СИСТЕМНИЙ
АНАЛІЗ

UDC 004.942

S. RAKHMETULLINA
Non-profit joint stock company “D. Serikbayev East Kazakhstan Technical University”, Ust-Kamenogorsk, Kazakhstan, e-mail: *SRakhmetullina@edu.ektu.kz*.

G. ZHOMARTKYZY
School of Information Technologies and Intelligent Systems of D. Serikbayev East Kazakhstan Technical University, Ust-Kamenogorsk, Kazakhstan,
e-mail: *gzhomartkyzy@edu.ektu.kz*.

Iu. KRAK
Taras Shevchenko National University of Kyiv, V.M. Glushkov Institute of Cybernetics of the NAS of Ukraine, Kyiv, Ukraine, e-mail: *yuri.krak@gmail.com*.

A. KAMELOVA
D. Serikbayev East Kazakhstan Technical University, Ust-Kamenogorsk, Kazakhstan,
e-mail: *kamelova.ayaulim@gmail.com*.

DEVELOPMENT OF AN ALGORITHM FOR SOLVING AN ASYMMETRIC ROUTING PROBLEM BASED ON THE ANT COLONY METHOD

Abstract. One of the major problems of transport logistics is planning optimal delivery routes. Solving this problem leads to combinatorial optimizations that require complex computations. The present research considers an asymmetric problem of transport routing with a limitation of the carrying capacity of transport facilities, the duration of the route and a heterogeneous transport facilities fleet. An algorithm for solving the routing problem based on the ant colony method is proposed. The web application that has been developed implements the proposed algorithm for solving this problem. The obtained optimal routes were compared with the results of route building by other cartographic services. The proposed algorithm showed the best result.

Keywords: optimization, asymmetric routing problems, graph route search, web applications, ant colony method.

INTRODUCTION

Transport logistics, both for individual enterprises and for the country as a whole, plays an important part in the modern world. For enterprises or organizations engaged in the delivery or transportation of goods or cargo the correct organization of transportation processes affects not only the reduction of their shipment costs, but also an increase in the flow of customers due to the timely provided services. Therefore, optimization of transport logistics processes is and remains an urgent issue. One of the main transport logistics problems is the planning of optimal delivery routes. Its resolving leads to the need of investigating such a current in the field of combinatorial optimization as the Vehicle Routing Problem (VRP). VRP tasks, as a rule, are aimed at minimizing the distance, cost or time associated with transportation by means of finding the optimal order of customer visits for transportation facilities (TF). Due to the practical significance and at the same time significant complexity of these tasks, they attract special attention of researchers.

The classical formulation and algorithmic approach to solving a practical problem, the purpose of which was to build a route for the supply of gasoline from the main pipeline station to a large number of service terminals, was proposed in the paper [1]. Paper [2] describes the use of several TFs in the formulation of the problem; it also proposed a more efficient heuristic solution method based on a greedy algorithm. Currently there are many varieties of routing problems and formulation options that differ mainly in the various constraints imposed on the resulting solution. However, in many cases such models do not allow to simultaneously take into account multiple factors affecting the routing process. According to a new trend, research in this field seeks to describe multifactorial real-life situations, which leads to more complex and generalized variants of the transport routing problem.

To date, metaheuristics are actively used optimization methods in various fields, such as science, commerce and engineering [3–5] etc. The meta-heuristics of swarm intelligence have been subject to increased interest from researchers recently. In particular, papers [6, 7] deal with the possibilities of using swarm intelligence algorithms, namely the ant algorithm and the bee swarm algorithm for analysing data. Paper [8] proposes methods for solving the problem of TF routing using a mobile genetic algorithm, while investigations [9, 10] a combined method based on the ant algorithm is presented. It is worth noting the development and effective use of ant algorithms and combinatorial optimization for constructing routes not only for above ground vehicles, but for unmanned flying vehicles as well [11]. This paper proposes an algorithm based on the ant colony method for solving the complex problem of transport routing [12].

