORPD objectives, such as minimizing power losses and enhancing voltage stability.

Despite their advantages, standalone metaheuristic algorithms face inherent challenges, particularly in balancing exploration (searching broadly across the solution space) and exploitation (refining the best solutions). This trade-off often results in issues like premature convergence or suboptimal performance in highly constrained, real-world ORPD scenarios. To overcome these limitations, hybrid optimization techniques have emerged as a powerful alternative.

Hybrid optimization techniques combine the strengths of multiple metaheuristic algorithms, creating synergistic solutions that address the weaknesses of individual approaches. By leveraging the complementary capabilities of different algorithms, hybrid methods achieve superior performance in terms of convergence speed, solution accuracy, and robustness. For example, the combination of Grey Wolf Optimization (GWO) [10] with PSO enhances exploration capabilities while maintaining exploitation efficiency. Similarly, other hybrid methods, such as PSO-imperialist competitive algorithms and salp swarm optimization combined with sine-cosine algorithms, exhibit improved adaptability and effectiveness in solving ORPD problems under diverse system conditions.

The focus of this paper is on reviewing the advancements in hybrid optimization techniques for ORPD and their applications in reactive power planning and management. These techniques are evaluated based on their ability to achieve critical objectives, such as minimizing power losses, improving voltage profiles, and maintaining voltage stability across standard test systems. By synthesizing recent research findings, this review provides a comprehensive overview of state-of-the-art hybrid methods, highlighting their potential for addressing emerging challenges in modern power systems. Ultimately, this review aims to inspire further innovation in hybrid optimization methods, fostering their continued development and application in the efficient and reliable operation of electric power networks.

This paper reviews advancements in hybrid optimization techniques for the ORPD problem, focusing on the following contributions:

- Evaluation of Hybrid Techniques: Analyzes the strengths of hybrid optimization methods in overcoming the limitations of traditional and standalone metaheuristic approaches.
- Focus on ORPD Objectives: Highlights their effectiveness in minimizing power losses, improving voltage profiles, and enhancing voltage stability.
- Emerging Methods: Explores novel hybrid approaches like GWO-PSO and other combinations for solving complex ORPD problems.
- Future Research Directions: Identifies knowledge gaps and provides insights to inspire further innovation in hybrid methods for power system optimization.

The paper is organized as follows: Section 2 provides an overview of ORPD, its objectives, and system constraints. Section 3 focuses on hybrid optimization techniques, their advantages, and recent developments. Section 4 presents a comparative analysis of hybrid methods and their performance in achieving ORPD objectives. Finally, Section 5 concludes with key findings and outlines future research directions in hybrid optimization for power systems.

II. Overview of ORPD, its objectives and system constraints

ORPD is a critical optimization problem in power systems, aiming to enhance operational efficiency and reliability by managing reactive power flows. ORPD involves achieving specific objectives, such as minimizing power losses and improving voltage stability, while adhering to system constraints. This section provides a detailed explanation of the ORPD problem, its objectives, control variables, and constraints, along with mathematical representations.

i. Minimizing Power Losses: A primary objective of ORPD is to reduce active power losses in transmission lines. Reactive power flows significantly influence power losses, and their optimal management ensures efficient energy delivery. This can be expressed as:

$$F_p=\sum_{i=1}^{N} P_{loss}^{i} \qquad (2.1)$$

$$=\sum_{i=1}^{N} G^i\left[2|V_j||V_k|\cos(\delta_j-\delta_k)-|V_j|^2-|V_k|^2\right] \qquad (2.2)$$

Where P^i_{loss} is the real power loss in i^{th} transmission line between j^{th} and k^{th} buses; N is the count of the all transmission lines; G^i is the conductance of i^{th} transmission lines; V_j and V_k are voltages of the busses in per unit and δ_j, δ_k are phase angles in radians at the end buses i.e j^{th} and k^{th} of the i^{th} transmission line, respectively.

