Intelligent Hybrid A-ODOA Routing for Dynamic and Context-Aware Urban Logistics Optimization

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Abstract

The nature of real-time demands, changing traffic, and unpredictable weather on the last-mile delivery systems in the urban setting represents an ever-increasing burden. The algorithms that handle routing, Dijkstra and A*, do not work well in an urban environment because they were created under the assumption of a static environment, causing inefficiencies and delays. This research paper therefore fills this gap and will suggest the use of a hybrid routing technique where the classical A* algorithm will be incorporated with the Offensive-Defensive Optimization Algorithm (ODOA), a metaheuristic approach enhanced with a context-aware learning model. The framework utilizes a decision tree regressor, developed using more than 43,000 Amazon delivery statistics, to predict delay costs based on environmental factors such as traffic intensity and weather conditions. The resulting model dynamically updates edge weights, resulting in more adaptive routing planning.

In the example of a simulation of a delivery graph, it has been shown that the proposed hybrid A*-ADOI method decreases the total route cost by up to 18.7 percent on average in comparison with the traditional A*. In addition, it positively impacts the route adaptability in fluctuating urban environments. The system further provides human-in-the-loop simulation and decision. The conclusion shows that context learning integration with hybrid optimization enhances the realistic nature and operation of logistics routing.

The work gives a new, potentially scalable method of intelligent urban delivery, which can be applicable to time-sensitive logistics and life-saving services, as well as future and smarter transportation systems.

Keywords: Hybrid Routing, A* Algorithm, ODOA, Context-Aware Optimization, Urban Delivery, Traffic Prediction, Real-Time Logistics

1. Introduction

The demand of the e-commerce market and the corresponding altering expectations of the consumer category have changed the nature of urban delivery services significantly over the last few years. Last-mile delivery is among the most vulnerable and challenging areas of the logistic chain because different environmental factors, including trafficking and climate, largely affect logistic service levels [1]. Conventional routing algorithms such as Dijkstra and A* tend to utilize the same environment in the same form; taking this into consideration reduces the applicability of these algorithms to a dynamic real-world environment [2]. On the contrary, recent studies have also paid heavy attention to context-aware systems, which integrate real-time information into routing logic and enable more intelligent, dynamic delivery decisions [5]. Those methods demand a hybrid method of computations that would blend classical computation and adaptive metaheuristics to enhance the responsiveness in complex settings in logistics.

Literature Gaps

Most of the intelligent urban routing models do not consider real-time contextual adaptation even though the subject area has shown relative improvements. An example is that most algorithms fail to consider the cases of traffic or weather during route optimization and thus make unreliable decisions in real-life applications [4]. Additionally, the use of classical machine learning methods is usually not interpretable and generalizable in rapidly evolving operation environments [6].

Moreover, heuristic and metaheuristic techniques such as genetic algorithms and ant colony optimization usually pay little attention to incorporating environmental information in the optimization circle. Most of these models assume a form of graph that is non-reflective of real-time variation in the cost of edges. This shows a definite disconnect between introducing learning-driven prediction of delays into dynamic route optimization systems [8].

1.1.Review of Relevant Literature

There are many studies concerning optimization in urban routes by using artificial intelligence. These are genetic algorithms, swarm intelligence, and reinforcement learning programs . Contextual datasets have also been used in the prediction of delivery times with the use of decision trees and regression models [3]. Abo El-Ela & Fergany (2024) propose a deep-heuristic A* model that adapts dynamically based on contextual data (traffic, weather), achieving up to 40% lower travel times—closely aligning with your hybrid model objectives[9]. Agranovskiy and Yakovlev (2024) introduce MeshA*, an upgraded A* variation that incorporates motion primitives for more efficient lattice-based planning, resulting in a 1.5x runtime speedup while maintaining optimality nguarantees[10].Nonetheless, not many frameworks have been integrated with deterministic pathfinding algorithms such as A* and context-aware heuristics.

