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The Development of the Ant Algorithm for Solving the Vehicle Routing Problems

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Abstract: This article presents the results of research and development of modification of ant algorithms for solving vehicle routing problems with a variety of verification. The problem is NP-hard - this class of problems has a no polynomial complexity, they do not have accurate decisions now. The ant algorithm belongs to a class of algorithms based on «Swarm intelligence». The concept of swarm intelligence was introduced by Gerardo Beni and Wang jing in 1989 [1]. Swarm intelligence is a self-organizing system, consisting of many agents, representing a multi-agent system. Agents obey simple rules of behavior in the environment. Their simple interaction determines a collective adaptation. Thus, the formation of swarm intelligence is based on the behavior of simple agents. Due to the interaction between the agents, the system forms a collective "mind", "memory", which is used by all the participants of the system. Examples of such systems are ant colony [2-3], a swarm of bees [4-5], a flock of birds, fish, etc.

Key words: Ant algorithms · "Swarm intelligence" · Simple agents

INTRODUCTION

Standard ant Algorithm: Research in the field of ant algorithms began in the mid 90-ies of XX century, the author of the idea is Marco Dorigo [6-8]. This idea is based on modeling the behavior of ant colonies. Ant colony is a system with very simple rules for autonomous behavior of individuals. However, despite the primitive behavior of each individual ant, the behavior of the whole colony is quite judicious [9]. The basis of the behavior of an ant colony is a low-level communication, through which, overall, the colony is a judicious multi-agent system. A special chemical substance - a pheromone secreted by ants on the passed way, determines the interaction. To select a direction an ant proceeds not only from a desire to go the shortest way, but from the experience of other ants whose information it gets directly from the level of pheromone on each way. The concentration of pheromone defines the individuals desire to choose one or other way [10-11]. The problem of reaching a local optimum is solved by the evaporation of the pheromones, which is a negative feedback. Thus, the way that took less time, had less evaporation, therefore, the concentration of pheromones on the best route would maintain longer [9]. Let's define the properties of ant according to the example of the Traveling Salesman Problem (TSP). This problem has a particular interest also because it refers to other graph tasks. Based on it, we can solve the following tasks [12]: the search for a Hamiltonian cycle, the task of finding an Euler cycle, planning, the development of the shortest framework, assignments, etc.

- Each ant has its own "memory" that stores the list of cities $J_{i,k}$ (tabu list), that the ant k, which is in the city i has to visit.
- Ants have a "vision»: $\eta_{ij} = 1/D_{ij}$.
  "Vision" defines the "greed" of the ants' choice. The closer is the vertex of the graph, the better it is "seen" and the more the agent wants to go into it.
- Each ant is able to capture the pheromone trail, which will determine the ant's desire to pass on this edge. The pheromone level at time t on the edge D_{ij} will match $\tau_{ij}(t)$.
- The probability of the ants' transition from the peak i to the peak j will be determined by the following equation [6]:

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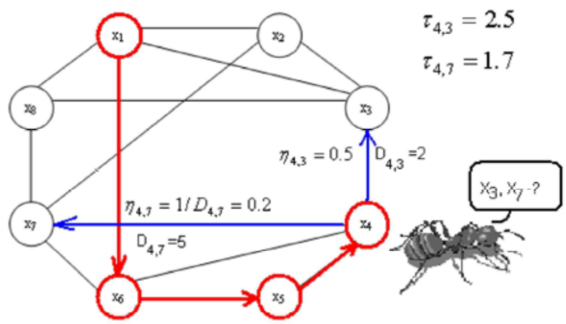

Fig. 1: The choosing of a rib by the agent.

$$\begin{cases} P_{ij,k}(t) = \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum\limits_{l \in J_{i,k}} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}(t)]^{\beta}}, j \in J_{i,k} \\ P_{ij,k}(t) = 0, j \notin J_{i,k} \end{cases} \quad (1)$$

where α, β - are the parameters that define the weight of the pheromone trail, the coefficients of heuristics. The parameters α and β determine the relative importance of the two parameters and their influence on the equation (1) [13]. They determine the "greed" of the ant. When α = 0 the ant tends to choose the shortest edge, with β = 0 - the edge with the most amount of pheromone. It is easy to see that this expression has the effect of "roulette wheel".

Fig. 1 shows an example of the behavior of an ant. As can be seen from Fig. 1the ant has gone over the peaks 1-6-5-4 and being in the peak 4 it picks out between peak 7 and 3 for further travel.

