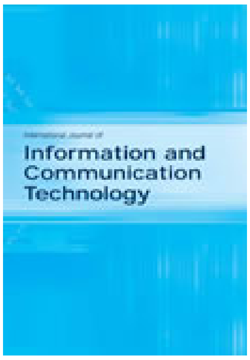

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Elastic dynamic scheduling algorithm for instant delivery logistics vehicles using multi-objective optimisation techniques

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Elastic dynamic scheduling algorithm for instant delivery logistics vehicles using multi-objective optimisation techniques

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Abstract: This study addresses real-time vehicle management challenges in instant delivery logistics, where conventional methods face dynamic demands causing inefficiencies and higher costs. It proposes the elastic dynamic scheduling algorithm (EDSA), integrating real-time data (e.g., delivery requests, traffic) and a multi-objective genetic algorithm optimising delivery time, operational costs, and energy consumption. EDSA dynamically adjusts routes amid disruptions like congestion or new orders. Simulations compare it with PPO-DRL, HGA, and MOPSO, showing superior performance: lower average delivery time, cost, and energy use; 12.2% higher peak delivery efficiency than PPO-DRL; and 5.6% reduced CO emissions versus HGA. This research fills gaps in existing methods via real-time adaptability and multi-objective optimisation, offering a scalable, holistic solution balancing cost, time, and environmental impact, providing actionable insights for logistics firms.

Keywords: elastic dynamic scheduling algorithm; EDSA; instant delivery logistics; multi-objective optimisation; genetic algorithm; energy efficiency; real-time.

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1 Introduction

Online businesses and selling products via the internet have boosted the need for quick delivery services in all sectors. Today's customers want their purchases delivered within the shortest time possible, ranging from within the same day, especially if it is a grocery or an electronics purchase. Such change in the consumption pattern has placed a lot of pressure on logistics service providers to satisfy these requirements more efficiently (Jeon et al., 2017). Due to the increasing tendencies towards the availability of products on demand, logistics as a service has become visible and vital in companies' fight (Rajesh Chauhan et al., 2022). However, the real-time vehicle scheduling problem is one of the most significant issues the logistics industry faces (Liu and Ma, 2010). More structured traditional scheduling systems, developed for the expected and comparatively stable delivery scenarios, cannot provide sufficient solutions for unpredictable and rapidly increasing instant delivery requirements. Real-time scheduling is the dynamic revision of delivery routes and time for delivery to incorporate new orders, traffic congestion, and other factors. This task is more challenging and involves high-speed analysis with decision-making capabilities from several aspects (Hyon and Jeong, 2015).

There is a need for a more prominent and an adequate solution to tackle these issues (Yang, 2020). The flexibility of changing delivery routes and schedules in response to varying situations is crucial for decreasing the fuel cost and the time of delivery. This research aims to design an elastic dynamic scheduling algorithm (EDSA) for an instant delivery logistics application. The proposed algorithm will dynamically change delivery routes and timings over time and when new data avails itself. Specifically, the algorithm aims to solve the multi-objective problem with decision variables meant to minimise delivery time and operational costs and maximise vehicle usage (Wang et al., 2022b).

In this research, multi-objective optimisation technique is utilised to decrease the time of delivery and operational charges. The EDSA is presented as an innovative approach to address the issues of accurate time vehicle scheduling in instant delivery logistics (de Oliveira Mota, 2021; Zhang et al., 2015). Thus, introducing flexibility and adaptability into the scheduling process is more effective than traditional algorithms, and the proposed algorithm is more effective in solving real-life logistics problems. This multi-objective optimisation approach enables the scheduling process to achieve the delivery deadlines besides overseeing the general implications for operations and cost control. Thus, by serving multiple objectives simultaneously, the proposed EDSA is a more holistic approach for instant delivery logistics. This research also has the advantage of further scaling and applying it to different contexts within the logistics industry. The EDSA can generate the responses to various varying delivery parameters to find the most optimal route (Huang et al., 2020). This research also contributes to operation research by improving knowledge of dynamic scheduling and multi-objective optimisation in logistics. Due to the constant technological advances and demand for instant delivery, flexibility in scheduling has become a significant factor in the logistics industry. Conventional scheduling algorithms that utilise static data and a fixed route schedule must be revised to address the realism of delivery logistics demands. This research aims to solve these challenges by proposing an EDSA using multi objective optimisation that provides a more flexible way of addressing the issue of vehicle schedules in instant delivery systems. This research's findings offer scientific and practical values that allow for developing better practices to improve logistics operations while contending with a constantly evolving world.