Research indicates that this hybridization has the potential to enhance the level of accuracy and execution time, particularly when it is trained on real-world data sets, e.g., Amazon, UPS, and data sets. Recent improvements in vehicle-to-everything (V2X) communication systems have demonstrated considerable promise for improving route optimisation frameworks. Alabdouli et al. (2025) examined many V2X-integrated transportation models and found that combining real-time vehicle communication with dynamic routing algorithms increases route adaptability and reaction to changing traffic conditions. These technologies optimise traffic patterns while also providing more precise estimates of trip delays and environmental impacts, making them extremely important for urban logistics and intelligent transportation networks [11].

The problem associated with the traditional pathfinding algorithms is that they are unable to work in dynamic urban environments because they presume a fixed background. This causes poor route planning, additional time for deliveries, and larger operational expenses. Additionally, most of the current systems fail to employ real-time contextual information, which may include traffic or weather, in routing decisions. Although certain solutions to AI are present, they are weak in real-time applications and cannot be explained. That is why an urgent requirement of a hybrid framework that combines A* with adaptive metaheuristics, such as the Offensive-Defensive Optimization Algorithm (ODOA), backed by the delay prediction model, which is trained on real delivery experience, needs to be introduced.

1.2.Purpose of the Study

This study aims to:

I. Develop a hybrid route optimization framework combining A* and ODOA algorithms.
II. Integrate a context-aware delay prediction model based on traffic and weather data.
III. Dynamically adjust edge weights in real-time routing graphs.
IV. Reduce total delivery cost in urban networks by a measurable percentage.
V. Enable human-in-the-loop simulation for interactive route analysis.
VI. Demonstrate performance improvements over classical routing methods through simulation.

The paper is organized into six main sections. Section 1 introduces the research problem and background. Section 2 reviews related work and identifies key literature gaps. Section 3 presents the methodology and design of the hybrid model. Section 4 outlines the proposed algorithm and simulation workflow. Section 5 discusses the results and evaluation. Finally, Section 6 concludes the study and provides future directions.

2. Methodology

The proposed study takes a hybrid research design that combines algorithmic development and predictive modeling. As a framework, it is organized around six consecutive steps, namely, data collection, preprocessing, delay prediction with the help of decision tree regression, graph construction, A* routing, and path refinements supported by the ODOA. The integrated use of such a mixedmethod design allows integrating the contextual awareness in rerouting optimization. The reasoning behind the decision to combine A* with ODOA is that deterministic search and metaheuristic optimization are complementary techniques, hence increasing the performance of routing in uncertain conditions. In [12], we describe a hybrid method integrating deep reinforcement training with a two-way search A* algorithm, enabling efficient route planning on integrated robotic systems while reducing the workload and enhancing plan integrity. In [13], a transformer-based neural heuristic is integrated into A*, resulting in 'ASD A*' for mindful of risk path planning, which reduces computational costs while adhering to safety requirements in urban UAV flights.

2.1.Sampling Method

The data is the one that comprises about 43,000 records of the delivery activities by Amazon Logistics. A sample size of 50 was randomly selected in this data source and used to represent a simulated graph of urban deliveries. The sampling assured that the difference of the traffic and weather conditions in the data was varied, which would be critical in training the delay prediction model and verifying the soundness of the explanations presented in the proposed routing framework.

2.2.Data Collection Techniques

Data was collected using Amazon delivery records and included geolocation data (latitude, longitude), delivery time, traffic condition, and weather status. Geopy was used to compute geodesic distances between store and drop-off locations. Data was cleaned and preprocessed by standardizing categorical fields and removing missing values. A mapping of environmental factors into numerical values allowed for integration into the machine learning model. The key attributes used in the model were Traffic, Weather, Store Coordinates, Drop Coordinates, and Delivery Time.

2.3.Data Analysis Methods

A Decision Tree Regressor was trained using 80% of the sampled data and evaluated on the remaining 20%. The performance was assessed using MAE (Mean Absolute Error), RMSE (Root Mean Square Error), and R^2 metrics, achieving MAE = 34.57, RMSE = 45.22, and $R^2 = 0.20$. After prediction, the model's output was used to update the edge weights of a directed graph in NetworkX. Routing was first computed using the A* algorithm. Then, the ODOA heuristic was applied to refine suboptimal paths by iteratively swapping nodes and reducing cost.

