



Multi Objective Quantum Evolutionary Algorithms for Global Supply Chain Optimization

P. Pushpalatha^{1*}, Dr.K. Rajamani², J. Monisha³, Dr. Utkarsh Anand⁴

^{1*}Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Tamil Nadu, India. E-mail: pushpalathap@maher.ac.in

²Associate Professor (Sr. Grade), Mepco School of Management Studies, Mepco Schlenk Engineering College, Sivakasi, Tamil Nadu, India. E-mail: rajamani.pradeep@gmail.com, <https://orcid.org/0000-0001-5672-0304>

³Assistant Professor, Department of Management Studies, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Tamil Nadu, India. E-mail: jmonishamba@maher.ac.in

⁴Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India, E-mail: ku.utkarshanand@kalingauniversity.ac.in, <https://orcid.org/0009-0007-2124-6666>

Abstract

Global supply chain systems become complex with respect to globalization and the requirement of making fast decisions, sometimes with several conflicting objectives in terms of costs, time delivery, emissions, and resilience. Classical MOEA approaches, such as the genetic algorithm approach and the NSGA-II framework, have been used for such supply chain problems but are subject to premature convergence and poor scalability issues. The Quantum Evolutionary Algorithm (QEA) method is proposed for this study to combine the ideas of quantum computation with the concept of MOEA. The problem variables are represented in the form of qubits to perform parallel exploration of different solution candidates. QEA-based crossover and mutation operators can be used for the probabilistic variation of candidate solutions. The idea of Pareto front ranking helps preserve the optimal solutions. Benchmark datasets related to global supply chains were analyzed in this paper, and their performance was compared with classical MOEA algorithms. The QEA algorithm was found to perform better than its rivals in terms of hypervolume and convergence speed. Through ablation studies, the significant contribution of the quantum operator towards the enhancement of quality solutions and faster convergence rate has been proven. The study shows that QEA offers a realistic and efficient technique for dealing with the multi-objective problems associated with the complexities in global supply chains. For future research work, efforts will be made to scale-up the process using large quantum computers, apply the methodology to the dynamic nature of supply chains, and explore hybrid classical and quantum optimization techniques.

Keywords Quantum Evolutionary Algorithm, Multi-Objective Optimization, Global Supply Chain, Quantum Computing, Pareto Front, Convergence, Sustainability.

1. Introduction

Global supply chain management has become more complicated in light of the increasing trend towards globalization, market instabilities, and the need for instant response capabilities. Organizational entities confront several contradicting objectives that include minimizing operational costs, reducing delivery times, and mitigating risks within the supply chain. Conventional optimization techniques usually face challenges in traversing huge search spaces, especially when working in dynamic and uncertain circumstances. Classical evolutionary algorithms like the genetic algorithm and particle swarm optimization have been found effective when applied to multiple objective optimizations, yet suffer from problems of premature convergence and lack of scalability when used for large-scale global supply chains.

The integration of concepts of quantum computing with the evolution strategy is a promising approach that could solve the problem. Using quantum superposition and entanglement properties, multi-objective optimization based on quantum evolutionary algorithms becomes feasible in tackling the multi-objective optimization problem in global supply chains [1][7].

Research Questions:

1. Can QEA surpass traditional multi-objective methods for solving supply chain optimization problems?
2. How does the application of quantum-based operators affect convergence and solution quality?

Contributions:

1. The development of a quantum evolutionary approach to address multi-objective supply chain optimization,
2. Performance assessment compared to traditional approaches, and
3. Scalability analysis and applicability within complex supply chain environments.

The paper outlines the problems associated with global multi-objective optimization in supply chains, explaining the need to apply Quantum Evolutionary Algorithms (Section I). Literature review of classical evolutionary algorithms and quantum-based optimizations is provided with the focus on their weaknesses (Section II). The architecture of the proposed QEA framework, its operators, multi-objective optimization, and quantum representation are presented (Section III). Performance of the developed QEA in comparison with traditional optimization algorithms on a series of benchmark tests is presented by means of such criteria as hypervolume, convergence, spread, and running time (Section IV). Evaluation and discussion of results are carried out (Section V).

2. Literature Review

There has been extensive use of classical multi-objective evolutionary algorithms (MOEAs) for optimization in the supply chain domain, where objectives like minimizing cost, efficient deliveries, and effective resource utilization are often at conflict [4] [6]. There have been several successful implementations using genetic algorithms and heuristics within renewable energy microgrids, energy supply chain networks, and sustainable supply chains [2] [3]. These classical optimization approaches may suffer from premature convergence and lack of diversification when dealing with huge and evolving domains. Quantum computing has proved to be a valuable optimization tool due to its ability to exploit the superposition principle and entanglements. This is applied in the context of logistics in the supply chain with quantum annealing, quantum-based hyper-heuristics for solving dynamic multi-objective combinatorial optimization problems, and quantum-aware particle swarm optimization in cold chain logistics [5][8].

