10.48047/jocaaa.2026.35.02.03

Quantum-AI Optimization of National Supply Resilience

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Received: 03.02.2026 Accepted: 08.02.2026

Abstract

Resilience of the supply chain has turned out to be a critical national concern due to the revelations of vulnerabilities in the global networks of logistics that cannot be sufficiently managed by traditional optimization tools. Artificial intelligence and quantum computing can provide revolutionary answers to complex supply chain challenges, addressing them using new computational paradigms. Quantum algorithms use superposition and entanglement to search a solution space that is exponentially larger than the space available to classical computers, and Ireland enables optimal resource allocation in large networks. Hybrid quantum-classical systems are a strategic allocation of computational workload where quantum processors are processing combinatorial optimization kernels and classical systems are doing data preprocessing and solution validation. The quantum algorithms used to optimize the transportation network during disruption conditions are useful in optimizing the network due to the presence of multiple routing strategies in various circumstances of failures. Manufacturing coordination deals with the issue of production scheduling, inventory distribution, and supplier redundancy by quantum formulations that trade off conflicting operational goals. Existing hardware limits put a lower bound on the achievable practical implementation, but the current fast development of qubit quality, connectivity, and error correction implies that a practical quantum advantage soon will be reached in large-scale optimization of supply chains. Quantum computing and supply chain management integration create new principles of ensuring the preservation of critical resource flows in the case of emergencies, which proves the possibilities of increased national resiliency to pandemics, geopolitical conflicts, and natural disasters.

Keywords: Quantum Computing, Supply Chain Optimization, National Resilience, Hybrid Algorithms, Transportation Networks

I. Introduction to Quantum-Enhanced Supply Chain Resilience

The issue of supply chain resilience has become an issue of national concern after a series of disruptions in supply chain networks that have exposed the essential weaknesses in international logistics systems. The conventional optimization tools can hardly handle the exponential complexity of the large-scale supply chain problems, when a large number of variables should be taken into consideration simultaneously, including transportation, manufacturing, and distribution systems. Resolution of these problems through radically new, fundamentally different computational paradigms, previously unavailable in classical computational methods, is available through the convergence of quantum computing and artificial intelligence.

Quantum computing uses quantum mechanical properties like superposition and entanglement to search solution spaces of an exponential size compared to those available to classical computers. Combined with machine learning algorithms, quantum systems can derive the best patterns of resource allocation in complex networks with many nodes and constraints. Application of quantum computing in the

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optimization of supply chains is a revolutionary opportunity because such systems can address intractable combinatorial optimization problems that cannot be solved by other algorithms. Quantum processors implemented on hybrid systems that use classical computing infrastructure allow the decomposability of large problems into small subproblems and do not compromise the quality of solutions on the whole network [1].

Efforts to design quantum algorithms with the express purpose of solving optimization problems have made considerable progress, such as the quantum approximate optimization algorithm and quantum annealing, which may find a practical use. These algorithms work by encoding optimization problems into quantum Hamiltonians, with the lowest state being an optimal solution. The equations that the quantum system follows are the Hamiltonians, and the quantum system takes on a variety of solution paths in parallel through quantum superposition. This parallel exploration ability is of more importance as the dimension of the problem increases, more especially when dealing with supply chain networks with complex inter-dependency between transportation routes, manufacturing facilities, and distribution centers [2].

The key to the resilience of the national supply is the capacity to restructure the flows of the resources quickly in case of the primary channels being disrupted. In response to pandemics, geopolitical crises, or natural disasters, decision-makers have to assess a large number of alternative routing and allocation possibilities with a very tight time-constrained time horizon. Real-time resilience planning is based on quantum-enhanced optimisation systems and allows the government to keep critical supply flows operational, even in the case of significant parts of the logistics infrastructure being disrupted. Quantum computing, combined with artificial intelligence, forms adaptive systems that can learn the pattern of disruptive events in history and calculate the optimal response to new emergencies, and this will become the new paradigm of managing national supply chains that focuses on resilience as well as efficiency.

