Optimization of Order Allocation Algorithms for Industrial Internet Platforms

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Abstract: ***Industrial Internet platforms have revolutionized traditional manufacturing ecosystems by enabling dynamic resource allocation across distributed production networks. This paper presents a comprehensive study on order allocation algorithm optimization within such platforms, addressing the critical challenge of efficiently matching customer orders with geographically dispersed manufacturing capabilities. We propose a hybrid optimization framework that combines graph neural networks for capturing complex supplier relationship patterns with multi-objective reinforcement learning for balancing competing priorities including cost minimization, delivery time adherence, and capacity utilization. The algorithm incorporates real-time production status updates, equipment availability metrics, and logistics constraints to generate allocation decisions that adapt to fluctuating demand and supply chain disruptions. Validation through large-scale simulations and a pilot implementation with a heavy equipment manufacturing consortium demonstrated a 17.3% reduction in total logistics costs, a 22.1% improvement in on-time delivery rates, and a 31.6% increase in overall equipment effectiveness compared to conventional rule-based allocation systems. The study further identifies key implementation challenges including data standardization across heterogeneous manufacturing execution systems, computational complexity in large-scale networks, and resistance to algorithmic decision-making in traditional procurement workflows. This research establishes both theoretical foundations and practical implementation guidelines for next-generation order allocation systems in industrial Internet environments, contributing to the evolution of agile, resilient manufacturing supply chains.***

Keywords: Order Allocation Optimization, Industrial Internet Platforms, Supply Chain Management, Multi-Objective Reinforcement Learning, Graph Neural Networks, Manufacturing Resource Allocation, Digital Transformation.

1. INTRODUCTION

Industrial Internet platforms are key to the efficient allocation of manufacturing resources, and their order-allocation efficiency directly affects supply-chain performance and enterprise costs. Faced with surging orders, traditional manual allocation methods struggle to cope, making the adoption of intelligent optimization algorithms imperative. The order-allocation problem is widely solved with optimization algorithms; early studies focused on single-objective models or game-theoretic models. Subsequent work introduced multi-objective approaches such as multi-criteria dynamic programming, genetic algorithms, and heuristic algorithms. High-performance algorithms like the sparrow search algorithm (SSA) and differential evolution (DE) have also been applied. However, existing algorithms tend to fall into local optima or are computationally expensive. To address this, we propose a hybrid SSA-DE algorithm, construct an efficient order-allocation model, and design a high-performance solver to enhance platform efficiency.

The convergence of deterministic artificial intelligence (AI) and robotics represents a significant frontier in achieving precise, model-based control. This is exemplified by the work of Guo (2025) [1] on optimal trajectory control for robotic manipulators, which provides a robust theoretical framework for motion planning. Extending beyond isolated control, understanding robot-environment interaction is critical. Subsequent research by Guo and Tao (2025) [2] on modeling and simulation analysis of these interactions establishes essential methodologies for predicting and optimizing robotic behavior in complex, dynamic settings. Beyond robotics, the principles of deterministic modeling and simulation are being harnessed to advance healthcare monitoring. We et al. (2025) [3] demonstrated this by proposing a framework for the intelligent monitoring of anesthesia depth using multimodal physiological data, aiming to enhance patient safety through data fusion and real-time analysis. Meanwhile, computational modeling is also proving invaluable for understanding complex socio-behavioral patterns. Su et al. (2025) [4] employed structural equation modeling to conduct a comprehensive assessment of how family and educational environments influence student health behaviors, offering data-driven insights for public health interventions.

