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A Review of Intelligent Optimization Algorithms in Supply Chain Networks

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Abstract

Supply chain networks, which integrate nodes such as suppliers, manufacturers, and retailers to achieve efficient coordination and allocation of resources, serve as a critical component in enhancing corporate competitiveness. With the rapid advancement of *artificial intelligence* (AI) technologies, intelligent optimization algorithms have been increasingly applied in supply chain networks. This paper highlights classic algorithms such as *genetic algorithm* (GA), *ant colony optimization* (ACO), and *particle swarm optimization* (PSO), and expounds improved versions of these algorithms. By analyzing algorithmic enhancement strategies, including quantum GA, dynamic pheromone update mechanisms on ACO, and adaptive inertia weight adjustments on PSO, the development trends of intelligent optimization algorithms are outlined.

Keywords

Supply Chain Networks, Intelligent Optimization Algorithm, Optimization Problem, Multi-Objective Optimization, Uncertainty Management

1. Introduction

Supply chain network optimization [1] aims to maximize efficiency, minimize costs and enhance customer satisfaction by adjusting production, logistics, inventory and other links. Traditional methods have limitations in the complex and changeable supply chain environment, while intelligent optimization algorithms have become important tools due to their global search ability and adaptability. For example, genetic algorithm (GA) can rapidly approach the optimal solution under multiple constraints by simulating the natural selection mechanism. In recent years, relevant policies such as the "Guiding opinions on actively promoting supply chain innovation and application" have also deepened the application of intelligent algorithms in the supply chain field. Notably, intelligent optimization algorithms represented by GA and particle swarm optimization (PSO) have provided new methodological breakthroughs for the dynamic optimization of supply chain networks with their self-organizing, parallel computing and global optimization capabilities.

In the research field of intelligent optimization algorithms, the improved intelligent optimization algorithms exhibit a trend of diverse development. This paper only briefly expounds on typical improvement types; in practical applications, it is necessary to make adaptive adjustments and targeted improvements to the intelligent optimization algorithms according to the characteristics of specific problems and solving requirements.

2. Classification of Optimization Problems in Supply Chain Networks

Classification of supply chain problems based on optimization objectives and scenario characteristics:

(1) Single-objective optimization:

A decision-making method that focuses exclusively on optimizing one objective function, such as minimizing transportation costs or maximizing order processing efficiency. Its mathematical model can be expressed as:

$$\begin{aligned} &\min/\max\ f(x) \\ &\text{s.t}\quad g_i(x) \le 0,\ i=1,2,\cdots,m \\ &\qquad h_j(x)=0,\ j=1,2,\cdots,n \\ &\qquad x \in R^k \end{aligned}$$

$f(x)$ represents the single optimization goal function; $g_i(x)$ and $h_j(x)$ define operational limitations.

(2) Multi-objective optimization [2]:

It requires simultaneous optimization of multiple conflicting objectives, such as minimizing transportation costs, delivery time, and carbon emissions. The vector of objective functions is defined as:

$$\begin{aligned} &\min/\max\ F(x) = \left(f_1(x), f_2(x), \cdots, f_k(x)\right) \\ &\text{s.t.}\quad g_i(x) \le 0,\ i=1,2,\cdots,m \\ &\qquad h_j(x)=0,\ j=1,2,\cdots,n \\ &\qquad x \in X \end{aligned}$$

$k \ge 2$ represents the number of objective function; $F(x)$ represents the vector objective function; $g_i(x)$ and $h_j(x)$ represent constraint function; X represents the decision variable space.

(3) Optimization under uncertainty [3]:

It refers to incorporating various uncertainty factors during the optimization process to ensure the robustness and reliability of the optimized results in practical applications. Key methodologies for addressing uncertainties include three approaches: robust optimization, stochastic programming and fuzzy programming.

$$\begin{aligned} &\min/\max\ f(x) \\ &\text{s.t.}\quad h(x,\xi)\le 0 \\ &\qquad\ x\in X \\ &\qquad\ \xi\in U \end{aligned}$$

$f(x)$ represents the objective function; $h(x,\xi)$ represents the constraint condition function; x represent decision variables; ξ represents uncertain parameters; U represents as a set of uncertain parameters.