II. Quantum Algorithm Foundations for Resource Allocation

Quantum annealing is one of the best-developed methods of finding solutions to the combinatorial optimization problems, which are applicable in supply chain management. The method maps logistics problems and goals to a quantum tunneling energy landscape where quantum tunneling allows the system to escape local minima into which classical algorithms are trapped. The basic idea is to formulate the optimization problem as a quadratic and unconstrained binary optimization problem where the decision variables are discrete decisions made in all parts of the supply network. The quantum annealers are defined by initializing a system in a superposition of all possible states and evolving towards those configurations that optimize the objective function and thus take advantage of quantum fluctuations to cover the solution space better than thermal fluctuations used in classical simulated annealing [3].

The quantum approximate optimization algorithm can offer an alternative method that is specifically important when using gate-based quantum computers with a particular circuit structure that is targeted at the solution of combinatorial problems. QAOA switches among mixing and problem-specific Hamiltonians, forming quantum states that represent high-quality solutions at a measurably large probability scale. The algorithm design is a collection of parameterized quantum circuits with parameters optimized using classical feedback loops, forming a quantum-classical optimization system. This method proves to be especially effective with issues of complicated constraint natures, e.g., supply chains in which regulatory constraints, capacity constraints, and timing constraints generate complicated feasibility areas that provoke classical solution designs [4].

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Variational quantum algorithms are variants of hybrid optimization algorithms that make use of quantum circuits as versatile functional approximators as part of larger optimization problems. Such techniques utilize the representativeness of parameterized quantum circuits to model complex optimization landscapes and use classical optimization to parameterize circuits by stages. The variational method is particularly useful when applied to supply chain problems, where the problem structure can be decomposed into subproblems that are solvable with the existing hardware limitations. Variational methods are able to satisfy the quality of a competitive solution by tailoring the quantum circuit architecture to the symmetries of the problem and patterned constraints and can address the inherent limits of qubit counts and coherence times of near-term quantum devices [4].

Theoretical bases of quantum optimization algorithms display the essential benefits of exploration of the solution space over classical methods. As compared to classical algorithms, in which a candidate solution has to be sequentially evaluated or gradient information has to be used, which can cause local minima, quantum algorithms use superposition to concurrently test many configurations. It can also be improved by quantum entanglement, which establishes a correlation between decision variables indicating the structure of the problem, and thus allows the quantum system to find promising regions of solutions more quickly. The actual implementation of these theoretical benefits is, however, highly reliant on the maintenance of quantum coherence during the optimization procedure and therefore needs attention in terms of error reduction measures and the algorithms' design decisions that balance optimization of quantum resource usage to solution quality demands to supply chain resilience applications.

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Algorithm Type	Optimization Approach	Problem Encoding	Circuit Structure	Primary Advantage
Quantum Annealing	Energy landscape mapping with quantum tunneling	Quadratic Unconstrained Binary Optimization (QUBO)	Adiabatic evolution	Escape from local minima through quantum fluctuations
Quantum Approximate Optimization Algorithm (QAOA)	Alternating Hamiltonians	Parameterized quantum states	Problem-specific and mixing layers	Handles complex constraint structures effectively
Variational Quantum Algorithms	Hybrid quantum-classical iteration	Flexible function approximation	Problem-adapted ansätze	Accommodates current hardware limitations
Superposition-Based Methods	Parallel solution evaluation	Quantum state encoding	Entangled decision variables	Simultaneous configuration assessment

Table 1: Quantum Algorithm Performance Characteristics for Supply Chain Optimization [2-4]

III. Hybrid Quantum-Classical Architecture for Critical Supply Networks

Hybrid quantum-classical architectures have to be tuned for the supply chain use cases to run at maximum efficiency. In this distributed architecture, classical compute nodes play a key role in data processing and management, as well as performing high-precision arithmetic, while quantum processors contribute speedups in optimization kernels that can be combinatorial in nature. Additional challenges in the architecture involve basic problem formulation, which includes mapping real-world constraints and objectives of a supply chain problem to mathematical formulations applicable to quantum computing. These include selecting decision variables, determining constraint penalties, designing objective functions that reflect operational preferences, and ensuring compatibility with quantum algorithm requirements [1].