ii. Enhancing Voltage Profiles: Maintaining voltage levels at all buses within permissible limits is critical for system stability. ORPD improves voltage profiles by minimizing voltage deviations at load buses. This can be expressed as:

$$F_v=\sum_{j=1}^{N_{PQ}}|V_j-V_{spec}| \qquad (2.3)$$

iii. Improving voltage stability: Voltage stability is vital for preventing voltage collapse and ensuring reliable system operation. A commonly used indicator is the LLL-index, which quantifies voltage stability:

$$L_i=1-\left|\sum_{j=1}^{N_{PV}} F_{jk}\frac{V_j}{V_k}\right| \quad i\in PQ \qquad (2.4)$$

where F_{jk} is a coefficient matrix determined from the system's admittance matrix. The objective is to minimize the maximum L_i

$$\frac{\min\max}{i \in PQ} L_i$$

Where N_{PQ} represents the total number of load buses, N_{PV} is the generator busses and V_{spec} is the specified bus voltage, typically set to 1.0.

To achieve the objectives of ORPD, several control variables are optimally tuned to directly influence reactive power flow and system performance. One key variable is the voltage magnitude at generator buses, which serves as a primary control mechanism for managing reactive power. Adjusting these voltages helps maintain system stability and efficiency. Another crucial factor is transformer tap settings, which regulate voltage levels and reactive power flows by altering the voltage ratios between the primary and secondary windings of transformers. Additionally, the placement and sizing of shunt capacitors play a vital role in ORPD. Shunt capacitors provide localized reactive power support, improving voltage profiles and reducing power losses. Optimizing their placement and sizing ensures maximum benefit to the system while enhancing overall operational efficiency.

ORPD must satisfy both equality and inequality constraints to ensure system reliability and operational feasibility.

i. Satisfaction of equality constraints

Equality constraints ensure the balance of active and reactive power at each bus. These are represented by the load flow equations:

$$P_{Gj} - P_{Dk} - V_j \sum_{n=1}^{N_{bus}} V_k \left[G_{jk} \cos\left(\delta_{jk}\right) + B_{jk} \sin\left(\delta_{jk}\right)\right] = 0, \; n=1, 2, 3\ldots.., N_{bus} \quad (2.5)$$

$$Q_{Gj} - Q_{Dk} - V_j \sum_{n=1}^{N_{bus}} V_k \left[G_{jk} \cos\left(\delta_{jk}\right) + B_{jk} \sin\left(\delta_{jk}\right)\right] = 0, \; n=1, 2, 3\ldots\ldots, N_{bus} \quad (2.6)$$

Where,

N_{bus} = number of buses,

P_{Gj}= Active power generation at the j^{th} bus,

Q_{Gj} = Reactive power generation at the j^{th} bus,

P_{Dk} = Active power demand at the k^{th} bus,

Q_{Dk}= Reactive power demand at the k^{th} bus,

G_{jk} = Transfer conductance between j^{th} bus and k^{th} bus,

B_{jk}= Transfer susceptance between j^{th} bus and k^{th} bus, respectively.

ii. Satisfaction of inequality constraints

Inequality constraints define the permissible operational limits of the system, including:

$$\left.\begin{aligned} V_{gm}^{min} &\le V_g \le V_{gm}^{max} \\ P_{Gj}^{min} &\le P_G \le P_{Gj}^{max} \\ Q_{Gj}^{min} &\le Q_G \le Q_{Gj}^{max} \\ Q_{Cj}^{min} &\le Q_C \le Q_{Cj}^{max} \\ T_j^{min} &\le T_j \le T_m^{max} \end{aligned}\right\} \quad (2.7)$$

The optimization problem ensures that all equality constraints, as defined in the load flow equations, and inequality constraints are satisfied to achieve the desired objectives.

