DYNAMIC ROUTING WITH STATIC DELIVERY TIME WINDOWS IN URBAN LAST-MILE TRANSPORT LOGISTICS

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Resume

To address the challenges of dynamic routing in the last-mile transport logistics, an adaptive method has been developed for solving a multi-criteria dynamic vehicle routing problem with static time windows, taking into account the actual configuration of the urban road network and the non-stationary traffic dynamics on its sections. At the same time, the method enables the use of consolidated real-time data on the dynamic characteristics of traffic flow on sections of the transport network from any sources available at the time of optimization (e.g., GIS, road sensors, mobile devices, etc.). The results of simulation studies using the ant colony optimization method indicate the promising potential of the proposed approach.

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1 Introduction

One of the key approaches to improving the efficiency of urban last-mile transport logistics is enhancing delivery performance through the effective organization of supply processes and route optimization. Given the dynamic nature of urban road networks, practical solutions require the implementation of dynamic routing technologies that utilise the real-time data collection on urban road network conditions and advanced methods of discrete route optimization.

While the primary objective of general dynamic routing is to optimize overall costs and travel time, in last-mile e-commerce logistics, meeting delivery within a specified time window is a critical factor. Therefore, solving the Dynamic Vehicle Routing Problem with Time Windows (DVRPTW) is particularly important for the development of efficient, environmentally sustainable, and customer-oriented logistics in the context of the digital economy, as it enables a balance between the delivery optimality and customer requirements. The effective implementation of DVRPTW should contribute to the sustainable development of cities, the reduction of carbon footprint, and the improvement of accessibility and quality of delivery services in e-commerce.

Indeed, urbanization and the growing volume of e-commerce deliveries lead to increased traffic congestion and higher emissions of harmful substances. A systematic approach to analyzing the challenges of sustainable urban last-mile transport (ULMT) logistics involves the use of innovative operational and organizational solutions, including, in particular, the deployment of urban micro-consolidation centers (UMCCs), which reduce delivery distances, optimize routes, lower transport costs, and enhance accessibility for customers. In addition to traditional vehicles, this requires the adoption of alternative modes of transport to enhance efficiency and sustainability - such as cargo bikes and scooters, autonomous delivery robots, and unmanned aerial vehicles - which help to reduce congestion and are suitable for diverse urban environments. Accordingly, solving the DVRPTW problem enables not only the optimization of overall delivery routes, while accounting for traffic dynamics on sections of urban road network, but the efficient allocation of courier resources as well, by minimizing idle times and empty trips, as well as synchronizing operations with other services such as food, medicine, and bulky item deliveries.

Despite the significant progress, the development of effective dynamic routing systems remains a complex and challenging task. Although modern motion sensors and GPS/Galileo systems have significantly improved the real-time collection of road network data, the implementation of intelligent optimization methods - particularly for complex delivery configurations such as the dynamic traveling salesman problem - remains largely confined to simulation studies without full integration of actual traffic dynamics. Existing approaches address individual aspects of the last-mile delivery, such as route planning, scheduling, and fleet allocation. At present, there are no advanced online routing methods that simultaneously integrate delivery time windows and adapt to real-time traffic conditions. This problem can be addressed through adaptive dynamic routing systems capable of responding to demand fluctuations, optimizing transport efficiency, accounting for delivery time windows, and accommodating newly emerging orders. The development of such systems is the focus of this study.

2 Literature review

Urban last-mile freight transport logistics plays a key role in the functioning of modern urban ecosystems. With the rapid growth of e-commerce, increasing order volumes, and rising consumer expectations regarding delivery speed and timeliness, last-mile logistics processes are facing unprecedented challenges. These challenges include road congestion and traffic jams, high levels of pollution, low delivery efficiency, unpredictable shifts in consumer expectations and order patterns, and limited urban space for unloading and parking. This situation, in particular, results in the last link of the e-commerce supply chain accounting for 50% or more of total logistics costs, along with substantial greenhouse gas emissions and energy consumption [1]. Thus, addressing the challenges of urban last-mile transport logistics is crucial not only for ensuring economic efficiency and customer satisfaction but also for environmental sustainability.

The application of a systems approach to analyzing the identified challenges necessitates the development of appropriate pathways for achieving sustainable urban last-mile transport logistics, which are linked to the implementation of innovative organizational, transport, and operational solutions [2]. In recent years, the key directions for implementing organizational innovations have included the deployment of urban micro-consolidation centers, decentralized logistics hubs, robotic warehouses, and the use of shared logistics platforms that enable different companies to share infrastructure and delivery routes. The integration of such distribution logistics centers, automated parcel lockers, and various crowdsourced delivery models provides a strategic advantage by minimizing travel distances, thereby increasing operational efficiency [2]. These innovations are essential for ensuring fast and convenient delivery to recipients while simultaneously reducing the carbon footprint associated with long travel distances ([3] Mutavdzija et al., 2024). Simulation models, such as LOCAMM (Logistics and City Architecture Multilevel Model), demonstrate their effectiveness in urban freight management. Studies conducted in Dresden show that micro-hubs reduce the load on the road network while maintaining the efficiency of last-mile delivery operations [4].

