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ADAPTABLE DYNAMIC ROUTING SYSTEM IN URBAN TRANSPORT LOGISTICS PROBLEMS USING GIS DATA

Summary. To solve the problems of online route optimization in urban transport logistics, an adaptive dynamic routing system based on GIS data is proposed. Here, it is possible to simultaneously take into account the actual configuration of the urban road network (URN) and the real-time dynamics of traffic flows. Route optimization is performed on a weighted bidirectional graph for an asymmetric dynamic traveling salesman problem using a modified ant colony optimization algorithm. The system allows automatically updating the weights of the graph depending on the current changes in the characteristics traffic in the URN sections, obtained from GIS data, and fixing the optimal configuration of a partially completed route before updating the graph. To test the proposed system, the simulation of dynamic routing processes was conducted in real-time, using the delivery of goods to Żabka grocery stores in Warsaw as an example. The results indicate the proposed method's feasibility for solving practical urban transport logistics management problems under complex traffic.

Keywords: intelligent transportation systems, AI optimization methods, information technology, geographic information systems, transport logistics

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1. INTRODUCTION

One of the most critical ways to enhance the efficiency of urban transport logistics is by improving the productivity of freight delivery processes through route planning and optimization. Given the dynamic nature of urban road networks (URN), the practical solution to such problems lies in employing innovative dynamic routing technologies that operate in real-time, leveraging advanced software, timely acquisition, and transmission of primary URN state data, and fast intelligent discrete route optimization methods.

Despite advances, the development of effective dynamic routing systems remains a challenge. Real-time data acquisition about URN states (traffic characteristics, weather conditions, vehicle technical specifications, etc.) has improved with modern motion sensors and GPS systems. However, the development and application of intelligent route optimization methods, particularly for complex delivery point configurations such as the traveling salesman problem (TSP), are often limited to simulation studies on model examples without considering real traffic conditions on URN sections.

This paper presents the development results of a dynamic routing system for goods delivery within the dynamic TSP (DTSP), utilizing GIS data on current traffic conditions in URN sections. The route optimization is performed using a modified ant colony optimization algorithm (ACO_{mod}). The study results on dynamic routing, using a section of the Warsaw URN as an example, demonstrate the proposed method’s potential for solving practical transport and logistics management problems in complex traffic conditions.

2. LITERATURE REVIEW AND PROBLEM STATEMENT

Currently, the problem of Vehicle Routing (VRP) in transportation logistics is often formulated as a generalized Traveling Salesman Problem (TSP) [1]. In this context, the TSP involves finding a set of optimal routes for visiting a given set of nodes with a specified number of vehicles based at a depot so that each node is typically visited once. Therefore, the aim is to minimize the total cost of the route. The TSP is often represented as either a directed or bidirectional graph with a static or dynamic set of vertices (nodes) connected by edges (arcs) with defined weights. Based on these weights, a corresponding cost matrix is constructed and analyzed. The costs may include distances between delivery points, travel time, fuel consumption, trip expenses, etc. [1].

Depending on the nature of the evolution of input data, VRP can be classified into two main categories: static VRP (SVRP), where input data is known in advance and remains unchanged, and dynamic VRP (DVRP), where input data changes over time [1]. Until recently, routing and planning problems in transport-logistics systems were mainly solved using methods for SVRP (see, for example, [2]). In these cases, transport-logistics operations were carried out with fixed or minimally variable system characteristics during service time [2].

Solving urban transport logistics issues is possible within the DVRP approach, which must account for variable factors related to time and service changes during transit. This requires modern innovative online dynamic routing technologies that contain appropriate software, systems for timely acquisition data of URN state, as well as fast intelligent methods for routes discrete optimization [3].

The rapid development of intelligent transportation systems (ITS) over the past decade has sparked significant interest in solving DVRP routing problems among researchers. This interest is related to the development and application of innovative technologies for acquisition and processing data, as well as the development of modern methods of intelligent solutions within the framework of ITS.

