Жамият ва инновациялар –
Общество и инновации –
Society and innovations
Journal home page:
https://inscience.uz/index.php/socinov/index

# Leveraging deep learning models for optimized cargo tracking and transportation efficiency in Logistics

**Azam NURULLAEV**[1]

University of Cumberlands in KY

**ARTICLE INFO**

***Article history:***
Received October 2024
Received in revised form
15 November 2024
Accepted 15 December 2024
Available online
25 January 2025

***Keywords:***
smart logistics algorithms,
route optimization,
advanced reinforcement learning,
data analysis, enhancement of transportation efficiency.

**ABSTRACT**

Amid the digital transformation of the logistics industry, smart logistics algorithms have emerged as a crucial technology to enhance efficiency and reduce costs. This paper reviews the evolution of traditional logistics technologies and highlights the pivotal roles played by advancements such as the Internet of Things, big data analytics, artificial intelligence, and automation in driving logistics innovation. It delves into the application of intelligent logistics algorithms across areas like path optimization, intelligent scheduling, data mining and prediction, and smart warehousing. To address the challenge of inconsistencies between training and testing objectives, the paper introduces DRL4Route, a deep reinforcement learning-based framework for path optimization, along with the DRL4Route-GAE model. Extensive offline experiments and online deployments validate that the model significantly outperforms existing optimal benchmark methods on real datasets, improving metrics like location deviation squared and top-three location prediction accuracy. These research findings provide essential support for advancing the intelligent development of the logistics industry.

2181-1415/© 2024 in Science LLC.
DOI: https://doi.org/10.47689/2181-1415-vol5-iss6-pp181-192


[1] Master's Graduate, University of Cumberlands in KY, USA. E-mail: nurullayevazam4@gmail.com

# Логистикада юкларни монитор қилиш ва транспорт самарадорлигини оптималлаштириш учун чуқур ўрганиш моделларидан фойдаланиш

***Калит сўзлар:***
ақлли логистика алгоритмлари, йўналишни оптималлаштириш, илғор мустаҳкамлашга асосланган ўрганиш; маълумотларни таҳлил қилиш, транспорт самарадорлигини ошириш.

**АННОТАЦИЯ**

Логистика соҳасининг рақамли трансформацияси давомида ақлли логистика алгоритмлари самарадорликни ошириш ва харажатларни камайтириш учун муҳим технологияга айланди. Ушбу мақолада анъанавий логистика технологияларининг ривожланиши таҳлил қилиниб, Internet of Things(IoT), катта маълумотлар таҳлили, сунъий интеллект ва автоматлаштириш каби ютуқларнинг логистика инновациясини ривожлантиришдаги асосий роллари таъкидланади. У ақлли логистика алгоритмларининг йўналишни оптималлаштириш, ақлли режалаштириш, маълумотларни қазиб олиш ва прогнозлаш, ҳамда ақлли омборни бошқариш каби соҳалардаги қўлланилишига тўхталади. Тренинг ва тест мақсадлари ўртасидаги номувофиқлик муаммосини ҳал қилиш учун мақолада DRL4Route-GAE – йўналишни оптималлаштириш учун чуқур мустаҳкамланишга асосланган ўқув тизими, шунингдек DRL4Route-GAE модели тақдим этилади. Кенг кўламли офлайн тажрибалар ва онлайн жорий этишлар моделнинг ҳақиқий маълумотлар тўпламида мавжуд оптимал мезон усулларидан сезиларли даражада устун эканлигини тасдиқлайди, масалан, жойлашувдаги четланиш квадрати ва энг яхши учта жойлашув прогнози аниқлиги каби кўрсаткичларни яхшилайди. Ушбу тадқиқот натижалари логистика соҳасининг ақлли ривожланишини қўллаб-қувватлашда муҳим асос бўлиб хизмат қилади.

# Использование моделей глубокого обучения для оптимизации отслеживания грузов и повышения эффективности транспортировки в логистике

***Ключевые слова:***
умные алгоритмы логистики, оптимизация маршрутов, продвинутое обучение с подкреплением, анализ данных, повышение эффективности транспортировки.