2 Literature review

Due to the rising need to enhance the performance of logistics operations, especially in the context of fast delivery services, many studies have been conducted to investigate the characteristics of a vehicle scheduling algorithm. Several dynamic scheduling algorithms have been utilised to tackle the issues resulting from real-time logistics management. These algorithms are used to determine the best routes and schedules that the vehicles take in light of new requests, traffic, and available vehicles.

The current approaches for vehicle scheduling problems in logistics can further be divided into static and dynamic algorithms. The static scheduling techniques have evolved from fixed routes and schedules based on past vehicle performances (Wang et al., 2022b). These algorithms cannot cater to real-time changes in the logistics environment, which poses a significant problem when dealing with instant delivery services. However, dynamic scheduling algorithms are designed with real-time data that enable the modification of vehicle routes and schedules in real-time. Such algorithms have been progressively adopted as there was a realisation of the need for faster logistics operations. Despite the advancement in multi-objective optimisation methods that enhance the flexibility and adaptability of scheduling algorithms, some issues in the real-time logistics environment still make the scheduling algorithms problematic. One of the challenges is the real-time solution of multi-objective problems through integrated mathematical functions. The more objectives and constraints there are, the more potential solutions the search algorithm needs to evaluate, and therefore the longer it takes to find a solution close to the optimal one. The other problem is that many existing multi-objective optimisation algorithms are susceptible to their parameters. Over the last few years, the improvement of logistics and delivery systems has attracted considerable interest, and different researchers have suggested more effective algorithms for improving efficiency and reducing costs. Luo (2024) study used dynamic multi-agent algorithms in logistics distribution systems based on path finding and vehicle scheduling. These algorithms consider several parameters and have been established to enhance the speed and precision of logistics distribution, especially when fast delivery is required. A study by Qu (2023) worked to enhance the overall logistics performance through the memetic algorithm and multi-objective management optimisation. Their study proposed a dynamic logistics network model and proved that this approach can improve a country's logistics capacity by solving multi-logistics objectives problems. Zhang and Jia (2023) developed an improved genetic algorithm (GA) to address task assignments within multiple mobile robots. This algorithm dynamically adjusts the crossover probability and the fitness function, meaning that the speed at which the algorithm converges is faster, and better convergence of the overall population is achieved, thus enhancing the optimisation of tasks in logistics.

Zeng et al. (2023) contributed to developing a multi-type logistics distribution scheduling mathematical model with the aid of an improved GA. This approach maximised speed and minimised the number of calculations and the intricacy of the algorithm, which is why it can be considered a suitable solution for logistical scheduling problems. In another research work, Wang et al. (2022a) used a mixed integer programming approach to solve the problem of instant delivery order assignment and courier scheduling with different grades for a third-party instant delivery platform. This model improved operations and solved realistic logistical issues. Wang's research focused on solving the vehicle routing optimisation problem in the express logistics joint distribution alliances. By reusing vehicles after goods arrive at the distribution centre in bulk, the actual logistics problem of transportation costs can be solved. Sun et al. (2019) proved in the experiments that the dynamic algorithm framework can effectively manage the dynamic pick-up and delivery problem with time windows (DPDP-TW) and show promise for improving actual-time logistical operations. That's why this research study has been developed to mitigate these issues. EDSAs have been designed to accommodate real-time data and implement decision-making based on real-time data, ensuring that logistics companies effectively meet the needs of instant delivery services.

