Research on the Impact of Intelligent Optimization Algorithms on Low-Carbon City Distribution Issues

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Abstract: Driven by the rapid urbanization and the "dual carbon" goals, the low-carbon transformation of urban distribution has become a key issue in green development. Currently, the proportion of carbon emissions from urban logistics continues to rise. Issues such as unreasonable routes, high vehicle empty load rates, and extensive scheduling in traditional distribution models exacerbate the pressure to reduce emissions, urgently requiring technological solutions. Intelligent optimization algorithms construct optimization models by simulating natural laws, enabling distribution decision-making optimization under complex constraints. Their core role lies in reducing carbon emissions through precise decision-making. Research has shown that they can affect low-carbon distribution from multiple levels: at the route level, they can shorten ineffective mileage through multi-constraint optimization, reducing carbon emissions by 10%-20%; at the scheduling level, they optimize vehicle selection and loading rates, increasing the utilization rate of new energy vehicles by over 40%; at the collaborative level, they balance "low carbon - cost - timeliness" through multi-objective optimization, outputting optimal solutions. However, the application of algorithms is limited by data quality, dynamic adaptability, and implementation costs. In the future, technological integration and measure coordination are needed to unleash their value in low-carbon distribution and provide support for the transformation of urban green logistics.

Keywords: Intelligent Optimization Algorithm; Low-Carbon City Distribution; Route Optimization; Vehicle Scheduling; Multi-Objective Optimization

1. Introduction

1.1 The Background and Significance of the Research

The significance of this study is elaborated through the following two aspects:

(1) Intelligent optimization algorithm

Many optimization problems in the real world are typically composed of multiple objectives, and solving multi-objective problems is quite challenging, as the relationships between objectives are often coupled and conflicting. Improving the performance of one objective often leads to a decrease in the performance of other objectives, making it impossible to achieve optimality for all objectives simultaneously. Therefore, for multi-objective optimization problems, it is necessary to find a set of trade-off solutions, namely the Pareto optimal set or the non-dominated set. The process of making each objective as optimal as possible is known as multi-objective optimization. Optimization problems with more than three objectives are referred to as high-dimensional multi-objective optimization problems [1], which are also the more common multi-objective optimization problems in real life. Due to the large number of objectives that need to be handled in high-dimensional multi-objective optimization, the quality of solutions becomes more difficult to evaluate, and the complexity of the search space rapidly increases with the number of objectives, making it even more challenging to balance the convergence and distribution of the solution set [2]. Therefore, MaOP is recognized as a difficult research area in the field of optimization, and its problem-solving complexity is the highest among all optimization problems.

In dealing with MaOP, traditional multi-objective evolutionary algorithms (MOEA), especially those based on Pareto dominance, encounter significant challenges. The convergence and diversity of the obtained Pareto optimal solution set are not ideal. The main reason is that there are not only multiple objectives, but also most of them have conflicting relationships, which greatly increases the complexity and search difficulty of solving MaOP. The number of non-dominated solutions in the population will increase sharply with the increase in the number of objectives (as shown in **Figure 1**). Even in the early stages of evolution, almost all solutions in the population are non-dominated, which greatly weakens the selection pressure on the population and makes it difficult for the population to evolve. Research on these aspects has become a focus for many scholars.

With the rapid development of science and technology and the significant enhancement of production capacity, the application of high-dimensional multi-objective optimization has not only become an urgent demand in daily life but also emerged as a focal point in the field of optimization. Currently, the application demands of high-dimensional multi-objective optimization in numerous domains such as logistics and distribution, engineering optimization, petrochemical industry, network communication, face recognition, and data mining are increasingly prominent. Therefore, conducting research on high-dimensional multi-objective optimization holds significant theoretical importance and immense practical value.