Data preprocessing is a critical part of hybrid architectures because raw data from the supply chain must be transformed into a problem representation that can be run on a quantum computer. Geographic representations are discretized as nodes and edges with transportation capacities, costs, and reliability characteristics. The patterns of demand must be modeled with mathematical objects that capture the uncertainty of the consumption rate and timing. The modes of transport and manufacturing capabilities define the constraint matrices. The preprocessing pipeline must balance the trade-off of preserving the problem and reducing the problem size to one that can be tackled by current quantum systems, with domain knowledge often being required to determine which details are essential for solution quality [5].

The quantum circuit design of the supply chain variable implements any known dynamic programming or optimization problem designs by representing the supply chain optimization problem's binary decision variables as single-qubit states following a specific pattern. The continuous variables are encoded as discretized binary values, with the levels of precision depending on the solution and qubit requirements. The circuit must also encode the objective of the optimization, as well as any constraints to the problem, typically as penalty terms that prohibit infeasible solutions. More complicated circuit implementations

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may use problem-specific ansatzes exploiting the structure of the supply chain networks, e.g., based on a hierarchical decomposition of the networks into geographic regions, as well as a decomposition into decisions about transportation and those about manufacturing [6].

Classical post-processing statistics and solution validation allow quantum measurements to be translated into supply chain decisions. Quantum algorithms produce probability distributions, and therefore multiple runs of the same algorithm may be required to find satisfactory solutions that are trustworthy. The measurement output is statistically evaluated to identify the solutions most often found, which correspond to the configuration that maximizes the objective function. The decoded solutions are validated by checking against all operational constraints, and the candidate solutions are iteratively refined if initial solutions were not able to meet capacity or timing constraints. Particularly challenging is the need to run the entire hybrid optimization loop, including preprocessing, quantum execution, and post-processing, within operationally relevant time frames, so that the optimization routine can respond in near real time to changes to the disruption scenario; to achieve this, the classical components of the algorithm must also be optimized [7].

Architecture Component	Processing Paradigm	Primary Functions	Problem Transformation	Integration Requirement
Data Preprocessing	Classical Systems	Geographic network discretization, demand pattern encoding	Node-edge representation with capacity parameters	Domain expertise for complexity reduction
Quantum Circuit Design	Quantum Processors	Decision variable encoding, constraint representation	Binary mapping with penalty terms	Problem-specific ansätze development
Optimization Kernel	Quantum Processors	Combinatorial optimization execution	Quantum Hamiltonian evolution	Circuit depth management
Post-Processing	Classical Systems	Statistical aggregation, solution validation	Measurement outcome interpretation	Iterative refinement mechanisms

Table 2: Hybrid Architecture Components for Critical Supply Networks [1, 5-7]

IV. Transportation Network Optimization Under Disruption Scenarios

Optimizing the multi-modal interconnections between road, rail, marine and air carriers allows the flow of critical resources to continue during unplanned disruptions. Quantum algorithms excel at optimizing trade-offs in transportation networks between cost, speed, reliability and carrier types across heterogeneous service levels. Mathematical abstraction of multi-modal routing problems employs graphs with each mode represented by a set of nodes (transfer points) and arcs (transportation links), with the latter containing attributes for the corresponding modes. When each mode has distinct attributes such as limitations on capacities, pricing structure, speeds, and resistance to disruptions, optimization algorithms balance these attributes under feasibility and optimality considerations of the network [8].

Dynamic rerouting functionality enables the adaptation of supply networks with respect to circumstances, such as destroyed infrastructure (due to natural disasters, warfare, or technical reasons). A typical route optimization problem assumes that the network topology is static. Therefore, rerouting, if destruction of

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infrastructure occurs, is limited to a complete recomputation, which does not take cascading effects into account. Quantum optimization techniques can also be applied in such cases of disruption through formulations that take uncertainty and multiple failure scenarios into account. Due to the principle of quantum superposition, solutions that may be helpful for multiple failure scenarios can be effectively searched by considering all failure scenarios at once [9].