In particular, GPS integrated to modern geographic information systems (GIS), the Internet of Things (IoT), blockchain (BC), big data (BD), and modern information and communication technologies enables automated dynamic routing through real-time data integration. This includes tracking vehicle movements and changes in customer requests, traffic updates, information exchange among participants in the transport process, weather forecasting, etc. [4]. Modern examples of such devices include GPS trackers, traffic sensors (often digital cameras), weather sensors, mobile applications, etc. [5].

As the analysis shows, until recently, significant attention has been devoted to using GIS data for dynamic routing problems, mainly without considering traffic updates on network segments during vehicle movement [6–9]. For example, in [6], dynamic route planning in logistics for urban public sports facilities is studied based on GIS and Multi-agent systems. In [7], using ArcGIS software with network analyst extensions and regression analysis, a set of the fastest delivery routes for fresh vegetables was determined. In [8], a cluster method for flexible routing was presented, incorporating GIS and discrete-event simulation. Here, results of optimal delivery route forecasting (including time and distance) for variable freight delivery addresses and reverse trip pickups were provided. In [9], a platform offering an efficient solution for CVRP and GVRP routing tasks was proposed, employing a K-means algorithm to dynamically define different geographical delivery zones and plan routes considering current traffic GIS data. These studies typically leverage GIS's advantages by using data about the real configuration of the transport network segments connecting any two nodes, as well as relevant attributes (speed limits, traffic jams, intersection waiting times, real-time traffic data, etc.). Here, route optimization is mainly performed using classic discrete optimization methods for small-sized transport-logistics problems.

In recent years, the papers with using of traffic data on URN sections obtained through different types of traffic sensors have been less represented in literature compared to one with GIS data. Depending on the chosen measurement technology, this may be primarily due to high costs, significant installation and maintenance expenses, limited coverage radius, etc. For example, in [10], an intelligent system for real-time trip optimization was developed using machine learning based on traffic data from 52 sensors placed on California highways. In [11], results of simulation modelling using real-time VANET (Vehicular Ad hoc NETwork) traffic data and simulators such as OmNet++ (network communication simulator) and SUMO (urban mobility simulator) for traffic light management processes to form optimal route sets for travelers were presented.

Now, heuristic or metaheuristic methods, typically based on artificial intelligence (AI), as well as their modifications, and hybrids, are using in ITS to ensure high-speed solutions for large-scale DVRP discrete optimization problems. It should be noted that DVRP is an NP-hard problem, with computation time increasing significantly as the number of nodes grows. Therefore, most developments and research on AI methods for DVRP discrete optimization have so far focused on reducing computation time and finding the global minimum during optimization [12]. In this case, as a rule, a model representation of the URN is considered in the form of a graph for a certain number of nodes with variable arc weights, which, at best, correspond to the average values of the parameters of the dynamics of traffic flows on URN sections or to extreme cases (for example, traffic jams) at a certain point in time [13].

Most dynamic routing solutions are simulated on model examples without considering the actual URN state and configuration.

As analysis shows, a significant number of works within the DVRP framework focus on solving problems for vehicle routing with dynamic time windows (DVRPTW) and variable demands (VRPVD). For instance, in [14], a hybrid ant colony algorithm is used to study a multi-objective vehicle routing problem with flexible time windows, integrating road costs, fixed vehicle usage costs for delivery, and penalty costs incurred for early or late service into a single objective function. In [15], DVRPTW was solved as a multi-time window problem within a sliding horizon using heuristic optimization methods. It should also be noted that to solve multi-parametric problems (variable time windows, customer demands, etc.), hybrid algorithms combining AI-based discrete optimization methods with artificial neural networks (ANN) of machine learning are often used [16]. Here, ANN is employed either for forecasting specific transport processes or for tuning heuristic parameters of intelligent optimization methods under changing environmental conditions.