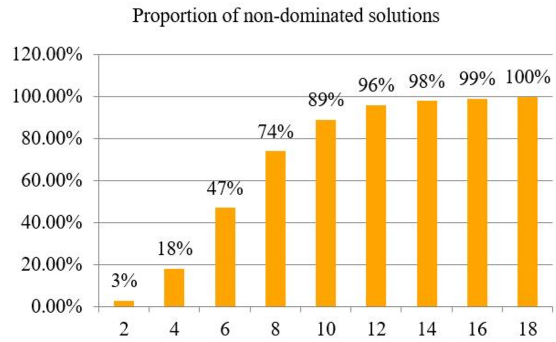

Figure 1. Shows the Relationship between the Target Dimension and the Proportion of Non-dominated Solutions

(2) Vehicle path planning

With the rapid development of China's market economy and the substantial improvement in people's living standards, there is an increasing demand and expectation for better services in the commodity distribution industry. Therefore, it is no longer sufficient to focus solely on one aspect; instead, multiple objectives and considerations should be taken into account. The multi-objective optimization problem in vehicle distribution is widespread in real life and holds a significant position. Research on this practical issue is often complex and challenging, falling within the primary field of study in operations research. Consequently, exploring MOEA to address the vehicle routing problem with multiple objectives has become a hot topic among scholars.

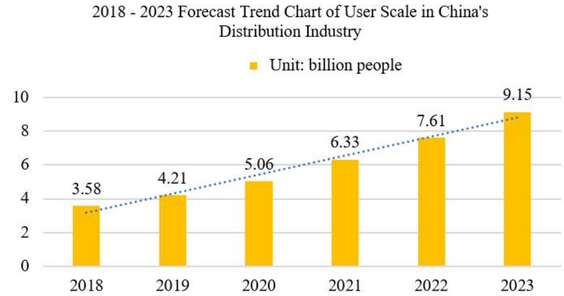

Figure 2. Shows the User Scale of China's Instant Delivery Industry

Figure 3. Shows the Scale of Order Volume in China's on-demand Delivery Industry

Researching VRP holds strategic significance in two aspects: Firstly, in terms of economic profits. According to the "2023 China Instant Delivery Industry Market Prospects and Investment Research Report" by the Prospective Industry Research Institute, the future development prospects of the urban distribution market are extremely broad. As can be intuitively seen from Figure 2-3, the economic profits achieved by urban distribution in China have been continuously increasing over the past five years. To maximize the benefits of urban distribution in China and achieve more rational resource allocation, research on VRP is extremely important. Therefore, conducting research on urban vehicle distribution issues has considerable economic benefits. Secondly, in terms of environmental protection. Since 1958, Keeling has recorded the concentration of CO_2 in the atmosphere, and the curve formed by these measurements is known as the Keeling curve. As can be intuitively seen from Figure 4, the concentration of CO_2 has been on an upward trend. According to the International Energy Agency's statement, transportation is the second largest source of CO_2 emissions. Research results show that in 2020, the proportion of CO_2 emissions from China's transportation industry in total CO_2 emissions will increase to 18% to 20% [3]. By analyzing the characteristics, influencing factors, and emission reduction of CO_2 emissions in China's transportation industry, we can promote CO_2 emission reduction in the transportation industry by improving the efficiency of the transportation system, optimizing the transportation structure, and strengthening low-carbon transportation policies. Reducing CO_2 emissions in vehicle transportation is an effective measure to lower China's carbon emissions. Therefore, researching low-carbon VRP has great practical significance [4].

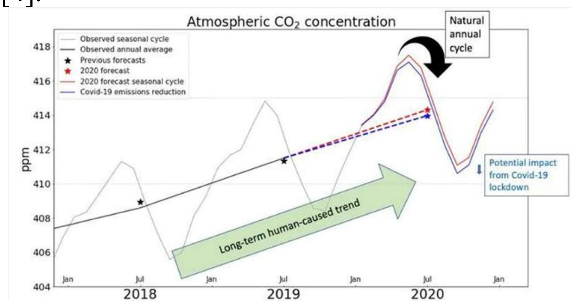

Figure 4. Keeling Curve

1.2 Research Status Quo

The current research status of this article is elaborated through the following two aspects:

(1) High-dimensional multi-objective optimization algorithm

When solving high-dimensional multi-objective optimization problems, existing multi-objective optimization methods face two difficulties [5-6]: Firstly, the number of non-dominated individuals in the evolutionary population increases rapidly with the increase in the number of objectives, leading to a rapid decrease in selection pressure during the evolutionary process, thereby reducing the search performance of evolutionary algorithms based on Pareto dominance. Secondly, in high-dimensional objective spaces, the number of evolutionary individuals required to cover the Pareto front increases exponentially, greatly increasing the complexity of solving the problem. To overcome the aforementioned difficulties, researchers have proposed numerous algorithms, primarily categorized into five types: First, those based on new Pareto dominance methods, which generate stronger selection pressure on the PF, such as θ dominance [7], grid dominance [8], fuzzy Pareto dominance [9], etc. These dominance relationships extend their dominance regions to some extent. Second, decomposition-based methods [10], which decompose a M-dimensional objective problem into a series of single-objective subproblems based on aggregation functions and solve them simultaneously. The most renowned among them is the decomposition-based multi-objective evolutionary algorithm. Subsequently, many other improved versions of MOEA/D have been proposed, such as MOEA based on dominance and decomposition [11], and improved decomposition-based evolutionary algorithms. Third, indicator-based algorithms [12] introduce performance indicators as fitness values to guide the population evolution process. Commonly used algorithms in this category include the hypervolume estimation algorithm based on the R2 indicator, the multi-objective metaheuristic algorithm based on metric selection, and the indicator-based evolutionary algorithm. Among these indicators, hypervolume is the most popular one due to its good theoretical properties. However, as the number of objectives increases, the computational cost becomes very expensive, limiting its application in programs. Fourth, MOEAs based on reference points [13], which rely on multiple predefined reference points for multi-directional search. This type of algorithm mainly includes NSGA-III and evolutionary algorithms based on θ dominance. Reference points play a crucial role in maintaining convergence and diversity. Fifth, hybrid-based methods [14], which not only increase the pressure on the population to evolve towards true genes but also maintain population diversity during the evolutionary process. Typical algorithms include Two-Arch2 and MOEA/D-U. The main goal of these algorithms is to balance convergence and diversity.

The multi-objective evolutionary algorithm based on reference points employs a set of reference points uniformly distributed in the objective space to guide the direction of population search and evolution, which not only enhances the diversity of the algorithm but also reduces the difficulty of solving Multi-Objective Problems (MaOP). Currently, the multi-objective evolutionary algorithm based on reference points is one of the popular application techniques for solving MaOP. According to the "no free lunch" theorem, everything has its two sides. Although this algorithm demonstrates its unique advantages in solving MaOP, there are still deficiencies in its design and application. The algorithm used in this project will be based on the high-dimensional multi-objective evolutionary algorithm based on reference points, and further research will be conducted to address the aforementioned issues.

(2) Vehicle path planning problem

To meet the needs of both supply and demand sides in distribution services, the problem of how to appropriately use vehicles and deliver goods from distribution points to customer points through a reasonable design of distribution routes is known as the vehicle routing problem (VRP). Currently, there has been considerable research on urban distribution routing both domestically and internationally. Initially, researchers focused on a limited number of objectives in the modeling and algorithmic solution of vehicle routing problems, such as C. Prins' research, which was limited to reducing transportation costs and optimizing the number of distribution vehicles and driving distances. The rise of the express delivery industry has led to increased demands for distribution services, and more constraints need to be considered during modeling. In the bi-objective vehicle routing problem with time window constraints, Park constructed a linear H-norm G model and adopted a heuristic strategy to alleviate the complex computational process in the GP model. Subsequently, Zitzler and Thiele proposed the Pareto dominance method to solve the VRP, and through improvements in model solving algorithms, computational efficiency was further enhanced. Raluca Necula et al. used an improved ant colony algorithm to solve the VRP with time window constraints, which not only met user requirements but also reduced the number of vehicles used for distribution. Compared to foreign countries, research on the VRP in China started later, but through unremitting efforts and dedication, Chinese researchers have also achieved many significant results. For example, Liao Liangcai et al. combined genetic algorithms with the C-W saving algorithm, resulting in a hybrid algorithm with superior convergence performance and significantly improved solution quality. In the e-commerce environment, Gao Zijian et al[15]. studied the VRP and created a four-step optimization algorithm, which can achieve effective cargo allocation and route optimization. Wang Chao et al[16]. used a distributed parallel genetic algorithm to solve the multi-vehicle routing problem. The aforementioned examples demonstrate an increasingly comprehensive consideration of practical problems, leading to an increase in the number of objectives considered. Therefore, research on high-dimensional VRPs is imperative.

