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An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives

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ABSTRACT

Vehicle routing problem (VRP) is one of the widely researched areas in transportation science, mainly due to the potential cost savings and service improvement opportunities which brings to organizations involved in physical distribution of goods. In this paper, we develop a multi-depot green vehicle routing problem (MDGVRP) by maximizing revenue and minimizing costs, time and emission, and then, apply an improved ant colony optimization (IACO) algorithm that aims to efficiently solve the problem. The IACO model developed in this research uses an innovative approach in updating the pheromone that results in better solutions. The results achieved through the IACO demonstrate satisfying performance, which have higher solution quality when compared to the conventional ACO. The IACO algorithm used in this paper demonstrated a good level of responsiveness and simplicity when solving MDGVRP with multiple objectives.

1. Introduction

A key component of every distribution system is the routing of vehicles to service customers (Osaba et al., 2017). Accordingly, research in mathematical modelling of transport systems and network optimization has received additional momentum over the last three decades in optimizing such systems (Laporte, 1992; Ho et al., 2008; Braekers et al., 2016). In particular, a large number of studies have shown that the use of operations research and computerized procedures for designing and planning of distribution networks will not only reduce transportation costs, but also assists the decision makers to achieve desired service levels (Chebbi and Chaouachi, 2016; Lai et al., 2016; Soleimani et al., 2018). The success of operation research techniques in this area is considerably owed to the advancement of computers (both hardware and software) and applications of information and communications technology (ICT) in design, management and monitoring of transportation systems (Toth and Vigo, 2002).

In this context, vehicle routing problem (VRP) is one of the most researched combinatorial optimization problem that deals with the optimal allocation of vehicles in a fleet to the desired destinations. VRP was formally introduced by Dantzig and Ramser (1959) as the truck dispatching problem, and since then, several variations have emerged, including capacitated VRP (CVRP), VRP with time window (VRPTM), VRP with pickup and delivery (VRPPD), VRP with multiple trips (VRPMT) and open VRP (OVRP). As the result of mounting transportation costs, limited resources and increasing customer expectations, VRP models have been playing an essential role in providing practical solutions to management and operations of physical distribution systems (Soleimani et al., 2018; Zohal and Soleimani, 2016). Govindan et al. (2014) proposed a multi-objective optimization model for a two-echelon location–routing problem with time-windows for sustainable supply chain network design.

The issue of organizing the routing is of the core strategic decisions in a transport and logistics business (Kahfi and Tavakkoli-Moghaddam, 2015). Since the strategic goals of transportation companies differ from one to another, the structure, objectives and constraints of VRPs become extremely diverse and complex.

Thus, it is important to acknowledge real-world distribution networks are far more complex and multifaceted when meeting

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operational, tactical and strategic objectives (Melián-Batista et al., 2014; Darbari et al., 2019) While the classic VRP is suitable to solve single depot problems, predominantly, supply chain networks consist of multi-depots and multiple delivery points, which require more robust and all-inclusive approaches such as multi-depot vehicle routing problem (MDVRP). Furthermore, there exists a mounting pressure on transportation and logistics businesses to minimize their environmental footprints. Recognizing this increasing complexity, development of models that are capable to address economic, social and environmental challenges associated with management and operations of supply chain networks is on soaring demand.

Therefore, considering a double-tier distribution chain, this paper presents a multi-depot green vehicle routing problem (MDGVRP) to simultaneously satisfying multiple objectives of cost minimization, profit maximization, travel time minimization and emission reduction. To solve the problem, an improved ant colony optimization (IACO) approach was applied and compared with other methods. The main contribution of this research is observed in development of the model which considers four conflicting objectives into a single integrated function, including green criteria. Also, this paper applies an improved ACO, into a VRP domain, which is based on a new method of updating pheromone that produce slightly better solutions. The remaining of this paper is as follows. Section 2 present a brief review of the literature on MDVRP, GVRP and use of ACO in similar problems. The mathematical model is formulated in Section 3 and the algorithm is presented and tested in Section 4. Experimental results are summarized in Section 5. Finally, concluding remarks and direction for future research are drawn in Section 6.

2. Literature

This review of literature first aims to provide a summary on the development of VRP research necessary to understand the development of MDVRP. It then summarizes the most relevant works in terms of objective and solution approach. Next, some of the recent and influential research in the area of GVRP are reported. Finally, a brief review of literature on the applications of ACO in VRP research is presented.

To overcome the increasing complexity associated with design and management of distribution networks, VRP has been studied in several forms. One of the common forms of VRP linked to the context of this research is the capacitated VRP (CVRP), where a fleet of delivery vehicles with uniform capacities serve pre-determined customers for a single commodity from a single depot with a minimum transit cost. MDVRP is an extension of CVRP with the objective to minimize travel time and fleet size that is operated from multi-depots (Ai and Kachitvichyanukul, 2009; Zachariadis et al., 2009; Leung et al., 2011; Akpinar, 2016; Yu et al., 2017). MDVRP models are capable to incorporate the practical considerations of real world distribution systems, particularly when designed to solve multiple objectives. Within the VRP models, MDVRP is considered as a NP-hard problem that simultaneously selects the routes for a number of vehicles from more than one depot to a group of delivery points, and then returning to the same depots without going beyond the capacity of vehicles (Luo and Chen, 2014; Soto et al., 2017). Tillman (1969) proposed the first MDVRP to solve the multiple terminal delivery problem with probabilistic demands.

The general assumption of MDVRP considers several depots to serve a set of customers. Typically, when the customers are grouped around a particular depot, the problem can be solved as a set of independent VRPs. However, if customers and warehouses are dispersed, MDVRP is a practical approach (Laporte et al., 1988). Since customer demand is subject to change and capacity constraints exist in terms of vehicle load, MDVRP formulation and solution approaches are relatively more complex and challenging. Furthermore, organizations involved in multi-depot/multi-delivery distribution aim to simultaneously satisfy several tactical and strategic objectives such as cost reduction, pollution control and profit maximization, which needs development of practical models. The remaining of this section aims to present a brief review of recent studies on MDVRP research.

Wu et al. (2002) proposed a methodology to solve the multi-depot location-routing problem (MDLRP) by dividing the general problem into the location-allocation problem and general VRP. The authors solved the sub-problems in a sequential and iterative approach using simulated annealing (SA) algorithm. Hassan-Pour et al. (2009) developed a MDVRP model to solve the stochastic location-routing problem (SLRP) that minimizes the costs of transportation and facility establishment, while maximizing the probability of delivery to customers. The authors solved their model in two steps: (i) solving the facility location problem (FLP) using a mathematical algorithm and (ii) solving the multi-objective MDVRP (MO-MDVRP) through a hybridized SA that used genetic operators (mutation and crossover).

An integrated bi-objective MDLRP model was proposed by Tavakkoli-Moghaddam et al. (2010) to meet the total demand and minimizing the fixed and variable costs of depots and delivery costs. To solve the model, a multi-objective scatter search (MOSS) algorithm was developed to obtain the Pareto frontier and Elite Tabu Search (ETS) was used to validate the model in terms of solution quality and diversity level. Prodhon (2011) studied the MDVRP from the perspective of location routing and periodic routing problems and proposed a hybrid heuristic based on the Randomized Extended Clarke and Wright Algorithm (RECWA) to develop the solutions.

Gulczynski et al. (2011) studied the MDVRP considering split delivery using an integer programming-based heuristic model and solved the model using a two-stage heuristic approach called EMIP-MDA + ERTR. Yu et al. (2011) explored the MDVRP by including a virtual central depot (V-MDVRP), which makes it similar to classic VRP. To solve the mode, authors presented an improved ACO with coarse-grain parallel strategy, ant-weight strategy and mutation operators. The application of MDVRP in emergency logistics was explored by Li et al. (2011), in which authors presented a parallel GA with Graphics Processing Unit (GPU) by assigning the computing tasks for each chromosome to independent threads. Noori and Ghannadpour (2012) proposed a hybrid High-Level Relay Hybrid (HRH) in three levels and benefited from a GA as the main optimization approach and tabu search as the improvement method to solve a MDVRP with time windows problem. In this study, authors presented an operator deletion-retrieval strategy to enhance the efficiency of the method. Salhi et al. (2014) investigated the MDVRP with heterogeneous vehicles. This study implemented an efficient version of variable neighborhood search (VNS) that includes a preprocessing strategy to identify borderline delivery points, a mechanism that aggregates and disaggregates routes between multiple depots, and a neighborhood reduction test that significantly reduces computing time in large-scale distribution networks.