Although there have been significant improvements, however, limitations still exist in the application of multi-objective quantum evolutionary algorithms (QEA) to the challenges posed by complex global supply chains, especially concerning simultaneous optimization for cost, risk, and performance in a real-world dynamic environment. This leads to the need for developing a QEA-based model for global supply chains[9][10].

3. Methodology

The proposed framework uses the Quantum Evolutionary Algorithm (QEA), which is specially designed for multi-objective optimization in global supply chains. The architecture integrates quantum-based solution representation along with evolutionary operations to search for optimal solutions effectively.

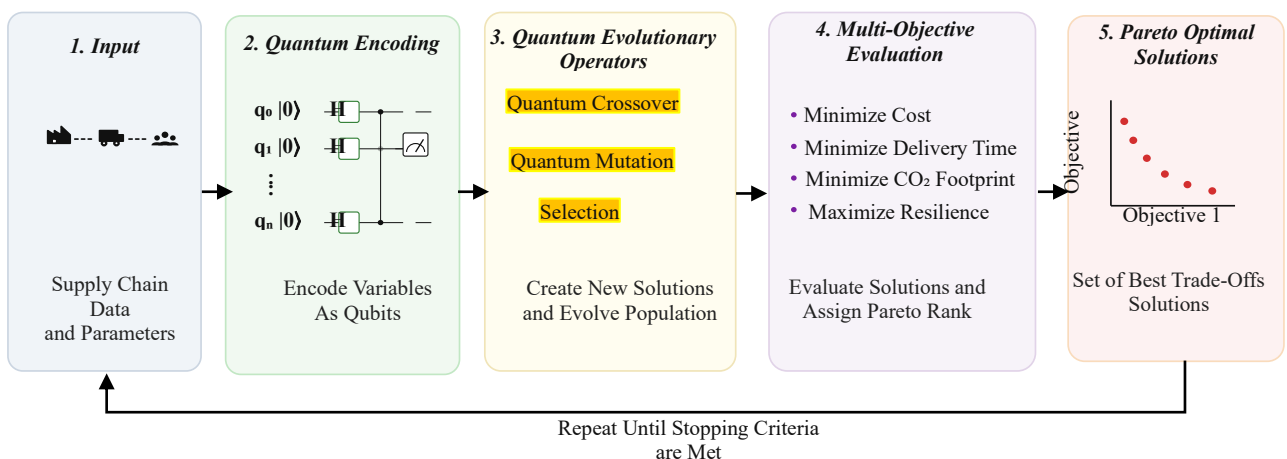


Figure 1: Quantum Evolutionary Algorithm Framework for Multi-Objective Supply Chain Optimization

Figure 1 depicts the process flow of the QEA approach, which involves initializing quantum-encoded candidate solutions, quantum crossover and mutation operations, objective function evaluations, Pareto front selections, and repeated evolutionary processes until convergence is achieved.

The supply chain-related parameters, such as production amounts, transportation arrangements, and stock holdings, are encoded in the form of qubits that can be put into superposition states to generate several candidate solutions. Quantum representation is more efficient than its classical counterpart, as the former can accelerate the convergence process while ensuring better diversity among solutions. Quantum-inspired crossover and mutation operations facilitate the probabilistic combination and modification of candidate solutions while the selection operation is utilized to evaluate and retain Pareto optimal solutions through successive generations. In addition, multi-objective optimizations are performed on several objective functions, such as the sum of total costs, delivery time, carbon footprint, and supply chain resilience, in order to consider economic and environmental metrics. Such operations can be implemented in quantum simulators, such as Qiskit Aer and PennyLane, together with classical optimizers, in order to adjust quantum parameters iteratively.

4. Experimental Setup and Results

The designed Quantum Evolutionary Algorithm (QEA) was tested with realistic supply chain benchmark data sets, including production-distribution network data consisting of multiple suppliers, manufacturers, logistics, and volatile customer demand. Classical multi-objective evolutionary algorithms, including NSGA-II and regular genetic algorithms, were taken as benchmarks for comparison. The evaluation made use of traditional multi-objective performance metrics that include hypervolume for assessing the quality of Pareto fronts, convergence for evaluating algorithmic efficiency towards obtaining an optimum solution, spread for diversity, and computational efficiency for measuring the run-time of the algorithm.

The QEA demonstrated superior performance over classical benchmarks on all objectives. Table 1 presents the comparison, where higher hypervolume and faster convergence with lower computational cost can be observed. An elaborate plot (Figure 2) depicts the development of the Pareto front over iterations. Quantum crossover and quantum mutation have been shown to improve the exploration and exploitation of the search space. In order to determine the significance of quantum operations in QEA, an ablation study was conducted by turning off the quantum crossover or mutation operation separately. The resultant performance shows a significant degradation in solution quality and slower convergence, which proves the importance of the quantum operations.

