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Full Length Article

A metaheuristic solution approach to capacitied vehicle routing and network optimization

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ABSTRACT

The vehicle routing problem (VRP) is one of the problem types that are sought after for a long time by trying out different techniques and attracting attention in terms of optimization. In most VRP types, route cost is associated with distance, and a shorter distance solution is considered a more successful solution. While the shortest distance goal provides significant advantages in terms of cost and time to businesses, this makes it attractive for further research. When examining the types of problems having different directions and areas devised from different points of view on vehicle routing, it can be said that the closest approach to practical application is the vehicle routing problem with simultaneous delivery and pickup (VRPSDP). In this study, a solution proposal is presented for the VRPSDP using the Artificial Bee Colony (ABC) algorithm and the application is tested with the benchmark problem data sets commonly used for VRPSDP in the literature. When the results are compared with the least cost route solutions in the literature, it is observed that despite the few parameters, the proposed method can produce low-cost solutions very close to the most successful solutions in the literature.

1. Introduction

Technological developments in transportation and communication, has globalized trade worldwide. Therefore, intense competition in today's market, short-lived products and increasing expectations of customers have forced producers to pay more attention to distribution systems. According to Toth and Vigo [40], especially in the field of transportation, savings in the range of 5%–20% can be achieved, with computer-aided methods. In this context, the solution of the VRP, which is defined as the problem of determining the best routes of the vehicles that will go out from one or more depots for the delivery and pickup service of geographically scattered customers, can provide a significant advantage for reducing costs [6]. The basic approach in the VRP is to provide all distribution needs by providing that demands of all customers with known demand quantities are fulfilled from a single depot and that each customer is visited with only one transport vehicle [4]. A study of Dantzig and Ramser in 1959 aiming minimizing the route cost of the truck fleet distributing gasoline can be considered as the systematic first study on VRP [9]. From 1959 onwards, different solutions have been suggested for VRP on a large part of the logistics transport and distribution departments of production and service sectors, from automotive to foodstuff, textiles to cargo [28,19]. When studies on VRP are examined, it is possible to come across different types of problems in which delivery and pickup on the nodes are performed at different times independently of each other [12]. In VRP types, the VRPSDP type comes to the forefront in terms of similarity to real life logistics activities in particular. The most distinctive feature of VRPSDP is that all the goods to be delivered to the customers are sent from the warehouse and all the goods to be received from the customers are sent to the same warehouse [1]. Various kinds of heuristic and metaheuristic methods are used as well as exact methods for VRPSDP solutions.

Within the scope of this study, it is aimed to develop an algorithm having acceptable range of solution times, that finds low cost routes for vehicles of limited capacity that carry out simultaneous delivery and pickup activities in various types of multi-client network models. The lower cost of the route will also bring advantages such as higher efficiency, lower fuel consumption and shorter delivery times while reducing the number of vehicles to be used as well. In the framework of the above-mentioned targets, ABC algorithm has been preferred as the method. ABC algorithm can be used for other types of problems for which metaheuristic methods can be used, and it is observed to yield successful results

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in many applications for especially NP-Hard kinds of combinatorial optimization problems. The ABC algorithm is a population-based efficient algorithm that can scan a wide range of solutions, spreading to many different points at the same time, in addition to its successful performance in the local search. By using the ABC algorithm, we aimed to be able to successfully scan search spaces that has different levels of fluctuation due to variations in inter-node distances and load demands of VRPSDP problems.

1.1. Mathematical formulation of VRPSDP

VRPSDP can be defined as: In the closed graph model $G = (V, E), V = \{0, 1, \ldots, n\}$ is the set of nodes. Node 0 represents the warehouse center; others represent the customers to visit. $E = \{(i,j) : i,j \in V\}$ is the set of edges and each edge has the cost c_{ij} cost (distance). All vehicles (M) in the vehicle vault in the warehouse are homogeneous (Q) and there is no restriction on the number of vehicles. The vehicles move from warehouse simultaneously and return to the warehouse at the end of the route. Vehicle capacity should not be exceeded along the route for each vehicle. Each customer $(i \in V)$ is only visited by one vehicle and only once. The amount of d_i is delivered to each customer and the amount of p_i is picked up from each customer. Mathematical formulation of the VRPSDP can be defined as follows:

$$min \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \tag{1}$$

$$\sum_{j=0}^{n} x_{ij} = 1 \quad \forall i = 1, \ldots., n \tag{2}$$

$$\sum_{j=0}^{n} x_{0j} \leq m \tag{3}$$

$$\sum_{j=0}^{n} x_{ij} = \sum_{j=0}^{n} x_{ji} \quad \forall i = 1, \ldots., n \tag{4}$$

$$\sum_{j=0}^{n} P_{ij} - \sum_{j=0}^{n} P_{ji} = p_i \quad \forall i = 1, \ldots., n \tag{5}$$

$$\sum_{j=0}^{n} D_{ij} - \sum_{j=0}^{n} D_{ji} = d_i \quad \forall i = 1, \ldots., n \tag{6}$$

$$P_{ij} + D_{ij} \leq Q \quad \forall i = 1, \ldots., n \quad \forall j = 1, \ldots., n \tag{7}$$

$$P_{ij}, D_{ij} \geq 0 \quad \forall i = 1, \ldots., n \quad \forall j = 1, \ldots., n \tag{8}$$

$$x_{ij} \in \{0, 1\} \quad \forall i = 1, \ldots., n \quad \forall j = 1, \ldots., n \tag{9}$$

The objective function (1) gives the sum of the total cost of the vehicles. Constraints (2) mean that only one arc can be exited for each customer. The maximum number of vehicles is guaranteed by constraints (3). Constraints (4) show that number of exited and entered arcs for each customer are same. Equality Eqs. (5) and (6) insure that the quantity of pickup and delivery goods of each customer is fully satisfied in one visit. Constraints (7) state that the vehicle capacity is never exceeded. Restrictions (8) force the flow to remain non-negative and finally, constraints (9) describe that each arc in the network has the value 1 if it is used and 0 otherwise.

