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Accelerated Cuckoo Optimization Algorithm for Capacitated Vehicle Routing Problem in Competitive Conditions

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ABSTRACT

Transportation represents one of the major human activities all over the world; besides, it is an important part of economy, the improvement of which results in a considerable reduction in costs. Routing is one of the most well-known problems in the field of transportation optimization, which is of high complicacy due to being categorized as an NP-hard problem. In this research, in order to approximate this problem to real conditions, the customer satisfaction is considered in the model along with cost reduction. The main innovation of this study is to consider the competitive conditions as well as customer satisfaction in vehicle routing; besides, another innovation is to present a developed meta-heuristic algorithm based on cuckoo optimization algorithm (COA) in order to solve the problem in a short time and with a high quality. COA is a subset of the evolved computations, which is directly related with the artificial intelligence (AI); in fact, this algorithm is a subset of AI. In the proposed algorithm, instead of k-means clustering, the simulated annealing algorithm (SAA) is used to accelerate the cuckoo clustering. The results show that the proposed algorithm can accurately solve the problem with large dimensions in a reasonable time and with minimum errors. In this regard, a case study on dairy products distribution is conducted and solved using the proposed algorithm, and accordingly the efficacy and effectiveness of the developed algorithm and model are proved by sensitivity analysis of the main parameters.

Keywords: Vehicle Routing, Accelerated Cuckoo Optimization Algorithm (ACOA), Simulated Annealing Algorithm (SAA), Increasing of Satisfaction Level, Competitive Conditions.

Computing Classification System (CCS): I.2, B.7.2, I.5.3, and G.2.1.

1. INTRODUCTION

Since distribution of goods, on average, accounts for nearly 20% of the total production cost, the improved efficiency of the goods transportation would lead to considerable saving in the final cost as well as competition in the regional economy. Most of the problems in the field of commodity distribution can be considered as vehicle routing problem (VRP), which is indeed the generalized version of the traveling salesman problem (TSP); thus, the afore-mentioned problem is one of the most important problems among the combined optimization problems, for solution of which numerous heuristic methods have been devised so far.

Effective vehicle routing is economically of great importance for both private and public sectors. The vehicle routing problem has been defined as a broad field of study (Ombuki-Berman and Hanshar, 2009), which is not limited to merely a few academic courses that apply it only for traffic management. The general VRP model includes a set of customers, so that the demand of each customer is clear and every customer is served completely for only once. It is assumed that all the vehicles are homogeneous, the starting and ending point of each vehicle is a certain depot, and the main purpose is to minimize the total distance traveled by all vehicles (Eksioglu *et al.,* 2009). Due to the constraints found in the real world, some limitations are added to the classical model.

In this research, in order to approximate the VRP to the more realistic conditions, some important instances are added to the problem, and modeling is performed again. The innovation of this study in the problem definition includes consideration of the competitive conditions, customer satisfaction, and cost reduction simultaneously. The customer satisfaction can be interpreted as the amount of the demand that has been met; furthermore, the transportation costs also include the costs of utilizing the vehicles as well as the route traveling costs. A comprehensive investigation of COA and analysis of its weak points show that to accelerate this algorithm and improve its quality, the simple-structured evolutionary algorithms can be used; thus, the most important innovation of this research in the solution approach is development of the COA in order to improve its quality as well as its function speed. On this basis, the SAA is used to accelerate the cuckoo clustering.

An overview of the considered problem structure has been presented in Fig. 1.

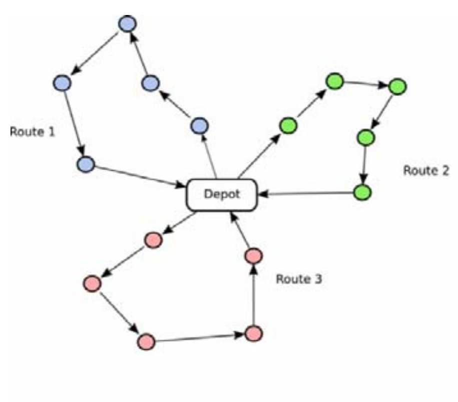

Fig. 1. Overall structure of the research problem.

The rest of research is organized as follows: Section 2 describes some of the most important and most recent relevant studies. In Section 3, the detailed mathematical model is described, and Section 4 presents the solution approach including the classical cuckoo algorithm as well as the ACOA along with the relevant equations. Section 5 includes the numerical results of the simulated sample, as well as a case study, report, and sensitivity analysis along with the comparisons of solutions of the two algorithms. And finally, Section 6 provides the conclusion as well as some suggestions for further studies.

2. LITERATURE REVIEW

Liu and Lee considered the customer's random demand, which included the expenditures in the routing location problem. The primary solution was obtained by customers clustering methods based on increased order of the marginal inventory costs. For each cluster, the nearest depot was assigned, and then the traveling salesman problem (TSP) was solved (Liu and Lee, 2003). Fukasawa *et al.* (2006) investigated the precise solution of the capacitated VRP; accordingly, they introduced branch and bound, lagrangian relaxation, and column generation as the exact and absolute solution for this problem, and then presented a hybrid approach for faster solution of the problem. Ngueveu *et al.* (2010) investigated the capacitated VRP with the aim of reducing the total delivery time. In this problem, they defined the travel (tour) length limitation for each vehicle. Xiao *et al.* (2012) introduced a fuel consumption optimization model in the capacitated VRP. Subsequently, to solve the problem, they presented a SAA, and then added the hybrid displacement operators in order to improve its performance. Asawarungsaengkul *et al.* (2013) presented a multi-size compartment VRP with split pattern that focused on the delivery of liquid products from depot to customers. Their main objective was minimizing of the total traveling cost.

A literature review, including the fleet composition and road and sea transportation routing problems, was presented by Hoff *et al.* (2010). This study investigated a total of 120 researches on fleet determination and routing, and subsequently presented a mathematical model for this group of problems. Soonpracha *et al.* (2014) presented a review of the literature on fleet-sizing and vehicle routing, routing of the vehicles with different fleets, as well as development of these problems; besides, they investigated the new studies on this field.

Ruttanateerawichien *et al.* (2014) investigated the capacitated VRP; accordingly, for the given problem, they considered a two-objective mathematical model with the aim of minimization of the total travelled distance and vehicles. Jin *et al.* (2014) solved the capacitated VRP by simultaneous use of cooperative game and meta-heuristic methods in order to minimize the number of vehicles. López-Sánchez *et al.* (2014) conducted a research with respect to the European Union's labor insurance law, according to which the accident insurance only applies to one hour before and after the working hour and the workers should be sent home after at most one hour. They modeled the problem using the BOVRP (Balanced Open VRP) approach with the aim of minimizing the Makespan. Khmelev and Kochetov (2015) studied the split delivery VRP which was a variant of the classical capacitated VRP in which a customer's demand could be split among several vehicles. They divided the split delivery

VRP into two sub-problems: finding of the best permutation and finding of the best vehicle routes for an arbitrary permutation.

