DYNAMIC ROUTING IN URBAN TRANSPORT LOGISTICS UNDER LIMITED TRAFFIC INFORMATION

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Resume

A method for online dynamic routing of freight delivery under limited traffic information using an ant colony algorithm, has been proposed. This method leverages real-time IoT data on traffic flow (TF) intensity from traffic sensors on urban road network (URN) sections, combined with averaged historical data on TF parameters (speed, density, intensity) obtained from traffic sensors on representative sections of homogeneous clusters within the URN. The procedure for forming homogeneous clusters within the URN and identifying representative sections is described. The results of simulation studies using the URN of Kyiv as an example indicate the potential of this method for urban transport logistics in conditions of complex traffic.

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1 Introduction

Dynamic routing plays a key role in modern urban transportation logistics, enabling real-time management of traffic flows, ensuring consistent service quality for customers, improving road safety, and reducing negative environmental impacts. This requires the use of systems for timely collection and processing data of current dynamic characteristics of traffic flow on sections of the urban road network (URN), as well as efficient intelligent methods for discrete route optimization based on the analysis of this data.

Today, there are numerous advanced innovative technologies available for obtaining the relevant data, such as GPS technologies combined with modern geographic information systems (GIS), the Internet of Things (IoT) with traffic sensors, VANET systems, and others, which allow for automated dynamic routing through the integration of real-time data. Each of these technologies has its own advantages and disadvantages, necessitating further comprehensive research for their improvement.

One of the most promising approaches to monitoring the current state of the URN remains the use of traffic sensors combined with IoT technologies. Unlike many other approaches, this one provides the high accuracy in measuring the dynamics of traffic flow characteristics and allows for real-time data collection and analysis. However, it also has its drawbacks, including the high cost of modern sensors, such as digital video cameras with computer vision, and the limited coverage area, which requires the installation of a large number of sensors to obtain a complete picture. Moreover, there are currently no perfect methods for the real-time discrete route optimization that simultaneously consider the actual configuration of the URN and the dynamics of traffic flows on its sections.

In this context, developing and improving dynamic routing methods in urban transportation logistics to overcome existing shortcomings remains a relevant problem.

2 Literature review

The problem of dynamic vehicle routing (DVRP) involves finding optimal routes for vehicles in real-time when some or all types of input data change over time [1]. Addressing the challenges of dynamic vehicle routing is crucial for enhancing the efficiency, cost-effectiveness, environmental sustainability, and safety of urban transportation logistics, especially in the context of rapid urbanization and increasing motorization of society. In a fast-changing environment, transport logistics companies, operating within limited time frames, must continuously adapt to these changes and ensure consistent service quality.

Recently, solving of DVRP tasks for e-commerce or last-mile commerce, which is rapidly growing, has become particularly relevant. Therefore, the development of effective and sustainable technologies is imperative to meet this demand and maintain high service levels. Multimodal deliveries, crowdshipping, and parcel lockers offer flexible options for e-commerce, contributing to hyper-connected urban logistics (HCL) for courier services [2-3]. Despite their potential, the effective use of these technologies is hindered by the absence of a comprehensive mathematical apparatus capable of tackling the complex modelling challenges for delivery processes. Here it is necessary to take into account numerous dynamic parameters and real-world constraints, including delivery times, freight volumes, travel distances, fleet characteristics, demand uncertainties, and stochastic customer requirements [2-3]. In this regard, DVRP problems are currently mainly solved taking into account individual constraints. At the same time, a large number of such DVRP are related to the problems of optimizing the route of delivery of goods with changing time windows, the nature and number of customer requests, the influence of weather conditions, etc. [2-7]. However, one of the main factors, affecting the dynamic impact of the environment on the effectiveness of transport logistics companies, remains the unpredictable and sudden changes in traffic on urban road network (URN) sections.

This necessitates the use of systems for timely collection and processing of data on the current dynamic characteristics of traffic flow on URN sections, data processing, and fast intelligent methods for discrete route optimization based on the analysis of this data.

Today, numerous advanced innovative technologies exist for collection and processing relevant data, such as GPS/Galileo technologies combined with modern GIS systems; VANET systems; Internet of Things (IoT) with traffic sensors; big data (BD) processing; blockchain (BC), among others (see, for example, [8-20]). These technologies allow for automated dynamic routing in real-time through the integration of data with modern artificial intelligence (AI) methods for discrete route optimization. The most suitable methods include swarm intelligence (SI) techniques, particularly ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC) algorithms; genetic algorithms (GA); simulated annealing (SA); tabu search (TS); artificial neural networks for machine learning and deep learning; their modifications and hybridizations [21-26].

As the analysis shows, until now, practical aspects of DVRP have largely focused on the use of GIS data, which are derived from global navigation satellite systems (GNSS) technologies, primarily GPS. (see, for example, [8-12]). Typically, the main advantages of GPS technologies, such as wide coverage, integration with other systems, obtaining data on the actual configuration of URN sections, and relevant attributes of these sections (speed limits, congestion, waiting times at intersections, real-time traffic data, etc.) have been utilized. However, most studies have primarily explored the problems of dynamic planning for optimal delivery routes in transport logistics [8-12]. Moreover, route optimization has generally been carried out using classical methods of discrete optimization for small-scale transport logistics problems using historical GIS data. It is also worth noting that one of the most promising directions involves utilizing Galileo GNSS data. Indeed, Galileo PPP and/or Galileo RTK/RTN technologies offer several advantages over GPS technologies. These include higher positioning accuracy, improved signal penetration, and greater compatibility and integration with other GNSS systems, including GPS [13-14]. However, under current conditions, GNSS technologies present several limitations for solving DVRP. For instance, GNSS remains less effective compared to road IoT sensors in urban canyons with complex configurations or tunnels due to multipath signal propagation caused by reflections from structures. Additionally, GNSS PPP requires a relatively long data initialization time (up to 20 minutes [13]), which currently prevents its application for real-time dynamic routing tasks in scenarios involving complex traffic conditions.

In recent years, the use of VANET network systems has played an important role in improving the road safety, enhancing the efficiency of transport logistics systems, and providing convenient services for participants in the transport process (see, for example, [15-17]). Vehicular Ad-Hoc Network (VANET) is a self-organizing network used in the transport environment for communication between vehicles

(V2V technology), between a vehicle and roadside infrastructure (V2I technology), and with personal mobile devices [15]. It is assumed that to solve transport logistics problems, travelers have access to real-time traffic information through V2V/V2I infrastructures and make route decisions accordingly [16-17]. However, VANET presents unique challenges due to its dynamic nature, requiring significant efforts to address. These challenges are related both to data transmission routing in a highly dynamic V2V/V2I information environment and to dynamic routing of logistics paths in a non-stationary URN environment while ensuring stable VANET communication [15-17].

