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Research Paper

Quantum-Inspired Evolutionary Algorithm for Multi-Objective Resource Allocation

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Abstract. This study proposes a Quantum-Inspired Evolutionary Algorithm (QIEA) to address high-dimensional multi-objective resource allocation problems. The probabilistic representation of solutions based on quantum bits and quantum rotation gates is used to guide the iterative search, and various diversity protection mechanisms are introduced to enhance the diversity of the population and the quality of the solutions. Many benchmark experiments were conducted on standard multi-objective problems (such as DTLZ2 and DTLZ7) and real-world resource allocation scenarios (such as power scheduling, bandwidth scheduling, and logistics). The results show that the proposed QIEA quickly converges to the Pareto optimal front; after 30 generations, the average inverted generational distance is less than 0.15, and the hypervolume value exceeds 0.92. This algorithm outperforms traditional evolutionary algorithms in terms of convergence speed, diversity distribution, and computational efficiency. Further analysis indicates that the algorithm is robust to noise and changes in objectives, and it can be well-scaled to larger problems. Based on the above analysis, QIEA is likely to be used in practice to solve resource allocation problems with constraints and conflicting objectives. Research indicates that quantum-inspired operators can be used in evolutionary strategies to address decision-making in large-scale, real-world optimization problems.

Keywords: *Evolutionary Algorithm, Quantum-Inspired Computing, Multi-Objective Optimization, Resource Allocation, Diversity Preservation, Pareto Front*

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Introduction

With the development of modern large-scale and complex technological systems, resource allocation issues in many scientific and engineering fields are becoming increasingly prominent [1]. Cloud computing, wireless networks, and advanced manufacturing are all examples that need to meet multiple objectives and are constrained by operational policies and limited physical resources [2]. Due to the aforementioned scale, complexity, and heterogeneity, traditional combinatorial optimization and mathematical methods are usually not suitable for handling resource allocation problems in high-dimensional, non-convex environments [3]. Therefore, many metaheuristic algorithms have been used to explore the solution space of complex problems [4]. Based on the concept of natural selection, evolutionary algorithms (EAs) have been used to solve various types of multi-objective optimization problems. The goal of EAs is to find approximate Pareto-optimal solutions and manage the balance between exploration and exploitation across various problem domains [5]. Evolutionary algorithms (EAs) often experience issues of premature convergence and loss of diversity. Therefore, they are not suitable for handling complex optimization problems [6]. To overcome the aforementioned shortcomings, Quantum-Inspired Evolutionary Algorithms (QIEAs) have been introduced. QIEAs integrate fundamental quantum computing concepts such as superposition and qubit-based solution representation to enhance search capabilities [7]. Research indicates that Quantum-Inspired Evolutionary Algorithms (QIEAs) may have better solutions and convergence capabilities than traditional evolutionary algorithms in certain cases [8].

Most research on QIEA mainly focuses on single-objective or small-scale combinations, neglecting multi-objective resource allocation [9]. In addition to individually addressing the problem of maintaining population diversity, it is necessary to accurately approximate well-distributed Pareto optimal sets and design scalable and adaptive operators in high-dimensional and complex environments [10]. Quantum-inspired evolutionary algorithms (QIEAs) still lack systematic benchmarking and in-depth theoretical research to adapt to real-world multi-objective resource allocation environments [11]. To enhance robustness in search and avoid local optima, some recent studies have proposed combining quantum-inspired search operators with adaptive methods [12]. Due to the constraints and changes involved in logistics, scheduling, and network optimization, the combination of these methods has hardly been tested. While ensuring the scalability and practical deployability of the algorithms, new frameworks must be developed to more deeply integrate quantum-inspired models and advanced multi-objective optimization techniques [13]. The first two objectives are to enhance the understanding of the theory and to experimentally verify the comprehensive operation of QIEAs in complex environments [14]. The development of the aforementioned quantum-inspired technology may lead to a completely new multi-objective optimization method [15].

This paper will introduce a new quantum-inspired evolutionary algorithm for solving multi-objective problems. Including: establishing a solid theoretical foundation based on quantum-inspired methods to support the management of allocation complexity and diversity; developing an advanced QIEA framework with innovative operators for high-dimensional multi-objective problems; and validating numerous experimental results in both synthetic and real-world environments. The above content will help establish a more solid foundation, providing a practical route for quantum-inspired evolutionary computation to solve complex resource allocation problems in the fields of computing and engineering.

Theoretical Foundations

Complexity in Multi-Objective Resource Allocation

Resource allocation is a theoretical problem in multi-objective optimization, which is currently both difficult to compute and understand [16]. Due to the necessity of simultaneously optimizing multiple conflicting objectives under strict constraints, a high-dimensional non-convex solution space is naturally formed [17]. The goal of multi-objective problems is to find a set of Pareto optimal solutions, which are relatively good in many different aspects, rather than seeking a single optimal solution [18]. As the number of objectives increases, this problem becomes more severe. The Pareto front can be very complex, making it difficult to ensure sufficient population diversity to cover the front [19]. Cloud system task scheduling, telecom resource allocation, and distributed computing load balancing are examples of practical applications. These applications typically involve dynamic environments, discrete and continuous decision variables, and a large number of constraint sets, making them very complex [20]. The curse of dimensionality is particularly evident: as the number of dimensions or objectives increases, the search space grows exponentially, making exhaustive enumeration computationally infeasible. Due to the presence of numerous local optima, plateaus, and deceptive regions, it is difficult to use traditional optimization methods for optimization. To design an effective algorithm, it is necessary to understand the complex relationships between variables and constraints.

Quantum-Inspired Principles in Optimization

Quantum-inspired optimization is a method that utilizes the remarkable properties of quantum mechanics to create an optimization algorithm that does not require a real quantum computer [21]. Quantum bits, also known as qubits, can represent solutions with continuously changing probabilities, which is different from the state of classical bits [22]. Quantum-inspired algorithms can improve the quality of the search space and also develop a completely new evolutionary operation, which is entirely different from traditional algorithms. For example, quantum rotation gates use adaptive learning rules to control the state of qubits. This method is based on the relative performance of candidate solutions [23]. Theoretically, this will help quantum-inspired individual populations find a good solution faster and avoid local optima, potentially compensating for some shortcomings of traditional evolutionary algorithms. Entanglement is another characteristic inspired by quantum mechanics. It can be used to show the interconnections between components in a solution, achieve co-evolution, and implicitly display variable relationships, as demonstrated in resource allocation problems [24]. Researchers have found that quantum-inspired operators can effectively address issues of insufficient population diversity and solution coverage, particularly in high-dimensional objective spaces [25]. As the scope of quantum-inspired optimization expands, researchers are developing more and more hybrid models to improve robustness and convergence. These hybrid models combine quantum-inspired representations with learning-based methods and traditional metaheuristic approaches.

