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Optimization and control strategy for reactive-power and voltage-quality improvement in distribution networks based on GA-MOPSO

Lingtong Cao^{1,*} and Mian Fu²

¹ School of Electrical Engineering, China University of Mining and Technology, Xuzhou 221100, China

² Yongchuan Power Supply Branch, State Grid Chongqing Electric Power Company, Chongqing 402160, China

* Correspondence author; E-mail: ts23230074p31@cumt.edu.cn.

Abstract: Because power-quality mitigation devices in distribution networks often lack a system-wide optimal regulation strategy, this paper proposes an integrated optimization and control strategy based on a genetically enhanced multi-objective particle swarm optimization (GA-MOPSO) algorithm to coordinate the control schemes of reactive-power devices. Crossover-based genetic operations are incorporated into the multi-objective computation, enabling MOPSO to explore a broader search space and further accelerate convergence. A 10 kV simulation model is built on the IEEE 33-bus system, with dispersed integration of loads exhibiting reactive-power deficiency to emulate power-quality issues. Simulation results verify the feasibility and high efficiency of the proposed optimization and control strategy.

Keywords: multi-objective particle swarm optimization; genetic algorithm; optimization and control strategy.

1. Introduction

Power quality (PQ) issues are becoming increasingly prominent with the growing penetration of power-electronic devices and distributed generation in distribution networks. The widespread integration of nonlinear and impact loads further aggravates PQ deterioration, impairing normal network operation and posing risks to end-use equipment [1]. Under current conditions, where reactive-power deficiencies and voltage deviations coexist at many nodes, conventional PQ control strategies struggle to coordinate heterogeneous compensators effectively, often leading to a mismatch between investment and benefit [2]. How to allocate limited compensation capacity to appropriate nodes so that local PQ satisfies system-level operational requirements has therefore become a key research focus.

In recent years, a number of studies have further advanced reactive-power and voltage-quality optimization in distribution networks. Recent works have investigated coordinated voltage control using OLTCs, capacitor banks, and DG reactive-power regulation under high penetration of renewable generation. Other contributions have developed hybrid meta-heuristic algorithms that combine PSO, GA, and differential evolution to improve convergence speed and solution diversity in multi-objective settings.



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Moreover, PQ-oriented planning approaches have been proposed to jointly consider investment cost, network losses, and voltage deviation indices in radial distribution systems [3]. For example, optimally places capacitors using an improved PSO [4] with nonlinear trigonometric functions under power-factor and resonance constraints, but only a single type of PQ device is considered, limiting generality, while employs an NNC [5] framework combined with PSO variants to address multi-objective optimization. Building on this work, this paper proposes a reactive-power-oriented PQ device optimization and control strategy that improves dynamic response. Capacitor banks (CBs) are taken as representative compensation devices, and the framework is in principle extendable to static var generators (SVGs) and DG reactive-power control [6]. An integrated optimization and control framework for reactive-power and voltage-quality improvement in distribution networks is proposed. An improved GA-MOPSO algorithm with adaptive mutation and selective crossover is developed to enhance convergence performance. The effectiveness of the proposed method is validated on an enhanced IEEE 33-bus system through comparative simulations.

2. Multi-objective particle swarm optimization with genetic mutation

The MOPSO algorithm [7] converges rapidly but may cause the particle swarm to become trapped in local optima and fail to escape [8]. Given that genetic algorithms (GAs) offer strong global search capability and broad exploration, incorporating genetic mutation into the MOPSO procedure can enlarge the search scope. Therefore, this paper introduces a genetic mutation operator into the multi-objective optimization and coordination strategy. By combining MOPSO's fast convergence with GA's wide-ranging exploration, an improved GA-MOPSO algorithm is employed to optimize and coordinate power-quality devices in the distribution network.