By the time, the probability of selecting the shortest path increases, since, according to [7] the amount of the secreted pheromone is inversely proportional to the length of the route and is in the following form:

$$\Delta\tau_{ij,k}(t) = \begin{cases} \dfrac{Q}{L_k(t)}, (i,j) \in T_k(t) \\ 0, (i,j) \notin T_k(t) \end{cases} \quad (2)$$

where Q – is a parameter with a value of the range of the optimal path, $L_k(t)$ – is the length of the route $T_k(t)$. The evaporation of pheromone is determined by the following expression:

$$\tau_{ij}(t+1) = (1-p) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij,k}(t) \quad (3)$$

where m - is the number of ants, p – is evaporation coefficient (0 ≤ p ≤ 1)

In this simple ant algorithm, the initial position of the ant colony is defined as followed: the number of agents is equal to the number of peaks in the graph and each agent corresponds to a peak, from which it begins its journey. In the article [10] there are further modifications of ant algorithm. Experiments were conducted on standard benchmarks Eilon [14] - graphs with 30, 50, 75 and 98 peaks. The results were compared with the known best solutions obtained by using the modified genetic algorithm [15].

All the considered graphs are fully connected, so we give only the coordinates of the peaks, the edge weights is defined as the Cartesian distance between the peaks. A computer program was developed for studies. Fig. 2 shows a screenshot of the graphic of program solution for solving the travel agents task, depending on benchmarks Eilon with 30 peaks.

As we can see from the graph, the algorithm coincided in less than a second. Let us consider in detail this experiment in Fig. 3. On the left there is a picture of the solution. Note that the solved problem is the

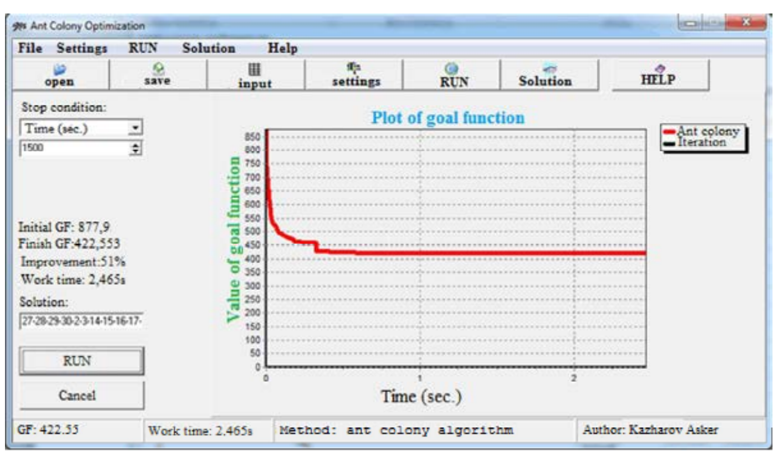

Fig. 2: The external interface of the program.

