Improvement of information system of cargo transportation routing management

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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 has 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 values 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

To analyze the initial information when making decisions, a separate direction or type of information system has developed - information and analytical systems (IAS), representing a complex of hardware, software, information resources, and methods, which together form the information and analytical model of the company. These models are used to automate analytical work to justify and make management decisions.

The process of managing the interaction of subjects within the enterprise from the standpoint of managing information flows implies the need to use the capabilities of modern information technologies that ensure the efficiency of communication and integration of participants in business processes, thereby improving the quality of management decisions made at the strategic, tactical and operational levels of management. Management of the interaction of functional subjects of a single information space is implemented through IAS monitoring, within which the following occurs:

1) study of the actual state and dynamics of the development of the company's activities;

2) identification of problematic links in the chains of management, causing failures in solving managerial problems;

3) improvement of the cargo transportation management system;

4) substantiation of proposals and recommendations to prevent possible threats and overcome the negative consequences of activities.

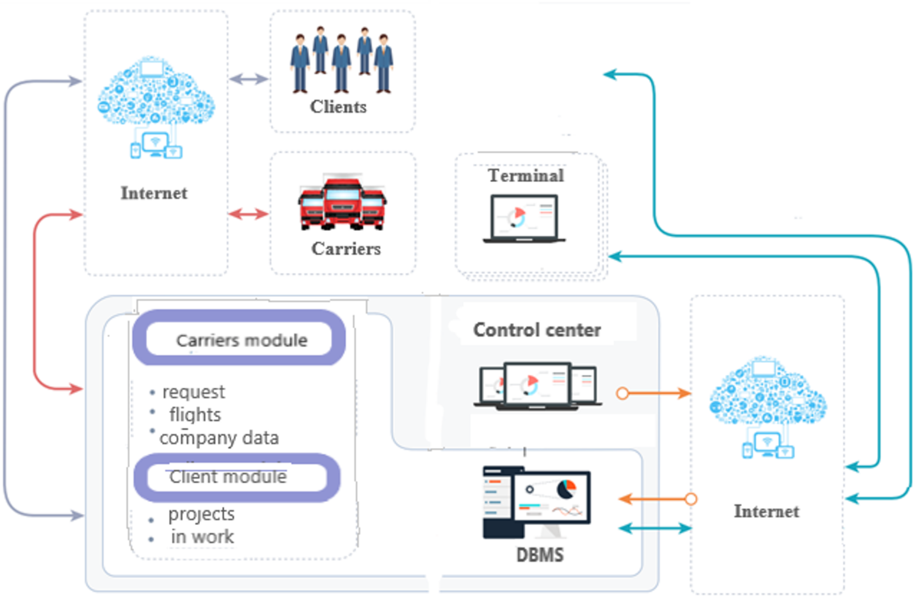

Fig. 1. Architecture information system.

The system consists of the following:

Cargo transportation management subsystems, including:

• Order and shipment management;

• Trips management;

• Management of accounts, services, and tariffs;

• Interaction with ERP-system (Enterprise Resource Planning);

• Management of clients and contractors;
• Generation of reports;
• Maintenance of directories;
• Administration;
• Management of incoming and outgoing cargo flows within the framework of trips.
Process control subsystems on the terminal, including:
• Planning and cargo handling;
• Accounting for the work of personnel;
• Generation of invoices;
• Formation of tasks from the work plan;
• Actions on cargo;
• Information about cargo.

Thus, there is an objective need to form a tool for managing information flows in the interaction processes between enterprise departments, and other economic entities of the information and analytical monitoring system for managing enterprise information flows with differentiated access to information and the possibility of interactive data exchange.

3 Vehicle routing problems

Transportation planning is an important task in logistics: the share of expenses for transporting goods can be 25-35% of its value. Transportation optimization is becoming a serious competitive advantage both among the representatives of cargo transportation services and among manufacturers of goods. When solving practical transport problems, in most cases, planners need an intelligent decision support system [1].

The problems of vehicle routing (search for optimal routes for the movement of vehicles) are NP-hard; that is, algorithms with polynomial running time have not yet been developed to solve them. However, there are special cases of these problems that are polynomially solvable.