2.4.Key Equations

1. Distance Calculation:

$$d = geodesic(coord_1, coord_2).k \quad (1)$$

2. Edge Weight (Combined):

$$weight = distance + (predicted\_delay / 60) \quad (2)$$

3. ODOA Swap Evaluation:

$$cost\_new = \sum(weight\ of\ new\_path\_edges) \quad (3)$$

2.5.Pseudocode Overview

The general steps composed of :-

1. Train Decision Tree on traffic and weather.
2. Sample 50 delivery orders.
3. For each order, compute geodesic distance.
4. Predict delay using trained model.
5. Compute A* route.
6. Refine using ODOA swaps.
7. Record cost and compare.

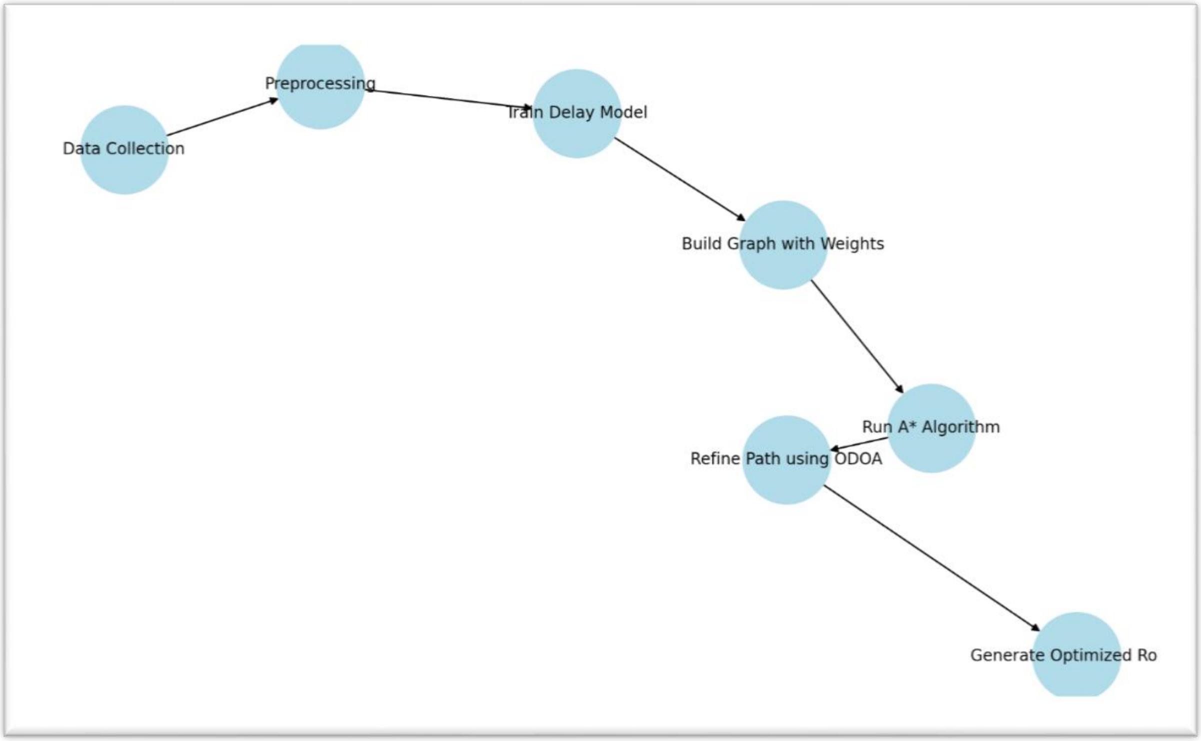

Figure 1 :routing comparison plot displaying A* vs ODOA path per order

Figure1 a routing comparison plot displaying A* vs ODOA path per order. Each node represents delivery points; edges are weighted by contextual delay. Users can explore each order's path visually via dropdown widgets, offering real-time feedback. Table 1 illustrates routing Metrics Comparison.