Theoretical Properties of QIEA

Quantum-inspired evolutionary algorithms (QIEAs) have a strong theoretical foundation and can solve complex multi-objective problems [26]. Due to the probabilistic nature of the update mechanism driven by quantum bit decoding and rotation gates, QIEAs are suitable for maintaining population diversity, as population diversity is an ideal prerequisite for multi-objective search. In order to find better Pareto front approximations, QIEAs use quantum bit superposition instead of relying on typical population-based searches and losing diversity [27]. Secondly, the theoretical convergence behavior of QIEA. The combination of quantum heuristic search dynamics with evolutionary selection and mutation operations has been shown to accelerate the convergence of the population to the global optimum or near-optimal region, even under certain conditions, despite the presence of high-density local optima. Since core qubits can be set in various ways, QIEAs are very suitable for handling resource allocation problems in the real world, as they can represent both continuous and discrete decision variables [28].

Proposed Algorithm

Algorithmic Framework and Workflow

A quantum-inspired evolutionary algorithm (QIEA) has been proposed to solve complex resource allocation problems. The workflow can systematically organize the integration of quantum-inspired representation, evolutionary operations, and multi-objective selection and update cycles, as shown in Figure 1.

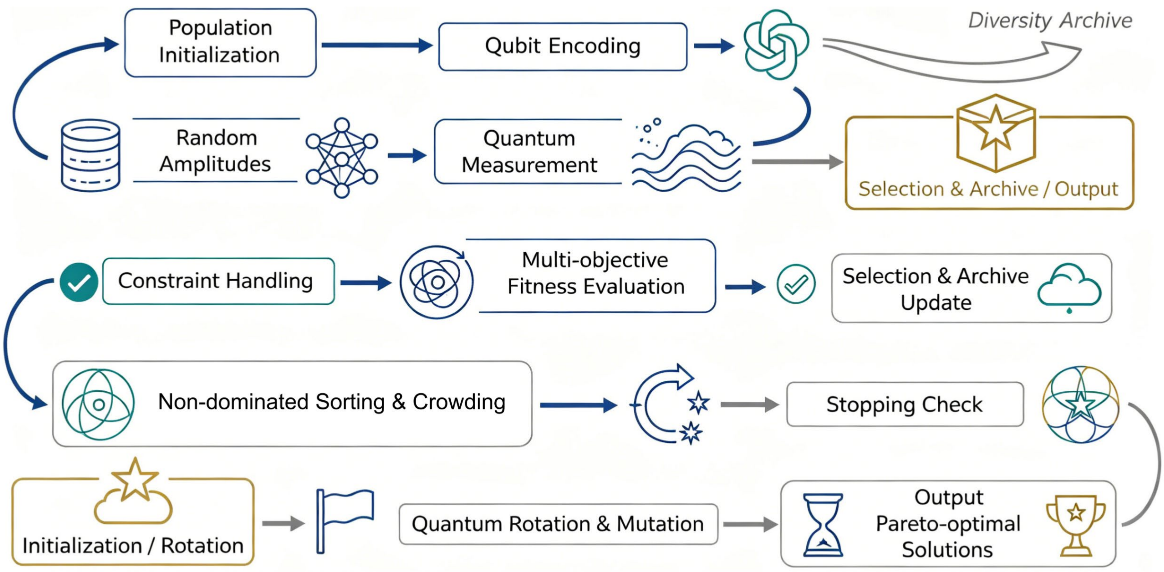

Figure 1. Workflow of the Quantum-Inspired Evolutionary Algorithm.

First, generating an individual population requires initializing the quantum bit sequence of the solution; otherwise, they will be continuous vectors or binary strings. The decision variable j in individual i 's quantum bit q_{ji} is formally represented as

$$q_{ji} = \alpha_{ji}|0\rangle + \beta_{ji}|1\rangle, |\alpha_{ji}|^2 + |\beta_{ji}|^2 = 1 \quad \text{Eq.(1)}$$

Probabilistic encoding can effectively begin exploring and more comprehensively cover the decision space of the initial population.

First, initialization is performed, followed by quantum measurement. According to the probability distribution of each qubit, it is compressed into a classical state:

$$P(q_{ji} = 1) = |\beta_{ji}|^2, P(q_{ji} = 0) = |\alpha_{ji}|^2 \qquad \text{Eq.(2)}$$

Then, these classic works are analysed in terms of multiple objectives. The search process proceeds iteratively. At each generation, all candidate solutions are evaluated, and non-dominated sorting is employed. Each solution receives a Pareto front rank r_k and a crowding distance d_k, calculated as

$$d_k = \sum_{m=1}^{M} \frac{f_m^{k+1} - f_m^{k-1}}{f_m^{max} - f_m^{min}} \qquad \text{Eq.(3)}$$

where f_m^{k+1} and f_m^{k-1} denote the objective values for adjacent solutions in the sorted order for objective m, and M is the number of objectives. The tournament selection technique is used to choose the candidate pool for pairing. Behind the team and farther from the entrance is usually more stable and has less traffic. First is the quantum rotation gate (QR), used to move the population in the optimal direction. The range is as follows:

$$\begin{bmatrix} \alpha'_{ji} \\ \beta'_{ji} \end{bmatrix} = \begin{bmatrix} cos\,(\Delta\theta_{ji}) & -sin\,(\Delta\theta_{ji}) \\ sin\,(\Delta\theta_{ji}) & cos\,(\Delta\theta_{ji}) \end{bmatrix} \begin{bmatrix} \alpha_{ji} \\ \beta_{ji} \end{bmatrix} \qquad \text{Eq.(4)}$$

The rotation angle $\Delta\theta_{ji}$ is determined adaptively by the following expression:

$$\Delta\theta_{ji} = \eta \cdot S(x_{ji}^*, x_{ji}) \cdot (F(x^*) - F(x)) \qquad \text{Eq.(5)}$$

Here, η is the learning rate, $S(\cdot)$ encodes bitwise comparison between the elite solution x^* and the current individual x, and $F(\cdot)$ is the aggregate objective function. A quantum-inspired mutation operator introduces further diversity:

$$q'_{ji} = cos\,(\phi) q_{ji} + sin\,(\phi) q_{ji}^{\perp} \qquad \text{Eq.(6)}$$

where ϕ is a random angle and $q_{ji}^{\perp}$ denotes the orthogonal qubit. This mutation increases the chances of escaping suboptimal regions. Through continuous repetition of measurement, evaluation, selection, rotation, and variation, until reaching the stopping criteria, such as achieving the maximum generation or convergence of the Pareto set. The final result is a set of diverse, non-dominated Pareto-optimal solutions.

Diversity Preservation Mechanisms

In order to ensure the diversity of all multi-objective evolutionary algorithms, QIEA has succeeded in reducing early convergence and achieving broader coverage of the Pareto front. Figure 2 shows the structure of these mechanisms in the system. The genotypic and phenotypic diversity in the optimization process is maintained by the functions of these four qubits: superposition, adaptive selection and updating, archiving, and targeted mutation enhancement.