To embed genetic mutation into MOPSO, we introduce a genetic mutation probability factor g . In the early iterations, a large gap typically exists between the swarm's candidate set and the Pareto set, calling for wide exploration; accordingly, g is set high to broaden the search for the PQ-device control strategy. As iterations proceed and the gap narrows, g should be reduced to accelerate convergence. Hence, g is designed to decrease with the iteration count, which can be expressed as:

$$g^{iter} = \left(1 - \frac{iter-1}{ITER-1}\right)^{\frac{1}{\mu}} \quad (1)$$

where $iter$ denotes the current iteration index, $ITER$ is the maximum number of iterations, and μ a shaping (regulation) factor. The crossover-mutation operator consists of two parts. Let pm denote the mutation probability; then:

$$\begin{cases} \text{perform crossover, } rdm > pm \\ \text{perform mutation, } rdm \leq pm \end{cases} \quad (2)$$

where $rdm \sim U(0,1)$ is a uniform random variate. *Crossover* is implemented using standard operators such as intermediate recombination, linear recombination, or simulated binary crossover.

The simulated binary crossover operator is defined as follows:

$$\begin{cases} y_{1j}(t) = \left[(1 + \gamma_j) x_{1j}(t) + (1 - \gamma_j) x_{2j}(t) \right] / 2 \\ y_{2j}(t) = \left[(1 - \gamma_j) x_{1j}(t) + (1 + \gamma_j) x_{2j}(t) \right] / 2 \end{cases} \quad (3)$$

where $x_{1j}(t)$ and $x_{2j}(t)$ denote the t dimensional components of the two parent individuals, while $y_{2j}(t)$ are the corresponding components of the two offspring. γ_j is the crossover factor, computed as follows:

$$\gamma_j = \begin{cases} (2u_j)^{\frac{1}{\eta+1}} & u_j < 0.5 \\ (\frac{1}{2(1-u_j)})^{\frac{1}{\eta+1}} & u_j \geq 0.5 \end{cases} \quad (4)$$

where u_j is a random number uniformly distributed within $[0,1]$, and η is the distribution index of the crossover operator.

From Equation (3), when the t -th components of two parents are similar, the corresponding offspring component becomes nearly identical, a limitation shared by intermediate and linear recombination. With mutation embedded in the MOPSO framework, this redundancy is most pronounced in late iterations, when particles have already clustered near the Pareto front and differ only slightly. At this stage, MOPSO's intrinsic convergence is sufficient to obtain satisfactory solutions, and the additional crossover yields little benefit while increasing computational cost.

To address this, an approximation factor γ is introduced to determine whether crossover is necessary before executing it. Specifically, the algorithm evaluates particle similarity through γ , and only performs crossover when particle differences exceed a predefined threshold. This selective-crossover mechanism reduces redundant computations and enhances overall optimization efficiency.

$$Cross(t) = \begin{cases} 0, & |x_{1j}(t) - x_{2j}(t)| < \gamma \\ 1, & |x_{1j}(t) - x_{2j}(t)| > \gamma \end{cases} \quad (5)$$

where $Cross(t)$ is the decision variable that determines whether the t dimensional component participates in crossover. When the absolute difference between the two parental components at dimension t is smaller than the approximation factor, the corresponding crossover flag is set to zero, $Cross(t) = 0$, indicating that the t component does not undergo crossover. Conversely, when the difference exceeds γ , $Cross(t) = 1$, and the crossover operation is executed for that dimension.

This necessity check reduces redundant computation by skipping unnecessary crossover operations. The resulting genetic-mutation mechanism adapted for MOPSO is illustrated in Figure 1

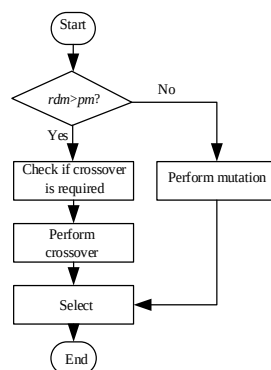


Figure 1. Block diagram of mutation steps adapted to MOPSO.

As shown in Figure 1, at each iteration the algorithm uses Equation (2) to decide whether to perform a GA-based mutation in which parents drawn from the non-dominated archive recombine with the current particle and, via elitist selection, the fittest offspring replaces it, thereby preserving high-quality

solutions, broadening the search for optimal PQ control strategies, and reducing the risk of convergence to local optima.