To solve routing problems, various algorithms with multimodal time are used, including the Dijkstra and Floyd-Warshall algorithms, etc. The shortest path problem is presented in deterministic graphs, in which the edge weights are independent, fixed, and predefined values. If the edge weights in these algorithms change dynamically, the optimal solution may not be found since the overall graph with the least graph change will have to be reanalyzed. For this reason, researchers are considering algorithms for shortest path problems in dynamic graphs in which edge weights and/or graph structure dynamically change over time [2-6].

The problem of constructing a schedule of exchanges over a channel with centralized control belongs to the class of problems of constructing single-server schedules without interruptions. It is known in scheduling theory as the problem of choosing the maximum number of compatible claims, which is NP-hard. In contrast to the problems of choosing the maximum number of compatible requests considered in scheduling theory, in the problem of constructing exchanges over a channel with centralized control, additional restrictions are imposed on the correctness of the schedule, which is due to the features of the software and the hardware [4,7,8]. Single-instrument scheduling problems arise in various areas, including routing and transport logistics, and are special cases of more complex practical problems.

The main problem when using algorithms based on greedy strategies and limited search strategies is their adjustment to solve particular problems (restrictions are imposed on the possible values of the input data) [1]. This is connected with the problem of forming restrictions on the initial data in such a way as to "clearly" highlight a particular problem for which the algorithm will certainly find a solution with acceptable accuracy and

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complexity. 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 [7,8] 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 [9], the knapsack problem [10], and the scheduling problem [11-14].

4 Formulation of the problem. Capacitated vehicle routing problem modeling

Single-type (unimodal) transportation is considered. One mode of transport is sufficient for the delivery of goods. His choice is determined by the type and volume of cargo. This option is suitable when the start and end points are known, and there are no intermediate operations - warehousing and cargo handling. The greatest influence on the transportation process is exerted by uncertainty in the time of movement of vehicles and in the time the car is at the client (when loading and unloading operations, waiting in line at the client, processing documents, and so on).

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 [6] (Fig.2).

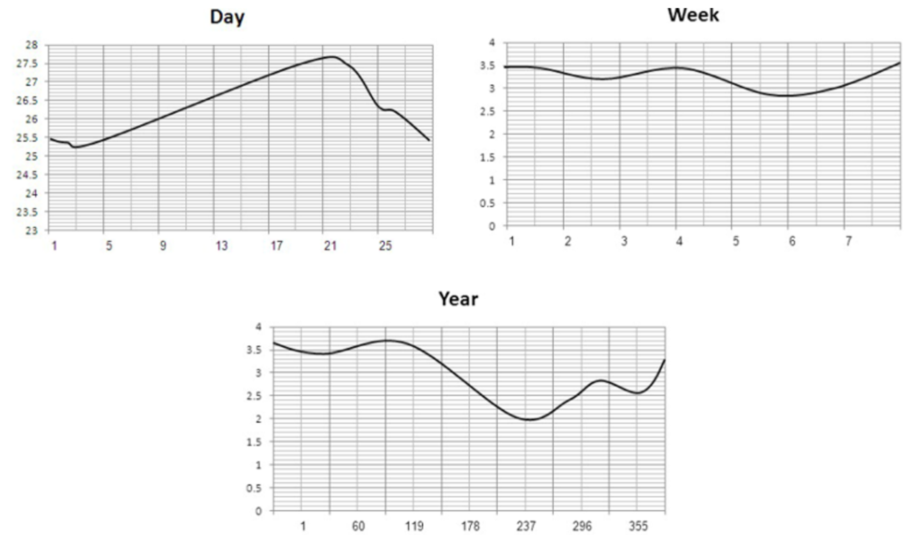

Fig. 2. Time graphs for daily, weekly, and annual trips.

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 $V = \{v_0, \dots v_n\}\}$ 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; $D = \{d_{ij}, i, j = 0,1, \dots n\} -$ 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 (k=1,...,m) value.