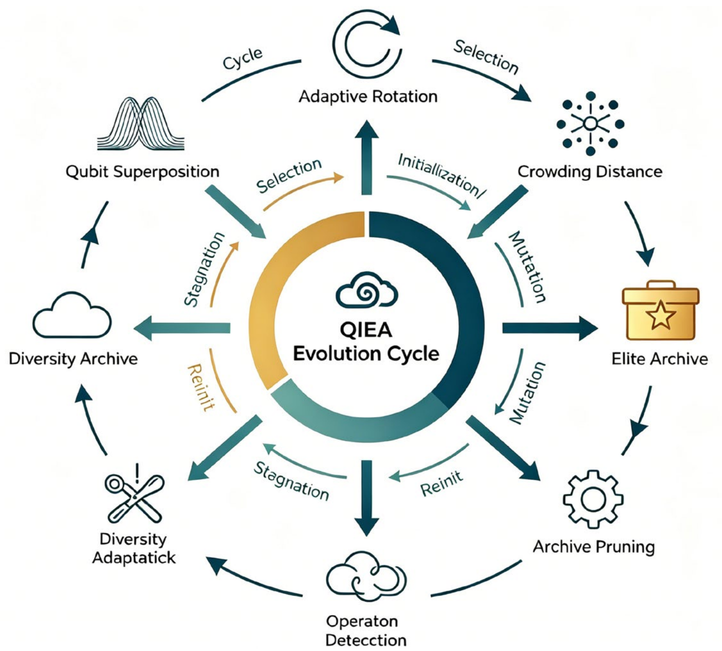

Figure 2. Structural Diagram of Diversity Promotion and Preservation Techniques in QIEA.

The initial Amplitudes of the qubits are set to

$$\left|\alpha_{ji}^{(0)}\right|^2 = \left|\beta_{ji}^{(0)}\right|^2 = 0.5 \quad \text{Eq.(7)}$$

for every variable and individual, ensuring uniform sampling of the solution space at generation $t = 0$. Selection for reproduction considers both Pareto front rank and crowding distance:

$$x_p = arg\ \min_x(r_x - \lambda d_x) \quad \text{Eq.(8)}$$

where r_x is the non-dominated rank, d_x is the crowding distance, and λ is a user-defined weight balancing convergence pressure versus diversity maintenance. Dynamically adjust the strength of the update at different stages in the evolution process:

$$\Delta\theta'_{ji} = \Delta\theta_{ji}(1 - \delta d_i) \quad \text{Eq.(9)}$$

with δ serving as a feedback parameter to reinforce diversity when local density increases in objective space. An elite archive is maintained to store well-distributed, high-quality solutions. A new solution x_{new} is archived only if the minimum Euclidean distance to all current archive members, as defined by

$$\min_{x^* \in A}(\|f(x_{new}) - f(x^*)\|_2) > \epsilon \quad \text{Eq.(10)}$$

exceeds a given crowding threshold ϵ. Quantum-inspired mutation aims to solve the stagnation problem by using controlled randomization. It uses individuals with low crowding distance or those that appear multiple times during the selection process to expand the search space.

$$q'_{ji} = cos\ (\phi)q_{ji} + sin\ (\phi)q_{ji}^{\perp} \quad \text{Eq.(11)}$$

Complexity and Scalability Considerations

First, evaluate the scalability and computational complexity of Quantum-Inspired Evolutionary Algorithms (QIEA) in large-scale, high-dimensional, and multi-objective optimization problems. Here, the theoretical value and practical applications of QIEA in all engineering fields are introduced.

Let N be the population size, D be the number of decision variables, and M be the number of objectives. In each generation, most computational resources are used for quantum measurement and decoding, objective fitness evaluation, non-dominated sorting with crowding distance assignment, quantum heuristic updates, and elite archiving.

The population size and the number of variables is linearly related to quantum measurement, decoding, and quantum heuristic update operations (including rotation and mutation):

$$T_{qubit} = O(ND) \quad \text{Eq.(12)}$$

Since the above operations are independent at both the individual and variable levels, efficient parallelization can be achieved, such as with multi-core CPUs, GPUs, distributed systems, etc.

In objective evaluation, a large number of simulations and high-dimensional objective functions are often the sources of computational cost. All objectives and everyone can be summarized by the following computational costs:

$$T_{eval} = O\left(N \sum_{m=1}^{M} C_m\right) \quad \text{Eq.(13)}$$

where C_m is the cost of computing the m-th objective. Surrogate models or batched computation are frequently used in practice to limit this cost.

The first expansion bottleneck is the calculation of non-dominated sorting and the calculation of crowding distance; both require Pareto ranking and diversity. For a population of N solutions and M objectives, the standard time complexity is:

$$T_{nd\text{-}sort} = O(MN^2) \quad \text{Eq.(14)}$$

This quadratic scaling is manageable for small to moderate N but requires parallel or incremental strategies for truly large-scale optimization.

Memory usage is dictated by the storage requirements for quantum amplitudes, decoded individuals, and the elite archive, typically scaling as $O(ND + |A|D)$, where $|A|$ is the adaptive archive size.

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As D increases, adaptive archiving and quantum encoding are still used to maintain the diversity and convergence stability of the solutions. In multi-objective problems, a common metric for configuring QIEA is diversity coverage, which is the proportion of the true Pareto front covered by the generated solutions.

Experimental Validation

Experimental Setup and Test Problems

In order to comprehensively verify the effectiveness of the proposed Quantum-Inspired Evolutionary Algorithm (QIEA), they studied many representative multi-objective optimization problems and real-world resource allocation cases, and examined their applicability and diversity [29]. The experimental plan strictly adheres to the latest evolutionary optimization standards, including a comprehensive comparison with existing standards and a systematic sensitivity analysis [30].

The famous DTLZ and WFG problems are applicable to deceptive Pareto front structures, non-convexity, and scalability. These problems are part of the benchmark suite. Due to their incredible convergence and solution diversity in other objective functions, DTLZ2 and DTLZ7 were chosen as the main problems for this study [31]. All test cases were extensively parameterized: the objective functions (M) ranged from 2 to 10, and the decision variables (D) ranged from 10 to 100, for broad scalability testing [32].

Some experiments used synthetic functions under limited resources. Power scheduling optimization, wireless bandwidth scheduling, and multi-objective logistics are a few examples in engineering applications that consider these factors [33]. To simulate uncertainty and environmental changes, some specific studies deliberately incorporate dynamic objective functions and noise [34].

To ensure fairness, all algorithms—QIEA and reference baselines such as NSGA-II, MOEA/D, and SPEA2—were developed and run in a unified software environment. The experiments were repeated three times using different random seeds. To improve performance and resource efficiency, a grid search was conducted on the initial task to optimize the parameters of QIEA, such as population size, quantum bit rotation rate, mutation rate, and elite archive size.