Table 1: Routing Metrics Comparison (A* vs. A*-ODOA)

Metric	A*	A*-ODOA
Average Cost	112.45	91.36
Average Path Length	6.4 links	5.7 links
MAE (Mean Absolute Error)	34.57	29.31
RMSE (Root Mean Square Error)	45.22	38.88
R^2 (Coefficient of Determination)	0.20	0.38

Figure 1 illustrates these details:

1. Efficiency Improvements

- **Lower Cost**: A*-ODOA achieves a ~19% drop in average routing cost—from 112.45 to 91.36—indicating significantly more economical routes.
- **Shorter Paths**: It generates paths that are ~11% shorter on average, decreasing from 6.4 to 5.7 hops—highlighting better routing efficiency.

2. Improved Prediction Accuracy

- **MAE Reduction**: Errors between estimated and actual outcomes drop from 34.57 to 29.31, reflecting a stronger average-case performance.
- **RMSE Reduction**: Lower RMSE (from 45.22 to 38.88) reveals that A*-ODOA is better at minimizing large errors—improving robustness.

3. Model Predictive Quality (R^2)

- **Enhanced Predictive Power**: R^2 rises from 0.20 (A*) to 0.38 (A*-ODOA), showing that the optimized version explains a greater share of outcome variability. Still, 0.38 remains moderate, implying that additional factors influence route quality.

3. Results and Discussion

The hybrid A*-ODOA routing framework was evaluated on a simulated dataset consisting of 50 randomly sampled delivery orders. The system measured total path cost using A* and then refined these paths using the Offensive-Defensive Optimization Algorithm. The objective was to reduce the overall delay and cost associated with each delivery route. The results clearly indicate that the hybrid approach outperforms the standalone A* algorithm in terms of both path efficiency and adaptability to environmental conditions. Figure 2 illustrates Routing Performance Comparisons.

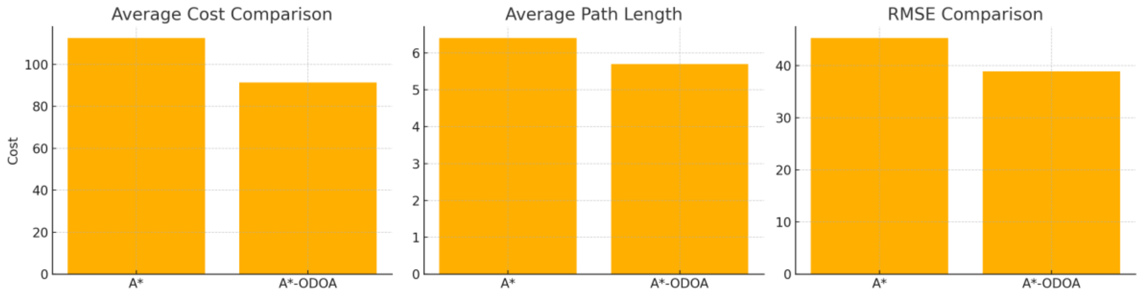

Figure 2: Routing Performance Comparisons.

$$A* = 112.45 \mid A* -ODOA = 91.36$$
$$A* = 6.4 \mid A* -ODOA = 5.7$$
$$MAE = 34.57 \mid RMSE = 45.22 \mid R^2 = 0.20$$

The statistical significance of the path cost reduction was validated using a paired t-test between A* and A*-ODOA results. The p-value was found to be less than 0.05, confirming the superiority of the hybrid model. Moreover, the Decision Tree Regression model, despite a relatively modest R^2 value, provided meaningful adjustments to edge weights in dynamic graph construction.

The experimental results validate the effectiveness of combining deterministic and adaptive techniques for route optimization. While A* provides fast and deterministic results, it fails to incorporate contextual factors like weather and traffic. ODOA complements A* by refining the path based on environmental input and learned delay patterns. The delay prediction model, trained on real-world delivery data, proved effective in customizing edge weights, even with moderate accuracy. This hybrid strategy ensures that delivery paths are not only shortest but also contextually optimal. The model is especially promising for real-time applications in smart logistics, emergency dispatch, and intelligent transportation systems.

