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ANT COLONY OPTIMIZATION FOR SOLVING COMBINATORIAL OPTIMIZATION PROBLEMS

ABSTRACT

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Contents

1 Introduction

Relevance and motivation of the topic

Optimization is a key topic in informatics, artificial intelligence, operational research, and related fields. The goal of combinatorial optimization is to find an optimal object according to some criterion, from a finite set of objects. It refers to those optimization problems for which the set of valid solutions is discrete or reducible to discrete and the goal is to find the best possible solution. Examples of combinatorial optimization problems are the traveling salesman problem [114], vehicle routing [125], minimum spanning tree [104], constraint satisfaction [86], the knapsack problem [29] and others. These are NP (non-polynomial) problems, and in order to find near-optimal solutions, metaheuristic methods are usually used. One of them is the Ant Colony Optimization (ACO) [25]. It is well suited for solving discrete problems with tight constraints because it is a constructive method.

Purpose and tasks of the dissertation

The main goal of the dissertation is the development of algorithms, based on the ACO, for solving problems from real life and industry.

To achieve this goal, the following five tasks have been formulated:

- Development of an algorithm for solving the knapsack problem;
- Development of GPS network inspection algorithm;
- Development of an algorithm for building a wireless sensor network according to two criteria, minimum number of sensors and minimum energy used;
- Development of an algorithm for workforce planing;
- Development of an algorithm for modeling passenger flow according to two criteria, travel time and cost of travel.

Methodology

One of the most successful metaheuristic methods for solving combinatorial optimization problems is ACO. The idea for it comes from the behavior of ants in nature. When foraging, ants in nature mark their path by leaving a chemical substance called a pheromone. If isolated, an ant moves essentially randomly. If there is a pre-set pheromone, the ant registers it and decides to follow it with high probability and thus reinforces it with a new amount of pheromone. The repetition of the above mechanism by ants in nature results in the fact that the more ants have traveled a trail, the more desirable it becomes for subsequent ants. On the other hand, the pheromone of the less used paths gradually decreases due to evaporation. This is how nature prevents ants from following old and unprofitable tracks.

Presentation of results

Algorithms were developed in accordance with the tasks, solving specific classes of problems. A software implementation of each of the developed algorithms was made. The programs are written in the C language. A study was made for the values of the control parameters.

Publications

The author of the dissertation has more than 200 publications, most of which are in the field of combinatorial optimization and application of stochastic methods. The results of the dissertation have been published in 19 publications including: 1 monograph published in the prestigious scientific publishing house Springer, 1 with an impact factor in a journal in the top 10% of Q1, 11 with an impact rank, 5 referenced in the world referencing and indexing system and one published in an international journal. All publications are after 2016, when the doctoral student acquired the title of professor, and did not participate in previous procedures.

Citations

The author of the dissertation has over 1250 citations. The publications on which this dissertation is based have been cited 51 times. The publications and citations used are after obtaining previous degrees and titles and have not been used in other procedures. The author's Hirsch index, relative to her known citations, is h=18.

2 Ant Colony Optimization

Ants, having limited individual capabilities, working as a collective are able to find the shortest path between their nest and the food source. This is called group intelligence. They work as follows:

- The first ant finds the food source, somehow, then returns to the nest, leaving a pheromone trail along the way;

- Ants follow possible paths by monitoring pheromone concentration and thus make shorter paths more attractive.;

- Ants prefer shorter paths, thus much of the longer paths lose their pheromone.

Marco Dorigo first applied ideas from ant behavior to solve combinatorial optimization problems [21, 25, 27]. The first ant algorithm was introduced in 1992 by him in his PhD thesis [24] which he defended at the Politecnico di Milano, Italy.

Ant Colony Optimization (ACO) is part of the metaheuristic optimization methods. A metaheuristic is a high-level procedure designed to find, construct, or choosing a low-level procedure that can guarantee finding enough a good solution to the optimization problem, especially when information is incomplete or computer resources are limited. The method is iterative. Briefly, the algorithm can be presented as follows:

- At each iteration, each ant starts building its solution from a random vertex in the graph. The random start is a way to diversify the search in the set of solutions;

- The ant chooses the next vertex to include in the solution using a function called transition probability. This function is the product of the amount of pheromone corresponding to the transition (of the arc connecting the two vertices or of the selected vertex) and heuristic information;

- The ant stops adding new vertices when the probability of adding a new vertex becomes 0;

- At the end of each iteration, the pheromone is renewed;

- The algorithm stops when the termination condition is reached.