(4) Large scale optimization [4]:

It refers to an optimization scenario involving high-dimensional variables or complex constraints, where the number of variables or the scale of constraint conditions exceeds the effective processing range of traditional optimization algorithms.

(5) Constrained optimization [5]:

A constrained optimization problem refers to finding the optimal value of an objective function (e.g., cost minimization or performance maximization) while satisfying a set of equality or inequality constraints.

$$\begin{aligned} &\min/\max\ f(x) \\ &\text{s.t}\begin{cases} g_i(x)\le 0,\ i=1,2,\cdots,m \\ h_j(x)=0,\ j=1,2,\cdots,p \end{cases} \end{aligned}$$

$f(x)$ represents the objective function; $g_i(x)$ represents inequalities function; $h_j(x)$ represent equality function.

3. Common Intelligent Optimization Algorithms

Genetic algorithm (GA) [6]: GA is an intelligent optimization algorithm that simulates biological evolution processes. It iteratively searches for the optimal solution through mechanisms such as natural selection, crossover recombination, and mutation. Rooted in Darwinian evolutionary theory and Mendelian genetics, GA encodes potential solutions to a problem as “chromosomes” and achieves gradual refinement of solutions via population evolution. The flowchart is presented in Figure 1.

Ant colony optimization (ACO) [7] [8]: ACO is a heuristic algorithm that simulates the foraging behavior of ant colonies. It addresses combinatorial optimization problems (e.g., path planning, resource allocation) through a positive feedback mechanism via pheromone deposition and collective collaboration. The core idea lies in how artificial “ants” iteratively release pheromones on selected paths and probabilistically choose routes based on pheromone concentrations, ultimately guiding the swarm to gradually converge to the optimal solution. The flowchart is presented in Figure 2.

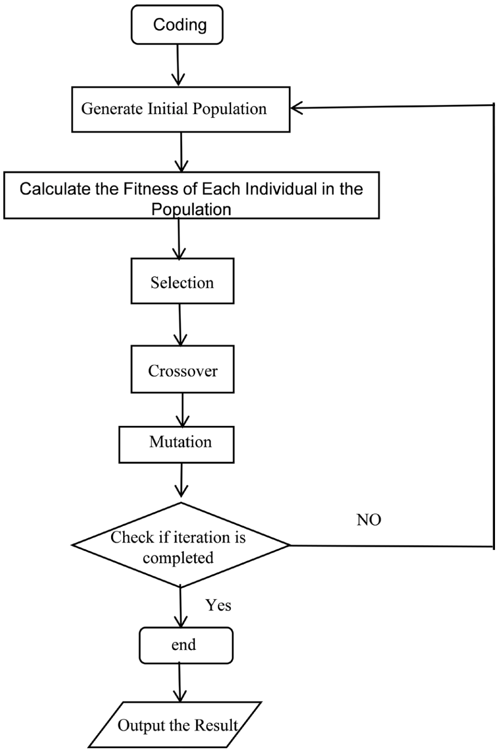

Figure 1. GA flowchart.

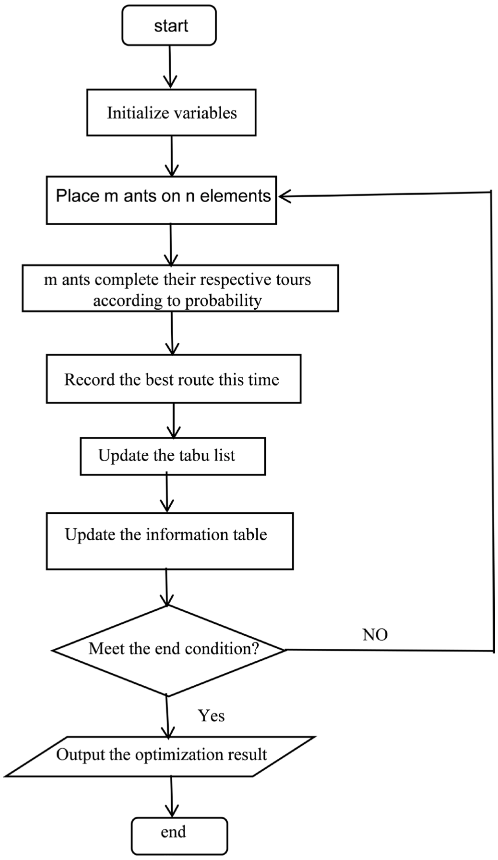

Figure 2. ACO flowchart.