One of the most promising approaches to monitoring the current state of the URN remains the use of traffic sensors combined with IoT and AI technologies. Unlike many other approaches, this one ensures high accuracy in measuring traffic flow dynamics and allows for the real-time data collection and analysis. However, in recent years, the use of traffic data on URN sections obtained through various types of traffic sensors has been relatively less represented in the literature compared to, for example, GIS-derived data (see [18-20]). For instance, authors of [18] presented an intelligent dynamic routing system using machine learning technology to predict speed profiles based on historical traffic data from road sensors. The system includes neural networks for short-term speed prediction depending on the day of travel, congestion levels, and distances between individual sensor locations along the route. In [19], an effective dynamic routing strategy is proposed, which includes the possibility of continuously updating travelers' knowledge of travel times considering adaptive traffic signal control in real transport networks. In [20], a calibration model of an urban network consisting of two mini-roundabouts and one uncontrolled intersection is presented. The simulation process is carried out in the SUMO environment, and traffic data and speeds are collected from recorded video for the selected URN.

Thus, as the analysis shows (see, for example, [18-20]), dynamic routing of logistics flows, considering the non-stationary dynamics of traffic flows on URN sections, has mainly been performed using historical IoT data. The possibility of dynamic route optimization for freight delivery based on real-time IoT and BD data processing about non-stationary traffic dynamics on URN sections was first demonstrated in [21-22]. However, in [21], the computational operations during route optimization using the API from Bing and VRP_Spreadsheet_Solver are too slow, preventing the full real-time implementation. In [22], the input data block for dynamic traffic characteristics on URN sections is limited to manual entry. Moreover, simulation studies on route optimization are conducted within the framework of solving the symmetric dynamic traveling salesman problem (DTSP), which does not fully account for the real configuration and traffic conditions on URN sections [22].

Based on the conducted analysis, the current understanding of dynamic routing of logistics flows under the rapidly changing and non-stationary dynamics of traffic flows on URN sections using IoT data from traffic sensors is incomplete and imperfect. This is primarily due to the limited availability of traffic information from a larger number of different types of sensors and the limited coverage areas of these sensors, which requires the installation of a large number of sensors to obtain a complete picture. However, the installation of modern sensors, such as digital video cameras with computer vision, is not always possible due to their high cost. These reasons also partly explain the lack of adequate adaptive methods for the discrete route optimization for freight delivery (see, for example, [23-26]), which would simultaneously consider the actual configuration of the URN and the real dynamics of traffic flows on its sections during transportation in real-time.

In this context, the objective of this work was to develop an online dynamic routing method for urban transport logistics under limited traffic information. This method is based on the use of current IoT traffic data from sensors on URN sections and averaged historical data on traffic flow parameters obtained from sensors on representative sections of homogeneous clusters that make up the URN.

3 Research methodology

3.1 Description of the method

When modern means of measuring dynamic parameters (intensity q, and density ρ, average speed $\langle v \rangle$) of traffic flow (TF) are available on URN sections, optimizing routes in real-time does not present fundamental difficulties [20]. However, in the real-world operation of URNs, particularly in Ukrainian cities, relatively inexpensive traffic sensors are typically used, which measure only some TF parameters, such as TF intensity q values on specific sections over certain time intervals. This limitation prevents obtaining fully accurate information about the dynamic state of the URN and, consequently, restricts the ability to perform adequate real-time routing under complex traffic conditions. It is important to note that for most AI methods used in routing problems, the optimization parameters are time and/or distance of the route, which often requires knowledge of the average speed $\langle v \rangle$ on URN sections. Therefore, solving the problem of adequate simulation of the dynamic routing processes under limited information about TF dynamic parameters on network sections at specific times is relevant.

A method for online dynamic routing in urban transport logistics under limited traffic information is proposed. This method is based on the use of current IoT data on TF intensity (q) from traffic sensors on URN sections and averaged historical data on TF parameters (q, ρ, $\langle v \rangle$) obtained from traffic sensors on representative sections of homogeneous clusters that form the URN.

In the first stage, it is proposed to establish a rational TF monitoring network on the URN (see section 3.2) by implementing a step-by-step iterative procedure to identify representative elementary sections within specific homogeneous URN clusters [27-28]. It is recommended to place the traffic sensors that measure dynamic TF parameters (q, ρ, $\langle v \rangle$) on these sections. Accordingly, traffic sensors that measure TF intensity q in real-time are placed on other URN sections.

The formation of a rational TF monitoring network on the URN is based on the assumption that within the studied URN, there is always a certain number of homogeneous URN clusters, where the static and dynamic properties of TF formation on these sections are similar. This means that the TF dynamics across all the modes of its formation, and consequently the shape of the curves representing the relationship $q = q(\langle v \rangle)$ have qualitatively identical characteristics for all sections within a homogeneous URN cluster, differing only in their quantitative values of q and $\langle v \rangle$. Additionally, this means that the normalization coefficients for formation $q = q(\langle v \rangle)$ or a set of sections within a specific URN cluster remain constant. Thus, knowing these normalization coefficients, one can construct the relationship curves $q = q(\langle v \rangle)$ for each section of a homogeneous cluster. Then, using experimentally measured data (q, ρ, $\langle v \rangle$) obtained from sensors on a representative section of the cluster and experimental data q obtained from sensors on other sections of this cluster, it is possible to construct a family of calibration curves $q = q(\langle v \rangle)$ for all the sections of each homogeneous URN cluster. Subsequently, for each calibration curve, the values of $\langle v \rangle$ can be determined based on the known experimental data q. The procedure for constructing such a family of calibration curves is described in section 3.3.

Section 3.4 presents the results of developing an adaptive dynamic routing system for urban transport logistics tasks under limited traffic information. This system implements the procedure for simulating online optimization with dynamic route updates for freight delivery to destinations using a selected AI method of discrete optimization. The system allows simultaneous consideration of the actual URN configuration and the real TF dynamics on its sections during transportation. The optimization problem is solved using an example of the asymmetric dynamic traveling salesman problem (DTSP), where the URN is represented as a weighted bidirectional graph [1]. The graph nodes correspond to delivery points, and the weights of the graph edges are assigned relative discrete values according to the optimization criterion. For instance, this could be the distance between graph nodes, the average travel time or speed, fuel consumption, transportation cost, ecological characteristics, etc. The cost matrix for such a graph contains indirect elements, such as the set of weights corresponding to a specific set of URN section characteristics that the vehicle sequentially overcomes between delivery points. The system enables the construction and dynamic updating of the graph based on real-time TF dynamic parameters obtained from traffic sensors.