**АННОТАЦИЯ**

В условиях цифровой трансформации логистической отрасли интеллектуальные алгоритмы логистики стали ключевой технологией для повышения эффективности и снижения издержек. В данной статье рассматривается эволюция традиционных логистических технологий, а также подчеркивается важная роль таких достижений, как Интернет вещей (Internet of Things), аналитика больших данных, искусственный интеллект и автоматизация, в стимулировании инноваций в логистике. В статье исследуются области применения интеллектуальных логистических алгоритмов, включая оптимизацию маршрутов, интеллектуальное планирование, добычу данных и прогнозирование, а также умное управление складскими процессами. Для решения проблемы несоответствий между целями обучения и тестирования представлена система DRL4Route, основанная на глубоком обучении с подкреплением, для оптимизации маршрутов, а также модель DRL4Route-GAE. Широкие оффлайн-эксперименты и онлайн-развертывания подтверждают, что предложенная модель значительно превосходит существующие оптимальные эталонные методы на реальных наборах данных, улучшая такие показатели, как квадрат отклонения от местоположения и точность прогнозирования местоположения в топ-3. Результаты исследования обеспечивают важную поддержку для дальнейшего интеллектуального развития логистической отрасли.

**Introduction**

With the digital transformation of the logistics industry, intelligent logistics algorithms have become essential for boosting efficiency and cutting costs. By harnessing advanced technologies like Big Data and Artificial Intelligence, logistics companies can optimize data for smart decision-making and streamlined operations. These algorithms are crucial in several areas:

1. **Route Planning (Alternative path for Pick up/Delivery):** They significantly reduce transport time and costs, improving overall transport efficiency.
2. **Demand Forecasting and Inventory Management:** They optimize supply chain management, lowering inventory costs and minimizing the risk of stock-outs.
3. **Real-Time Monitoring and Quick Response:** Intelligent algorithms enhance the flexibility and resilience of logistics systems by enabling immediate reactions to abnormalities, resulting in more efficient resource allocation.
4. **Logistics Demand Prediction:** Accurate forecasting improves customer experience and satisfaction.

Overall, intelligent logistics algorithms improve efficiency, lower costs, and enhance customer service. This paper explores strategies and methods for optimizing logistics cargo tracking and transport efficiency using data science and deep learning models, supporting the ongoing development of intelligent logistics systems.

**Related work**

*2.1 Traditional Logistics Technologies (TLT):*

The rapid acceleration of digital transformation has ushered in a new era of smart logistics, driving technological innovation within the industry. By leveraging digital technologies, companies can fundamentally transform their business models, significantly improving the efficiency and accuracy of logistics processes. Central to these advancements are real-time data availability and seamless collaboration across supply chain segments. Digital platforms, for instance, enable real-time collaboration, enhancing the flow of supply chain information and boosting overall operational efficiency.

Historically, logistics technology relied on manual records and basic computer systems, which were prone to errors and inefficiency. In the late 20th century, the adoption of barcode and radio frequency identification (RFID) technologies greatly improved data collection and processing. The introduction of Electronic Data Interchange (EDI) further modernized logistics by enabling faster, more accurate information transmission across supply chain segments.

Entering the 21st century, the intelligent logistics era emerged, emphasizing automation and data-driven decision-making. Technologies like artificial intelligence (AI) and the Internet of Things (IoT) became integral to logistics innovation. Companies like Amazon, for example, use intelligent path planning and inventory management systems to optimize operations, cut costs, and boost transport efficiency [1]. Emerging technologies such as blockchain and edge computing have also created new opportunities. Blockchain enhances data security and transparency, while edge computing improves real-time monitoring and responsiveness.

Overall, logistics technology has evolved from manual systems to intelligent, automated solutions. Technologies like barcodes, RFID, and EDI laid a crucial foundation, while advancements in AI, IoT, blockchain, and edge computing continue to drive innovation and ensure the industry's sustainable growth. These developments highlight the vast potential and transformative possibilities for logistics in the digital age.

*2.2 AI-Driven Logistics Technology Innovation*

Logistics technology innovation is driven by key advancements, including the Internet of Things (IoT), big data analytics, artificial intelligence (AI), and automation. IoT enables real-time monitoring of logistics by connecting devices and sensors, providing essential data for intelligent decision-making. For instance, IoT temperature monitoring systems track perishable goods in transit, ensuring their safety. According to McKinsey, applying IoT technology can boost logistics efficiency by 10-15% [2].