AI methods for solving DVRP for large-scale dynamic TSP (DTSP), considering real-time ITS traffic data, are currently imperfect, far from practical application, and require further development. For example, in [17], DVRP was carried out within DTSP using various AI methods and historical ITS data on transport flow dynamics. Here, it was also shown that one of the most effective algorithms for solving such problems is the Ant Colony Optimization (ACO). It was found to have better optimization effects for DVRP within DTSP (shorter time and higher solution accuracy) compared to, for example, ESA and GA [17]. Additionally, ACO and most of its modifications are more versatile, allowing routing problems on URN for both small and large-scale DTSP [17]. In [18], DTSP is used as a basic task for creating dynamic test cases, considering two types of DTSP: (a) changes in the number of nodes and (b) changes in edge weights. Population-based ACOs utilizing pheromone evaporation and memory archives for adaptation to dynamic changes are applied to enhance DTSP performance [18]. In [19], a dynamic ACO (DAACO) was proposed to improve global minimum finding efficiency, incorporating two enhanced strategies: a convex hull initialization strategy and K-means clustering, as well as a local search strategy between two neighbors. Experimental results indicate that the proposed algorithm outperforms modern DFACO and DEACO algorithms [19].

In [20], simulation modelling of time-based discrete route optimization with dynamic updating of client visit sequences during movement was conducted for the first time. Here, traffic sensor information was used both in real-time and as averaged historical traffic data. However, in [20], route optimization was performed using a spreadsheet solver with open-source software for VRP, and computational operations for route optimization were excessively slow, preventing full real-time mode implementation [20].

Therefore, this study aims to develop an adaptable dynamic routing system for freight delivery within the DTSP framework, utilizing GIS traffic data for route discrete optimization with AI method. Here, the use of GIS traffic data is essential for considering the actual URN configuration and real traffic dynamics. To ensure high performance and adaptability in route optimization with dynamic updates under non-stationary traffic conditions, a ACO_{mod} is proposed.

3. METHODOLOGY

This study examines the asymmetric dynamic traveling salesman problem (DTSP) as a weighted bidirectional graph in the context of the urban road network (URN). The graph consists of nodes (*0*, …, *n-1)* with respective Cartesian coordinates, where each node represents a delivery point, and node 0 is the depot. In this study, the number of nodes is fixed. Each edge of the graph is composed of a set of URN sections that represent the optimal route between each pair of nodes, as determined by GIS data. The attributes of the graph's edges include the travel time and length of these section sets, corresponding to the optimal route between the nodes. The weight of each edge is determined by a function based on the attributes of the URN section sets, travel time, and the total length of these URN sections. Depending on the optimization criteria, the optimization procedure focuses on corresponding attributes of this function.

An adaptable dynamic routing system for freight delivery is defined as a system designed for real-time route re-optimization in response to changes in the URN state due to traffic flow dynamics on its sections during freight transport [1].

The proposed method involves three main stages for the functioning of the adaptable route optimization system in the asymmetric DTSP using ACO_{mod} :

- Building the initial graph for the URN's initial state and constructing the optimal route for this graph.
- Dynamically updating the graph according to changes in road conditions (traffic flow dynamics, congestion, accidents, temporary road closures, etc.).
- Optimizing the route on the updated graph.

GIS data on the current traffic conditions on URN sections are used to account for the actual URN configuration. This data is obtained using the Routes API of the Bing Maps service (GIS developed by Microsoft) [21]. This service finds the most optimal route between two points, specified by coordinates or addresses, and provides discrete characteristics such as route time and length, considering the current load of URN sections, accidents, temporary closures, etc.

Thus, the graph construction uses optimal routes obtained from real-time GIS data to connect each pair of delivery points. The constructed graph models the DTSP for the current state of the URN section, considering its actual configuration and traffic flow dynamics. The route optimization or re-optimization process for the constructed or updated graph is then performed based on real-time traffic data provided by the Bing Maps Routes API, which includes current changes in traffic dynamics on URN sections.

