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THE OPTIMIZATION OF CARGO DELIVERY PROCESSES WITH DYNAMIC ROUTE UPDATES IN SMART LOGISTICS

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The object of research is the processes of transport logistics management under the influence of non-stationary factors of different nature on the functioning of street-road networks (SRN) in cities. The task of dynamic routing at large and variable loading of SRN sections is solved by managing the processes of cargo delivery in real time within the framework of the implementation of the Smart Logistics concept.

Simulation studies of cargo delivery routing with dynamic real-time route updating using a modified ant colony algorithm and data on the dynamics of traffic flow (TF) were conducted using an SRN in the city of Kyiv as an example. Here, experimental data were obtained using motion sensors of intelligent transport systems. During the optimization, current data were used acquired online within the framework of the Internet of Things technology, as well as historical data obtained over past periods of time and averaged using Big Data (BD) technology. Route optimization at each stage of real-time updates was achieved using a modified ant colony algorithm. This method has a sufficiently high optimization performance and makes it possible, unlike many other intelligent methods, to directly take into account the non-stationary dynamics of TF within SRN. It is shown that the use of properly averaged BD historical data allows for more efficient planning of transport routes.

The simulation studies indicate the possibility of using the proposed approach by transport companies and authorities to solve the problems of managing logistics flows in an automated mode under conditions of complex, unpredictable traffic

Keywords: dynamic routing, intelligent methods, smart logistics, Internet of Things, big data

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1. Introduction

The globalization of the modern world economy, increased intensity, and circulation of flows of goods objectively require intellectual support for managing these processes in real time.

Along with this, accelerated motorization under the conditions of lagging behind the development of street-road networks (SRNs) of large cities leads to a number of negative consequences. Among the main consequences is a sharp decrease in the efficiency of transport infrastructure (significant unevenness of transport load, decrease in the speed of traffic flows (TFs), congestion, traffic accidents, etc.) [1]. This, in particular, causes significant delays in the transportation of goods, which leads not only to time loss but also to significant economic losses.

In general, this situation leads to a significant decrease in the sustainable development of cities and settlements as one of the important factors for the sustainable development of society.

The analysis shows [2] that under modern conditions the most effective solution to these problems, including the issue of logistics process management, is the implementation of the Smart Logistics concept. Accordingly, the implementation of this concept is associated with the design, implementation, and application of intelligent transport systems (ITS). The effective use of modern innovative information and telecommunication technologies of the Internet of Things (IoT), blockchain (BC), big data (BD), and artificial intelligence (AI) plays an important role here.

It is with the effective use of ITS that the improvement of safety and efficiency of transport systems, including SRN, management of logistics operations, mobility, and comfort of movement of road users, is mainly associated with.

Meanwhile, the use of intelligent information technologies for the effective organization, optimization, and management of logistics processes in real time with a large and variable workload on SRN is fragmented and imperfect. This is primarily due to the lack of adequate methods for discrete optimization of routes for the delivery of goods with the dynamic updating of these routes under the influence of changes in the dynamics of TF along the SRN sections during transportation. The use of such methods will allow transport companies to solve a set of tasks for the delivery of goods depending on the needs of users, estimating the generalized costs of transportation according to various criteria (for example, travel time or the length of the optimal route). In addition, the use of adequate methods of route optimization will solve the social problem of increasing the sustainability of the functioning and development of cities, reducing the environmental burden on SRN.

In this regard, solving these problems is extremely relevant both in fundamental and applied scientific research.

2. Literature review and problem statement

The Vehicle Routing Problem (VRP) is a well-known NP-complex problem of discrete (combinatorial) optimization. Its main idea is to plan routes for a fleet of vehicles to service a certain number of spatially spaced points (customers, logistics centers, warehouses, etc.) at the lowest cost [3].

It should be noted that until recently, the problems of discrete optimization and route planning for logistics systems were in most cases solved using appropriate methods for static VRP, in particular, within the framework of the traveling salesman transport problem (TSP). Here, the process of sending deliveries is carried out on pre-built, fixed routes without any deviations [4, 5]. Static VRPs with certain approximations include VRP with load limits (capacitated VRP-CVRP), VRP with multiple depots (MDVRP), and VRP with fixed time windows (VRPTW). In VRPTW, we have fixed or slightly variable properties of the system during the service time [6, 7].

Meanwhile, in real conditions, when delivering goods to destinations, it is necessary to take into account a large number of parameters associated with uncertainty, dynamism, and other actual constraints.

Moreover, modern processes of globalization, acceleration of scientific and technological progress, increase in the intensity of circulation of flows of goods and provision of services, objectively lead to the need for intellectual support for the management of these processes in real time.

Accordingly, for many transport and logistics companies operating in a rapidly changing market environment and under the conditions of non-linear-dynamic functioning of SRN, reducing the cost of distribution of goods delivery is an acute problem. Most of these companies should be able to work under strict time constraints while ensuring guaranteed quality of service, continuous adaptation to changes in the external environment. At the same time, the environment in which they work is often uncertain, and therefore the time factor plays a decisive role.

The static routing approach prevents the company from creating a route based on real-time information. It also provides no means of communication between managers and drivers, resulting in delayed delivery of goods, economic losses, business and customer losses.