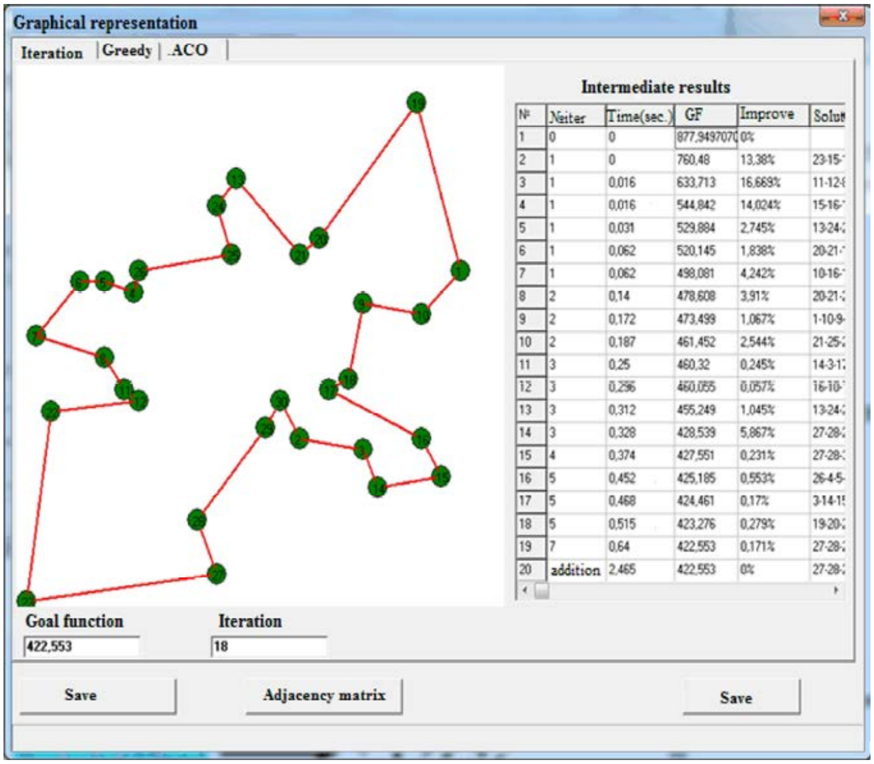

Fig. 3: Detailing of the experiment.

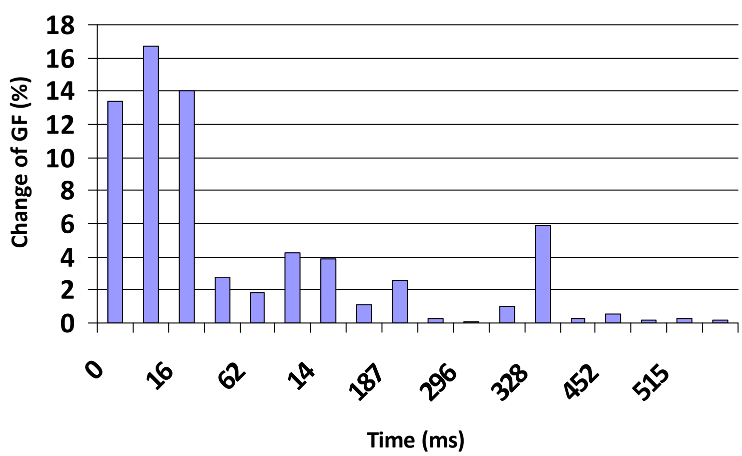

Fig. 4: Graph of the CF changes in%.

verification of the classical TSP - geometric TSP. Each peak has two-dimensional coordinates and the length of the edges is equal to the Euclidean distance between the connected peaks. The number of "useful" iterations to stagnation - 7, the size of the colony - 1000 ants. On the right, there is a complete detailing of the solution, which shows that the initial solution has been improved twice. Fig. 4 displays the graph of the CF, which shows that the ant algorithm quickly finds a "good" solution to the first iterations.

Fig. 5-6 shows the comparison of the received results with the existing results on Eilons' benchmarks [14]. On the left we can see the existing results, on the right - the received ones.

A Modified Ant Algorithm for Solving the Problem of Vehicles with Multiple Depots and Time Windows Routing: The developed algorithm was used also for solving transport problems. To adapt the ant algorithm to solve the problem of vehicle routing with (VRP) [15] we

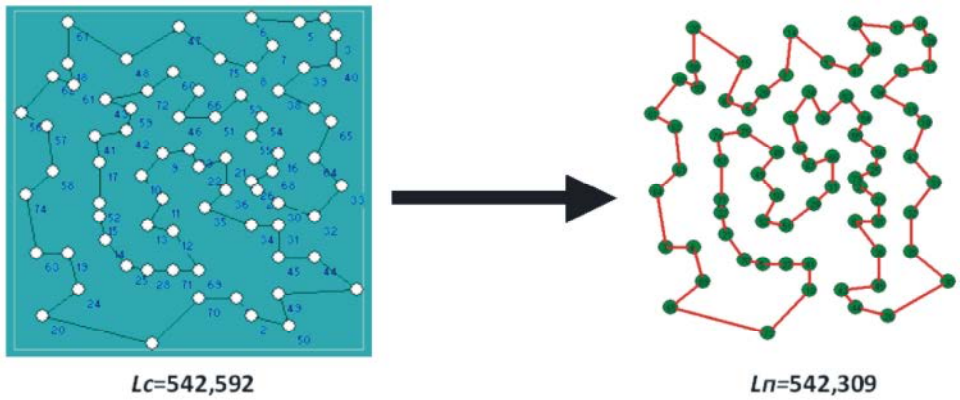

Fig. 5: A benchmark with 75 peaks.