To provide high performance and adaptability of the route optimization process with the possibility of dynamic updates under non-stationary traffic conditions, a modified ant colony optimization algorithm ACO_{mod} is proposed (see Figure 1).

In this ACO_{mod}, the weights of the graph are automatically updated based on changes in dynamic characteristics on URN sections, while fixing the optimal configuration of a partially completed route before updating the graph. The algorithm for fixing the optimal configuration of a partially completed route is described as follows:

$$p_k^{ACO_{mod}}(i) = \begin{cases} 1, & (j,i) \in \mathrm{Pre_k} \\ 0, & \exists x\colon x \neq j \wedge (j,x) \in \mathrm{Pre_k} \\ p_k^{ACO}(i), & otherwise \end{cases} \tag{1}$$

According to (1), fixing the optimal configuration of a partially completed route involves adding partially defined optimal routes to the memory of the ants. The ACO_{mod} algorithm introduces Pre_k – a list of graph edges that ant *k* must follow within the optimal configuration of the partially completed route, ignoring the probabilistic rule p_k^{ACO} of the classic ant colony algorithm described in [22]. Thus, when at node *j=Pos(k)* in the graph, ant *k* moves to node *i* if $(j, i) \in Pre_k$; otherwise, the next node is determined by the classic probabilistic rule p_k^{ACO} (see Figure 1 and (1)). The second condition in (1) describes the list of graph edges that do not belong to the partially completed optimal route.

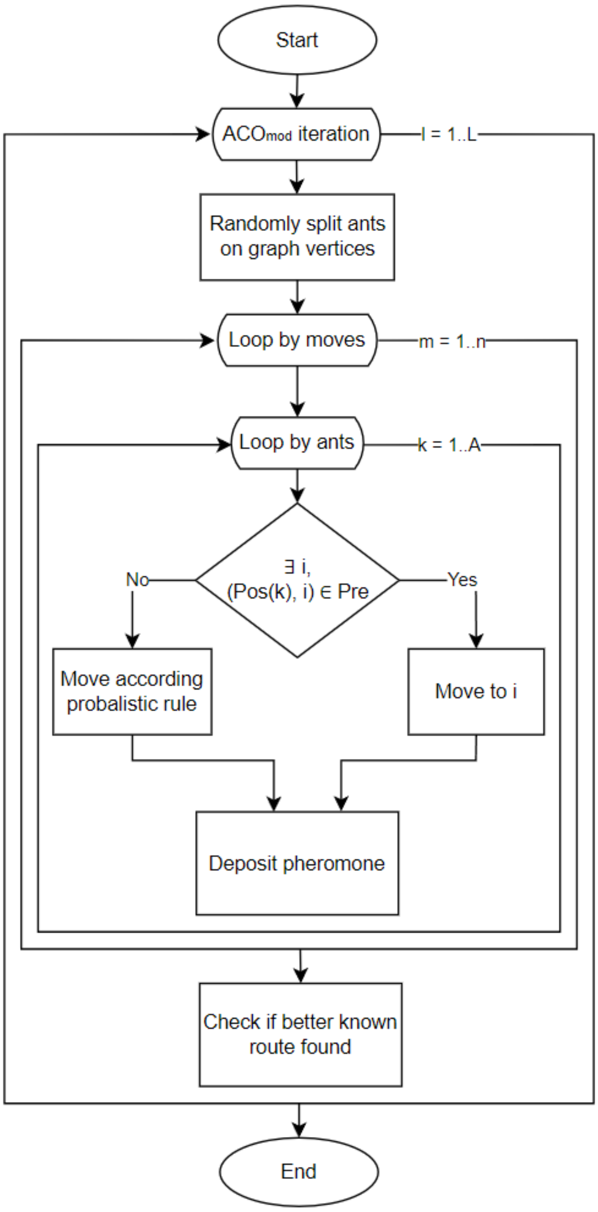

Fig. 1. Block diagram of the proposed modified ant colony optimization algorithm ACO_{mod}

The general scheme of the adaptable dynamic routing system for freight delivery within the DTSP framework using GIS data is shown in Figure 2.