PROBLEM STATEMENT AND MATHEMATICAL MODEL

The statement of the problem proposed in this paper will allow taking into account additional conditions that may be quite significant in practice and may affect the quality of the resulting solution when searching for rational routes for a heterogeneous TF fleet. It considers the asymmetric problem of transport routing, which allows simultaneously taking into account such limitations as data asymmetry, TF load capacity, maximum route duration and heterogeneous TF fleet. Under current conditions, it is likely for companies concerned with transportation to have a large transport fleet with different classes of transport. In this connection, logistics operations in such companies require taking into account the characteristics of a particular transport facility. Although ignoring the differences in the characteristics of transport facilities would simplify the search for solutions by existing methods, this would not nevertheless correspond to real conditions. Therefore, in the proposed formulation, the problem must be solved taking into account the heterogeneity of the transport fleet, namely, different load capacities, while there is a fixed number of TFs of each type.

The assumption that the paths between points will be identical regardless of the direction of movement contradicts real conditions. In addition, the data provided by most of the common software tools allowing to automatically build routes between points takes into account the chosen direction. Therefore, despite the complexity, it would be advisable to consider an asymmetric problem, with the use of a directed graph for modelling.

The mathematical model of this problem is based on models of already known problems such as the asymmetric TF routing problem [13] and the routing problem of TFs with limited load capacity [14]. Let’s given a complete directed graph

$G=(A, E)$, with a set of vertices $A=\{0,1, \ldots, n\}$ and a set of arcs E. The vertex a_0 is the depot, the other vertices of the graph correspond to the points of consumption. For each customer, the demand value q_i is set, and for each TF v its load capacity Q_v is set. Each arc is associated with the values of input parameters characterizing the TF path: d_{ijv} is a distance between vertices (i, j) for TF v; t_{ijv} is a travel time between vertices (i, j) for TF v.

When choosing the parameters d_{ijv} and t_{ijv}, which characterize roads, real information about the path between two points provided by various software tools for routing is taken into account. It is assumed that information about roads is defined for different types of TFs, so an additional index corresponding to a specific TF type is used in the designation. If the TF fleet were homogeneous, then the input parameters and variables would be assumed to be the same for all v. The problem is solved using a set of logical variables $x_{ijv} \in X$, which correspond to the graph arcs, so that:

$$x_{ijv}=\begin{cases}1, & \text{if arc } (i, j) \text{ belongs to route } v, \\ 0, & \text{if arc } (i, j) \text{ does not belong to route } v.\end{cases}$$

If the total number of TFs is denoted by m, the number of delivery points (customers) by n, the amount of cargo delivered from the TF depot v to the ith customer by y_{iv}, and the maximum allowable duration of routes by T, then we present the asymmetric routing problem with a limited load capacity, the duration of the route and with a heterogeneous TF fleet in the form of minimizing the distance F:

$$F=\sum_{v=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ijv} x_{ijv} \rightarrow \min, \tag{1}$$

meeting the following conditions:

$$\sum_{i=0}^{n} \sum_{v=1}^{m} x_{ijv}=1, \quad j=1, \ldots, n; \tag{2}$$

$$\sum_{i=0}^{n} x_{izv}-\sum_{j=0}^{n} x_{zjv}=0, \quad z=0, \ldots, n, \quad v=1, \ldots, m; \tag{3}$$

$$y_{iv} \leq q_i \sum_{j=1}^{n} x_{ijv}, \quad i=1, \ldots, n, \quad v=1, \ldots, m; \tag{4}$$

$$\sum_{v=1}^{m} y_{iv}=q_i, \quad i=1, \ldots, n; \tag{5}$$

$$\sum_{i=1}^{n} y_{iv} \leq Q_v, \quad v=1, \ldots, m; \tag{6}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijv} x_{ijv} \leq T, \quad v=1, \ldots, m; \tag{7}$$

$$d_{ijv} \neq d_{jiv}; \tag{8}$$

$$t_{ijv} \neq t_{jiv}; \tag{9}$$

$$x_{ijv} \in\{0,1\}, \quad i=0, \ldots, n, \quad j=0, \ldots, n, \quad v=1, \ldots, m; \tag{10}$$

$$y_{iv} \geq 0, \quad i=0, \ldots, n, \quad v=1, \ldots, m. \tag{11}$$

Here, formula (2) reflects the condition that each point will be visited strictly only once, condition (3) means that for each vertex the number of incoming arcs should be equal to the number of the outgoing ones. Inequation (4) shows that servicing customer i by TF υ is possible provided that the latter passes through i, condition (5) guarantees satisfaction of each customer's demand, and formula (6) reflects that the amount of cargo delivered from the TF υ depot to the ith customer does not exceed the TF load capacity. Constraints (7) shows that the total duration of the route for one TF should not exceed the specified value T. Condition (8) reflects the asymmetry of the distance matrix, and condition (9) reflects the asymmetry of the time matrix.