For online discrete route optimization with dynamic updates within the DTSP task, a modified version of the classic ant colony optimization (ACO) algorithm was used [29]. Here, it is possible to fix the optimal configuration of a partially traversed route before automatically updating the graph weights based on changes in the dynamic characteristics of URN sections. To achieve this, the algorithm introduces Pre_k - list of graph edges that ant k is required to traverse, disregarding the probabilistic rule of the classical ant colony algorithm. Specifically, while at vertex i of the graph, ant k moves to vertex j if $(i,j) \in Pre_k$; otherwise, the next vertex is determined by the probabilistic rule.

The choice of the ACO modification (ACO_{mod}) for solving urban transport logistics tasks in this work is due to several reasons. First, ACO and its modifications are more versatile compared to most other AI optimization methods (see, for example, [22-23, 25]). This allows for solving routing problems on URNs of the required scale [22]. Moreover, ACO and its modifications generally have higher performance [22-23]. Additionally, the optimization mechanisms in ACO and its modifications are similar to the dynamics of TF, especially in high-density modes. Indeed, according to Boris Kerner's theory [30], the observed phase transition effects between different TF states are due to the manifestation of synergistic self-organization effects resulting from non-equilibrium non-stationary TF dynamics. Similarly, the path optimization process in ACO occurs due to the self-organization effects of ant colony agents during food search and delivery [29]. It is worth noting that such synergistic effects are observed in nonlinear non-equilibrium dissipative systems of various physical natures (see, for example, [31-33]). Thus, the use of ACO_{mod} allows for the simulation of the route optimization processes with dynamic updates in real-time, considering the actual TF dynamics on the transport network sections.

3.2 Formation of a rational traffic flow monitoring network

The primary goal of forming a rational traffic monitoring network is to ensure, on the one hand, the acquisition of reliable information about the current state of the URN and, on the other hand, to reduce the volume of observations required to monitor the dynamics of TF on URN sections.

In this work, the formation of such a monitoring network is based on the assumption outlined in section 3.1. It is proposed to form a rational TF monitoring network on URN sections for the Kyiv city by implementing a step-by-step iterative procedure to identify the representative elementary sections within specific homogeneous URN clusters using the k-means clustering method [27-28]. On these sections, it is recommended to place expensive traffic sensors that can fully measure the main dynamic characteristics of TF (average speed $\langle v \rangle$, intensity q, density ρ). On other sections, it is sufficient to place inexpensive sensors that measure TF intensity q.

The formation of homogeneous clusters that comprise the URN is carried out according to certain individual and group structural characteristics of streets and roads, in stages, with different numbers of steps in the partitioning of the URN, separately for each category of streets and roads (according to DBN B.2.3-5:2018) [34], until the minimum discrepancies between the values of the analyzed structural characteristics of URN elements in each formed cluster are achieved. Group and individual structural characteristics for each URN element are determined based on the magnitude of their impact on traffic parameters. The following are considered as group structural characteristics:

- The implemented traffic scheme concerning permitted directions of movement (one-way or two-way traffic);
- Parameters of the transverse profile of the roadway (number of lanes, lane width, etc.);
- The density of traffic signal regulation (the ratio of the number of traffic lights on each street to its total length).

This division is due to the fact that the impact of road conditions on the main TF parameters is often decisive, as the more frequently road conditions change along a street, the more complex the interaction between vehicles in the TF becomes.

At the same time, it should be noted that in this work, URN elements with a traffic signal regulation density not exceeding 0.5 were classified into separate clusters. This allowed for consideration of the impact of such traffic control devices as traffic lights on the dynamics (character) of TF.

The individual structural characteristics chosen is the parameters of the longitudinal profile of the roadway (length, area, slope, etc.).

The iterative procedure for determining representative sections involves the following sequential steps:

- dividing URN into elements (streets and roads) by categories according to the current classification of streets and roads;
- dividing the elements (streets and roads) into elementary sections with fixed structural features that define the nature and parameters of traffic flow distribution within URN;
- forming homogeneous groups of elementary street and road sections with similar group structural features;
- establishing the nature and parameters of the distribution of individual structural features within the formed homogeneous groups of elementary street and road sections;
- identifying representative elementary sections of streets and roads based on the distribution parameters of the individual structural features within the formed homogeneous groups.

In the first step of implementation of the step-by-step iterative procedure for finding the representative sections, the URN is divided into groups of elements - streets and roads that belong, in accordance with the current classification of roads, to the following categories: city-wide main streets, district main streets, and local streets and roads. Then, within each of the formed groups of streets and roads, the URN elements are divided into sections characterized by specific group and individual structural features. A section is defined as a part of a street or road of a particular category between the two closest intersections, within which the structural configuration of the section remains consistent.

In this context, it should be noted that the functioning of traffic flows on the streets and roads of a city is influenced by various factors, with road conditions often playing a decisive role in the main parameters of traffic flow. The more frequently road conditions change along a street, the more complex the interaction of vehicles in the traffic flow becomes. Therefore, in light of these circumstances, the decision was made to consider the city's streets and roads as a set of elementary sections.

The structural features of the elementary sections of URN were determined using the cartographic web service Google Maps [35], specifically through the combined use of this web service, its Measure Distance tool, and the regulatory document DBN B.2.3-5:2018, which specifies the parameters of various types of cross-sectional profiles of roadways for streets and roads in settlements according to their category.

After this, homogeneous groups (clusters) containing elementary sections with common group structural features are formed. As a result of the step-by-step clustering, city-wide main streets were

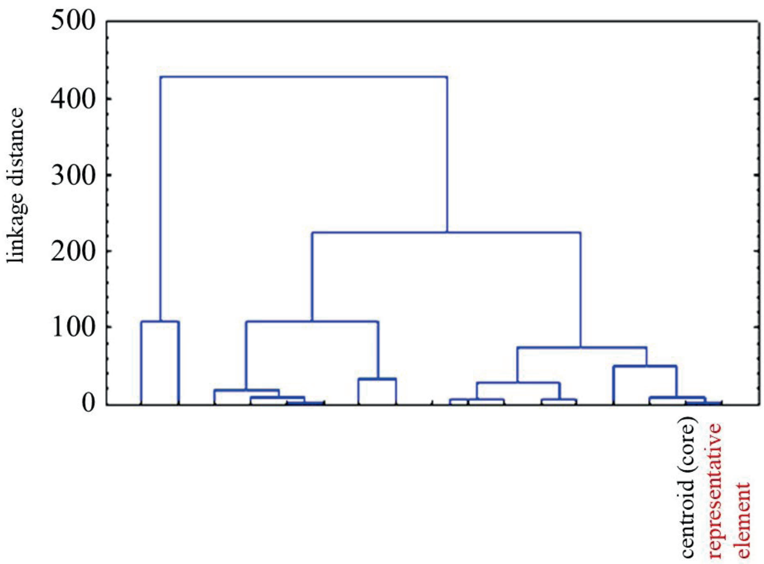


Figure 1 *Dendrogram for Identifying a Representative URN Element (Example of a Homogeneous Cluster)*

divided into three clusters, district main streets into eight clusters, and local streets and roads into 32 clusters.