The implementation of multi-echelon logistics systems, intermodal transport solutions, and advanced monitoring systems is also one of the key approaches to achieving sustainable urban last-mile transport logistics [5]. Particular importance is attached to the ongoing digitalization of transport and logistics processes, which has become increasingly evident in recent years. Studies show that digitalization affects logistics infrastructure, vehicle routing, and inventory management, enhancing both efficiency and resilience [6-7]. Digital logistics systems support the implementation of ESG principles (Environmental, Social, and Governance) by integrating logistics operations with clean technologies and the sustainable development goals of cities [6]. The use of digital twins for modeling urban logistics systems enables more effective decision-making [8]. The use of IoT, real-time GPS/Galileo data, predictive analytics, and artificial intelligence in planning leads to increased efficiency of transport operations, reduced load in the urban road network, improved environmental performance, and lower operational costs [9].

In addressing the last-mile delivery challenges, a variety of solutions are employed concerning the selection of different types of vehicles for executing deliveries. Here, the potential use of innovative transport modes - such as electric vehicles, cargo bikes, ground and aerial drones - is significant for reducing energy demand and mitigating the environmental impact associated with last-mile delivery [10-13].

However, the implementation of environmentally friendly transport modes faces a number of challenges. In particular, for electric vehicles, these challenges include operational limitations (such as limited driving range), battery-related issues (such as long charging times), and both infrastructural and financial difficulties in replacing existing fleets with more sustainable alternatives due to the need for charging stations and the high cost of vehicle acquisition (see, for example, [2]). Accordingly, the limited speed and load capacity of cargo bikes (CBs), along with the need for a new road infrastructure, represent major drawbacks for their use. Drone-based delivery also requires additional investments, such as the development of landing stations (see, for example, [2]). As a result, in most countries - particularly in less developed ones - the last-mile delivery is carried out within the framework of multimodal transport, using conventional vehicles at least during the initial stages of the supply chain [10].

The implementation of modern innovative operational solutions in sustainable urban last-mile transport logistics is linked to the optimization of dynamic routing processes, delivery time windows, the location of distribution centers, environmental impact, crowdsourcing, and business models based on collaboration between the private enterprises and public authorities. As the analysis shows, this set of operational challenges can be effectively addressed within the framework of the generalized DVRPTW model [14-15]. Indeed, such a model makes it possible to account for traffic dynamics on sections of the urban road network, the stochastic nature of customer orders, optimize courier resource allocation by minimizing idle times and empty runs, and synchronize goods delivery across different transport modes within multimodal systems. The implementation of such a real-time dynamic routing, while considering static delivery time windows, is crucial for reducing environmental impact, enhancing operational efficiency, and supporting the integration with urban sustainability initiatives.

However, it should be noted that existing approaches currently address only individual aspects of urban last-mile transport logistics, optimizing specific logistics tasks, such as route planning, scheduling and allocation of vehicles, handling the stochastic nature of customer orders, minimizing emissions, and improving vehicle utilization. This is due to the complexity of developing adaptive multi-factor mathematical models for the DVRPTW optimization, particularly for complex delivery configurations that could, in real time, simultaneously minimize delivery costs and maximize customer satisfaction. It is necessary to account for a large number of parameters, including traffic dynamics, delivery time, shipment volume, fleet size and composition, as well as the uncertainty and variability of customer requests during vehicle movement. Accordingly, [16] presents a DVRPTW variant that incorporates dynamic customer requests and variable time windows. In this case, a multiple ant colony algorithm combined with powerful local search procedures is proposed to solve the DVRPTW. In [17], a literature review is presented on shortest path optimization for courier services using heuristic and metaheuristic algorithms. In [18], the vehicle routing problem, involving multiple vehicles, time windows, and heterogeneous fleets, was addressed using ant colony optimization. To integrate the dynamic routing with urban micro-consolidation centers, where customer requests are directed to alternative third-party transshipment points in accordance with existing time window allocations, Adaptive Large Neighborhood Search algorithms are applied [19].

Recent research on DVRPTW solution methodologies indicates a trend towards the integration of heuristic and metaheuristic optimization algorithms with AI-based machine learning methods [15]. For example, hybrid models, combining deep reinforcement learning and simulated annealing-based optimization heuristics, are applied to vehicle routing problems that take into account time windows, as well as both known and stochastic customer behavior [20]. This enables the use of machine learning potential to search for adaptive routing solutions. Such models improve real-time route optimization by analyzing historical traffic patterns and fluctuations in delivery demand [21], enabling highly efficient management of the delivery process [22]. In [23], the application of metaheuristic and traditional algorithms to intelligent logistics planning is examined. It is shown that the highest performance and accuracy are achieved using ant colony optimization (ACO) algorithms. In [24], an analysis is provided on the prospects of integrating the neural network-based predictive analytics, route optimization algorithms, real-time tracking systems, and sustainable practices to address last-mile delivery challenges. In [25], to enhance the effectiveness of forecasting based on deep learning neural networks, the use of social media data is proposed. The proposed traffic forecasting framework, based on historical data, allows for the integration of additional analytical methods to further improve vehicle routing. These include modelling tools such as agent-based simulation, discrete-event simulation, and system dynamics modelling. The approaches presented in [15, 19, 21-22, 25] have the potential to reduce the delivery costs through fuel savings and increased efficiency; however, they do not resolve the challenge of real-time routing.