Rahimi-Vahed *et al.* (2015) focused on the optimal fleet-sizing problem considering three different modes of the VRP problems. These three modes included: 1) multi-depot VRP problem, 2) periodic VRP problem, and 3) multi-depot periodic VRP problem. In each of these problems, to approximate the conditions to the real world, they considered three constraints of vehicle capacity, route traveling duration, and budget, and then solved the proposed model using modular algorithm. Bozorgi-Amiri *et al.* (2015) investigated the SDVRP (Split Delivery VRP) problem, and presented a memetic algorithm for solving it; furthermore, they used 21 standard problems to assess efficacy of the algorithm. Chen *et al.* (2016) stated that the VRP in distribution centers with cross-docking operation is more complex than its traditional mode. In this paper, they investigated the VRP in distribution centers with multiple cross-docking operation with the aim of reducing the total cost of the operation. Given the high complexity of the model, a PSO algorithm with self-learning strategy, known as SLPSO (self-learning particle swarm optimizer), was used. Meta-heuristic algorithms have been used widely in literature like as the previous reviewed papers, for a simple and related example, Sait *et al.* (2016) employed the COA to solve their problem. Because their investigated problem was strongly NP-hard and these problems aren't solved without using an efficient algorithm in large dimensions. Some of the latest applications of other algorithms used in optimization introduced and studied in the papers of Ali et al. (2016) and Chen et al. (2017).

Lin and Tsai (2014) presented a model for ship routing and transportation for allocation of daily transportation operation of the marine lines in order to minimize the costs and delays. According to their paper, the ship routing problem is essentially an OVRP problem, since the ship does not necessarily return to its origin. Saidi Mehrabad et al. (2017) investigated simultaneous optimization of the total costs of a multi-level supply chain and customer satisfaction. They presented a multi-objective hybrid particle swarm algorithm (MOHPSO) in order to obtain optimal solutions of the model; then, compared its results with those of the NSGA-II algorithm. Yousefikhoshbakht *et al.* (2016) pointed to a heterogeneous fixed fleet open vehicle routing problem (HFFOVRP), in which several types of vehicles were used to serve the customers. Since their presented problem was of NP-hard type, they used a hybrid heuristic algorithm, called SISEC, composed of various algorithms including sweep, insertion sort, 2-opt improvement initiatives, elite ant system (EAS), and column generation (CG) to solve the HFFOVRP problem.

Sitek (2014) investigated and modeled a multilevel capacitated VRP, so that the levels included depot and customer. To solve the problem, they used a multi-factorial method. Shaabani and Kamalabadi (2016) added the problem of inventory-routing of perishable products with fixed life to the literature. This problem was an integration of a multi-period/multi-product problem in a two-level supply chain, in which the products were delivered in the manufacturer unit to multiple retailers with transport strategies by a capacitated fleet. They solved the problem using the population-based simulated annealing algorithm (PBSA). Penna *et al.* (2016) presented the hybrid electric fleet routing problem with time window and charging stations using local search algorithm. The electric transportation would be an opportunity to reduce the greenhouse gas emission in nature; however, the driving limitation in a longer interval as well as the charging time limitation were among the obstacles of implementing these projects.

Zhang *et al.* (2016) investigated a new mode of the routing problem called the traveling salesman problem with profits and stochastic customers (TSPPSC) with the aim of simultaneous optimization of profits and traveling costs. This mode of the problem dealt with stochastic presence of the customer in an environment in which the benefit was achieved with the customer’s visiting and being served. Cheng *et al.* (2017) added to the literature the problem of green inventory-routing with heterogeneous fleet, which was a developed version of the conventional inventory-routing problem regarding the environmental effects and heterogeneous vehicles. This study was mainly aimed to minimize the inventory and routing costs, including the cost of drivers’ wage, fixed vehicle costs, and costs of fuel and emissions. Veenstra *et al.* (2017) presented the PDTSPH (pickup and delivery TSP with handling costs), is the aim of which was to find the possible routes so that the total costs, including the travel cost and fine expenses, could be minimized. Punitha and Manickam (2017) presented an authentication and privacy preservation on secure geographical routing protocol for vehicular networks.

Nadizadeh and Kafash (2017) developed the fuzzy capacitated location-routing problem with simultaneous pickup and delivery demands (FCLRPSPD) to minimize the costs. They considered a set of customers whose pickup and delivery demands should be met by a fleet at the same time. Furthermore, they solved the model using the greedy clustering method. Dinc Yalcın and Erginel (2015) presented for the first time a new algorithm based on fuzzy multi-objective programming for the VRPB (vehicle routing problem with backhauls). This algorithm included three phases of clustering, routing, and local search. In the clustering phase, the customers were allocated to the vehicles by multi-objective programming model; then, in the routing phase, each vehicle was mapped as a TSPB. Chávez *et al.* (2016) added to the literature a multi-objective mathematical model for investigating the multi-depot VRPB. Their model included minimization of three objectives, including the total distance traveled, total journey time, and energy consumption.

Wu *et al.* (2016) investigated the heterogeneous VRP with mixed backhauls and time window limit to minimize the total service cost. Their innovation was in the simultaneous investigation of two assumptions of backhauls and diversity of received goods, which had been previously studied as a single-product case. As the most recent research in this field, but not necessarily the last, Wassan *et al.* (2017) investigated a new mode of the multi-travel routing problem with backhauls (MTVRPB). The classic MTVRP model was converted to the new MTVRPB model by taking into account the aspect of backhauls. Furthermore, to solve the problem in large scales, a developed two-level VNS (variable neighborhood search) algorithm was used.

Table 1 represents a summary of the recent relevant researches.

Table 1. Review of recent relevant studies along with the present study.

Researchers	Multi-depot routing	Minimizing costs	Limited capacity of fleet	Competitive conditions	Approximate solution approach
Sitek (2014)		*	*		
Lin & Tsai (2014)	*	*	*		
Ruttanateerawichien et al. (2014)		*	*		
Rahimi-Vahed et al. (2015)	*	*			
Dinc Yalcın & Erginel (2015)	*				*
Bozorgi-Amiri et al. (2015)		*	*		*
Chen et al. (2016)		*	*		*
Yousefikhoshbakht et al. (2016)		*	*		*
Penna et al. (2016)		*	*		*
Zhang et al. (2016)	*	*	*		
Chávez et al. (2016)	*	*	*		
Wu et al. (2016)		*		*	*
Wassan et al. (2017)	*	*	*		
Cheng et al. (2017)		*	*		
Veenstra et al. (2017)		*			
Nadizadeh & Kafash (2017)	*		*		*
This Paper	*****	*****	*****	*****	*****

Reviewing the earlier studies may reveal the consideration of the competitive conditions along with the customer satisfaction as well as the use of new high-speed solution algorithms as the gap in this field; therefore, the present study attempts to cover this research gap as much as possible.