Shared depot resources considering time windows was incorporated into MDVRP by Li et al. (2016). The problem was modelled as an integer programming model considering several operational factors such as time window, capacity, route duration, fleet size and parking capacity. Accordingly, a hybrid GA with adaptive local search was proposed to solve the problem. To solve the MDVRP with short computational time, Luo and Chen (2014) proposed a unique multi-phase modified shuffled frog leaping algorithm

(MPMSFLA) approach by benefiting from the K-means to better perform the clustering task for all customers.

Time window constraint was included in MDVRP by Biswas (2017) using an age-layered population structure (ALPS) genetic algorithm. This study aimed to optimize the number of vehicles and the total distance traveled by the fleet using Pareto ranking technique to keep the objectives independent. Similar to this study, Ma et al. (2017) solved the MDVRP with time window using an IACO that combines the nearest neighbor search method to identify the optimal solution.

Shen and Chen (2017) approached the MDVRP using a two-tier particle swarm optimization (PSO) approach using an external PSO and an internal PSO to determine the optimal depot locations. The application of fuzzy techniques in MDVRP setting was studied by Du et al. (2017), which included development of a fuzzy bi-level programming model for minimizing the total transportation risk when delivering hazardous materials to customers from multi-depots.

More recently, Galindres-Guancha et al. (2018) proposed a MOMDVRP with the aim to minimize the traveled arc costs and the balance of routes. Authors developed a three-stage solution approach using constructive heuristic, iterated local search multi-objective metaheuristics (ILSMO) and concepts of dominance. Zhang et al. (2018a) presented a MDVRP model considering green criteria and used ACO to solve the model. The proposed distribution network uses Alternative Fuel-Powered Vehicles (AFVs) and aimed to optimize the system knowing the complications arising from limited alternative fuel stations. This is a key issue for companies interested in employing electric and hybrid vehicles. Table 1 summarizes the most relevant works to this paper and analyzes them from the view of objective and solution approach.

According to Table 1, many MDVRP studies have aimed to determine the optimal figures for travel time, transport cost, environmental impacts, travel distance and revenue generation objectives. While most of studies only focus on two objectives, the proposed model in this research aims to satisfy four objectives of minimizing transport cost, travel time and distance, and maximizing the revenue. In terms of solution approaches, various types of algorithms were utilized such as PSO, ABC-ACO, hybrid large neighborhood search, SA, simulation-based heuristic algorithms and hybrid algorithms. In this study we have benefited from ACO system to solve the MDVRP. ACO is a computational optimization approach that is inspired by the behaviors of ants (Dorigo et el. 1996). When ants find a source of food, they leave markers on the ground to create the best path that should be followed by other members of the colony. This nature inspired metaheuristic mechanism has become a practical approach to solve many complex real-world problems.

Shifting the focus to environmental aspects, it is important to recognize that organizations involved in collection and distribution of goods are increasingly under pressure to further implement greener strategies to minimize the negative impacts of their logistics activities on the society and environment (Govindan et al., 2018). A form of MDVRP that focuses on reducing the environmental impacts of distribution systems such as Carbon Dioxide (CO2) is the multi-depot green VRP (MDGVRP), which has recently gained an increasing level of attention.

In this context, Kuo (2010) proposed a model to minimize the total fuel consumption for the time-dependent VRP. In this research, fuel consumption reduction was controlled based on the speed of vehicle, travel time and vehicle load. Erdoğan and Miller-Hooks (2012) introduced the green vehicle routing problem (GVRP) concept to provide a solution to companies with alternative fuel-powered fleet facing difficulties from limited vehicle operating range and limited refueling infrastructure. The GVRP was constructed as a MIL program and it was solved through heuristic approaches, including Modified Clarke and Wright Savings heuristic and the Density-Based Clustering Algorithm. The model was tested and resulted in optimized total distance traveled by alternative fuel vehicles in a specific day. Lin et al. (2014) presented a survey of GVRP studies. The authors classify the Green VRP studies into three classifications of Green-VRP, pollution routing problem (PRP) and VRP in reverse logistics (VRPRL). The first category deals with optimization of energy consumption, the second and third

Table 1
Summary of relevant MDVRP research from objective perspective.

Year	Authors	Type of objective							Demand	Solution method
		Cost	Time	Income	Emission	Distance	Risk	Number of Vehicles		
2002	Wu et al.	*								Simulated Annealing Algorithm (SAA)
2009	Hassan-Pour et al.	*								SA with genetic operators
2010	Tavakkoli-Moghaddam et al.	*							*	Multi-objective scatter search (MOSS)
2011	Prodhon	*								Randomized Extended Clarke and Wright Algorithm (RECWA)
2011	Gulczynski et al.	*								EMIP-MDA + ERTR
2011	Yu et al.	*								Parallel improved ACO
2011	Li et al.	*	*							Parallel GA with GPU
2012	Noori and Ghannadpour		*							HRH with GA and tabu search
2014	Luo and Chen	*	*							MPMSFLA
2014	Salhi et al.	*								VNS
2015	Stodola and Mazel		*			*				ACO
2016	Li et al.	*								Hybrid GA
2016	Wang et al.	*								ACO
2016	Gao et al.	*				*				IACO
2017	Biswas	*				*		*		Age-layered population structure genetic algorithm
2017	Du et al.	*					*			Simulation-Based Heuristic Algorithms
2017	Jabir et al.	*			*					ACO
2017	Ma et al.	*								IACO
2017	Shen and Chen	*				*				Two-tier PSO
2018	Galindres-Guancha et al.	*				*				local search multi-objective metaheuristics
2018	Zhang et al.(a)				*	*				ACO
This study		*	*	*	*					**IACO**

categories focus on reduction of pollution and optimizing the distribution systems used in reverse logistics (Govindan et al., 2015). This study falls between the first and second category that simultaneously aims to optimize the use of energy and reduce pollution levels. Finally, Tiwari and Chang (2015), use a Block recombination algorithm consider the minimum distance traveled by each vehicle from depot to calculate the minimum distance and minimum CO_2 emission by using angel and capacity based allocation method to generate the better artificial chromosomes. The authors generated different cluster for each visiting city by different trucks, where each cluster represents as a block.

Yu et al. (2017) focused their attention on vehicles that were using hybrid energy sources and developed a mathematical model to minimize the cost of traveling with the vehicles. In this study, SA was employed with a restart strategy to solve the model in two versions. The first version regulates the acceptance probability of a worse solution by a Boltzmann function and the second version uses the Cauchy function to produce the acceptance probability of a worse solution.

The problem of limited refueling facilities for AFV fleets was studied by Affi et al. (2018) in a form of a G-VRP model. The main objective of this model was to minimize the total distance, waiting times and number of Electric Vehicles (EV) to serve a set of customers by integrating alternative fuel stations nodes at each route in order to eliminate the risk of running out of fuel. To solve the problem, authors used modified Clarke and Wright savings algorithm (MCWS) which benefits from a savings condition and eliminating redundant AFSs by integrating the routes and a density-based clustering algorithm (DBCA) as a cluster-first and route-second method. Using goal programming, Poonthalir and Nadarajan (2018) introduced a bi-objective Fuel-efficient Green VRP (F-GVRP) to explore the impacts of varying speed environment on the system in relation to fuel consumption and route cost. Authors used a PSO algorithm with Greedy Mutation Operator and time varying acceleration coefficient to solve the problem. The results show that more efficient routing with lower fuel usage can be attained under varying speed condition.

Niu et al. (2018) proposed an optimization model for companies to minimize the total costs, including fuel consumption, CO_2 emissions and driver wages. In this study, the mathematical model of the green open VRP with time windows based on the comprehensive modal emission model was designed in which vehicles do not return to the deport after serving the customers. The authors deigned a hybrid tabu search algorithm with neighborhood search to solve the model. The results show open routed reduce the total cost by 20% compared to closed routes (including fuel and cost of CO_2). Zhang et al. (2018b) developed a joint optimization model including green vehicle scheduling and routing problem with time-varying speeds, in which extra wages for non-working hours and soft time-window constrains were considered. To solve the problem, authors benefited from an adaptive large neighborhood search algorithm. The results of this study provides practical implications in VRP research. For example, authors indicate that the shortest route does not assure less energy consumption and the departure time strongly impacts on fuel consumption and CO_2 levels.