Big data analytics is also crucial, as it allows logistics companies to process vast amounts of information for predictive analysis and real-time monitoring. By analyzing historical data, companies can forecast market demand, optimize transport plans, and quickly address issues in the supply chain. A DHL study shows that big data-driven forecasting systems can improve accuracy by 20-30%, significantly lowering inventory and transport costs.

Artificial intelligence enhances logistics through intelligent path planning and automated decision-making. Machine learning optimizes transport routes, boosting efficiency, while deep learning enables more effective automated operations. For example, machine learning-based cargo loading systems increase vehicle loading efficiency, reducing transport costs. Studies indicate that AI-driven route planning can enhance transport efficiency by 25%.

Automation technology reduces dependency on manual labor and boosts operational efficiency. Automated systems enable rapid storage and retrieval in warehouses, while autonomous vehicles improve transport safety and efficiency. Amazon's automated warehouse robots, for example, have cut costs and increased picking efficiency, with The Economist reporting a 30-40% improvement in operational efficiency through automation [3].

The integration of these technologies has revolutionized logistics, enhancing efficiency and accelerating digital transformation. By leveraging IoT, big data, AI, and automation, logistics companies can achieve comprehensive, intelligent, and automated operations, staying ahead in a competitive market. As these technologies continue to evolve, the logistics industry is set for a more efficient, secure, and intelligent future.

*2.3 Alternative Logistics Algorithms*

Intelligent logistics algorithms rely on sensing technology for real-time data collection and advanced data processing to transform raw data into actionable insights. **Sensing technology** enables continuous monitoring, tracking the location, temperature, and status of goods. For example, temperature sensors are crucial in cold chain logistics to maintain product quality, and GPS systems optimize route planning by tracking vehicle locations.

**Data processing** uses big data analysis to extract meaningful patterns, support decision-making, and predict future logistics needs. Real-time decision-making ensures quick responses to changing conditions, while predictive analytics combines historical and current data to anticipate demand and plan efficiently. Together, sensing technology and data processing form the backbone of intelligent logistics algorithms, driving optimized and efficient logistics operations.

**Key Intelligent Logistics Algorithms**

***1. Path Optimization Algorithms***

These algorithms, grounded in graph theory, find the shortest or most efficient paths within a network. Popular methods include Dijkstra's algorithm, which employs a greedy approach for weighted graphs, and the A* algorithm, which enhances search efficiency using heuristics. Genetic algorithms introduce biological evolution concepts to solve complex network problems, making them ideal for large-scale urban planning [4].

***2. Intelligent Scheduling Algorithms***

These optimize resource allocation and task scheduling using genetic algorithms, simulated annealing, and ant colony algorithms. Genetic algorithms improve vehicle routing and cargo loading by simulating natural selection processes. Simulated annealing avoids local optima by accepting suboptimal solutions with a certain probability, aiding in global optimization. Ant colony algorithms simulate collective behavior, optimizing routes and enabling vehicle cooperation.

***3. Data Mining and Predictive Algorithms***

Data mining techniques uncover relationships within logistics data to enhance operations. For instance, association rule mining identifies item correlations for improved inventory layout and combined shipments. Time series analysis forecasts demand and transit times, revealing trends to refine planning. Machine learning predicts future demand based on historical sales, optimizes routes considering traffic and weather and identifies risks within the supply chain.

***4. Intelligent Warehousing Algorithms***

These improve warehouse efficiency using automation and intelligent systems. Cargo distribution algorithms streamline goods movement and picking, while machine learning-driven picking systems optimize sequences to reduce time and errors. Dynamic scheduling allocates tasks to automated equipment in real-time, maximizing efficiency. Automated storage systems use robots to manage inventory, and real-time monitoring ensures accuracy and rapid response to issues.

***5. Methodology***

Recent advances in route prediction leverage learning-based approaches, such as deep neural networks, to model courier patterns from historical data. Techniques like oSquare and DeepRoute transform delivery predictions into next-location forecasting, employing recurrent neural networks, Transformer-based encoders, and dynamic graph networks. However, existing methods face performance challenges due to discrepancies between training and testing objectives, often using mismatched metrics like cross-entropy loss and position squared deviation. Addressing this inconsistency is crucial for enhancing model performance in real-world applications.

