Improvement of information system of cargo transportation routing management

L. F. Sulyukova 1, and Z. I. Akhmedjanova 2

1 “Tashkent Institute of Irrigation and Agricultural Mechanization Engineers” National Research University, Tashkent, Uzbekistan
2 Samarkand branch of the Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Samarkand, Uzbekistan

Abstract. The architecture of the information system is proposed in this article, which consists of two subsystems: management of cargo transportation and information flows with centralized management. The tasks and requirements for modern information systems of transport logistics have been analyzed. The task is to find the optimal route plan according to a given criterion for vehicles planning on a directed graph with irregular edge weights, considering the implementation of the delivery concept “right on time”. To consider daily, weekly, and seasonal fluctuations in traffic intensity, the concept of a time layer of the model is introduced. An algorithm for solving the problem of transport routing with load capacity restrictions is developed based on modifying the algorithm of ant colonies.

1 Introduction

Due to the formation of economic ties between countries, the role of cargo transportation of agricultural products is increasing. The situation is characterized by an increase in the level of competition and the level of customer requirements in the provision of services for the organization of cargo transportation.

The problem of cargo transportation management can be represented as follows. It is necessary to choose such a variant of control actions on the system to deliver the cargo with the best quality indicators value under given restrictions and initial conditions. In this case, the competitiveness of a transport company lies in the use of program-technique solutions that provide planning, optimization, and management of the transportation process. The fulfillment of the conditions creates the need to improve the methods and methods of decision-making in managing the technological process of organizing transportation.

The problem can be solved by creating specialized software to ensure optimal cargo transportation management, designed for planning and implementing cost-effective routes. These circumstances force the use of currently available highly developed software and hardware. The wide and effective use of these tools has become one factor in the company's survival and success in a competitive environment.

Automated information systems (IS) have become widespread.

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2 The structure of information flow management of transport logistics companies

The structure of information flow management of transport logistics companies includes the following subsystems:

- Order and shipment management;
- Trips management;
- Management of accounts, services;
- Interaction with ERP systems;
- Research and forecast.

Fig. 1. The architecture of the information system.
3 Vehicle routing problems
In most cases, it is possible to obtain only statistical estimates of the accuracy and complexity of the algorithm. One of the promising approaches for the effective solution of transport routing problems is developing hybrid methods, including ant colony algorithms. Ant colony optimization (ACO) algorithms belong to the group of "swarm intelligence" algorithms and are considered in the theory of artificial intelligence as optimization methods. ACO algorithms are used to find approximate solutions to various combinatorial optimization problems: traveling salesman, finding routes on graphs, knapsacks, assignments, and scheduling problems.

ACO algorithms allow you to automatically adjust to an example of a problem (specific values of the initial data are given) by additional labeling of the initial data, which is used to construct a solution at each iteration of the algorithm and is refined as the number of iterations increases. In other words, when using ant algorithms, there is no problem with the "clear" selection of a particular problem. Algorithms based on the use of ant colony optimization have been successfully applied to solve such combinatorial problems as the quadratic assignment problem, the knapsack problem, and the scheduling problem.

4 Formulation of the problem. Capacitated vehicle routing problem modeling

We will represent the transport network as a directed graph, the arcs of which correspond to sections of the road network, and the vertices correspond to the connection points of two or more such sections. To account for daily, weekly, and seasonal fluctuations in traffic intensity, the model's concept of a time layer is introduced - a set of time intervals during the year during which traffic intensity parameters are approximately the same.
The model of the transport routing problem with load capacity restrictions is the most suitable within the considered transportation problems and their limitations. It looks like this.