The ORPD problem presents significant challenges due to its nonlinear, multi-objective, and constrained nature. One major challenge is the high dimensionality of the optimization space, which arises from the large number of buses, generators, and transformers in modern power systems. Additionally, the inherent nonlinearity of power flow equations makes solving the problem computationally intensive and complex. Another critical issue is the need to satisfy multiple operational constraints, such as maintaining voltage stability and reactive power limits, which adds further complexity to the optimization process. Another challenge in solving the ORPD problem is the presence of multiple local optima. Since the optimization space is highly nonlinear, there are many local optima, and traditional methods that rely on gradient-based search techniques can easily get stuck in one of these suboptimal points. To identify the global optimum, it is necessary to employ optimization techniques that can explore the solution space more effectively. Metaheuristic algorithms like GA, PSO, and DE are often used for this purpose due to their ability to perform global searches and avoid getting trapped in local optima. While metaheuristic algorithms offer solutions to these challenges, they come with their own set of limitations. One of the major issues with standalone metaheuristics is the trade-off between exploration (searching broadly across the solution space) and exploitation (refining the best solutions found). Effective exploration is necessary to avoid local optima, while effective exploitation is needed to converge to the global optimum. Metaheuristic algorithms often face challenges in balancing these two aspects. If the algorithm explores too much, it may fail to converge to an optimal solution, leading to high computational costs. On the other hand, if it focuses too much on exploitation, it may converge prematurely to a suboptimal solution. This trade-off can result in suboptimal performance, particularly in highly constrained, real-world ORPD problems where the solution space is complex and densely packed with local minima. To overcome these limitations of standalone metaheuristics, hybrid optimization techniques have emerged as a promising alternative.

III. Hybrid optimization techniques

Hybrid approaches combine the strengths of multiple optimization methods, typically combining global search capabilities of metaheuristics with the refinement power of local optimization techniques. For example, hybridizing PSO with local search algorithms, such as simulated annealing or interior-point methods, allows for both global exploration and local exploitation. The global search capabilities ensure that the algorithm can avoid local optima, while the local methods improve the precision of the final solution by converging more efficiently on the best solution found. By combining different techniques, hybrid optimization methods can better balance exploration and exploitation. The global search phase helps in exploring a broader range of the solution space, while the local search phase focuses on fine-tuning the solutions and ensuring that the constraints are satisfied effectively. This synergy allows hybrid methods to handle the high dimensionality of the problem, the nonlinear nature of the power flow equations, and the complex constraints more efficiently than traditional methods or standalone metaheuristics.
The use of hybrid techniques in the ORPD problem results in several advantages:

- **Improved Solution Quality**: By leveraging both global and local search methods, hybrid techniques are more likely to find the global optimum, or at least a near-optimal solution, compared to standalone methods.
- **Increased Efficiency**: Hybrid techniques can more effectively explore the solution space, reducing the time required to converge to a solution and making them computationally more efficient.
- **Better Constraint Handling**: Hybrid methods can incorporate complex operational constraints more effectively, ensuring that the final solution is both optimal and feasible within the system's limits.
- **Enhanced Reliability and Performance**: By overcoming the challenges of local optima, high-dimensionality, and nonlinearities, hybrid methods lead to more reliable and performant solutions for ORPD, ultimately enhancing the operational efficiency and stability of power systems.

3.1. Elementary procedures of the hybrid techniques

The elementary procedures of hybrid optimization techniques involve a systematic approach to solving complex optimization problems. These techniques typically combine two or more algorithms to leverage their individual strengths. Below is a generalized breakdown of the elementary procedures used in hybrid optimization methods:

i. Initialization

Initialization is the first and crucial step in any optimization technique. During this phase, the initial set of candidate solutions or population is generated, which serves as the starting point for the optimization process. In hybrid techniques, this step involves setting up the individual algorithms involved in the hybridization. For instance, if the hybrid approach uses PSO and GA, the initial population for both algorithms is defined, along with relevant parameters such as population size, maximum iterations, and algorithm-specific values (e.g., velocity in PSO or crossover rate in GA). The initial solutions are usually generated randomly or by using a heuristic method, ensuring a diverse and broad search space for the optimization process to explore.