Thus, the conducted analysis reveals that the literature lacks comprehensive solutions to DVRPTW problems for urban last-mile transport logistics that simultaneously account, in real time, for the actual configuration and non-stationary traffic dynamics of the urban road network. Recent studies on dynamic vehicle routing within the traveling salesman problem (TSP) framework, conducted in [26-28] without consideration of time windows, indicate the promising potential of the approaches developed in these works for addressing DVRPTW problems.

Building upon [26-28], the results of developing a method for solving multi-criteria DVRPTW that accounts, in real time, for non-stationary traffic dynamics on the sections of the urban road network, are presented in this paper. The optimization criteria in this case are the minimization of total transport costs (in terms of route time) and the maximization of overall customer satisfaction. The solution strategy is based on the use of a modified AI method for the ant colony optimization (ACO_{mod}), which contains the concept of Pareto optimality for multi-objective optimization. Based on the developed method, an adaptable information system for dynamic vehicle routing with time windows is proposed for use in urban last-mile transport logistics. Within the adaptable information system DVRPTW framework, it is possible to take into account the actual configuration of the urban road network and utilise consolidated data on the dynamic characteristics of traffic flows on sections of this network from any sources available at the time of operation (e.g., GIS, road sensors, mobile devices) during the optimization process.

3 Research methodology

In this article are presented the results of developing a real-time DVRPTW solution method for urban last-mile transport logistics, based on solving an asymmetric Dynamic Traveling Salesman Problem with Time Windows, taking into account the actual configuration of the urban road network and traffic flow dynamics on its sections. Following [26], the urban road network is represented as a bidirectionally oriented weighted graph, where the nodes correspond to delivery points with time windows and depots. The arcs contain a sequence of urban road network sections, the traversal of which defines the optimal route between the corresponding pair of delivery points at specific times of the day. The solution of the DVRPTW in urban last-mile transport logistics is based on the following assumptions.

Delivery points may include customers, hubs, and parcel lockers. Parcel lockers are located in easily accessible areas for both couriers and customers, such as large residential neighborhoods or near public transport hubs.

The dynamic nature of the problem is due to the fact that routes may change in real time as a result of new orders or unforeseen events (e.g., changes in traffic flow dynamics on the urban road network sections, road congestion, weather conditions, etc.).

The delivery time windows (slots) generally differ for each delivery point, depending on factors such as order priority; however, the overall delivery timeframe is defined within the limits of a single day (e.g., night to morning, morning to noon, noon to evening, etc.).

For hubs and parcel lockers, the volume of goods and the number of delivery points are sufficiently large, and the delivery points are spaced far apart, making the use of pedestrian couriers and couriers on "green" transport modes inefficient in Dynamic Traveling Salesman Problem with Time Windows solutions. The use of bicycles, drones, or electric scooters is applied for short distances - from hubs to parcel lockers and from parcel lockers to customers - which aligns with the concept of sustainable development.

In urban settings, dynamic routing for deliveries from hubs to parcel lockers and from parcel lockers to customers is generally not relevant, as the movement is largely unaffected by traffic dynamics (couriers travel on foot, by bicycle, or scooter over relatively short distances).

The distribution of time windows at the delivery points allows all deliveries in the dynamic problem under consideration to be performed by a single vehicle.

To solve a Dynamic Traveling Salesman Problem with Time Windows, the use of a modified ant colony optimization algorithm, ACO_{mod}, is proposed. The choice of the ant colony optimization algorithm, as an AI optimization method for solving the last-mile urban transport logistics problems, is motivated by several factors. First, the ACO and its modifications are more versatile compared to most other heuristic optimization methods (see, for example, [28]), allowing for the solution of routing problems in urban road networks of the required scale. In addition, the ACO and its modifications often demonstrate higher performance [28]. Moreover, due to their synergetic nature, the optimization mechanisms of ACO and its modifications resemble the dynamics of traffic flow, particularly in high-density areas [28]. It should be noted that such synergetic effects are observed in nonlinear, nonequilibrium, dissipative systems of various physical natures (see, for example, [29-30]).

The modification of the classical ACO algorithm [31], to account for the time windows, which is used in this paper, is described in [32]. Here, the original transition rule of the classical ACO algorithm, which governs the movement of an ant from node i to node j, takes the following form in the modified algorithm ACO_{mod}:

$$j = \begin{cases} \underset{z \in N_i}{\operatorname{argmax}} \ (\tau_{iz})^{\alpha} (\eta_{iz})^{\beta} (g_{iz})^{\theta} (h_{iz})^{\gamma} & if\ q \leq q_0 \\ S, & otherwise \end{cases}, \quad (1)$$

where: τ_{iz} is represents the current amount of pheromone on the path from node i to node z; η_{iz} is denotes visibility, which in the classical algorithm is defined as the inverse of the distance $(\eta_{iz} = 1/d_{iz})$; g_{iz} is a heuristic that ensures prioritization of transitions to nodes whose upper time window bounds are closer to the ant's expected arrival time at the node z; h_{iz} is a heuristic that aimed at minimizing the ant's waiting time in cases where it arrives at a node before the lower bound of the time window; q_0 $(0 \leq q_0 \leq 1)$ is a user-defined parameter that determines the probability of selecting the most attractive node for the next move; q is a random number drawn from a uniform distribution over the interval [0, 1]; N_i is the set of nodes not yet visited by the ant; $\alpha, \beta, \theta, \gamma$ are user-defined parameters that control the influence of $\tau_{iz}, \eta_{iz}, g_{iz}$ and h_{iz} respectively; S is a probabilistic transition rule that defines the probability P_{ij} of an ant moving from node i to node j.