3. PROPOSED MODEL DESCRIPTION

In the present study, a network of the given points is considered, which includes a depot and several customers. The vehicles start to move from the depot and come back to the depot after passing a route through the customers. The use of each of the vehicles have a fixed initial cost; besides, coverage of the route by each vehicle will also entail transportation costs. The limited capacity of vehicles, in some cases, will make it impossible to meet the customer's demand; accordingly, under such circumstances, a higher number of vehicles should be used. Thus, in such cases, creating a tradeoff between the additional costs and meeting a higher amount of demands will become more important; so that, the more the demands that are met, the greater the customer's satisfaction will be.

The present study is aimed to provide a new approach for designing the transportation fleet routes. The previous studies have mainly focused on reduction of the costs as well as timely delivery; however, in this research, the level of customer satisfaction is considered as a key index. In the non-competitive conditions, if the customer's demand is not met by a vehicle, another transportation vehicle can compensate it; while, in competitive conditions, if the customer doesn't receive his demand completely at a certain time, his demanded product may be provided by other competitors.

Therefore, an optimal service time can be defined for each customer, which can facilitate specifying the amount of the customer's demand that can be supplied.

In this problem, to find the optimal service time with statistical sampling, the competitors' service interval is obtained in order to determine the mathematical hope for providing services for customers before other competitors. Accordingly, the interval $[t_1, t_2]$ is introduced as the interval in which the competitors can provide services for the intended costumer. Now, the customer demand can be calculated depending on the arrival of the vehicle, as shown in Fig. 2.

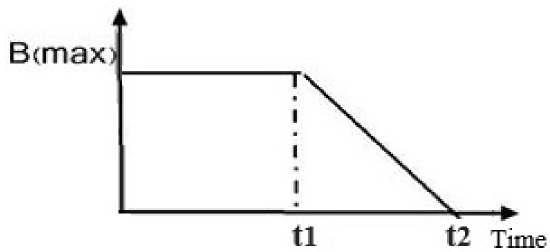

Fig. 2. Customer demand behavior in time horizon in competitive conditions.

Under such conditions, amount of the customer demand may not be equal to the amount scheduled for delivery; therefore, in this research, the customer satisfaction in competitive conditions is used based on the amount of the delivered goods.

As mentioned in "Introduction", two objectives are considered in this problem, including: 1) minimizing the total transportation, and 2) Maximizing the satisfaction of demand points by supplying the demand of different products or, in other words, minimizing the unmet demand. In order to convert these two objectives to a single one, the two objectives are located with a certain conversion ratio in an objective function.

3.1. Model assumptions

The assumptions used in this model included:

- In this problem, there are some nodes with a specific and unchanged demand before initiation of planning, and the demand is met through a single depot.
- There is possibility for not using a vehicle in the given time horizon.
- The objective of planning is to meet the demand in a period in competitive conditions.
- There are several vehicles with limited weight capacity.
- Vehicles start to move from depot, pass through the nodes, and then return back to the depot.
- A type of product is considered that its total volume and value are equal.
- Service time affects the customer's demand.
- Customer satisfaction can be interpreted as a percentage of the met demand.

In the following, the indices, parameters, and decision variables of the developed model will be introduced.

3.2. Notations

Indices:

(i, j, f)	Set of nodes (depot and customers)
k	Vehicles

Parameters:

Cap^k	Capacity of vehicle k
d_i	Maximum demand of node i
c_{ij}	Distance between node i and node j
tr_{ij}^k	Time of travelling from node i to node j by vehicle k
$[t_i^1, t_i^2]$	Interval of favorability of services to the i^{th} customer
$\gamma_1 - \gamma_2$	Coefficients of coordination of objectives and their importance
$bigM$	Large enough positive value

Decision variables:

x_{ij}^k	0 and 1 variable, if the path *i-j* is passed by vehicle k, it will be 1, and otherwise 0
α_i^k	A percentage of the demand of node i that is met by vehicle k
D_i^k	Supplied demand of customer i by vehicle k
y_k	0 and 1 variable, if vehicle k is used, it will be 1, and otherwise 0
u_i^k	Time to reach node i by vehicle k
S_i^k	Equal to 1, if vehicle k provides service for customer i at interval $[0, t_i^1]$, and otherwise 0
R_i^k	Equal to 1, if vehicle k provides service to customer i at interval $[t_i^1, t_i^2]$, and otherwise 0

3.3. Mathematical model

The mathematical model developed for the investigated problem is as follows:

$$\min \quad Z = \quad \gamma_1 \sum_i \sum_j \sum_k c_{ij} x_{ij}^k \; + \; \gamma_2 \sum_i (d_i - \sum_k D_i^k) \tag{1}$$

$s.t.$

$$\sum_i x_{ij}^k \le y_k \qquad \forall \, j = 2, \ldots, N \;\; , \;\; k \tag{2}$$

$$\sum_i x_{if}^k - \sum_j x_{fj}^k = 0 \qquad \forall f, k \tag{3}$$

$$\sum_j x_{1j}^k = y_k \qquad \forall k \tag{4}$$

$$u_i^k + tr_{ij}^k \le u_j^k + bigM(1 - x_{ij}^k) \qquad \forall i \ne 1, j \ne 1, k \tag{5}$$

$$u_1^k = 0 \qquad \forall k \tag{6}$$

$$\sum_k x_{ii}^k = 0 \qquad \forall i \tag{7}$$

$$\sum_{i>1} \alpha_i^k D_i^k \le Cap^k \qquad \forall k \tag{8}$$

$$\alpha_i^k \le \sum_j x_{ij}^k \qquad \forall i \ne 1, k \tag{9}$$

$$\alpha_i^k \le y_k \qquad \forall i \ne 1, k \tag{10}$$

$$D_i^k = \sum_k (S_i^k d_i + R_i^k \frac{t_i^2 - u_i^k}{t_i^2 - t_i^1} d_i) \qquad \forall i \ne 1 \tag{11}$$

$$(\mathrm{t}_i^2 \text{-} \mathrm{u}_i^k) + \mathrm{bigM}(1\text{-}\mathrm{S}_i^k) \ge 0 \quad \forall i \ne 1, k \tag{12}$$

$$(\mathrm{t}_i^1 \text{-} \mathrm{u}_i^k) + \mathrm{bigM}(1\text{-}\mathrm{R}_i^k) \ge 0 \quad \forall i \ne 1, k \tag{13}$$

$$(\mathrm{t}_i^1 \text{-} \mathrm{u}_i^k) + \mathrm{bigM}(1\text{-}\mathrm{S}_i^k) \le 0 \quad \forall i \ne 1, k \tag{14}$$

$$x_{ij}^k, S_i^k, R_i^k \in \{0,1\} \qquad \forall i, j, k \tag{15}$$

$$u_i^k, \mathrm{D}_i^k, \alpha_i^k \ge 0 \qquad \forall i, \mathrm{k} \tag{16}$$

According to Equation (1), the objectives include transportation cost minimization and supplied demand maximization, respectively.