However, although existing research has made progress in improving scheduling efficiency and multi-objective processing, there is generally a lack of systematic handling of dynamic conflicts between targets, and most of them have not fully considered the uncertainty of real-time road conditions and multi vehicle collaboration. For example, although Haopin Luo's multi-agent method improves response speed, it lacks coordination efficiency in high concurrency orders. Ji Li's meme algorithm optimises the global objective, but struggles to adapt to frequently changing real-time constraints. These limitations indicate that existing research still faces the common challenges of real-time performance, robustness, and target balancing mechanisms in multi-objective dynamic scheduling. The EDSA proposed in this study is aimed at filling this research gap. Through continuous performance feedback loops and dynamically adjustable weight coefficients, EDSA can adjust optimisation tendencies in real-time based on the current system state, thereby achieving dynamic transfer of target priorities.

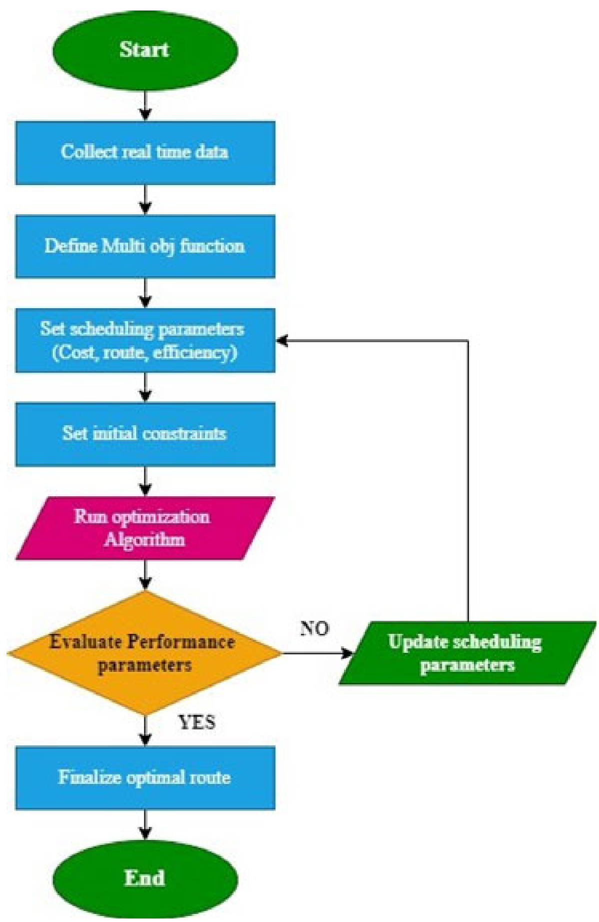
3 Methodology

In this research, the EDSA is created to solve the problem that appears in instant delivery logistics services regarding real-time vehicle scheduling. This section will describe the algorithm design method, apply multi-objective optimisation functions, and test and evaluate its performance.

3.1 Elastic dynamic scheduling algorithm

The EDSA provides the flexibility and adaptability required in real-time vehicle scheduling. Elasticity in this algorithm refers to the idea that it will dynamically adjust vehicle routes and schedules according to real-time data. Traditional approaches use fixed data to route a request, but the EDSA always updates its decision based on the latest data (Zhang et al., 2023; Li et al., 2023). To make an effective decision to find the most suitable route to save delivery time, increase energy efficiency and fuel cost, the EDSA uses incoming delivery requests, the vehicle's exact position, and other parameters. Real-time data integration is one of the important features of the EDSA. This component receives and analyses the information from different sources including customer delivery requests, the status of available vehicles (for instance the location and capacity), and the current traffic status. As a result, with the help of internet of things, this feature enables the EDSA to quickly respond to new delivery request and so on which will greatly reduce waiting time and increase the satisfactions of their customers.

Figure 1 A proposed flowchart of elastic dynamic scheduling algorithm for instant delivery logistics vehicles using multi-objective optimisation (see online version for colours)



Another factor contributing to elasticity is the algorithm's flexibility. For instance, if there are more than one delivery requests, the algorithm can reschedule the paths for the several vehicles in parallel to deliver all the deliveries within the specified time period (Liu et al., 2024). Besides, the algorithm is intelligent enough to adjust to any form of intersession interference, like traffic jams or any other issue related to the path blockage, and reroute the vehicle. This versatility is important because logistics, especially in instant delivery services, requires a certain degree of flexibility to maintain productivity without compromising on delay time. The EDSA also has a performance feedback loop in order to ensure updates for further enhancement. After every delivery, it then considers factors such as time of delivery, amount of fuel used, and rating from customers. On the basis of these parameters, it evaluates the performance of the algorithm over time, in this way it produces the most optimal results.