Delivery and pickup activities are carried out simultaneously at each node designated as a "stop point" along the route. Since the solution space exponentially expands with the number of nodes, such problems are considered to be in the class of NP-hard problems [42]. Applegata et al. [2] conducted detailed analyzes with the Bellman-Held-Karp algorithm which contains dynamic solutions for NP-hard problem solutions. They examined the complexity of the problems and the solution time with Bellman-Held-Karp algorithm. The $n^2 2^n$ running time and memory requirement overwhelms the implementation as we increase the number of cities. When we reach n = 29, the memory requirement exceeds 12 GBytes and the test was terminated without computing an optimal tour. Since the vehicle capacity becomes insufficient as the number of nodes increases in the problem, a two-step solution approach in which the nodes are grouped and then routed is developed [31].

1.2. Brief literature review of VRPSDP

The first approach to a multi-node VRP solution with simultaneous distribution/ aggregation is proposed by Min [31]. In Min's study, two transport vehicles were assigned for all books to be distributed from a single depot and the transport vehicles were routed to visit 22 libraries. Developed solution consists of three stages: creating clusters for customer nodes, assigning the appropriate transport vehicle for each cluster that is created, and routing the cluster to which each transport vehicle belongs. Dethloff [11] developed a heuristic method based on addition and achieved more successful results than Min. Bianchessi and Righini [5] used Dethloff's formula in the Tabu Search (TS) algorithm and obtained successful results from Dethloff. Another method developed for VRP with delivery and pick up is presented in the literature by Nagi and Salhi [32]. The algorithm is useful for VRPSDP as well as a general solution for some mixed-case situations where only delivery is performed for some of the customers and only picking up is performed for some of the customers. Cetin et al. [6] argued that this new model was more successful than Min's method. Tang and Galvão [39] proposed two heuristic solutions for local search using tour partitioning and sweep algorithms. A number of solutions have been proposed for the tour partition approach. One of them is the algorithm developed by Cristofides, Mingozzi and Toth [15,8,13]. Crispim and Brandao [7] used metaheuristic method for the first time in the simultaneous delivery/pick-up VRP solution. Ai and Kachitvichanukul [1] developed a different mathematical model and tried this model with the Particle Swarm Optimization (PSO) Algorithm. First, they compared the approach they offered to meet the current needs of the logistics world to the test data of Solomon [38] and got successful results, then they created new comparison problems. When Yousefikhoshbakht et al. [41] examined the solutions developed for VRPSDP, they realized that metaheuristic solutions were more successful and formed a hybrid system by combining the modified TS and the elite ant system algorithms for the solution of such problems. Mancini [29] exemplifies the simultaneous delivery and pickup transportation system employing a multi-repository, multi-period heterogeneous capacity transport fleet that can be encountered in real life. Mancini proposed a mixed integer programming formulation in such a network and proposed a metaheuristic-based adaptation of wide neighborhood search approach. Salhi et al. [36] addressed a similar problem and worked on a variable neighborhood search application with new features in addition to neighborhood and local search operators. With the algorithm developed for the solution, more successful results were obtained in 23 of the 26 samples published in the literature. In a different study developed for the VRP solution, Hosseinabadi et al. [17] proposed a new meta-heuristic optimization algorithm which is based on the law of gravity and group interactions. Their proposed algorithm uses two of the four basic parameters of velocity and gravitational force in physics based on the concepts of random search and searching agents, which are a collection of masses that interact with each other based on Newtonian gravity and the laws of motion. Hosseinabadi et al. [18] proposed a new combinatorial algorithm named OVRP_-GELS based on gravitational emulation local search algorithm for solving OVRP which is a different kind of VRP. Kalayci and Kaya [21] developed a hybrid metaheuristic method based on ant colony system (ACS) and variable neighborhood search (VNS). In this method, the algorithm was tried to be strengthened by reinforcing the performance of the VNS in the local search with the strong memory structure of the ACS. Avci and Topaloglu [3] upheld that the proposed solution approaches for VRPSDP are also applicable to Vehicle Routing Problem with Mixed Pickup and Delivery (VRPMPD). They have developed a hybrid approach using the simulated annealing (SA) algorithm and the Variable Neighborhood Descent (VND) algorithms together. Rieck et al. [34] developed two mixed integer linear model formulations which they call "A vehicle-flow" and "A commodity-flow" for VRPSDP. In order to strengthen the models, Rieck outlined domain-reducing preprocessing techniques, and effective cutting planes. By employing Multiple Neighborhood Guided Local Search Algorithm (MN_GLS), Zhu et al. [44] designed a model with 3 stages. First, they used the nearest neighborhood method to create the initial solution. They used multiple operators in the initial solution in the second stage and they tried to find the optimal solution for the local search with varying values of objective functions and penalty points and in the third stage they chose the most successful solution from the local optimal solutions. Sayyah et al. [37] used an effective ant colony optimization (EACO) algorithm that includes addition, jump and 2-Opt movements instead of classical ant colony optimization (ACO). The method they propose has proven successful when tested with literature examples, and it has also been shown that they can compete with other metaheuristic algorithms such as TS, large neighborhood search (LNS), PSO and GA.