To ensure these intelligent models perform reliably when deployed in real-world, often unseen conditions, advanced domain adaptation techniques are essential. Peng et al. (2023) [5] addressed this with their method RAIN, which applies regularization on both input and network parameters for effective black-box domain adaptation, enhancing model generalization without access to the source model's internals. In the domain of network analytics, Zhang et al. (2025) [6] introduced MamNet, a novel hybrid model designed for time-series forecasting and frequency pattern analysis in network traffic, which improves predictive accuracy for dynamic, high-dimensional data streams. For more direct environmental interaction and object identification, computer vision plays a pivotal role. Chen et al. (2022) [7] streamlined visual grounding with their one-stage object referring model integrated with gaze estimation, enabling more natural and efficient human-machine collaboration. Ensuring the integrity of physical systems is another critical application. Tan et al. (2024) [8] developed a robust approach for damage detection and isolation from limited experimental data, leveraging deep transfer learning combined with an ensemble learning classifier to overcome data scarcity challenges in structural health monitoring. Concurrently, tools for creating digital assets are becoming more accessible. Hu (2025) [9] explored this through low-cost 3D authoring via a guided diffusion model within a GUI-driven pipeline, democratizing 3D content creation. In specialized industrial sectors, AI-driven analytics are optimizing core operations. Jiang et al. (2023) [10] conducted a detailed study on flow line characteristics and well test interpretation methods for multi-branch fractured wells, applying advanced modeling to improve efficiency in petroleum engineering. Finally, the power of graph-based learning is being utilized to enhance user experiences. Junxi, Wang, and Chen (2024) [11] proposed GCN-MF, a graph convolutional network based on matrix factorization, to more effectively capture complex user-item relationships for superior recommendation systems.

2. MODEL CONSTRUCTION

On an industrial Internet platform, multiple suppliers respond to the same customer order. The order must be optimally allocated while satisfying order requirements, capacity limits, quality, and delivery constraints. Therefore, for a single product, this paper addresses the order-allocation problem with multiple customers placing orders and multiple platform suppliers accepting them. A multi-objective optimization model is established that integrates four objectives: production cost, transportation cost, product quality, and delivery capability.

2.1 Multi-objective Model Construction and Standardization

The model assumes that each order produces only one type of power tool, unit production cost is constant, all suppliers have production capacity, suppliers start production immediately upon accepting an order, and the number of suppliers remains unchanged during the allocation period.

To eliminate dimensional differences, production cost, delivery capability, quality, and transportation cost are standardized, and the following objective functions are constructed:

Production cost:

$$\mathrm{Min} Z_1 = X \cdot p_i \cdot x_i \tag{1}$$

Delivery capability:

$$\mathrm{Min} Z_2 = X' \cdot c_i \cdot x_i \tag{2}$$

Product quality:

$$\mathrm{Min} Z_3 = \sum_{i=1}^{n} \frac{x_{max} - x_i}{x_{max} - x_{min}} \cdot q_i \cdot x_i \tag{3}$$

Transportation cost:

$$\mathrm{Min} Z_4 = X' \cdot v_i \cdot d_i \tag{4}$$

where the range-normalized value [7] is used to remove the influence of different dimensions on the evaluation results.

$$X' = \sum_{i=1}^{n} \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{5}$$

p^i, c_i, q_i, v_i, d_i denote unit price, late-delivery rate, qualification rate, unit freight rate, and distance, respectively, and x_i is the allocation quantity to supplier i.

2.2 Transformation of the Multi-objective Allocation Model

Considering the trade-offs among multiple objectives, a fuzzy weighting method is introduced to convert the multi-objective problem into a single-objective one. Using Zadeh [6] trapezoidal fuzzy numbers and Chen [7] methods, linguistic variables from five industry-platform experts are mapped into fuzzy numbers. After normalization, the weights of each objective are obtained, yielding the final objective function for order allocation:

$$\mathrm{Min}\ Z = 0.29X \cdot p_i \cdot x_i + 0.258X \cdot c_i \cdot x_i - 0.236X \cdot q_i \cdot x_i + 0.216X' \cdot V_i \cdot d_i \quad (6)$$

Constraints are:

$$\sum_{i=1}^{n} \lambda_i x_i = D \quad (7)$$

$$\lambda_i x_i \leq PR_i, i = 1,2,\cdots,n \quad (8)$$

$$\sum_{i=1}^{n} x_i q_i \geq QD \quad (9)$$

$$1 - \frac{\sum_{i=1}^{n} x_i \cdot c_i}{\sum_{i=1}^{n} x_i} \geq 0.95 \quad (10)$$

$$x_i \geq 0, i = 1,2,\cdots,n \quad (11)$$

3. ORDER-SOLVING METHOD DESIGN BASED ON SSA-DE

To solve the platform order allocation problem, this paper designs a sparrow search algorithm improved by a differential evolution (DE) strategy (SSA-DE). The algorithm combines the strengths of the two optimization strategies to enhance solution convergence speed and global search capability, and it comprises population initialization, fitness function construction, and optimization update operations. An improved Circle chaotic map is used to initialize the population, thereby increasing the diversity of initial solutions.