3.2 Multi-objective optimisation

Instant delivery logistics decisions may involve a trade-off of one or several decisions with several objectives, many of which may be conflicting. Such objectives often include delivery time reduction, operational cost reduction, and reduction of energy use, which are often conflicting goals. To counter this difficulty, the EDSA uses a multi-objective optimisation approach that makes it easier to identify various solutions systematically (Li et al., 2023).

Figure 2 Multi-objective optimisation parameters (see online version for colours)

3.3 Delivery time minimisation

Out of three objectives, the first objective is to minimise the delivery time. Hence the objective function is given by:

$$T_d = \sum_{i=1}^{n} t_i \tag{1}$$

t_i indicates the time taken for each delivery and n denotes the total number of deliveries.

3.4 *Operational cost minimisation*

The objective of operational cost minimisation is to minimise the operational and maintenance expenses sine it plays an important role in determining profitability. It includes parameters such as fuel cost, maintenance cost, and labour cost.

$$Opt_{cost} = \sum_{j=1}^{m} O_i \tag{2}$$

Opt_{cost} indicates the cost for each delivery and m denotes the total number of delivery routes.

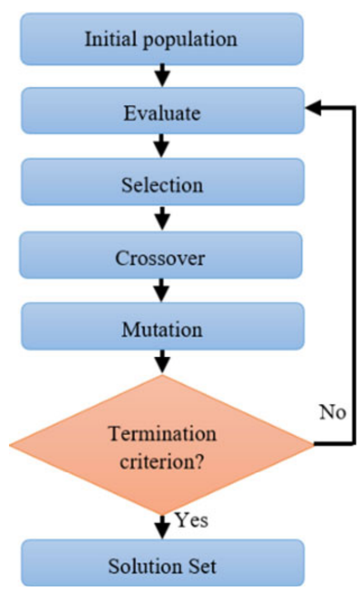
3.5 *Energy consumption minimisation*

Energy consumption minimisation relates to reduction in the energy used during deliveries because this reduces both costs and has environmental benefits. The function for energy consumption minimisation is given by:

$$E_{con} = \sum_{k=1}^{p} F_k \tag{3}$$

E_{con} indicates total energy consumption which is measured in term of fuel used during each delivery and k shows the number of deliveries.

Figure 3 Methodological steps of GA (see online version for colours)



Multi-objective optimisation is, hence, the process of finding the set of solutions that balance the trade-offs between multiple objectives as best as possible given the limitations of the context. Multi-objective function is given by:

$$\min f = \alpha(T_d) + \beta(Opt_{cost}) + \gamma(E_{con}) \tag{5}$$

where:

T_d is the delivery time minimisation

Opt_{cost} indicates the operational function minimisation

E_{con} represents the energy consumption in term of fuel consumption

α, β, γ are three objective functions so these weightages are assigned to them.

These weightages depend on the priority of the logistic company. If they select a higher value of alpha, then it means that they are preferring delivery time minimisation over other two objective functions.

3.6 Methodological steps of GA

GA is very effective for solving multi-objective problems, which are present in the instant delivery context. GA mimics the process of natural selection and searches a large solution space to obtain an efficient optimal or nearly-optimal solution (Chen, 2025). Conventional optimisation approaches work well for solving a single objective function, but they face difficulties in solving a multi-objective function because of the conflicting nature of different objective functions. GA processes a set of multiple solutions within a given domain, gradually generating a better set of solutions through operations such as selection, crossover, and mutation. This capability is crucial to logistics organisations that operate in a complex and rapidly changing environment (Liu et al., 2025). GA can solve multi-objective functions more effectively and are able to solve problems of different constraints. Unlike the traditional approaches, GA includes different types of decision variables – continuous, binary, integer, etc., which allows to create more realistic and accurate models of complex logistical conditions. This level of adaptability is notably beneficial in instant delivery logistics, where quickly changing conditions necessitate fast changes to routing and scheduling choices (Zhen et al., 2023; J. of Sensors, 2023).