When the literature summary is examined, it has been determined that the ABC method which can perform detailed searches in a short period of time is not used although the metaheuristic methods are generally preferred in VRPSDP solutions. The ABC algorithm is a metaheuristic method that can produce successful solutions with large parameter values even in large volume optimization problems. In this study, the ABC algorithm is chosen considering its efficiency of combinatorial optimization problems. With the proposed method, the solution routes obtained by the ABC algorithm in the optimal solution search process and the graphical drawings of these routes can be tracked in detail.

The following sections of the article are designed as follows: In Section 2 the ABC algorithm is described. In Section 3, the method developed by applying the ABC algorithm to the VRPSDP solution is introduced in detail. In Section 4, parameter set of the proposed method are designed and the proposed is tested on benchmark problems. In Section 5, the results of the proposed method in VRPSDP test problems are compared with the most successful results observed in the literature. Finally, in Section 6, the results of the developed method and literature comparison are interpreted and discussed for performance improvement.

2. ABC algorithm

ABC was developed in 2005 by Dervish Karaboga [23], which was developed for real parameter optimization based on the foraging behaviors of honey bee colonies in natural life. Algorithm has been applied successfully in different fields of different engineering disciplines [26,27,25,30,22]. According to Karaboga, honey bees are divided into three groups according to the division of labor in the colony life [24]:

- Scout Bees: Bees who go out to forage and are randomly disperse and start the search process. When food sources are identified, these bees now function as service bees.
- Employed Bees: They are responsible for carrying the nectar from the sources found. They also search for other sources around food sources because they perform their duties according to the neighborhood principle. The other duty of these bees is to describe the address of the food source to the onlooker bees in the hive. If the food source that the employed bee has been carrying food from is exhausted, this bee starts working as a scout bee and disperses to find new food sources.
- Onlooker Bees: This group of bees which wait in the hive, observe the vibrations that other bees perform in order to transfer food location information. They head towards the food source they prefer considering their acquired information about the food quality and quantity.

The scout bees control the exploration process, while the employed bees and onlookers' carryout the exploitation process in the search space [33]. The percentage of scout bees varies from 5% to 30% according to the information into the nest. The mean number of scouts averaged over conditions is about 10% in natüre [20]. A food source in the world of bees correspond to any possible solution in the ABC algorithm. Therefore, the quality of the food source relates to the value of the determined solution [24].

The basic steps in the ABC algorithm can be listed according to the behaviors of the bees in their natural life as below [24]:

- The first set of food sources is determined
- Repeat
- Employed bees are sent to the determined food sources
- The possibility values that will be used for choosing food sources is calculated according to the quality of the nectar that was brought by the employed
- Onlooker bees choose their preferred set of food sources using the possibility values
- Scout bees disperse to find new food sources
- Until requirements are met

The variables used in the mathematical expression of the algorithm

r_{ab}	:	r denotes food source, a denotes the source number, b denotes the appropriate parameter number
s_e	:	randomly chosen source
ϕ_{ab}	:	randomly chosen weighting number $[-1, 1]$
t_a	:	found new source

If we assume the largest area with the hive as the center, that the bees can disperse for looking for food sources (r) as the search space, the algorithm starts working with randomly chosen points in this area. While choosing random points, these points have to be chosen inside the related area as expressed with the Eq. (10). In other words, while generating the random locations of the set of points, low and high bounds of the required parameters must be considered [25]. In proposed method for VRPSPD solution, the lower limit is 1, and the upper limit is the number of nodes to be visited.

$$r_{ab} = r_{\min b} + rand(0,1) * (r_{\max b} - x_{\min b}) \tag{10}$$

The bees that are directed towards food sources also visit nearby food sources. In the ABC algorithm context, this visiting behavior can be implemented using various methods. If the new resource produced by this or similar methods is more qualified