**How methodology works?**

An intuitive solution to the problem would be to directly transform the test targets into loss functions for updating the model parameters. However, this approach is not feasible because the test targets in this task, such as position squared deviation and Kendall rank correlation coefficient, are non-differentiable. These test targets measure the similarity between the real and predicted routes, with the predicted routes being generated step by step based on the maximum values of the probability distributions from the model outputs. Due to the non-differentiability of these test targets, it becomes challenging to use them directly for model training.

To address this issue, a promising solution lies in utilizing **reinforcement learning**. Reinforcement learning has proven effective in optimizing non-differentiable objectives across various tasks such as machine translation, text summarization, and image captioning. In these domains, reinforcement learning has shown superior performance over traditional supervised deep learning methods, making it a viable approach for improving model performance on non-differentiable test metrics [6].

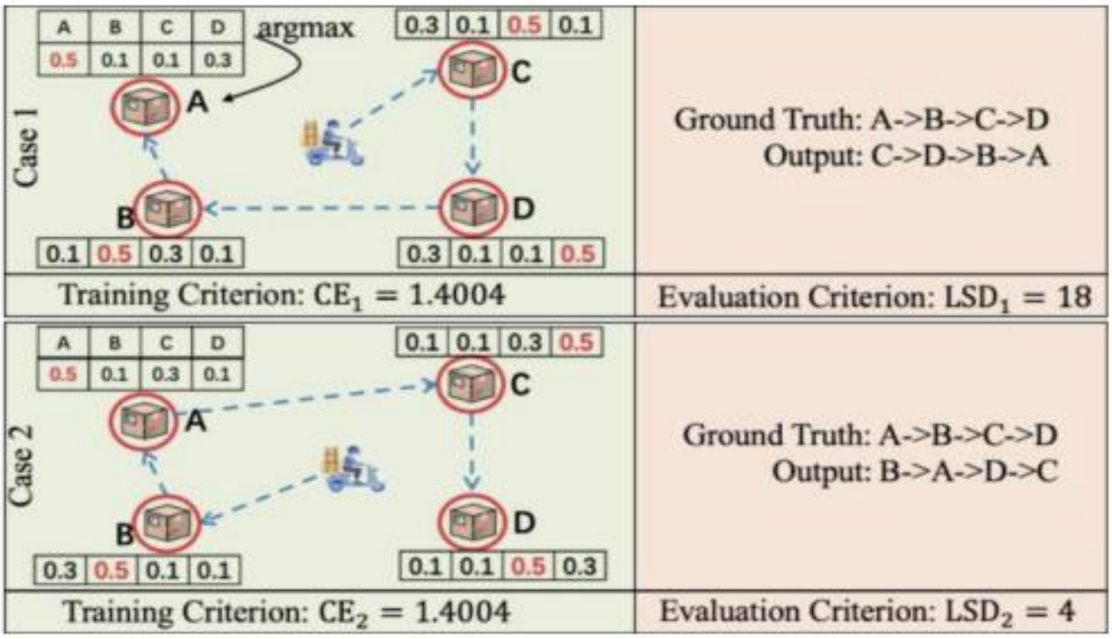


**Figure 1. An illustration highlighting the discrepancy between training and testing objectives. The vector at each location represents the transition probabilities associated with A, B, C, and D.**

I also want to highlight a novel approach to modeling the route prediction problem in dispatching through a reinforcement learning perspective. It introduces the DRL4Route framework, which employs a policy-based reinforcement learning methodology. By leveraging rewards derived from non-differentiable test objectives, the framework optimizes a deep neural network using a policy gradient approach to address the inconsistency between training and testing objectives. Within this framework, the DRL4Route-GAE model is developed specifically for route prediction in logistics collection services.

The model employs a strategy gradient algorithm to reduce variance in gradient estimation by utilizing an actor-critic framework. While this framework introduces some bias due to the critic and actor models' limitations in accurately estimating the value function, a generalized advantage estimation method is used to strike a balance between bias and variance during gradient estimation. The dominance value approximation is applied when updating the loss function to refine the process.

Key contributions of this paper include:

1. **Reinforcement Learning Framework for Route Prediction**: This is the first study to approach collection and delivery route prediction from a reinforcement learning perspective, proposing the DRL4Route framework. It combines reinforcement learning's capability to optimize non-differentiable objective functions with deep neural networks' ability to learn historical behavior patterns, offering an improvement over traditional supervised learning methods.