The primary reason for optimizing transportation networks is capacity constraints. These constraints prevent additional demand from being supplied regardless of the demand's level, resulting in nonlinearities with respect to routing choices as well as congestion effects when the system operates at high levels. On the other hand, quantum optimization algorithms exploit capacity constraints through penalty functions that strongly penalize the usage of infrastructure beyond its capacity, while allowing the optimizer to explore values close to the capacity. Penalty weights in quantum circuits used to encode penalty functions must be carefully chosen to avoid violating the constraints due to penalties being insufficient to maintain capacity limits or the inverse situation of the algorithm penalizing too much and avoiding good feasible solutions [10].

Systems that must respond in real-time to changes often use continuous state information gathering as well as faster reoptimization. For example, sensor networks and logistics tracking networks can provide a continuous stream of information about traffic, infrastructure, and demand. The development of a hybrid quantum-classical adaptive optimization framework has been eased by efficient problem-updating methods, which update the parameters of a quantum circuit with new information, without requiring a full rerun for the problem, in emergencies where transportation networks face sequential or cascading failures. The quantum optimization system can calculate an updated routing plan based on the state of the network, and can even accommodate incipient or planned network disruptions, providing advanced rather than merely reactive supply chain management.

Optimization Strategy	Network Component	Quantum Capability	Constraint Handling	Adaptation Mechanism
Multi-Modal Coordination	Road, rail, maritime, air	Trade-off evaluation across carrier types	Graph-based formulation with mode-specific attributes	Heterogeneous service level balancing
Dynamic Rerouting	Infrastructure links	Parallel disruption scenario evaluation	Uncertainty incorporation through superposition	Real-time topology updates
Capacity Management	Physical infrastructure	Penalty formulation for throughput limits	Nonlinear congestion modeling	Near-capacity exploration
Adaptive Optimization	Sensor networks	Parameter modification without reformulation	Cascading failure consideration	Proactive disruption anticipation

Table 3: Transportation Network Optimization Strategies Under Disruptions [8-10]

V. Manufacturing Network Coordination and Bottleneck Resolution

Production scheduling determines what and when to produce across a network of factories in order to meet demand while minimizing cost and resource consumption. It is complicated by precedence constraints among production stages, contention for resources some products share with others, and

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coordination among factories that produce complementary components of larger products. Quantum optimization techniques often model scheduling as a constraint satisfaction problem, where the variables indicate production assignment and timing decisions to be made, while the objective function balances overall production costs, inventory holding, due dates, and the use of machines at efficient rates without incurring excessive wear costs [8].

When inventory is spatially distributed, the trade-off between local stocks for a fast response and holding costs at multiple locations becomes more difficult to manage. So the spatial configuration of reserves becomes more important when lead-times from central inventory, due to disruption in transportation networks or possible shocks to the transportation network, increase. The models also consider spatial demand distributions, the transport network, storage capacities, and product features such as the perishability of products or special handling properties. Quantum algorithms search for solutions in the space of all possible inventory configurations in the form of quantum states, while the quantum state is modified by an objective function, for example, the total cost and service level of the system [11].

If suppliers are redundant, the supplier selection problem can determine how many and which suppliers to select for each component type, as well as how much to order from the set of selected suppliers to buffer against disruption. The quantum optimization formulation determines the cost premium associated with maintaining multiple suppliers against the risk-reduction benefits that can be gained by diversifying supply. It does so while considering supplier pricing schemes, minimum order quantities, quality and reliability histories, geographic location, and disruption risk correlations. It must balance redundancy against the cost of maintaining and trading with many suppliers, and the cost of processing orders. [12]

If production schedules are not coordinated with transportation availability, then the products that are manufactured have to wait in an inventory bottleneck in one or more factory locations until it is their turn to be shipped. This wastes storage space in warehouses and causes working capital to be tied up. The joint optimization of production and transportation can be captured by the quantum optimization framework, which includes both production and transportation variables and considers production dates in conjunction with transportation scheduling and capacity constraints. This matches a common operational practice of link-based modeling, where production variables are synthesized with transportation variables. The results illustrate the power of quantum computing for solving optimization problems across multiple domains, such as those typically arising in modern supply chain management, simultaneously identifying operational plans that minimize total system cost while ensuring feasible coordinated paths between each pair of operational domains.