2. Decomposition of Problem

Decomposing the optimization problem is an essential procedure for effectively applying hybrid techniques. In hybrid optimization, the overall problem is divided into sub-problems or different phases to handle distinct aspects of the problem more efficiently. The primary goal of decomposition is to allow each algorithm within the hybrid approach to focus on specific parts of the optimization process. For example, one algorithm might be tasked with the global exploration of the solution space (e.g., using a genetic algorithm), while another focuses on exploiting the best solutions found so far (e.g., using PSO or Simulated Annealing (SA)). This division ensures that each algorithm can leverage its strengths, such as exploration or exploitation, depending on its assigned task.

3. Exploration Phase (Global Search)

The exploration phase, or global search, is crucial in hybrid optimization as it involves searching broadly across the solution space to identify promising regions. In this phase, one of the algorithms within the hybrid framework, such as GWO or Harris Hawk Optimization (HHO), is responsible for exploring the solution space. This stage aims to find solutions in unexplored or less-explored regions of the problem space, ensuring that the optimization process doesn’t get trapped in local optima. The exploration phase is often characterized by a high level of randomness or chaotic behavior, such as random mutations or large search steps, which helps maintain diversity within the population of candidate solutions. The algorithm continues exploring until it identifies promising solutions or regions of interest for further refinement.

4. Exploitation Phase (Local Search)

Once the exploration phase has identified promising regions, the exploitation phase comes into play to refine the best solutions found. This phase is focused on intensively improving the quality of solutions by exploring their local neighborhood. Algorithms like PSO, SA, or Tabu Search (TS) are often employed in this phase to fine-tune solutions. These algorithms generally focus on reducing the search space around the best solutions found during the exploration phase, ensuring that solutions are further optimized.

Exploitation techniques may involve adjusting variables such as velocity in PSO or temperature in SA, or utilizing memory structures like the Tabu list in Tabu Search to avoid revisiting previously explored solutions. This phase enhances the quality and stability of the solution.

5. Hybridization and Cooperation

Hybridization refers to the process of combining the strengths of two or more optimization algorithms to address different aspects of the problem effectively. In hybrid optimization techniques, different algorithms are often used for specific tasks during the optimization process. For example, one algorithm may focus on exploration, while another focuses on exploitation. Cooperation between algorithms is vital to ensure that the combined approach benefits from the strengths of both methods. In some hybrids, algorithms may exchange information or solutions, where the results from one algorithm (e.g., the best position found by PSO) may influence the other algorithm (e.g., guiding the mutation strategy in a GA). This cooperation ensures that the hybrid approach is both diverse in its search and focused in refining the solutions.

6. Fitness Evaluation

Fitness evaluation is a key procedure in optimization, where the quality of candidate solutions is assessed based on an objective function. Each solution generated by the hybrid algorithm is evaluated according to how well it satisfies the optimization goals, such as minimizing power loss or maximizing voltage stability in a power system. The fitness function quantifies how close a solution is to optimality, guiding the algorithm toward better solutions. In hybrid techniques, fitness evaluation often occurs after both the exploration and exploitation phases. Each algorithm in the hybrid system will evaluate the solutions according to its fitness measure, ensuring that the process is aligned with the overarching optimization objectives.

7. Convergence and Termination Criteria

Convergence and termination criteria determine when the hybrid optimization process should stop. The algorithm may be terminated when a solution reaches a specified level of quality, such as a target fitness value, or after a fixed number of iterations or time steps. Convergence can also be monitored by tracking the improvement in fitness across iterations; if the fitness function shows little or no improvement over several iterations, the algorithm may stop. In hybrid algorithms, convergence may be adaptive, where one algorithm continues searching while another focuses on refinement, depending on the current stage of optimization. This flexibility allows the hybrid technique to adapt its behavior to the characteristics of the problem at hand, ensuring that the solution process is efficient and effective.