THE PROBLEM SOLVING ALGORITHM

The very core of the ant algorithm, also called the optimization algorithm by imitation of an ant colony, is the analysis and application of the described behaviour model of an ant colony to solve various kinds of problems of finding routes on graphs.

For this, ant colony optimization algorithms use a task model graph, which defines them as a class of model-oriented algorithms [15]. In this paper, it is proposed to use the ant colony algorithm based on the Q-learning method [16, 17].

As a result of a detail study of the presented ideas for the implementation of the limitations and features of the asymmetric VRP presented in this work with restrictions on carrying capacity, route length and with a heterogeneous fleet of vehicles, an algorithm for its solution was developed and in the form of a block diagram presented on Fig. 1.

The transition of each ant from point i to point j takes place depending on the so-called ant memory, visibility and the virtual pheromone trace. The ant's memory is a list of centres visited by an ant, which cannot be visited again.

Thanks to this list, the possibility of an ant visiting the same centres twice is excluded. Of course, in the process of drawing up the route this list is updated, and at the beginning of the iteration it is reset to zero. Visibility means the inverse of distance, which is a kind of local static information expressed by a heuristic desire to head for point j from point i. Moreover, the closer the point is, the greater the desire to visit it. Of course, all this is not enough to determine the optimal route. For this purpose, the concept of a virtual pheromone trace on the edge (i, j) is introduced, which reflects the desire confirmed by the experience of the ant colony to head for point j from point i. The difference between the pheromone trace and visibility is that it represents more global and dynamic information that changes after each iteration and reflects the experience of the ant colony. As a result, the probability of the kth ant moving from point i to point j at a certain iteration is calculated by the formula:

$$P_{ij,k} = \begin{cases} \dfrac{t_{ij}^{\alpha} * \left(\dfrac{1}{D_{ij}}\right)^{\beta}}{\sum_{l \in J_{ik}} t_{il}^{\alpha} * \left(\dfrac{1}{D_{il}}\right)^{\beta}}, & \text{if } j \in J_{i,k}, \\ 0, & \text{if } j \notin J_{i,k}, \end{cases} \tag{12}$$

where τ_{ij} is the amount of virtual pheromone on the edge (i, j); D_{ij} is the distance between points; $J_{i,k}$ is the list of points for ant k, to visit; α and β are two controllable parameters that determine the weight of the pheromone trace and visibility when choosing a route. When the value of α, is zero, the nearest point will be selected, which characterizes the greedy algorithm in the classical optimization theory. At a zero value of β, only pheromone intensification works, which leads to a rapid reduction of routes to one suboptimal solution. It is worth noting that in formula (12) only the probability of choosing one or another point is determined. The direct selection of a point is carried out according to the