The operation of the GA within the framework of the proposed multi-objective function involves several key steps:

- Initialisation: the GA starts with an initial generation of a population of individuals that is a stochastic set of potential solutions where each solution is a different vehicle schedule and route assignment. Every member in the population is evaluated according to its fitness with respect to the objective function.
- Fitness evaluation: the fitness of every individual solution is calculated based upon the achievement level of each particular objective. Hence, each solution gets a fitness score which describes the degree of achievement of these objectives based on the given criteria.
- Selection: from the given population set, the individuals are selected as parents on the basis of their fitness values. Different selection techniques can be used, for instance, the tournament selection or the roulette wheel selection where individuals are selected on the basis of the best fitness values.
- Crossover: during the crossover phase, all the selected parents are combined to form offspring. It mimics crossover operation of genetic recombination so as to permit the swapping of information between the parent solutions. Crossover can be one-point,

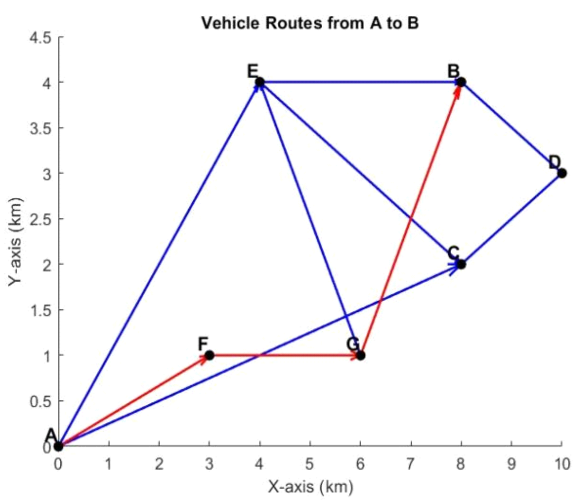
two-point or uniform method and it is an important aspect because it provides basis for searching for new solution space.

- Mutation: the mutation process provides new variations into the offspring solutions set and thus does not allow the premature convergence on local optima. The last of them entails random modification of some of the solution parameters, keeping diversity in the population and encouraging search for new area in a population.
- Replacement: every time crossover and mutation produce offspring, they take the place of some or all of the present population, creating a new generation of solutions. The above-mentioned selection, crossover and mutation are operated continuously over many generations and make replacements.
- Convergence: this is quite important since the proposed stopping criteria are not always very effective, and the GA continues to evolve the population until one of these criteria is met, the number of generations or the level of fitness. The last population will consist of a number of Pareto-optimal solutions that capture the trade-off between the objectives (Wang et al., 2022).

4 Results

The experimental results of the EDSA are significant for assessing its performance and possible application to instant delivery logistics. A set of tests was performed to evaluate the algorithm's performance using a range of critical parameters for logistics activity. These included delivery time, cost-effectiveness, and efficacy in finding the best short route (Xu et al., 2023; Mo and Jiang, 2024).

Figure 4 Optimised route for the vehicle (see online version for colours)



The delivery time is the time taken from when the delivery request is made to when the delivery is done. This metric is critical, especially in situations where these companies are delivering their products instantly to customers, and the delivery time is an essential determinant of the level of satisfaction of customers (Sun and Zhao, 2023). The EDSA was created to reduce the delivery time by constantly changing vehicle schedules based on actual information (Zeng and Wang, 2023). In instant delivery logistics, transport efficiency is crucial. In this case, the vehicle has to deliver logistics from points A to B. There are many delivery routes exit between these two points. The GA searched for the most optimal path from the points A to B to minimise the operational costs, increase energy efficiency in term of reducing fuel consumptions and minimise the time of delivery. The simulation results proved that the algorithm cut down delivery time, being best when facing high demands or frequent changes to the delivery orders.

Table 1 Distance comparison of optimal path with other paths

Route no.	*Path*	*Distance (km)*
1	A → E → B	13
2	A → E → C → D → B	17
3	A → C → D → B	13
4	A → F → G → B	10
5	A → F → G → E → B	13

Cost efficiency is another essential factor that is taken into consideration. To elaborate on the basic logistics concept, operational costs may fluctuate based on fuel usage, labour, or vehicle maintenance. The EDSA also involves cost as one of the objectives in minimising cost while striving to have the best services (Zhu., 2023). From the experimental findings, the research shows that the algorithm cuts down the operational costs to a significant level by choosing the most optimal path.