Knowing this inherent complexity, developing accurate models and solutions for large-scale VRPs using conventional mathematical programing techniques is difficult and time consuming. Therefore, researchers benefit from metaheuristic approaches such as genetic algorithm (GA), artificial bee colony (ABC) algorithm, ant colony optimization (ACO) that are capable to produce a close-to-the optimal solution in a reasonable time-frame, while incorporating multiple objectives (sometimes conflicting objectives) (Chao et al., 1993).

Garai et al. (2013) states that there has been an increasing number of studies attempting to improve the performance of ACO with or without hybridization for solving problems in discrete and continuous settings. In particular, ACO has been widely applied to VRP and its variants (Demirel and Yilmaz, 2012). For example, Gong and Fu (2010) proposed a multi-objective VRP with time window by including fixed vehicle cost, operation cost, shelf life loss and default cost. The authors benefited from a two-generation ACO with ABC customer classification (ABC-ACO) which resulted in 20.8% faster computational time and 15.9% cost reduction. ACO was applied to a capacitated MDVRP by Stodola and Mazal (2015) where new parameters such as methods of selecting depots was introduced. Wang et al. (2016) proposed a novel hybrid ACO-based algorithm in which ants go in and out of depots for multiple rounds (ACOMR). This model was then applied to a combined cumulative VRP and MDVRP. An IACO with saving algorithms, mutation operation and adaptive ant-weight strategy was presented by Gao et al. (2016) to solve MDVRP with time window in an automotive parts delivery problem. Similarly, Jabir et al. (2017) presented an efficient algorithm based on ACO and variable neighborhood search to solving a MDGVRP with the objective of minimizing cost and emission.

In conclusion, due to mounting operational cost and pressure to reduce environmental impacts of transport activity, VRP remains one of the key challenging areas in logistics and transportation industry. Given the evolving nature of vehicles, customer requirements and interface of physical distribution network with marketing channels, research on VRP and its variants has become a dynamic and developing area. Relevant to the context of this study which is focused on the application of ACO in VRP, a growing number of studies aim to improve model practicality and solution quality of ACO in combinatorial optimization problems. Due to its guided search capability and use of Elitist phenomenon where the good solutions receive more weights to influence the search direction, ACO is extremely practical to solve multi-objective MDVRP with reliable solutions in a logical time frame. In summary, the contributions of this paper can be listed as:

- From modelling perspective, this paper proposes a model which incorporates a number of practical objectives, including a green approach based on the CO2 emission function is incorporated into the design of the proposed model.
- From solution-approach perspective, a developed ant colony optimization algorithm, is applied to solve the presented MDVRP, in which the process of updating pheromone is improved in comparison to the classical ACO.

3. Problem description and formulation

Organizations that deal with the delivery, collection, and movement of objects and humans face unique challenges when designing their transport network. As noted, VRP is one of the most practical and common issues in transportation systems. Over time, VRP has been developed and several different branches exist, which was discussed in the literature. In particular, businesses involved in distribution of goods are keen to reduce the total kilometers traveled by vehicles when serving customers through employing multiple hubs and distribution centers. For example, in a food distribution scenario, a vehicle may commence its trip from Hub_1 and serves 10 supermarkets. Then, the vehicle is reloaded in Hub_2 with more goods to serve the next group of customers. In this case, Hub_2 is closer to the centrum of second group of customers, and thus, vehicle travels less distance. Such situations were also observed in emergency logistics (Li et al., 2011) and alternate fuel vehicles optimization (Zhang et al., 2018a).

To model the problem, we benefit from a branch of routing related to the graph theory. Graph theory is one of the most widely discussed topics in operation research. Usually, in graph theory, there are nodes that are connected by the edges. Graphs are usually represented by G = (V, E), where V is the set of vertices and E is the set of edges. In this MDVRP problem, customers are introduced as nodes and communication paths as the edges of this graph. Thus, $N = \{1, \ldots, N\}$ is a set of vertices, and each vertice represents a customer with a specific demand (Dem_j).

Fig. 1 provides and overview of the MDVRP problem in which customers, depots and edges between are shown. In this figure, vehicles start moving from depots and serve customers that are shown by circles.

In this paper, the routing problem considers loading space constraints where the vehicle serving customer has a limited capacity. The routing problem with loading space constraint can be generally categorized into two main categories. The first category includes problems in which there is only one action along the path and the second group includes problems in which loading and unloading operations along the path are performed in parallel. In this paper, the first category is considered. In other words, there are several starting points for vehicles, and one can proceed from each of them, depending on the assumption or arbitrariness of the problem.

Assumptions:

1. The problem is designed as a discrete network
2. Each vehicle returns to the departing depot
3. Customer delivery is satisfied with one truck visit
4. Each vehicle is loaded only in one depot
5. Vehicles are homogeneous
6. Vehicles are not transferable to other depots

Parameters:

N: Set of customers' nodes
N_0: Set of depots' nodes
A: Set of edges (paths)
$Dist_{ij}$: Distance between node i and node j
$Dist_{sj}$: Distance between depot s and node j
$Dist_{is}$: Distance between node i and depot s
Dem_j : Demand in node j
$Price$: Product price
$Poll$: The amount of emission produced by vehicle during transportation
$Time_{ij}$: Travel time between node i and node j
$Time_{sj}$: Travel time between depot s and node j
$Time_{is}$: Travel time between node i and depot s
$Time_j^{out}$: Unloading time at node j
$Time_{sj}^{in}$: Loading time for shipping from depot s to node j
$Trans_{ij}$: Transportation cost per unit of product from node i to node j
$Trans_{sj}$: Transportation cost per unit of product from depot s to node j
$Trans_{is}$: Transportation cost per unit of product from node i to depot j
$Vehi$: Available vehicle number
Cap_{vehi} : Capacity of vehicles

Decision variables.

$Flow_{ij}$: Total quantity of products between node i and node j
$Flow_{sj}$: Total quantity of products between depot s and node j

$$x_{ij} = \begin{cases} 1 : \textit{if a vehicle travels from node i to node j} \\ 0 : \textit{otherwise} \end{cases}$$

$$x_{sj} = \begin{cases} 1 : \textit{if a vehicle travels from depot s to node j} \\ 0 : \textit{otherwise} \end{cases}$$

$$x_{is} = \begin{cases} 1 : \textit{if a vehicle travels from node i s to depot s} \\ 0 : \textit{otherwise} \end{cases}$$

The proposed MDGVRP model with vehicle capacity limitation has four objectives. The first and second objective functions consist of revenue maximization (Z_1) and cost minimization (Z_2) respectively. These two objectives are incorporated into one integrated profit objective function. The third objective is focused on minimizing the traveling time of vehicles in the network to satisfy the demand. Finally, the fourth objective function is concerned with reducing the level of CO_2 emissions. These objective functions are presented as follows:

$$max\ Z_1 = \sum_S \sum_{j \in N} Flow_{sj} .\ Price\ .\ x_{sj}$$

$$min\ Z_2 = \sum_S \sum_{j \in N} Flow_{sj} .\ Trans_{sj}\ .\ x_{sj} + \sum_{i \in N} \sum_S Trans_{is}\ .\ x_{is} + \sum_{(i,j) \in A} Flow_{ij}\ .Trans_{ij}\ .\ x_{ij}$$

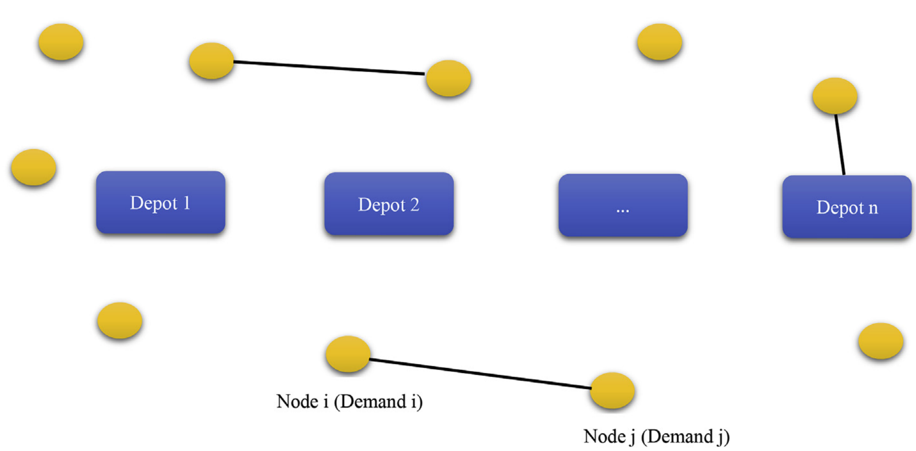

Fig. 1. An overview of customers and edges in MDVRP.