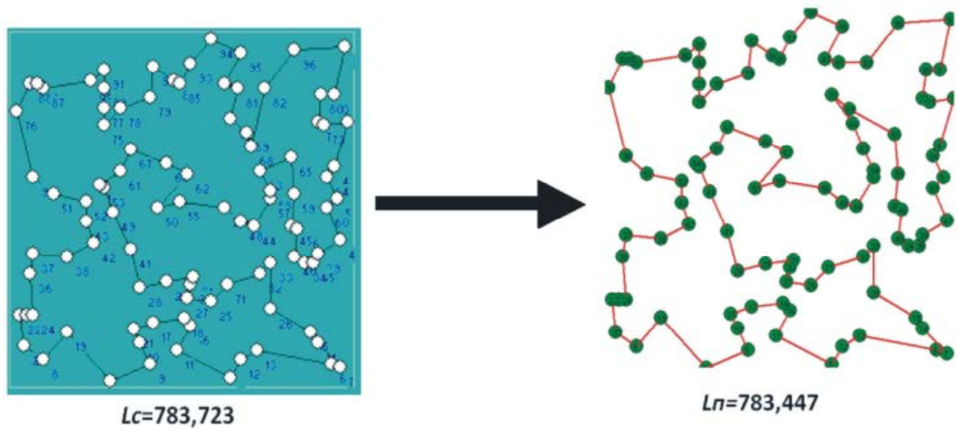

Fig. 6: A benchmark with 98 peaks.

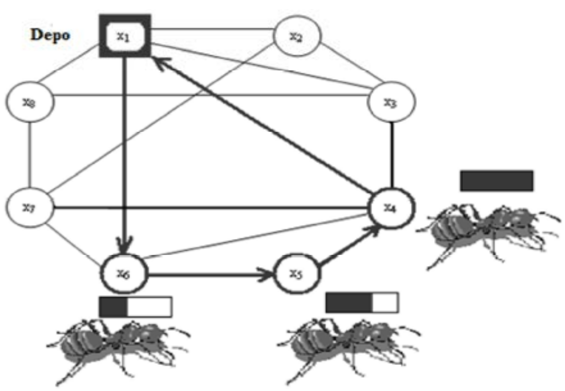

Fig. 7: The behavior of an ant with an additional constraint.

should impose additional restrictions on the properties of ant. When collecting food, the ant, according to the model described above, tries to go round all the points (the location of food) by the shortest way, but it is able to "take the load" of only limited weight. After earning the maximum possible load, the ant returns to the colony and "gets unloaded". Then it repeats these steps in the not visited locations of food, until all the food is collected. The described model of the ants' behavior can solve the verification of the problem of vehicle routing CVRP (with a restricted carrying capacity of the vehicles). Figure 7 shows an example of an ant's behavior for the tasks VRP. A strip in Figure 7 reflects the load of the ant. Reaching the peak 4, the ant definitely returns to the colony (depot) without computing the probability of transition to the other peaks. Next, the trip of this ant will continue with zero loads and the peaks 1, 6, 5, 4 will remain prohibited according to the taboo-list (a list of prohibited peaks). It should be noted that, if we accept transport carrying capacity equal to infinity or sufficiently large, the problem is reduced to finding the minimum of a Hamiltonian cycle.

In the simplest case, the criterion for the optimization problem is the total length of the routs traveled over by the auto park. Also, one of the important criteria to optimize vehicle routing problem is the number of used vehicles. The optimization goal in this case is to reduce this number. Denote the number of involved vehicles by variable m '.

$$\begin{cases} F = \sum_{i=1}^{m'} \left(\sum_{j=1}^{|r_i|} C_{r_{i,j}, r_{i,j+1}} + C_{r_{i,|r_i|}, h_i} \right), \\ m' \le m \\ \sum_{i=1}^{m'} |r_i| = |V| - |V_0| \\ \sum_{j=1}^{|r_i|} d_{r_i} < w_i, 1 < i < m', \end{cases} \quad (4)$$

where $r_{i,j}$ – is j-th order of traveling of the client i - th transport,

$V = \{V_0, v_1, ..., v_n\}$ - is a set of peaks, where
$V_0 = \{v_{01}, v_{02}, \ldots, v_{0k}\}$ - is a set of peaks, where the depot is ;
$\{v_1, \ldots, v_n\}$ - is a set of peaks, where the customers are (many cities) ;
E – is a set of edges.

We also have the following inputs:

- C - is the distance matrix, c_{ij} – is the distance between a pair of peaks in the set V;
- d - is the vector of customers inquiries, where d_i stores cargo information - the weight of goods;
- m - is the number of vehicles available;
- h - is the vector of the vehicles belonging to various depots, where hi - is the depot, to which the i-th transport belongs;
- w - is the vector carrying capacity of the vehicles, where wi - is carrying capacity of i-th vehicle and the vectors length is m.

