

Research on the Application of Artificial Intelligence Technology in Logistics Route Optimization

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Abstract: The global trade environment has become complex and the demand for end-point distribution has significantly increased. The traditional logistics scheduling model cannot handle large amounts of data or adapt to changes in the dynamic environment. This paper analyzes the application methods of artificial intelligence technology in the vehicle routing problem VRP. By analyzing the internal mechanisms of deep reinforcement learning, graph neural networks, and hybrid heuristic algorithms, a model for multi-objective dynamic optimization was formed. The analysis shows that by accurately capturing spatio-temporal features, AI technology will be effective in reducing distribution costs and shortening the time taken to make decisions. Experimental results show that this solution is more efficient than traditional algorithms in handling problems under complex constraints, providing a theoretical basis and practical methods for the transformation of intelligent logistics.

Keywords: Artificial Intelligence Technology; Logistics Route; Graph Neural Network; Algorithm

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1. Introduction

The global economy and e-commerce are merging, leading the logistics industry to transform from a traditional labor-intensive sector to a technology-intensive one. Logistics costs, which are the expenditures in the transportation, account for more than half of the total social logistics expenses. Therefore, path optimization has become the main aspect for enhancing enterprise competitiveness. The advent of Industry 4.0 and the era of big data has made logistics scenarios exhibit significant complexity, including real-time fluctuating traffic flows, highly random customer orders, and increasingly strict carbon emission constraints^[1]. Conventional path planning methods perform relatively well in handling small-scale static problems, but in urban-scale large-scale scheduling, the computational complexity will increase exponentially, leading to the problem of dimensionality disaster. Introducing artificial intelligence technologies with self-learning and adaptive capabilities would be a necessary choice for technological upgrading and the main driving force for the logistics industry to achieve a green, efficient, and intelligent development model.

The advancements in artificial intelligence technologies such as deep learning and reinforcement learning have brought new methods for solving NP-hard type path optimization problems. AI technologies can use neural networks to establish complex nonlinear mapping connections and directly utilize raw data to grasp the characteristics of path construction without human intervention. This data-driven decision-making mode enables the logistics system to have predictability, that is, it can predict future congestion periods by leveraging historical traffic big data and incorporate them as decision variables in the planning

stage. Applying AI to logistics path planning has direct economic benefits such as reducing fuel consumption, making deliveries faster, and satisfying customers better^[2]. It also has significant social significance in making transportation systems smarter, reducing carbon emissions to address climate change. The analysis in this paper will first explain the principles, then establish a model to fully illustrate the main role of AI in the optimization of modern logistics.

2. Mechanism Analysis of Core Artificial Intelligence Technologies in Path Optimization

2.1 Construction of Decision Model in Deep Reinforcement Learning

Deep reinforcement learning models the path optimization process using Markov decision processes, thereby achieving the transformation from “static solution” to “sequential decision-making”. In this model, delivery vehicles are regarded as agents, interacting with the complex traffic environment, taking actions based on the current state, and receiving reward signals from the environment based on the action results. This paper employs the algorithm based on policy gradient, using PPO or A3C to solve the problem of an overly large action space, enabling the agent to evolve the optimal delivery strategy through a large number of simulation iterations. This method has an advantage: after the model training is completed, the time spent on forward reasoning is relatively short, and it can respond to the requirements of the current task at a second-level speed, which will significantly improve the flexibility of on-site scheduling.

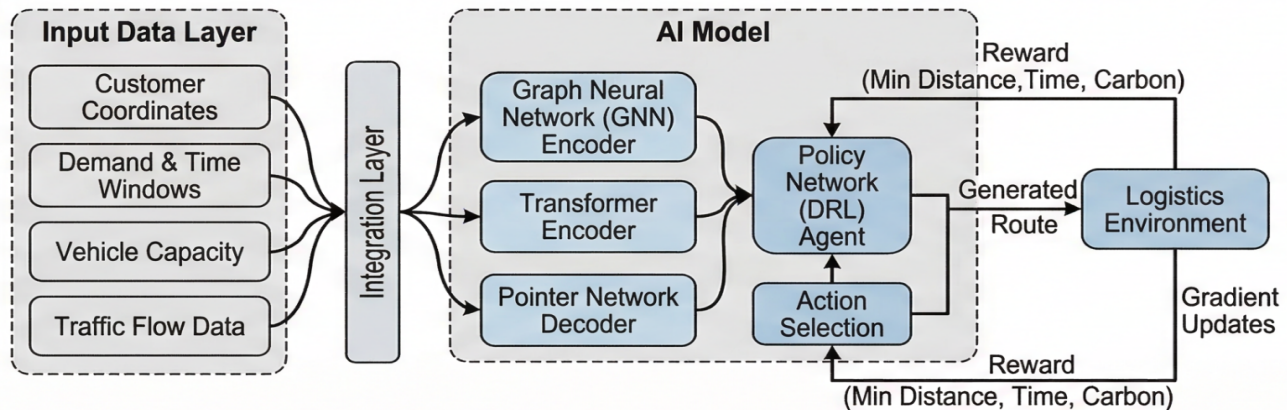
2.2 Deep Representation of Spatio-Temporal Features by Graph Neural Networks