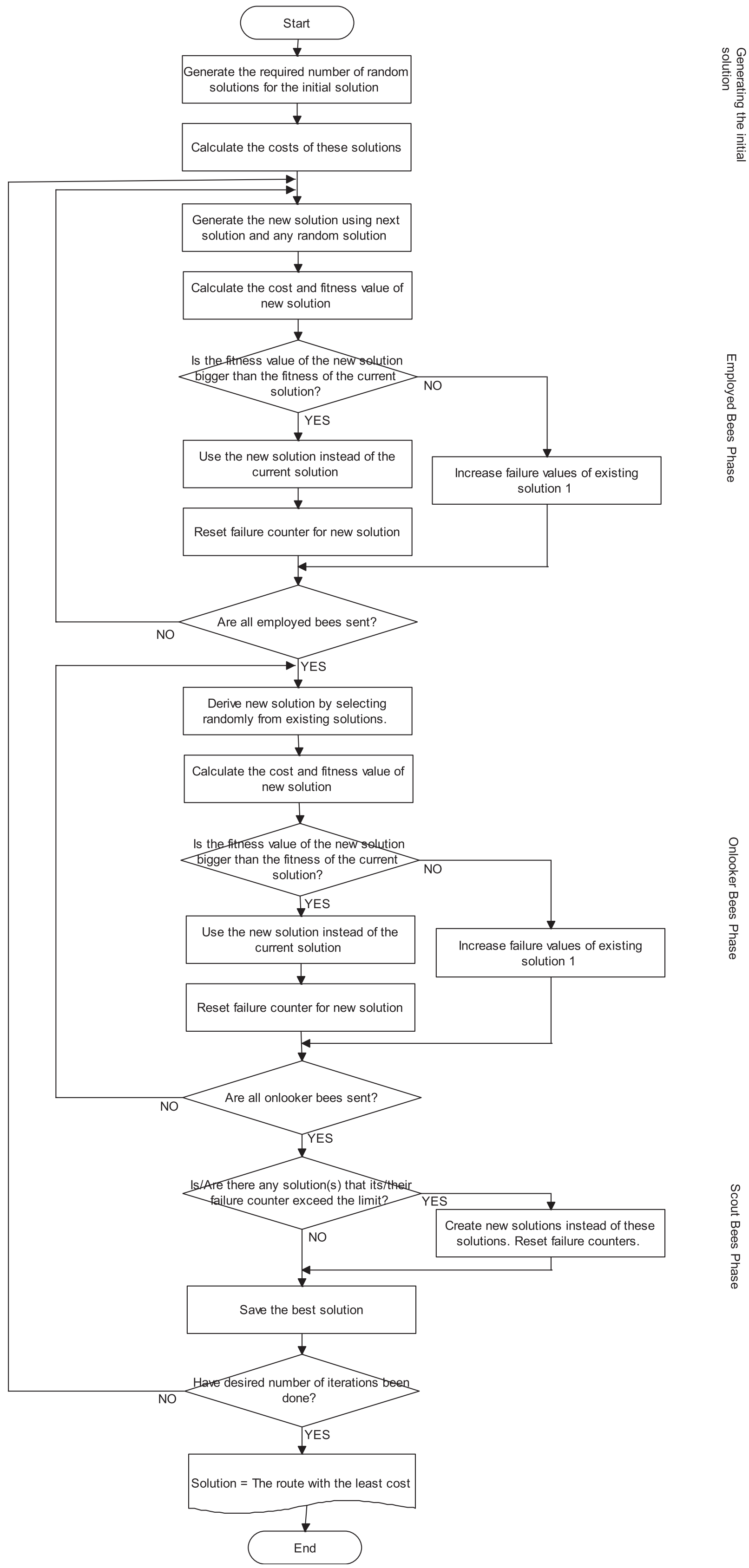

Fig. 1. The ABC algorithm developed for VRPSDP.

0	28	41	37	16	…	19	25	***0***	49	32	11	***0***	3	29	…	***0***

Fig. 2. An example solution generated by proposed method.

Next solution	***0***	28	41	37	16	…	19	25	***0***	49	32	11	***0***	3	29	…	***0***
Chosen solution	***0***	46	13	36	21	…	14	20	37	44	***0***	15	2	47	9	…	***0***
Derived solution	***0***	28	41	16	30	…	25	20	37	44	***0***	15	2	47	***0***	…	***0***

Fig. 3. Derive new solution with OX crossover method.

than the existing resource, this new resource is stored. This new source, which is noticed in the neighborhood of the source, is expressed by the Eq. (11):

$$t_{ab} = r_{ab} + \phi_{ab}(r_{ab} - s_{eb}) \tag{11}$$

In the expression (2), b parameter of source r_a, b parameter of source s_e, ϕ_{ab}parameter are all parameters which are randomly selected in the range [1..D]. Difference between parameter b of the r_a source, and the randomly selected s_e source b. parameter of the s_e food source is weighted with value of ϕ_{ab} parameter is calculated. Then this difference is used to find a new t_a resource. The difference between the b parameter of the r_a source and the b parameter of the other s_e source is weighted by ϕ_{ab} parameter to find a new t_a source. If the newly found t_{ab} source is more qualified than the r_a source, this source will be used from then on.

All bees on duty, Transfer their information to the onlooker bees in the hive. The onlooker bees choose a source according to the information they receive and head towards that source. This probabilistic preference of onlooker bees is made according to the fitness values expressing the nectar quality in the algorithm model. In the ABC algorithm, the roulette wheel method is generally preferred for this selection. The expression for the use of the roulette wheel is shown by Eq. (12).

$$P_i = \frac{fitnes(S_i)}{\sum_{i=1}^{SN} fitnes(S_i)} \tag{12}$$

Honey bees leave a source they visit in the resource search process, when the nectar is consumed in that source. Nectar depletion in one source means that honey bees using that source can no longer benefit from the source. In the ABC algorithm, the sources that are exhausted are determined by failure counters. When all the bees in the source search return the hive (when a cycle is completed) the new sources that are found are compared against the current sources to update the values for "not being able to develop a solution" counter. When the not being able to develop a solution counter of a bee exceeds a predetermined limit value, that bee leaves the source that it has been visiting, assumes scout bee role and start searching for new sources randomly [24].

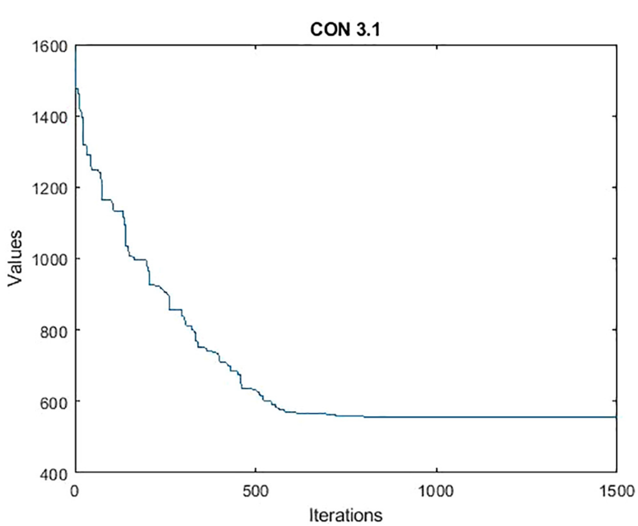

Fig. 4. Results of the application for the CON3.1 problem.