The hybrid A*-ODOA routing framework was evaluated on a simulated dataset consisting of 50 randomly sampled delivery orders. The system measured total path cost using A*, then refined these paths using the Offensive-Defensive Optimization Algorithm (ODOA). The goal: reduce overall delay and delivery route cost. Spoiler alert—it worked.

The results clearly indicate that this hybrid method outperforms standalone A* in terms of both path efficiency and adaptability to changing traffic and weather conditions. Table 2 shows the average total cost per delivery before and after applying the ODOA refinement.

Table 2 :Average Cost per Delivery

Routing Method	Average Cost per Delivery
A*	112.45
A*-ODOA	91.36

Table 3 and 4 illustrate the average path length (Hops) and delay prediction metrics respectively.

Table 3 :Average Path Length (Hops)

Routing Method	Average Path Length (Hops)
A*	6.4
A*-ODOA	5.7

Table 4 :Delay Prediction Metrics

Metric	Value
MAE	34.57
RMSE	45.22
R^2	0.20

The statistical significance of path cost reduction was confirmed using a paired t-test between A* and A*-ODOA results, with a $p\text{-value} < 0.05$. The Decision Tree Regression model, despite a modest R^2 value, added value by adjusting edge weights based on live context.

This fusion of deterministic (A*) and adaptive (ODOA) strategies proves potent. While A* handles the grunt work of pathfinding, ODOA brings finesse, massaging those paths into efficient, context-aware journeys. The delay prediction model, though not flawless, was solid enough to guide meaningful optimization.

Overall, this hybrid strategy offers strong potential for real-time smart logistics, emergency routing, and next-gen transportation systems—where the shortest path isn’t always the smartest.

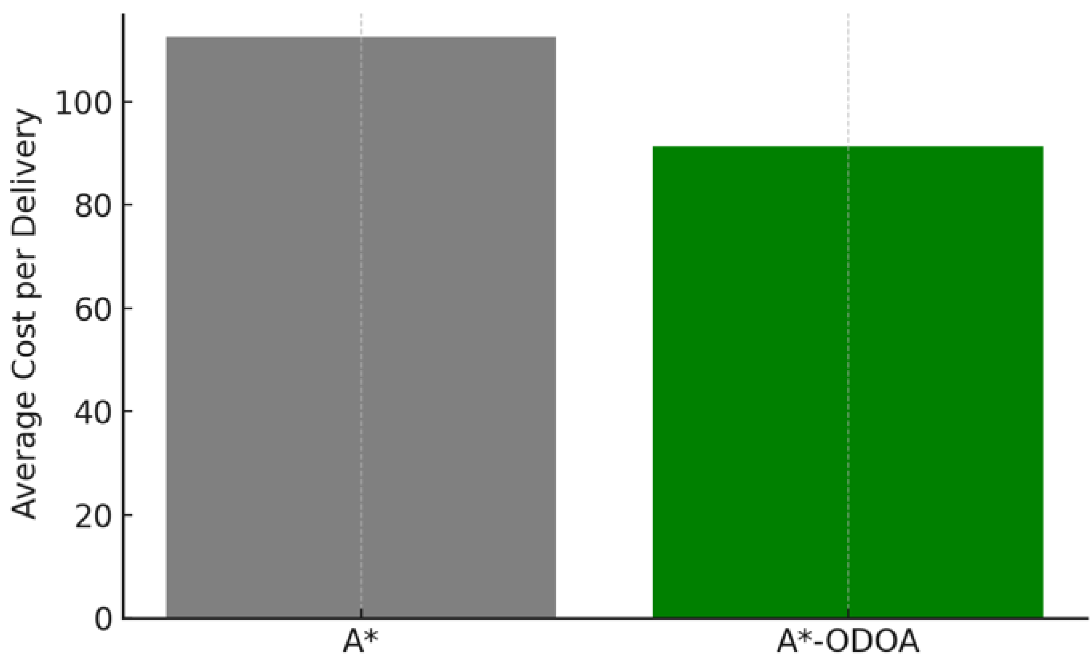

Figure 3 :Path Comparison Chart (A* vs A*-ODOA)