The purpose of the classical routing problem is to minimize the function of F. Thus, the solution of the problem is to minimize the total length of the routes, i.e. fuel consumption and the number of transports involved and the solution for this problem is developing route sheets for each vehicle. While solving the problem we must take into account the time limit, as this task is dynamic and time of conversion becomes idle time of the transport. Let’s describe a typical task of cargo transportation around the city. Typically, each depot \storehouse has its own controller - logistician, who solves this problem for the auto park available to him. Accordingly, the problem is reduced from vehicle routing with multiple depots (MDVRP) [16] to the classical with one depot, so the problem is solved separately for each store. Twice a day (noon and evening) the controller collects information about incoming orders. This may be data from the electronic system, checks, etc. Next all the points of unloading / delivery of goods are marked on the map. The optimization criterion can vary depending on the boundary conditions. Depending on the type of activity, the enterprise has periods of active marketing of goods and vice versa. For example, cold drink in the summer has a much greater demand than in winter. Thus, in certain periods the enterprises' auto park is more loaded and the risk of lack of transport appears. In this case, the enterprise has to use the services of cargo carrying companies, which is more expensive than using its own auto park. Thus, the main criterion of optimization in the summer is the size of used auto park and the controller needs to focus on solving the problem of packaging. On the other hand, during the period when orders are less intense and the risk of a lack of transport for the delivery of goods is minimal, the problem of route optimization appears, since fuel consumption become essential. In this case, the basic optimization criterion is the length of the route.

The other boundary condition is the speed of the algorithm. Terms of the task may change dynamically; there are different reasons for this - the changing of the delivery address, the rejection by the customer of goods, the changing of the time window, the human factor in information collection, etc. It is therefore necessary to recalculate the route, which is unfavorable for labor-intensive algorithms. In this situation, the recalculating of the route becomes idle time for the driver. "Acceptable" is the time of recalculating to 10 minutes. Note that at the initial stage the calculation time can be about 30 minutes, as all the transports are initially in the fleet in the initial positions.

Based on the real model of the task, on the example of the transports' department work, we can make a logical conclusion that the problem is a multicriterion and the criteria prices during the period are not constant values. The objective function has to be a multiplicative function of the form:

$$\begin{cases} F' = \left(\frac{m'}{m}\right)^a * \left(\frac{F}{Q}\right)^b \\ 0 \le a, b \\ F \le Q \end{cases} \quad (5)$$

where
m '- is the size of the fleet involved;
m - is the size of the whole fleet;

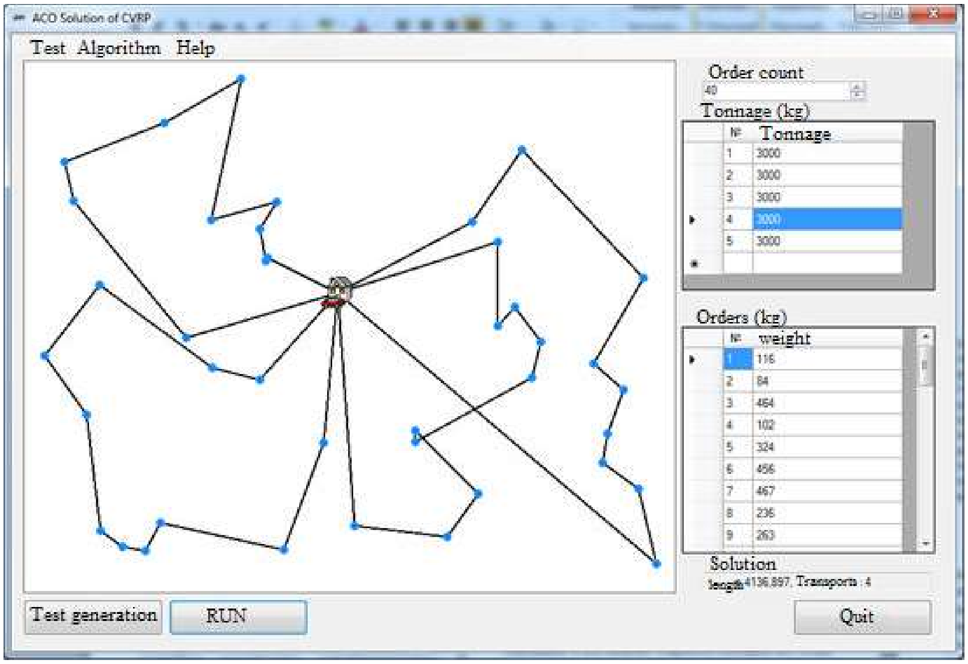

Fig. 8: An example of CVRP solution with the following parameters: $\alpha = 1$, $\beta = 4$, working time = 5 seconds.