3. Proposed method: ABC for VRPSDP

In Section 2, operations in ABC steps are described with original design developed for numerical optimization problems. In the proposed method, the ABC algorithm is designed to determine the minimum cost of transport vehicles in different multi-point network structures where collection and distribution activities are carried out simultaneously. ABC algorithm is constructed as in Fig. 1 for the VRPSDP which a kind of discrete problem is.

Each solution in which all the nodes are visited to meet the desired conditions is considered as a "food source" in the ABC algorithm. In this context, "nectar quality" is inversely proportional to "route cost". Therefore, the algorithm looking for "top quality nectar" is designed to find the lowest cost route. The number of employed bees and onlooker bees who are guided to the food sources in each cycle is equal to the number of food sources initially determined. In addition, the limit value at which the algorithm will end the cycle and the limit value the feed source is to be abandoned are other parameters that can be determined by the user.

3.1. Generating the initial solution

The algorithm starts with the creation of random solutions by the determined number of food sources. The solutions created within the scope of the application are the vehicle route clusters targeted to be created in the minimum number. In VRPSDP, the first node, denoted by "0", is depot; other nodes are customer nodes. So, the vehicle routes are number sequences that begin with 0 and continue till the next 0. In this context, each solution is a series of numbers which contains "the number of vehicles +1" times 0 and all other node numbers each used exactly once. Therefore, this situation should not be overlooked while random solutions are being created or new solutions are derived from existing solutions. In Fig. 2, an example solution is presented.

3.2. Employed bees phase

In this phase, new solutions are derived by changing the order of the nodes in the initialize solutions. In the proposed method, the new solutions are derived with the order crossover (OX) technique developed by Davis [10]. Within this scope, each existing solution is crossed by the OX technique from another solution selected from the existing solutions by the roulette wheel. OX algorithm initially selects two solution route and two randomly cut-off points on each of these solution routes, with an equal number of nodes remaining between them. When deriving new solutions, the nodes between the breakpoints are mutually displaced and the remaining nodes are arranged in the order of the current solutions. Fig. 3 presents a dual-point OX crossover method used in new solution derivation.

If the existing solutions used in the derivation of the new solution fail to derive more successful solutions, the "failure counter" value of these solutions is increased. Solutions, Failure counter values of which reached limit values are deleted, new solutions are created instead of these solutions, and the failure counter value of these newly generated solutions are set to 0.

3.3. Onlooker bees phase

In onlooker phase, again OX method is used when generating a new solution. Alternatively, both solutions to be used in crossing over are randomly selected by the roulette wheel. If the existing solutions used in the derivation of the new solution fail to derive more successful solutions, the "failure counter" value of these

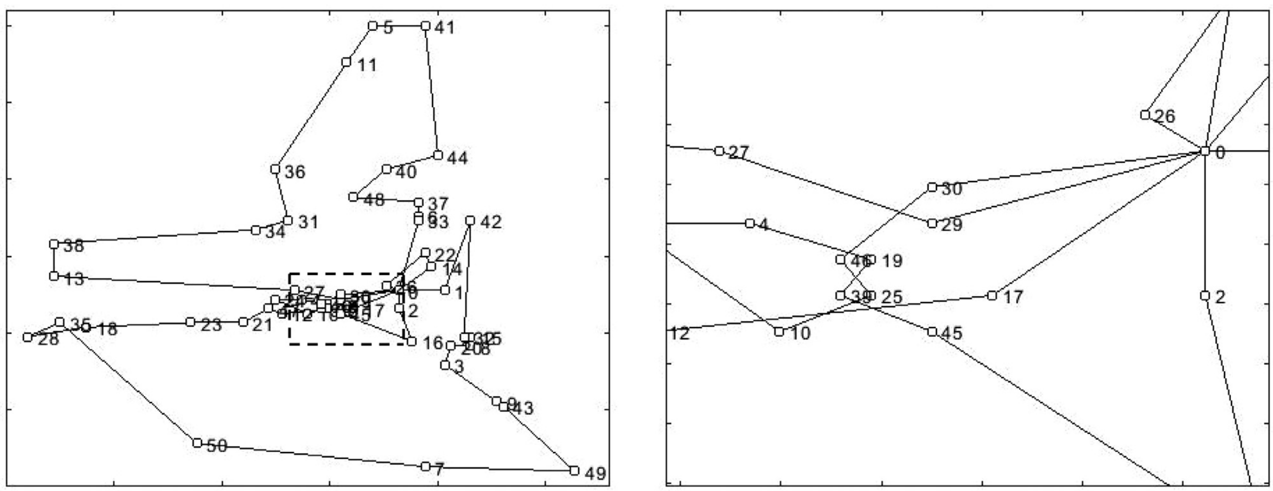

Fig. 5. Solution plot for the CON3.1 test problem of the application.