Constraint (2) implies that if a vehicle is used, it can cover the route between two certain points. Constraint (3) ensures that we should exit any node that we have entered it. Any vehicle that is used should exit the depot, which is represented by Constraint (4) (it is assumed that depot is the node-1). Constraints (5) to (7) are related to elimination of the sub-tour; however, Constraint (5), in addition to eliminating the sub-tour, calculates the time of delivery to the customers for each vehicle.

Constraint (8) represents limitation of the vehicle's capacity. Constraint (9) ensures that a value between 0 and 1 is assigned to the satisfaction rate; besides, this constraint forces this rate to get a value only in case of the vehicle's passage to the relevant node. Constraint (10) indicates that the demand points meet their needs from the applied vehicles. Constraint (11) calculates the suppliable demand in competitive conditions based on the delivery time. This equation is in accordance with the general structure of the customer demand behavior in Fig. 2. Constraints (12) to (14) specify the auxiliary variables. And finally, Constraints (15) and (16) define the decision variables.

4. SOLUTION APPROACH: CUCKOO METAHEURISTIC ALGORITHM

Similar to other evolutionary algorithms, the COA is also started with an initial population consisted of cuckoos, which have some eggs that are put in the nest of some host birds. Some of these eggs, which are more similar to the host bird's eggs, have more chance for growing and maturing; however, other eggs are detected and destroyed by the host bird. The number of the grown eggs indicates suitability of the nests in that region. The more the number of the eggs that are capable to live and survive in a region, the more the profit that is allocated to that region; therefore, a situation, where a higher number of the eggs are survived, will be a parameter that COA seeks to optimize it (Dejam *et al.,* 2012). More researchers used the COA for solving their models (Mohanty and Parhi, 2016).

By considering the number of eggs laid by a cuckoo as well as the distance of the cuckoos from the current optimal area for living, several egg laying radii are calculated and formed; then, the cuckoos begin random laying in the nets within their egg laying radius (ELR). This process continues until achieving the best place for laying (area region with maximum profit). The optimal place is a region where the highest number of cuckoos is gathered. When the chicks are hatched and matured, they form some groups and communities, so that each group has its own location for living. The best place for residence of all the groups will be the next destination of cuckoos in other groups. All the groups migrate to the best currently available area and each group resides in area region near the best current situation. It should be noted that some researchers studied on the migration algorithms. The readers can see a good paper of Vaščák (2012) for studying more about these algorithms.

4.1. Production of primary habitats of cuckoos (initial population of candidate solutions)

To solve an optimization problem, it is necessary to form the values of variables in the form of an array. In genetic algorithm (GA) and particle swarm optimization (PSO), these arrays are specified as "chromosome" and "particle position"; while, in COA, this array is called “habitat”. In an optimization problem, a habitat is an $1 \times N_{var}$ array, representing the current situation of cuckoos. This array is defined as (Dejam *et al.,* 2012):

$$habitat = \left(x_1, x_2, \ldots, x_{Nvar}\right) \tag{17}$$

Suitability (or value of profit) in the current habitat is obtained by assessing the profit function (f_p) in the habitat. Therefore:

$$profit = f_p\left(habitat\right) = f_p\left(x_1, x_2, \ldots, x_{Nvar}\right) \tag{18}$$

As can be seen, COA is an algorithm that maximizes the profit function. In order to use the COA for solving the minimization problems, it is enough to multiply a minus sign by the cost function. To start the optimization algorithm, a habitat matrix with size of $N_{pop} \times N_{var}$ is produced; then, for each of these habitats, a random number of eggs is assigned. In nature, each cuckoo lays 5-20 eggs; accordingly, these numbers are used as the lower and upper limits of assignment of the eggs to each cuckoo in various iterations.

Another habit of the cuckoos is that they lay their eggs in a specific domain called ELR, as:

$$ELR = \alpha \times \frac{Number\,of\ current\,cuckoo's\,eggs}{Total\,number\,of\ eggs} \times \left(Var_{hi} - Var_{low}\right) \tag{19}$$

4.2. Cuckoos method for laying eggs

Each cuckoo randomly lays the eggs in the nest of the host birds that are in their own ELR (Fig. 3) (Dejam *et al.,* 2012).

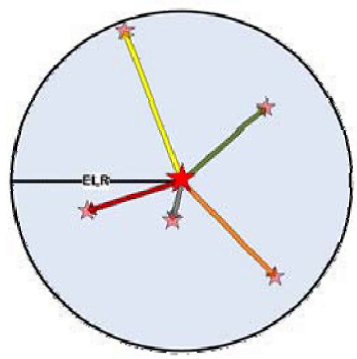

Fig. 3. Egg laying radius (ELR) is a red star at the center of the circle of current habitat of the cuckoos with 5 eggs, and pink stars indicate the new nests of eggs (Rajabioun, 2011).

Once all the cuckoos lay their eggs, some of the eggs, which are less similar to the host bird's eggs, will be detected and thrown out of the nest; thus, after each time of egg laying, p% of the eggs (10%) with lower profit function will be destroyed. The remaining chicks will grow in the host nests (Dejam *et al.,* 2012).

Another interesting point about the cuckoo chicks is that in each nest only one egg can grow, because once the cuckoo chicks are hatched, they throw out the host birds' eggs. Furthermore, in case that the host bird's chicks are hatched earlier, the cuckoo chicks will eat the highest amount of food provided by the host bird, and after a few days, the host bird's chicks will die and only the cuckoo chicks will survive (Mousavirad and Ebrahimpour-Komleh, 2014).

4.3. Cuckoos migration

Once the cuckoo chicks are matured, they will live in their groups for a while, but at the time of egg laying, they will migrate to better habitats with higher chance of survival. After forming the cuckoo groups in various residential regions (problem search space), the group with best situation will be selected as the target point of migration for other cuckoos.