2. **Development of DRL4Route-GAE**: The DRL4Route-GAE model applies an actor-critic framework to compute rewards at each decoding step based on test objectives. It introduces generalized advantage estimation to balance bias and variance during gradient estimation, enhancing the training process.

3. **Validation and Performance**: Extensive offline experiments using real datasets and online deployments confirm the effectiveness of the proposed method. Compared to the optimal baseline, DRL4Route-GAE demonstrates improvements in location bias squared metrics by 0.9%-2.7% and top-three location prediction accuracy metrics by 2.4%-3.2%.

***3.2. DRL4Route***

The DRL4Route (Deep Reinforcement Learning for Route Optimization) model is a cutting-edge algorithm designed to tackle complex logistics route planning challenges through deep reinforcement learning. By leveraging reinforcement learning strategies, the model autonomously learns and optimizes transportation routes, effectively reducing both transit time and costs. Its advantages in logistics forecasting include the following [7]:

1. **Dynamic Adaptability**: The DRL4Route model adjusts in real-time to fluctuating logistics demands and traffic conditions, delivering optimal solutions dynamically.

2. **Efficiency in Handling Large-Scale Data**: It processes extensive datasets efficiently and identifies optimal paths within complex networks swiftly.

3. **Continuous Improvement**: By consistently learning and refining its approach, the model enhances the accuracy and efficiency of route planning over time, significantly boosting the overall performance and responsiveness of logistics systems.

The framework optimizes parameters based on rewards derived from test objectives using a policy gradient method. This enables it to address non-differentiable objective functions for more precise route predictions. Actions that align with improving test metrics receive higher reward values, incentivizing the model to favor such decisions. Conversely, actions that negatively impact test metrics result in lower rewards, prompting parameter updates to avoid such choices. This iterative learning process ensures increasingly accurate and efficient route optimization.

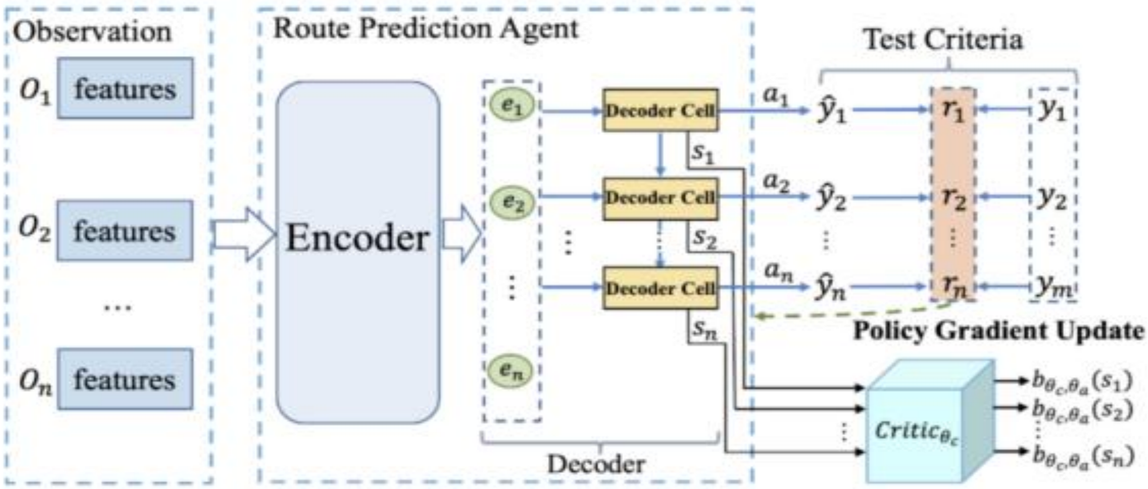


**Figure 2. DRL4Route Framework**

In this paper, based on the DRL4Route framework, a model named DRL4Route-GAE is proposed for parcel collection services in logistics scenarios to illustrate the effectiveness of the proposed framework. DRL4Route-GAE generates the spatio-temporal representation of the unfinished task using a transformer-based encoder and models the decision-making process of the courier by using an attention mechanism and recurrent neural network-based decoder to model the courier's decision-making process [8].