A graph \( G = (V, A, D) \) is given, where \( V = \{v_0, \ldots, v_n\} \) is a set of vertices (\( v_0 \) is a seller, other vertices are clients); \( A \) is a set of arcs connecting the corresponding vertices of the graph; \( \{c_{ij}\} \) is a set of non-negative numbers, which most often have the meaning of the path length, time, or cost of transportation along the arc between the vertices \( d_i \) and \( d_j \); (hereinafter, for brevity, we will simply call them \( i \) and \( j \)), they can be considered as a generalization of all types of costs for the transportation of products from \( i \) to \( j \). For a client at vertex \( i \) (client \( i \)), a non-negative demand \( c_i \) is set for some product or product. There are \( m \) vehicles in the warehouse, the carrying capacity of each of which is limited by the \( C_k \) value (\( k = 1, \ldots, m \)).

The task has the following restrictions:
- each client must be visited exactly once;
- the place of the beginning and the end of all routes of vehicles is a warehouse.

The goal of the problem is to construct routes of the minimum total cost that satisfy the demand of all customers and do not violate the restrictions described above. The complete mathematical model is written as follows:

\[
\begin{align*}
\min & \quad \sum_{i=1}^{n} \sum_{j=1}^{n} F_{ij} X_{ij} \\
\text{subject to} & \quad \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} X_{ij} \leq C_k \quad \forall k = 1, \ldots, m
\end{align*}
\]

Fig. 2. Time graphs for daily, weekly, and annual trips.
The value $X_{ij}$ takes the value 1 if transport system $k$ follows from client $i$ to client $j$, and 0 otherwise. $S_k$ is the set of pairs of vertices that define the route of car $k$. The objective function (1) minimizes the cost of all routes of all vehicles. Inequality (2) guarantees that each vehicle's carrying capacity limitations are met. Constraints (3) and (4) determine that each vehicle cannot leave the supplier and return more than once. Equality (5) shows that each client is served by only one transport system and only once. Condition (6) means that if a vehicle arrives at a vertex, then it also leaves this vertex. Condition (9) excludes splitting the vehicle route into disconnected cycles.

Ant colony algorithms are well-established metaheuristic methods for finding approximate solutions to the applied optimization problems on the graphs. The essence of the approach is to simulate the behavior of a real ant colony, which can find the shortest paths in the foraging process observed during experiments under controlled conditions. Marking better paths with more pheromones is the basis of ant colony algorithms. Ants can sense pheromones and tend to probabilistically choose paths marked with stronger pheromone concentrations [9-13].

The basis of the social behavior of ants is self-organization—a set of dynamic mechanisms that ensure the achievement of a global goal by the system as a result of the low-level interaction of its elements. The principal feature of such interaction is the use of only local information by the elements of the system. In this case, any centralized management and access to a global image representing the system in the outside world are excluded. Self-organization results from the interaction of the following four components: randomness, repetition, positive feedback, and negative feedback. Ants use two methods of information transfer: direct—food exchange, mandibular, visual and chemical contacts, and indirect—stigmergy. Stigmergy is a type of interaction spaced apart in time when one subject of interaction changes some part of the environment, and the subject of interaction modifies its behavior based on this change.
5 The main stages of the modified ant colony algorithm for the problem of transport routing with accepted restrictions

\[ \tau_{ij} = \tau_{ij} + \sum_{s \neq j} \beta \frac{\tau_{is}}{\tau_{js}} \eta_{ij} \]

\[ \tau_{ij}^\alpha = \frac{\tau_{ij}}{\sum_{s \neq j} \beta \frac{\tau_{is}}{\tau_{js}} \eta_{ij}} \]

\[ \tau_{ij} = \begin{cases} \tau_{ij} + \sum_{s \neq j} \beta \frac{\tau_{is}}{\tau_{js}} \eta_{ij} & \text{if } s \neq j \\ 0 & \text{if } s = j \end{cases} \]
1. Set the values of the parameters $\alpha$, $\beta$, $q_0$. $\alpha$ is a parameter that characterizes the pheromone evaporation rate, $\beta$ is the probability of using a determinate principle when choosing the next client.