3. Optimization model formulation and solution

This work formulates an optimization framework that balances power–quality enhancement and device investment cost. The decision variables correspond to the installation capacities of PQ devices at each node of the distribution network. Subject to PQ–compliance constraints, the optimization seeks to minimize total device investment while maintaining adequate reactive–power compensation. Two objective functions are thus defined for the reactive–power components. The first objective quantifies the mitigation effectiveness, given by:

$$OF_1 = P_{\text{loss}} + \Delta V + OV + \Delta V_i \quad (6)$$

For the reactive–power problem, the function f_Q is defined to represent the effectiveness of reactive–power compensation, expressed as:

$$\begin{cases} P_{\text{loss}} = \sum_{m,n \in \Omega} g_{mn} (U_m^2 + U_n^2 - 2U_m U_n \cos \theta_{mn}) \\ \Delta V = \frac{\sum_{i \in \Omega} |V_m - 1|}{M} \\ OV = \sum_{i \in \Omega} A \left(\frac{\Delta V_i}{V_{\max} - V_{\min}} \right)^2 \\ \Delta V_i = \begin{cases} V_i - V_{\min}, & V_i < V_{\min} \\ 0, & V_{\min} < V_i < V_{\max} \\ V_i - V_{\max}, & V_i > V_{\max} \end{cases} \end{cases} \quad (7)$$

where g_{mn} represents the conductance between nodes m and n ; U_m and U_n denote the RMS voltages of nodes m and n ; θ_{mn} is the phase–angle difference between their voltages; V_m is the per–unit voltage magnitude at node m ; A is the penalty coefficient for voltage–limit violations; and $V_{\max}$ and $V_{\min}$ are the upper and lower voltage–deviation limits, respectively.

Accordingly, the objective function representing the investment cost of mitigation devices, denoted as OF_2 , can be expressed as:

$$OF_2 = f_{Q\text{Cost}} \quad (8)$$

In addition, according to the requirements specified in the national standards, the constraints on reactive–power indices are defined as follows:

$$\begin{cases} V_{\min} < V_i < V_{\max} \\ PF_{\min} < \cos \varphi_i < PF_{\max} \\ Q_{\min} < Q_{Ci} < Q_{\max} \end{cases} \quad (9)$$

where $\cos \varphi_i$ represents the power factor at node i ; V_i is the voltage magnitude at node i ; Q_{Ci} denotes the reactive–power compensation capacity of the device installed at node i ; $Q_{\max}$ and $Q_{\min}$ are the upper and lower limits of the reactive–power compensation provided by the intelligent capacitor bank at the main transformer of the distribution area. Since the intelligent capacitor operates with discrete switching steps, Q_{Ci} is treated as a discrete variable.

In the proposed GA–MOPSO framework, the power–quality performance objective OF_1 and the investment–cost objective OF_2 serve as the algorithm’s fitness functions. The decision variables include the configuration states of PQ devices at each node—specifically, the number of engaged groups of intelligent capacitor banks.

4. Case study and simulation

To verify the feasibility and effectiveness of the proposed optimization and coordination strategy, an improved IEEE 33–bus distribution system is modeled using MATLAB/Simulink. The network topology is shown in Figure 2.

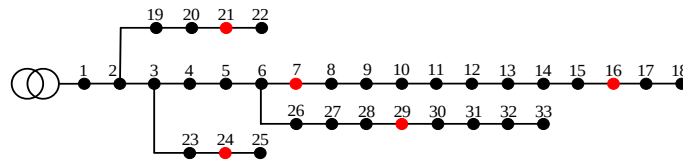


Figure 2. Schematic diagram of the IEEE 33–bus distribution network.

To emulate realistic active–power (P) and reactive–power (Q) operating conditions in a distribution network, the parameters of each node in the IEEE 33–bus standard system are adjusted, with residential, commercial, and industrial loads, as well as distributed generation (DG), connected in a decentralized manner. The distribution of these loads is presented in Table 1. In this case study, capacitor banks are used as the main reactive–power mitigation devices in the feeder areas. Each intelligent capacitor bank has a nominal capacity of 40 kVar, divided into 8:4:2:1 capacitor groups.