The model training is guided by the strategy gradient so we can optimize the non-differentiable test objective to solve the problem of inconsistency between the training and test objectives, furthermore, we use a generalized dominance estimation method to compute an approximation of the dominance to balance the bias and variance during gradient estimation, so we can get better strategies as well as better results.

***3.3. Experimental Data Sets and Methods***

We conduct offline experiments on the logistics parcel-acquisition dataset provided by Cainiao, and the sample ratio of the training set, validation set, and test set is about 6:2:2, and the data statistical information is shown in Table 1.

**Table 1**

| Type | Time Range | City | ANUT | #Workers | #Samples |
|---|---|---|---|---|---|
| Logistics-I1Z | 07/10/2021-10/10/2021 | Ilangzhou | | 1,117 | 373,072 |
| Logistics-SI1 | 03/29/2021-05/27/2021 | Shanghai | | 2,344 | 208,202 |

**Baseline Methods**

This study incorporates several baseline methods alongside state-of-the-art deep learning models across different scenarios, such as food distribution and last-mile logistics, to facilitate comparisons [9]:

1. **Time Greedy**: Routes are generated by prioritizing locations based on the remaining time until task timeout, ensuring tasks with imminent deadlines are addressed first.

2. **Distance Greedy**: At each step, the courier selects the nearest location to visit, constructing the route incrementally by continuously choosing the closest subsequent destination.

**Baseline Methods for Comparison**

1. **OR-Tools:** A heuristic algorithm designed to find the shortest path, optimized for minimizing travel distance.

2. **OSquare:** An XGBoost-based approach that sequentially generates routes one node at a time.

3. **FDNET:** A model tailored for takeaway scenarios that combines LSTM and attention mechanisms to predict paths and times.

4. **DeepRoute:** A deep learning-based route prediction model employing a Transformer encoder and attention decoder.

5. **DeepRoute+:** An enhanced version of DeepRoute that incorporates a courier decision preference modeling module for more personalized route predictions.

6. **Graph2Route:** A novel approach using graph structures to represent locations. It employs a GCN-based encoder with an attention mechanism to better capture spatial and temporal relationships and improve path predictions.

**Experimental Results Summary**

The comparative analysis, summarized in Table 2, reveals key insights from testing on two datasets:

- **Limitations of Greedy Methods**: Distance-based and time-based greedy approaches (as well as OR-Tools) focus solely on optimizing a single aspect, such as distance or time. Consequently, they fail to account for complex spatiotemporal constraints, offering suboptimal solutions in real-world logistics scenarios.
- **OSquare's Weaknesses**: The tree-based OSquare model struggles to model spatiotemporal correlations effectively. Furthermore, its objective is limited to maximizing the probability of predicting the next position, rather than optimizing the entire route.
- **Challenges with Sequence-Based Models**: Models like FDNET and DeepRoute face difficulties in capturing neighborhood relationships among locations, often resulting in unreasonable route outputs.
- **Advantages of Graph2Route**: By incorporating a graph-based encoder, Graph2Route excels at modeling decision context information and spatiotemporal relationships, addressing key limitations of sequence-based models and producing more coherent and realistic routes [10].

**Table 2.**

| Method | Logistics-HZ n E(0.25) | Logistics-HZ n (0.11) | Logistics-SH n E(0.25) | LogisticsSH n (0.11) |
|---|---|---|---|---|
| | HR@I | ACC@3 | KRC | LMD |
| Time-Greedy | 33.15 | 20.32 | 41.92 | 1.7 |
| Distance-Greedy | 33.13 | 51.82 | 136 | 5.73 |
| OR-Tools | 53.93 | 1.23 | 4.68 | 1.46 |
| OSquare | 54 | 33.1 | 58.5 | 1.16 |
| FDNET | 52.76 | 33.22 | 55.47 | 1.18 |
| DeepRoute | 54.76 | 34.64 | 58.61 | 1.1 |

| | | | | |
|---|---|---|---|---|
| DeepRoute+ | 55.42 | 35.63 | 59.32 | 1.08 |
| Graph2Route | 56.45 | 36.12 | 60.63 | 1.05 |
| DRLAROute-REINFORCE | 55.88 | 29.02 | 59.97 | 1.38 |
| DRL4Route-AC | 56.36 | 36.16 | 60.86 | 1.05 |
| DRL4Route-GAE | 57.72 | 37.23 | 61.47 | 1.03 |
| Improvement | 2.20% | 3.10% | 1.40% | 1.90% |

Building on DeepRoute, **DRL4Route-REINFORCE** delivers superior performance, particularly in reducing the squared deviation of position. This improvement stems from its ability to directly optimize evaluation metrics, effectively resolving the inconsistency between training and testing objectives.