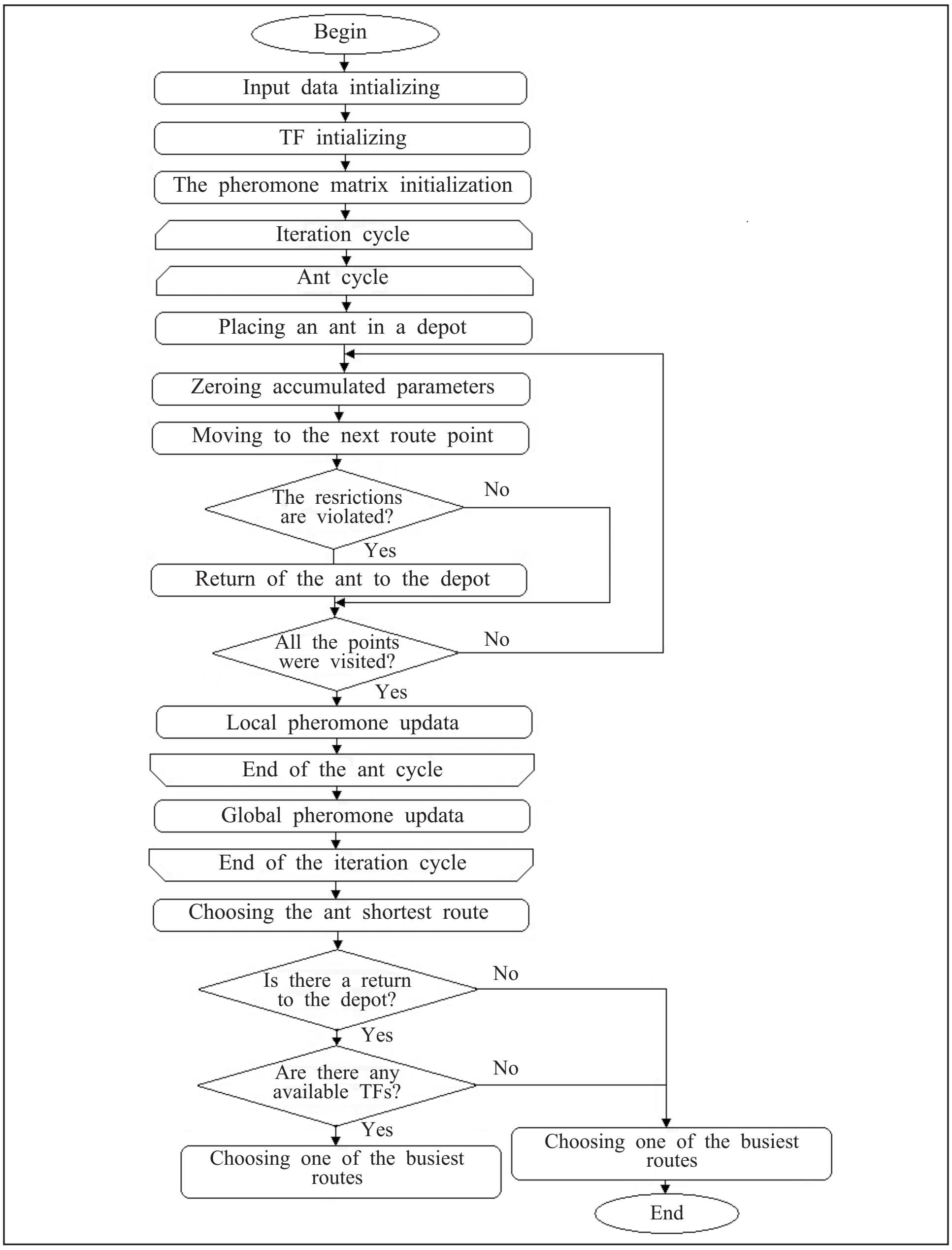

Fig. 1. Block diagram of the algorithm

"roulette wheel" method: each point on it belongs to a certain sector with an area proportional to the probability, which is calculated by the formula (12). In order to select a point, you need to "throw the ball on the roulette wheel", that is, generate a random number, and determine the sector where this "ball" will stop. Initially, all points have the same weight, and the primary value of the pheromone matrix is calculated by the formula [18, 19]:

$$\tau_{ij}^{0} = \frac{1}{(n+1) * \min D_{ij}}, \tag{13}$$

where D_{ij} is a distance between two points, n is the number of delivery points. When the kth ant completes the route, it deposits a certain amount of pheromone on the edge (i, j). If the edge (i, j) is not included in the constructed route, then there is no increase; otherwise if this edge is part of the kth ant's route, then this value is determined by the formula:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, & \text{if } (i,j) \in T_k, \\ 0, & \text{if } (i,j) \notin T_k, \end{cases} \tag{14}$$

where T_k is the route built by ant k, $L_k \neq 0$, is the length of this route, Q is a controllable parameter, the order of the set value of which, as a rule, is the same as that of the length of the optimal route (hence the name of the Q-learning method).

In order to explore the entire space of solutions, it is necessary to ensure pheromone evaporation, that is, a decrease in the amount of pheromone accumulated as a result of previous iterations over time. We shall accept to calculate the pheromone update value at iteration $t+1$ using the following formula [17, 18]:

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}, \tag{15}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \tau_{ij}^{k},$$

where ρ is the pheromone evaporation coefficient, which takes a value from 0 to 1, $\Delta\tau_{ij}$ is the pheromone increases on the edge (i, j).