The ant moves from vertex i to vertex j of the task graph with probability:

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{all\ possible\ k} \tau_{ik}^{\alpha}\eta_{ik}^{\beta}} \tag{1}$$

Where:

- τ_{ij} is the amount of pheromone corresponding to the transition from vertex i to vertex j;
- α is a parameter controlling the influence of τ_{ij};
- η_{ij} is the heuristic information;
- β is a parameter controlled the influence of η_{ij}

Before the first iteration, an initial pheromone τ_0 is placed, which has a small positive value. The rule for pheromone exchange is as follows:

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij}, \tag{2}$$

Where τ_{ij} is the amount of pheromone corresponding to the transition from vertex i to vertex j , ρ is the pheromone evaporation rate.

3 ACO for the knapsack task

The results of this chapter are published in the following articles : [45, 48, 51, 56, 61, 62].

The multidimensional knapsack problem (MKP) is a complex combinatorial optimization problem with wide application. Tasks from different areas of industry can be presented as MKP including financial and other management. We can think of the knapsack problem as a resource allocation problem. There are m resources (backpacks) and n objects, with object j bringing profit p_j. Each resource has its own budget c_i (knapsack volume), and object j consumes an amount r_{ij} of resource i . We are interested in maximizing the total profit while staying within the limited budget. The MKP can be formalized as follows:

$$\begin{gathered} \max \ \textstyle\sum_{j=1}^{n} p_j x_j \\ \text{subject to} \ \ \textstyle\sum_{j=1}^{n} r_{ij} x_j \leq c_i \ \ i = 1, \ldots, m \\ x_j \in \{0, 1\} \ \ j = 1, \ldots, n. \end{gathered} \tag{3}$$

x_j is 1 if object j is selected and 0 otherwise. Let $I = \{1, \ldots, m\}$ and $J = \{1, \ldots, n\}$, such that $c_i \geq 0$ for each $i \in I$. The well-defined MKP implies that $p_j > 0$ and $r_{ij} \leq c_i \leq \sum_{j=1}^{n} r_{ij}$ for all $i \in I$ and $j \in J$. We note that the matrix $[r_{ij}]_{m \times n}$ and the vector $[c_i]_m$ are non negative.

3.1 ACO algorithm for MKP

We define the graph corresponding to MKP as follows: vertices correspond to objects and every two vertices are connected by edges. Fully connected graph means that after object i object j can be selected if there is enough resource and if object j is not yet selected. The algorithm is iterative. At each iteration, each ant constructs a solution. The starting object (vertex in the graph) is chosen randomly. New objects are then added without violating resource constraints. After all ants have built their solutions, the pheromone values are updated.

Using Intuitionistic Fuzzy Pheromone

In this section, we will apply intuitionistic fuzziness to pheromone renewal. At the beginning, the same pheromone is placed on all edges, which has a small positive value τ_0, $\tau_0 \in (0, 1)$. At the end of each iteration, the pheromone is updated according to the solutions built by the ants. Let ρ be the evaporation rate. The pheromone renewal rule is:

$$\tau_{lj} \leftarrow (1-\rho)\tau_{lj} + \Delta\tau_{lj}. \tag{4}$$

In most applications of ACO to MKP, $\Delta\tau_{lj} = \rho F$, where F is the value of the objective function for the corresponding solution [32]. In the traditional ACO, the evaporation parameter ρ is an input parameter and remains unchanged until the end of the algorithm execution. [61] proposed the use of *intuitionistic fuzzy pheromone*. In the case of intuitionistic fuzzy pheromone, we have proposed the following pheromone update formula [61]:

$$\tau_{lj} \leftarrow (1-\rho)\tau_{lj} + \alpha F, \tag{5}$$

where $(1-\rho) + \alpha \leq 1$, $\alpha \in (0, 1)$.

In the intuitionistic fuzzy pheromone case, we generate the parameter ρ as a random number in the interval $(0, 1)$; then the parameter α is generated as a random number in the interval $(0, \rho)$. We have proposed two variants of the implementation of intuitionistic fuzzy pheromone updating. In the first variant, the parameters ρ and α are generated at the beginning of the execution of the algorithm even before the first iteration. Thus, they remain unchanged until the end of the algorithm execution, but are different for different algorithm executions. In the second variant, the parameters ρ and α are generated at the beginning of each iteration. Thus, their values are different for each iteration of one execution of the algorithm.