Particle swarm optimization (PSO) [9]**:** It is a swarm intelligence-based meta-heuristic algorithm inspired by the collective social behaviors of biological groups such as bird flocks and fish schools (e.g., cooperative foraging). The core principle involves simulating interactions between individuals and their environment to guide particles (candidate solutions) toward optimal regions within the search space, ultimately converging to global or local optima. The flowchart is presented in Figure 3.

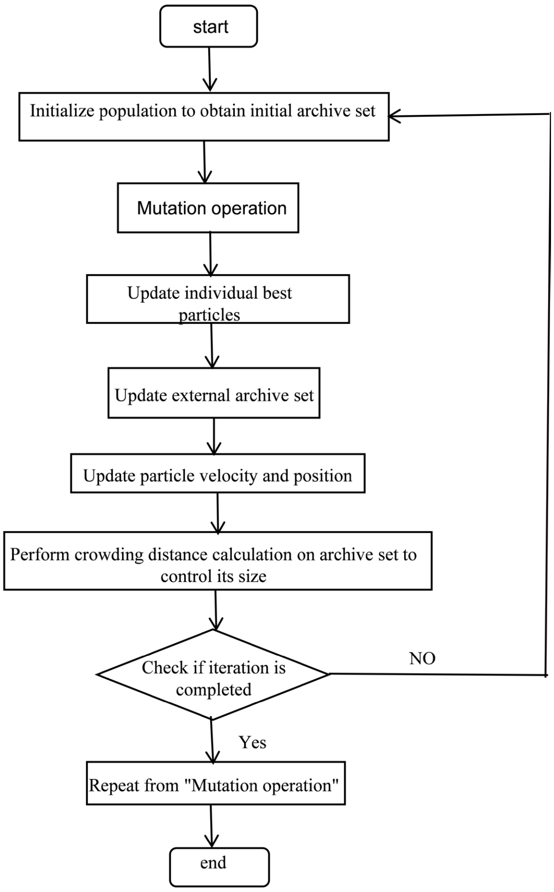

Figure 3. PSO flowchart.

4. Improvement of Intelligent Optimization Algorithms [10]

Common intelligent optimization algorithms are often combined with strategies such as hybrid approaches, adaptive parameter adjustment, and multi-objective optimization mechanisms to form the improvement of intelligent optimization algorithms, thereby overcoming the limitations of single methods. The core of these improved algorithms is to specifically address the weaknesses of common intelligent optimization algorithms. In practical applications, it is often necessary to design hybrid strategies tailored to the characteristics of the problem. According to the shortcomings of the common intelligent optimization algorithms mentioned above, the following improved intelligent optimization algorithms are expounded.

4.1. Quantum Genetic Algorithm (QGA) [11]

The improved algorithm of GA [12] [13] is primarily optimized to address issues such as premature convergence, weak local search capability, and sensitivity to parameters.

Quantum genetic algorithm (QGA) mainly makes improvement to address the following core drawback of GA, as shown in Table 1.

Table 1. The corresponding relationship between the disadvantage in GA and the improvement in QGA.

Disadvantage in GA	Improvement Strategy in QGA	Principle
Premature convergence	Enhance the global search ability through the diversity of quantum states	Quantum population initialization: Generate an initial population with high diversity based on the quantum superposition state to reduce the risk of being trapped in local optima.
High parameter sensitivity	Adaptive quantum gate rotation mechanism	Dynamically adjust the search direction: Use quantum rotation gates to adjust the search step size according to the fitness feedback, reducing the dependence on fixed crossover/mutation probabilities.
Weak local search ability	Enhance neighborhood exploration through quantum entanglement	Collaborative search: Quantum entanglement enables more efficient information sharing between particles, improving the ability of local fine grained search (e.g., warehouse location optimization)
Insufficient ability to handle large-scale problems	Accelerate fitness evaluation through quantum parallel computing	Theoretical acceleration advantage: The parallelism of quantum computing can handle an exponential solution space simultaneously, which is suitable for optimizing ultra large scale supply chain networks.