Table 2 Fuel cost for all routes

Route no.	*Path*	*Fuel consumption* (*ltr*)	*Opt. charges* (*$*)
1	A → E → B	13	4.16
2	A → E → C → D → B	17	5.45
3	A → C → D → B	13	4.16
4	A → F → G → B	10	3.20
5	A → F → G → E → B	13	4.16

Table 3 Delivery time for vehicle

Route no.	*Path*	*Distance* (*km*)	*Delivery time* (*min*)
1	A → E → B	13	4.33
2	A → E → C → D → B	17	5.67
3	A → C → D → B	13	4.33
4	A → F → G → B	10	3.33
5	A → F → G → E → B	13	4.33

The third parameter is the vehicle's efficiency in finding and selecting the best possible short route to decrease the delivery time. The EDSA increases the efficiency of the vehicle in choosing the most optimal route to deliver the logistics to the customer within less time. The simulation results show how the algorithm enhanced the vehicle efficiency, particularly when the demand level occasionally increases or decrease. In this way, the algorithm helped reduce logistics activity costs by choosing the most optimal path for the delivery.

To further validate the effectiveness of the proposed EDSA in actual logistics environments, the study used actual order data from a city's instant delivery logistics company for the year 2023, including approximately 500–800 delivery requests per day, 30 vehicles, and delivery coverage in the central area of the city. The experimental simulation runs for one week, considering real-world constraints such as real-time traffic, dynamic order arrivals, and vehicle capacity limitations. The proposed algorithm was compared with proximal policy optimisation deep reinforcement learning (PPO-DRL), hybrid genetic algorithm (HGA), and multi objective particle swarm optimisation (MOPSO) algorithms. Average delivery time, total operating cost, and total energy consumption were utilised as evaluation indicators. The performance comparison results of the four algorithms are shown in Table 4. The proposed EDSA algorithm had the lowest average delivery time, total operating cost, and total energy consumption, which were 28.6 minutes, 12,320 Yuan, and 1900L, respectively.

Table 4 Performance comparison of four algorithms

Algorithms	*Average delivery time/min*	*TOTAL operating costs/Yuan*	*Total energy consumption/L*
PPO-DRL	31.1	13,140	2,040
HGA	29.8	12,750	1,980
MOPSO	30.6	12,960	2,020
EDSA	28.6	12,320	1,900

To quantitatively evaluate the performance of the proposed EDSA, three typical daily demand scenarios were simulated by adjusting the order arrival rate based on the aforementioned city logistics data. Including

1 steady scenario: orders arrive uniformly, simulating a regular workday

2 Medium fluctuation scenario: orders arrive in a concentrated manner during lunchtime and evening, simulating promotions or weekend demand

3 Peak fluctuation scenario: orders arrive explosively in a short period of time, simulating extreme stress testing during large-scale shopping festivals.

The performance of the four algorithms mentioned above was compared in three typical demand scenarios. Each scenario was independently simulated and run 30 times, and the results were reported in the form of 'mean ± standard deviation', and significance analysis was performed using paired sample t-test. The performance test results of the four algorithms in different demand scenarios are shown in Table 5. Among the three different demand scenarios, the proposed EDSA had the shortest average delivery time, carbon emissions, and total energy consumption. In peak fluctuation scenarios, the average delivery time of EDSA was 33.2 minutes, and the vehicle delivery efficiency was 12.2% higher than PPO-DRL, with a statistically significant difference ($p < 0.05$). The average CO_2 emission of EDSA was 5579.4kg, which is 5.6% lower than that of HGA, and the difference is statistically significant ($p < 0.05$).