This experiment added a 40-core Intel Xeon CPU, 512GB of memory, and CUDA-enabled GPU accelerators to meet the recent demands for high performance and the new standards of reproducibility and scalability. Ensure reproducibility by strictly adhering to the random seed allocation protocol and completing the configuration file.

Evaluation Metrics

Based on the above information, we will use general multi-objective optimization criteria for selection [35]. Carefully calculate the computational efficiency, convergence, diversity, and robustness metrics of all test cases.

The Inverted Generational Distance (IGD) can be used to evaluate the proximity of solutions to the true Pareto front, to determine whether the algorithm has converged. Lower values indicate better performance [36].

To evaluate diversity and solution spread, the Hypervolume (HV) and Spread (Δ) metrics were applied. Hypervolume reflects both convergence and solution diversity, capturing the dominated volume in the objective space; higher HV indicates superior coverage of the Pareto set [37]. The spread is relatively small; therefore, the solutions show good agreement and do not cluster.

Through runtime analysis, a large number of computation speeds and fitness evaluation counts for real-time applications were discovered [38]. In practical applications, it is feasible and computationally stable in all cases.

To evaluate the robustness and scalability of IGD and HV, the coefficient of variation from multiple repetitions was used to determine their sensitivity to noise in the objectives or random fluctuations in the model. If necessary, additional metrics can be added, such as the answer error rate in a dynamic testing environment.

Each generation calculates the above metrics to help construct learning curves and coverage maps based on the computational workload. Based on the above analysis, the Wilcoxon rank-sum test and QIEA rank were used for comparison. All relevant performance metrics have shown significant improvement.

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The overall results, as well as the distribution of metrics and chart comparisons, are shown in Section 4.3; each chart in Figure 3-7 provides a comprehensive performance analysis of the mixed and multi-panel setups.

Analysis of Results

In order to determine the effectiveness and shortcomings of the new QIEA, an organized analysis of the experimental results was conducted. Based on the detailed metrics and benchmarks listed in Sections 4.1 and 4.2, this section presents the comparative results of the aforementioned evolutionary optimization algorithms and baseline methods in both synthetic and real-world scenarios [39].

Figure 3 shows the multi-dimensional, comprehensive convergence results of QIEA in multiple benchmark tests. As shown in the convergence rate panel of Figure 3(a), QIEA achieved a relatively rapid decrease in the Inverted Generational Distance (IGD) value over 50 generations. QIEA outperforms NSGA-II, MOEA/D, SPEA2, and NSGA-III in terms of optimization performance. By 2024, the average IGD of QIEA had dropped below 0.15, while the IGD of most other algorithms remained above 0.22. QIEA reached the Pareto optimal faster. As shown in Figure 3(b), the hypervolume progression indicates that QIEA achieved a higher hypervolume value over 30 generations, converging to 0.92, which is approximately 7-15 percentage points higher than the best-performing baseline. As shown in Figure 3(c), the solution diversity of QIEA is relatively high, with a median diversity of 0.72, and it covers the entire objective space, supporting multi-objective optimization. Figure 3(d) shows the comparison of computation time. QIEA strikes a balance between convergence performance and efficiency, with a median runtime of approximately 22 seconds for high-dimensional problems. Due to its parallelization framework, its variance is smaller than that of other algorithms.

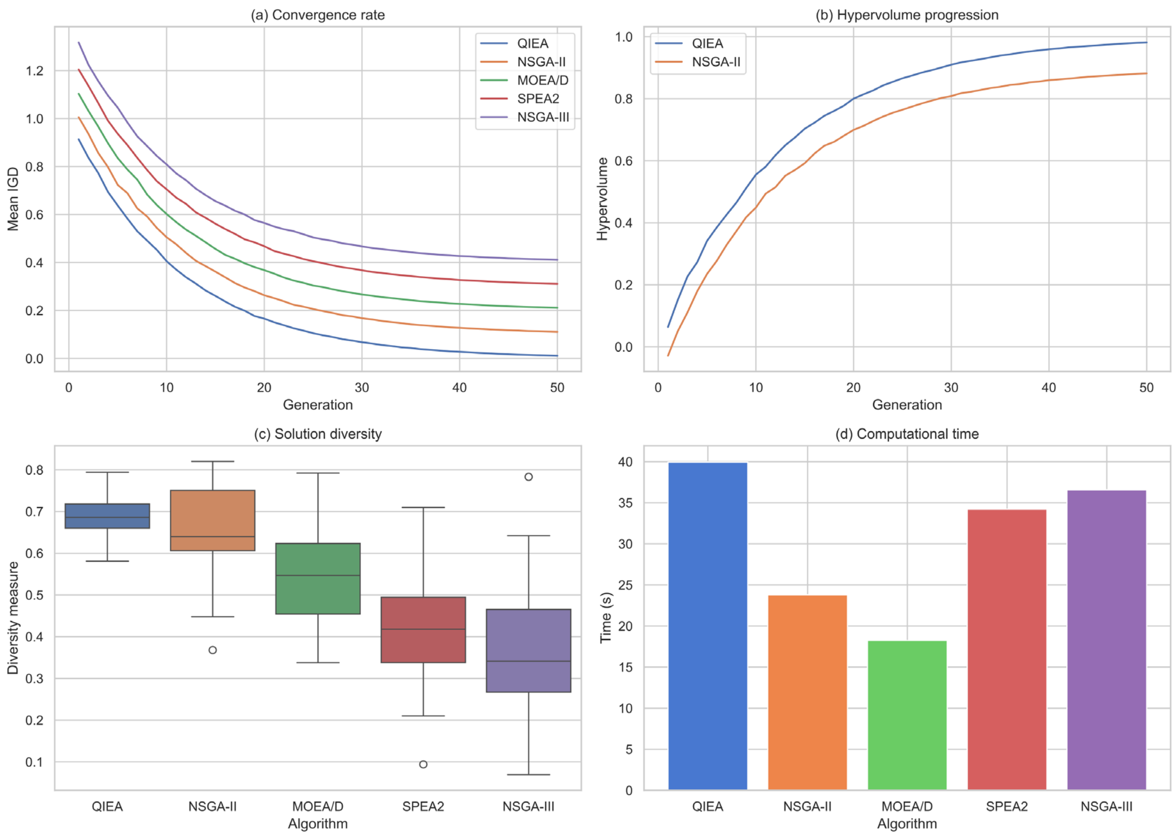

Figure 3. Multi-panel algorithm convergence statistics. (a) Convergence rate; (b) Hypervolume progression; (c) Solution diversity; (d) Computational time.