The flowchart of QGA is presented in Figure 4, takes qubit encoding and quantum gate evolution as its core. Through quantum parallelism, superposition state and entanglement mechanisms, it significantly improves the performance of the traditional GA in aspects such as the exploration efficiency of the solution space and the maintenance of diversity. Although it is limited by the current quantum hardware, its theoretical model provides an important direction for the development of future intelligent optimization algorithms, especially showing great potential in high dimensional, dynamic and multi-objective supply chain optimization scenarios.

The theoretical foundation of QGA stems from the principles of quantum superposition and entanglement. By encoding with qubits, it reduces the complexity of solution space exploration from $\left(O(N)\right)$ to $\left(O\left(\sqrt{N}\right)\right)$, offering the theoretical potential for acceleration in the optimization of ultra-large-scale logistics networks.

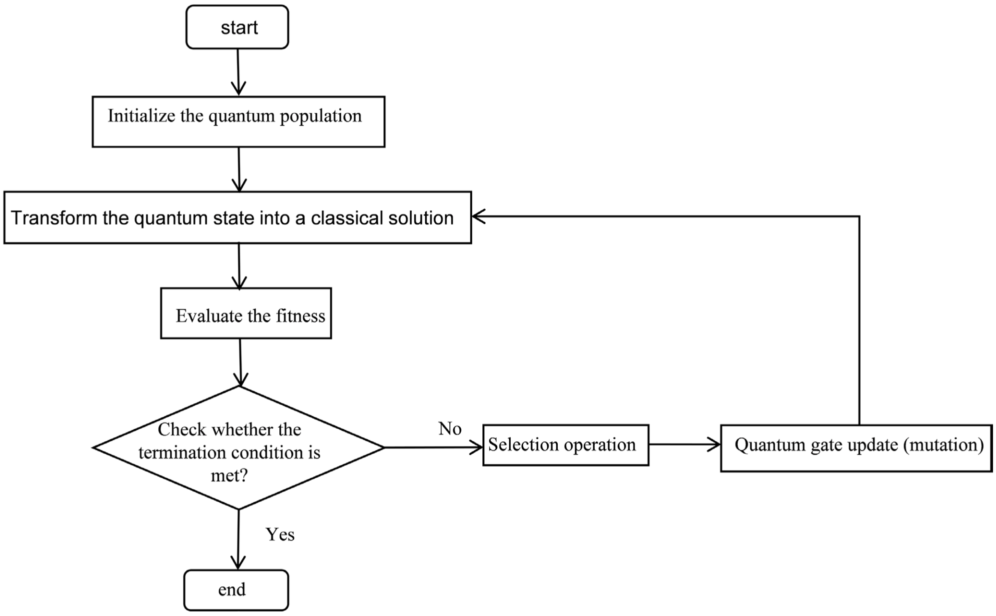

Figure 4. QGA flowchart.

4.2. Multi-Objective Ant Colony Optimization (MOACO) [14]

ACO [15] as a single-objective optimization algorithm, inherently faces limitations when addressing multi-objective problems. Multi-objective ant colony optimization (MOACO) overcomes these shortcomings by introducing mechanisms specific to multi-objective optimization, such as pareto dominance, external archives, and multi-dimensional pheromone systems.

MOACO mainly makes improvement to address the following core drawback in ACO, as shown in Table 2.

Table 2. The corresponding relationship between the disadvantage in ACO and the improvement in MOACO.

Disadvantage in ACO	Improvement strategy in MOACO	Principle
Limitations of single-objective approaches; Lack of handling for conflicting objectives	Pareto dominance; External archive for non-dominated solutions	Directly outputs the pareto front without predefined weights, encompassing all effective trade-off solutions (e.g., multi-performance balancing in engineering design).
Unidimensional pheromone bias	Multi-dimensional pheromone systems; Pareto rank-guided updating	Integrated multi-objective information guides the search to balance trade-offs between objectives (e.g., simultaneously optimizing “time” and “energy consumption” in scheduling problems).
Local optima traps; Low convergence efficiency	Elite Ant Strategy; Dynamic parameter adjustment	Rapid converges to the global pareto front; Adaptability to high dimensional complex solution spaces (e.g., multi-constrained multi-objective optimization in resource allocation).
Solution set homogenization; Premature convergence	Crowding distance calculation; Niching technique	Extension to constrained, time-varying multi-objective problems encompassing applications such as engineering optimization and real-time scheduling

The flowchart of MOACO is presented in **Figure 5**. MOACO achieves an upgrade from "single-objective optimal solution search" to "multi-objective pareto front exploration". The core advancements of MOACO explicitly handles the conflicted objectives, maintains the solution set diversity, and guides the balanced multi-objective search dynamically.