When the adult cuckoos live in the whole environment, it is difficult to recognize that each cuckoo belongs to which group; therefore, to solve this problem, the cuckoo grouping is performed using K-means classification method (K is often between 3 and 5). Now that the cuckoo groups are formed, the average profit of the group is calculated to obtain the relative optimality of that group's habitat;

then, the group with the highest average profit (optimality) is chosen as the target group, and other groups will migrate toward it. At the time of migrating to the target point, as seen in Fig. 4, the cuckoos will deviate only at a small part of the route (Dejam *et al.,* 2012). The migration operator formula in the cuckoo algorithm is as:

$$X_{NextHabitat} = X_{currentHabitat} + F\left(X_{GoalPoint} - X_{CurrentHabitat}\right) \tag{20}$$

where F is a parameter that causes the deviation. Each cuckoo moves toward the current ideal target only in F% of the whole route, and it also has a φ-radian deviation. These two parameters help the cuckoos search a larger environment. In this equation, F is a random number between 0 and 1, and φ is a number between π/6 and -π/6.

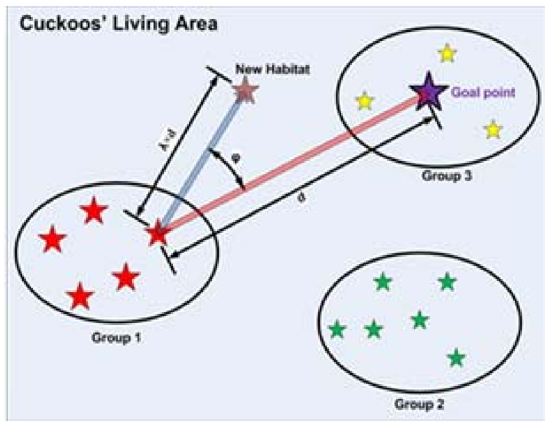

Fig. 4. Migration of cuckoos toward the target with the deviation (Rajabioun, 2011).

Once all the cuckoos migrate to the target point, and the new habitat of each one is specified, then each cuckoo will own some eggs. Due to the number of each cuckoo's eggs, an ELR is specified for it, and then egg laying is initiated. Regarding the fact that there is always a balance between the populations of birds, a number like N_{max} can limit the maximum number of cuckoos that can live in an environment.

According to the overall explained structure of the COA, a systematic presentation of the COA has been provided as shown in Fig. 5.

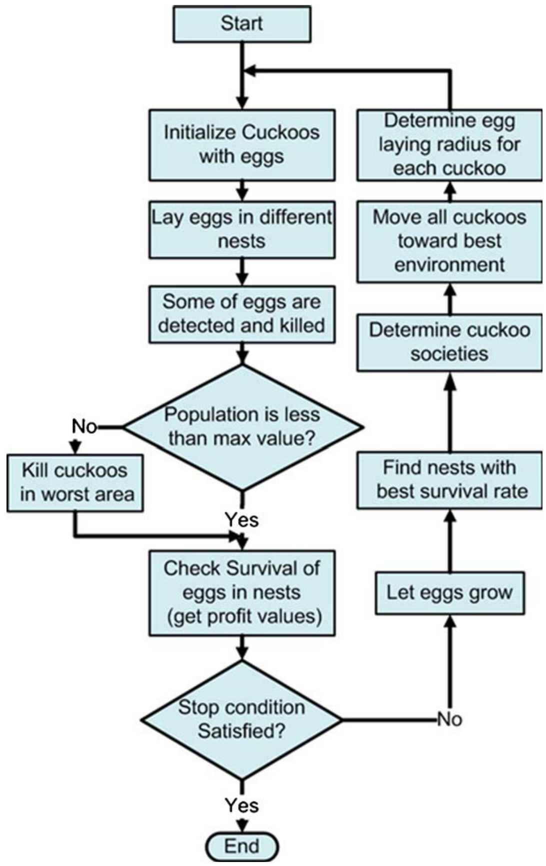

Fig. 5. A systematic presentation of the COA (Rajabioun, 2011).

4.4. Accelerated cuckoo algorithm (ACOA)

In previous sections, the COA was completely described. The algorithm is one of the new algorithms, which has been less considered by the researchers in the field of routing. One of the major attempts in this regard is a comprehensive investigation of the COA and analysis of its weak points. To develop the COA and improve its performance, it is attempted to improve the mechanisms of this algorithm in order to achieve a better performance of the COA.

One of the weak points of COA is the use of a simple heuristic method for clustering the cuckoos. As seen in COA steps, the k-means method is used for this purpose. In k-means method, first, k members (k is number of clusters) are randomly selected from among n members as the cluster centers. Then, n-k remaining members are allocated to the closest cluster. After allocating all the members, the cluster centers are recalculated and allocated to the clusters with respect to the new centers, and this continues until the cluster centers are fixed.

Regarding the heuristic nature of the k-means method, this method in large scales cannot enjoy a good quality; thus, in the present study, it is attempted to use the meta-heuristic methods for clustering the cuckoos. Since this clustering operation is performed at each COA iteration, the clustering method should be very fast and present the best clustering to COA in the shortest possible time. In order to accelerate this algorithm and improve its quality, the simple-structured evolutionary algorithms can be used. In this regard, in the present research, the SAA is considered to accelerate cuckoo clustering. The operating mechanism of the SAA uses a probabilistic framework to accept the solution on the basis of the analogy with the temperature decrease in metallurgy (Precup, Sabau and Petriu, 2015).

The SAA has been inspired by the process of cooling the material by slow reduction of the system temperature until conversion of the material to a fixed frozen state. This method moves toward the optimal solution by developing and evaluating the consecutive solutions step by step. In order for movement, a new neighborhood is randomly generated and evaluated. This method investigates the points near the given point in the search space. If the new point is a better point (if it reduces the cost function), it will be selected as the new point in the search space, and in case of being worse (if it increases the cost function), it will be selected again based on a probability function. In simpler words, to minimize the cost function, searching is always performed with the aim of reducing the cost function, but it is also possible that sometimes the movement is aimed to increase the cost function. To accept the next point, usually a criterion called Metropolis is used, according to Equation (21):

$$P(accept)=\begin{cases}1 & if \quad \Delta f \le 0 \\ e^{\frac{\Delta f}{c}} & if \quad \Delta f > 0\end{cases} \tag{21}$$

where P, C, and Δf represents the probability to accept the next point, a control parameter, and the cost variation, respectively.