2. Core Concepts and Theoretical Foundations

2.1 The Connotation and Goals of Low-carbon Urban Distribution

Low-carbon city distribution is a modern urban logistics distribution model with the core goal of "reducing carbon emissions". Its essence permeates the entire distribution process, encompassing multiple aspects such as route planning, vehicle selection, scheduling strategies, and loading schemes. It emphasizes achieving a green transformation of logistics activities through systematic optimization.

Its core objective is to establish a "efficiency-low carbon" synergy mechanism: on the basis of ensuring timely delivery and controlling operational costs, it aims to minimize carbon emissions through technological and management innovations. It not only focuses on the carbon emission intensity per unit of cargo volume but also pursues an absolute reduction in total carbon emissions from distribution, achieving the unity of economic value and environmental value.

However, this model faces multiple key issues in practice: path planning relying on experience leads to widespread detour transportation, high vehicle empty load rates result in energy waste, insufficient collaboration among multiple entities such as e-commerce and logistics enterprises and transportation departments creates management barriers, and the carbon emission quantification model lags behind real-time operational data, making it difficult to support precise emission reduction decisions. These have become prominent obstacles to achieving low-carbon goals.

2.2 The Types and Principles of Intelligent Optimization Algorithms

Intelligent optimization algorithms are a class of optimization methods that simulate natural laws or swarm intelligence behaviors. Their core logic lies in approximating the optimal solution in a complex decision space through an iterative optimization process, especially for multi-constraint and nonlinear problems that are difficult to solve using traditional mathematical methods. Compared to deterministic algorithms, these algorithms do not rely on precise mathematical models. Instead, they construct adaptive optimization mechanisms by simulating natural processes such as biological evolution, swarm collaboration, and physical phenomena, thereby selecting the optimal or near-optimal solution from a vast number of feasible solutions. This provides efficient solutions for practical problems such as path planning, resource scheduling, and parameter optimization.

Among mainstream intelligent optimization algorithms, genetic algorithms are typical representatives that draw on the theory of biological evolution. They simulate the evolutionary law of "natural selection and survival of the fittest" in nature, encoding feasible solutions to problems to be solved as "chromosomes" and achieving population iteration through three core operations: selection, crossover, and mutation. The selection operation filters high-quality individuals based on a "fitness function", similar to the retention of advantageous genes in biological evolution; the crossover operation simulates gene recombination by exchanging partial fragments of two parental chromosomes to generate offspring with characteristics of both parents, expanding the search range of solutions; the mutation operation simulates gene mutation by randomly changing a gene in a chromosome, avoiding the algorithm from falling into local optima. For example, in low-carbon distribution route optimization, genetic algorithms can encode the sequence of distribution nodes as chromosomes, using "total carbon emissions" as the fitness function, and filter out the combination of routes with the lowest carbon emissions through multiple generations of iteration. Its advantage lies in its strong global search capability and ability to handle multi-dimensional constraint problems.

The inspiration for the particle swarm optimization algorithm stems from the collective behavior of birds foraging or fish swimming in groups. Its core lies in achieving optimization through information sharing and collaboration among individuals within the group. The algorithm abstracts each feasible solution as a "particle", with all particles moving at a certain speed in the solution space. Their position represents the specific value of the solution, while their speed determines the direction and distance of movement. The movement of each particle is influenced by two factors: its own historical optimal position and the historical optimal position of the entire group. By continuously adjusting speed and position, the particle swarm gradually converges towards the global optimal solution. In dynamic traffic scenarios, particle swarm optimization can respond to changes in road conditions in real time: when a certain road section experiences sudden congestion, the algorithm adjusts its own movement direction based on the "optimal positions" of surrounding particles, quickly generating a new delivery route. Its advantage lies in its fast convergence rate, making it suitable for handling dynamic optimization problems with high real-time requirements.