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:

$$F = \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} X_{ij}^{k} \to \min \tag{1}$$

under restrictions

$$\sum_{i=1}^{n} c_i \sum_{j=0}^{n} X_{ij}^{k} \le C_k \quad \forall k = 1, \dots, m, \tag{2}$$

$$\sum_{j=1}^{n} X_{0j}^{k} \leq 1 \quad \forall k = 1,...,m, \tag{3}$$

$$\sum_{i=1}^{n} X_{i0}^{k} \leq 1 \quad \forall k = 1,...,m, \tag{4}$$

$$\sum_{k=1}^{m}\sum_{j=1}^{n} X_{ij}^{k} = 1 \quad \forall k = 1,...,m, \tag{5}$$

$$\sum_{i=0}^{n} X_{ih}^{k} - \sum_{j=0}^{n} X_{hj}^{k} = 0 \quad \forall k = 1,...,n, \quad \forall k = 1,...,m, \tag{6}$$

$$X_{ij}^{k} \in \{0,1\} \quad \forall i, j = 0,...,n, \ \forall k = 1,...,m, \tag{7}$$

$$X_{ii}^{k} = 0 \ \ \forall i = 0,...,n, \ \forall k = 1,...,m, \tag{8}$$

if $S_k = \{(i,j) : X_{ij}^{k} = 1\}$, then

$$\forall k = 1,...,m, \quad \forall (i,j) \in S_k \neq \varnothing \exists (j_p, j_{p+1}) \in S_k (p = 0,...,l):$$

$$j_0 = j_{l+1} = 0, \text{ v } r \leq l. \tag{9}$$

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 rest use information about its state later when they are in its vicinity [14].

Biologically, stigmergy is realized through a pheromone - a special secret that is deposited as a trace during the movement of an ant. Pheromone is a fairly stable substance; it can be perceived by ants for several days. The higher the pheromone concentration on the trail, the more ants will move along it. Over time, the pheromone evaporates, which allows the ants to adapt their behavior to changes in the external environment. The distribution of pheromones over the space of the ant movement is a kind of dynamically changing global memory of the anthill. Any ant at a fixed moment of time can perceive and change only one local cell of this global memory. Marking better paths with more pheromones is the basis of ant colony algorithms. Ants tend to probabilistically choose paths marked with stronger pheromone concentrations [9–14].

5 The main stages of the modified ant colony algorithm for the problem of transport routing with accepted restrictions

All parameters are initialized, including the initial value of the pheromone on the edges. The initial value of the pheromone is determined by the formula:

$$\tau_0 = ((n+1)\min_{i\neq j} d_{ij})^{-1} \tag{10}$$

where n is the number of clients.

The probability distribution that determines the choice of the next client is written as:

a) after building a complete route, each "ant" is asked to remember the best and the worst routes of one ant (among all ants), L, and R, respectively, and the costs of these routes.

b) if the path from client i to client j is included in the worst route, then the probability of choosing this movement decreases in proportion to the ratio of the costs of the best route to the worst one, i.e.

$$\tilde{P}_{k(i,j)} = \frac{L}{R}\tau_{ij}(\eta_{ij})^{\beta} / (\sum\nolimits_{v\neq j, v\neq M_k} \tau_{iv}(\eta_{iv})^{\beta} / R; \tag{11}$$

where L is the length of the best route τ_{ij} is the amount of pheromone on the way between clients i and j; η_{ij} is a value inversely proportional to the distance between clients (it is sometimes called "visibility" between clients i and j; β is a parameter characterizing the relative "importance" of the distance compared to the amount of pheromone (when β=0, the ant focuses only on the amount of pheromone);

c) in other cases ($s\neq j$), the distribution has the form

$$\tilde{p}_k(i,s) = \begin{cases} \tau_{ij}(\eta_{ij})^{\beta} / \sum\nolimits_{v\neq j, v\neq M_k} \tau_{iv}(\eta_{iv})^{\beta} / R \\ 0, s \in M_k \end{cases}, \text{ if } s \notin M_k \tag{12}$$

$p_k(i, s)$ is the probability with which ant k chooses to move from client i to client s, M_k is the set of clients included in the route

Let us give a simplified description of the modified algorithm.