The control parameter in the SAA plays the role of temperature in the physical phenomenon. First, the particle (indicating the current point in the search space) is demonstrated with a large amount of energy (indicating the high value of the control parameter C). This high energy allows the particle to escape from a local minimum. As the search continues, the particle's energy is reduced (reduction of C), and searching will finally tend toward the overall minimum. It should be also noted that at low temperatures, the algorithm's possibility to escape from local minimum would be reduced; therefore, the higher the initial energy, the more the possibility to reach the overall minimum (Torkaman, 2017).

The reason for selecting this algorithm is that it generates only one solution at each iteration and has a very simple mechanism, so that it can provide the best clustering in a very short time.

4.5. Solution representation

In order to design and implement the ACOA, it is necessary to introduce the solution string (coding system) defined in this research. The solution string of the main problem, which is used in COA, is a vector to the length of equal to the number of customers and the number of vehicles (N + k). In each cell, there is a value between 0 and 1. The first part of the solution string indicates the customer's priority for visiting, and the second part determines the percentage of customers for each vehicle.

For example, if N=5 and K=2, an example of such solution string will be as follows:

0.37	0.26	0.91	0.54	0.62	0.45	0.59

According to Equations (22) and (23), the first and second vehicles will visit 2 and 3 costumers, respectively:

$$N_1 = \frac{0.45}{0.45 + 0.59} \times 5 = 2 \tag{22}$$

$$N_2 = \frac{0.59}{0.45 + 0.59} \times 5 = 3 \tag{23}$$

In other words, the first vehicle visits the customers 3 and 5, and the second vehicle visits the costumers 4, 1, 2, respectively. However, if during visiting the customers, capacity of the vehicle is more than the customer demand, the unmet amount will be reported as the unmet demand value, and also will affect the objective function.

As mentioned earlier, for accelerating the clustering, the SAA is used in order to achieve the ACOA. The solution string of this algorithm is a vector with values between 0 and 1 and a length equal to the number of cuckoos (M). On this basis, if the number of the intended clusters is W, and if the value of each cell is between 0 and $\frac{1}{W}$, it will be allocated to the first cluster, and in case of being between $\frac{1}{W}$ and $\frac{2}{W}$, it will be allocated to the second one, and so on. This will be repeated for all the clusters.

For example, if the number of cuckoos is 1, and the number of clusters is 2, then a typical solution string will be as follows:

0.76	0.39	0.51	0.49	0.84	0.66	0.22	0.94	0.27	0.61

According to this solution string, the numbers lower than 0.5 and the numbers above 0.5 will be assigned to the first and second clusters, respectively; in other words, the cuckoos 2, 4, 7, and 9 belong to the first cluster, and the rest belong to the second one.

In order to evaluate this clustering, it is necessary to define a fitness function, by the help of which the SAA can find the best clustering. The given fitness function is such that the difference of the objective function for the inter-clustering cuckoos is minimized, and the total objective function of the cuckoos within each cluster is maximized.

In order to find the fitness function, first, a matrix is defined as $L = [\lambda_{ij}]_{W \times W}$, and its values are determined as:

$$\lambda_{ij} = \sum_{j \in cj} \sum_{i \in ci} (f_i - f_j) \quad \forall \ i \neq j \tag{24}$$

$$\lambda_{ij} = \sum_{j \in cj} \sum_{i \in ci} (f_i + f_j) \quad \forall \ i = j \tag{25}$$

In Equations (24) and (25), f is the fitness value of each cuckoo; accordingly, the fitness function is defined as:

$$fitness = \sum_{i} \sum_{j \neq i} \lambda_{ij} - \sum_{i} \lambda_{ii} \tag{26}$$

By defining such a solution string, the solutions obtained from clustering can be expected to have the highest intragroup similarity and highest intergroup difference in the ACOA.

4.6. ACOA steps

As already explained, steps of the developed ACOA will be as follows:

1. Determine the current habitats of cuckoos randomly,

2. Assign a number of eggs to each cuckoo randomly,

3. Determine the egg laying radius of each cuckoo,

4. Cuckoos lay their eggs in the nests of the hosts that are within their egg laying radius,

5. Eggs detected by the host birds are destroyed,

6. Eggs of the undetected cuckoos will grow,

7. Assess the habitat of new cuckoos,

8. Determine the maximum number of cuckoos that can live in any location, and then eliminate those that are in inappropriate places,

9. Cluster the cuckoos using simulated annealing (SA) method and

    9.1 Generate a solution (cuckoos clusters) randomly (x)

    9.2 Generate a neighbor solution of x (y)

    9.3 select y if it has better fitness value

    9.4 select y by a specified probability if it has worse fitness value

10. Determine the best cuckoo group as the target habitat,

11. New cuckoo population will move toward the target location and

12. In case of the stop condition, stop, otherwise, move to step 2.

5. NUMERICAL RESULTS

COA has a very wide working range, and with the increasing progress of science and technology, the use of this method for optimization and problem solving is being expanded. The COA is directly related with the artificial intelligence (AI); in fact, this algorithm is a subset of AI. The COA can be called a general search method that imitates the natural biological evolution laws; besides, the COA applies the “survival of the fittest” law on a series of the problem solutions in order to find better solutions.

In the Section 3, the investigated problem in this research was explained and in the Section 4, its optimization approach was completely presented. The used optimization approach is the development of the COA in terms of algorithm performance and solution speed. In this section, the efficiency of the proposed optimization method is proved. In order to investigate the efficiency of the ACOA in terms of solution quality, some various examples are randomly generated and optimized using proposed solution approach. Then, the calculated results are compare with the global optimal value. Some examples are generated in large dimensions for evaluating the speed of the ACOA and the results are compare with the COA performance in terms of the solution time.

It should be mentioned that the OR libraries have been used in order to validate the COA in optimizing of different problems (Rajabioun, 2011). In this paper, the defined problem is a new optimization problem and a real similar problem has not been seen in the literature according to the investigations. Thus, there are not any existing datasets in the scientific databases in order to investigate the efficiency of the COA on the presented problem. Therefore, the various examples are generated using random operators in MATLAB R2014 with the uniform statistical distribution. In fact, the data are generated in a rational range based on reality in accordance with the range of the data of the actual case study. Table 2 shows the range of the generated data, i.e. the related distribution. The exact solutions of these problems also are compared with the results of the COA. It also should be noted that since the number of algorithm iteration (stop criterion) is strongly influenced on the running time of the algorithm; thus the stop criterion has been considered reach to 1000 iterations in each of solved examples.

Table 2. The range of the generated data.