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Manufacturing Function	Optimization Objective	Decision Variables	Constraint Type	Coordination Requirement
Production Scheduling	Minimize costs and resource consumption	Production assignments, timing choices	Precedence and capacity constraints	Multi-facility component coordination
Inventory Distribution	Balance local reserves and holding costs	Location decisions, quantity allocations	Storage capacity and demand patterns	Strategic reserve placement
Supplier Redundancy	Cost premium versus risk reduction	Supplier selection, order allocation	Pricing structures, minimum quantities	Geographic diversification
Production-Transportation Sync	Minimize bottlenecks and capital tie-up	Production timing, vehicle schedules	Completion-departure consistency	Cross-domain operational planning

Table 4: Manufacturing Coordination and Resource Management [8, 11, 12]

VI. Implementation Challenges and Future Research Directions

Modern quantum hardware suffers from limited qubit counts and coherence times, which limit the circuit depth before noise causes the solutions to become unusable. With these bounds and the techniques to reduce circuit errors, the effective problem size that can be simulated with circuit mapping is smaller than realistic national supply networks. Basic hardware improvements are needed, but continuous improvement in qubit quality, connectivity, and error correction in the quantum computing ecosystem suggests that quantum advantage for large-scale supply chain optimization will be within reach as hardware matures and scales [7].

A related scalability issue is the connectivity structure and gate fidelity in implementations of optimization problems on supply chains. Supply chain optimization circuits can impose arbitrary connectivity requirements, which most current quantum hardware does not match. As circuit compilation techniques are important to enable scaling beyond current connectivity-constrained architectures, quantum processors of the next generation are expected to treat more problems natively and without overhead thanks to improvements to connectivity and reduced errors. Another approach to scalability is to develop problem decomposition techniques that divide large supply networks into weakly coupled subproblems to be solved in parallel on multiple quantum processors [5].

Even integration into existing supply chain management tools requires standard interface descriptions and data exchange protocols, and this is an area of continuing research. Existing enterprise resource planning and logistics management systems already use standard formats and optimization interfaces based on classical computing. Quantum optimization systems will need to ingest supply chain input data, map the data onto the optimization problem, execute the quantum optimization algorithms, and output results into the data semantics of conventional decision support systems. To implement these integration capabilities, suitable middleware layers for quantum optimization and conventional supply chain systems are a prerequisite and require productive collaboration between quantum computing and conventional supply chain experts to identify suitable abstraction levels and performance targets [6].

Quantum technology may enable future applications for supply chain optimization beyond current applications of quantum computing. Quantum machine learning algorithms may be used to train

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predictive models that forecast demand and the risk of disruptions to optimize the supply chain. Quantum communication networks could allow supply chain actors to collaborate more securely and without the need for trusted intermediaries, and allow stakeholders to optimize competition in the face of national emergencies. Quantum sensing technology can provide more granular information on logistics and manufacturing processes, allowing greater optimization. In turn, continued work on these quantum technologies will advance the potential to develop increasingly advanced systems that can fulfill the need for flow across the supply chain under stress conditions, and tackle central questions of how to optimally design a quantum algorithm for a logistics scenario.

Conclusion

Quantum computing provides unprecedented resilience in a national supply chain by utilizing quantum algorithms and AI to optimize resource allocation in a complex multi-modal transportation system and decentralized manufacturing infrastructure that exceeds classical algorithms' ability to solve combinatorial optimization problems. Hybrid quantum-classical architectures, with quantum processors solving combinatorial optimization kernels and data management/solution verification on conventional systems, have demonstrated quantum advantage for certain logistics problems. However, hardware limitations still prevent the running of applications on a full national transport network. As qubit quality, connectivity, and error correction techniques improve, the range of supply chain problems that can be solved as quantum computers scale will also increase. Standardized interfaces between quantum optimization systems and legacy enterprise systems will be an important technical challenge for deploying quantum optimization systems practically. In addition to computing and simulation, quantum computing and quantum technologies, such as quantum machine learning (QML) algorithms, secure communication networks, and quantum-improved sensing and imaging, could have transformational impacts on supply chains. This will position quantum-improved optimization as a key capability to maintain the flow of critical resources during disruptions and improve national resilience across a broad range of risks and trade-offs.

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