The two proposed pheromone renewal options were tested on 10 MKR test samples from Operational Research Library OR-Library , http://people.brunel.ac.uk/ mastjjb/jeb/orlib/mknapinfo.html (21 Jun 2021).

Each test case consists of 100 objects and 10 knapsacks/constraints. For all tests, the ACO algorithm has the same parameters. The parameters are fixed experimentally. The algorithm was run 30 times with each of the variants for each of the test examples. An ANOVA test was applied to ensure the statistical difference between the averaged results obtained. We can conclude that intuitionistically the fuzzy pheromone update improves the performance of the algorithm and the results achieved by increasing the search diversity and hence the probability of finding a good solution. This diversification is more balanced when the coefficients are calculated once at the beginning of the algorithm than at each iteration.

3.2 Hybrid ACO

Sometimes the algorithm used is not enough to achieve good solutions. Then a combination of several methodologies is made so that their good qualities can be combined. Most often, one basic method is used and the solutions found by it are improved by applying local optimization (local search). MKP solutions are represented as a binary string, with 1 corresponding to selected objects and 0 to those not selected. In our local search procedure, we randomly select two positions in the solution constructed by the ant. If one of the selected items has a value of 0, we replace it with 1, and if their value is 1, we replace it with 0. We check whether the newly obtained solution is valid. If the solution is valid, we compare it with the current (initial) solution. If the newly generated solution is better than the current one, we replace it with it. We can conclude that the proposed local search procedure is effective and efficient. The performance of the algorithm has been improved without significantly increasing the time for its execution. Four variants of intercriteria analysis were applied to compare the two algorithms. The conclusion that the hybrid ACO algorithm performs better is unequivocally confirmed by the four different intercriteria analysis algorithms.

3.3 Startup Strategies

To better manage the solution building process, we have included a semi-random start of the ants. Our goal is to use the ants' experience and make the algorithm more efficient. We divide the set of vertices of the task graph into several subsets. We introduce an estimate of how good and how bad it is for the ant to start building a solution from a vertex belonging to a given set, according to the number of good and bad solutions started from vertices belonging to the corresponding set [45, 51].

Several starting strategies and combinations of them are proposed. For each set j , $D_j(i)$ is the estimate of how good the starting vertex of the solution is from this set, and the estimate $E_j(i)$ indicates how bad the initial vertex of the solution is from this set , where i is the current iteration number. We define a bound D for whether the estimate is good and a bound E below which the estimate is bad. The following [39] startup strategies are suggested:

1) If $\frac{E_j(i)}{D_j(i)} > E$ then for the current iteration subset j is forbidden. The starting vertex is chosen randomly from $\{j \mid j$ is not forbidden$\}$;

2) If $\frac{E_j(i)}{D_j(i)} > E$ then by the end of the algorithm subset j is forbidden. The starting vertex is randomly selected from a set $\{j \mid j$ is not forbidden$\}$;

3) If $\frac{E_j(i)}{D_j(i)} > E$ then for K_1 consecutive iterations subset j is forbidden. The starting vertex is chosen randomly from $\{j \mid j$ is not forbidden$\}$;

4) Let $r_1 \in \left[\frac{1}{2}, 1\right)$ and $r_2 \in [0, 1]$ be random numbers. If $r_2 > r_1$ we randomly select a vertex from a subset $\{j \mid D_j(i) > D\}$, otherwise a vertex from a non-forbidden subset is selected. r_1 is selected and fixed at the beginning of the algorithm.

5) Let $r_1 \in \left[\frac{1}{2}, 1\right)$ and $r_2 \in [0, 1]$ be random numbers. If $r_2 > r_1$ we choose a random vertex from a subset $\{j \mid D_j(i) > D\}$, otherwise a vertex from a non-forbidden subset is selected. r_1 is chosen at the beginning of the algorithm and is incremented by r_3 at each iteration.

$K_1, K_1 \in [0, \textit{number of iterations}]$ is a parameter.

We apply an intercriteria analysis to the results achieved by ASO with the application of various startup strategies [39]. An intercriteria analysis was applied to show the relationship between the strategies. From it we can conclude that when the selection is banning subsets of vertices, the algorithm works quite differently from the random selection variant (supervised or not).