In the next step, within each cluster, the average statistical values of each individual structural characteristic are established, which serve as the centers of gravity (centroids) of the formed homogeneous groups. These centroids are used to identify representative URN elements through hierarchical cluster analysis (see Figure 1).

In this case, within each cluster, as the representative section is selected the one where TF dynamics are observed in all its modes (free flow, synchronized flow, moving wide cluster, congestion) with the maximum distribution of TF intensity throughout the day.

As a result of the research, conducted within the framework of the method for forming a rational traffic flow monitoring network, representative sections were identified for the studied URN, which allowed for the creation of a rational monitoring network of TF. The dimensionality of this network is approximately 15 times smaller than the dimensionality of the studied set of URN elements. The reduction in dimensionality of URN is achieved by representing the structure of URN as separate clusters, the elements of which are characterized by a high degree of similarity in terms of relevant structural features and the subsequent identification of typical elements (within each formed cluster), whose structural features, in general, provide a comprehensive understanding of both the structural state of the elements within each cluster and URN of the city as a whole. This is justified by, among other things, the main assertion of cluster analysis, which states that each cluster, as a result of such a multidimensional statistical procedure, consists of similar objects, while objects from different clusters are significantly different from each other.

As a result of the clustering, the identified elements of the studied urban road network (URN) of Kyiv reflect (in terms of structural features) 85% of the city-wide main street network, 90% of the district main street network, and approximately 80% of the local street and road network.

3.3 Evaluation of dynamic characteristics of traffic flow on urban road network sections

The relationships between the intensity q and density ρ is considered as a function of the average speed $\langle v \rangle$ of a vehicle in the domain of dense traffic flow, where, according to [26], the regimes of synchronized movement and wide moving vehicle clusters are realized. Here, the average speed $\langle v \rangle$ of the traffic flow (TF) becomes variable. The evaluation of TF dynamic characteristics on URN sections using data from the rational monitoring network was carried out under the assumption described in section 3.1. In this case, the values of the dynamic characteristics $\langle v \rangle$ are determined using the data obtained from the calibration curve of the q versus $\langle v \rangle$ relationship (see 3.1). The procedure for constructing a family of calibration curves for the set of sections within each homogeneous cluster of the studied URN is described below. To do this, the functional relationship $q = q(\langle v \rangle)$ is considered in the form of a polynomial:

$$q(\langle v \rangle) = a_0 + a_1\langle v \rangle + \cdots + a_n\langle v \rangle^n \quad (1)$$

and limit it to the cubic term.

Strictly speaking, Equation (1) should be considered at specific values of $\rho(\rho = const)$. However, in general, especially in the domain of dense TF, $\rho \neq const$, so there is a more complex dependence $q = q(\langle v \rangle)$ [30]. Nonetheless, for simulation process, it is sufficient to consider the dependence in this approximation, as it qualitatively captures the main features of TF behavior in the high-density region (synchronized flow, wide moving cluster, congestion) [30].

The following TF characteristics are introduced for a representative section *r* belonging to homogeneous cluster j : $\langle v \rangle_{rj}$ is the average speed of vehicles in the TF on section *r* of cluster *j* of the URN; $q_{rj} = \frac{N_{rj}}{\Delta t_{rj}}$ (vehicles/hour) is the TF intensity (the number of vehicles passing through a specific cross-section of section *r* during the measurement time Δt_{rj}, normalized to 1 hour); $\rho_{rj} = \frac{N_{rj}}{l_{rj}}$ (vehicles/km) is the TF density (the number of vehicles moving on section *r* of length l_{rj}, normalized to 1 km).

In the first stage, experimental measurements of q_{rj}, ρ_{rj}, $\langle v \rangle_{rj}$ are carried out on a specific URN section that is representative (*r*) for a specific *j* homogeneous cluster of sections of the studied URN. The experimental average values $\langle q \rangle_{rj} \pm \Delta q_{rj}$, $\langle v \rangle_{rj} \pm \Delta v_{rj}, \langle \rho \rangle_{rj} \pm \Delta \rho_{rj}$ are determined. Here, $\Delta q_{rj}, \Delta v_{rj}, \Delta \rho_{rj}$ are the corresponding confidence intervals of the standard deviation. Based on the obtained experimental data, the relationships $q_{rj} = q_{rj}(\langle v \rangle)$ are constructed. These relationships are approximated using polynomials in Equation (1) within the framework of regression analysis, determining the corresponding sets of coefficients $a_0, a_1, \dots a_n$ for the representative sections. Additionally, from the obtained polynomial relationships $q_{rj} = q_{rj}(\langle v \rangle)$, as well as from empirical data, the values $\langle v_{\min} \rangle_{rj}, q_{rj}(\langle v_{\max} \rangle)$, $\langle v_{rj}(q_{\max}) \rangle, q_{rj}(\langle v_{\min} \rangle)$, $(q_{\max})_{rj}$, $q_{rj}(\langle v \rangle = 0)$ are determined. The latter value corresponds to a traffic jam. Based on this data, normalization coefficients are formed, which characterize the shape of the curves of the $q = q(\langle v \rangle)$ relationship on the corresponding *i* sections of homogeneous cluster *j* of the URN. Namely:

$$k_{qj} = \frac{(q_{\max})_{rj}}{q_{rj}(\langle v_{\min} \rangle)}, l_{qj} = \frac{(q_{\max})_{rj}}{q_{rj}(\langle v_{\max} \rangle)}, \\ m_{qj} = \frac{(q_{\max})_{rj}}{q_{rj}(\langle v \rangle = 0)}. \tag{2}$$

Here, the normalization coefficients are determined based on the corresponding TF intensity values in the representative area *r* of cluster *j*: $(q_{\max})_{rj}$ is the maximum value of TF intensity; $q_{rj}(\langle v_{\max} \rangle)$ is the TF intensity when the vehicle is moving at the maximum speed $\langle v_{\max} \rangle$; $q_{rj}(\langle v_{\min} \rangle)$ is TF intensity when the vehicle is moving at the minimum speed $\langle v_{\min} \rangle$; $q_{rj}(\langle v \rangle = 0)$ is TF intensity when the vehicle is stationary $(\langle v \rangle = 0)$.