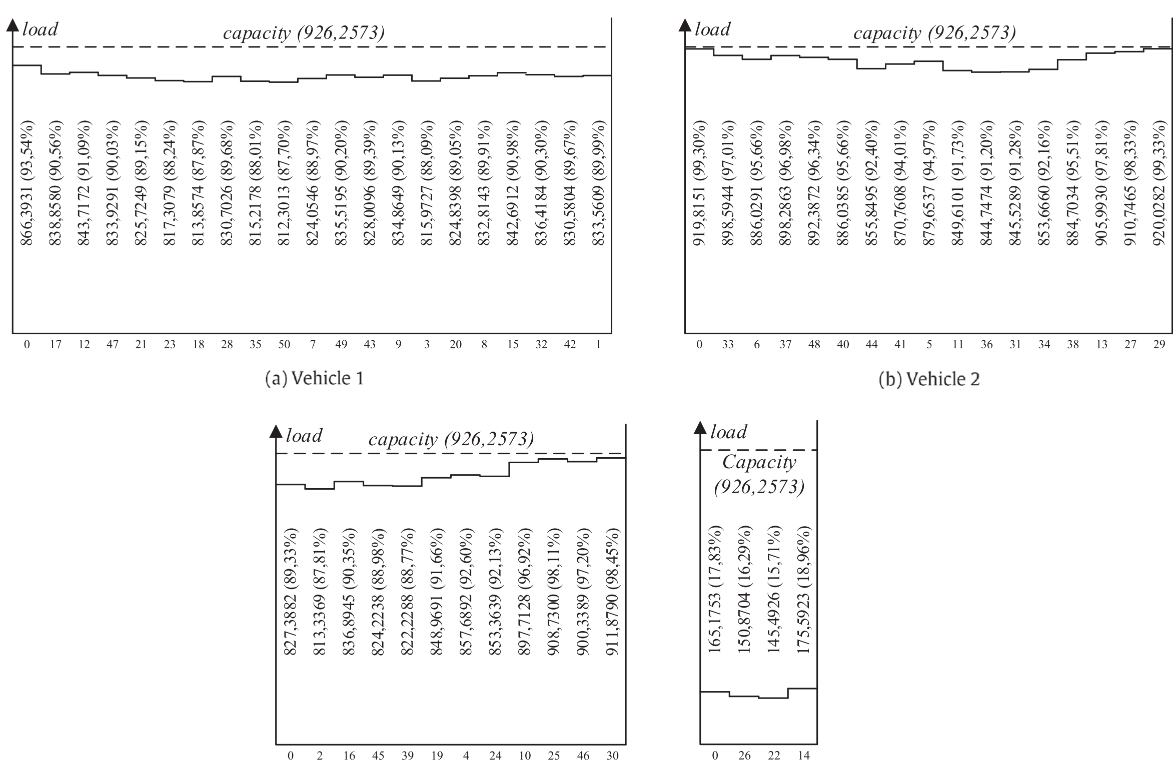

Fig. 6. Occupancy rates of transport vehicles on the solution route for the CON3-1 test problem of the application.

solutions is increased. Solutions, Failure counter values of which reached limit values are deleted, new solutions are created instead of these solutions, and the failure counter value of these newly generated solutions are set to 0.

3.4. Scout bees phase

In scout bees phase, solutions which their failure counter values reached limit values are deleted, new solutions are created instead of these solutions. Failure counter value of newly generated solutions are set to 0. The creation of a new solution is carried out in a similar manner to the initial operations.

Table 1
Literature studies for CON and SCA problems.

LNS (Large Neighborhood Search) [35]
ACS (Ant Colony System) [14]
PILS (Parallel Iterative Local Search) (Subramanian et al., 2010)
AMM (Adaptive Memory Methodology) [43]
h_PSO (hybrid Particle Swarm Optimization) [16]
MTSEAS (Modified Tabu Search and Elite Ant System) [41]
ACSEVNS (Ant Colony System Empowered Variable Neighborhood Search) [21]
ALS (Adaptive Local Search) [3]
MILP (Mixed-Integer Linear Programming) [34]
MN_GLS (Multiple Neighborhood Guided Local Search) [44]
EACO (Effective Ant Colony Optimization) [37]

4. Computational study

The proposed algorithm is coded in the .NET platform using the C # programming language. Application ran on a machine having 8 GB of RAM, i7-4710MQ 2.50 processor and Windows 7 operating system. When the test problems are examined as a result of extensive literature search for test problems aiming minimization of distance-based route cost, CON and SCA examples drew attention especially because of their different variations. Since their first preparation, it has been observed that algorithms that produce successful solutions for these examples are successful for other similar problems as well. For this reason, the developed application has been tested for these test problems. CON and SCA test problems were designed and developed by Dethloff for VRPSDP. Although there were 50 customers in both scenarios, in SCA model, customers were randomly distributed to the geographical area, and in the CON model, half of the customers were randomly distributed while the other half was concentrated on a specific area [16]. In both models two different vehicle types were used in different capacities.

When the values obtained for the CON3.1 problem are evaluated together with the parameter values of the algorithm, it is noticed that the algorithm can produce more successful solutions when the values of the food source and limit parameters are increased, the limit value is increased, and the number of iterations is decreased.

Table 2
Literature studies and their best solutions for CON and SCA problems.