Parameter	Name	Generated value
Cap^k	Capacity of vehicle k	U*(500,700)
d_i	Maximum demand of node i	U(50,90)
c_{ij}	Distance between node i and node j	U(10,50)
tr_{ij}^k	Time of travelling from node i to node j by vehicle k	U(5,30)
$[t_i^1, t_i^2]$	Interval of favorability of services to the ith customer	[U(30,100) , U(100,150)]
$\gamma_1 - \gamma_2$	Coefficients of coordination of objectives and their importance	[0.5 0.5]

*Uniform Distribution

In the first subsection, the ACOA performance is compared with the exact solution method; then, the results will be compared with those of the classical COA. And finally, the sensitivity analysis will be performed.

5.1. Comparing performance of COA with exact solution method

In order to investigate COA for this problem, this algorithm was coded in MATLAB-R2014; then, 10 problems are simulated with different dimensions. In generation of these typical problems, the demand of each point of the discrete uniform distribution is produced with lower bound of 1000 and upper bound of 2000. Each point is located in a 2D space with length of 150 and width of 150; furthermore, the cost of travelling between every two points corresponding to the distance of those two point is taken into account. Capacity of the vehicles ranged randomly between 8000 and 15000. It is evident that capacity of the vehicles has been selected in such a way that the total capacity of vehicles is higher than the total demand of the points. Other information of the problem is shown in Table 3.

Table 3. Simulated problem information.

Problem number	n	k	γ_1	γ_2
PR1	6	2	30	2
PR2	10	2	30	10
PR3	20	3	25	15
PR4	30	5	20	20
PR5	40	10	20	25
PR6	50	12	15	10
PR7	70	15	15	20
PR8	100	20	10	30
PR9	150	30	10	40
PR10	200	40	5	40

Results obtained from the exact solution of the problems simulated in GAMS are compared with those of COA. Since the solution time of this software is too much for the large-scale problems, a time limit of 3600 s is considered. It should be noted that if solving the problem in this software requires a time of more than one hour, then by achieving this amount of time, the software will provide a reasonable (but not necessarily optimal) solution, and subsequently execution of the program will be finished. Table 4 represents a summary of the results of the comparisons of GAMS and COA.

Table 4. Results of solving the typical problems.

Problem number	Exact solution with GAMS		COA		COA error (%)
	Objective function	Solution time (s)	Objective function	Solution time (s)	
PR1	13350	0.3	13350	11.43	0
PR2	15976	2.4	15976	13.9	0
PR3	29864	10.7	29950	15.9	0.0029
PR4	47968	34.2	57694	24.8	0.1686
PR5	76015	106.1	83948	36.9	0.0945
PR6	126975	539.1	149585	54.7	0.1511
PR7	249873	1489.3	284570	73.9	0.1219
PR8	589640	3600	551980	94.7	0
PR9	759316	3600	759573	129.7	0
PR10	957400	3600	906480	186.1	0
Average	286637.7	1298.27	285310.6	64.2	0.0539

As seen in Table 4, GAMS software couldn't find the optimal solution for the last three problems in less than an hour; on the other hand, for the same examples, COA has obtained better solution by spending a relatively shorter time.

In Fig. 6, the solution time chart of both methods can be seen.

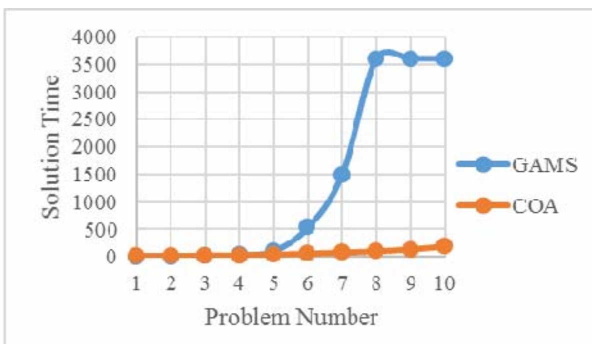

Fig. 6. Comparing the solution time of COA and GAMS.

As can be seen, the exact solution time of the problem in GAMS has an exponential increase, so that by increasing the problem dimensions, the solution time is increased significantly; while, in COA, the increase rate of the solution time is very insignificant.

Figure 7 demonstrates the diagram of the objective function obtained from the exact solution and meta-heuristic solution of the model.

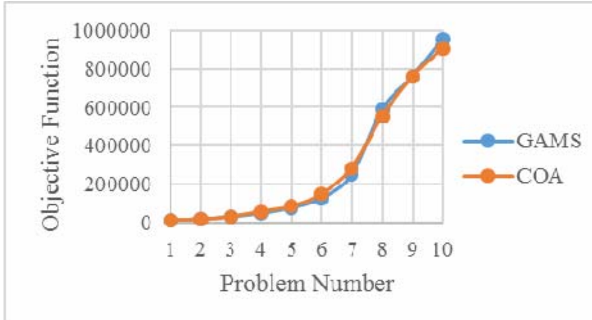

Fig. 7. Comparing the objective functions of COA and GAMS.

Figure 7 shows that in different problems, the COA is not significantly different from the exact solution; so that, in all the solved problems, this algorithm has exhibited only a 0.05% error compared to GAMS software, which indicates the good performance of COA in finding the optimal solution of the problem.

5.2. Comparing ACOA algorithm with classical COA

For a better comparison of the ACOA algorithm, some new typical problems are simulated, based on which the ACOA is compared with the classical COA. It should be noted that generated problems are all in large-scales, and it is impossible to provide their exact solutions by GAMS in a logical and reasonable time.

In all the problems in this subsection, the value of $\gamma_1=\gamma_2 = 10$ is considered. Information of the problem and the comparison results are presented in Table 5.

It should be noted that the sample problems have been executed for 10 times, and also the minimum value of the total objective function as well as their mean value have been reported.

Table 5. Results of solving the large-scale sample problems.

Problem number	N	K	ACOA			COA		
			Min $*10^6$	Avg $*10^6$	Time (s)	Min $*10^6$	Ave $*10^6$	Time (s)
PR1	250	50	395	428	258.9	428	489	253.4
PR2	300	70	549	611	272.1	561	631	267.5
PR3	350	100	704	754	289.3	733	795	282.4
PR4	400	150	864	909	295.7	907	928	303.8
PR5	500	200	1076	1128	359.3	1103	1139	333.4
Average					295.06			288.1

In Fig. 8, the solution time of ACOA is compared with that of classic COA.

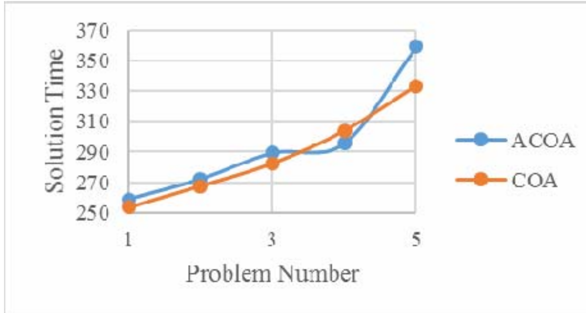

Fig. 8. Comparing solution times of the two algorithms.