Accordingly, a family of tasks called dynamic VRP (DVRP) should take into account the time factor or other variable factors, that is, variations in time and services on the road, if possible, online. This allows drivers to dynamically change their route while driving. These factors are due to dynamic time windows for pickup and delivery; non-stationary dynamics of TF along SRN sections; capacity (carrying capacity) of vehicles; size and composition of the fleet; uncertainty in orders, delivery time, demand, and quantity of customers, etc. [8].

The elimination of a complex of these problems in the management of logistics processes under modern conditions is associated with the implementation of the concepts of Smart Mobility and Smart Logistics, namely, the development, implementation, and effective use of ITS [2]. Here, it is possible to solve a set of combinatorial problems within DVRP, in which at least one of the parameters of the system is variable, provided that modern innovative information and communication technologies, namely, the Internet of Things (IoT), blockchain (BC), big data (BD), and artificial intelligence (AI) are employed [2].

In particular, the use of IoT technologies in ITS makes it possible to receive information about changes in the state of the external environment in real time. To solve discrete optimization problems within DVRP, heuristic or metaheuristic AI methods are mainly used, which have a sufficiently high computation speed. These include the ant colony algorithm (ACA), genetic algorithm (GA), evolutionary arson simulation method (ESA), taboo search (TS), dynamic adapted particle swarm optimization (DAPSO), and variable neighborhood search (VNS) [9].

As the analysis shows, a large number of works, where problems are solved within the framework of DVRP, consider solving the problems of optimizing the routing of vehicles with dynamic time windows (DVRPTW). In [10], a multicriteria problem of routing vehicles with flexible time windows (MOVRPFlexTW) based on the hybrid ACA algorithm is presented, where the vehicle fleet can serve multiple customers earlier and later than the required time with a given tolerance. Here, the optimization criteria are minimizing the overall transportation costs of transporting goods and maximizing overall customer satisfaction. At the same time, customer requests regarding the delivery time of the goods may change during the movement of the vehicle. In this task, the customer satisfaction associated with the route is represented as a convex function. This function depends on the time of arrival of the vehicle. This flexibility allows the logistics company to save the cost of distributing goods while ensuring customer satisfaction. However, the influence of TF dynamics on the routing process in [10] is also not taken into account. Paper [11] solved the problem of routing vehicles with multiple time windows (VRPMTW) using a hybrid algorithm consisting of GA and VNS algorithms, within certain constraints (load constraints, time windows, etc.). Here, GA represents a common framework for three evolutionary heuristics using three global strategies with multiple starts: disruption and reproduction, genetic crossing of the best parents, and random restart. The proposed hybrid algorithm uses route data received from motion sensors. This data is used to control operators to find the optimal route depending on the selected time window allocation. Study [12] simulated the routing of vehicles with diversification of arrival times for cash-on-the-go (CIT) companies using VRPMTW with no waiting time to develop routes with unpredictable times. Here, CIT transfers valuable goods to banks, ATMs, and shops. For security reasons and in accordance with legal regulations, these companies must use different routes. Since CIT orders arrive on short notice, CITs must plan current routes depending on the nature of the orders. The problem in [12] is modeled as a DVRPMTW routing task in which multiple time windows are built in the time sliding horizon settings by removing the arrival intervals that were on previous routes. However, both in [11] and [12], the dynamics of TF were not taken into account when solving DVRPMTW.

Recently, the solution to DVRP problems for e-commerce has become of great relevance, where it is necessary to take into account a large number of parameters associated with uncertainty, dynamism, and other real constraints [10]. The solution to such multiparameter optimization problems is often associated with the use of hybrid methods, which, in particular, combine artificial neural network (ANM) methods, both machine self-learning methods and discrete optimization AI methods (genetic, evolutionary, swarm, etc.). At the same time, ANMs are used either to predict certain transport processes, or to adjust the heuristic parameters of intelligent optimization methods in order to improve them when optimizing the route, taking into account the influence of the external environment. For example, in [13], an improved ant algorithm is proposed by updating its parameters using deep learning of ANM models using real-time traffic data. This makes it possible to find a more correct optimization of the path for the distribution of logistics under difficult road conditions. However, as noted by the authors in [13], due to realistic conditions and difficulties with data collection, it is not possible to demonstrate the advantages of the proposed route optimization algorithm under the influence of complex traffic.

Thus, as shown by the above review [10–13], a quite large number of works consider DVRP without taking into account the dynamics of TF. Relatively recently, research has expanded to solving DVRP problems, which take into account ITS data on the state of TF dynamics in real time at SRN sites or averaged data on its previous states. Thus, in [14], route optimization by distance and time was carried out using various AI methods using historical ITS data on TF dynamics. Paper [15] presents a model of urban demand for freight transportation, in which the authors try to estimate the flows of tours on the basis of route calculations using ITS data. The model in [15], based on the theory of entropy maximization, takes into account a set of estimates of cargo flight generation, a set of traffic calculations for certain time intervals, and the total cost of freight traffic in the network. Study [16] describes an agent-based simulation model combined with optimization procedures designed to predict the behavior of drivers and delivery persons delivering goods to customers in central areas of the city. The model makes it possible to optimize the routes of couriers by minimizing the cost of driving and walking using real-time information from ITS sensors about the availability and employment of loading areas.