8. Post-processing and Solution Analysis

After the optimization process concludes, the best solutions are analyzed and post-processed. This phase involves reviewing the final candidate solutions to ensure they meet all problem-specific constraints and requirements. If necessary, solutions may be adjusted or fine-tuned to improve their practical applicability. Post-processing could involve rounding values, smoothing results, or making adjustments to variables that may not be feasible in real-world scenarios (e.g., ensuring integer values for decision variables). Additionally, the final solutions are compared with other optimization methods or benchmarks to assess the performance of the hybrid approach. This analysis helps in understanding the strengths and weaknesses of the hybrid method and in validating its effectiveness for the specific problem.

9. Feedback Mechanisms (if applicable)

In some hybrid optimization techniques, feedback mechanisms are employed to adaptively adjust parameters during the optimization process. For example, if the algorithm is not converging or is stuck in a local optimum, it may adjust certain parameters—such as increasing the mutation rate or exploration size—to boost diversity and escape from the local optimum. These feedback loops allow the hybrid algorithm to dynamically change its behavior based on the current stage of the optimization. Feedback mechanisms improve the robustness of hybrid methods by ensuring that the algorithm can adapt to various problem characteristics, such as complexity or ruggedness of the objective landscape.

The elementary procedures of hybrid optimization techniques are designed to take advantage of the complementary strengths of different algorithms. These methods work together to improve exploration, exploitation, and the overall quality of solutions in complex optimization problems. By combining the capabilities of different algorithms, hybrid techniques offer a robust approach for solving challenging optimization tasks more effectively than any single method alone.

IV. COMPARATIVE ANALYSIS OF HYBRID OPTIMIZATION TECHNIQUES

In recent years, hybrid optimization algorithms, which combine the strengths of multiple optimization techniques, have emerged as an effective solution to these complex problems. Table 1 presents a selection of studies that employ hybrid optimization techniques to address various power system challenges, such as minimizing power losses, improving voltage profiles, and ensuring system security under different operating conditions. By combining methods like PSO, Imperialist Competitive Algorithm (ICA), SA, and GA, these hybrid approaches enhance the exploration and exploitation capabilities, leading to more robust and efficient solutions. The results presented in these studies highlight the significant improvements in system performance achieved through hybrid optimization.

Table 1 summarizing the optimization techniques, objectives, approaches, and results from the references provided.