A global pheromone update is performed according to formula (15). Let us note that in scientific research it is proposed to update the pheromone after the completion of the route by each kth ant [7]. Then the local update is calculated by the formula:

$$\tau_{ij}(t+1) = (1-\rho_2) * \tau_{ij}(t) + \rho_2 \tau_0, \tag{16}$$

where ρ_2 is the parameter affecting local pheromone correction, τ_0 is a small positive constant that characterizes the initial pheromone level on the edges, depending on the length of the route:

$$\tau_0 = \frac{1}{(n+1) * L_k}, \tag{17}$$

where n is the number of delivery points, L_k is the route length.

Table 1. Ways to implement the main limitations of the task

No.	Limitation	Description of the implementation method
1.	Asymmetry	It is supposed to use asymmetric matrices of distances and travel times between depots and delivery points, constructed using data received by the Google Maps API. The ant colony algorithm is also supposed to use a pheromone matrix asymmetric to the main diagonal.
2.	Limitation of TF load capacity	When developing a route by an ant, it is supposed to ensure its return to the depot when the maximum value of the TF load capacity is reached.
3.	Limiting the maximum duration of routes	In the process of developing a route, along with the TF load capacity, the duration of the route is checked, if it exceeds the maximum value, the ant returns to the depot.
4.	Fixed number of TF types	When developing routes by ants, the availability of an available TF is taken into account. If there are free TFs, then routes are supposed to be distributed between them, gradually reducing the search space and building a route for the next TF for a smaller number of points.
5.	Heterogeneity of the TF fleet	There are TFs characterized by different load capacity. The ant colony builds optimal routes for each TF, taking into account the carrying capacity of each of them. At the same time, if there is more than one TF with different load capacity, it is assumed to take into account rational filling so that the TFs are filled more evenly.

Thus, taking into account the considered characteristics of the ant colony algorithm, it is necessary to develop an algorithm for solving an asymmetric transport routing problem with limited load capacity, route duration and with a heterogeneous TF fleet. Table 1 presents the main limitations of the task and ways of implementing them using the ant colony algorithm.

PROGRAMMING IMPLEMENTATION OF THE ALGORITHM

In order to demonstrate the solution of the problem, a web application was developed. In it we implemented the proposed solution algorithm based on the ant colony method. The structure of the developed application is based on the MVC (model-view-controller) data separation scheme.

It should be noted that MVC is an information systems development architecture, which is most often used to develop web applications. The components of this architecture characterize the work of different parts of the system being developed and allow separating the user interface level from the business logic level [20]. The structure of the web application being developed can be represented in the form of a diagram shown in Fig. 2.

The algorithm for finding the optimal route based on the ant colony method is implemented in Python. The real distance and time data were obtained using the Google Maps API, namely using the Distance Matrix service [21].

The tests with a change in the number of iterations were conducted to track how the process of finding optimal routes takes place. It was established that with an increase in the number of iterations up to 1000 there is an improvement in the solution, yet, the value practically does not change further. Thus, optimal solutions can be found at iterations in the range from 500 to 1000.

However, an increase in the number of iterations leads to an increase in the running time of the algorithm. But it is worth noting that the operating time may also vary depending on the speed of the Internet connection, as the Internet is necessary to obtain data on the distances between delivery points.

However, this influence is not as noticeable as the influence of the number of TFs with different load capacity and the influence of the number of delivery points. The change in the operating time from the number of points for a different number of TF types is shown in Fig. 3.

As is seen in Fig. 3, with a small number of delivery points, the operating time of the algorithm does not change significantly with an increase in the number of TF types, although a direct relationship can be traced. Still, a significant increase in time is seen with an increase in the number of delivery points, which is quite expected when solving NP-hard problems. Despite this, the solution for 25 points and 3