Table 1. Station DG and load access.

Type	Parameter and Access Description
DG	(1) 400 kW at Bus 7 (active output 320 kW)
	(2) 400 kW at Bus 16 (active output 280 kW)
	(3) 400 kW at Bus 21 (active output 300 kW)
	(4) 400 kW at Bus 24 (active output 305 kW)
	(5) 400 kW at Bus 29 (active output 320 Kw)
Load	Residential loads: Buses 4, 7, 8, 10, 12, 14, 16, 18, 23, 25 (320 kW, 120 KVar each)
	Commercial loads: Buses 26, 29–32 (340 kW, 130 KVar each)
	Industrial loads: Buses 19, 20, 22 (350 kW, 200 KVar each)

Algorithm parameters are summarized in Table 2. Here, the PQ–improvement indicator is normalized using a voltage– and power–factor–based evaluation framework—smaller normalized values correspond to superior power–quality performance.

Table 2. Parameter setting of GA–MOPSO algorithm.

Parameter	Setting
Maximum number of iterations ITER	200
Number of particles N_p	100
Number of repository (dominant) particles N_{rep}	100
Inertia weight w	0.9
Learning coefficients c_1, c_2	2
Genetic–mutation regulation factor μ	0.5
Crossover probability P_{cross}	0.9

Following the principle of achieving the lowest investment cost under the constraint of meeting power–quality standards, the optimal configuration is identified as the final control scheme for the distribution network.

Figure 3 illustrates the node–by–node power distribution before and after compensation in the IEEE 33–bus system. As shown in the figure, the power values after compensation are consistently higher and much more stable across all nodes than those before compensation. Prior to compensation, the power profile exhibits noticeable fluctuations, with a significant drop around Nodes 21–23. After compensation, the overall profile becomes smoother and remains close to unity, indicating that the proposed compensation strategy effectively improves the power condition of the distribution network and enhances the operational performance of each node.

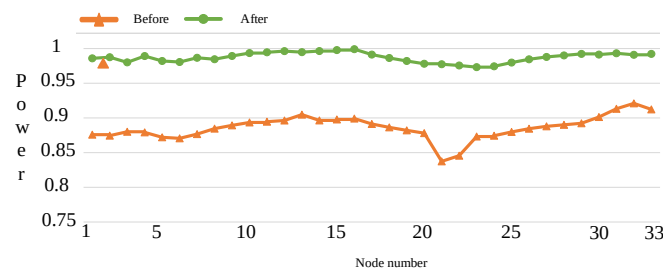


Figure 3. Comparison between the original state and the optimized state.

To verify the differences between the optimization and control strategies based solely on the MOPSO algorithm and the improved GA–MOPSO strategy, both methods are applied to coordinate the power–quality mitigation devices in the distribution network.

Their performance is comparatively analyzed in terms of convergence behavior, device–investment configuration, and PQ improvement effectiveness, thereby demonstrating the improvement achieved by the proposed algorithm.

During the iterative process, the particle that yields the minimum value of the PQ–effectiveness objective function OF1 within the current iteration’s non–dominated solution set is extracted. Based on the corresponding fitness values, iteration numbers, and computation times, the convergence curves of the MOPSO and GA–MOPSO strategies are obtained, as illustrated in Figure 4.