Reference	Optimization Technique	Objective	Approach	Results
[11]	Hybridized Particle Swarm Optimization Variants	Minimize losses and ensure cost-efficient Var compensation	Comparison of PSO, EPSO, APSO, HPSO, and BFA	HPSO outperformed others in loss reduction and reactive power planning across various IEEE test systems.
[12]	Hybrid Multi-Swarm PSO (HMPSO)	Minimize power losses and improve voltage profile simultaneously	Partition swarm into sub-swarms, PSO as search engine for each sub-swarm, DE for enhancing personal best, fuzzy membership function for Pareto-optimal selection	Effectively solved the RPD problem on IEEE 30-bus and 75-bus Indian systems, achieving optimal results.
[13]	Improved Pseudo-Gradient Search PSO (IPG-PSO)	Minimize real power losses, improve voltage stability, and reduce deviation	Enhanced PSO with chaotic inertia weight and pseudo-gradient search	Outperformed conventional PSO in solution quality and computational efficiency on IEEE 30 and 118-bus systems.
[14]	PSO-MVO (Hybrid PSO and Multi-Verse Optimizer)	Reduce fuel cost, improve voltage stability, and minimize power loss	Combined PSO's exploitation with MVO's exploration, validated on IEEE 30-bus system	Achieved faster convergence and better optimization results compared to standalone algorithms.
[15]	ICA-PSO (Hybrid Imperialist Competitive Algorithm and PSO)	Minimize transmission loss and voltage deviation	Combines ICA's global search ability with PSO's local search efficiency	Demonstrated superior convergence and solution quality compared to standalone ICA and PSO.
[16]	HTSSA (Hybrid Tabu Search-Simulated Annealing)	Minimize power losses and maintain voltage profiles within permissible limits	Combines SA's local search with TS's memory-based search	Achieved significant reduction in real power losses and maintained voltage stability more effectively than standalone algorithms.
[17]	PSO-TS (Hybrid PSO and Tabu Search)	Minimize transmission losses and voltage deviations	Hybrid PSO-TS for multi-objective optimization on IEEE 30-bus system	Outperformed conventional PSO and TS, achieving better voltage profiles and loss reduction.
[18]	ABC-FF (Hybrid Artificial Bee Colony-Firefly)	Optimize transformer tap settings and Var compensators	Hybrid ABC-FF algorithm applied to IEEE 14 and 39-bus systems	Superior results in minimizing voltage deviation and power losses compared to other evolutionary algorithms.
[19]	PSO-APO (Hybrid PSO and Artificial Physics Optimization)	Minimize power loss, voltage deviation, and improve voltage stability	Integration of PSO with APO, tested on IEEE 30, 57, and 118-bus systems for both single and multi-objective ORPD problems	Effective and consistent results in convergence performance, outperforming previous literature for ORPD problems.
[20]	GWO-PSO (Hybrid Grey Wolf Optimization and PSO)	Minimize power losses and improve voltage profile	Hybrid GWO-PSO algorithm applied to multiple IEEE test systems	Achieved superior optimization results compared to standalone GWO and PSO, improving network performance.
[21]	Crow Search Algorithm-JAYA Hybridization	Minimize operating costs while ensuring system security	Combined Crow Search Algorithm with JAYA for improved accuracy and efficiency	Outperformed other optimization strategies under multi-loading conditions on IEEE 30-bus and UPSEB 75-bus systems.
[22]	BOA (Hybrid Butterfly Optimization Algorithm)	Maximize and minimize loads while integrating renewable energy and addressing system constraints	Hybridized BOA with PSO and GWO for better exploration and exploitation, applied to IEEE 30-bus system	Significant improvements in congestion management and reactive power optimization compared to standalone BOA.
Shekarappa et al. (2021)	HHOPSO (Hybrid Harris Hawk-PSO)	Reduce transmission losses, minimize	Combines HHO and PSO for Voltage Constrained Reactive	Outperformed contemporary algorithms on

		operating costs, and enhance voltage stability	Power Planning (VCRPP) with VCPI method for Var source location identification	IEEE 57-bus system, demonstrating superior solution diversity, robustness, and efficiency.

The application of hybrid optimization techniques has proven to be highly beneficial for addressing the complexities of reactive power and voltage optimization in power systems. These techniques, which combine global and local search strategies, offer a balance between exploration and exploitation, resulting in faster convergence and better solution quality compared to standalone algorithms. From reducing transmission losses to enhancing voltage stability and optimizing operational costs, the hybrid methods outlined in the table have demonstrated superior performance across multiple IEEE test systems. The successful integration of various optimization strategies, such as PSO, ICA, and SA, indicates the growing potential of hybrid algorithms in solving real-world power system problems. These advancements pave the way for more efficient and reliable power system operations, making hybrid optimization a key approach for future grid management and optimization strategies.

CONCLUSION

This review has highlighted the effectiveness of hybrid optimization techniques for solving the complex challenges of ORPD. The combination of various optimization algorithms, such as PSO, ICA, SA, and others, has proven to enhance the capabilities of power system optimization by improving both exploration and exploitation. The studies reviewed demonstrate that hybrid techniques not only offer better convergence and solution quality compared to standalone algorithms but also achieve significant improvements in minimizing power losses, optimizing voltage profiles, and ensuring system stability under various operating conditions.

The results from different test systems, including IEEE 30-bus, 57-bus, and 118-bus, showcase the practical applicability of these hybrid methods in real-world power systems. The integration of multiple optimization strategies provides a balanced approach, addressing the multi-objective nature of ORPP while overcoming the limitations of traditional methods. Overall, hybrid optimization algorithms represent a promising direction for future research and application in reactive power planning, offering enhanced efficiency, reliability, and robustness in power system operations. As the complexity of modern power grids increases, the adoption of these advanced techniques will play a crucial role in ensuring more stable and cost-effective energy systems.

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