2. Calculate the initial value of pheromone $\tau_0$ using formula (10).

3. Loop through all iterations (until the stop rule is met).

3.1. Loop through all "ants" ($k = 1, \ldots, m$).

3.1.1. The set $M_k$ of clients included in the ant route $k$ is assumed to be empty.

3.1.2. Cycle one «ant» at a time (until the capacity of the «ant» $k$ is exhausted or there are no unserved clients). We replenish the set $M_k$ (next clients to visit) according to the formulas (11), (12) and $\{\text{arg max}\}_{i,j} (\sigma)_{ij}$.

3.1.3. The end of the cycle for one "ant".

3.1.4. We update the pheromone locally according to the formula $\tau_{ij}^{(1)} = (1 - \alpha) \tau_{ij}^{(0)} + \alpha \tau_{ij}$.

3.2. End of cycle on "ants".

3.3. We find the best and the worst (among all the "ants") routes. We update the pheromone globally according to the formula $\tau_{ij}^{(1)} = (1 - \alpha) \tau_{ij}^{(0)} + \alpha \tau_{ij}$.

4. End of the cycle by iterations.

5. Determine the best result from all iterations.

6 Discussion of experimental results

The parameters of the algorithms $\alpha$, $q_0$ varied from 0 to 1 with a step of 0.1, and the parameter $\beta$ varied from 0 to 5 with a step of 0.1 on the interval $[0;1]$ and with a step of 0.2 on the interval $(1;5)$. The number of iterations in both cases was set equal to 10000, and the number of available vehicles was taken equal to 20. The time for solving the problem ranged from 5 s (for 15-16 clients) to 10 min (for 100 clients). The table below shows the deviations of the values of the objective function $F$ obtained in the experiment from the optimal $F_{opt}$ for the versions of the classical and modified algorithms for some model problems.

The deviation was calculated using the formula $100\% \frac{F - F_{opt}}{F_{opt}}$. 

\[
\tau_{ij}^{(1)} = (1 - \alpha) \tau_{ij}^{(0)} + \alpha \tau_{ij}
\]
As can be seen from the table, the efficiency of the proposed modification exceeds the efficiency of the classical ant colony optimization algorithm (in terms of deviation from the optimum).

Figure 3 illustrates the relative deviation average value of the tested algorithms as a function of the number of tasks. This graph shows that the gap between the algorithms also grows with increased number of tasks. The modified version of the algorithm maintains high performance regardless of the number of jobs. It is also worth noting that the classical ACO algorithm and the ACO algorithm perform worse with an increase in the number of tasks. In contrast, the modified algorithm, on the contrary, works better.

One of the most difficult issues in the practical application of ACO algorithms is determining the optimal values of control parameters. In the functioning of a multi-purpose information system, information about the environment is accumulated in its knowledge base. This information can be used for optimization purposes [5,11]. In a multi-purpose information system, the knowledge base can be formalized, for example, in the form of production rules and used to influence the population. The main components of EA are the population of decisions and the knowledge base. They interact through two functions: acceptance and influence. The acceptance function determines the
The influence function specifies the rules by which knowledge influences the evolution of individuals in a population. In this case, it is possible to modify any existing operators that provide evolutionary changes in the population [15-17].

Experiments on benchmarks of well-known combinatorial optimization problems (Traveling salesman problem [11], dispatching problem [18], scheduling problem [15, 20], etc.) show that adaptation and evolution among individuals in a population occur faster using the knowledge base. There is an accumulation of knowledge that is passed on to other generations [19-21].

7 Conclusion

Using the example of the problem of transporting agricultural products, it is shown how the problem of transporting products with special transportation conditions can be reduced to the problem of routing vehicles with limited capacity. An algorithm for solving the problem of transport routing with load capacity restrictions based on modifying the ant colony algorithm has been developed. A modified algorithm of the same order of complexity improves the quality of the solutions obtained. Computational experiments were carried out, which confirmed the effectiveness of the proposed algorithms.

Further research can be aimed at developing efficient algorithms for solving transport routing problems and scheduling problems of higher dimensions, taking into account additional restrictions that arise in practice.

References


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