As shown in Figure 2, the system operates as follows: The user inputs the initial data into the system, including the starting point (depot), delivery points, and the route optimization criterion. The user also configures route update triggers, which are events that initiate graph rebuilding according to the current situation and find the optimal route on the updated graph. Triggers can be events caused by manual user interaction with the system (Manual trigger), events when the vehicle arrives at a delivery point (Arrival trigger), or events occurring according to a user-defined schedule (Schedule trigger), such as route updates every 5 minutes. The system allows multiple triggers to operate simultaneously.

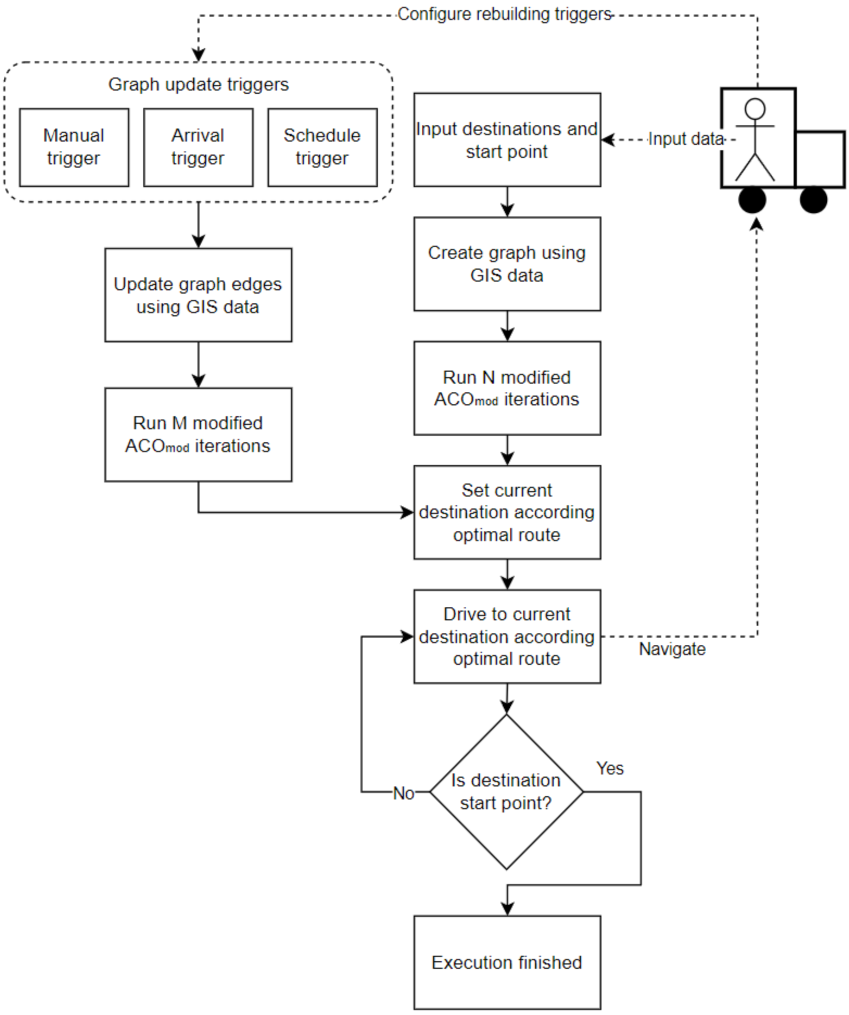

Fig. 2. Flowchart of the proposed adaptable dynamic routing system of freight delivery within the framework of the DTSP task using GIS data

According to Figure 2, at time t_0, before the vehicle departs from the initial point D_0 (depot), a graph $G(t_0)$ corresponding to the current state of the URN at time $t_0$is formed based on GIS data. By performing N iterations using ACO$_{mod}$, the optimal freight delivery route in the DTSP is found according to the specified criterion:

$$R_{opt}(t_0) = \{(D_0, D_{x_1}(t_0)), \ldots, (D_{x_{i-1}}(t_0), D_{x_i}(t_0)), \ldots, (D_{x_{(n-1)}}(t_0), D_0)\}\,. \qquad (2)$$