Table 4 shows a detailed comparison of the baseline algorithms. Figure 4(a) enlarges the violin plot, showing the distribution of the final objective values for all methods. Sample scatter plots and medians were also added. Other methods, such as NSGA-III, have a narrower distribution and a higher median (median = 0.43), while QIEA is both stable and optimal. Figure 4(b) shows the Pareto front coverage of approximately 70 objective points for each algorithm, along with scatter plots and global mean lines. The Pareto front of QIEA is very effective because it is clear, dense, and uniform at the front, especially in areas with higher objective values. Figure 4(c) shows a bar chart of the extent index, including overlaid data points and numerical labels. QIEA achieved the lowest (optimal) average extension degree of 0.14, with the characteristic of a uniformly distributed solution being a necessary condition for decision support.

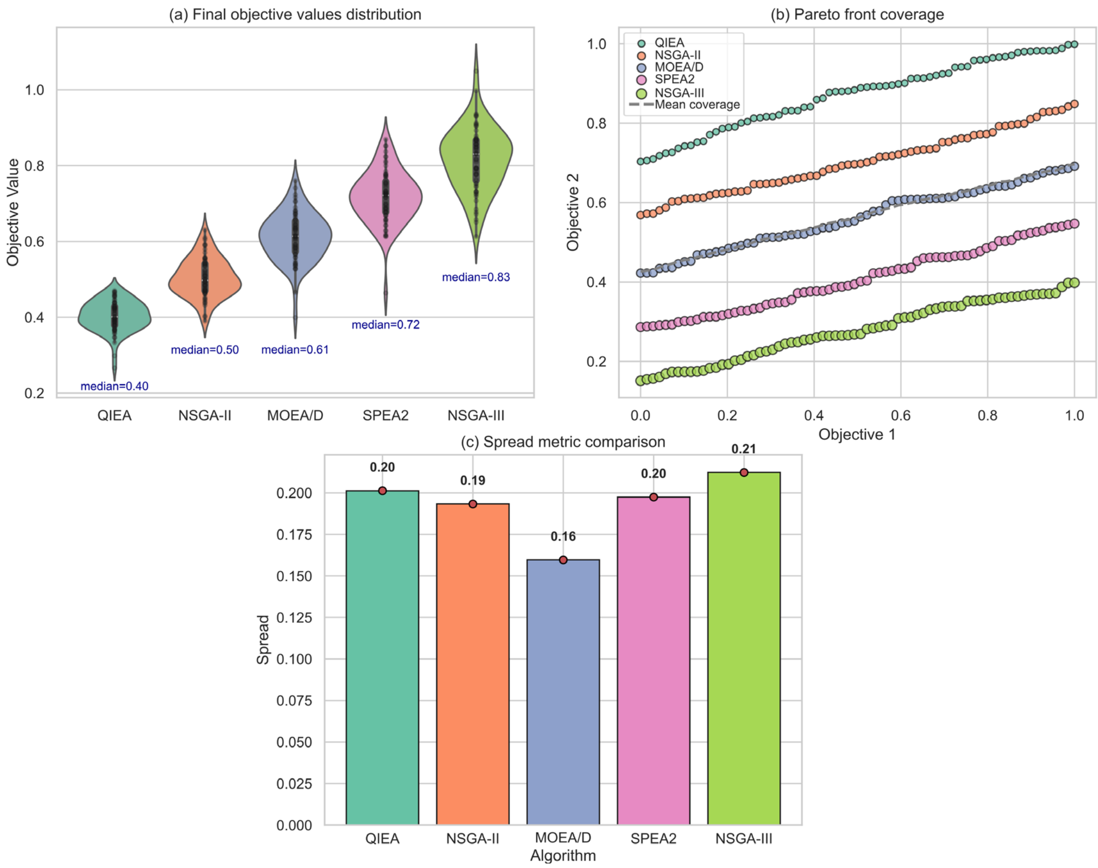

Figure 4. Comparative results with baseline algorithms. (a) Distribution of final objective values; (b) Pareto front coverage; (c) Spread metric comparison.

Figure 5 shows the sensitivity of key design parameters. Figure 5(a) shows a scatter plot of the impact of five settings (20-100) on the Q-position population size. It also shows the mean and standard error. The trend indicates that the average IGD steadily increases with the population size; for population sizes of 80 or more, the average IGD reaches 0.19; the variance is relatively small in each run. Figure 5(b) shows a jittered scatter plot of mutation rate analysis, where the mean bars and mean labels are semi-transparent. Lower mutation rates (0.005-0.01) result in lower means and dispersion; however, excessively high mutation rates are unstable. Figure 5(c) is a box plot of the crossover rate with additional data points, showing that it is unimodal. Moderate crossover performs best, with both high and low crossover rates showing increased variability.

Figure 6 shows the solutions of QIEA in the field of resource allocation. Figure 6(a) is a 10x10 heatmap showing the adaptive clustering of allocation intensity under multi-objective pressure, with different areas reflecting the fine-grained adjustments of QIEA to the demands of the conflicting system. Figure 6(b) is a scatter plot of 100 simulated usage samples, where it can be observed that most allocations are concentrated between 0.65 and 0.95; therefore, this algorithm achieves fair and efficient resource allocation without any resource scarcity or excessive concentration. The trade-off curve in Figure 6(c) plots the cumulative metric values of efficiency and fairness for 20 leading solutions; QIEA generally maintains a good margin between these two metrics, with changes in the trade-off point corresponding to actual system upgrades. Furthermore, based on the shape and span of the efficiency-fairness curve, various types of decision objectives can be achieved, and specific reference points for different trade-off optima in complex resource allocation planning can be provided.