According to the assumption introduced, within a certain URN cluster, the shapes of the $q = q(\langle v \rangle)$ and $\rho(\langle v \rangle) = \rho(\langle v \rangle)$ curves for all sections of this URN cluster are similar and may differ only in their numerical values of the TF dynamic characteristics corresponding to these curves. This means that the normalization coefficients for a set of sections within a specific URN cluster *j* are identical.

Then, for any section *i* of a specific URN cluster *j*, the numerical values of the polynomial coefficients in cubic approximations $a_0{}^*, a_1{}^*, a_2{}^*, a_3{}^*$ for $q^*{}_{ij} = q^*{}_{ij}(\langle v \rangle)$ of section *i* can be determined by solving a linear system of three equations (3).

Here, $(q_{\max})_{ij}$ is the maximum TF intensity on section *i* of cluster *j* of the URN; $q_{ij}{}^*(\langle v_{\min} \rangle) = \frac{(q_{\max})_{ij}}{k_{qj}}$ is the TF intensity corresponding to $\langle v_{\min} \rangle$ on section *i* of cluster *j*; $q_{ij}{}^*(\langle v_{\max} \rangle) = \frac{(q_{\max})_{ij}}{l_{qj}}$ is the TF intensity corresponding to $\langle v_{\max} \rangle$ on section *i* of cluster *j*. The values $(q_{\max}{}^*)_{ij}, q_{ij}{}^*(\langle v_{\min} \rangle), q_{ij}{}^*(\langle v_{\max} \rangle)$ are determined from the results of averaging the corresponding historical data over specific time intervals. In this case, the zero-order polynomial coefficient $a_0 = \frac{(q_{\max}{}^*)_{ij}}{m_{qj}}$ (the constant term in each equation of system - Equation (3)). After determining the polynomial coefficients $a_0{}^*, a_1{}^*, a_2{}^*, a_3{}^*$ according to Equation (3), the functional relationship $q^*{}_{ij} = q^*{}_{ij}(\langle v \rangle)$ is constructed for each section *i* of the corresponding cluster *j*.

Thus, as a result of this procedure, a family of calibration curves of the approximated relationship $q = q(\langle v \rangle)$ is formed on the URN sections for the entire set of homogeneous clusters that make up the studied URN.

Then, the procedure for simulation online discrete optimization with dynamic route updating is carried out using the selected AI method based on IoT data regarding *q*, obtained in real-time from each section of the studied URN. Here, during the optimization based on the time criterion, the calibration curves of the approximated relationship $q = q(\langle v \rangle)$ are used

$$\begin{cases} \frac{(q_{\max}{}^*)_{ij}}{k_{qj}} = a_3{}^* \langle v_{\min} \rangle_{rj}^3 + a_2{}^* \langle v_{\min} \rangle_{rj}^2 + a_1{}^* \langle v_{\min} \rangle_{rj} + \frac{(q_{\max}{}^*)_{ij}}{m_{qj}} \\ (q_{\max}{}^*)_{ij} = a_3{}^* \langle v_{rj}(q_{\max}) \rangle^3 + a_2{}^* \langle v_{rj}(q_{\max}) \rangle^2 + a_1{}^* \langle v_{rj}(q_{\max}) \rangle + \frac{(q_{\max}{}^*)_{ij}}{m_{qj}} \\ \frac{(q_{\max}{}^*)_{ij}}{l_{qj}} = a_3{}^* \langle v_{\max} \rangle_{rj}^3 + a_2{}^* \langle v_{\max} \rangle_{rj}^2 + a_1{}^* \langle v_{\max} \rangle_{rj} + \frac{(q_{\max}{}^*)_{ij}}{m_{qj}} \end{cases} \tag{3}$$

to determine the average TF speed $\langle v \rangle$ on the URN sections at specific moments in time. Then, the time to traverse each section i of cluster j is determined as $t_{ij} = \frac{l_{ij}}{\langle v \rangle_{ij}}$, where $l_{ij}, \langle v \rangle_{ij}$ are the length and average TF speed on section i of cluster j, respectively.

It is also worth noting that certain difficulties arise in determining $\langle v \rangle_{ij}$ from the calibration curve, as the same intensity value may correspond to two different $\langle v \rangle_{ij}$ values. To avoid this ambiguity, it is necessary to use the results of historical data on density ρ versus average speed $\langle v \rangle$ obtained on representative sections, or the results of real-time traffic observation analysis on the corresponding URN sections at specific times of the day.

3.4 Adaptive system for dynamic routing under limited traffic information

An adaptive system for dynamic routing of freight delivery is understood as an information system designed to re-optimize the delivery route in real-time as the state of the URN changes due to changes in TF characteristics on URN sections during the freight delivery process [11].

The system considers the freight delivery route optimization problem as an asymmetric dynamic traveling salesman problem (DTSP) represented as a weighted bidirectional graph in the context of the URN (see section 3.1). The general scheme of the system operation is shown in Figure 2.

In this case, the route optimization process is performed based on either distance or time criteria. For distance optimization, it is sufficient to use the structural data of URN sections. For time optimization, the system uses input data from the structural parameters of URN sections and the $\langle v \rangle$ values obtained directly from traffic sensors on representative sections, as well as from the family of calibration curves $q = q(\langle v \rangle)$ for other sections within each homogeneous URN cluster (see sections 3.1-3.3).

As shown in Figure 2, the system allows the user to input a set of delivery points and depot. The system then constructs a weighted bidirectional graph, where the nodes correspond to the delivery points and the depot. Each edge of the graph consists of a sequence of URN sections; whose traversal determines the optimal route between the corresponding pair of delivery points at a specific time of day. Each such URN section in the sequence is characterized by a