The principle of simulated annealing algorithm originates from the "annealing process" in physical chemistry, where atoms gradually arrange into the lowest energy stable state as a high-temperature object cools down slowly. The algorithm compares the objective function of the optimization problem to the energy of a physical system, and simulates the search process of solutions as a cooling process from high temperature to low temperature. In the high-temperature stage, the algorithm allows for a higher probability of accepting poorer solutions, simulating the random motion of atoms at high temperatures; as the temperature decreases, the probability of accepting poorer solutions gradually decreases, eventually focusing on the vicinity of high-quality solutions. This mechanism enables it to effectively escape from local optimum traps. For example, in the optimization of loading rates for delivery vehicles, traditional methods may overlook more optimal loading combinations due to the local rationality of the initial scheme. However, simulated annealing algorithm, through extensive exploration in the "high-temperature stage", has the opportunity to discover innovative schemes that can significantly improve the loading rate. Its core advantage lies in its strong local search capability, making it suitable for handling complex problems with multiple local optimum solutions.

The ant colony algorithm simulates the path selection mechanism of ant colonies during foraging. In nature, ants mark paths by secreting pheromones, and other ants tend to choose paths with higher pheromone concentrations. The shorter the path, the shorter the round-trip time for ants, and the faster the accumulation of pheromones, forming a positive feedback loop of "higher pheromone concentration in shorter paths — more ants choose — higher pheromone concentration". The algorithm abstracts this process as follows: virtual "pheromones" are set in the solution space, and each "ant" chooses its next action based on pheromone concentration and heuristic information, updating pheromones after completing a search. In multi-node distribution path optimization, the ant colony algorithm can quickly converge to a shorter path: initially, pheromones are evenly distributed, and ants explore randomly; as iterations progress, the pheromones of the optimal path gradually dominate, guiding subsequent ants to focus their choices, ultimately achieving a reduction in carbon emissions. Its advantage lies in its distributed computing characteristics, making it suitable for parallel processing of large-scale problems.

To compensate for the shortcomings of single algorithms, hybrid intelligent optimization algorithms have emerged, with the core being the integration of the advantages of different algorithms to form a more efficient optimization strategy. For example, the genetic-simulated annealing hybrid algorithm first utilizes the global search capability of genetic algorithms to generate a batch of optimal solutions (population), and then applies simulated annealing algorithms to each solution for local optimization. This approach not only avoids the problem of insufficient local search in genetic algorithms but also overcomes the low global exploration efficiency of simulated annealing algorithms. In multi-objective optimization for low-carbon city distribution (such as simultaneously optimizing carbon emissions, cost, and timeliness), such hybrid algorithms can balance global exploration and local refinement: genetic algorithms are responsible for generating diverse candidate solutions in the multi-objective space, while simulated annealing algorithms make fine adjustments to each solution, ultimately outputting a Pareto optimal solution that meets the needs of all parties. In addition, hybrid algorithms such as particle swarm-ant colony hybrid algorithms and ant colony-simulated annealing hybrid algorithms are also widely used, complementing each other in terms of convergence speed and solution diversity, significantly improving optimization performance in complex scenarios.

Overall, despite differing principles, various intelligent optimization algorithms have constructed adaptive optimization mechanisms by simulating natural laws, providing strong technical support for issues such as path planning, vehicle scheduling, and multi-objective collaboration in low-carbon urban distribution. In practical applications, it is necessary to select appropriate algorithms or design hybrid strategies based on the characteristics of the problem (such as static/dynamic, single-objective/multi-objective, small-scale/large-scale), in order to maximize their role in reducing carbon emissions and improving distribution efficiency.