In presented case, in the modified ant colony optimization algorithm ACO_{mod}, unlike the classical ACO, two additional local heuristics g_{iz} and h_{iz} are used in Equation (1). In addition, according to the delivery time minimization criterion in DTSPTW, the visibility $\eta_{iz} = 1/t_{iz}$, where t_{iz} - is the expected travel time from node i to node z. Then, taking into account the heuristics g_{iz} and h_{iz}, the transition probability P_{ij} is determined as follows:

$$P_{ij} = \begin{cases} \dfrac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}(g_{ij})^{\theta}(h_{ij})^{\gamma}}{\Sigma_{z \in N_i}(\tau_{iz})^{\alpha}(\eta_{iz})^{\beta}(g_{iz})^{\theta}(h_{iz})^{\gamma}}, & if\ j \in N_i \\ 0. & otherwise, \end{cases} \quad (2)$$

where the heuristic g_{iz} is calculated according to [32] as follows:

$$g_{iz} = \begin{cases} \dfrac{1}{1+\exp(\delta(G_{iz}-G_{avg}))} & G_{iz} \geq 0 \\ 0, & otherwise. \end{cases} \quad (3)$$

Here $G_{iz} = b_z - t_{iz}$, where b_z is the upper bound of the time window at node z, and t_{iz} is the estimated arrival time of the ant traveling from node i to node z; δ is user-defined parameter, which controls the slope of the function; G_{avg} is average of all G_{ij} where $G_{ij} \geq 0$, $j \in N_i$ [32]. It is worth noting that although Equation (3) formally allows $g_{iz} = 0$, in the algorithm implementation, it is advisable to replace zero with a sufficiently small non-zero value to avoid zero transition probabilities in Equation (2).

According to [32], the heuristic h_{iz} in Equations (1) and (2) is calculated as follows:

$$h_{iz} = \begin{cases} \dfrac{1}{1+\exp(\lambda(H_{iz}-H_{avg}))} & H_{iz} \geq 0 \\ 0, & otherwise. \end{cases} \quad (4)$$

Here $H_{iz} = a_z - t_{iz}$, where a_z is the lower bound of the time window at node z, and t_{iz} is the arrival time of the ant currently at node i, traveling to node z; λ is user-defined parameter, which controls the slope of the function; H_{ava} is average of all H_{ij} ,where $H_{ij} > 0, j \in N_i$ [32].

In the classical ant colony algorithm [31] ants are uniformly distributed across all the nodes at the start of each iteration to enhance exploration. In contrast to [31], the present approach requires placing all ants at the same node to correctly account for the time window constraints, as time window feasibility necessitates a consistent temporal reference across all the ants within a single iteration. Thus, in the proposed modification of the Ant Colony Optimization model, the artificial ants start each iteration from a single location - either from the current position of the vehicle in the dynamic version of the Travelling Salesman Problem with Time Windows or from the starting depot in its static version. Although this approach somewhat reduces the algorithm‘s exploration capabilities, this limitation can be mitigated by appropriately decreasing the value of the parameter q_0 in Equation (1).

Thus, the main advantages of using the proposed ACO_{mod} algorithm for solving the Dynamic Travelling Salesman Problem with Time Windows include its relatively high performance, configurational flexibility to meet user-specific needs, and the minimization of vehicle idle time at delivery points. At the same time, the optimization criterion can be defined by redefining η, while the degree of influence of the time windows is controlled through the user-defined parameters. For example, in the cases where the strict adherence to time windows is required, higher values can be assigned to the parameters θ, and γ. Conversely, if the priority is to minimize delivery time t_{min}, it is recommended to use $\eta_{iz} = 1/d_{iz}$ instead of $\eta = 1/t$ and to assign a higher value to the parameter β. Thus, the proposed method enables the implementation of the Pareto optimality concept for multi-objective optimization.

Based on the developed method, the adaptable information system DVRPTW system has been proposed for use in urban last-mile transport logistics. The model of this system is schematically illustrated in Figure 1. Adaptable information system DVRPTW performs two main functions: it monitors the state of the urban road network based on section characteristics obtained from various data collection sources, and it supports the dynamic online optimization of routes using current or historical urban road network condition data.

To address the urban road network state monitoring task, it is necessary to collect and process data from all the available sources of information regarding the dynamic and sections static characteristics of this network. In this context, a key role is played by the monitoring of dynamic characteristics of urban road network sections, such as traffic flow parameters (average speed, density and intensity), environmental indicators (emissions of carbon dioxide (CO_2), particulate matter (PM), nitrogen oxides (NO_x), sulfur oxides (SO_x), volatile organic compounds (VOCs), etc.), noise pollution and others. Particular attention should be given to monitoring of environmental indicators, which play a significant role in the implementation of modern urban transport logistics methods aimed at realizing the concept of sustainable development.