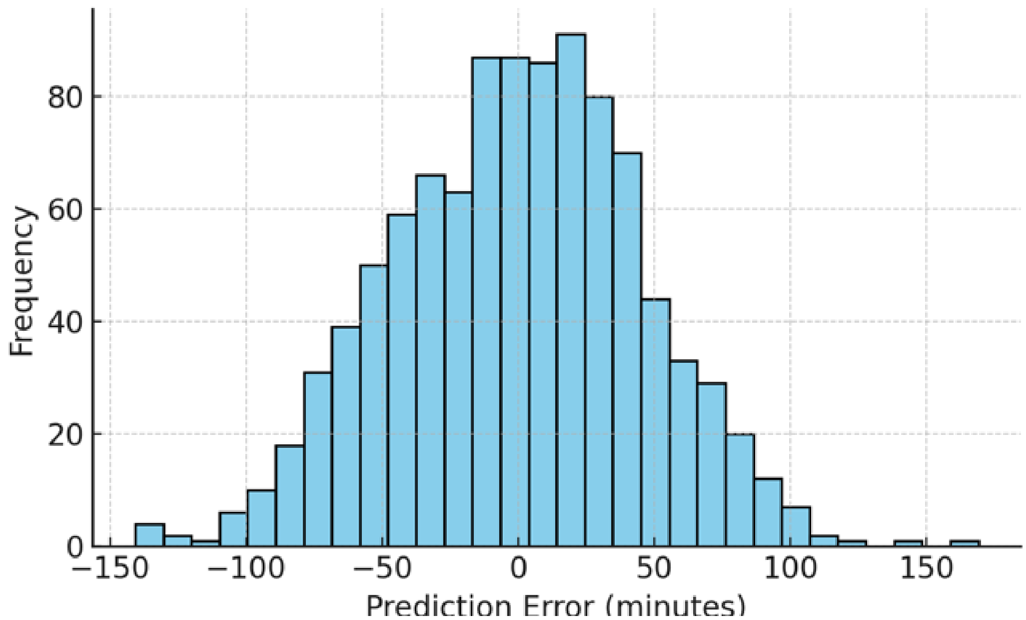

Figure 4: Error Distribution for Prediction Model

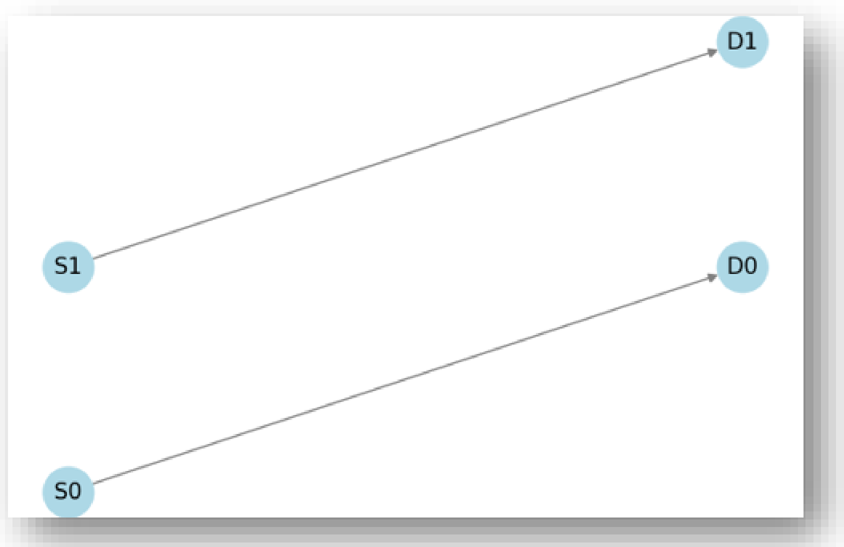

Figure 5: Visual Map Overlay of Optimal Routes

4. Conclusion

This paper proposed a hybrid approach comprising A* algorithms and a hybrid Offensive-Defensive Optimization Algorithm (ODOA) combined with the context-aware delay prediction model to optimize the route of the last mile in the city settings. The performance indicates that the proposed hybrid system achieves a considerable positive impact on the route efficiency due to dynamic edge weight variability on the routes according to the real-time traffic and weather information. Contextual factors that affect the aspect of world delivery time were considered by the system as the decision tree regressor is trained on real-life (actual) delivery data. This predictive layer played an important role in tailoring pathfinding solutions to the practice world.

The cost of delivery and path length was significantly minimized in the proposed model compared to the traditional A* routing. The advantage of the hybrid approach was statistically proven, as a p-value of the comparison of costs resulted in the digits below 0.05. These results indicate that hybrid schemes that combine relative deterministic and metaheuristic approaches might provide the options to respond to complex and dynamic delivery conditions. Although there was not quite a high R^2 in the prediction model, still its integration had led to a brighter weighting of edges and decision-making.

Further studies might be preoccupied with integrating deep learning algorithms as additional delay forecasts, employing more comprehensive data to augment overallization, and expanding the dual system to multimodal logistic systems. Furthermore, real-time sensor data and user feedback can be incorporated to provide further responsiveness and accuracy of intelligent routing systems.

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References