A unified formulation within the DVRP of the TSP problem, taking into account information about the dynamics of TF along SRN sections is reported in [17]. These data are obtained from ITS motion sensors both in real time and averaged historical data from the corresponding sensors. Within the framework of this model, appropriate simulations of discrete optimization of the route by time with dynamic updating of the sequence of customer visits while driving were carried out. Such updating of the route occurs due to current changes in the congestion of sections of SRN, affecting the time of delivery of goods along the previously established route. However, in [17], the route optimization was time-only using an open-source spreadsheet solution (API from Bing and VRP_Spreadsheet_Solver) to solve VRP [4]. At the same time, the execution of computational operations when optimizing the route using this package is too slow [4]. This does not allow us to fully implement the Smart Logistics concept and receive relevant information under a mode close to real time.

So, based on the review of [10–17], the idea of dynamic routing of logistic flows in real time under conditions of fast-paced, non-stationary dynamics of TF are incomplete and imperfect. In particular, this is due to the lack of scientific substantiation of the choice of effective methods of discrete optimization of routes for the delivery of goods with the dynamic updating of these routes under the influence of changes in the dynamics of TF in the sections of SRN during transportation.

3. The aim and objectives of the study

The aim of this work is to devise an approach to solving the optimization problem of cargo delivery with dynamic updating of the route in real time using data on the dynamics of TF in the SRN sections obtained using ITS motion sensors. The results of such studies should allow evaluating the usefulness of incorporating ITS capabilities emanating from IoT, BD, and AI technologies to improve routing in urban areas.

To accomplish the aim, the following tasks have been set:

– to conduct, within the framework of TSP, simulation studies of route optimization according to distance and time criteria for various cargo delivery scenarios using current data and BD historical data on TF dynamics, using an SRN fragment in the city of Kyiv as an example;

– to determine the conditions for the expediency of using the contribution of BD historical data on the dynamics of TF to the process of forecasting and planning the route under conditions of complex traffic.

4. The study materials and methods

The object of our research is the processes of transport logistics management under the influence of non-stationary factors of different nature on the functioning of SRN in cities. The task of dynamic routing at large and variable workload on SRN sections is solved by managing the processes of cargo delivery in real time within the framework of the implementation of the Smart Logistics concept.

The main hypothesis of the research assumes the possibility of solving the problem of dynamic routing within the Smart Logistics concept by using modern innovative IoT, BD, and AI technologies.

To carry out discrete optimization of the cargo delivery route within TSP, the street and road network is represented as a bidirectionally directed weighted graph. In the nodes of such a graph there are points of delivery of goods (warehouses, supermarkets, etc.) with the help of a vehicle moving through the sections of the SRN in the city. The edges connect each pair of nodes of the graph and correspond to sections of the SRN. The weights of the edges are generally attributes of the value of the path traveled while moving along the edges of the graph [17]. These can be distances between nodes (delivery points), average speeds, average travel time along SRN sections, fuel consumption, or the cost of travel of a vehicle in the traffic flow in certain parts of the network. Optimization of the vehicle route is carried out under certain assumptions (restrictions) and according to the criterion corresponding to one or another attribute.

As shown by the review of literary data [9–13], the most common methods of route optimization for solving DVRP are AI methods. However, most of these intelligent algorithms have certain limitations in their use. So, the application, for example, of the genetic algorithm GA, neural network method ANM leads to correct results in the case of solving high-dimensional routing problems. This is not always applicable to solving transport problems of the city. For example, the task of delivering small-scale cargo within the city often contains 10–50 destinations. In addition, in most studies, the use of these methods is associated with the use of historical data, which is not always acceptable under difficult conditions of traffic flow dynamics in urban road networks [14–16].

Accordingly, the classic ant ACA algorithm and most of its modifications are more universal. This makes it possible to solve routing problems on road networks of cities of required dimensionality [18]. In addition, as shown in [14], ACA has a better optimization effect for DVRP within TSP (lower time and greater solution accuracy) compared to ESA and GA.

In [18], a modified ant colony algorithm ACAmod was proposed, in which, unlike the ACA and all its known modifications, ant agents along the graph can move asynchronously at certain (even different) speeds. It is also possible to record the results of optimizing a partially traveled path to optimize the further route when changing the edge length of the graph while driving. This makes it possible, in particular, to carry out simulations of optimization and forecasting of the route in real time, taking into account the real dynamics of TF in sections of the transport network. Here, ant agents, as analogs of vehicles, move at appropriate speeds corresponding to the average speeds of TF in these areas [26]. In addition, paper [19] conducted simulation studies of discrete route optimization within TSP using various AI methods: GA, ESA, ACA, and ACA mod [18]. Here, the route optimization was carried out by time and distance on the example of a wide range of test tasks, where the number of nodes varied from 30 to 152. It is shown in [19] that ACAmod is the most effective method of optimizing logistics flows in Smart Logistics among the presented AI methods [18]. Its use makes it possible to reduce the time of finding the optimal solution by an average of 15 % and get better results of path optimization in most cases.

Based on the above review, in our paper, ACAmod was chosen [18] to conduct discrete route optimization with its dynamic updating, taking into account the non-stationary dynamics of TF along SRN sections.