In the absence of current values for certain dynamic characteristics of an urban road network section, they can be estimated based on the available current values of other characteristics and historical data. For example, in [27], the average traffic flow speed is calculated through an approximation using the current data on traffic intensity at the section under study and historical data on traffic density from a representative section within the homogeneous cluster of urban road network to which the section belongs.

To collect and store data on the characteristics of sections for the purpose of generating consolidated information on urban road network conditions, the proposed adaptable information system DVRPTW includes a dedicated subsystem called the “Urban Road Network State Monitoring Subsystem” (see Figure 1). This subsystem contains modules for processing and storing information on the condition of sections from various sources, such as GIS platforms, traffic sensors, air pollution detectors, VANET, MANET systems, and others. The system administrator configures access to available data sources and sets up update triggers

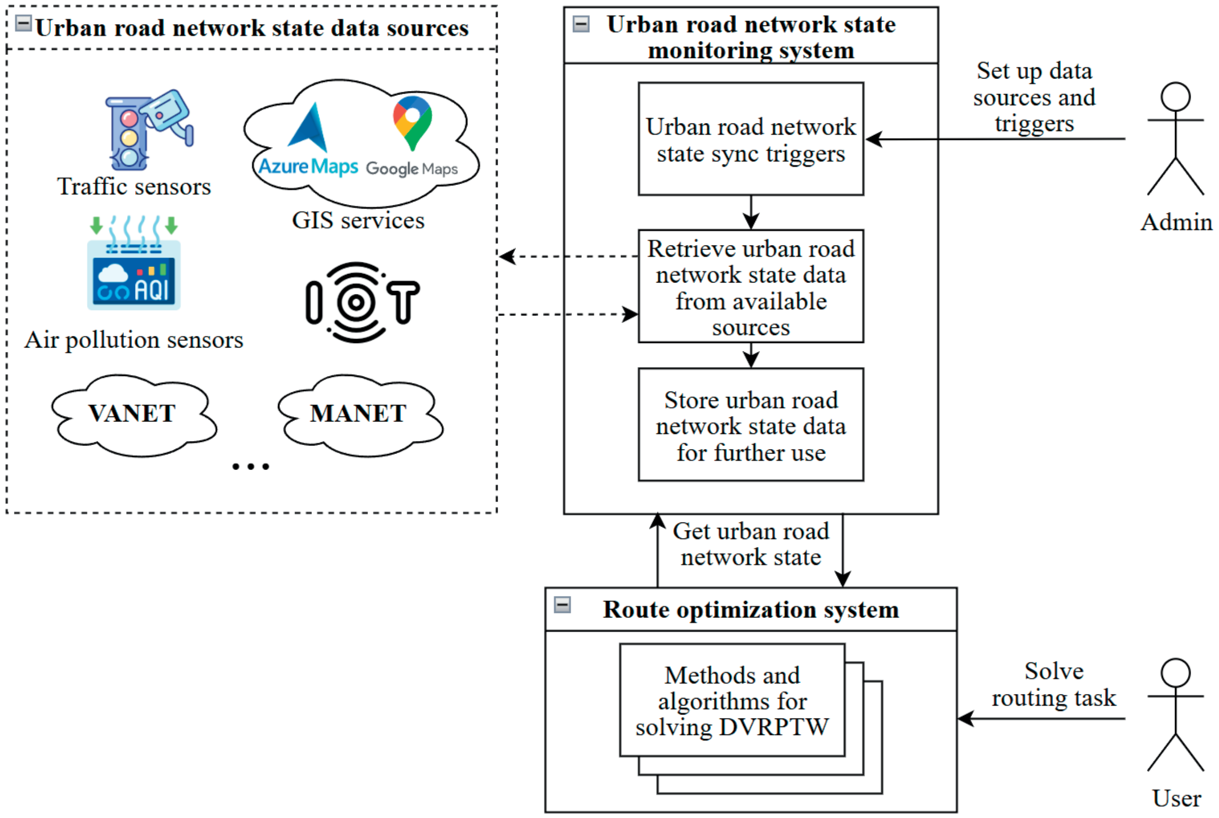

Figure 1 *Model of the adaptable information system for solving the DVRPTW with consideration of real-time urban road network conditions*

according to user requirements. The subsystem retrieves data on urban road network section conditions based on these predefined triggers and stores it for subsequent use in dynamic routing processes.

In the proposed adaptable information system DVRPTW, the task of dynamic user routing is handled by the "Route Optimization Subsystem" (see Figure 1). This subsystem incorporates various optimization methods and algorithms to solve different types of dynamic routing problems. It is important to emphasize that the optimization methods included in the system must be sufficiently versatile to address problems involving complex, multi-factor optimization criteria, while also being flexible and responsive to dynamic changes in the urban road network state. In this study, the ACO_{mod} algorithm is employed, with its application justified in the preceding sections.