In (2) $R_{opt}(t_0)$ is the sequence of graph edges $G(t_0)$ that corresponds to the optimal route configuration at time t_0; D_0, $D_{x_1}(t_0)$, … , $D_{x_i}(t_0)$, …, $D_{x_{(n-1)}}(t_0)$ are the delivery nodes corresponding to the optimal route configuration at time t_0; x_1, …, $x_i, \dots, x_{(n-1)}$ are variables determining the order of passing the graph nodes for the optimal route configuration at time t_0

After optimization procedure on the graph $G(t_0)$, the first edge $(D_0, D_{x_1}(t_0))$ in the optimal route sequence $R_{opt}(t_0)$: $(D_0, T(t_0)) = (D_0, D_{x_1}(t_0))$ is fixed. This means that during subsequent route re-optimization at future times t_j, the edge $(D_0, T(t_0))$ will be included in the optimal solution according to (1).

Upon the vehicle's arrival at delivery point $T(t_0)$ at time t_1, the graph $G(t_1)$ corresponding to the URN state at time t_1 is updated using the Bing Maps Routes API in response to the arrival trigger event. The optimal freight delivery route in the DTSP is then found according to the specified criterion:

$$R_{opt}(t_1) = \{(D_0, T(t_0)), (T(t_0), D_{x_2}(t_1)) \dots (D_{x_{(n-1)}}(t_1), D_0)\} \tag{3}$$

by performing M iterations using ACO_{mod}. In (3) D_0, $T(t_0)$, $D_{x_2}(t_1)$, … , $D_{x_i}(t_1)$, … , $D_{x_{(n-1)}}(t_1)$ are the delivery nodes corresponding to the optimal route configuration at time t_1. The next edge $(T(t_0), D_{x_2}(t_1))$ in the optimal route $R_{opt}(t_1)$ is then fixed: $(T(t_0), T(t_1)) = (T(t_0), D_{x_2}(t_1))$. Subsequent route re-optimization follows the described update algorithm, fixing the corresponding route edges optimized in previous stages.

If a route update trigger (see Figure 2) activates while the vehicle is moving, such as a schedule trigger event, the system updates the graph according to the current URN state and finds the optimal route by performing M iterations using ACO_{mod}. However, it is assumed that the vehicle has already arrived at point $T(t_j)$ to avoid introducing new intermediate nodes representing the vehicle's current position during optimization.

4. RESULTS AND DISCUSSION

4.1. Case Study: Goods Delivery to Żabka Grocery Stores in Warsaw

The proposed dynamic routing system in DTSP using the ACO_{mod} and GIS data was tested on a fragment of Warsaw's URN. In this task, 10 Żabka grocery stores were considered, with their locations specified by addresses. The graphical representation of the delivery points and the current state of the URN is shown in Figure 3. These stores were selected based on the following assumptions:

- The depot is located at point n=0 (Krucza 46, 00-509 Warsaw, Poland).
- The delivery route type is circular, with sequential delivery of goods.
- The date and time of delivery are considered, but unloading time at delivery points, nomenclature, mass, and volume of the ordered goods are not considered.
- In each set of URN sections corresponding to a particular graph edge, there will always be alternative routes.
- Changes in average travel time mainly depend on changes in traffic flow dynamics, including stops or delays due to traffic signals, congestion, and other traffic complications affecting vehicle speed on URN sections.

A basic implementation of the proposed system was developed on the .NET 6 platform using C#. The research was conducted on an Intel Core i5-8400 CPU @ 2.80GHz with 16 GB DDR3 RAM and Windows 10 OS. The studies showed that building a graph with 10 nodes or updating it according to the current URN state took an average of 5.37 seconds, while finding the optimal solution for a graph with 10 nodes using 1000 iterations of ACO_{mod} took an average of 926ms. The graph construction/update speed was limited by the service limits of the Routes API for the developer license. Performance could be significantly improved with production-level license.