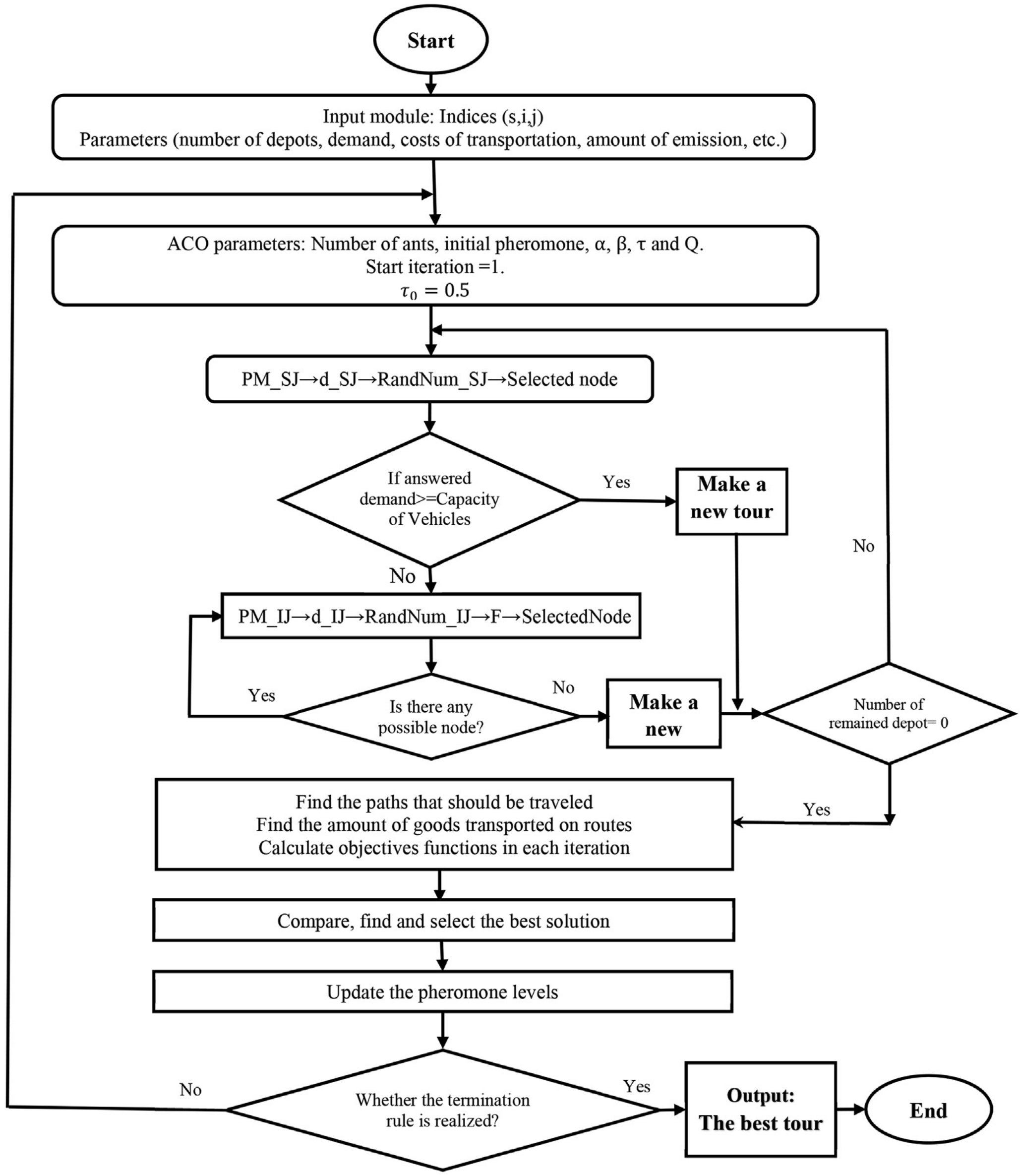

Fig. 2. Structure of the heuristic ACO algorithm.

$$min\ Z_3 = \sum_S \sum_{j \in N} Time_{sj}.\ x_{sj} + \sum_{i \in N} \sum_S Time_{is}\ .\ x_{is} + \sum_{(i,j) \in A} Time_{ij}\ .\ x_{ij} + \sum_S \sum_{j \in N} Time^{in}_{sj}.\ Flow_{sj}.\ x_{sj} + \sum_{j \in N} Time^{out}_j .Dem_j$$

$$min\ Z_4 = Poll\ .\ \left[\sum_S \sum_{j \in N} Dist_{sj}.\ x_{sj} + \sum_{(i,j) \in A} Dist_{ij}\ .\ x_{ij} + \sum_{i \in N} \sum_S Dist_{is}\ .\ x_{is} \right]$$

Z_1 is the revenue from selling products which is calculated by multiplying total demand and price. Z_2 represents the total costs including transportation cost. Z_3 indicates the time to discharge, load and also travel between depots to nodes, nodes to nodes and nodes to depots. Finally, Z_4 describes the emission function, which is the level of pollution produced by the vehicles. The final construction of the model is presented as:

$$maximize[Z_1]$$

$$minimize[Z_2,\ Z_3,\ Z_4]$$

The formulations of constraints are demonstrated as follows:

Table 2
Tuning values for various levels of the parameters.

Factor	Level 1	Level 2	Level 3	Selected level
A	0.1	0.5	1	Level 3
Q	10000	50000	100000	Level 1
ρ	0.01	0.5	0.9	Level 3
τ_0	0.1	0.5	0.9	Level 2
MaxIt	100	1000	2000	Level 2
nAnt	50	100	200	Level 2

Table 3
Examples of MDGVRP networks.

Example No.	Number of depots	Number of nodes	Demand levels in nodes										Total number of decision variables
			1	2	3	4	5	6	7	8	9	10	
1	1	2	200	100	–	–	–	–	–	–	–	–	12
2	1	5	110	120	80	300	100	–	–	–	–	–	60
3	1	8	200	50	80	150	170	100	100	120	–	–	144
4	2	5	100	150	110	80	90	–	–	–	–	–	80
5	4	4	100	150	80	75	–	–	–	–	–	–	88
6	5	10	100	200	150	180	110	50	100	200	300	100	220

Table 4
Different weights for six instances.

Example No.	Lingo (Separated)				LP-Metric (Total objectives)			Diff (%)	
	Objective 1	Objective 2	Objective 3	Objective 4	Lingo	ACO	IACO	ACO & Lingo	IACO & Lingo
1	500000	550	1180	150	−0.2179	−0.2179	−0.2179	0.00%	0.00%
2	1420000	3230	3697	390	−0.48177	−0.16787	−0.48117	65.16%	0.12%
3	1940000	10210	10043	1950	−0.084109	0.0047603	−0.067725	105.66%	19.48%
4	1060000	11650	5034	1300	−0.69857	−0.34966	−0.60559	49.95%	13.31%
5	810000	1950	2616	610	−22.0424	−17.3147	−21.0681	21.45%	4.42%
6	2980000	27710	31690	2230	−65.6224	−62.3865	−64.5341	4.93%	1.66%

$$(1) \sum_{j\in N} x_{ij} = 1 \quad ; \quad \forall_i \in N_0$$

$$(2) \sum_{i\in N} x_{ij} = 1 \quad ; \quad \forall_j \in N_0$$

$$(3) \sum_{j\in N} x_{sj} \le Vehi \quad ; \quad \forall_s \in S$$

$$(4) \sum_{S}\sum_{j\in N} Flow_{sj} = \sum_{j\in N} Dem_j$$

$$(5)\ Dem_j x_{ij} \le Flow_{ij} \le (Cap_{vehi} - Dem_j)x_{ij} \ ; \ \forall (i,j)\in A \ ?!$$

$$(6)\ Flow_{ij} \ge 0 \ ; \ \forall (i,j)\in A$$

$$(7)\ Flow_{is} = 0 \ ; \ \forall_i \in N \ , \ \forall_s \in S$$

$$(8) \sum_{i\in N} Flow_{ij} - \sum_{i\in N} Flow_{ji} = Dem_j \ ; \ \forall_j \in N$$

$$(9)\ Flow_{ij} \le Cap_{vehi} x_{ij} \ ; \ \forall (i,j)\in A$$

$$(10) \sum_{j\in N} x_{ij} - \sum_{j\in N} x_{ji} = 0 \ ; \ \forall_i \in N_0$$

$$x_{ij} \in \{0,1\} \ ; \ \forall (i,j)\in A$$

Constraints (1) and (2) indicate the flow balance of the network. Constraint (3) restricts the number of vehicles up to the available vehicles. Constraint (4) shows that all demand points must be satisfied. Constraint (5) checks the product availability for the next delivery when the demand is satisfied. Constraint (6) indicates that all flows must be equal to and larger than zero. Constraint (7) assures that vehicles return to the depots. Constraint (8) guarantees that the quantity remaining after visiting customer j is exactly the load before visiting this customer minus its demand. Constraints (9) ensures that the vehicle capacity is not violated. Constraint (10) guarantees that a customer leaving a depot (or returning to a depot) cannot be linked to a different depot respectively.