Test Problems	LNS	ACS	PILS	AMM	h_PSO	MTSEAS	ACSEVNS	ALS	MILP	MN_GLS	EACO
SCA3-0	636.10	635.62	635.62	635.62	635.62	635.62	635.62	635.62	677.35	635.66	635.93
SCA3-1	697.84	697.84	697.84	697.84	697.84	697.84	697.84	697.84	758.90	697.84	697.84
SCA3-2	659.30	659.34	659.34	659.34	659.34	659.34	659.34	659.34	735.18	659.34	659.34
SCA3-3	680.60	680.04	680.04	680.04	680.04	680.04	680.04	680.04	735.79	680.04	680.04
SCA3-4	690.50	690.50	690.50	690.50	690.50	690.50	690.50	690.50	741.75	690.50	690.50
SCA3-5	659.90	659.90	659.90	659.90	659.90	659.91	659.91	659.90	702.45	659.96	659.90
SCA3-6	651.10	651.09	651.09	651.09	651.09	651.09	651.09	651.09	707.72	651.09	651.09
SCA3-7	666.10	659.17	659.17	659.17	659.17	659.17	659.17	659.17	708.24	659.17	659.17
SCA3-8	719.50	719.47	719.48	719.47	719.47	719.48	719.48	719.47	771.94	719.47	719.47
SCA3-9	681.00	681.00	681.00	681.00	681.00	681.00	681.00	681.00	726.77	681.00	681.00
SCA8-0	975.10	961.50	961.50	961.50	961.50	961.50	961.50	961.50	1026.79	961.50	964.81
SCA8-1	1052.40	1049.65	1049.65	1049.65	1049.65	1052.04	1049.65	1049.65	1127.41	1049.65	1049.65
SCA8-2	1044.50	1042.69	1039.64	1039.64	1039.64	1039.64	1039.64	1039.64	1126.12	1039.64	1042.64
SCA8-3	999.10	983.34	983.34	983.34	983.34	983.34	983.34	983.34	1062.99	983.34	983.34
SCA8-4	1065.50	1065.49	1065.49	1065.49	1065.49	1065.49	1065.49	1065.49	1114.12	1065.49	1065.49
SCA8-5	1027.10	1027.08	1027.08	1027.08	1027.08	1027.08	1027.08	1027.08	1085.96	1027.08	1027.08
SCA8-6	977.00	971.82	971.82	971.82	971.82	971.82	971.82	971.82	1038.59	971.82	975.19
SCA8-7	1061.00	1052.17	1051.28	1051.28	1051.28	1061.00	1051.28	1051.28	1114.17	1051.28	1051.28
SCA8-8	1071.20	1071.18	1071.18	1071.18	1071.18	1071.18	1071.18	1071.18	1165.08	1071.18	1071.18
SCA8-9	1060.50	1060.50	1060.50	1060.50	1060.50	1060.50	1060.50	1060.50	1145.71	1060.50	1062.34
CON3-0	616.50	616.52	616.52	616.52	616.52	616.52	616.52	616.52	667.46	616.52	616.52
CON3-1	554.50	554.47	554.47	554.47	554.47	554.47	554.47	554.47	590.82	554.47	554.47
CON3-2	521.40	518.00	518.00	518.00	518.00	518.01	518.00	518.00	558.89	518.00	519.89
CON3-3	591.20	591.19	591.19	591.19	591.19	591.19	591.19	591.19	634.93	591.19	591.19
CON3-4	588.80	588.79	588.79	588.79	588.79	588.79	588.79	588.79	627.95	588.79	588.79
CON3-5	563.70	563.70	563.70	563.70	563.70	563.70	563.70	563.70	603.56	563.70	563.70
CON3-6	500.80	499.05	499.05	499.05	499.05	500.80	499.05	499.05	539.58	499.05	500.21
CON3-7	576.50	576.48	576.48	576.48	576.48	576.48	576.48	576.48	627.05	576.48	576.48
CON3-8	523.10	523.05	523.05	523.05	523.05	523.05	523.05	523.05	561.65	523.05	523.05
CON3-9	586.40	578.25	578.25	578.25	578.25	578.25	578.25	578.25	619.95	578.25	578.25
CON8-0	857.20	857.17	857.17	857.17	857.17	857.17	857.17	857.17	918.21	857.23	859.93
CON8-1	740.90	740.85	740.85	740.85	740.85	740.85	740.85	740.85	772.44	740.85	740.85
CON8-2	716.00	712.89	712.89	712.89	712.89	712.89	712.89	712.89	738.99	712.89	712.89
CON8-3	811.10	811.07	811.07	811.07	811.07	811.07	811.07	811.07	857.35	811.07	811.07
CON8-4	772.30	772.25	772.25	772.25	772.25	772.25	772.25	772.25	816.81	772.25	772.25
CON8-5	755.70	754.88	754.88	754.88	754.88	755.70	754.88	754.88	798.07	754.88	754.88
CON8-6	693.10	678.92	678.92	678.92	678.92	678.92	678.92	678.92	718.36	678.92	678.92
CON8-7	814.80	811.96	811.96	811.96	811.96	814.80	811.96	811.96	863.39	811.96	812.55
CON8-8	774.00	767.53	767.53	767.53	767.53	767.53	767.53	767.53	808.17	767.53	767.79
CON8-9	809.30	809.00	809.00	809.00	809.00	809.00	809.00	809.00	843.84	809.00	809.00

Table 3
Comparison of ABC results with the most successful solutions in the literature.