1. Set the values of the parameters α, β, q_0. α is a parameter that characterizes the pheromone evaporation rate, $q_0(0 \le q_0 \le 1)$ is the probability of using a determinate principle when choosing the next client.

2. Calculate the initial value of pheromone τ_0 using formula (10).

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

3.1. Loop through all "ants" (k=1,…,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

$$j = \begin{cases} \left\{ \arg\max[\tau_{iu}(\eta_{iu})^{\beta}] \right. \\ S_1 - q_0 \end{cases}$$

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

3.1.4. We update the pheromone locally according to the formula

$$\tau_{ij}^{new} = (1-a)\tau_{ij}^{old} + \alpha\tau_0 .$$

3.2. End of cycle on "ants".

3.3. We find the best and the worst (among all the "ants") routes. 3.3. We update the pheromone globally according to the formula

$$\tau_{ij}^{new} = (1-a)\tau_{ij}^{old} + \frac{\alpha}{L} .$$

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 α, q_0 varied from 0 to 1 with a step of 0.1, and the parameter β 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

$$A = \frac{F - F_{opt}}{F_{opt}} \times 100\%$$

Table. Relative deviation of tested algorithms.

A task	A, %	
	ACO algorithm	Modified ACO algorithm
A-n32-k5	7.7	6.7
A=n39-k5	11.1	10.0
A-n54-k7	12.6	10.1
B=n43-k6	6.2	6.3
B-n45-k5	5.9	5.5
P=n23-k8	0.9	0.9
P-n40-k5	11.7	11.3
P-n60-k10	11.1	11
P-n76-k5	21	13.6
E=n30-k3	5.9	4.9
E-n51-k5	14.3	13.8

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).

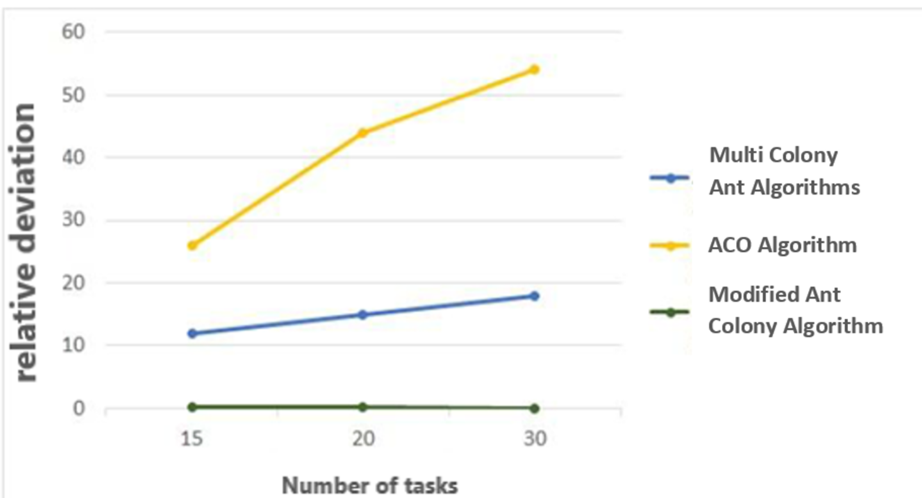

Fig. 3. Average relative deviation depending on number of tasks.

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 set of best decisions that correct the knowledge base. 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.

The proposed algorithm is used in an instrumental system for constructing data exchange over a channel with centralized control in cases where the accuracy of Greedy algorithms is insufficient.