4. Solution approach

ACO is a meta-heuristic method that has been successfully used in solving a large number of optimization problems. ACO algorithm was introduced as a tool for solving the traveling salesman problem (TSP) by Dorigo and Stutzle in 1999. This algorithm, which is a multi-agent system, has been inspired by the food searching mechanism of ants, so that each agent is an artificial ant. The algorithm is also a successful example of a group's intelligent systems in which each agent performs a simple operation. Despite this simplicity in operations, ACO is capable to solve NP-Hard problems such as TSP and VRP in a very efficient fashion. The solution approach used in this research is a developed version of the ACO that was presented in Soleimani and Zohal (2017) and Zohal and Soleimani (2016). In this algorithm, each artificial ant looks to find the shortest path between a pair of nodes of a graph in which the problem is structured on. Thus, the problem is divided into subproblems where the artificial ants must choose the next node based on the pheromone and distance. The decision rule for an ant located at a node follows the formula proposed by Dorigo et al. (1996):

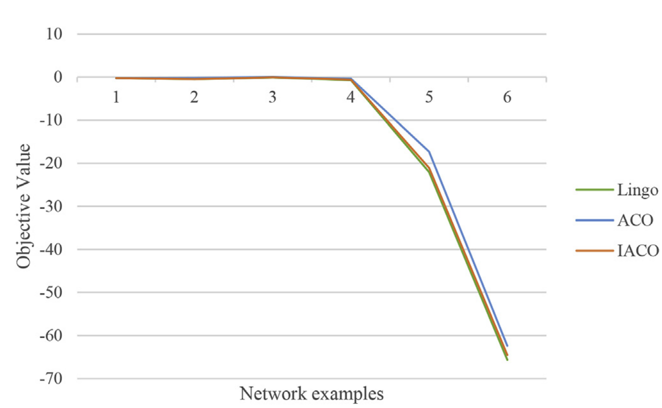

Fig. 3. Comparison of objective function values by Lingo, ACO and IACO (Small scale).

$$PM_{ij}^{w}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{j\in N_i}^{N}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}} & ; \quad if\ j\in N_i \\ 0 & ; \quad otherwise \end{cases}$$

In this equation, $\tau_{ij}(t)$ represents the value of the pheromone on the edge (i,j) , and $\eta_{ij}(t)$ represents the heuristic information. Both parameters are interconnected in values. To avoid rapid convergence of ants to an optimal path, pheromone evaporation is considered, which means the pheromone concentration is automatically reduced to value ρ in each repetition. In other words, if τ is the pheromone matrix on the related graph edges, the matrix is updated in each replication by the following formula (Dorigo et al., 1996):

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij} + \sum_{w}\Delta\tau_{ijij}^{w}$$

In this equation, $\Delta\tau_{ijij}^{w}$ represents the value of the pheromone on the edge *(I,j)*, which is cast by ant *w*. In other words, each ant creates a pheromone when it passes through a path. To update the development of pheromone, an Ant-Weight Strategy (AWS) by Panicker et al. (2013) is used as follows:

$$\Delta\tau^{w} = \begin{cases} \dfrac{Q}{\mathrm{global-best(It)}} & , \quad if\ allocation\ is\ done\ by\ ant\ w \\ 0 & , \quad otherwise \end{cases}$$

In this formula, *Q* represents the evaporation rate of pheromone and Global-best represents the total cost of the best assignment by ant w in the previous repetition. The aim of pheromone update is to reduce its value for an inferior solution and increasing its amount for the best solution (Socha and Dorigo, 2008).

Once the parameters are determined, the probability matrix (PM) must be developed, and accordingly, the cumulative probability matrix (d) with the random number is selected and compared. Knowing the selected number from the matrix, the depot and first node (customer) is obtained. Once, the first demand is satisfied, if the capacity of the vehicle is full or unable to accept new request, it returns to the selected depot and creates a tour. However, if the vehicle is available, the probability matrix is again created (between two nodes). This process continues until the capacity of the vehicle is completed and then it returns to the depot, and thus, no demand node remains. The value of objective function is computed and then compared with the values from previous iterations to select the Global-best value. Levels of pheromone are updated until the termination rule is reached. Fig. 2 demonstrates the steps of the structure of the IACO algorithm for solving the multi-objective MDGVRP.

According to Fig. 2, after entering the model parameters, it is time to calculate the probability matrix (PM). Then, the cumulative PM is calculated (d) and the random number is selected for comparison. Given the selected number of matrix, the depot and first node (customer) is obtained. Once the first demand is met, the vehicle returns to the selected depot and creates a tour, if the capacity is completed or unable to accept another request. However, the vehicle is available, the PM is again created (between two nodes). This process will carry on until the capacity of the vehicle is completed and it returns to the depot. This iteration continues until all demand points are satisfied. The value of the objective functions are computed and compared with the results from previous iterations and, then the best ones are selected (called Global-best). Next, the level of pheromones must be updated and this loop continues until the termination rule is reached. Finally, the results and best

Table 5
Configurations of large-scale networks.

Example No.	Number of depots	Number of nodes	Demand																																			Decision variables
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	
1	5	10	100	200	150	180	110	50	100	200	300	100	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	380
2	6	10	120	150	40	200	300	10	130	55	110	80	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	420
3	7	11	180	120	90	150	230	170	110	140	70	210	110	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	528
4	8	15	200	100	110	90	10	80	285	190	185	55	240	100	90	70	210	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	960
5	10	15	60	260	20	300	210	290	75	80	140	65	25	45	150	25	110	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1020
6	15	15	120	45	170	80	25	220	236	90	40	60	220	150	116	260	90	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1320
7	15	20	230	170	110	140	290	110	165	25	45	150	120	150	40	200	100	130	190	150	220	90	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1960
8	30	25	90	20	230	190	110	180	285	190	185	55	240	100	90	70	210	30	120	45	170	80	25	220	300	110	65	–	–	–	–	–	–	–	–	–	–	4255
9	30	30	285	190	185	220	117	125	110	140	250	110	80	70	28	237	220	90	140	220	120	50	210	90	115	221	38	40	90	225	110	75	–	–	–	–	–	5340
10	40	35	75	80	140	119	230	123	237	30	55	225	59	230	100	270	300	222	60	220	150	116	210	30	120	45	170	80	230	170	110	140	290	110	165	25	45	9540

Table 6
Summary of the results for large scale instances.

Networks	Total value of the objective function for ACO	Time ACO (second)	Total value of the objective function for IACO	Time IACO (second)	$\left(\frac{\lvert IACO - ACO\rvert}{IACO} \times 100\right)$	
					Objective function	Time
1	−0.146	12.896599	−0.23095	12.916787	36.78%	0.16%
2	−0.02385	12.687051	−0.32203	13.080925	92.59%	3.01%
3	−0.086067	14.459477	−0.12105	14.778725	28.90%	2.16%
4	0.085737	19.837434	−0.087732	20.31254	197.73%	2.34%
5	0.0024234	19.947741	−0.215	23.039892	101.13%	13.42%
6	−0.15666	21.661662	−0.19374	23.061892	19.14%	6.07%
7	0.064027	31.247733	0.027419	32.141537	133.51%	2.78%
8	0.14576	47.580705	0.066035	48.807289	120.73%	2.51%
9	0.22143	60.964766	0.073831	62.534975	199.91%	2.51%
10	0.36992	82.471088	0.30288	82.506562	22.13%	0.04%

solution are reported at the end of algorithm.