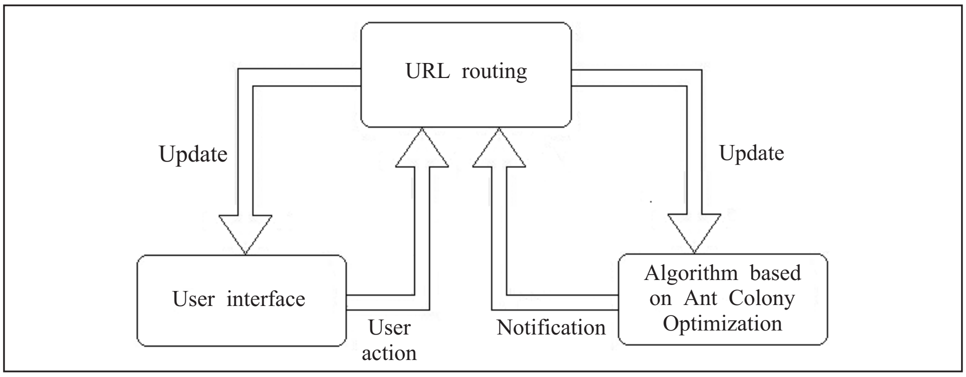

Fig. 2. Web application structure

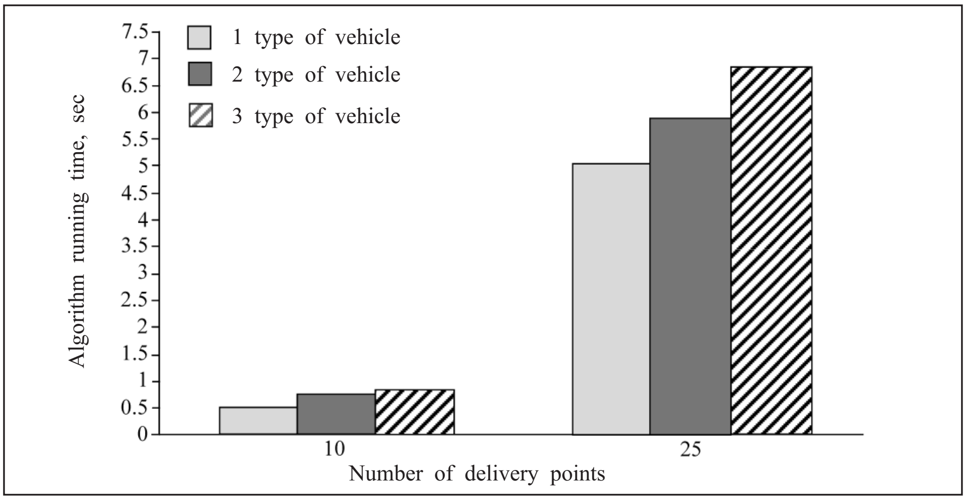

Fig. 3. Dependence of the algorithm operation time on the number of delivery points and TFs

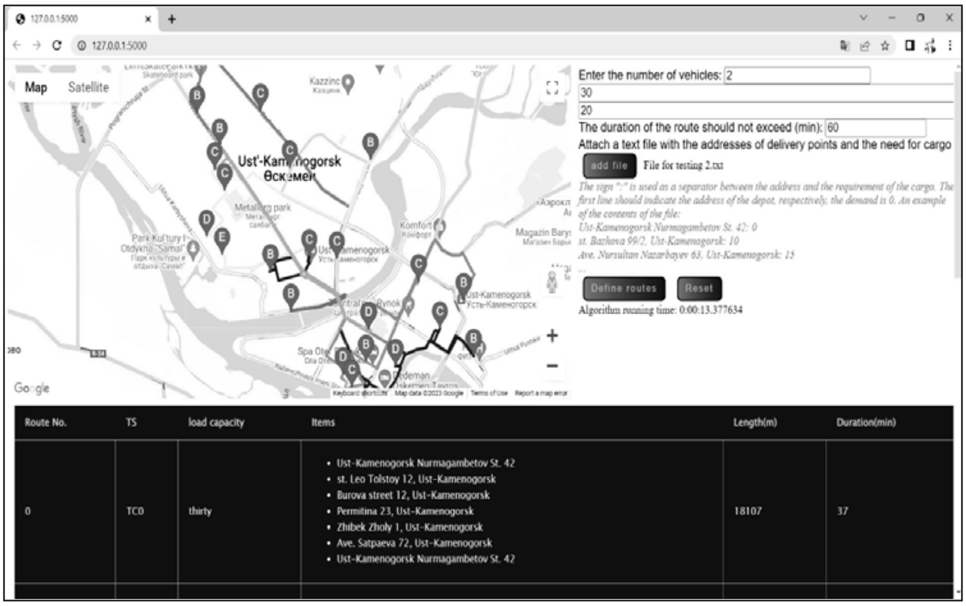

Fig. 4. The result of the route building with the proposed algorithm

different TF types was obtained in no more than 7 seconds, which suggests that the algorithm still coped with the solution of the problem.

For the purpose of checking the optimality of route building, the results of the developed algorithm were compared to the results of route building embedded in well-known cartographic services.