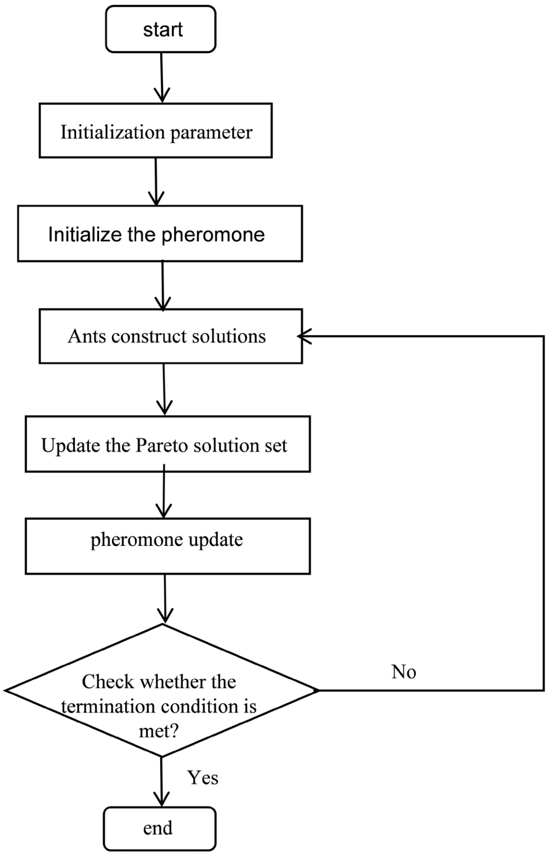

Figure 5. MOACO flowchart.

MOACO fundamentally upgrades the paradigm from "single-objective optimal solution search" to "pareto front exploration". By leveraging multi-dimensional pheromone guidance, diversity preservation mechanisms, and dynamic convergence strategies, MOACO explicitly addresses multi-objective conflicts. These enhanced capabilities enable MOACO to demonstrate significant advantages in complex system optimization scenarios including engineering design, intelligent scheduling, and environmental decision-making, establishing it as a pivotal tool in multi-objective optimization domains.

4.3. Multi-Objective Particle Swarm Optimization (MOPSO) [16]

Particle swarm optimization (PSO) solves optimization problems by simulating swarm intelligence behavior. However, traditional PSO [17] suffers from defects such as premature convergence, lack diversity, and weakness of local search capability.

Multi-objective particle swarm optimization (MOPSO) mainly makes improvement to address the following core drawback of PSO, as shown in Table 3.

Table 3. The corresponding relationship between the disadvantage in PSO and the improvement in MOPSO.

Disadvantage in PSO	Improvement Strategy in MOPSO	Principle
Lack of diversity and the bias of single global best-induced guidance	External archive mechanism	Generate pareto solution with uniformly distributed to cover more objective trade-off scenarios.
Easy to premature convergence and inadequate exploitation of global information	Multiple leaders and neighborhood selection	Reduce dependence on local optima and guide particles to explore diverse regions of the pareto front.
Parameter sensitivity and insufficient maintenance of diversity	Dynamic parameters and mutation operations	Balance exploration and exploitation across different optimization phases to enhance algorithm robustness and adaptability in complex problem solving scenarios.
The native PSO is solely applicable to static unconstrained environments	Handling of constraints and dynamic environments	Uniform distribution of the pareto front to prevent solution clustering (e.g., preserving diverse routes such as “shortest”, “safest”, and “most economical” in routes path planning).

The flowchart of MOPSO is presented in Figure 6. The core of MOPSO addresses the critical challenges of “pareto front approximation” and”uniform distribution of solution sets” in multi-objective optimization by incorporating pareto dominance theory and a solution set diversity maintenance mechanism, and enhances convergence to the pareto front and balanced coverage of non-dominated solutions.