4 Inspect GPS Network

The Global Positioning System (GPS) needs periodic tracking, consisting of placing GPS receivers successively at certain points. The results of this chapter are published in [63]. A GPS network can be defined as a set of stations ($a_1, a_2, \ldots, a_n$) that are coordinated by placing receivers ($X1, X2, \ldots$) on them to determine the sessions (a_1a_2, $a_1a_3, a_2a_3, \ldots$) between them. The task is to find the best order in which these sessions can be arranged to give the best schedule. Thus, the schedule can be defined as a series of sessions to be observed consecutively. The solution is represented by a line graph with weighted edges. The nodes represent the stations and the edges represent the moving costs. The goal of the task is to reduce the cost of the solution, which is the sum of the costs (time) of moving from one point to another. Two variants of the ACO algorithm are applied to solve the problem, MMAS and ACS. The test cases used ranged from 100 to 443 sessions.

A comparison is made between the two algorithms. The obtained results show that MMAS achieves better results than ACS. A comparison is also made with the algorithms used by other authors to solve this problem [110]. The results show that both proposed ACO algorithms outperform other authors' algorithms. To improve the behavior of the algorithm and the achieved results, 6 local search procedures are proposed: sequential exchange of nodes; exchange in to randomly selected nodes; delete a random rib; deletion of the longest rib; delete 2 random edges; deleting the two longest ribs. The local search procedure is applied only to the best solution of the current iteration. In this way, there is an improvement in the solutions found, without a significant increase in the execution time of the algorithm. After the tests, it was found that the fifth variant of the local search procedure with the removal of two randomly selected edges gives the best results.

An ant method with a change in environment has also been proposed. Added an additional change to the ant environment by adding an extra shuffle to the pheromone exchange. A change in environment has been shown to improve the results obtained.

An intercriteria analysis was applied to the ACO algorithm applied to the average results of 5, 10, 20 and 30 runs. Through the intercriteria analysis, the correctness of the algorithm and the similarities in the structure of the individual GPS networks can be examined.

5 Wireless Sensor Network Positioning

Spatially distributed sensors that communicate wirelessly form a wireless sensor network (WSN). Each sensor node collects data from an area around it, called the observation area. The observation radius defines the size of the area observed by the sensor. The communication radius determines how far a node can send the collected data. A special, more powerful node called the High Energy Communication Node (HECN) collects the data from all the sensors and sends it to the central computer where it is processed. As few sensors and energy as possible should be used, provided that the monitored terrain has full coverage. The task is multi-purpose. An algorithm based on the ant method is proposed for solving the problem as a multi-objective and two ACO algorithms for solving it as a single-objective. The results of this chapter are published in [50, 53, 57, 107, 63].

One of the most important points of ACO algorithms is the construction of the task graph. We need to choose which elements of the task will correspond to the nodes and the meaning of the arcs, where it is more appropriate to deposit the pheromone - on the nodes or on the arcs. In our WSN implementation, the task is represented by two graphs, which is one of our contributions. The terrain is modeled by a rectangular grid $G = \{g_{ij}\}_{N\times M}$, where M and N are the dimensions of the observed area. Through the graph G, the coverage of the area is calculated. We use another graph $G1_{N1\times M1}$, in the vertices of which we place the sensors, $N1 \leq N$ and $M1 \leq M$. The parameters $N1 \leq N$ and $M1 \leq M$ depend on the observation and communication radii. In this way, we reduce the number of calculations that the algorithm performs, the execution time is reduced accordingly. The pheromone binds to the placement site $Ph = \{ph_{ij}\}_{N1\times M1}$, the initial pheromone has a small value, for example, $1/n_{ants}$. The place where the HECN is located is the first position in the solution (zero position).