As can be seen, in various problems, the solution times of both algorithms are equal, and only in the fourth problem, the developed solution time exhibits a slight increase compared to the classic method. In Fig. 9, the best solution found by the two algorithms is shown.

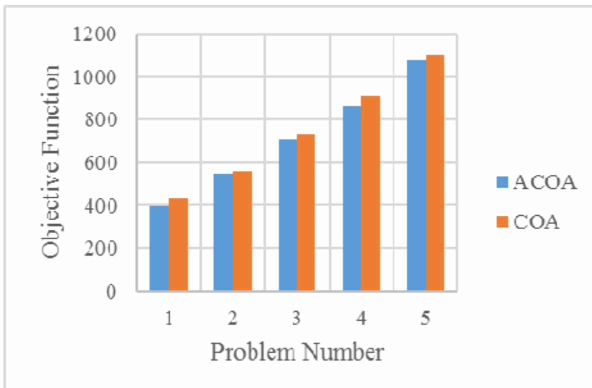

Fig. 9. Comparing objective functions of the two studied algorithms.

As seen in the Fig. 9, due to the metaheuristic clustering mechanism, ACOA has accomplished providing a lower objective function value in all the sample problems compared to COA.

In terms of the objective function and solution time, these comparisons indicate that the ACOA could improve the designed problem by spending a little more time and provide better results.

5.3. Case study

For a better understanding of the proposed model, data of the year 2015 related to one of the dairy products distribution companies in Iran, namely Isfahan Pegah, are used. This company has started working since 1956, and by having 40 trucks, is currently providing services for a network embracing over 350 customers in the city.

To study the model in this company, at the first step, the company's products are studied. In order to collect information from experts of the distribution company, the factors such as primary demand, current fleet capacity, as well as transportation costs have been taken into account. For homogenization of the units, the demand rate of each customer is considered equal to a single unit; and accordingly, the capacity of each of the available trucks is considered equal to 1500 units. The travel costs are also specified based on the distance between the customers. Regarding the large scales of the problem, the problem is solved using ACOA. After solving the problem in optimal conditions, the total transportation cost and total satisfaction level are obtained equal to 164742 and 5.63, respectively. For a better understanding of the results and providing the managerial results for company's managers, it would be necessary to perform the sensitivity analysis on the parameters of demand and vehicle capacity.

In order to investigate the effect of the parameters of demand and capacity on the final output of the problem, various changes are applied on them, and then the final output is investigated by GAMS. Tables 6 and 7 represent the obtained results.

Table 6. Results of sensitivity analysis.

Vehicles capacity	1500	2500	3500	5000
Objective function value	5.623	12.025	18.325	33.1

Table 7. Results of sensitivity analysis.

Demand value	1	2	3
Satisfaction value	19.325	2.394	0.239

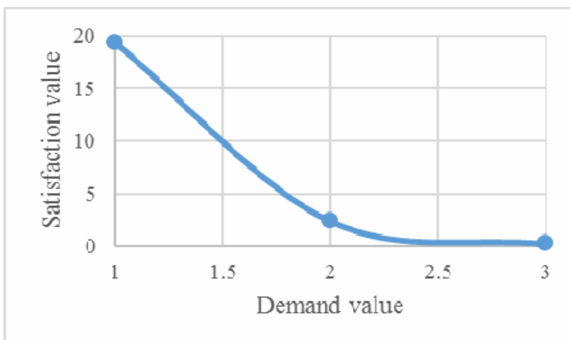

Fig. 10 Customer satisfaction based on the demand behavior.

Based on the sensitivity analysis in Fig. 10, in case the customer demand is increased, the satisfaction level will be reduced considerably, which is due to the lack of timely response with regard to the available capacity. In these conditions, it is essential for the company to make the necessary predictions in order to increase its transportation fleet and provide the on-time product delivery.

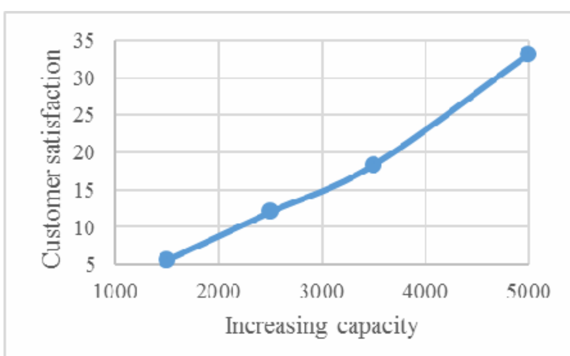

Fig. 11. Customer satisfaction based on the increased capacity.

Figure 11 represents the results of sensitivity analysis of the transportation fleet's capacity. The results indicate that if the company develops its transportation fleet and improve its capacity, it will significantly affect the customer satisfaction level. Such impact is too high in case the capacity is increased from 3500 to 5000. Accordingly, by creating a tradeoff between the transportation fleet development costs and customer satisfaction level, the company must apply the best policy in order to improve its current status.

6. CONCLUSION AND FUTURE RESEARCH

In the present research, a new mathematical model was proposed for vehicle routing in competitive conditions with the aim of increasing the customer satisfaction as well as reducing the costs. The basic innovation of this research was considering the competitive conditions along with customer satisfaction and developing the cuckoo algorithm for the given problem. COA is a subset of the evolved computations, which is directly related with the artificial intelligence (AI); in fact, this algorithm is a subset of AI. In order to accelerate COA and improve its quality, the simple-structured evolutionary algorithms can be used. The fundamental development of the COA in the present research was the use of the simulated annealing algorithm (SAA) in order to accelerate the cuckoo clustering and improve the solution quality. In order to evaluate the proposed method, first, the developed algorithm was compared with GAMS software and its resulting exact solution; then, at the next step, it was also compared with the classic COA. The obtained results showed that ACOA can provide solutions close to the optimal solution in a short time, and also can have a better performance than the primary COA structure. Finally, in order to show the efficiency and effectiveness of the developed model and solution algorithm, a case study was conducted for Isfahan Pegah Dairy Company. The results of the case study and sensitivity analysis showed that if the company increases its transportation capacity, it will significantly affect the satisfaction level of its customers.

There can be many future directions in this area for developing the model proposed by this study. First, the given model can be considered with uncertain demand at different periods (for example, under various scenarios). Second, non-linear and multi-breakpoint concepts of risk and cost functions can be included in the modeling. Third, in this model, it is possible to set the emissions reduction from transportation or delivery time minimization as other objective functions.

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