MOPSO upgrades the “single-objective optimization search” of traditional PSO to “multi-objective solution set optimization”, establishing itself as a high-performance algorithm for solving complex multi-objective problems. The core strength of MOPSO lies in the integration of efficiency through inheriting PSO’s rapid convergence capability and multi-objective adaptability demonstrated in handling conflicting objectives while maintaining solution diversity. This dual advantage enables its widespread applications across engineering optimization, machine learning, resource allocation, and various other domains requiring complex decision making.

4.4. Development Trends of the Intelligent Optimization Algorithms

The future research on the intelligent optimization algorithms needs to focus on theoretical deepening such as the proof of high dimensional convergence, technological integration such as the combination of control theory and deep learning, and scenario innovation such as applications in bioinformatics. The core development trends include below:

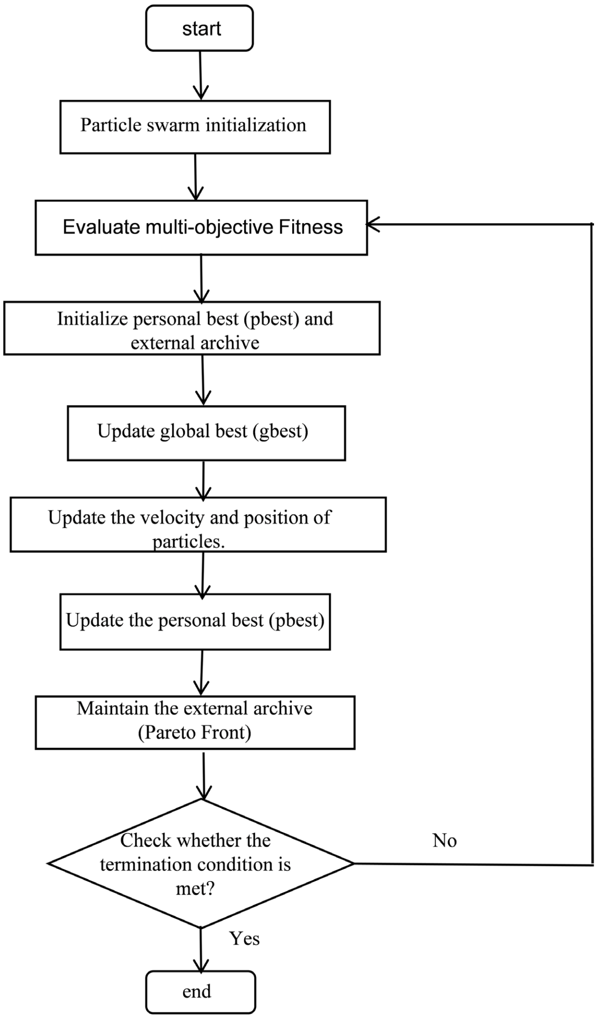

Figure 6. MOPSO flowchart.

Intelligence and adaptability: Use meta-learning and reinforcement learning to achieve fully automated adjustment of algorithm parameters and strategies.

Lightweight and real-time performance: Enable real-time application of optimization algorithms on edge devices through model compression and parallel computing.

Interdisciplinary collaboration: Integrate with control theory and data science to solve the challenges in complex systems such as smart grids and autonomous driving.

The breakthroughs in these directions will drive optimization algorithms to evolve from "problem solving tools" to "intelligent decision making engines", and provide the core technical support for national strategies such as industry 4.0 and carbon neutrality.

5. Conclusions

Intelligent optimization algorithms provide end-to-end optimization solutions for supply chain networks, spanning from production scheduling to inventory management, through multi-objective coordinated optimization and dynamic adaptive adjustments. These algorithms significantly enhance efficiency in key scenarios such as demand forecasting, logistics adjustments, and inventory management within supply chain operations.

Future advancements of intelligent optimization algorithms in supply chain management must prioritize dynamic adaptability, trustworthiness, and sustainability, and integrate the emerging technologies (e.g., quantum computing, digital twins) to overcome computational bottlenecks. Research trajectory should balance theoretical innovation with practical implementation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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