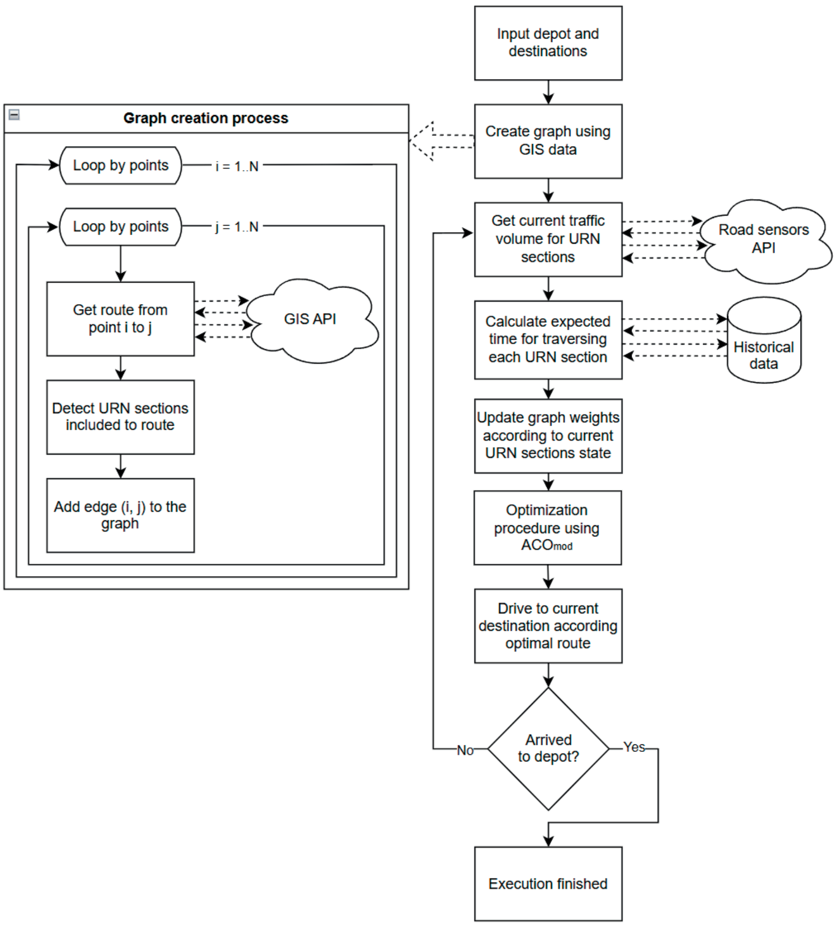


Figure 2 *Flowchart of the adaptive system for dynamic routing of freight delivery within the DTSP problem using the data on changing TF characteristics on URN sections*

certain identifier (road name), length, number of lanes, and traffic direction. In the proposed system, the creation of such a graph is based on GIS data. As shown in Figure 2, for each pair of points (*i, j*) system queries GIS to retrieve the route from point *i* to *j* including a sequence of URN sections in the route and preprocesses this information for subsequent use in graph updates. This data can be obtained using the Routes API service of Bing Maps [36].

After the graph is formed, a procedure is performed to update the graph according to the current state of the URN at a specific time of day. The update procedure involves obtaining the real-time data on the current TF intensity from traffic sensors located on the corresponding URN sections for each section that characterizes each edge of the graph. Using this data and the family of calibration curves $q = q(\langle v \rangle)$ constructed based on historical data on URN characteristics for representative sections of homogeneous clusters, the current average speed of TF on each URN section is determined in the corresponding traffic direction. Using the current speed values on the URN sections and the structural parameters of each section, the expected time to travel the corresponding section is calculated. Ultimately, this allows determining the expected time to traverse each graph edge as the sum of the expected times to traverse the sequence of URN sections that characterize the corresponding graph edge (see Figure 2). Thus, the weights of the edges of the updated graph are characterized by the expected traversal time of each edge, taking into account both the current TF dynamics and the actual URN configuration.

After updating the graph, the freight delivery route optimization procedure is carried out using the modified ant colony algorithm ACO_{mod} (see section 3.1, Figure 2). According to the determined optimal route, the user is directed to the next delivery point.

Upon the user's arrival at this point, the next graph update is performed according to the current URN state. After that, the route re-optimization procedure is carried out using ACO_{mod} on the updated graph. The proposed ACO_{mod} implementation allows fixing the optimal configuration of the partially traversed route before updating the graph, as well. Thus, within the proposed adaptive dynamic routing system, the route re-optimization procedure is carried out until the user is directed back to the depot after completing deliveries to all the specified points.

4 Results and discussion

For the simulation studies, 19 points on the URN of Kyiv were selected (numbered from 0 to 18), corresponding to the addresses of branches of the Ukrainian postal operator "Nova Poshta" [37]. Figure 3 shows the location of delivery points on the Kyiv map. The task was to find the optimal time-based route for a vehicle departing from the depot (point 0) on September 25, 2023, at 07:30:00, delivering goods to points 1-18, and returning to the depot.

The simulation studies were conducted with the following assumptions:

- The type of delivery route is a circular route with sequential delivery of goods;
- The date and time of day are taken into account, but the unloading time at delivery points, the nomenclature, weight, and volume of the cargo are not considered;
- Each edge of the graph corresponds to a fixed sequence of URN sections, describing the optimal path between each pair of delivery points;
- Changes in the expected travel time between nodes depend on current changes in TF characteristics on URN sections;
- Graph updates and route re-optimization are performed while the vehicle is at a delivery point.

To perform the dynamic routing of the delivery process, a basic implementation of the proposed adaptive system was developed on the .NET 6 platform using the C# programming language. The studies were conducted on equipment with an Intel(R) Core(TM) i5-8400 CPU @ 2.80GHz processor, 16 GB of DDR4 RAM, and running Windows 10. The studies showed that the initial construction of the graph with 19 nodes using GIS data took an average of 18.11 seconds, updating the graph based on current information from the traffic sensors took 594 ms (excluding the time to receive information from the traffic sensors), and finding the optimal solution for the graph with 19 nodes by performing 1000 iterations of ACO_{mod} took an average of 2.67 seconds.

The input data array for the dynamic TF characteristics was formed using the q, ρ and $\langle v \rangle$ data obtained from field experiments conducted on representative sections, and the q data obtained in real-time from traffic sensors located on the sections of the studied URN. This is due to the fact that Flir Traficam 2 sensors [38], which are currently used on the URN sections of Kyiv, measure only TF intensity ρ in real-time with a discretization of 2 minutes. Therefore, to construct a family of calibration curves of the approximated $q = q(\langle v \rangle)$ relationship on URN sections for the entire set of homogeneous clusters, field experiments were conducted to determine q, ρ and $\langle v \rangle$ on the representative sections of each URN cluster. During the working days from September 11, 2023, to September 15, 2023, the corresponding values of q, ρ and $\langle v \rangle$ were measured. Averaging was carried out over five measurements. As an example, Figure 4 shows graphs of the dependence of average intensity and average density on the average speed of TF for a representative URN section - Brovary Avenue, exit (Chernihiv direction), which belongs to a homogeneous cluster of the city-wide main streets.