5. Experimental results

This section presents the procedures used to validate reliability of the IACO using parameters obtained and tuned from experimental results. Taguchi and Wu (1979) method of robust design is adopted to find the optimum combination of parameters in the IACO. To enhance the performance of the model, the parameters values are considered in three levels of instances and the means are reported. Table 2 provides the levels of parameters values for tuning process.

Accordingly, Qualitek-4 software was used to determine and select the parameters' values based on the value of objective function and solving time. Using the results Qualitek-4, the appropriate value levels are selected for each parameter. Level 3 is selected for α as the value of objective function is maximized in this level. Although the computation time is minimized in Level 2, the difference is not significant when compared to Level 3. For Q, the value of the objective function is maximized in Level 1, but the time minimization occurs in the Level 2. However, the difference in solution time between Levels 1 and 2 can be ignored.

Level 3 is selected for ρ as the value of the objective function is higher in comparison to other levels, but the time difference is ignorable. Level 2 is selected for τ_0 as the objective function is maximized in this level and the difference of computation time with other levels is not significant.

The objective function is maximized when *MaxIT* is selected in the Level 2. However, computation time is minimized in Level 1 mainly because of the iteration effects. Thus, Level 2 is preferred for a better objective function value within a reasonable time. For *nAnt*, we choose Level 2 due to maximized objective function value.

5.1. Validation of L-P metric

The metric distance in the L-P method is used to measure the proximity of an existing solution to the ideal solution. As the value of L-P metric is influenced by the measurement scale of existing objectives (if scales are different), the following formula is used (Yu, 1973):

$$L-P = \left\{ \sum_{j=1}^{J} \gamma_j \left[\frac{f_j(x^{*j}) - f_j(x)}{f_j(x^{*j})} \right]^p \right\}^{\frac{1}{p}}$$

Where x^{*j} represents the ideal solution to optimize objective j, x represents a given solution, γ_j represents the degree of importance (weight) for the objective j and $1 \leq p \leq \infty$ expresses the parameter of L-P family identifier. The value of p specifies the degree of emphasis

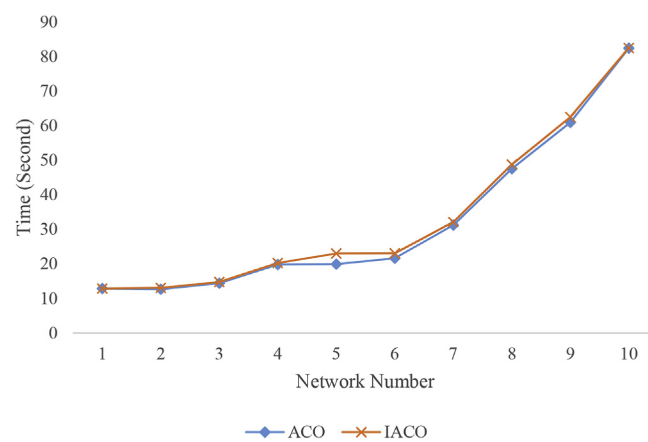

Fig. 4. Comparison of computation time for ACO and IACO (Large scale).

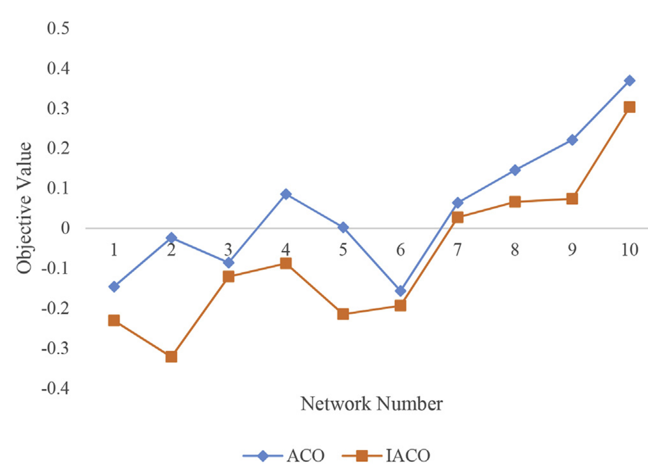

Fig. 5. Comparison of objective function values for ACO and IACO (Large scale).

on deviations, where the emphasis will be on the greatest deviation and the L-P compatible function must be minimized in order to minimize the deviation from the ideal solution.

Since MDGVRP is a multi-objective model with conflicting objective functions (Z_1, Z_2, Z_3 and Z_4 in our model), LP-metric method solves the problem considering each function separately and minimize the summation of normalized differences between each objective and their optimal values (Mirzapour Al-e-hashem et al., 2011).

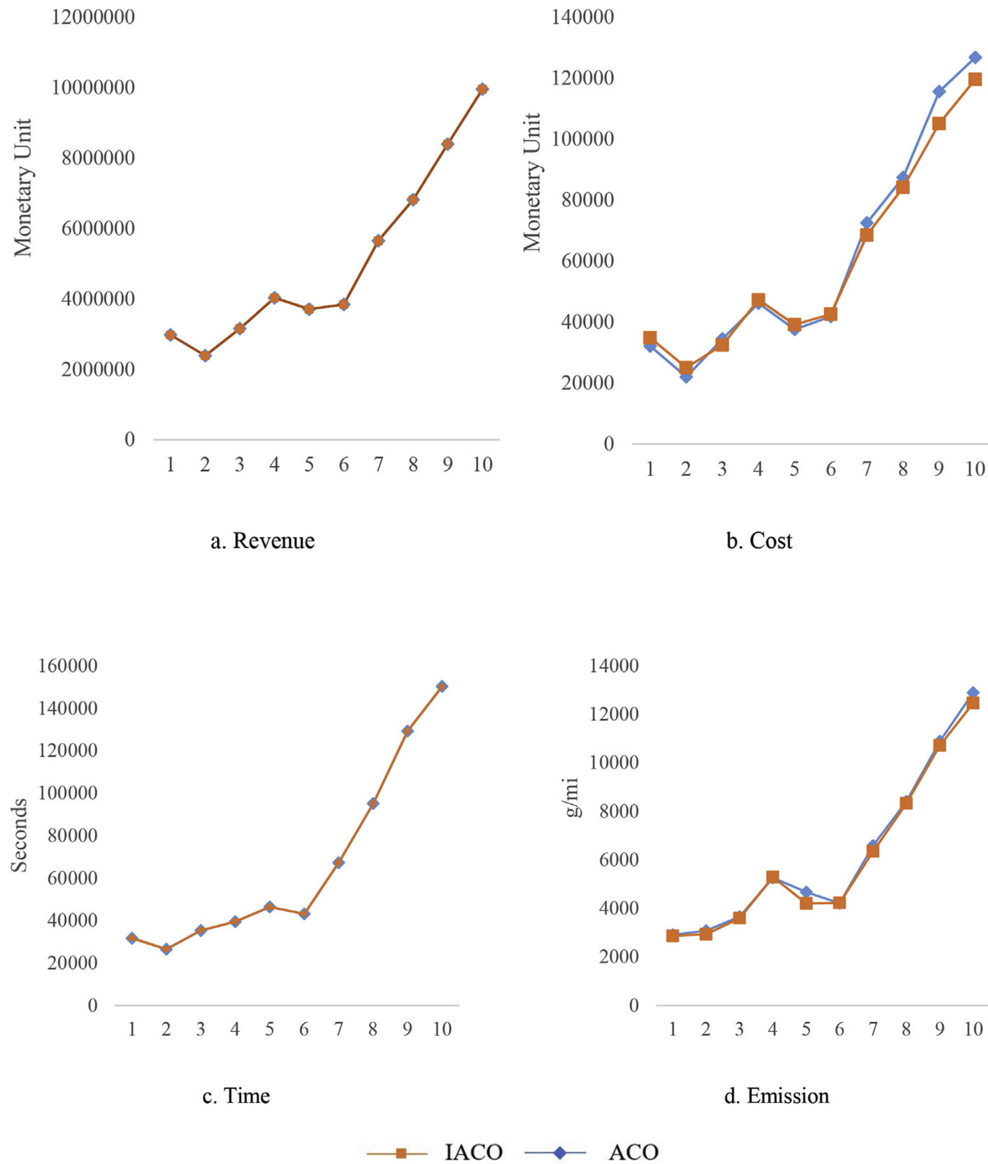

Fig. 6. Comparison of objective values between ACO and IACO for 10 network configurations.

In order to validate the IACO algorithm,[1] two validation settings are designed in small and large-scale sizes. The small-scale arrangement is developed due to its ability to be compared with the global optimum solution, while the larger setting demonstrate the practicality of the model in real-world conditions.