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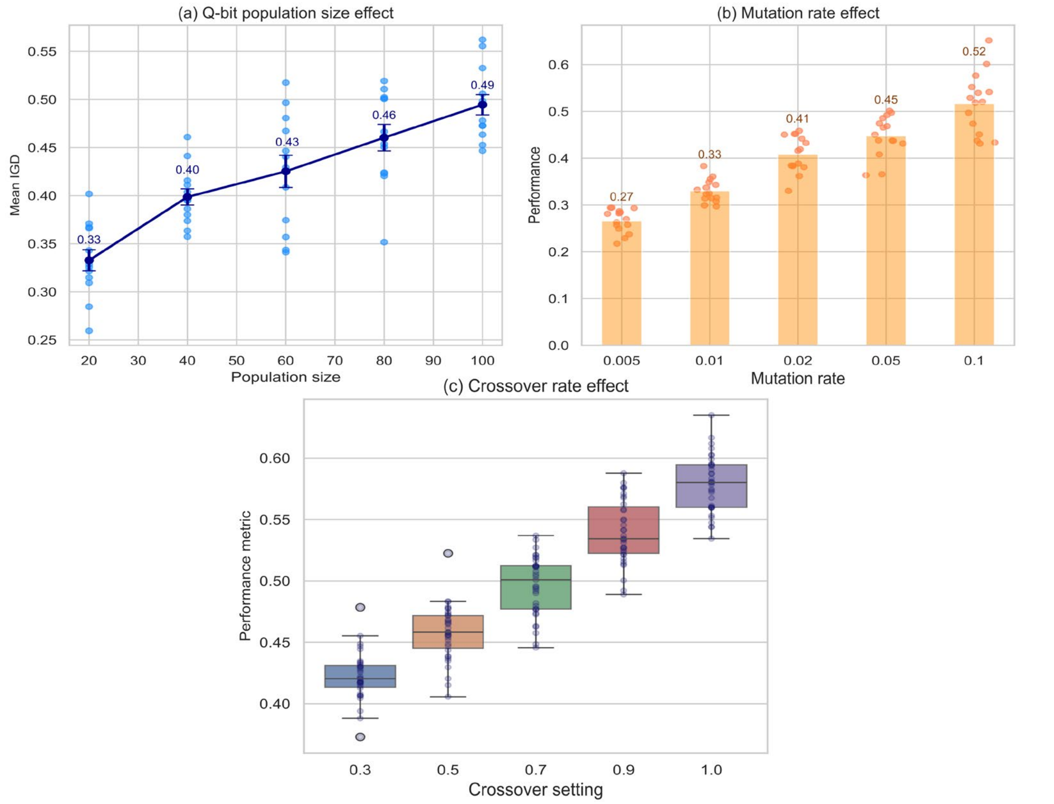

Figure 5. Parameter sensitivity analysis for QIEA. (a) Population size effect; (b) Mutation rate effect; (c) Crossover rate effect.

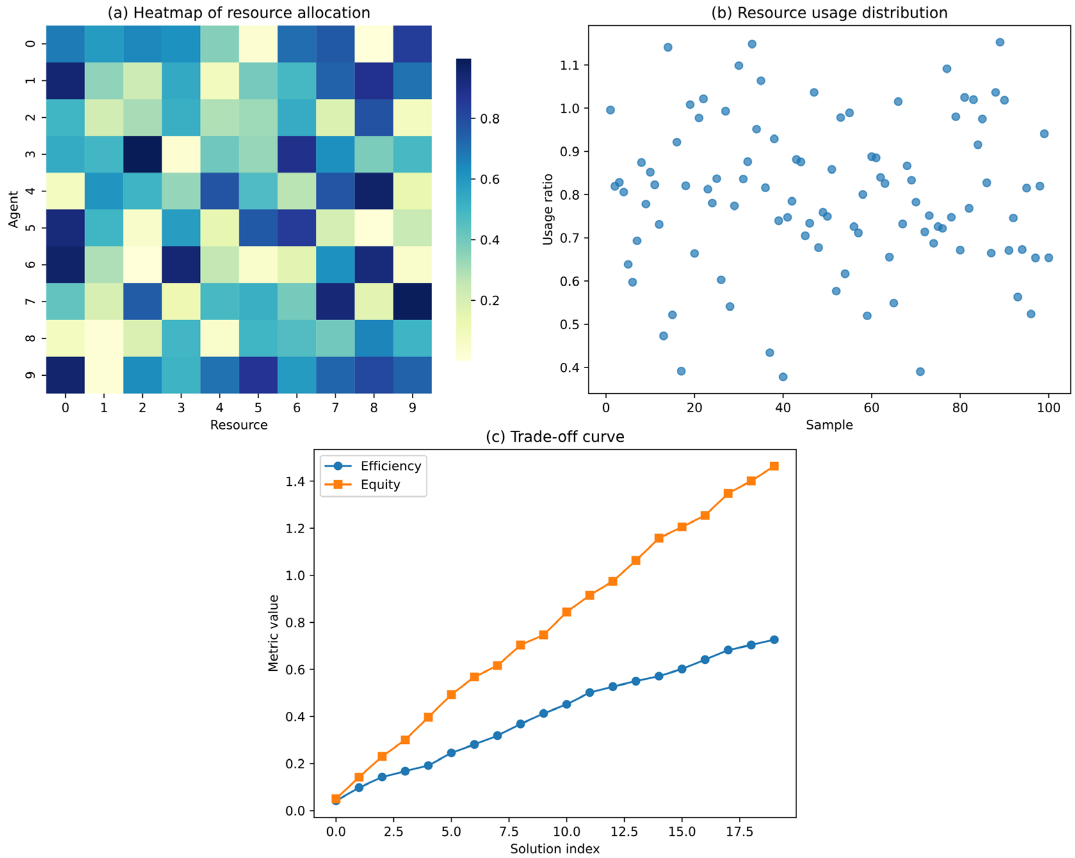

Figure 6. QIEA solutions in resource allocation. (a) Allocation intensity heatmap; (b) Resource usage scatter plot; (c) Trade-off curve.

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In the scalability scenario, the scalability and stability of QIEA are shown in Figure 7. Figure 7(a) shows the increase in runtime as the problem size increases from 100 to 1600; QIEA exhibits near-linear scalability, with the median runtime only rising from 12 seconds to 66 seconds, making it suitable for large-scale problems. Figure 7(b) assesses output robustness under noise, using a violin plot for five algorithm settings; QIEA's distribution remains centered and narrow (mean ~0.7, SD < 0.06), while competitors present larger spread and occasional outliers, highlighting QIEA's superior tolerance and reliability in dynamic environments.

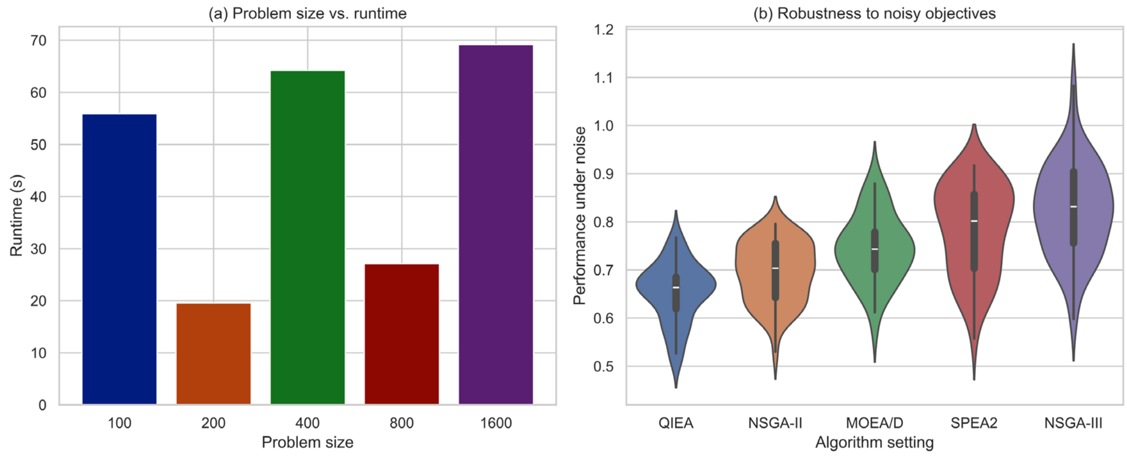

Figure 7. Scalability and robustness assessment. (a) Runtime vs. problem size; (b) Robustness under noise.