At the start of the journey from the depot, the user submits a request to the system, including all the necessary input data according to the specific VRP type, such as the route optimization criterion, the locations of delivery points, their respective time windows, and/or other constraints. The Route Optimization Subsystem retrieves current data on the state of the urban road network in the required representation based on the problem type, determines the optimal solution using the most appropriate method for the given task, and sends the optimized solution back to the user. Dynamic re-optimization of the route occurs during the execution of the optimized path, depending on changes in current traffic characteristics on urban road network sections, the appearance of new orders, and other factors.

The operation of each subsystem is closely linked to the specifics of accessing information sources regarding the urban road network characteristics. To store historical data and enable its subsequent analysis, the system includes a dedicated data warehouse. For deploying such a system, the use of modern cloud technologies is recommended.

In authors' prior work [33] the architectural implementation of adptable intelligent transport system for dynamic routing is presented. The system's technical implementation leverages Amazon Web Services (AWS), which provides high level of cybersecurity, reliability, and system performance. The urban road network monitoring subsystem is built on a serverless architecture, enabling the robust scalability and efficient resource utilization when processing large volumes of real-time data from diverse sources. A dedicated data synchronization process leverages the AWS services such as Lambda, SQS, and DynamoDB to collect and store current urban road network characteristics. This real-time data is then consumed by the route optimization subsystem to support dynamic re-optimization. The re-optimization process is automatically triggered during route execution according to user-defined configurations, ensuring that the system remains both responsive and reliable.

***Table 1** Warehouse and shops (delivery points) with time windows*

Point ID	Address	Time Window
0	82 Kyrylivska Street	
1	24 Beresteiskyi Avenue	9:30 - 13:00
2	40 Mytropolyta Vasylia Lypkivskoho Street	9:30 - 11:30
3	50 Antonovycha Street	9:00 - 12:30
4	2 Vasylkivska Street	9:30 - 11:30
5	24 Lesi Ukrainky Boulevard	8:30 - 11:00
6	3A Mykhaila Hryshka Street	8:30 - 10:30
7	22/20 Petra Hryhorenka Avenue	8:00 - 11:00
8	2A Kharkivske Highway	8:00 - 10:30
9	12V Voskresenska Street	6:30 - 9:30
10	7/11 Khreshchatyk Street	6:00 - 9:00

4 Result and discussion

To evaluate the proposed DVRPTW method within the context of urban last-mile transport logistics, a series of simulation studies were conducted. The selected case involved the distribution of goods to retail outlets in Kyiv. During the simulation, a Dynamic Traveling Salesman Problem with Time Windows was solved in which a delivery vehicle transported customer orders from a warehouse (depot) to 10 designated delivery points and then returned to the depot. Those delivery points corresponded to branches of the well-known e-commerce retailer „Rozetka," which possesses a developed logistics infrastructure including stores, pickup points, and parcel lockers [34].

The addresses of the stores (delivery points) and the corresponding time windows for receiving the goods are summarized in Table 1. The column "Point ID" contains the identifiers of the points (the depot is assigned ID 0, and delivery points are numbered 1-10); the column "Address" specifies the address of each point; and the column "Time Window" indicates the time interval during the day which the respective delivery point can accept goods from the depot.

A graphical representation of the delivery point locations is shown in Figure 2.

The simulation studies were conducted under the following conditions:

- A truck loaded with customer orders departs at 7:30 AM from the warehouse (depot) - Point 0 (82 Kyrylivska Street).
- Due to the specific organization of store operations (e.g., workload balancing, urgent orders, etc.), each store has its own delivery schedule, meaning a static time window during which the delivery point is able to accept goods (see Table 1).
- The optimization criterion is the minimization of the total time spent on delivering goods to the specified stores in strict compliance with the defined time windows, followed by a return to the warehouse (depot). The optimization was carried out using the proposed method described in Section 3, with the following parameter values: $q_0 = 0.9$, $\alpha = 1$, $\beta = 5$, $\theta = 0.5$, $\gamma = 3$, $\delta = \lambda = 0.05$, $\rho = 0.1$, $m = 10$. This parameter configuration, except q_0, was adopted from [32]. The value of q_0 was reduced to enhance ACO_{mod} exploration, which refers to the algorithm's ability to search a broader range of potential solutions rather than prematurely converging. Such exploration is particularly important for the re-optimization process in dynamic scenarios.
- Unloading of goods at each store takes 15 minutes.
- Route re-optimization is performed after the goods are unloaded at a delivery point, and before the vehicle departs for the next destination.
- In the course of the simulation studies based on the proposed method, dynamic routing is carried out using the real-world data on the state of the urban road network, including GIS-based traffic data for sections (obtained from the Azure Maps service [35]) and data from road sensors located on selected sections.
- After completing deliveries to all the stores, the truck must return to the warehouse (depot).