As can be seen from Figure 4(a), a single intensity value can correspond to two different speed values: the left-hand wing of the curve corresponds to dense traffic, and the right-hand wing to free flow. The current traffic mode is determined based on historical data on traffic flow density in similar time periods relative to the current one for the representative sections of homogeneous clusters.

Table 1 presents the traffic flow characteristics of some URN sections used in the simulation studies. The column "Time" specifies the time at which the traffic data was recorded. For each URN section,

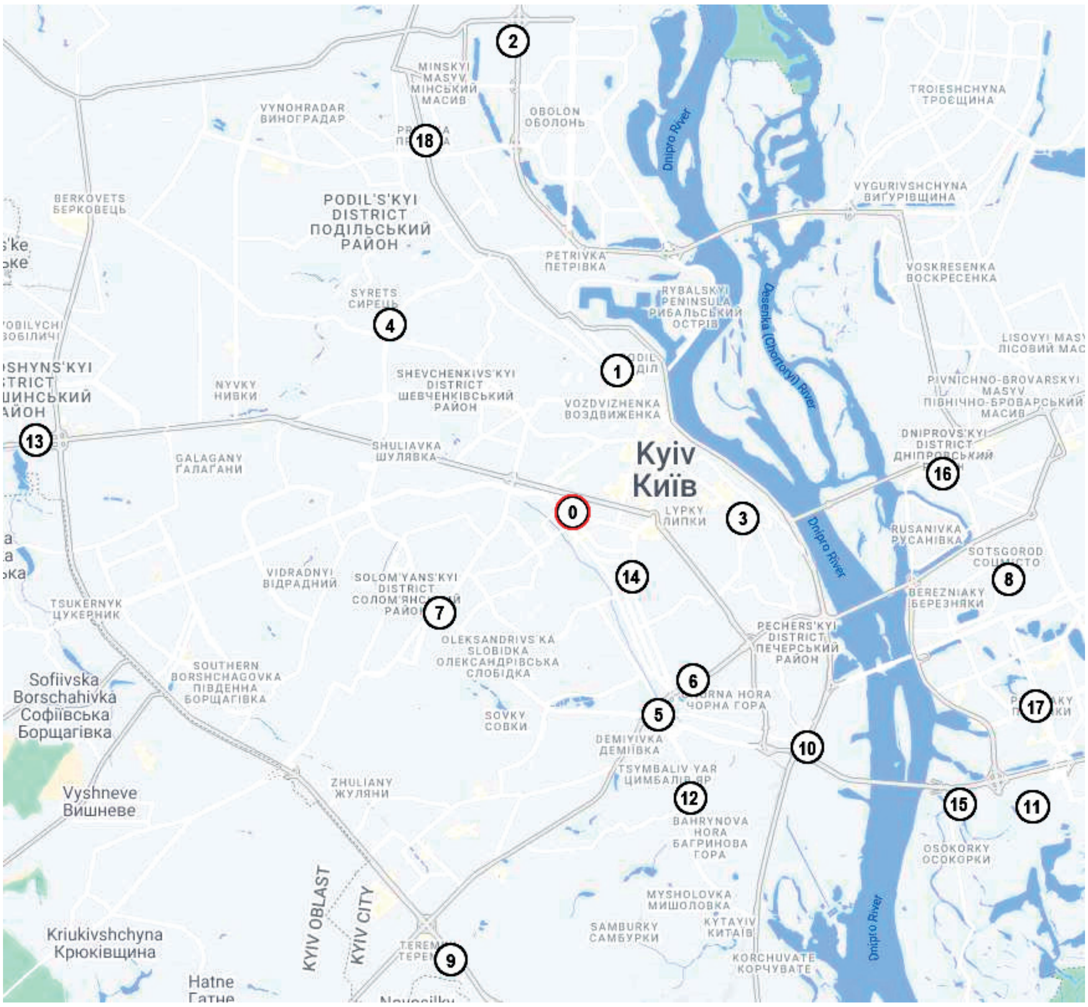
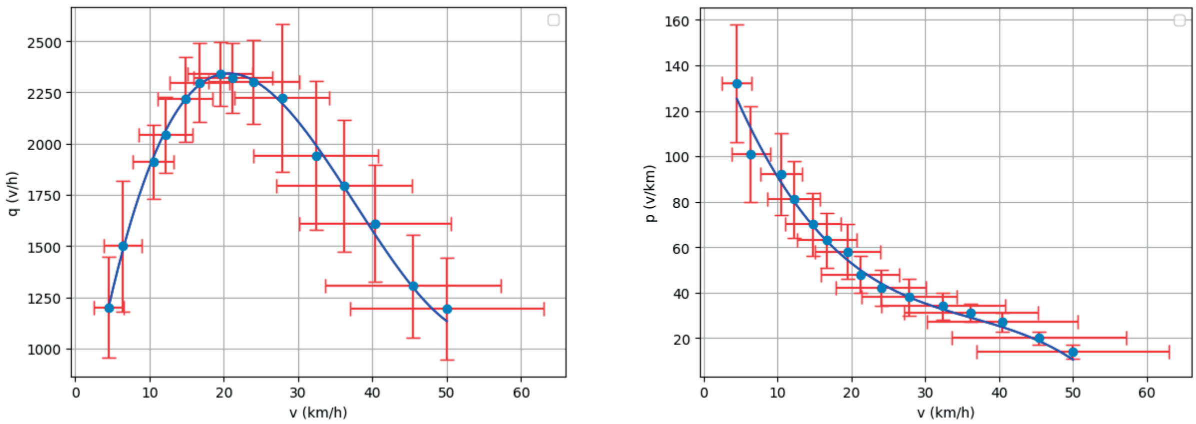


Figure 3 *Locations of the depot (0) and delivery points (1, …, 18) on the map of Kyiv*



(a) *(b)*

Figure 4 *Graphs of the dependence of average intensity (a) and average density (b) on the average speed of traffic flow based on field experiments: points represent the average values of the TF dynamic parameters; line segments indicate confidence intervals* two sub-columns are provided: q is experimental traffic flow intensity (vehicles per hour, v/h); $\langle v \rangle$ is average traffic flow speed (kilometers per hour, km/h) calculated based on the intensity. The included URN sections, with the moving direction specified in brackets, are as follows: Section 1 is Beresteiskyi Avenue (SE), Section 2 is Avtozavodska Street (SE), Section 3 is Akademika Zabolotnoho Street (SE), Section 4 is Akademika Zabolotnoho Street (NW), Section 5 is Petra Hryhorenka Avenue (SE), Section 6 is Nauky Avenue (SE).