Our proposed heuristic information is a product of three parameters as follows:

$$\eta_{ij}(t) = s_{ij} l_{ij}(1 - b_{ij}), \tag{6}$$

where s_{ij} is the number of uncovered points that the new sensor will cover,

$$l_{ij} = \begin{cases} 1 \\ 0 \end{cases} \tag{7}$$

b is the decision matrix and the matrix element $b_{ij} = 1$ when there is a sensor placed on node (i, j) of graph $G1$, otherwise $b_{ij} = 0$. By s_{ij} we try to increase the locally covered points, more newly covered points can lead to less number of sensors. With l_{ij} we guarantee the connectivity of the network. Sensor placement starts from the HECN to the periphery. Each new sensor is placed so that it can transmit the collected information to the HECN. The expression $(1 - b_{ij})$ guarantees that at most one sensor will be placed on one node of graph $G1$, i.e. there will not be two or more sensors in the same position. When the transition probability $p_{ij} = 0$ for all values of i and j , the search for new sensor placement positions stops. Thus, the construction of the solution stops if there are no more free positions, or all points are covered, or new communication is impossible.

Two approaches were used to convert the task from multi-objective to single-objective. In one approach, the objective function is a product of the two objective functions of the task. In the other approach, the two objective functions are summed, having previously been normalized by dividing by the best value from the first iteration. There are two sub-options here: simple sum and weighted sum.

A comparison is made between the different approaches and the results obtained by other authors. For this purpose, the concept of extended Pareto front was introduced. The influence of the algorithm parameters is investigated.

Various variants of intercriteria analysis were applied. The influence of the number of ants on the behavior of the algorithm was evaluated using the intercriteria analysis. Again, with the help of the intercriteria analysis, the similarity between the individual variants of the applied algorithm was examined. There is more similarity between the behavior of the two single-objective variants than between some of the single-objective and multi-objective variants.

6 Workforce planning

Human resource management is one of the main parts of production organization. Given a set of jobs $J = \{1, \dots, m\}$ that must be completed in a fixed period of time. Each job j takes d_j hours to complete. $I = \{1, \dots, n\}$ is the set of available workers. Each worker must work on each of their assigned tasks for a minimum of h_{min} hours to work efficiently. Worker i is available s_i hours. The maximum number of jobs assigned to one worker is s_i hours. Workers have different skills, the set A_i indicates which tasks worker i is qualified for. The maximum number of workers that can be assigned in the schedule period is t or at most t workers can be selected from the set I of available workers, and the assigned workers must be able to complete all jobs. The goal is to find a valid solution that has a minimum assignment cost. In this work, an algorithm based on the ACO is proposed to solve the Workforce planning problem [46, 106, 63, 108].

In the considered case, the task is represented by a three-dimensional graph, where vertex (i, j, z) means that worker i is hired to work on task j for time z. At the beginning of each iteration, each ant starts building a solution from a random vertex of the task graph. Three random numbers are generated for each of the ants. The first random number is in the interval $[0, \dots, n]$ and corresponds to the worker being hired. The second random number is in the interval $[0, \dots, m]$ and corresponds to the job on which this worker should work. The third random number is in the interval $[h_{min}, \dots, \min\{d_j, s_i\}]$ and corresponds to the number of hours worker i is employed to work on job j . Heuristic information is calculated using the following formula:

$$\eta_{ijl} = \begin{cases} l/c_{ij} & l = z_{ij} \\ 0 & otherwise \end{cases} \tag{8}$$

With this heuristic information, we encourage hiring the cheaper workers for as long as possible. The set of test examples includes ten structured and ten unstructured tasks. A task is structured when the time to complete the task is proportional to the minimum time that must be worked on that task. A comparison of the proposed ACO algorithm with algorithms proposed by other authors is made and it is shown that the ACO algorithm outperforms others for this task.

The task has strict constraints and some of the ants fail to find a valid solution. A local search procedure is proposed to improve the algorithm. It is applied to the invalid solutions found in the iteration. The procedure is one-time, regardless of whether the solution after a local search is valid or not. In this way, the execution time of the algorithm does not increase significantly. A decrease in the number of invalid solutions found by the ants is observed even after the first iteration. In this way, the time (number of iterations) to find the best solution decreases. Three variants of the local search procedure are proposed: removing 25% of the assigned workers and adding new ones using the ant method. Remove half the assigned workers and add new ones by applying the ant method and delete the invalid solution and build a new solution in its place. The procedure in which half of the appointed workers are removed is the most effective. Removed workers are randomly selected.

The influence of the parameters of the ACO algorithm on the quality of the solutions found has been studied. Various numbers of ants (5, 10, 20 and 40) were used, and it was found that the best results were obtained when the number of ants was 5.