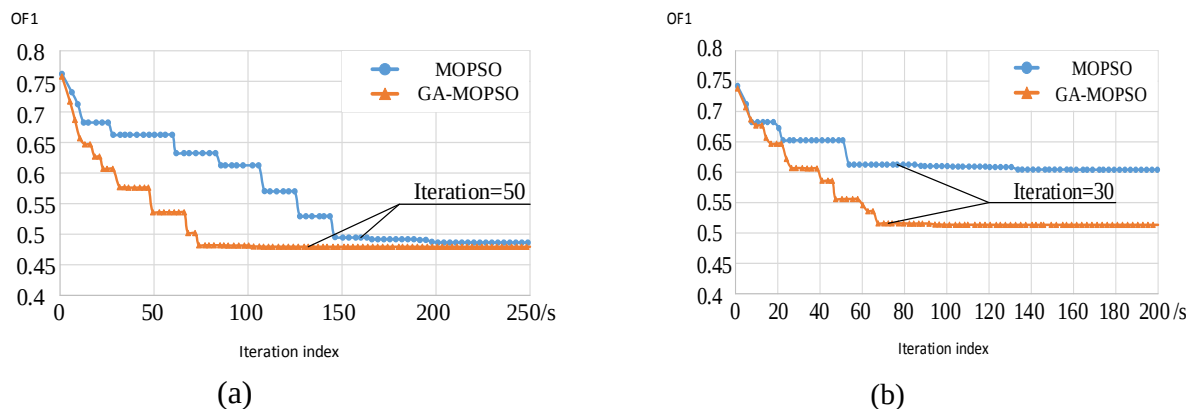


Figure 4. Comparison of convergence curves between MOPSO and GA–MOPSO strategy. **(a)** Iterative convergence curves of both algorithms under normal operating conditions; **(b)** Iteration curve when MOPSO becomes trapped in a local optimum.

As shown in Figure 4a, when both optimization algorithms converge, the proposed GA–MOPSO exhibits a markedly faster convergence rate and higher computational efficiency than conventional MOPSO. In contrast, for optimization problems with local optima (Figure 4b), MOPSO becomes trapped in a local minimum and converges prematurely, whereas the genetic operators in GA–MOPSO enhance its global search capability and enable it to escape local minima. The optimal solutions obtained by both algorithms are then applied to the simulation model, where power–quality indices, device investment, and mitigation performance before and after optimization are evaluated. The comparative results in Figure 5 demonstrate the improvements achieved by the proposed strategy. the final scheme is selected as the solution that satisfies all PQ–standard constraints while yielding the minimum investment cost, thus providing a clear engineering decision rule.

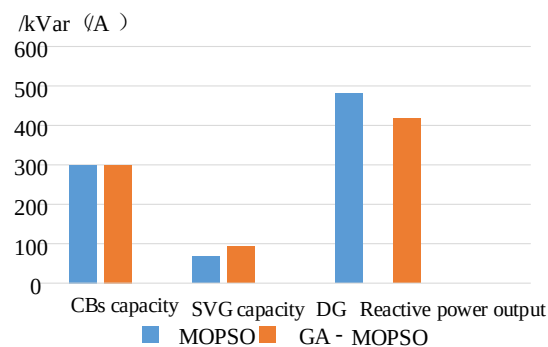


Figure 5. Comparison of optimization costs between MOPSO and GA–MOPSO.

5. Conclusion

In conclusion, this paper presents an integrated optimization and control strategy for reactive–power mitigation in distribution networks based on an improved GA–MOPSO algorithm. By jointly optimizing the configuration and switching states of capacitor banks, a bi–objective model is formulated to balance voltage–quality indices and device investment costs under practical PQ–compliance constraints. Algorithmically, an adaptive mutation operator and a similarity–based selective crossover mechanism are embedded into MOPSO to expand the search space, suppress premature convergence, and enhance dynamic responsiveness. Simulation studies on an improved IEEE 33–bus distribution system with diversified DG and load configurations show that the proposed strategy attains a superior trade–off between reactive–power/voltage–quality improvement and investment cost compared with conventional MOPSO, thereby confirming its effectiveness and novelty.

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Authors' contribution

Conceptualization, Lingtong Cao and Mian Fu; methodology, Lingtong Cao; software, Lingtong Cao; validation, Lingtong Cao and Mian Fu; formal analysis, Lingtong Cao; investigation, Lingtong Cao; resources, Mian Fu; data curation, Lingtong Cao; writing—original draft preparation, Lingtong Cao; writing—review and editing, Lingtong Cao; visualization, Lingtong Cao; supervision, Mian Fu; project

administration, Mian Fu; funding acquisition, Lingtong Cao. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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