3. The Influence Mechanism of Intelligent Optimization Algorithms on Low-Carbon Urban Distribution

3.1 Impact on the Optimization of Distribution Routes: Reducing Ineffective Carbon Emissions

The core impact of intelligent optimization algorithms on distribution route optimization lies in reducing ineffective transportation through precise calculations, thereby lowering carbon emissions. Traditional route planning often relies on human experience or simple rules (such as "nearest distribution" and "division by region"), which exhibit significant flaws in scenarios with multiple nodes and constraints. When confronted with complex conditions such as dozens of distribution points, restricted traffic periods, and time-sensitive requirements, manual planning is prone to issues like circuitous routes and repeated trips. Especially in densely populated urban traffic networks, the proportion of ineffective mileage can reach over 20%, directly leading to increased fuel consumption and carbon emissions.

Intelligent optimization algorithms address this pain point through mathematical modeling and iterative optimization. Taking genetic algorithms as an example, they can convert parameters such as distribution nodes, distances, and traffic restrictions into mathematical encodings. Through a "fitness function" (with "total carbon emissions" as the core indicator), they screen the optimal path combination, maximizing the reduction of total mileage while meeting the timeliness requirements of each node. The particle swarm optimization algorithm excels at dynamic adjustment: when traffic congestion occurs unexpectedly during the distribution process, the algorithm can receive real-time traffic data and, through iterative updates of particle positions and velocities, generate a new path within 10-30 seconds, avoiding long periods of vehicle idling and reducing additional carbon emissions caused by congestion.

Practical data shows that the application of such algorithms yields remarkable results: in urban distribution scenarios covering 30-50 nodes, intelligent optimization algorithms can reduce the total distribution distance by 15%-30%. Based on the average carbon emissions of trucks per 100 kilometers being 8-10kg, this is equivalent to an indirect reduction of 10%-20% in carbon emissions. This optimization not only reduces the environmental burden but also enhances distribution efficiency by reducing inefficient transportation, achieving synergy between "low carbon" and "high efficiency".

3.2 Impact on Vehicle Dispatching: Enhance the Efficiency of Resource Utilization

The impact of intelligent optimization algorithms on vehicle scheduling is primarily manifested in enhancing resource utilization through precise matching, thereby reducing carbon emissions. Traditional vehicle scheduling exhibits notable shortcomings: the matching of vehicles with orders heavily relies on experience, often resulting in the phenomenon of "a big horse pulling a small cart" - using large trucks to deliver small batches of goods, leading to waste of transportation capacity. Simultaneously, the scheduling of new energy vehicles and fuel vehicles is fragmented, without dynamic allocation based on factors such as delivery distance and cargo weight, which not only increases operational costs but also exacerbates carbon emissions due to the overuse of fuel vehicles.

Intelligent optimization algorithms achieve refined upgrades of scheduling strategies through multi-dimensional parameter modeling. The ant colony algorithm excels in vehicle selection, as it can convert data such as order weight, delivery distance, and road restrictions into "pheromone" parameters. By simulating the path selection mechanism of ants foraging, it matches optimal vehicle types for different orders: for example, small-batch orders within 3 kilometers are automatically allocated to new energy micro-vans, while medium-batch orders over 20 kilometers are allocated to hybrid trucks, resulting in a vehicle utilization rate increase of over 30%. The simulated annealing algorithm focuses on optimizing loading rates. By simulating the random search process of physical annealing, it continuously adjusts the stacking order and placement of goods, increasing the loading rate from the traditional 60% to over 80% while meeting vehicle load capacity constraints, directly reducing the number of trips by 15%-25%. The genetic algorithm optimizes fleet size, using "minimum total carbon emissions" as the fitness function. Through selection, crossover, and mutation operations, it iteratively calculates the minimum necessary number of vehicles, avoiding unnecessary empty trips due to redundant capacity. After applying this algorithm, a logistics enterprise reduced the proportion of idle vehicles from 20% to 8%, saving over 10,000 kilometers of empty travel annually.

After these optimizations were implemented, the issue of resource waste in vehicle scheduling was significantly improved. This not only reduced the carbon emission intensity per unit of cargo volume but also enhanced overall operational efficiency through transportation capacity intensification, achieving dual benefits of low carbon footprint and economic efficiency.