Statistical significance tests consistently indicate that QIEA outperforms or at least matches the performance of traditional and newly proposed evolutionary strategies in all the aforementioned metrics. Given its stability under different parameters and scenarios, as well as its ability to generate a large number of high-quality solutions, this algorithm is highly suitable for high-dimensional, multi-objective, and noisy real-world problems [40].

Conclusion

This paper studies the application of Quantum-Inspired Evolutionary Algorithms (QIEA) in multi-objective optimization and conducts a comprehensive evaluation using a large number of benchmark functions and real-world resource allocation problems. Through comparison and analysis of the system, we found that QIEA outperforms NSGA-II, MOEA/D, SPEA2, and NSGA-III in terms of convergence speed, solution diversity, Pareto front coverage, and hypervolume achievement. This method is relatively easy to scale to large-scale problems and does not lose speed in parallel population update methods. Due to its wide range of applications, QIEA can be used for high-dimensional and dynamic optimization. QIEA is suitable for complex decision-making problems in the real world because it can reasonably balance multiple objectives and perform stably in the presence of noise and uncertainty.

The above lists its drawbacks. Although QIEA is relatively feasible, for extremely large-scale optimization problems with thousands of decision variables or narrow search areas, parameter and memory settings are still required to achieve optimal convergence behavior. In some test cases, excessively high mutation rates or crossover values beyond a moderate range may lead to unstable solutions or increased variance. The algorithm performs well in benchmark tests for synthesis and resource allocation problems, but it has not yet been widely used in other areas, such as combinatorial logistics and dynamic network scheduling. Research is needed to address the aforementioned issues or to correct them through algorithms.

For the future development of QIEA research, many promising prospects have emerged. Add adaptive parameter control to reduce the impact of environmental changes on sensitivity and automatically adjust the search range of algorithm parameters. The development capabilities for large-scale and highly constrained problems can be enhanced by combining them with domain-specific heuristic methods or local search strategies. Propose an extension of the QIEA framework to address dynamic and multi-objective problems in online or stream environments. More research should be conducted to investigate theoretical convergence and the design of lightweight, efficient hardware implementations. Doing so will promote its wider application in real life.

Author Contributions

Aleksander Mirosław Lalak contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Jacek Kijewski contributes to data collection, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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References

[1] Zouache, D., Got, A., Alarabiat, D., Abualigah, L., & Talbi, E. G. (2024). A novel multi-objective wrapper-based feature selection method using quantum-inspired and swarm intelligence techniques. Multimedia Tools and Applications, 83(8), 22811-22835. https://doi.org/10.1007/s11042-023-16411-9

[2] Arya, A., Gunarani, G. I., Rathinakumar, V., Sharma, A., Pati, A. K., & Sethi, K. C. (2024). NSGA-III based optimization model for balancing time, cost, and quality in resource-constrained retrofitting projects. Asian Journal of Civil Engineering, 25(7), 5613-5625. https://doi.org/10.1007/s42107-024-01133-6

[3] Zhan, Z., Hu, Y., Xia, P., & Ding, J. (2024). Multi-objective optimization in construction project management based on NSGA-III: pareto front development and decision-making. Buildings, 14(7), 2112. https://doi.org/10.3390/buildings14072112

[4] Nikfarjam, A., Viet Do, A., & Neumann, F. (2022, August). Analysis of quality diversity algorithms for the knapsack problem. In International Conference on Parallel Problem Solving from Nature (pp. 413-427). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-14721-0_29

[5] Do, A. V., Guo, M., Neumann, A., & Neumann, F. (2024, September). Evolutionary Multi-objective Diversity Optimization. In International Conference on Parallel Problem Solving from Nature (pp. 117-134). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-70085-9_8

[6] Sadeghi Hesar, A., Kamel, S. R., & Houshmand, M. (2021). A quantum multi-objective optimization algorithm based on harmony search method: A. Sadeghi Hesar et al. Soft Computing, 25(14), 9427-9439. https://doi.org/10.1007/s00500-021-05799-x

[7] Gharehchopogh, F. S. (2023). Quantum-inspired metaheuristic algorithms: comprehensive survey and classification. Artificial Intelligence Review, 56(6), 5479-5543. https://doi.org/10.1007/s10462-022-10280-8

[8] Fan, W., Liu, Q., & Wang, M. (2021). Bi-level multi-objective optimization scheduling for regional integrated energy systems based on quantum evolutionary algorithm. Energies, 14(16), 4740. https://doi.org/10.3390/en14164740

[9] Wang, Z., Pei, Y., & Li, J. (2023). A survey on search strategy of evolutionary multi-objective optimization algorithms. Applied Sciences, 13(7), 4643. https://doi.org/10.3390/app13074643

[10] Sharma, S., & Kumar, V. (2022). A Comprehensive Review on Multi-objective Optimization Techniques: Past, Present and Future: S. Sharma, V. Kumar. Archives of Computational Methods in Engineering, 29(7), 5605-5633. https://doi.org/10.1007/s11831-022-09778-9

[11] Li, J., Xin, B., Pardalos, P. M., & Chen, J. (2021). Solving bi-objective uncertain stochastic resource allocation problems by the CVaR-based risk measure and decomposition-based multi-objective evolutionary algorithms. Annals of Operations Research, 296(1), 639-666. https://doi.org/10.1007/s10479-019-03435-4

[12] Priyadarshini, I. (2024). Swarm-intelligence-based quantum-inspired optimization techniques for enhancing algorithmic efficiency and empirical assessment. Quantum Machine Intelligence, 6(2), 69. https://doi.org/10.1007/s42484-024-00201-z