With this aim in view, we took 10 random points, one of which is a depot (that is, the route should start and end at this point), and built routes in Google Maps services and in the developed web application. Figure 3 shows the result of the route building with the developed algorithm.

As is clear from Fig. 4, the length of the constructed route is 28.9 km (kilometres). The length of the route with the same points built in Google Maps turned out to be 39.8 km. It is worth noting that the Google Maps service does not provide an option to optimize the route, so it is necessary to manually specify the order for the points to be visited. Nevertheless, the length of the route built by the developed algorithm is almost 11 km shorter. This allows us to conclude that in practice the use of a route search algorithm for transportation planning can contribute to the rapid compilation of shorter routes than if it were performed by a human using Google Maps.

It is also specified that the algorithm proposed in this paper, based on the ant colony method, showed the best result compared to, some other services, which unlike Google Maps, have the opportunity to optimize the route.

CONCLUSIONS

The research conducted makes it possible to conclude that the problem of transport routing, which takes into account such limitations as data asymmetry, TF load capacity, TF maximum duration, and a diverse in terms of load capacity TF fleet, can be solved by using the ant colony algorithm.

The developed algorithm allows building routes using the optimization of an ant colony and taking into account the limitation of the TF carrying capacity and the maximum duration of the route when building. And in order for routes to be built for different TFs, there is a gradual decrease in the search space, due to the removal of points of already built routes.

The choice of routes for a particular TF is carried out depending on its workload: the route that contains more cargo is selected. This also contributes to a more rational loading of transport, and a gradual decrease in the search space leads to a decrease in the running time of the algorithm. The optimality of the built routes was compared to the results of route building by other cartographic services, and the developed algorithm showed the best result.

The experiments held with a different number of iterations made it possible to determine that with an increase in the number of iterations, improvements in the solution are observed. However, this also leads to an increase in the running time of the application, which is especially noticeable when the number of different TF types increases. However, despite this, for problems of small dimensions, the solution is determined within an acceptable period of time.

Thus, further research can be aimed at optimizing the considered algorithm for solving the problem in order to reduce its operating time with a large data set.

REFERENCES

1. Dantzig G.B., Ramser J.H. The truck dispatching problem. *Management Science*. 1959. Vol. 6, N 1. P. 80–91.
2. Clarke G., Wright J.W. Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research*. 1964. Vol. 12, N 4. P. 568–581.
3. Bozorg-Haddad O., Solgi M., Loáiciga H.A. Meta-Heuristic and Evolutionary Algorithms for Engineering Optimization. Hoboken: Wiley, 2017. 304 p.
4. Wu Yi-W., Wang Y. Collection line optimisation in wind farms using improved ant colony optimisation. *Wind Engineering*. 2021. Vol. 45, Iss. 3. P. 589–600. https://doi.org/10.1177/0309524X20917319.
5. Pamosoaji A.K., Setyohadi D.B. Novel graph model for solving Collision-Free Multiple-Vehicle Traveling Salesman Problem using ant colony optimization. *Algorithms*. 2020. Vol. 13, Iss. 6. 153. https://doi.org/10.3390/a13060153.
6. Kiatwuthiamorn J., Thammano A. Swarm optimization algorithm based on the ant colony life cycle. *Malaysian Journal of Computer Science*. 2019. Sp. Iss. 2. P. 1–14. https://doi.org/10.22452/mjcs.sp2019no2.1.
7. Chanpa R., Jabraeil Jamali M.A., Hatamlou A., Anari B. An optimized swarm intelligence algorithm based on the mass defence of bees. *International Journal of Nonlinear Analysis and Applications*. 2022. Vol. 13, Iss. 1. P. 3451–3462. https://doi.org/10.22075/ijnaa.2022.6108.