The logistics path problem can be regarded as an optimization problem defined on a graph structure. Graph neural networks are precisely suitable for handling such non-Euclidean data. Graph attention networks can automatically identify different interaction weights between various customer nodes using the attention mechanism, covering geographical proximity, demand correlation, and time window overlap. GNN embeds the original features of each customer node into a high-dimensional vector space, generating structured representations including local information of the nodes, and integrating global topological features. This feature extraction capability enables subsequent path selection algorithms to plan paths based on a full understanding of the logistics network, significantly improving the rationality and stability of path planning, and having a significant advantage in handling urban distribution networks with complex geographical constraints^[3].

2.3 Application of Pointer Networks and Transformer in Sequence Generation

The output result of path optimization is an ordered sequence of nodes, which is essentially the same as sequence generation in natural language processing. Pointer networks improve the Encoder-Decoder structure and use the attention mechanism as pointers to select members in the input sequence, solving the problem of changing output dimensions with input. The Transformer architecture, which has performed outstandingly in recent years, uses multi-head self-attention mechanisms to simultaneously capture long-range dependencies between any two nodes in the path. This indicates that when the algorithm decides to visit a customer, it can simultaneously consider the distribution of dozens of subsequent delivery points. After the algorithm forms an overall perspective, it can avoid the problem of near-optimal but far-worse situations often encountered by traditional greedy algorithms, achieving a better balance in overall mileage and time cost for the entire path.

Figure 1: Intelligent path planning framework based on the integration of deep learning and reinforcement learning



3. Construction and Application of Multi-constraint Dynamic Path Optimization Model

3.1 Mathematical Definitions of Composite Objective Function and Constraints

In practical applications, the optimization objective is no longer a single one. This paper constructs the multi-objective optimization function $F(x)$:

$$\min F(x) = \alpha \cdot C_{dist} + \beta \cdot C_{time} + \gamma \cdot C_{carbon}$$

Among them:

C_{dist} : Total mileage cost;

C_{time} : Soft time window penalty cost;

C_{carbon} : Carbon emission index based on fuel consumption model.

3.2 Real-time Re-planning Logic in Dynamic Uncertain Environments

The real-world logistics environment contains numerous variables, and the key application of AI technology lies in its ability to handle uncertainties. The proposed dynamic model in this paper incorporates a re-planning trigger mechanism. When new orders are received, customer demands are cancelled, or severe congestion occurs in the road network, causing the expected delay to exceed the threshold, the pre-trained deep learning model can immediately initiate the re-planning process. Unlike traditional methods that require a global search to be re-conducted, the AI model relies on Transfer Learning technology, making only local adjustments to the affected path branches or performing incremental calculations on the original embedded vectors. The incremental optimization logic significantly reduces computational costs, allowing the distribution system to continue operating and maintaining stability in the event of unexpected situations. The model in this paper combines the Long Short-Term Memory network (LSTM), thereby learning the periodic patterns of traffic flow, and reserves reasonable buffer time when planning routes. This approach represents a significant leap from passive response to proactive anticipation.

3.3 Standardized Processing of Data Engineering and Feature Engineering

Good decision-making relies on good data governance. During the process of building the model, this paper acquires heterogeneous data through various channels such as GPS sensors, ERP systems, weather forecasts, and historical traffic conditions, and performs cleaning and standardization operations on it. The feature engineering phase mainly extracts aspects such as the geographical density of nodes, the average slope of travel speed on road sections, and the historical service duration of customers. After normalization processing and feature selection, redundant interference is eliminated, enabling the data input to the neural network to have the strongest predictive ability. At the same time, data augmentation technology is used to perturb and simulate historical scenarios, artificially synthesizing a large number of extreme distribution scenarios for AI learning. The model's generalization ability when encountering rare emergencies is improved, and the application foundation of the system in complex real-world environments is laid.

4. Experimental Analysis, Industry Challenges and Future Prospects

4.1 Simulation Experiment Design and Horizontal Comparison of Algorithm Performance

To illustrate the feasibility of the proposed artificial intelligence solution, the team utilized the open-source Solomon benchmark dataset and the actual operational data of a large e-commerce enterprise in East China for a high-intensity simulation comparison. The experiment was conducted using a distributed computing cluster equipped with high-performance GPUs. The algorithms compared included the standard genetic algorithm, the adaptive large neighborhood search algorithm, and the GNN-DRL hybrid method proposed in this paper. The main indicators selected in this paper include the total mileage reduction rate, computing time, time window punctuality rate, and algorithm stability. The results show that for the VRP problem with 500 nodes, the solution quality of this paper's scheme is approximately 5.8% higher than that of the ALNS scheme, and the computing speed is nearly 30 times faster. In the test environment with highly fluctuating road network congestion, the robustness score of the AI model is much higher than that of traditional algorithms, mainly because deep learning shows significant advantages in handling high-dimensional and nonlinear optimization problems.