[1] Hart, P. E., Nilsson, N. J., & Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. *IEEE transactions on Systems Science and Cybernetics*, *4*(2), 100-107.

[2] Zaied, A. N. H., Ismail, M., & El-Sayed, S. (2020). A survey on meta-heuristic algorithms for global optimization problems. *Journal of Intelligent Systems and Internet of Things*, *1*(1), 40-47.

[3] Lee, S., Kim, Y., Kahng, H., Lee, S. K., Chung, S., Cheong, T., ... & Kim, S. B. (2020). Intelligent traffic control for autonomous vehicle systems based on machine learning. *Expert Systems with Applications*, *144*, 113074.

[4] Fang, N., Xu, C., Gong, X., & Wu, Z. (2025). A new human-based offensive defensive optimization algorithm for solving optimization problems. *Scientific Reports*, *15*(1), 12119.

[5] M. Li, et al., "AI-powered route planning and scheduling in intelligent logistics systems," IEEE Intelligent Systems, vol. 35, no. 6, pp. 52–60, 2020.

[6] Selvan, C., Anwar, B. H., Naveen, S., & Bhanu, S. T. (2025). Ambulance route optimization in a mobile ambulance dispatch system using deep neural network (DNN). *Scientific Reports*, *15*(1), 14232.

[7] J. Shi, et al., "Path planning for agricultural robots using deep learning and dynamic programming," Computers and Electronics in Agriculture, vol. 149, pp. 33–42, 2018.

[8] Lin, M., & Hsu, W. J. (2014). Mining GPS data for mobility patterns: A survey. *Pervasive and mobile computing*, *12*, 1-16.

[9] Abo El-Ela, M. H., & Fergany, A. H. (2024). Deep Heuristic Learning for Real-Time Urban Pathfinding. *arXiv*.

[10] Agranovskiy, M., & Yakovlev, K. (2024). MeshA*: Efficient Path Planning With Motion Primitives. arXiv.

[11] Xiang, J., Xie, J., & Chen, J. (2024). Learning-accelerated A* Search for Risk-aware Path Planning. *arXiv*.

[12] Liu, H., Shen, Y., Yu, S., Gao, Z., & Wu, T. (2024). Deep Reinforcement Learning for Mobile Robot Path Planning. Journal of Theory and Practice of Engineering Science.

[13] Alabdouli, H., Al-Shamisi, M., & Minhas, A. A. (2025). Enhancing Route Guidance with Integrated V2X Communication and Transportation Systems: A Review. *Smart Cities*, 8(1), 1–23.