Simulation studies of route optimization by the ACAmod method according to the distance and time criteria for the delivery of goods within TSP, using IOT and BD data on the dynamics of TF, were conducted on the basis of the approach proposed in [17]. Here,

$$X_{hk}^{fo}\left[\tau,t\right]=\xi X_{hk}^{BD,fo}\left[\tau,t\right]+\left(1-\xi\right)X_{hk}^{IoT}\left[\tau,t\right], \qquad (1)$$

where $X_{hk}^{fo}\left[\tau,t\right]$ is the X_{hk} value of the attribute h of the cost of the path k traversed during movement along the edges of the graph, which is predicted in our work by the results of optimization using the ACAmod method applying the observed current and historical data on the state of the dynamics of TF along SRN sections, obtained in the framework of IoT and BD technologies, respectively, at time τ of days of week t;

$X_{hk}^{BD,\,fo}\left[\tau,t\right]$ is a corresponding value of the attribute X_{hk}, predicted by the results of optimization by the ACAmod method using historical data obtained as part of BD technology at time τ day of the week $\tilde{t}$. For example, data from the database of the intelligent decision-making system of the automated traffic management system ITS is used, which stores averaged observed data for past periods of time (day of the week, week, month, year, etc.);

$X_{hk}^{IoT}\left[\tau,t\right]$ is a corresponding value of the attribute X_{hk}, predicted by the results of optimization by the ACAmod method using the observed current data obtained, for example, from IoT motion sensors in real time (at time τ of the day of the week t);

$\zeta\in\,]0,1]$ is the weight factor of the value $X_{hk}^{BD,\,fo}$.

Thus, conducting simulation for different values of ζ according to (1) will allow comparing the simulation results for different routing scenarios with dynamic updating of the route under the influence of changes in the dynamics of TF along SRN sections. Accordingly, the analysis of the results of such simulation studies will assess the feasibility of using historical data and the importance of using current data on the dynamics of TF, obtained in real time, to solve this class of DVRP.

When conducting simulation studies, the following factors were taken into account:

– type of cargo delivery route – roundabout with sequential delivery of goods;

– date and time of delivery, time of unloading and loading of cargo at delivery points, nomenclature, and volume of ordered cargo, address of the consumer's location;

– the nomenclature and volume of goods for each client was specific, which did not depend on the day of delivery;

– along all SRN sections, the movement of the vehicle is carried out within the framework of a two-lane two-way TF;

– in each set of sections of the SRN, corresponding to a certain edge of the graph, there will always be alternative travel options;

– the mass of cargo transported from the manufacturer to each consumer (supermarket) is not taken into account when optimizing the delivery route;

– changes in average travel time and average travel speed mainly depend on changes in traffic flow dynamics modes, and also contain stops or delays due to the actions of traffic lights regulating signals;

– availability of free vehicles in the depot, fuel consumption for the delivery of goods, availability of special equipment for the delivery of perishable goods;

– availability of the required quantity of goods at the distribution center (warehouse of the enterprise);

– the occurrence of congestion and other complications of traffic along SRN sections that affect the speed of movement of TF is not excluded.

Simulation studies of cargo delivery route optimization, within TSP, using IOT and BD data on TF dynamics, using the ACAmod method [18], were conducted using an SRN fragment in the city of Kyiv as an example (Fig. 1). This fragment was selected taking into account the factors above. The search for the optimal route of cargo delivery was carried out from the distribution center (1) to the locations of customers (2–10). The company must serve customers during the working day. The attributes of the cost of the path, which were optimized, in contrast to [17], were the length and time of the route visited for all customers. The location of cargo delivery points is shown in Fig. 1.

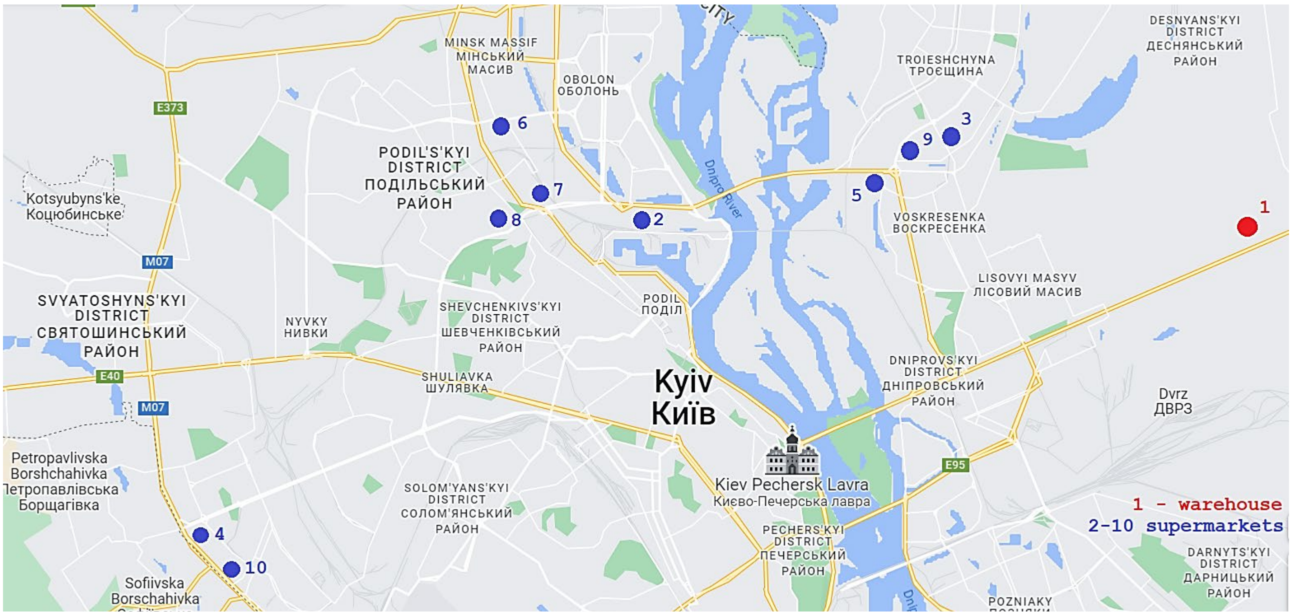

Fig. 1. Location of delivery points on the map of the city of Kyiv

Appropriate simulation studies were conducted for different scenarios corresponding to different SRN states and different optimization attributes (route time and length). When conducting simulation studies at each stage of optimization, the number of iterations was 500, the route optimization time was quite small and fluctuated in the range (20–800 ms). Accordingly, the total optimization time with dynamic route updates in the distribution center and all consumer locations for IoT and BD data ranged from 1 s to 9 s.