**DRL4Route-AC** surpasses DRL4Route-REINFORCE by incorporating dominance values computed from rewards at each time step to update model parameters. This approach mitigates the issue of error accumulation, leading to more robust results.

Finally, **DRL4Route-GAE** outperforms DRL4Route-AC by employing a generalized dominance estimation method. This technique balances bias and variance during gradient estimation, enabling even more precise and efficient route optimization.

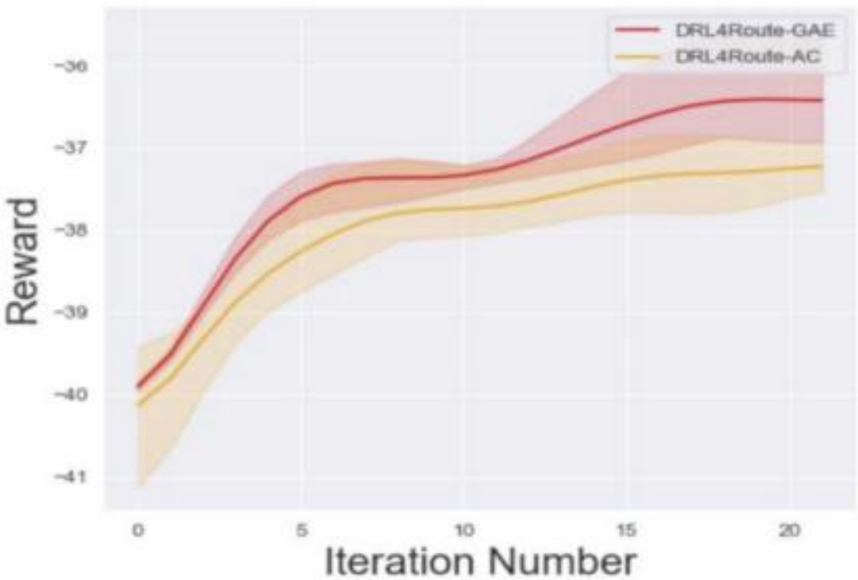


**Figure 3: Performance comparison curves for the algorithms DRL4Route-GAE and DRL4Route-AC, highlighting their distinct trends and effectiveness in addressing the route optimization problem.**

In **Figure 3**, the cumulative expected rewards for DRL4Route-AC and DRL4Route-GAE are compared throughout the training process. Both methods show increasing reward values with the progression of training rounds, demonstrating the effectiveness of the proposed framework. Notably, DRL4Route-GAE outperforms DRL4Route-AC, achieving higher reward values. This improvement highlights the efficacy of the generalized dominance estimation method in balancing bias and variance during gradient estimation, ultimately resulting in a superior strategy.

**Addressing Mismatched Objectives**

Deep models applied to range and delivery path prediction traditionally face challenges due to the non-differentiability of test objectives. Under a supervised training paradigm, these models cannot incorporate test criteria into the training process, causing a mismatch between training and test objectives and limiting their real-world performance.

To overcome these limitations, this paper introduces **DRL4Route**, a novel framework that integrates the behavioral pattern learning capabilities of deep neural networks with reinforcement learning's strength in optimizing non-micro objectives. This plug-and-play framework enhances the performance of existing deep models and introduces **DRL4Route-GAE**, an actor-critic-based model utilizing a generalized dominance estimation method to balance bias and variance in strategy gradient estimation [11].

**Experimental Validation**

Through extensive offline experiments and online deployments on real datasets, DRL4Route demonstrates significant improvements over competitive baseline models. The DRL4Route-GAE model achieves superior results, particularly in positional bias squared metrics and top-three positional prediction accuracy, solidifying its effectiveness in logistics route prediction tasks.