Table 1: Comparison of QEA and Baselines on Hypervolume, Spread, Convergence, and Computational Time

Algorithm	Hypervolume ↑	Spread ↓	Convergence ↓	Computational Time (s) ↓
QEA (Proposed)	0.873	0.092	0.021	35.6
NSGA-II	0.798	0.118	0.037	42.3
Standard GA	0.762	0.132	0.045	40.1

Table 1, QEA has proven itself superior to classical multi-objective evolutionary algorithms in both the quality of solutions (hypervolume, spread, and convergence) and speed of computation.

5. Discussion

The results of experiments have revealed that the developed Quantum Evolutionary Algorithm (QEA) is highly efficient in delivering higher-quality solutions than classical multi-objective evolutionary algorithms. In particular, the use of QEA yields better performance in terms of both hypervolume and spread. The use of quantum-inspired crossover and mutation operators allows considering several promising candidate solutions at once, thus avoiding the problem of premature convergence and helping to make the trade-offs between cost, delivery time, carbon dioxide emissions, and other competing objective factors.

However, there are also some drawbacks associated with this framework. For example, the implementation of these tests uses quantum simulators that do not have the ability to simulate precisely the performance and noise

levels observed in actual quantum devices. In addition, its scalability can be limited when it is applied to highly complex global supply chains. Its performance benefits can also vary based on the complexity of the objective function used. Overall, however, the presented QEA framework can serve as an invaluable tool for application in practice.

6. Conclusion and Future Work

The current study introduced an approach that used a Quantum Evolutionary Algorithm (QEA) for multi-objective optimization within global supply chains, considering different objectives, including costs, delivery time, carbon footprint, and resilience. The findings indicate that the Quantum Evolutionary Algorithm (QEA) surpasses classical multi-objective optimization evolutionary algorithms in terms of efficiency, quality of solutions, and their diversity. In addition, quantum-based algorithms allow performing multi-objective optimizations for several candidate solutions at once. Thus, the developed method can be considered as a real-life solution for organizations that have to deal with different goals within their supply chains. Future research would involve extending the scalability of the proposed QEA algorithm to quantum hardware with increased qubits to improve computational performance and increase diversification. Moreover, the extension of the model to dynamic real-time supply chains will allow adaptive management in dynamic markets. The integration of classical heuristic algorithms with the quantum-based algorithms can be used to solve industrial problems through hybrid optimization systems. In summary, the proposed model presents a basis for quantum evolutionary computation in the optimization of supply chains and offers theoretical contributions and practical advantages in multi-criteria optimization.

References

1. Nozari, H., & Yordanova, Z. (2025). Hybrid digital twin and quantum AI with fuzzy multiobjective modeling in supply chain management. *Edelweiss Applied Science and Technology*, 9(10), 609–628.
2. Bai, Q. (2026). Optimisation of energy supply chain and global value chain based on genetic algorithm. *International Journal of Information and Communication Technology*, 27(38), 23–41.
3. 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.
4. Danach, K., Harb, H., Saker, L., & Raad, A. (2025). Quantum-inspired hyperheuristic framework for solving dynamic multi-objective combinatorial problems in disaster logistics. *World Electric Vehicle Journal*, 16(6), 310.
5. Xia, C., & Yin, M. (2026). Quantum-aware particle swarm optimization for cold chain logistics path planning under time-varying temperature constraints. *Evolutionary Intelligence*, 19(2), 40.
6. Ehtesham Rasi, R., & Sohanian, M. (2021). A multi-objective optimization model for sustainable supply chain network with using genetic algorithm. *Journal of Modelling in Management*, 16(2), 714–727.
7. Antti Laine. (2026). Design and Implementation of a Real-Time Edge-Based IoT Monitoring System Using Embedded Multi-Sensor Networks. *Archives of Embedded and IoT Systems Engineering*, 2(1), 29–34.
8. B.M.Brinda. (2025). Development of a Smart Variable-Rate Planter Using IoT and Machine Vision for Precision Seeding. *Journal of Environmental Sustainability, Climate Resilience, and Agro-Ecosystems*, 2(1), 24–30.
9. G.F. Frire and F. de Mindonça, “Low-Complexity Deep Learning Architectures for Robust Signal Detection in Massive MIMO Systems”, *Electronics Communications, and Computing Summit*, vol. 2, no. 3, pp. 114–119, Sep. 2024.
10. Pushplata Patel and Prerna Dusi, “Optimization Models for Sustainable Energy Management: A Multidisciplinary Approach”, *Bridge: Journal of Multidisciplinary Explorations*, vol. 1, no. 1, pp. 1–10, Jul. 2025