So, taking into account the results of a comparative analysis of other intelligent methods of discrete optimization, given above, we can assume that solving DVRP in complex traffic is possible using a modified ACAmod [18]. Moreover, it should be noted that within the framework of the ACAmod method [18], unlike many others [14–16], it is possible to directly take into account the non-stationary dynamics of TF in SRN. All allows for dynamic routing and forecasting of logistics flows in real time under conditions of complex, often unpredictable traffic.

Experimental data on the intensity of TF were obtained with the help of digital cameras of motion sensors ITC-2 and ITC-2 MINI by SWARCO and ITMC companies with a discreteness of 2 min. ITC-2 and ITC-2 Mini are designed with the ability to use under any climatic conditions in compliance with the technical requirements of DSTU 4157-2003. These devices have a modular structure and are configured for all types of intersections. With TCP/IP or 3G modem, they can be directly connected to various types of control and monitoring systems. The installed sensors make it possible to obtain information about the intensity and composition of traffic flow through the RS485 interface: motorcycle, car, truck, public transport, etc.

The corresponding motion sensors were located at all investigated areas of the SRN in the city of Kyiv. Our work used the database for November 2022.

With the help of nonlinear regression analysis using experimental data in each of the studied cases, the dependence of the average values of velocities on the intensity of TF at each site of SRN was established according to [20]. The intensity of the traffic flow was measured for specified periods (2 minutes) and, subsequently, was reduced to a normalized observation time [20]. The regression coefficients were determined by statistical processing of experimental data, using the known provisions of mathematical statistics [20]. Accordingly, the lengths of SRN sections between delivery points were determined using the Google map API. The average values of the speeds and lengths of sections of SRN were used to determine the average travel time along each of these sections.

5. Results of route optimization with dynamic real-time update using the city of Kyiv as an example

5. 1. Results of simulation studies for different cargo delivery scenarios

5. 1. 1. Optimization results for a static network (scenario 0)

The corresponding data on distances (in km) and travel time (in minutes) along SRN sections between delivery points for the free state of TP are given in Table 1.

Table 1

Distances and travel time between cargo delivery points for the free state of TF along SRN sections

Parameter	Time, min.										
	0	1	2	3	4	5	6	7	8	9	10
	1	0	20	19	34	20	28	23	30	18	38
	2	17	0	18	24	6	7	2	28	10	18
	3	16	15	0	19	12	25	20	17	16	26
	4	28	20	16	0	30	25	22	2	34	7
Distance, km	5	17	5	10	25	0	13	8	34	4	24
	6	23	6	21	21	11	0	4	29	17	19
	7	19	2	17	18	7	3	0	25	12	16
	8	25	23	14	2	28	24	21	0	37	8
	9	15	8	13	28	3	14	10	31	0	28
	10	32	15	22	6	20	16	13	7	23	0

According to the results of optimization by time and length, it was revealed that in both cases the sequence of visits to delivery points is the same: 1–3–8–4–10–6–7–2–5–9–1. The length of the route is 82 km, travel time – 98 minutes.

5. 1. 2. Route optimization results, obtained in real time (scenario 1)

The optimization was carried out taking into account the time of customer service at delivery points (cargo unloading – cargo loading) within the limitations given in the research methodology. Table 2 gives the values of customer service time at the relevant delivery points.

Table 2

Customer service time at delivery points (hh:mm)

Customer								
2	3	4	5	6	7	8	9	10
0:21	0:19	0:26	0:17	0:22	0:19	0:22	0:20	0:19

When carrying out route optimization using BD historical data (scenario 1a), historical data were selected averaged per month (November 2022) for each moment in observation time (discreteness, 2 minutes) of each day of the month at each site of the SRN fragment. After that, based on these data, the time route was optimized with its dynamic updating at each cargo delivery point where the vehicle is located according to the results of the previous optimization step. At the same time, during the planning procedure for further optimal route, BD historical data were selected for the time of location of the vehicle at the corresponding point. Table 3, as an example, gives the optimization results based on BD historical data averaged for Wednesday of the four weeks in November: 02.11.22, 09.11.22, 16.11.22, 23.11.22. For comparison, Table 3 also shows the optimal route determined by scenario 0 of free movement of cars along SRN sections. Table 3 gives the average departure times from the distribution center (1) and from the corresponding delivery points; travel time; working hours. At the same time, travel time determines the time of full movement of the vehicle along the optimal route for the state of SRN at appropriate intervals. Working time includes travel time and service time at delivery points (Table 2).

Optimization of the route by time with its dynamic updating was carried out on the basis of IoT of current data obtained in real time, with a discreteness of 2 minutes (scenario 1b).