8. Jafari-Marandi R., Smith B.K. Fluid genetic algorithm (FGA). *Journal of Computational Design and Engineering*. 2017. Vol. 4, Iss. 2. P. 158–167. https://doi.org/10.1016/j.jcde.2017.03.001.
9. Wang H., Zhang J., Dong J. Application of ant colony and immune combined optimization algorithm in path planning of unmanned craft. *AIP Advances*. 2022. Vol. 12, Iss. 2. 025313. https://doi.org/10.1063/5.0077858.
10. Mutar M.L., Burhanuddin M.A., Hameed A.S., Yusof N., Mutashar H.J. An efficient improvement of ant colony system algorithm for handling capacity vehicle routing problem. *International Journal of Industrial Engineering Computations*. 2020. Vol. 11, Iss. 4. P. 549–564. https://doi.org/10.5267/j.ijiec.2020.4.006.
11. Horbulin V.P., Hulianytskyi L.F., Sergienko I.V. Optimization of UAV team routes in the presence of alternative and dynamic depots. *Cybernetics and Systems Analysis*. 2020. Vol. 56, N 2. P. 195–203. https://doi.org/10.1007/s10559-020-00235-8.
12. Greco F. (Ed.) Travelling Salesman Problem. Rijeka: In-The, 2008. 214 p. URL: http://www.exatas.ufpr.br/portal/docs_degraf/paulo/TravellingSalesmanProblem.pdf.
13. Borčinova Z. Two models of the capacitated vehicle routing problem. *Croatian Operational Research Review*. 2017. Vol. 8, N 2. P. 463–469. https://doi.org/10.17535/crorr.2017.0029.
14. Ban H.-B., Nguyen P.K. A hybrid metaheuristic for solving asymmetric distance-constrained vehicle routing problem. *Computational Social Networks.* 2021. Vol. 8, N 3. https://doi.org/10.1186/s40649-020-00084-7.
15. Sergienko I.V., Hulianytskyi L.F., Sirenko S.I. Classification of applied methods of combinatorial optimization. *Cybernetics and Systems Analysis*. 2009. Vol. 45, N 5. P. 732–741. https://doi.org/10.1007/s10559-009-9134-0.
16. Junaid M., Sohail A., Ahmed A., Baz A., Khan I.A., Alhakami H. A hybrid model for load balancing in cloud using file type formatting. *IEEE Access*. 2020. Vol. 8. P. 118135–118155. https://doi.org/10.1109/ACCESS.2020.3003825.
17. Vimal S., Khari M., Crespo R.G., Kalaivani L., Dey N., Kaliappan M. Energy enhancement using Multiobjective Ant colony optimization with Double Q learning algorithm for IoT based cognitive radio networks. *Computer Communications*. 2020. Vol. 154. P. 481–490. https://doi.org/10.1016/j.comcom.2020.03.004.
18. Dorigo M., Stützle T. Ant colony optimization: overview and recent advances. In: Handbook of Metaheuristics. Gendreau M., Potvin J.-Y. (Eds.). Cham: Springer, 2019. P. 311–351.
19. Pellonperä T. Ant colony optimization and the vehicle routing. problem. M.Sc. Thesis. University of Tampere School of Information Sciences, Computer Science, 2014. URL: https://core.ac.uk/download/pdf/250133821.pdf
20. MVC Architecture. URL: https://www.javatpoint.com/php-mvc-architecture.
21. API Google Maps. URL: https://developers.google.com/maps/documentation/distance-matrix/overview.

С.Ж. Рахметуліна, Г. Жомарткизи, Ю.В. Крак, А.А. Камєлова

РОЗРОБКА АЛГОРИТМУ РОЗВ'ЯЗАННЯ ЗАДАЧІ АСИМЕТРИЧНОЇ МАРШРУТИЗАЦІЇ НА ОСНОВІ МЕТОДУ МУРАШИНОЇ КОЛОНІЇ

Анотація. Однією з головних проблем транспортної логістики є планування оптимальних маршрутів доставки. Під час її розв'язання виникає потреба у дослідженні задачі маршрутизації транспорту, яка є задачею комбінаторної оптимізації. У статті запропоновано алгоритм розв'язання задачі маршрутизації на основі методів оптимізації. Розглянуто асиметричну задачу маршрутизації транспорту з обмеженням вантажопідйомності транспортного засобу, тривалості маршруту та різнорідним парком транспортних засобів. Розроблено вебзастосунок, в якому реалізовано запропонований алгоритм розв'язання цієї задачі на основі методу мурашиної колонії. Проведено порівняльній аналіз отриманих оптимальних маршрутів та результатів побудови маршрутів з використанням інших картографічних сервісів. Показано, що запропонований алгоритм забезпечив найкращий результат.

Ключові слова: оптимізація, асиметричні задачі маршрутизації, граф пошуку маршруту, вебзастосунок, метод мурашиної колонії.

Надійшла до редакції 20.03.2023