5.2. Validation process of the IACO algorithm

5.2.1. Small-sized instances analysis

To validate the accuracy of the IACO, 6 random examples of MDGVRP networks are developed with different features in Table 3. The details of example networks are provided in Appendices 1 to 5.[2]

After creating the example networks, weights are given and parameters are developed by the Taguchi tuning procedure. Table 4 compares the results of IACO with an optimal solution provided by LINGO.

According to Table 4, the difference between the global optimum values of LINGO and the global-best values of the IACO algorithm is minimal. The small error in values indicate that the performance of IACO is acceptable. On the other hand, the mean of differences between the results of IACO and Lingo demonstrates a satisfactory figure of 0.065.

As shown in Fig. 3, the IACO algorithm shows acceptable performance when compared with Lingo and conventional ACO. However, the performance and reliability of such algorithms must be tested in large scale configuration similar to real world distribution problems.

5.2.2. Large-sized instances analysis

A total of 10 large size MDGVRP networks with diverse characteristics are designed and presented in Table 5 for computational analysis.

Since the number of decision variables are large, ranging from

[1] The IACO algorithm is coded using Matlab 7.14 (R2012a) software.

[2] The details of Example Network 6 is not provided due to space limitation and size of tables.

380 to 9540, LINGO is not capable to solve the problem and we limit the analysis to compare the performance of IACO with ACO (Table 6).

As shown in Table 6, the values of computation times in both IACO and ACO are very similar, with the maximum variance of 13.42% and average difference of 3.5%. Although the computation time of the IACO is slightly longer in some of the cases, it resulted in proportionally better values for the objective functions. For example, a 2.34% increase in the computation time has improved the objective function by around 198% in Network 4. Results from Table 6 show that IACO achieves significantly better values for the objective functions, but in a slightly longer solving time. In other word, changing the structure of updating pheromone is an effective strategy to improve the quality of solutions without significant time variations. Figs. 4 and 5 show the comparison of computation times and values of objective functions between ACO and IACO.

In the following, it is necessary to evaluate the performance of both IACO and ACO algorithms in the calculation of individual objective functions.

As shown in the four parts of Fig. 6, IACO shows a better performance in cost and emission criteria, while the computation time and revenue are similar to ACO. In conclusion, the analysis of the small-scale networks and comparison with the results of LINGO shows that our IACO is capable to produce close-to-optimal results. In addition, by testing the algorithm in ten large-scale simulated networks, IACO provided high performing results, which shows its effectiveness to solve real world problems.

6. Conclusion and future research

Due to increasing transportation costs and greater legislative requirements, many retailers and manufacturing organizations are under pressure to improve the efficiency of their distribution network. When researching the topic of efficiency in transport systems, traditionally, a great amount of effort was devoted to the issues of cost reduction. However, in the contemporary business environments, there are other major factors that not only play a critical role in the success of a transport system, but are increasingly on demand by stakeholders such as minimizing environmental impacts. In this paper, we present a multi-objective linear mathematical model to solve a MDGVRP with conflicting objectives. To solve the model, we have improved the conventional ACO algorithm by proposing a new technique to update the development of pheromone. To validate the effectiveness of our IACO approach, six small-scale and ten large-scale networks were developed to test the performance of model in conditions close to real world distribution problems. The results achieved through IACO showed satisfying performance when compared to the optimal solutions produced by LINGO and outperformed another developed ACO algorithm. The results of this study suggest that original metaheuristics algorithms provide great platforms for solving complex problems, while producing close-to-optimal solutions at a significantly low cost. In particular, solution quality and time can be improved through innovative modification of population and nature-based approaches.

This study has some limitations. The proposed model of this research is a single product. Thus, it is recommended future research considers models capable of including multi-product cases. On the other hand, in real-world problem many of parameters follow nondeterministic behaviors such as demand and price. Therefore, it is important to consider stochastic, fuzzy, interval, or chaos approaches in future works.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.03.185.

References

Affi, M., Derbel, H., Jarboui, B., 2018. Variable neighborhood search algorithm for the green vehicle routing problem. Int. J. Ind. Eng. Comput. 9 (2), 195–204.
Ai, T.J., Kachitvichyanukul, V., 2009. Particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem. Comput. Ind. Eng. 56 (1), 380–387.
Akpinar, S., 2016. Hybrid large neighbourhood search algorithm for capacitated vehicle routing problem. Expert Syst. Appl. 61, 28–38.
Biswas, S., 2017. Multi-objective Genetic Algorithms for Multi-Depot VRP with Time Windows. Master Thesis. Brock university, St. Catharines, Ontario.
Braekers, K., Ramaekersa, K., Nieuwenhu, I., 2016. The vehicle routing problem: state of the art classification and review. Comput. Ind. Eng. 99, 300–313.
Chao, I.-M., Golden, B.L., Wasil, E., 1993. A new heuristic for the multi-depot vehicle routing problem that improves upon best-known solutions. Am. J. Math. Manag. Sci. 13 (3–4), 371–406.
Chebbi, O., Chaouachi, J., 2016. Reducing the wasted transportation capacity of Personal Rapid Transit systems: an integrated model and multi-objective optimization approach. Transport. Res. E Logist. Transport. Rev. 89, 236–258.
Dantzig, G.B., Ramser, J.H., 1959. The truck dispatching problem. Manag. Sci. 6 (1), 80–91.
Darbari, J.D., Kannan, D., Agarwal, V., Jha, P.C., 2019. Fuzzy criteria programming approach for optimising the TBL performance of closed loop supply chain network design problem. Ann. Operat. Res. 273 (1–2), 693–738.
Demirel, T., Yilmaz, S., 2012. A new solution approach to multi-depot vehicle routing problem with ant colony optimization. J. Mult.-Valued Log. Soft Comput. 18 (3–4), 421–439.
Dorigo, M., Stutzle, T., 1999. Ant Colony Optimization: a New Meta-Heuristic. Institut de Recherches Interdisciplinaires et de Developpements en Intelligence Artificielle, Bruxelles, Belgium.
Dorigo, M., Maniezzo, V., Colorni, A., 1996. Ant system: optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 26 (1), 29–41.
Du, J., Li, X., Dan, R., Zhou, J., 2017. Multi-depot vehicle routing problem for hazardous materials transportation: a fuzzy bilevel programming. Inf. Sci. 399, 201–218.
Erdoğan, S., Miller-Hooks, E., 2012. A green vehicle routing problem. Transport. Res. E Logist. Transport. Rev. 48 (1), 100–114.
Galindres-Guancha, L.F., Toro-Ocampo, E.M., Gallego- Rendón, R.A., 2018. Multi-objective MDVRP solution considering route balance and cost using the ILS metaheuristic. Int. J. Ind. Eng. Comput. 9, 33–46.
Gao, J., Gu, F., Hu, P., Xie, Y., Yao, B., 2016. Automobile chain maintenance parts delivery problem using an improved ant colony algorithm. Adv. Mech. Eng. 8 (9), 1–13.
Garai, G., Debbarman, S., Biswas, T., 2013. An efficient Ant Colony Optimization algorithm for function optimization. In: 2013 IEEE Congress on Evolutionary Computation. IEEE, Cancun, Mexico.
Gong, W., Fu, Z., 2010. ABC-ACO for perishable food vehicle routing problem with time windows. In: 2010 International Conference on Computational and Information Sciences. IEEE, Chengdu, China.
Govindan, K., Jafarian, A., Khodaverdi, R., Devika, K., 2014. Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. Int. J. Prod. Econ. 152, 9–28.
Govindan, K., Soleimani, H., Kannan, D., 2015. Reverse logistics and closed-loop supply chain: a comprehensive review to explore the future. Eur. J. Oper. Res. 240 (3), 603–626.
Govindan, K., Jafarian, A., Nourbakhsh, V., 2018. Designing a sustainable supply chain network integrated with vehicle routing: a comparison of hybrid swarm intelligence metaheuristics. Comput. Oper. Res. (in press).
Gulczynski, D., Golden, B., Wasilc, E., 2011. The multi-depot split delivery vehicle routing problem: an integer programming-based heuristic, new test problems, and computational results. Comput. Ind. Eng. 61 (3), 794–804.
Hassan-Pour, H., Mosadegh-Khan, M., Tavakkoli-Moghaddam, R., 2009. Solving a multi-objective multi-depot stochastic location-routing problem by a hybrid simulated annealing algorithm. Proc. IME B J. Eng. Manufact. 223 (8), 1045–1054.