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

1. Lebedeva O.A.; et al. Comparative analysis of methods for solving transport problems with optimal planning of the transportation process. Modern Technologies. System Analysis. Modeling. **3**(67): 134–139. (2020)
2. Balashov V.I, Balakhanov V.A., Kostenko V.A.. Technology for Scheduling of Data Exchange Over bus with Centralized Control in Onboard Avionics Systems. Journal Aerospace Engineering, **224**(9): 993–1004. (2010)
3. Fibre Channel. Pt 312: Avionics Environment Upper Layer protocol MIL-STD- 1553B Notice 2 (FC-AE-1553): Technical Report TR 14165-312:2009. International Organization for Standardization (ISO). Geneva, 84 p. (2009)
4. Kostenko V.A. and Gury'anov E.S.. An Algorithm for Scheduling Exchanges over a Bus with Centralized Control and an Analysis of Its Efficiency. Programming and Computer Software. **31**(6): 340–346. (2005)
5. Sulyukova L.F. and Akhmedjanova Z.I.. Algorithms for solving problems routing of transport and their application in information systems of cargo transportation management. International journal of theoretical and applied issues of digital technologies, **2**(2): 40-52. (2022)
6. Zandavi S.M. and Pourmirzaagha H. and Sendi A.Y. and Toosi E.S. and Zakariapour M.. Urban Path Routing Adjustable Optimization by Wavelet Transform and Multistage Genetic Algorithm. Journal of Applied and Computational Mechanics, **5**(4): 696–703. (2019)
7. Dorigo M. Optimization, Learning and Natural Algorithms PhD Thesis. Dipartimento

di Elettronica. Milano: Politechnico Di Milano. (1992).

8. Shtovba S.D. (2005) Ant Algorithms: Theory and Applications. Programming and Computer Software. 31(4):167-178. DOI: 10.1007/sl 1086-005-0029-1
9. Levine J. and Ducatelle F. Ant Colony Optimization and Local Search for Bin Packing and Cutting Stock Problems. Operational Research Society. **55**: 705–716. (2003).
10. Stuzle T. and Dorigo M.. ACO Algorithms for the Quadratic Assignment Problem. New Ideas in Optimization. Maidenhead: McGraw-Hill Ltd, 33–50. (1999)
11. Ben Jouida S. and Krichen S. A DSS Based on Optimizer Tools and MTS Meta-Heuristic for the Warehousing Problem with Conflicts. Information Processing Letters, **135**:14-21. Elsevier B.V. (2018). https://d0i.0rg/10.1016/j.ipl.2018.02.001
12. Blum C. and Sampels M. Ant Colony Optimization for FOP Shop Scheduling: A Case Study on Different Pheromone Representation. Proc. Congr. on Evolutionary Computation. Los Alamitos, CA: IEEE Computer Society Press, **2**: 1558–1563. (2002).
13. Ritchie G. Static Multi-processor Scheduling with Ant Colony Optimization and Local Search. Master's Thesis. Edinburgh: University of Edinburgh. (2003).
14. Grasse P.P. La reconstruction dun id et les coordinations inter-indioviduelles chez Bellicositemes natalensis et Cubitermes sp. La theorie de la stigmergie: Essai d'interpretation des termites constructeurs. Insectes Sociaux, **6**, 41-83 (1959).
15. Moscato P. Memetic algorithms. Handbook of Applied Optimization. Oxford: Uni Press. (2002).
16. Rodzin S.I. Smart Dispatching and Metaheuristic Swarm Flow Algorithm. The Journal of Computer and System Science. **53**(1): 109-115. (2014).
17. Sorensen C.G., Fountas S., Nash E., Pesonen L., Bochtis D., Pedersen S. M., Basso B., and Blackmore S.B. Conceptual Model of a Future Farm Management Information System. Computers and Electronics in Agriculture, **72**(1): 37–47. (2010).
18. Cormen T.H. and Leiserson C.E. and Rivest R.L. and Stein C. Introduction to Algorithms. MIT Press. (2009).
19. Rodzina L. and Kristofferson S. Context-dependent car Navigation as kind of human-machine collaborative interaction. Proc, of the Int. Conf, on Collaboration Technologies & Systems (CTS'San Diego, California, USA.). Published of the IEEE. 253-259. (2013).
20. Conway R. W. and Maxwel W.L. and Miller L.W. Theory of Scheduling. Courier Dover Publ. (2003).
21. Utamima A., Reiners T., Ansaripoor A. H. (2019). Evolutionary estimation of distribution algorithm for agricultural routing planning in field logistics. Procedia Computer Science*,* **161**, 560-567. https://doi.org/10.1016/j.procs.2019.11.156