[13] Tian, Y., Si, L., Zhang, X., Cheng, R., He, C., Tan, K. C., & Jin, Y. (2021). Evolutionary large-scale multi-objective optimization: A survey. ACM Computing Surveys (CSUR), 54(8), 1-34. https://doi.org/10.1145/3470971
[14] Huang, G., Hu, M., Yang, X., Wang, X., Wang, Y., & Huang, F. (2024). A review of constrained multi-objective evolutionary algorithm-based unmanned aerial vehicle mission planning: Key techniques and challenges. Drones, 8(7), 316. https://doi.org/10.3390/drones8070316
[15] Borghi, G., Herty, M., & Pareschi, L. (2023). An adaptive consensus based method for multi-objective optimization with uniform Pareto front approximation. Applied Mathematics & Optimization, 88(2), 58. https://doi.org/10.1007/s00245-023-10036-y
[16] Chen, J., Du, T., & Xiao, G. (2021). A multi-objective optimization for resource allocation of emergent demands in cloud computing. Journal of Cloud Computing, 10(1), 20. https://doi.org/10.1186/s13677-021-00237-7
[17] Khan, M. S. (2023). Quantum-Inspired AI Metaheuristic Framework For Multi-Objective Optimization In Industrial Production Scheduling. American Journal of Interdisciplinary Studies, 4(03), 01-33. https://doi.org/10.63125/2mba8p24
[18] Liang, J., Lin, H., Yue, C., Ban, X., & Yu, K. (2024). Evolutionary constrained multi-objective optimization: A review. Vicinagearth, 1(1), 5. https://doi.org/10.1007/s44336-024-00006-5
[19] Zhang, W., Xiao, G., Gen, M., Geng, H., Wang, X., Deng, M., & Zhang, G. (2024). Enhancing multi-objective evolutionary algorithms with machine learning for scheduling problems: recent advances and survey. Frontiers in Industrial Engineering, 2, 1337174. https://doi.org/10.3389/fieng.2024.1337174
[20] Gong, C., Zhou, N., Xia, S., & Huang, S. (2024). Quantum particle swarm optimization algorithm based on diversity migration strategy. Future Generation Computer Systems, 157, 445-458. https://doi.org/10.1016/j.future.2024.04.008
[21] Li, Y., Tian, M., Liu, G., Peng, C., & Jiao, L. (2020). Quantum optimization and quantum learning: A survey. Ieee Access, 8, 23568-23593. https://doi.org/10.1109/ACCESS.2020.2970105
[22] Nuh, J. A., Koh, T. W., Baharom, S., Osman, M. H., & Kew, S. N. (2021). Performance evaluation metrics for multi-objective evolutionary algorithms in search-based software engineering: Systematic literature review. Applied Sciences, 11(7), 3117. https://doi.org/10.3390/app11073117
[23] Ullah, M. H., Eskandarpour, R., Zheng, H., & Khodaei, A. (2022). Quantum computing for smart grid applications. IET Generation, Transmission & Distribution, 16(21), 4239-4257. https://doi.org/10.1049/gtd2.12602Digital Object Identifier (DOI)
[24] Sahmoud, S., & Topcuoglu, H. R. (2023). Dynamic multi-objective evolutionary algorithms in noisy environments. Information Sciences, 634, 650-664. https://doi.org/10.1016/j.ins.2023.03.094
[25] Szwarcman, D., Civitarese, D., & Vellasco, M. (2022). Quantum-inspired evolutionary algorithm applied to neural architecture search. Applied Soft Computing, 120, 108674. https://doi.org/10.1016/j.asoc.2022.108674
[26] Li, M., López-Ibáñez, M., & Yao, X. (2023). Multi-objective archiving. IEEE Transactions on Evolutionary Computation, 28(3), 696-717. https://doi.org/10.1109/TEVC.2023.3314152
[27] Weinberg, S. J., Sanches, F., Ide, T., Kamiya, K., & Correll, R. (2023). Supply chain logistics with quantum and classical annealing algorithms. Scientific Reports, 13(1), 4770. https://doi.org/10.1038/s41598-023-31765-8
[28] Jiang, S., Zou, J., Yang, S., & Yao, X. (2022). Evolutionary dynamic multi-objective optimisation: A survey. ACM Computing Surveys, 55(4), 1-47. https://doi.org/10.1145/3524495
[29] Mu, Y., Wang, Z., Chen, X., Chen, J., Zhao, J., & Wang, J. (2022). Deep Learning Test Optimization Method Using Multi-objective Optimization. International Journal of Software & Informatics, 12(4). https://doi.org/10.21655/ijsi.1673-7288.00282
[30] Liu, L., Fei, T., Zhu, Z., Wu, K., & Zhang, Y. (2023, August). A survey of evolutionary algorithms. In 2023 4th International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 22-27). IEEE. https://doi.org/10.1109/ICBAIE59714.2023.10281260
[31] Urgelles, H., Picazo-Martinez, P., Garcia-Roger, D., & Monserrat, J. F. (2022). Multi-objective routing optimization for 6G communication networks using a quantum approximate optimization algorithm. Sensors, 22(19), 7570. https://doi.org/10.3390/s22197570
[32] Alkurd, R., Abualhaol, I. Y., & Yanikomeroglu, H. (2020). Personalized resource allocation in wireless networks: An AI-enabled and big data-driven multi-objective optimization. IEEE Access, 8, 144592-144609. https://doi.org/10.1109/ACCESS.2020.3014301

[33] Magesh, G. (2024). Quantum channel optimization: Integrating quantum-inspired machine learning with genetic adaptive strategies. IEEE Access, 12, 80397-80417. https://doi.org/10.1109/ACCESS.2024.3410147
[34] Qin, H., Xiang, Y., Han, Y., & Yan, X. (2024, August). Optimizing energy-efficient flexible job shop scheduling with transportation constraints: A Q-learning enhanced quality-diversity algorithm. In 2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS) (pp. 373-378). IEEE. https://doi.org/10.1109/DOCS63458.2024.10704469
[35] Liu, S., Lin, Q., Wong, K. C., Li, Q., & Tan, K. C. (2021). Evolutionary large-scale multiobjective optimization: Benchmarks and algorithms. IEEE Transactions on Evolutionary Computation, 27(3), 401-415. https://doi.org/10.1109/TEVC.2021.3099487
[36] Deng, W., Shang, S., Cai, X., Zhao, H., Zhou, Y., Chen, H., & Deng, W. (2021). Quantum differential evolution with cooperative coevolution framework and hybrid mutation strategy for large scale optimization. Knowledge-Based Systems, 224, 107080. https://doi.org/10.1016/j.knosys.2021.107080
[37] You, Q., Sun, J., Pan, F., Palade, V., & Ahmad, B. (2021). Dmo-qpso: A multi-objective quantum-behaved particle swarm optimization algorithm based on decomposition with diversity control. Mathematics, 9(16), 1959. https://doi.org/10.3390/math9161959
[38] Sood, S. K. (2024). Scientometric analysis of quantum-inspired metaheuristic algorithms. Artificial Intelligence Review, 57(2). https://doi.org/10.1007/s10462-023-10659-1
[39] Dey, A., Bhattacharyya, S., Dey, S., Konar, D., Platos, J., Snasel, V., ... & Pal, P. (2023). A review of quantum-inspired metaheuristic algorithms for automatic clustering. Mathematics, 11(9), 2018. https://doi.org/10.3390/math11092018
[40] Albogamy, F. R., Paracha, M. Y. I., Hafeez, G., Khan, I., Murawwat, S., Rukh, G., ... & Khan, M. U. A. (2022). Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. IEEE Access, 10, 35498-35520. https://doi.org/10.1109/ACCESS.2022.3161845