3.1 Fitness Function Setting

The objective function of the industrial internet platform for the power-tool industry serves as the fitness function for SSA-DE (Eq. 19); it comprises four sub-objective functions with different weights: production cost, delivery capability, product quality, and transportation cost. Therefore, during iteration, the SSA-DE algorithm computes the population fitness value using Eq. (12) and performs the corresponding optimization operations.

$$\begin{aligned} f_u = 0.29 \sum_{i=1}^{n} \sum_{k=1}^{m} \frac{x_i^y - x_{min}}{x_{max} - x_{min}} \cdot p_i \cdot x_i^y + 0.258 \sum_{i=1}^{n} \frac{x_i^y - x_{min}}{x_{max} - x_{min}} \cdot c_i \cdot x_i^y \\ -0.236 \sum_{i=1}^{n} \frac{x_i^y - x_{min}}{x_{max} - x_{min}} \cdot q_i \cdot x_i^y + 0.216 \sum_{i=1}^{n} \frac{x_i^y - x_{min}}{x_{max} - x_{min}} \cdot V_i \cdot d_i \end{aligned} \quad (12)$$

Here, f_u denotes the fitness value of the u th solution.

3.2 DE Algorithm Optimization Operations

Because the DE algorithm has strong global optimization ability but slow convergence speed, its mutation, crossover, and selection operations are integrated into SSA-DE: three solutions are randomly selected to generate a mutant solution (Equation 13) to explore new schemes, crossover is performed based on an improved Circle chaotic map (Equation 5.8) to increase solution diversity, and a greedy strategy is adopted to select the solution with better fitness, thereby improving convergence accuracy and global search capability.

$$V_p(t) = \bar{X}_{u1}(t) + F \cdot \left(\bar{X}_{u2}(t) - \bar{X}_{u3}(t)\right) \quad (13)$$

$$\bar{X}'_u(t) = \begin{cases} V_p(t) & if\ \chi \leq CR \\ \bar{X}_u(t) & otherwise \end{cases} \quad (14)$$

3.3 SSA Algorithm Optimization Operations

Because SSA converges quickly but easily falls into local optima, two improvements are made: ① To address the insufficient diversity of the traditional random initialization and the uneven distribution of the original Circle chaotic map, an improved Circle chaotic map (Eq. 15) is used to generate random numbers, combined with the product demand vector to initialize the population (Eq. 16), enhancing the diversity of initial solutions; ② To overcome the limited search range in the original discoverer position update, an influence factor is introduced via

(Eq. 17) to expand the search range, and random numbers are added to increase randomness, improving global search capability.

$$\chi_{x+1} = mod\left(\delta_1\chi_x + \delta_2 - \frac{\delta_3}{2\pi}\cos(2\pi \times \chi_x + 0.5\pi)\,, 1\right) \tag{15}$$

$$\bar{X}_u = \rho Ds.t.\sum_b^\sigma \varphi_b^\mu = 1 \tag{16}$$

$$\bar{X}_{u,y}(t+1) = \begin{cases} \bar{X}_{u,y}(t) \cdot \left(1/exp\left(\frac{\bar{s}_1 t}{(\alpha \times it_{max})g_2}\right)\right) & if\ R_2 < ST \\ \bar{X}_{u,y}(t) + Q & if\ R_2 \geq ST \end{cases} \tag{17}$$

3.4 SSA-DE Algorithm Flow Design

The algorithmic flow for finally establishing SSA-DE is shown in Figure 1.