Table 5 Performance of four algorithms in different demand scenarios

Scene	*Algorithms*	*Average delivery time/min*	*CO_2 emissions/kg*	*Total energy consumption/L*
Stable	PPO-DRL	30.8 ± 1.6*	5,238.6 ± 139.8*	2,009.8 ± 50.2*
	HGA	29.3 ± 1.4*	4,979.5 ± 140.2*	1,930.6 ± 48.1*
	MOPSO	30.1 ± 1.5*	5,512.3 ± 144.8*	1,995.8 ± 51.8*
	EDSA	28.5 ± 1.2	4,749.4 ± 129.5	1,891.2 ± 44.7
Moderate fluctuation	PPO-DRL	33.6 ± 2.2*	5,780.7 ± 179.2*	2,149.8 ± 65.2*
	HGA	33.4 ± 1.9*	5,408.8 ± 168.9*	2,040.5 ± 57.9*
	MOPSO	32.5 ± 2.1*	5,619.7 ± 175.7*	2,109.6 ± 62.1*
	EDSA	30.2 ± 1.8	5,118.6 ± 159.2	1,981.4 ± 59.7
Peak fluctuation	PPO-DRL	37.8 ± 3.1*	6,419.1 ± 220.4*	2,379.6 ± 85.4*
	HGA	34.9 ± 2.8*	5,911.1 ± 199.8*	2,241.1 ± 78.5*
	MOPSO	36.2 ± 3.0*	6,149.2 ± 209.9*	2,320.2 ± 79.6*
	EDSA	33.2 ± 2.4	5,579.4 ± 189.5	2,150.1 ± 74.9

Note: '*' indicates a significant difference compared to EDSA, $p < 0.05$.

5 Discussion

The EDSA addressed real-time logistics challenges via multi-objective optimisation and real-time data adaptability. The results showed that the average delivery time, total operating cost, and total energy consumption of the proposed EDSA algorithm were 28.6 minutes, 12,320 Yuan, and 1900 L, respectively. The total operating cost was reduced by 3.4% compared to HGA. In steady, moderate, and peak fluctuation scenarios, the EDSA had the shortest average delivery time, CO_2 emissions, and total energy consumption. In peak fluctuation scenarios, the average delivery time of EDSA was 33.2 minutes, and the vehicle delivery efficiency was improved by 12.2% compared to PPO-DRL. The average CO_2 emission of EDSA was 5,579.4 kg, which was 5.6% lower than that of HGA, and the difference was statistically significant ($P < 0.05$). Unlike static methods, EDSA used real-time internet of things data and a feedback loop for dynamic route adjustments, outperforming traditional algorithms in handling demand fluctuations. Its elasticity framework and GA generate Pareto-optimal solutions, offering flexible trade-offs via adjustable weights. However, limitations include reliance on high-quality real-time data and potential manual intervention in complex conflicts. Future work could integrate hybrid algorithms (e.g., GA with deep learning) and edge computing for offline adaptability, enhancing robustness in real-world multi-city networks.

6 Conclusions

The efficacy of the proposed EDSA is the most important parameter for logistics companies in the context of instant delivery services. The scheduling method is more adjustable and practical to enhance the overall delivery services of logistics companies experiencing growing demands for fast and efficient deliveries. It can reroute or reschedule vehicles where necessary by choosing the most optimal path to decrease the operational cost and delivery time, which can result in increasing customer satisfaction. Another advantage of the proposed algorithm is scalability, another essential aspect of any efficient solution. This algorithm can be applied to any type of logistic operations, including those of a small company that transports goods in one city or large logistics networks in several regions. Its scalability ensures that it can quickly be scaled up or down to any level of operation. Another essential factor of the algorithm is its flexibility. It has been developed to handle every kind of delivery request, from simple deliveries to more complex cases when a vehicle needs to make multiple stops, serve clients in different time slots, or have specific delivery conditions. These features allow the algorithm to be used in various market sectors and logistics environments, making it desirable for the multiple organisations involved in diverse delivery operations. However, the EDSA framework proposed by the research also has the problem of relying on high-quality real-time data. In practical scenarios where data is incomplete, unreliable, or significantly delayed, the robustness of scheduling decisions may decrease, and even lead to suboptimal or infeasible path arrangements. Therefore, in future research, hybrid algorithms and edge computing should be further combined to achieve offline adaptability, and focus on enhancing the decision-making robustness of the system in the case of unreliable data, to improve its applicability in the actual multi city logistics network.

Declarations

The authors declare that they have no financial conflicts of interest.

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