Here, the procedure for dynamically updating the optimal route is similar to the procedure described for BD on historical data. As an example, the corresponding results of optimization with dynamic updating of the optimal route based on IoT data obtained in real time on sections of the SRN fragment in the city of Kyiv are shown in Table 4 for Wednesday, 30.11.2022).

Table 4 indicates the time of departure from the distribution center (1) and from the corresponding delivery points; travel time; working hours on Wednesday (30.11.2022). Here, travel time determines the time of full movement of the vehicle along the optimal route for the state of the SRN at appropriate points in time.

Table 3

Results of route optimization with its dynamic updating based on BD historical data (averaging for 02.11.22, 09.11.22, 16.11.22, 23.11.22, Wednesday, working day) along the sections of an SRN fragment in the city of Kyiv

Departure time	Order of visits to customers	Travel time	Working hours
Average value	Scenario 0; 1–3–8–4–10–6–7–2–5–9–1	1:38:00	4:43:00
9:30	1–2–6–7–10–4–8–3–9–5–1	2:05:00	5:10:00
10:11	2–7–6–10–8–4–3–5–9–1	1:43:00	4:48:00
10:33	7–6–5–9–3–8–4–10–1	1:44:00	4:49:00
10:59	6–9–5–3–4–8–10–1	1:48:00	4:53:00
11:36	9–3–8–4–10–5–1	2:05:00	5:10:00
12:15	3–5–10–8–4–1	2:16:00	5:21:00
12:44	5–10–4–8–1	2:30:00	5:35:00
13:30	10–4–8–1	3:07:00	6:12:00

Table 4

Results of route optimization with its dynamic updating based on IoT data obtained in real time (30.11.2022, Wednesday, working day) along the sections of an SRN fragment in the city of Kyiv

Departure time	Order of visits to customers	Travel time	Working hours
Average value	Scenario 0; 1–3–8–4–10–6–7–2–5–9–1	1:38:00	4:43:00
9:30	1–2–6–7–10–4–8–3–9–5–1	2:01:00	5:06:00
10:11	2–7–6–10–8–4–3–5–9–1	1:42:00	4:47:00
10:32	7–6–5–9–3–8–4–10–1	1:43:00	4:48:00
10:58	6–9–5–3–4–8–10–1	1:49:00	4:54:00
11:33	9–3–8–4–10–5–1	1:53:00	4:58:00
11:58	3–5–10–8–4–1	2:09:00	5:14:00
12:36	5–10–4–8–1	2:23:00	5:28:00
13:25	10–4–8–1	2:32:00	5:37:00

5. 2. Analysis of the contribution of historical data to the formation of the optimal route in real time

To assess the feasibility of using historical data BD and the importance of using current IoT data on TF dynamics, simulation studies of route optimization with dynamic updating according to (1) were carried out. As historical data BD, data on the dynamics of TF under scenario 1a were selected (averaging for 02.11.22, 09.11.22, 16.11.22, 23.11.22, Wednesday, working day). Accordingly, IoT data obtained in real time – according to scenario 1b (30.11.23). The values of the weight factor ζ varied from 0.9 to 0.1 in increments of 0.1. The results of the analysis are given in Table 5. It is revealed that the configuration of the optimal route with its dynamic update coincides throughout the studied time interval for all values x (Table 5). Accordingly, at ζ=0.4, deviations of BD data from IoT data are almost not observed for all optimization steps except the last, where the deviation is 9.86 %.

Similar results of the analysis of the contribution of historical data BD to the formation of the optimal route in real time were obtained for weekends. As an example, Table 6 gives data for the day of the week, Saturday, November 2022.

At the same time, already for ζ=0.7, deviations of BD data from IoT data are practically not observed in all cases. This testifies to the correct use of historical data BD here not only qualitatively (planning the correct optimal route to all points of delivery) but also quantitatively (time of delivery of goods to these points).

However, at the same time, the configuration and dynamics of the optimal route for weekends differ significantly from those obtained for working days (Tables 5, 6).

Also, an analysis of the contribution of historical data BD, averaged over a sufficiently long period of time, to the formation of an optimal route in real time was carried out. Here, as an example, Table 7 gives the results of the analysis for the historical data BD averaged for the week of 19.11.22–25.11.22.

In the case of incorrect selection of averaged BD data (Table 7), the DVRP solution may not always lead to adequate results, which is characterized by a deviation of the contribution of BD data to the formation of the optimal route.

Table 5

Results of the analysis of the contribution of historical data BD (averaging for 02.11.22, 09.11.22, 16.11.22, 23.11.22, Wednesday, working day) to the formation of the optimal route in real time (30.11.22, Wednesday, working day) according to (1)

Departure time	The order of visits to customers	The optimal route at every step of optimization					Deviation of the contribution of BD data to the formation of the optimal route according to IoT data		
		Route time, min.					$(t_{BD}-t_{IoT})/t_{IoT}$, %		
		IoT data (30.11), t_{IoT}	Historical data BD, t_{BD}	ζ/(1–ζ)			ζ/(1–ζ)		
				0.9/0.1	0.4/0.6	0.1/0.9	0.9/0.1	0.4/0.6	0.1/0.9
09:30	1–2–6–7–10–4–8–3–9–5–1	121	125	125	122	121	3.31	0	0
10:11	2–7–6–10–8–4–3–5–9–1	102	103	103	102	102	0.98	0	0
10:32	7–6–5–9–3–8–4–10–1	103	104	104	103	103	0.97	0	0
10:58	6–9–5–3–4–8–10–1	109	108	109	109	109	0	0	0
11:33	9–3–8–4–10–5–1	113	125	125	118	116	10.6	4.42	2.65
11:58	3–5–10–8–4–1	129	136	135	131	130	4.65	1.52	0.78
12:36	5–10–4–8–1	143	150	150	148	146	4.73	3.50	2.10
13:25	10–4–8–1	152	187	187	167	162	28.0	9.86	6.58