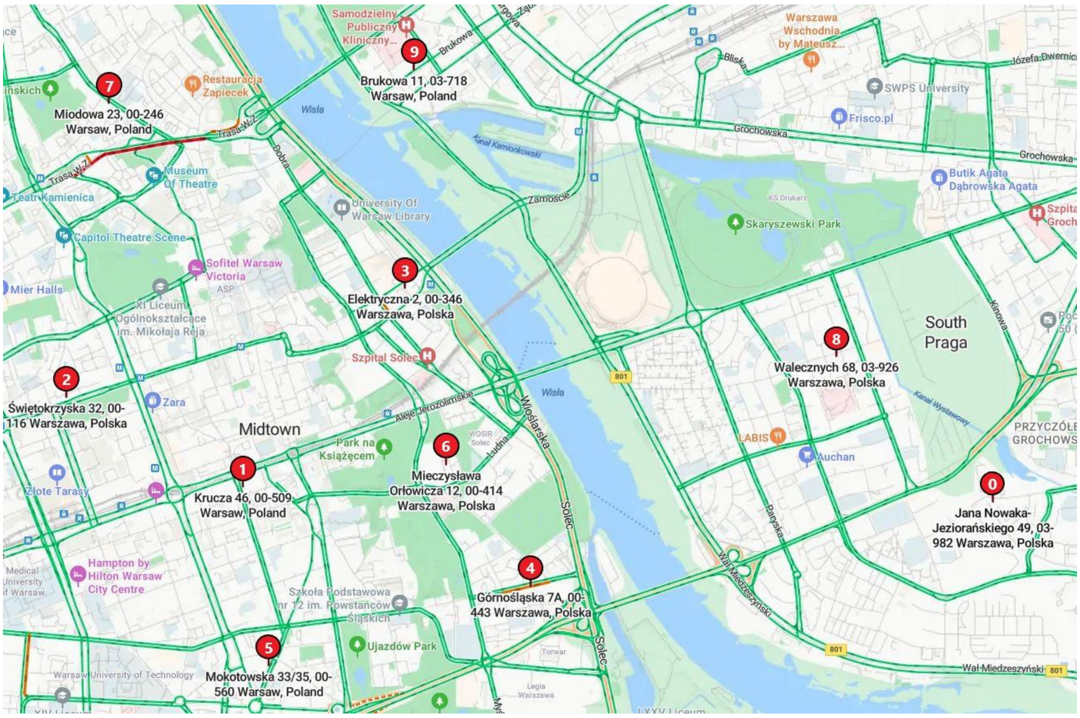

Fig. 3. Locations of the depot (n=0) and delivery points (n=1, …, 9) (Żabka grocery stores) on the map of Warsaw [21]

4.2. Routing in DTSP with Dynamic Updating of the Optimal Route During Goods Delivery Using GIS Data

In the DTSP task, for a vehicle departing from store 0 (depot) at t_0= 03.07.2024 at 17:45:00 UTC +1, the optimal time route for delivering goods to all other stores and returning to store 0 (depot) needs to be found, considering current URN state changes due to non-stationary traffic flow dynamics on URN sections. As an example, the studies were conducted with dynamic graph updates using a Schedule trigger regime (see Figure 2) with a 5-minute update frequency via the Bing Maps service. Route re-optimization occurred at the moments of the vehicle's arrival at the respective delivery points according to the Schedule trigger event algorithm (see Figure 2).