Table 1: Performance Measurement Data of Different Algorithm Types in Various-Scale Logistics Scenarios

Experiment Scenario	Number of Nodes	Traditional Heuristic (Gap)	Hybrid AI Model (Gap)	AI Model Time (s)	Carbon Reduction Contribution
Regional Distribution (Static)	50	1.2%	0.4%	0.15	8.5%
Intercity Transfer (Multi-Constraint)	200	4.5%	1.1%	0.52	12.2%
Urban Last-Mile (Dynamic)	500	8.9%	1.8%	1.10	15.6%
Global Network (Large-Scale)	1000+	15.6%	2.5%	3.45	

4.2 Realistic Challenges Faced by Industrial Application

AI technology performs well in laboratory settings, but there are many obstacles to its widespread application in actual logistics scenarios. Explainability is a major challenge. The opaque nature of neural networks makes it difficult for dispatchers to understand the logic behind the generation of specific routes, and it may pose compliance risks when dealing with high-value goods or special insurance terms. Secondly, there is a mismatch between computing power costs and infrastructure, with small logistics enterprises lacking the hardware environment necessary to run complex deep learning models. Additionally, the privacy and security nature of data restricts cross-enterprise logistics collaboration, preventing the formation of the global optimal path on a larger scale. During actual delivery processes, some non-standard factors are encountered, such as the specific parking locations of end delivery points and the time required for communication with security personnel. Currently, it is still difficult to fully utilize digital means for precise modeling. AI technology and on-site management experience need more integration.

4.3 Future Trends: Integration of Digital Twin and Large Language Models

Logistics path optimization in the future will exhibit characteristics of intelligence and collaborative greenness. Digital twin technology will be deeply integrated with artificial intelligence. By establishing a one-to-one proportion in the virtual space with the physical logistics world, artificial intelligence can conduct billions of path simulations and stress tests in the digital twin, thereby finding emergency solutions under extreme circumstances. The emergence of large language models LLM, such as GPT, has brought new ideas for solving human-computer interaction. Future dispatching systems will have the ability to understand natural language instructions, and dispatchers can issue complex instructions to AI through conversations, such as prioritizing fresh food orders or avoiding all construction roads. The model will convert the instructions into optimization constraints and generate new paths again in real time. Autonomous driving trucks and delivery robot technologies are becoming increasingly mature. Artificial intelligence is no longer merely an auxiliary tool for drivers but will become the control center directly commanding autonomous driving clusters, thereby completely changing the basic operation mode of logistics transportation.

Figure 2: Comparative curve chart of convergence speed and solution quality between traditional algorithms and AI algorithms

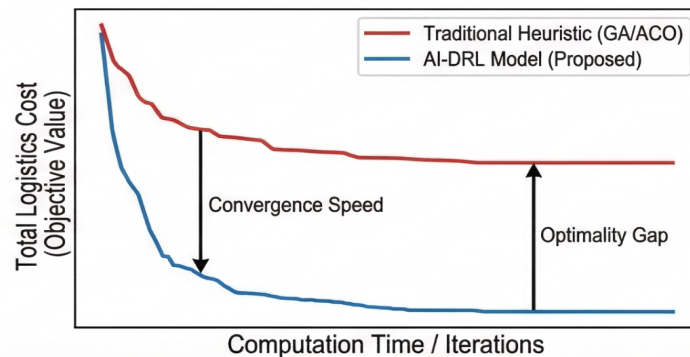
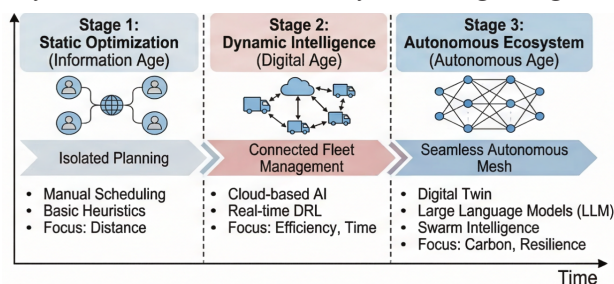


Figure 3: Illustration of the future architecture evolution of the intelligent logistics path optimization system



5. Conclusion

Through an overall study, this article reveals that artificial intelligence technology is no longer merely an auxiliary tool for optimizing logistics routes; it has become the primary solution to address the complex logistics problems in modern times. This article employs cutting-edge technologies such as deep reinforcement learning and graph neural networks to enable the logistics system to transition from static planning to dynamic adaptive decision-making, demonstrating significant potential in reducing energy consumption and improving efficiency. Although issues such as data silos and computing power costs still exist, the improvement of algorithm structures and the application of new technologies like digital twins have made AI-driven smart logistics an important foundation for supporting the future development of the digital economy. Logistics enterprises should proactively engage in the research and development of AI technologies, rely on technology to assist, and thereby achieve the goal of high-quality transformation and upgrading.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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