3.3 The Impact on Carbon Emission Quantification and Monitoring: Precise Targeted Emission Reduction

Intelligent optimization algorithms provide dynamic and precise tools for the quantification and monitoring of carbon emissions, driving the shift from "extensive" to "targeted" emission reduction. Traditional quantification of carbon emissions relies on post-event statistics, such as monthly fuel consumption reports or quarterly emission inventories. This approach suffers from significant data lag, making it difficult to reflect fluctuations in carbon emissions during real-time operations, resulting in a lack of timeliness in optimization decisions. For instance, a delivery route may experience a surge in carbon emissions due to chronic congestion, but post-event statistics may only reveal this the following month, missing the opportunity for immediate adjustments.

Intelligent algorithms break through this limitation by integrating real-time data: with the help of GPS positioning, dynamic information collected by on-board sensors such as vehicle speed, idle time, and fuel consumption, hybrid algorithms (such as genetic-particle swarm hybrid model) can construct a real-time mapping relationship of "route-fuel consumption-carbon emissions", updating carbon footprint data per unit of cargo volume every second. This dynamic model not only accurately identifies high-emission links (such as a certain road segment where idle carbon emissions account for more than 40%), but also drives decision-making upgrades through reverse optimization. For example, the ant colony algorithm incorporates the carbon emission coefficient into the pheromone update mechanism, enabling the algorithm to automatically favor low-carbon routes during route search, giving priority to road segments with fewer traffic lights and lower slopes. The genetic algorithm uses "minimum carbon emissions" as the core fitness function to deduce the optimal vehicle scheduling plan (such as preferentially allocating new energy vehicles to peak congestion road segments).

This closed-loop mechanism of "real-time quantification - reverse optimization" shifts carbon emission monitoring from "post-event tracing" to "in-process intervention", providing an operable technical path for precise emission reduction.

3.4 Impact on Multi-objective Collaboration: Balancing Low Carbon and Efficiency

Intelligent optimization algorithms provide a systematic solution to resolve the traditional contradiction between low carbon and efficiency, achieving dynamic synergy across multiple objectives. In traditional models, low carbon goals often conflict with cost and timeliness: for example, prioritizing the use of new energy vehicles can reduce emissions, but the time-consuming charging process may delay orders; choosing the shortest low carbon route may take a detour through remote areas, thereby increasing transportation costs. This contradiction leads enterprises to fall into the dilemma of "choosing one at the expense of the other" in their emission reduction practices.

Intelligent algorithms break this deadlock through multi-objective optimization models. Taking the NSGA-II algorithm as an example, it can simultaneously incorporate carbon emissions, operational costs, and delivery timeliness into optimization objectives. Through non-dominated sorting and crowding degree calculation, it selects a Pareto optimal solution set in the solution space - that is, a solution where "no single objective is superior while the other objectives remain unchanged or deteriorate". Enterprises can choose a balance point according to their actual needs, such as emphasizing timeliness during e-commerce promotions and focusing on low carbon emissions when carbon tax policies are tightened. At the same time, the algorithm supports dynamic weight adjustment, automatically changing the calculation weights of various objectives by receiving policy parameters (such as carbon tax rates) or enterprise instructions in real time, so that the optimization strategy always adapts to the external environment. This dynamic collaborative mechanism not only avoids the limitations of single-objective optimization but also provides enterprises with flexible and controllable decision-making tools, promoting the transition from "opposition" to "coexistence" between low carbon and efficiency.

4. Challenges and Prospects of Intelligent Optimization Algorithm Applications

4.1 Existing Challenges

The application of intelligent optimization algorithms in low-carbon urban distribution still faces multiple practical challenges. At the data level, the accuracy of the algorithms is highly dependent on high-quality data such as real-time traffic conditions, vehicle energy consumption, and carbon emission factors. However, the traffic data collection network in some cities is not yet perfect, and the penetration rate of energy consumption monitoring devices for freight vehicles is insufficient, leading to distorted input parameters for the algorithms and deviations between optimization results and actual needs.