Table 2 presents the results of the simulation study of dynamic freight delivery routing to the specified points of the "Nova Poshta" postal operator (some re-optimization steps that did not result in route reconstruction are not shown). The column "Current time" contains the current time of day; the column "Proposed route" contains the current optimal delivery route, with the current delivery point where re-optimization is performed marked with an asterisk (*); the column "Optimal route expected time" contains the expected time to complete the optimal route in seconds within the DTSP, obtained from the corresponding optimization results; the column "Current" contains the expected time of the current optimal route at the time of re-optimization; the column "Previous" contains the expected time of the optimal route obtained from the previous re-optimization, but for the current dynamic state of the URN; the column "Initial" contains the expected time of the optimal route obtained from the optimization at the time of departure from the depot, but for the current dynamic state of the URN. In parentheses is the part of the route that is rebuilt as a result of re-optimization.

As seen in Table 2, during the simulation studies using the proposed method of online dynamic freight delivery routing, several effects related to the rebuilding of the optimal route were observed. For example, significant route rebuilding occurs at the times 07:55:20, 08:04:05, and 09:01:28. Additionally, in all the cases, a significant increase in delivery time for the initial configuration of the optimal route is observed at the current times of day compared to

***Table 1** Traffic flow characteristics of some URN sections used in simulation studies*

Time	Section 1		Section 2		Section 3		Section 4		Section 5		Section 6	
	q	$\langle v \rangle$	q	$\langle v \rangle$	q	$\langle v \rangle$	q	$\langle v \rangle$	q	$\langle v \rangle$	q	$\langle v \rangle$
07:30:00	3246	32	1465	36	2190	23	1752	37	673	50	500	50
07:55:20	2488	41.5	2237	19.5	2340	23	1758	37	659	50	675	50
08:13:20	1895	47	2366	19	2322	23	1650	9.5	840	5	683	50
08:37:27	2164	44.5	2777	19	2328	23	1968	14	779	4	930	39
09:01:28	2336	43	1735	30.5	1896	34	1992	14.5	866	47	810	43.5
09:18:01	2222	44	1915	26	1968	32	2022	15	953	44.5	765	46
09:34:39	1667	49	1388	37.5	2286	23	1842	12	913	45.5	908	39.5
09:48:22	3132	34	1414	37	2238	23	1854	12	973	44	818	43.5
10:07:39	3094	34.5	1067	48	1975	32	1598	40	773	50	882	40.5
10:21:01	2993	36	1272	40	1873	34.5	1707	38	986	43.5	720	50

***Table 2** Results of dynamic freight delivery routing in the URN of Kyiv*

Current time	Proposed route	Optimal route expected time, s		
		Current	Previous	Initial
07:30:00	0*1-18-2-4-7-13-9-5-12-10-15-11-8-17-16-3-6-14-0	10390	-	-
07:40:14	0-1*18-2-4-13-9-5-7-12-10-15-11-(17-8)-16-3-6-14-0	10486	10525	10525
07:55:20	0-1-18*2-4-13-(9-12-10-15-17-11-8-16-3-6-5-7-14)-0	10438	10486	10525
08:04:05	0-1-18-2*4-13-(9-14-3-16-15-11-17-8-10-6-12-5-7)-0	12632	17696	15663
08:13:20	0-1-18-2-4*13-9-14-3-16-15-11-17-8-10-6-12-5-7-0	11845	11845	13477
08:23:13	0-1-18-2-4-13*9-14-3-16-15-11-17-8-10-6-12-5-7-0	11887	11887	14136
08:37:27	0-1-18-2-4-13-9*14-3-16-15-11-17-8-10-6-12-5-7-0	12220	12220	15015
08:52:17	0-1-18-2-4-13-9-14*3-16-15-11-17-8-10-6-12-5-7-0	11800	11800	14727
09:01:28	0-1-18-2-4-13-9-14-3*(10-15-11-17-8-16-6)-12-5-7-0	10732	10832	12590
09:13:05	0-1-18-2-4-13-9-14-3-10*15-11-17-8-16-6-12-5-7-0	10704	10704	13252
10:21:01	0-1-18-2-4-13-9-14-3-10-15-11-17-8-16-6-12-5-7*0	10746	10746	16742
10:29:06	0-1-18-2-4-13-9-14-3-10-15-11-17-8-16-6-12-5-7-0*	-	10746	16742

the time of the initial optimal route built at 07:30:00 (see Table 2). These effects are due to a significant increase and redistribution of the number of vehicles on the URN sections at the corresponding times of day. Re-optimization allows for finding such optimal routes in real-time, leading to a significant reduction in delivery time to the correspondent points. For example, at 08:04:05, the initial optimal route expected time is 15663 seconds, while the current optimal route expected time is 12632 seconds. This means that after re-optimizing the route at delivery point 2 (see Table 2), the delivery time is reduced by Δt =15663 s - 12632 s = 3031 s, representing an economic effect of 19.4%.

Thus, the results of the studies conducted within the framework of the online dynamic routing method under the limited traffic information indicate the potential of using the proposed method for urban transport logistics in conditions of complex traffic.

5 Conclusions and recommendations

A method for online adaptive dynamic routing of freight delivery in cities under limited traffic information has been proposed. This method is based on the use of real-time IoT data on traffic flow intensity from the traffic sensors on URN sections and averaged historical data on TF parameters (speed, density, intensity) obtained from traffic sensors on representative sections of homogeneous clusters that make up the URN. An algorithm for forming a rational TF monitoring network in the URN has been developed based on the k-means clustering method to identify homogeneous clusters that constitute the URN and the representative sections within them.

An automated adaptive information system for dynamic routing in urban transport logistics under limited traffic information has been developed. This system includes a procedure for online optimization with dynamic route updating using a modified AI ant colony algorithm. The system allows for simultaneous consideration of the actual URN configuration and the real TF dynamics on its sections during transportation. The optimization problem is solved using an asymmetric DTSP, where the URN is represented as a weighted bidirectional graph.

The results of simulation studies, conducted on the example of Kyiv's URN, indicate the potential of the proposed method for use by transport companies and authorities in urban transport logistics under complex traffic conditions.

In the future, the results of the research could contribute to a promising approach to reducing the carbon footprint. The method facilitates the integration of environmental considerations, particularly through the route optimization based on criteria such as fuel consumption and CO_2 emissions. Aligned with corporate sustainability goals, this creates opportunities to integrate reporting and decarbonization mechanisms into the transport logistics. Furthermore, the proposed method could serve as a foundation for developing a dynamic routing system that considers not only transportation costs and pollutant emissions but the economic incentives for minimizing emissions, such as carbon credits, as well. This would provide a comprehensive approach to enhancing the efficiency of transport logistics and reducing its environmental impact.

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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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