Table 6

Results of the analysis of the contribution of historical data BD (averaging for 05.11.22, 12.11.22, 19.11.22, day off, Saturday) to the formation of the optimal route in real time (26.11.22, day off, Saturday)

Departure time	The order of visits to customers	The optimal route at every step of optimization					Deviation of the contribution of BD data to the formation of the optimal route according to IoT data		
		Route time, min.					$(t_{BD}-t_{IoT})/t_{IoT}$, %		
		IoT data (26.11), t_{IoT}	Historical data BD (05.11, 12.11, 19.11), t_{BD}	ζ/(1–ζ)			ζ/(1–ζ)		
				0.9/0.1	0.7/0.3	0.1/0.9	0.9/0.1	0.7/0.3	0.1/0.9
09:30	1–9–5–2–7–6–10–4–8–3–1	106	102	102	105	106	3.77	0.94	0
09:49	9–5–2–7–6–10–4–8–3–1	104	101	102	104	104	1.92	0	0
10:15	5–2–7–6–10–4–8–3–1	104	102	103	104	104	0.96	0	0
10:37	2–7–6–10–4–8–3–1	102	99	99	101	102	2.94	0.98	0
11:00	7–6–10–4–8–3–1	103	102	102	103	103	0.97	0	0
11:23	6–10–4–8–3–1	105	101	102	104	104	2.86	0.95	0.95
11:58	10–4–8–3–1	106	104	105	106	106	0.94	0	0
12:27	4–8–3–1	106	104	105	106	106	0.94	0	0

Table 7

Results of the analysis of the contribution of historical data BD (averaged for the week of 19.11.22–25.11.22) to the formation of the optimal route in real time (day off, Saturday, 26.11.22)

Departure time	The order of visits to customers	The optimal route at every step of optimization			Deviation of the contribution of BD data to the formation of the optimal route according to IoT data				
		Route time, min.					($t_{BD}-t_{IoT}$)/t_{IoT}, %		
		IoT data (26.11), t_{IoT}	Historical data BD, (19.11.–25.11), t_{BD}	ζ/(1–ζ)			ζ/(1–ζ)		
				0.9/0.1	0.4/0.6	0.1/0.9	0.9/0.1	0.4/0.6	0.1/0.9
09:30	1–9–5–2–7–6–10–4–8–3–1	106	118	117	110	107	10.38	3.78	0.94
09:49	9–5–2–7–6–10–4–8–3–1	104	110	107	105	104	2.88	0.96	0
10:15	5–2–7–6–10–4–8–3–1	104	110	107	105	104	2.88	0.96	0
10:37	2–7–6–10–4–8–3–1	102	112	110	108	104	7.84	5.88	1.96
11:00	7–6–10–4–8–3–1	103	113	111	108	104	7.77	4.85	0.97
11:23	6–10–4–8–3–1	105	119	118	110	108	12.38	4.76	2.86
11:58	10–4–8–3–1	106	127	126	121	112	18.87	14.15	5.66
12:27	4–8–3–1	106	134	132	124	114	24.5	16.98	7.55

6. Discussion of research results on route optimization using Big Data and Internet of Things

As part of TSP, simulation studies of cargo delivery processes optimization with dynamic real-time route updating were carried out using data on TF dynamics along SRN sections obtained using ITS motion sensors. Solving such a DVRP under conditions of complex traffic along SRN is possible using modern AI methods of discrete optimization, in particular, modified ACAmod [18].

As as shown by Table 3, the time-optimized route based on historical data BD from the distribution center to customers at 9.30 am differs significantly from the optimal route under scenario 0. In addition, the travel time under scenario 1a is much longer than under scenario 0 (2 hours 5 minutes versus 1 hour 38 minutes, Table 3). This means that at 9.30 there is a significant unevenness of the transport load in the areas of the investigated SRN fragment with a significant increase along its individual sections. This leads to a significant restructuring of the optimal route in comparison with that for the free mode of movement of the vehicle, reducing the average speed of TF along certain sections of SRN. Further, at 10.30 in some areas, the load is significantly reduced, which leads to a slight restructuring of the optimal route but to a significant reduction in travel time (Table 3). Accordingly, at 12.15, due to a further significant change in the distribution of TF along SRN, a further significant restructuring of the optimal route takes place. This is accompanied by a certain increase in the time of full movement of the vehicle along the optimal route for the corresponding state of SRN (Table 3). Further procedure for updating the optimal route does not lead to its change, which indicates the invariability of the distribution of TF along SRN at this period of time. However, at 13.30, there is a significant overload of SRN with a significant increase in the travel time along the route (Table 3).

As shown by Table 4, the configuration of the optimal route obtained using real-time IoT and historical data BD averaged for the same day of the week during the corresponding month coincide. However, here, the time of delivery of goods at each step of updating the optimal route for IoT data is usually less than for historical data BD (Tables 3, 4). Our results of simulation modeling indicate that the use of historical data BD, averaged properly, makes it possible to qualitatively obtain an adequate configuration of the optimal route. Here, only certain deviations of the delivery time values from those received in real time are possible.