**CONCLUSION**

This research underscores the transformative role of intelligent logistics algorithms in modern systems. By examining the evolution of logistics technologies and the integration of IoT, big data analytics, AI, and automation, the study highlights how innovations like DRL4Route drive advancements in logistics path optimization, intelligent scheduling, and prediction accuracy. The results offer valuable technical support and direction for the intelligent development of the logistics industry, improving the efficiency and accuracy of logistics transportation significantly.

**Major Trends in Future Logistics Technology Innovation**

❖ **Advancement of Intelligent Logistics Systems**

➢ **Integration of Emerging Technologies**: Automation, artificial intelligence (AI), and big data analytics will become more deeply embedded in logistics processes.

➢ **Enhanced Decision-Making**: Deep learning algorithms will improve data processing and decision-making capabilities, enabling smarter operations.

➢ **Real-Time Response**: The adoption of edge computing will facilitate faster data processing and quicker responses to real-time events.

➢ **Human-Machine Collaboration**: Technologies that promote cooperation between humans and intelligent systems will boost logistics efficiency.

❖ **Widespread Application of Emerging Technologies**

➢ **5G Technology**: High-speed data transmission will improve real-time monitoring and enable seamless remote operations.

➢ **Internet of Things (IoT)**: The expansion of IoT will connect a growing number of devices and sensors, creating more interconnected logistics networks.

➢ **Edge Computing**: By processing data at the edge of the logistics network, edge computing will reduce latency and improve operational efficiency.

❖ **Emergence of Green Logistics Technologies**

➢ **Sustainable Transport**: The use of electric and self-driving vehicles will contribute to reduced carbon emissions.

➢ **Circular Economy**: Initiatives like the reuse of packaging materials will minimize waste.

➢ **Smart Energy Management**: Optimizing energy usage will help reduce resource consumption and environmental impact.

**Future Vision**

In the coming years, intelligent green port management systems and circular economy logistics networks will become integral to the industry. These innovations will foster smarter, more efficient, and environmentally sustainable logistics systems, aligning the industry with global sustainability goals.

**REFERENCES:**

1. Liang, P., Song, B., Zhan, X., Chen, Z., & Yuan, J. (2024). Automating the training and deployment of models in MLOps by integrating systems with machine learning. Applied and Computational Engineering, 67, 1- 7

2. Li, A., Yang, T., Zhan, X., Shi, Y., & Li, H. (2024). Utilizing Data Science and AI for Customer Churn Prediction in Marketing. Journal of Theory and Practice of Engineering Science, 4(05), 72-79.

3. Xu, J., Wu, B., Huang, J., Gong, Y., Zhang, Y., & Liu, B. (2024). Practical applications of advanced cloud services and generative AI systems in medical image analysis. Applied and Computational Engineering, 64, 82-87.

4. Zhang, Y., Liu, B., Gong, Y., Huang, J., Xu, J., & Wan, W. (2024). Application of machine learning optimization in cloud computing resource scheduling and management. Applied and Computational Engineering, 64, 9-14.

5. Huang, J., Zhang, Y., Xu, J., Wu, B., Liu, B., & Gong, Y. Implementation of Seamless Assistance with Google Assistant Leveraging Cloud Computing.

6. Lin, Y., Li, A., Li, H., Shi, Y., & Zhan, X. (2024). GPU-Optimized Image Processing and Generation Based on Deep Learning and Computer Vision. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, 5(1), 39-49.

7. Chen, Zhou, et al. "Application of Cloud-Driven Intelligent Medical Imaging Analysis in Disease Detection." Journal of Theory and Practice of Engineering Science 4.05 (2024): 64-71.

8. Wang, B., Lei, H., Shui, Z., Chen, Z., & Yang, P. (2024). Current State of Autonomous Driving Applications Based on Distributed Perception and Decision-Making.

9. Li, Zihan, et al. "Robot Navigation and Map Construction Based on SLAM Technology." (2024).

10. Fan, C., Ding, W., Qian, K., Tan, H., & Li, Z. (2024). Cueing Flight Object Trajectory and Safety Prediction Based on SLAM Technology. Journal of Theory and Practice of Engineering Science, 4(05), 1-8.

11. Sarkis, R. A., Goksen, Y., Mu, Y., Rosner, B., & Lee, J. W. (2018). Cognitive and fatigue side effects of antiepileptic drugs: an analysis of phase III add-on trials. Journal of neurology, 265(9), 2137-2142.