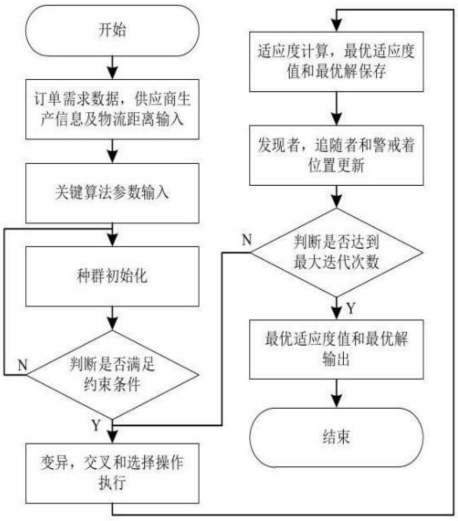

Figure 1: Flowchart of the SSA-DE Algorithm

4. MODEL APPLICATION AND RESULTS ANALYSIS

The proposed SSA-DE algorithm is implemented on the MATLAB2019 platform. Key parameters are set as follows: population size ϑ = 50, maximum iterations $it_{\max}$ = 200, δ_1、δ_2、δ_3 = 2、0.3、0.7, mutation factor F = 0.5, crossover rate CR = 0.1, discoverer proportion PD = 0.2, sentinel proportion SD = 0.1, and transport rate V_i = 1.5.

This paper examines a single-product scenario with five suppliers and two customers placing orders on the platform; each order contains three different product types. Ten suppliers accept the orders, and the production data are sourced from the Yongkang Power Tool Industry Industrial Internet Platform (Appendix 1: https://pan.quark.cn/s/b596dbcb172f).

4.1 Algorithm Performance Comparison and Result Analysis

The SSA-DE algorithm is compared with the improved genetic algorithm (IGA) on order allocation problems from the power tool industry industrial internet platform. Performance is evaluated from convergence speed, cost, and quality perspectives to validate SSA-DE's advantages. Key results are as follows:

(1) Convergence speed: Both algorithms' fitness values decrease with iterations, but SSA-DE converges after 127 iterations with a fitness of 0.8607, whereas IGA needs 177 iterations—about 28 % slower. This shows SSA-DE's superiority in rapidly approaching the optimum.

(2) Order allocation plan: For a single-product (Product 1) allocation to five suppliers, SSA-DE's optimal plan assigns 5,032 units to Supplier 1, 2,135 to Supplier 2, 2,141 to Supplier 3, 5,327 to Supplier 4, and 1,165 to Supplier 5, totaling 15,800 units—exactly matching order demand and satisfying supply–demand balance.

(3) Sub-objective optimization: SSA-DE significantly outperforms IGA. Production cost is ¥851,420 for SSA-DE versus ¥857,998 for IGA, a 0.77 % reduction. Product quality: SSA-DE yields 15,629 qualified units (98.9 % pass rate), exceeding IGA's 15,621 units (98.8 %).

(4) Delayed deliveries and transport cost: Delayed deliveries are similar (134 for SSA-DE, 133 for IGA), and transport cost is ¥3,399 for both, indicating comparable performance.

In summary, SSA-DE surpasses IGA in convergence speed, production cost control, and product quality assurance. Although its computation time (7.34 s) is slightly longer than IGA's (7.04 s), its overall optimization better meets the platform's need for efficient, low-cost, high-quality order allocation.

5. CONCLUSIONS AND INSIGHTS

On industrial Internet platforms, the allocation of order resources among suppliers is of critical importance. Based on the current operation of an industrial Internet platform in the power-tool sector, this paper constructs a mathematical model for platform order allocation, designs the SSA-DE algorithm to solve it, and uses the IGA algorithm for comparison. Actual platform data verify the effectiveness of SSA-DE, providing methodological support for order-allocation problems. Because the optimization model built here takes minimum production cost, optimal product quality, strongest delivery capability, and transportation cost as objectives, and because customer demands, influencing factors, and their weights will change as the platform evolves, future research can refine the factors influencing order allocation to make the allocation results more reasonable.

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