Ho, W., Ho, G.T., Ji, P., Lau, H.C., 2008. A hybrid genetic algorithm for the multi-depot vehicle routing problem. Eng. Appl. Artif. Intell. 21 (4), 548–557.
Jabir, E., Panicker, V., Sridharan, R., 2017. Design and development of a hybrid ant colony-variable neighbourhood search algorithm for a multi-depot green vehicle routing problem. Transport. Res. Transport Environ. 57, 422–457.
Kahfi, A., Tavakkoli-Moghaddam, R., 2015. Solving Multi-Ride Routing vehicle problem based on risk reduction using a multi-objective bat algorithm. J. Transport. Eng. 6, 507–522.
Kuo, Y., 2010. Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem. Comput. Ind. Eng. 59 (1), 157–165.
Lai, D.S., Caliskan Demirag, O., Leung, J.M., 2016. A tabu search heuristic for the heterogeneous vehicle routing problem on a multigraph. Transport. Res. E Logist. Transport. Rev. 86, 32–52.
Laporte, G., 1992. The vehicle routing problem: an overview of exact and approximate algorithms. Eur. J. Oper. Res. 59 (3), 345–358.
Laporte, G., Nobert, Y., Taillefer, S., 1988. Solving a family of multi-depot vehicle routing and location-routing problems. Transport. Sci. 22 (3), 161–172.
Leung, S.C., Zhou, X., Zhang, D., Zheng, J., 2011. Extended guided tabu search and a new packing algorithm for the two-dimensional loading vehicle routing problem. Comput. Oper. Res. 38 (1), 205–215.
Li, J., Lv, X., liu, L., 2011. A parallel genetic algorithm with GPU accelerated for large-scale MDVRP in emergency logistics. In: IEEE International Conference on Computational Science and Engineering, Dalian, China.
Li, J., li, Y., Pardalos, P.M., 2016. Multi-depot vehicle routing problem with time windows under shared depot resources. J. Comb. Optim. 31 (2), 515–532.
Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H., Lam, H.Y., 2014. Survey of green vehicle routing problem: past and future trends. Expert Syst. Appl. 41 (4), 1118–1138.
Luo, J., Chen, M.-R., 2014. Multi-phase modified shuffled frog leaping algorithm with extremal optimization for the MDVRP and the MDVRPTW. Comput. Ind. Eng. 72, 84–97.
Ma, Y., Han, J., Kang, K., Yan, F., 2017. An improved ACO for the multi-depot vehicle routing problem with time windows. In: Proceedings of the Tenth International Conference on Management Science and Engineering Management. Advances in Intelligent Systems and Computing, vol. 502. Springer, Singapore.
Melián-Batista, B., De Santiago, A., AngelBello, F., Alvarez, A., 2014. A bi-objective vehicle routing problem with time windows: a real case in Tenerife. Appl. Soft Comput. 17, 140–152.
Mirzapour Al-e-hashem, S., Malekly, H., Aryanezhad, M., 2011. A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. Int. J. Prod. Econ. 134 (1), 28–42.
Niu, Y., Yang, Z., Chen, P., Xiao, J., 2018. Optimizing the green open vehicle routing problem with time windows by minimizing comprehensive routing cost. J. Clean. Prod. 171, 962–971.
Noori, S., Ghannadpour, S.F., 2012. High-level relay hybrid metaheuristic method for multi-depot vehicle routing problem with time windows. J. Math. Model. Algorithms 11 (2), 159–179.
Osaba, E., Yang, X., Diaz, F., Onieva, E., Masegosa, A.D., Perallos, A., 2017. A discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy. Soft Computing 21 (18), 5295–5308.
Panicker, V.V., Vanga, R., Sridharan, R., 2013. Ant colony optimisation algorithm for distribution allocation problem in a two-stage supply chain with a fixed transportation charge. Int. J. Prod. Res. 51 (3), 698–717.
Poonthalir, G., Nadarajan, R., 2018. A fuel efficient green vehicle routing problem with varying speed constraint (F-GVRP). Expert Syst. Appl. 100, 131–144.
Prodhon, C., 2011. A hybrid evolutionary algorithm for the periodic location-routing problem. Eur. J. Oper. Res. 210, 204–212.
Salhi, S., Imran, A., Wassan, N.A., 2014. The multi-depot vehicle routing problem with heterogeneous vehicle fleet: formulation and a variable neighborhood search implementation. Comput. Oper. Res. 52, 315–325. Part B.
Shen, Y.-M., Chen, R.-M., 2017. Optimal multi-depot location decision using particle swarm optimization. Adv. Mech. Eng. 9 (8), 1–15.
Socha, K., Dorigo, M., 2008. Ant colony optimization for continuous domains. Eur. J. Oper. Res. 185 (3), 1155–1173.
Soleimani, H., Zohal, M., 2017. An Ant Colony approach to forward-reverse logistics network design under demand certainty. Journal of Optimization in Industrial Engineering 10 (22), 103–114.
Soleimani, H., Chaharlang, Y., Ghaderi, H., 2018. Collection and distribution of returned-remanufactured products in a vehicle routing problem with pickup and delivery considering sustainable and green criteria. J. Clean. Prod. 172, 960–970.
Soto, M., Sevaux, M., Rossi, A., Reinholz, A., 2017. Multiple neighborhood search, tabu search and ejection chains for the multi-depot open vehicle routing problem. Comput. Ind. Eng. 107, 211–222.
Stodola, P., Mazal, J., 2015. Tactical models based on a multi-depot vehicle routing problem using the ant colony optimization algorithm. International Journal of Mathematical Models and Methods in Applied Science 9, 330–337.
Taguchi, G., Wu, Y., 1979. Introduction to Off-Line Quality Control. Central Japan Quality Control Association, Magaya, Japan.
Tavakkoli-Moghaddam, R., Makui, A., Mazloomi, Z., 2010. A new integrated mathematical model for a bi-objective multi-depot location-routing problem solved by a multi-objective scatter search algorithm. J. Manuf. Syst. 29 (2–3), 111–119.
Tillman, F.A., 1969. The multiple terminal delivery problem with probabilistic demands. Transport. Sci. 3 (3), 192–204.
Tiwari, A., Chang, P.-C., 2015. A block recombination approach to solve green vehicle routing problem. Int. J. Prod. Econ. 164, 379–387.
Toth, P., Vigo, D., 2002. The Vehicle Routing Problem. Society for Industrial and Applied Mathematics, Philadelphia, PA.
Wang, X., Choi, T.M., Liu, H., Yue, X., 2016. A novel hybrid ant colony optimization algorithm for emergency transportation problems during post-disaster scenarios. IEEE Transactions on Systems, Man, and Cybernetics: Systems 48 (4), 545–556.
Wu, T.-H., Low, C., Bai, J.-W., 2002. Heuristic solutions to multi-depot location-routing problems. Comput. Oper. Res. 29 (10), 1393–1415.
Yu, P.L., 1973. A class of solutions for group decision problems. Manag. Sci. 19 (8), 936–946.
Yu, B., Ynag, Z.-Z., Xie, J.-X., 2011. A parallel improved ant colony optimization for multi-depot vehicle routing problem. J. Oper. Res. Soc. 62 (1), 183–188.
Yu, V.F., Redi, A.P., Hidayat, Y.A., 2017. A simulated annealing heuristic for the hybrid vehicle routing problem. Appl. Soft Comput. 53, 119–132.
Zachariadis, E.E., Tarantilis, C.D., Kiranoudis, C.T., 2009. A guided tabu search for the vehicle routing problem with two-dimensional loading constraints. Eur. J. Oper. Res. 195 (3), 729–743.
Zhang, S., Zhang, W., Gajpal, Y., Appadoo, S.S., 2018a. Ant colony algorithm for routing alternate fuel vehicles in multi-depot vehicle routing problem. In: Deep, K., Jain, M., Salhi, S. (Eds.), Decision Science in Action. Asset Analytics (Performance and Safety Management). Springer, Singapore.
Zhang, D., Wang, X., Li, S., Ni, N., Zhang, Z., 2018b. Joint optimization of green vehicle scheduling and routing problem with time-varying speeds. PLoS One 13 (2) e0192000.
Zohal, M., Soleimani, H., 2016. Developing an ant colony approach for green closed-loop supply chain network design: a case study in gold industry. J. Clean. Prod. 133, 314–337.