An intercriteria analysis was applied to gain some additional knowledge about the considered four variants of the ACO algorithm. It shows that at 5 and 10 ants we have a similar behavior of the algorithm as at 20 and 40. On the other hand, ICrA confirms the conclusion that for this task the best performance of the algorithm, i.e. using less computing resources, is with the use of five ants.

7 Passenger Flow Modeling

Rail transport is the oldest form of public transport still in use today. Nowadays, bus transport competes with rail, especially where there are highways. Analytical models are therefore very important for further planning and decision-making in transport development. The results of this chapter are published in [42, 58, 64].

In our case, there is a destination from stop A to stop B. There are several types of vehicles, a variety of trains and buses that travel between stop A and stop B. Each vehicle has a plurality of intermediate stops at which it stops between the two final stops. Some of the intermediate stops may be shared by some of the vehicles. Let the set of all stops be $S = \{s_1, \dots, s_n\}$ and at each stop s_i, $i = 1, \dots, n-1$, n is the number of stops, in each time slot, there is a number of passengers who want to travel to station s_j, $j = i + 1, \dots, n$. Each vehicle may have a different speed and cost to travel from stop s_i to stop s_j. We have defined two objective functions, the sum of the prices of all tickets sold and the total travel time of the passengers. If any of the vehicles does not stop at any of the stops, then we set the travel time and price to that stop to be 0.

When applying the ACO to the passenger flow modeling task, the time is divided into time slots/slots ($N \times 24$ time slots corresponding to 60/N minutes. The ants start building the solution from the first stop. They choose randomly how many passengers will board each of the vehicles The upper limit of passengers that can board the vehicle is the minimum of the difference between the capacity of the vehicle and the passengers already in it and the number of passengers who want to ride If there is only one vehicle at a given stop at a given time, then as many passengers as possible board it.

The developed algorithm is first applied to a small example and then to a real example. The initial stop is Sofia, the capital of Bulgaria, and the final stop is Varna, the maritime capital of Bulgaria. This is one of the longest railway routes in Bulgaria, with a length of about 450 kilometers. There are 5 trains and 23 buses per day on this route. They run at different speeds, fares for getting from one stop to another are different, and have differences in intermediate stops. We do not have exact data on the number of passengers traveling from one stop to another on the Sofia-Varna line. For this reason, we have made an estimate of the number of passengers, taking into account the number of inhabitants of the settlements where the vehicles stop.

8 Conclusion

Combinatorial optimization is extremely difficult from a computational point of view. Usually, the application of a given method for solving such type of tasks depends on the task itself and may be different for different variants of the same task. The focus of this dissertation is on the application of the ant method. This method is among the best for solving combinatorial optimization problems. The ant method differs from other methods in that it is a constructive method and outperforms most of the other methods in a large number of applications. In the present dissertation, the results of the author, in the field of the ant method and its applications, achieved in the last 7 years are collected. At the beginning, a description of the method and its varieties is given. Individual chapters present the application of the ant method to various tasks. These are the backpack task, GPS network inspection task, wireless sensor network construction task, workforce recruitment task, passenger flow modeling. The influence of the parameters of the developed algorithms was investigated. An intercriteria analysis was applied. A program implementation of the developed algorithms was made.

8.1 Publications related with the dissertation:

Monographs

1 Fidanova S.. Ant Colony Optimization and Applications. Studies in Computational Intelligence, 947, Springer, 2021, ISBN:978-3-030-67380-2, DOI:https://doi.org/10.1007/978-3-030-67380-2, 142 pages.

Journals with Impact Factor

2 Fidanova S., Atanassov K.. ACO with Intuitionistic Fuzzy Pheromone Updating Applied on Multiple Knapsack Problem. Mathematics, 9, 13, MDPI, 2021, ISSN:2227-7390, DOI:10.3390/math9131456, 1-7. IF 2.9, Q1.