The results of the simulation study on dynamic routing of goods deliveries to the specified "Rozetka" stores, taking into account time windows, are presented in Table 2. The symbol * marks the delivery point at which re-optimization is performed. The column "Current Time" indicates the time of day when the route was re-optimized. The column "Optimal Route" lists the optimal sequence of delivery points obtained as a result of re-optimization at the respective delivery point. The column "Current" provides the expected time (in seconds) for the optimal route obtained through re-optimization at that delivery point. The column "Previous" shows the expected time of the optimal route obtained from the previous re-optimization but recalculated for the current dynamic state of the network. The column "Initial" gives the expected time for the optimal route obtained from the initial optimization (at the time of departure from

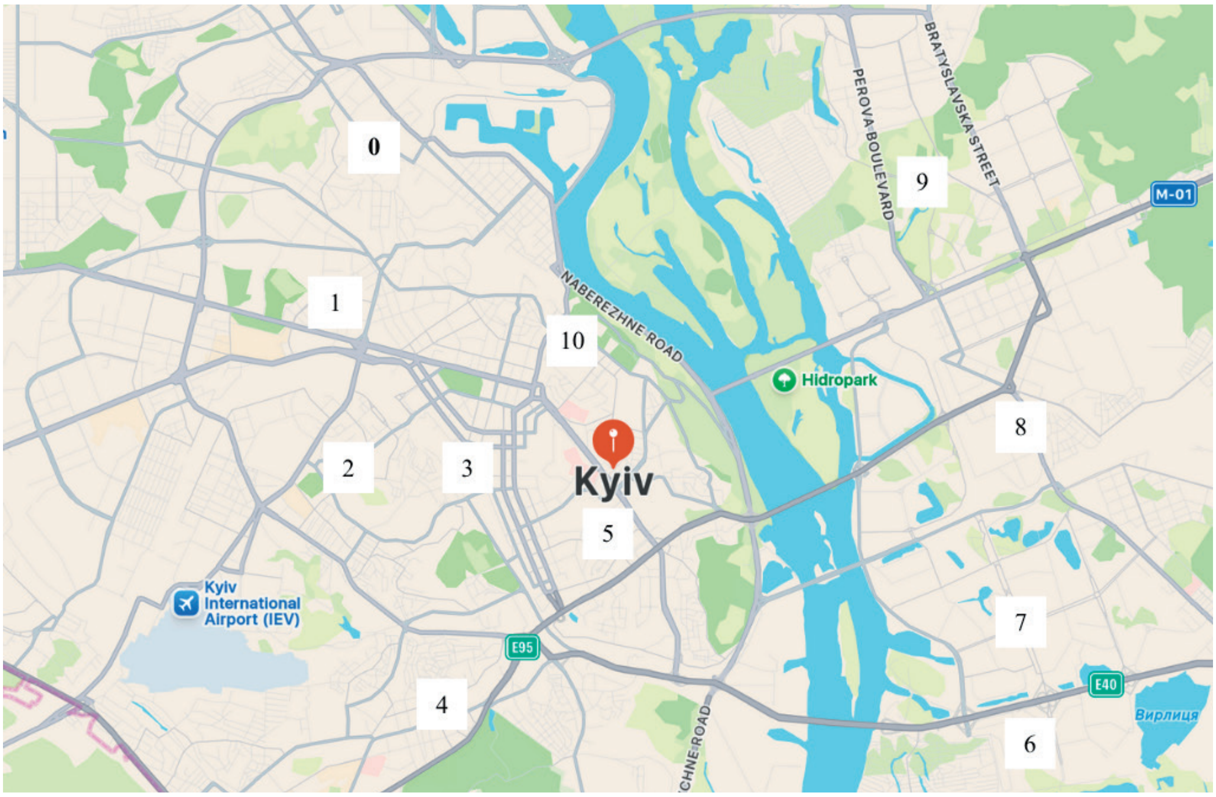

***Figure 2** Locations of the warehouse (0) and delivery points (1, ..., 10) on the map of Kyiv*

***Table 2** Results of dynamic freight delivery routing with time windows in the* urban road network *of Kyiv*

Current time	Optimal route	Optimal route expected time, s		
		Current	Previous	Initial
07:30:00	0*10-9-8-7-6-5-4-3-2-1-0	15792	-	-
07:57:15	0-10*9-8-7-6-5-4-3-2-1-0	15755	15755	15755
08:24:26	0-10-9*8-7-6-5-4-(2-3)-1-0	18247	17974	17974
08:48:53	0-10-9-8*(5-7-6)-4-2-3-1-0	18420	18625	18248
09:16:05	0-10-9-8-5*(6-7)-4-(3-2)-1-0	17342	18469	17517
09:42:30	0-10-9-8-5-6*7-4-3-2-1-0	16645	16645	16766
10:01:12	0-10-9-8-5-6-7*4-3-2-1-0	16335	16335	16438
10:29:03	0-10-9-8-5-6-7-4*3-2-1-0	16237	16237	16359
10:53:36	0-10-9-8-5-6-7-4-3*2-1-0	16168	16168	16283
11:15:42	0-10-9-8-5-6-7-4-3-2*1-0	16197	16197	16331
11:36:35	0-10-9-8-5-6-7-4-3-2-1*0	16184	16184	16324
11:59:44	0-10-9-8-5-6-7-4-3-2-1-0*	-	16184	16324

* the current delivery point where re-optimization is being performed

the depot), but recalculated for the current dynamic state of the network, as well. In parentheses is shown the section of the route that is modified as a result of the re-optimization.

As evident from Table 2, the simulation studies, conducted using the proposed DVRPTW method in urban last-mile transport logistics, revealed several effects associated with the restructuring of the optimal route. For example, at specific times of day - 08:24:26, 08:48:53, and 09:16:05 - the optimal route is rebuilt (see Table 2) due to changes in traffic flow load distribution across the urban road network sections and the failure of some delivery time windows to align with the arrival times generated by the previously optimized route configurations, based on earlier (previous) states of traffic dynamics.