The complexity of the algorithm itself also poses a barrier. In dynamic scenarios such as sudden orders and traffic restrictions, the algorithm requires frequent iteration and updating of solutions, while the computation time of complex models may exceed the delivery response time limit. For example, when dealing with temporary orders during peak periods, the path replanning of some algorithms can take up to several minutes, making it difficult to meet the timeliness requirements of "instant delivery".

In terms of implementation costs, small and medium-sized enterprises (SMEs) generally face bottlenecks in technology and funding. The deployment of algorithms requires supporting data collection terminals, computing power, and professional operation and maintenance personnel. The annual investment for a basic optimization system can reach hundreds of thousands of yuan, far exceeding the affordability of small and medium-sized logistics enterprises.

In addition, there are barriers to multi-agent collaboration. Urban distribution involves multiple parties such as e-commerce platforms, logistics enterprises, and traffic management departments. Algorithm optimization requires the sharing of sensitive information such as order data, road network information, and vehicle status. However, due to concerns about data security and benefit distribution, cooperation among these parties is hesitant. The cross-agent data sharing mechanism has not been effectively established, which restricts the overall optimization effect of the algorithm.

4.2 Future Prospects

In the future, the application of intelligent optimization algorithms in low-carbon urban distribution will deepen along the path of technology integration, algorithm innovation, and policy coordination. At the technological level, the deep integration of the Internet of Things (IoT), big data, and artificial intelligence will break through the bottleneck of dynamic scenario adaptation. By utilizing on-board sensors and roadside equipment to collect real-time traffic flow and vehicle energy consumption data, combined with AI prediction models to anticipate road condition changes 15-30 minutes in advance, route optimization will shift from "passive response" to "active planning". For instance, during heavy rain, it can automatically avoid waterlogged road sections, reducing carbon emissions from idling.

Algorithm innovation will focus on practicality upgrades: On the one hand, lightweight hybrid algorithms will be developed to reduce dependence on computing power by simplifying iteration logic and compressing parameter dimensions, enabling small and medium-sized enterprises to deploy basic optimization functions at a cost of just a few thousand yuan. On the other hand, the introduction of "carbon cost" parameters will convert carbon emission trading prices, carbon taxes, and other factors into economic indicators and incorporate them into the model, directly linking low-carbon decisions to corporate profits and enhancing the motivation for emission reduction.

Policy coordination is the key to implementation. The government needs to take the lead in building a public data platform, integrating scattered data from traffic management, meteorological, and logistics enterprises, and formulating unified carbon emission quantification indicators (such as carbon emission coefficient per unit of cargo volume) to promote the standardization of algorithm output. At the same time, by subsidizing algorithm research and development, pilot demonstration projects, and other means, the application threshold for enterprises can be lowered, ultimately forming a low-carbon distribution ecosystem with a linkage of "technology - market - policy".

5. Conclusion

In the dual context of urbanization and the "dual carbon" goals, intelligent optimization algorithms provide crucial technical support for addressing the challenge of high carbon emissions in urban distribution. By simulating natural laws to construct optimization models, they enable precise optimization of distribution decisions under complex constraints, promoting low-carbon transformation from multiple dimensions: at the route level, they effectively shorten ineffective mileage through multi-constraint optimization, reducing carbon emissions by 10%-20%; at the vehicle scheduling level, they optimize model selection and loading rates, increasing the utilization rate of new energy vehicles by over 40%; at the multi-objective coordination level, they balance the relationship between "low carbon - cost - timeliness" and output optimal solutions; meanwhile, their quantification and monitoring functions for carbon emissions achieve precise targeted emission reduction.

However, the application of algorithms still faces practical challenges such as insufficient data quality, weak dynamic adaptability, and high implementation costs. In the future, technological integration (such as combining 5G and AI to enhance algorithm performance) and policy coordination (such as improving data sharing mechanisms and subsidy policies) are needed to break through application bottlenecks. Overall, intelligent optimization algorithms not only provide an operable technical path for low-carbon urban distribution but also promote the transformation of the logistics industry from "experience-driven" to "data-driven", providing important support for the sustainable development of urban green logistics and having significant theoretical and practical value.

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