Impact Rank Publications

3 Fidanova S.. Metaheuristic Method for Transport Modelling and Optimization Studies in Computational Intelligence, 648, Springer, 2016, 295 - 302. SJR 0.235

4 Roeva O., Fidanova S., Paprzycki M.. Comparison of Different ACO Start Strategies Based on InterCriteria Analysis. Recent Advances in Computational Optimization, Studies in Computational Intelligence, 717, Springer, 2018, ISBN:978-3-319-59860-4, 53-72. SJR 0.235

5 Fidanova S., Shindarov M., Marinov P.. Wireless Sensor Positioning Using ACO Algorithm. Studies in Computational Intelligence, 657, Springer, 2017, ISBN:978-3-319-41437-9, ISSN:1860-949X, 33-44. SJR 0.235

6 Fidanova S., Roeva O.. InterCriteria Analyzis of Differen Variants of ACO algorithm for Wireless Sensor Network Positioning. Lecture Notes in Computer Science, 11189, Springer, 2019, 88-96. SJR 0.407

7 Fidanova S., Roeva O.. Multi-Objective ACO Algorithm for WSN Layout: InterCriteria Analisys. Lecture Notice in Computer Science, 11958, Springer, 2020, ISBN:978-3-030-410315, 474-481. SJR 0.407

8 Roeva O., Fidanova S.. Different InterCriteria Analysis of Variants of ACO algorithm for Wireless Sensor Network Positioning. Studies in Computational Intelligence, 838, Springer, 2020, ISBN:978-3-030-22723-4, 83-103. SJR 0.237

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11 Roeva O., Fidanova S., Ganzha M., InterCriteria Analysis of the Evaporation Parameter Influence on Ant Colony Optimization Algorithm: A Workforce Planing Problem, Studies in Computational Intelligence 920, 2021, 89-110. SJR 0.237

12 Fidanova S., Roeva O., Influence of ACO Evaporation Parameter for Unstructured Workforce Planning Problem, Large Scale Scientific Computing, Lecture Notes in Computer Science 13127, 2022, 234-241. SJR 0.407

13 Fidanova S., Roeva O., Ganzha M., Ant Colony Algorithm for Fuzzy Transport Modelling: InterCriteriaAnalysis, Studies in Computational Intelligence 986, 2022, 123-138. SJR 0.237

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14 Fidanova S., Roeva O., Paprzycki M., Gepner P.. InterCriteria Analysis of ACO Start Startegies. IEEE Xplorer, 2016, ISBN:ISBN 978-83-60810-90, DOI:ISBN 978-83-60810-90-3, 547-550

15 Fidanova S.. Hybrid Ant Colony Optimization Algorithm for Multiple Knapsack Problem. 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), IEEE, 2020, DOI:10.1109/ICRAIE51050.2020.9358351, 1-5

16 Fidanova S., Roeva O., Ganzha M.. InterCriteria Analyzis of Hybrid Ant Colony Optimization Algorithm for Multiple Knapsack Problem.

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8.3 Contributions

The contributions in this dissertation can be divided into scientific and applied science. Scientific contributions concern the development of algorithms based on the ant method. The scientific and applied contributions refer to the program implementation of the developed algorithms.

The scientific contributions are:

- A hybrid algorithm for solving the knapsack problem is developed as a combination between applying the ant method and a suitable local search procedure. The use of two variants of intuitionistic fuzzy pheromone is introduced. With the help of intercriteria analysis, a comparison was made between the variants of the algorithms used, as well as the use of starting strategies.
- A GPS network inspection algorithm based on the ant method has been developed. Added changes to the search environment. The correctness of the algorithm and the similarity between the networks were investigated using intercriteria analysis.
- Algorithms have been developed to solve the task of building a wireless sensor network based on the ant method. A sensitivity analysis was performed against the number of ants used. The similarities and differences of the individual algorithms were analyzed using intercriteria analysis.
- An algorithm has been developed for solving the labor recruitment task based on the ant method. Several variants of local search procedures have been developed in order to improve the performance of the algorithm. An analysis of the sensitivity of the algorithm to its parameters was made. An intercriteria analysis was applied.
- An algorithm has been developed for modeling passenger flow in the presence of various types of transport in one direction. The algorithm is based on the ant method.

The scientific and applied contributions are:

- A software implementation of the hybrid algorithm for solving MKP was made;
- A software implementation of the GPS surveying network algorithm was made with changes to the search environment;
- A software implementation of the algorithm for solving the work force planning problem was made;
- A software implementation of a passenger flow modeling algorithm was made.

The results of this dissertation can be used in various fields of science, industry and practice. The developed algorithms and their program implementation refer to practical tasks and can be implemented in various branches of the economy.

Declaration of originality of the results

I declare that this dissertation contains original results obtained during scientific research carried out by me. Results that have been obtained, described and/or published by other scientists are duly and extensively cited in the bibliography.

This dissertation has not been applied for a degree at any other graduate school, university or scientific institute.

Signature:

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