It should also be noted that the DVRP solution with dynamic updating of the route at the optimization stages presented in our work makes it possible to deliver goods along the fastest and most economical route, providing customers with timely delivery. For example, as studies show, the sequence of customer visits on the most optimal route of cargo transportation on working days with complex traffic along the SRN in the city of Kyiv as a result of a phased renewal of the route is 1–2–7–6–9–3–5–10–4–8–1 (Tables 3, 4). Here, in the case of routing with dynamic real-time update according to IoT data, the route length is 112 km, the route time is 152 minutes (Table 4). Accordingly, the sequence of customer visits when optimizing the route by distance under the mode of free movement of vehicles along SRN sections (scenario 0) is 1–3–8–4–10–6–7–22–5–9–1. The length of this route is 82 km. However, calculations of the travel time along the route of scenario 0 under conditions of complex traffic along SRN on 30.11.22, determined from the current IoT data on that day (Table 4), give a value of 254 minutes. Consequently, the implementation of DVRP with dynamic route update using IoT data and the corresponding method of real-time route optimization leads to a gain in time (254–152)=102 (min), which is 67.1 %.

The original results were obtained by analyzing the contribution of historical data BD to the formation of the optimal route in real time based on approach (1) [17]. In particular, it was found (Tables 5–7) that the configuration of our optimal route with its corresponding dynamic update completely coincides for the weekend (Saturday, 26.11.22) and does not fundamentally coincide with that for the working day of the week (30.11.23). At the same time, even on the day off, 26.11.22, the time of delivery of goods to the corresponding points for historical data BD differs markedly from that for current IoT data. This means that in this case, for correct quantitative estimates of forecasting the current dynamics of the optimal route, using historical data BD is impractical. Indeed, only at ζ=0.1 we obtain acceptable deviations of quantitative results of route optimization from those for IoT data obtained in real time.

Consequently, the use of historical data BD, properly averaged (Tables 5, 6), makes it possible to predict the optimal route at each stage of its update with a configuration that corresponds to the configuration obtained in real time when using IoT data. At the same time, deviations in the time of delivery of goods to the relevant points even under conditions of complex traffic (Tables 3–5), as a rule, are insignificant (Tables 3–6). In the opposite case, namely, the incorrect selection of averaged BD data, solving DVRP cannot always lead to adequate results (Table 7). Thus, the analysis of the contribution of historical data BD to the formation of the optimal route in real time based on approach (1) (Tables 5–7) indicates the possibility of using such data for forecasting and planning the route under conditions of complex traffic. This possibility may occur in the case of their proper averaging.

In general, the results of simulation studies within the framework of the advanced approach to solving DVRP in real time with dynamic updating of the route according to BD and IoT data, carried out in this work, indicate the possibility of performing one of the main tasks of Smart Logistics. This task is associated with the need to manage logistics flows under an automated mode under conditions of complex, non-stationary, often unpredictable traffic along SRN. Performing this task makes it possible to reduce the number of delivery errors, avoid last-mile complications, provide the customer with faster delivery, reduce fuel costs, reduce environmental pollution.

The use of properly averaged historical data BD within this approach also allows for more efficient planning of transport routes, ensuring the coordination of optimal delivery intervals for customers, minimizing the time and distance of the route.

In this work, dynamic updating of the route was carried out at the points of delivery of goods. Obviously, to implement the process of managing logistics flows under a continuous mode under conditions of complex traffic, further comprehensive research is needed to improve the tools for monitoring and processing data and methods for discrete route optimization.

In addition, the approach developed in this work can be the basis for the development of information technology for dynamic routing of freight transportation, taking into account non-stationary (real) dynamics of TF along the SRNs of large cities. This will expand the intellectual capabilities to support the adoption of effective decisions on the management of transport and logistics systems under difficult conditions of environmental influence.

Our simulation studies within the framework of the developed approach to solving the problem of dynamic routing indicate the possibility of its use by transport companies and authorities. They can be used to solve tasks of managing logistics flows in an automated mode under conditions of complex, often unpredictable traffic.

7. Conclusions

1. As part of the traveling salesman's task, simulation studies were carried out to optimize cargo delivery processes with dynamic updating of the route in real time. For this purpose, IoT and BD data on the dynamics of traffic flows along SRN were employed using the city of Kyiv as an example. Experimental data were obtained using motion sensors of intelligent transport systems. Solving such a DVRP under the conditions of non-stationary dynamics of TF along SRN is possible using modern intelligent methods of discrete optimization, in particular, the modified ant colony algorithm ACAmod.

According to the results of our research, it was revealed that with a significant and dynamic unevenness of the transport load along the sections of SRN, there is a significant restructuring of the optimal route in comparison with that for the free mode of movement of the vehicle. At the same time, the DVRP solution with dynamic route updating at each stage of optimization makes it possible to deliver goods along the fastest and most economical route, providing customers with timely delivery. Studies have shown that dynamic updating of the route using IoT data and the ACAmod optimization method under an online mode leads to a 70 % gain in time.

2. The results of simulation modeling of the contribution of historical data BD to the formation of the optimal route in real time indicate the possibility of assessing the feasibility of their use for forecasting and planning the route under conditions of complex traffic. It is shown that the use of properly averaged historical data BD within the framework of this approach allows for more efficient planning of transport routes, ensuring coordination of optimal delivery intervals for customers, minimization of time and distance of the route, etc.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

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