Table 1 presents the routing results with dynamic optimization of the delivery route to Żabka grocery stores in Warsaw. Column 1 shows the vehicle's arrival/departure time at/from the respective delivery point according to the assumptions in this work (see Section 3). Column 2 shows the sequence of delivery points for the optimal route based on re-optimization results according to the Schedule trigger event algorithm (see Figure 2, Section 3). Here, red indicates visited nodes, blue indicates the next node based on re-optimization results, and gray highlights the part of the optimal route rebuilt due to re-optimization compared to the initial (planned) optimal route. Column 3 contains the time (in seconds) for the route optimized at previous stages before the vehicle's arrival at the respective point (see (3) Section 3). Column 4 contains the expected time (in seconds) to complete the remaining route based on re-optimization results according to the current URN state at the time of route re-optimization at the respective delivery point. Column 5 shows the time of the last graph update according to the Schedule trigger event algorithm at the time of route re-optimization based on GIS data at the respective delivery point.

Tab. 1

Routing results with dynamic route optimization for goods delivery to Żabka grocery stores in Warsaw using GIS data on 03.07.2024

Arrival / departure time	Sequence of visits with dynamic route optimization	Time of optimal route		URN state per Schedule trigger
		From start (s)	Expected to finish (s)	
1	2	3	4	5
17:45:00	0->8->6->3->9->7->2->1->5->4->0	0	4327	17:45:00
17:52:27	0->8->6->3->9->7->2->1->5->4->0	447	3751	17:50:00
18:01:36	0->8->6->4->5->1->2->7->3->9->0	996	3295	18:00:00
18:05:27	0->8->6->4->5->1->2->7->3->9->0	1227	3101	18:05:00
18:10:16	0->8->6->4->5->1->2->7->3->9->0	1516	2808	18:10:00
18:14:25	0->8->6->4->5->1->2->7->3->9->0	1765	2559	18:10:00
18:20:40	0->8->6->4->5->1->2->7->3->9->0	2140	2170	18:20:00
18:28:58	0->8->6->4->5->1->2->7->9->3->0	2638	1614	18:25:00
18:36:38	0->8->6->4->5->1->2->7->9->3->0	3098	1153	18:35:00
18:44:28	0->8->6->4->5->1->2->7->9->3->0	3568	662	18:40:00
18:55:30	0->8->6->4->5->1->2->7->9->3->0	4230	0	18:55:00

As Table 1, the studies revealed that significant traffic redistribution on URN sections can lead to substantial route adjustments. For instance, at 18:01:36, re-optimization for the current URN state at 18:00:00 resulted in rebuilding the optimal route (0->8->6->4->5->1->2->7->3->9->0) compared to the initial (planned) optimal route (0->8->6->3->9->7->2->1->5->4->0) when vehicle departs from the depot at 17:45:00 (see Table 1). In addition, at 18:28:58, re-optimization during the vehicle's stay at point 9 led to partial route reconstruction from 3->9->0 to 9->3->0. Thus, at the vehicle's return to the depot at 18:55:30, the optimal route was 0->8->6->4->5->1->2->7->9->3->0, differing from the initial optimal route at 17:45:00 (0->8->6->3->9->7->2->1->5->4->0). The travel time was reduced to 4230 seconds compared to the planned 4327 seconds (see Table 1).

5. CONCLUSIONS

This work proposes, for the first time, an adaptable dynamic routing system for urban transport logistics, enabling the simultaneous consideration of the actual configuration of the urban road network (URN) and the real-time dynamics of traffic flows on its sections during goods transportation. The optimization process was carried out within the framework of an asymmetric DTSP on a weighted bidirectional graph. The dynamic route optimization procedure during goods delivery is executed using a modified ant colony optimization algorithm ACO_{mod}. Within the developed ACO_{mod}, the graph weights are automatically updated based on current changes in the dynamic characteristics of URN sections, obtained via the Bing Maps Routes API. Additionally, the system ensures the fixation of the optimal configuration of the partially completed route before graph updating.

To validate the proposed system, comprehensive simulations of dynamic routing processes were conducted online, using time as the optimization criterion, exemplified by goods delivery within the DTSP framework to Żabka grocery stores in Warsaw. The study results demonstrate the potential of the proposed method for solving practical urban transport logistics management problems under complex traffic conditions.

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