For instance, at 08:24:26, the optimal route was adjusted: the section 4-3-2-1 was restructured to 4-2-3-1. In this case, the travel time of the newly optimized route (18247 s ≈ 304 min) became longer than that of the previously determined optimal route (17974 s ≈ 300 min) due to an increase in traffic density - and consequently, a decrease in average speed - on certain sections of the urban road network. At the same time, an interesting observation is made (see Table 2). Route optimization at Point 9 at 08:24:26 reveals that the previously determined optimal route at Point 10 at 07:57:15 (0-10*-9-8-7-6-5-4-3-2-1-0) fails to ensure compliance with the delivery time windows at some of the subsequent points according to the specified optimal route configuration. Specifically, according to this route, arrival and completion of unloading at Point 2 is scheduled for 11:36:52 (see Table 2), whereas the time window for Point 2 is 09:30 - 11:30 (see Table 1). In contrast, for the updated optimal route generated at Point 9 at 08:24:26 - taking into account the current urban road network states - arrival and completion of unloading at Point 2 occurs at 11:12:49, which ensures compliance with the established delivery time window.

Next, at Point 8 at 08:48:53, the optimal route is further rebuilt - based on updated trafic data - to the configuration (0-10-9-8*-5-7-6-4-2-3-1-0), resulting in a reduction of the expected total delivery time from 18,625 s (≈ 310 min) to 18,420 s (≈ 307 min) (see Table 2). Accordingly, at Point 5 at 09:16:05, re-optimization also results in a rebuilding of the optimal route to the configuration (0-10-9-8-5*-6-7-4-(3-2)-1-0), which reduces the expected total route time by 6.1% (1,127 s ≈ 19 min) - from 18,469 s (≈ 308 min) to 17,342 s (≈ 289 min) (see Table 2). Interestingly, the rebuilding of the optimal route at Point 5 resulted in a reverse inversion of the sequence (3-2) to (2-3), which had previously occurred during the re-optimization at Point 9. Such a change in route configuration, resulting from decreased traffic intensity on urban road network sections, not only shortened the total route duration, but restored compliance with the time windows that had been violated at Point 9 at 08:24:26, as well. Now, the completion of delivery and unloading at Point 2 is scheduled within the designated time window of 09:30 - 11:30, specifically at 11:26:13.

Thus, the results of the simulation studies demonstrate the sufficient effectiveness and adaptability of the developed dynamic routing method with static time windows for urban last-mile transport logistics.

5 Conclusion

This study addressed the dynamic routing problems in urban last-mile transport logistics by developing a multi-criteria DVRPTW method that accounts non-stationary traffic dynamics on urban road network sections in real time.

The optimization criteria in this case are the minimization of total transport costs (in terms of route time) and the maximization of overall customer satisfaction. The solution strategy is based on a modified AI optimization method using the ant colony system, ACO_{mod}, which incorporates the concept of Pareto optimality for multi-objective optimization. Based on the developed method, an adaptable information system for dynamic vehicle routing with static delivery time windows has been proposed. The presented system is a universal solution for addressing the dynamic routing problems in transport logistics, as it incorporates capabilities for accounting for the actual configuration of the urban road network and enables the real-time use of consolidated data on dynamic traffic characteristics across network sections from any available sources at the time of operation (e.g., GIS, road sensors, mobile devices, etc.).

To validate the proposed method, simulation studies were conducted to determine the optimal route within the framework of an asymmetric Dynamic Traveling Salesman Problem with Time Windows, using travel time as the optimization criterion. These studies conducted in the urban road network of Kyiv, with deliveries to e-commerce retailer Rozetka pickup points, demonstrated the method's effectiveness and adaptability. The results showed that the optimal route is dynamically restructured in response to changing traffic load, ensuring that the deliveries remain within designated time windows. For example, some deliveries that would have violated their time windows under previously determined routes were successfully rebuilt through real-time optimization, and total travel time reductions of up to 6% were observed due to improved route sequence. These findings highlight the method's capability to adjust to traffic fluctuations, restore compliance with delivery schedules, and reduce overall route durations, confirming its practical value for urban last-mile logistics.

Despite these positive results, some limitations should be noted. The method was tested in a medium-sized urban segment with a single-vehicle case, and scaling to very large metropolitan networks may significantly increase computational requirements. While the architecture of the proposed system theoretically does not impose strict limitations on computing capacity, in practice its performance and stability are strongly influenced by the hosting environment, including the cloud infrastructure configuration and resource allocation. In addition, the approach assumes reliable and continuous access to traffic and environmental data; in the real-world conditions, incomplete or inconsistent data streams may reduce solution accuracy. Finally, the applicability of the method in other contexts - such as multimodal logistics systems, suburban areas, or cross-border transport corridors - remains to be further investigated. These limitations outline promising directions for future research.

Overall, the study demonstrates that developed method and information system DVRPTW propose a practical and adaptable approach to dynamic routing in urban logistics, effectively balancing operational efficiency and delivery reliability.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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