Test Problem	Dethloff	Literature Best	ABC				
			Best	AVG.	Standard Deviation	% GAP (ABC best compared to Dethloff)	% GAP (ABC best compared to Literature)
SCA3-0	689.00	635.62	640.55	684.05	27.88	7.03	−0.78
SCA3-1	765.60	697.80	697.84	735.60	22.16	8.85	−0.01
SCA3-2	742.80	659.30	659.30	725.43	38.88	11.24	0.00
SCA3-3	737.20	680.04	683.11	731.93	27.40	7.34	−0.45
SCA3-4	747.10	690.50	692.57	738.13	23.09	7.30	−0.30
SCA3-5	784.40	659.90	659.90	706.73	32.18	15.87	0.00
SCA3-6	720.40	651.09	651.09	678.07	35.17	9.62	0.00
SCA3-7	707.90	659.17	666.54	717.83	35.17	5.84	−1.12
SCA3-8	807.20	719.47	723.44	762.13	19.10	10.38	−0.55
SCA3-9	764.10	681.00	685.16	734.50	31.51	10.33	−0.61
SCA8-0	1132.90	961.50	961.50	1015.65	15.19	15.13	0.00
SCA8-1	1150.90	1049.65	1060.63	1131.80	18.60	7.84	−1.05
SCA8-2	1100.80	1039.64	1045.12	1092.20	16.37	5.06	−0.53
SCA8-3	1115.60	983.34	983.34	1051.93	8.47	11.86	0.00
SCA8-4	1235.40	1065.49	1072.39	1131.13	13.73	13.19	−0.65
SCA8-5	1231.60	1027.08	1027.08	1099.73	15.07	16.61	0.00
SCA8-6	1062.50	971.82	980.71	1049.40	15.43	7.70	−0.91
SCA8-7	1217.40	1051.28	1059.28	1136.24	24.11	12.99	−0.76
SCA8-8	1231.60	1071.18	1080.02	1141.53	12.53	12.31	−0.83
SCA8-9	1185.60	1060.50	1060.50	1132.97	19.59	10.55	0.00
CON3-0	672.40	616.50	616.50	657.93	19.19	8.31	0.00
CON3-1	570.60	554.47	554.47	582.47	8.26	2.83	0.00
CON3-2	534.80	518.00	523.47	538.97	7.35	2.12	−1.06
CON3-3	656.90	591.19	595.46	619.33	14.75	9.35	−0.72
CON3-4	640.20	588.79	591.37	620.73	15.75	7.63	−0.44
CON3-5	604.70	563.70	563.70	608.77	16.42	6.78	0.00
CON3-6	521.30	499.05	502.63	527.43	14.34	3.58	−0.72
CON3-7	602.80	576.48	580.87	621.87	16.70	3.64	−0.76
CON3-8	556.20	523.05	523.94	547.03	17.76	5.80	−0.17
CON3-9	612.80	578.25	578.25	610.90	21.94	5.64	0.00
CON8-0	967.30	857.17	864.52	895.77	10.12	10.63	−0.86
CON8-1	828.70	740.85	745.91	773.03	6.76	9.99	−0.68
CON8-2	770.20	712.89	712.89	749.77	8.89	7.44	0.00
CON8-3	906.70	811.07	816.38	860.58	16.29	9.96	−0.65
CON8-4	876.80	772.25	774.90	801.80	7.66	11.62	−0.34
CON8-5	866.90	754.88	758.33	779.83	5.68	12.52	−0.46
CON8-6	749.10	678.92	683.21	717.87	5.41	8.80	−0.63
CON8-7	929.80	811.96	811.96	844.77	8.78	12.67	0.00
CON8-8	833.10	767.53	771.19	796.90	5.26	7.43	−0.48
CON8-9	877.30	809.00	809.00	834.70	4.88	7.79	0.00

Table 4
Comparison of Literature with ABC on VRPSPD instances of Dethloff [11].

Test Problem	Literature Average best solution	ABC Average best solution
SCA3	673.39	675.95
SCA8	1028.15	1033.06
CON3	560.95	563.07
CON8	771.65	774.83

5. Computational results and comparisons

For the CON3.1 problem solution of the algorithm, the values obtained at 1500 iterations with parameter values as 1300 for the food source and 250 for the limit are shown in Fig. 4.

The most successful result was recorded as 554.47 units, the solution of which is as follows:

0-17-12-47-21-23-18-28-35-50-7-49-43-9-3-20-8-15-32-42-1-***0***-33-6-37-48-40-44-41-5-11-36-31-34-38-13-27-29-***0***-2-16-45-39-19-4-24-10-25-46-30-***0***-26-22-14-***0***

In Fig. 5, a graphical illustration of the resulting solution route is shown. In the solution route, four transport vehicles are needed for transportation. Fig. 6 shows the updated quantities of these four transport vehicles of 926.2573 units capacity, which are updated after delivery/pickup at each node on the routes.

As the CON31 problem for which detailed analysis of the algorithm outputs are explained, solutions for all other CON and SCA examples is sought using the ABC algorithm as well as the CON31 problem. The results obtained were compared with those of the most successful results of the literature studies that obtained solutions for these test problems. The different approaches that produce results for the CON and SCA examples and the hardware features of the machines on which these approaches are applied are presented in Table 1.

Table 2 presents the most successful results of the solutions which are improved by testing different approaches for CON and SCA.

In Table 3, the most successful results for the CON and SCA problem solutions for the approaches developed for VRPSDP solution are compared with the ABC results. Table 3 also shows the average values obtained by ABC for each problem, the standard deviation data, the CPU time spent in finding the best result, and the average CPU time spent solving each problem. Looking at Table 3, it can be seen that the proposed method can produce much lower cost routes than Dethloff, and that it lags behind the most successful results in the literature up to recently with a percentage of up to 1.12%. Given the time and standard deviation data, ABC appears to be able to produce solutions at reasonable times and at low standard deviations.

When the comparison data (in Table 3) were examined, it is seen that, the average of the most successful results obtained with the ABC algorithm (761.73) was only 3.2 points (0.4%) behind the average of the most successful results in the literature (758.53). Table 4 presents the average of the most successful results obtained by the ABC algorithm and the average of the most successful results obtained in the literature for each the problem groups.

6. Conclusion

In this study, a new solution for VRPSDP is suggested using ABC algorithm. The developed algorithm is run for the publicly known related benchmark problems, and results are compared with the most successful results in the literature obtained until today. As a result, it has been observed that the ABC algorithm is applicable to combinatorial optimization problems at different fluctuation levels such as VRPSDP. The ABC algorithm also yields approximate results to other metaheuristic methods. When the application's result values are analyzed, it is observed that without tackling to local best solutions, the algorithm can direct itself towards other areas of the search space. In order to increase applicability in real life in the logistics field, metaheuristic methods can be developed which can schedule for flexible ARP models with varying number and capacity of vehicles and can also produce dynamic solutions to unexpected problems encountered during travel. Also, applicability of the application to real life situations can be improved by using data obtained from logistic firms, and leaning towards "first group, then route" approach.

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