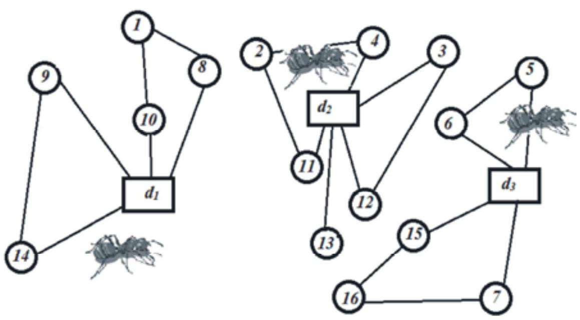

Fig. 9: The behavior of an ant with additional restrictions.

F - is total length of the route;

Q - is the total length of the routes of the initial solution;

a - is a coefficient characterizing the "importance" or "price" of the criterion of the number of transports involved;

b - is a coefficient characterizing the "importance" or "price" of the criterion of the total length of routes.

The goal of the optimization - minimization of the function of *F* '. The weights *a* and *b* are input parameters for the developed algorithm and should be regulated by the controller. This allows to change the assessment of the effectiveness of problem solving for the same algorithm without major changes in the model specification. Note that if the coefficient *a* is zero, the size of the fleet involved does not affect the final solution and the task becomes a classic one-criterion. Conversely, if *b* = 0, the length of the route does not affect.

The listed modification (elite ants, the initial location of the colony, templates and rectifiers) remain actual for this behavior of ants. However, for the considered verification VRP, in consideration of its specificity, the strategy of initial location of the ants' colony may be only "focusing" - a strategy in which the whole colony is located at a one peak [10], as shown in Fig. 8.

In this case, the agents will be initially located at the peak which corresponds to the depot. When solving the MDVRP task, when there are many depots, we use the strategy of "shotgun" - agents are placed at the peaks which correspond to the depot / stores and consistently find the routes. Figure 9 shows an example of solving MDVRP.

In solving the verification VRPTW (with time windows) we must add dependence on the time frames in the calculation of the transition probability of the *k* ant from peak *i* to peak *j*. For this, we introduce the following rules.

Rule 1: If the load of the agent when it reaches peak *j* from the peak *i*, exceeds the given carrying capacity *c*, the transition probability *Pij* = 0.

Rule 2: If routs time by reaching the peak *j* from the peak *i*, exceeds the interval of the time window *fj*, the transition probability *Pij* = 0.

Rule 3: If the probability of transition to any other previously not visited peak, insufficient depot, from the peak *i* is equal to zero, the agent completes the route returning to the depot.

Considering the first two rules, the expression (1) takes the following form:

$$\begin{cases} P_{ij,k}(t) = \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum\limits_{l \in J_{i,k}} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}(t)]^{\beta}} \\ P_{ij,k}(t) = 0, j \notin J_{i,k} \\ P_{ij,k}(t) = 0, T_{k,i} + D_{i,j} > f_j \\ P_{ij,k}(t) = 0, W_{k,i} + d_j > c \end{cases} \tag{6}$$

where

Pij, k (t) - is the probability of transition of the *k* ant from peak *i* to peak *j* in the *t* iteration;

τij (t) - is pheromone level at time *t* on the edge *Dij;*

α, β - are the parameters that define the weight of the pheromone trail, the coefficients of heuristics;

ηij = 1/Dij;

Tk, i - is time spent by the *k* of ants on reaching the peak *I*;

fj - is the end of the time window of *j*-th customer;

Wk, i - is congestion of the *k* ant, upon reaching the top of *I*;

dj - is weight of the goods of *j* customer;

c - is load capacity of transport.

CONCLUSION

This article gives a modified algorithm based on the ideas of swarm intelligence for solving the vehicle routing problem, considering the verifications CVRP, VRPTW, MDVRP. A modified ant algorithm was developed, it takes into account the specificity and the boundary conditions of the problem. A mathematical model of the problem is presented, a multiplicative objective function was developed, it takes into account all the criteria for the task. Computer software applications were developed, they implement the described algorithms. The conducted experimental researches showed the effectiveness of the proposed modifications of the ant algorithm compared to the standard ant algorithm.

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