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Comparing Two-Echelon and Single-Echelon Multi-Objective Capacitated Vehicle Routing Problems

Mehraneh Esmaeili [1] and Rashed Sahraeian [2]*

[1]*Department of Industrial Engineering, Shahed University, Tehran, Iran (mehrane.esmaili@yahoo.com)*
[2]*Department of Industrial Engineering, Shahed University, Tehran, Iran*

***Corresponding Author:** *Rashed Sahraeian (Email: sahraeian@shahed.ac.ir)*

***Abstract–** This paper aims to compare a two-echelon and a single-echelon distribution system. A mathematical model for the Single-Echelon Capacitated Vehicle Routing Problem (SE-CVRP) is proposed. This SE-CVRP is the counterpart of Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) introduced in the authors' previous work. The proposed mathematical model is Mixed-Integer Non-Linear Programming (MINLP) and minimizes 1) the total travel cost, 2) total waiting time of customers, and 3) total carbon dioxide emissions, simultaneously, in distributing perishable products. Applying some linearization methods changes the MINLP model into the Mixed Integer Linear Programming (MILP). In 2E-CVRP, shipments are delivered to customers by using intermediate depots named satellites while in SE-CVRP, direct shipments are used. Considering SE-CVRP, it was assumed that, by eliminating satellites, the large vehicles in depot were used for distribution. Because of the NP-hardness of the Vehicle Routing Problem (VRP) and its extensions, the NSGA-II algorithm was applied to solve the model. The objective functions of both distribution systems were compared in different size issues. The obtained results indicated that by considering large vehicles in an SE-CVRP, this distribution system would outperform the two-echelon one for all objectives of the small-size problems, the first two objectives of medium-size problems, and the first and third objectives of large-size problems.*

***Keywords–** Distribution systems, 2E-CVRP, SE-CVRP, Linearization, NSGA-II.*

I. INTRODUCTION

In much recent research, logistics has gained increasing attention due to its significant effect on transportation cost and distance enhancement with regards to the importance of cost mitigating factors in this area and the necessity of fast supply to the customers. The vehicle routing problem (VRP) has been regarded as one of the main contexts in supply chain management, which aims at assigning the best routes to the vehicles providing to a set of consumers. Requirements and legal regulations have led to different types of shipment such as direct or multi-echelon in transportation industry. Multi-echelon distribution networks, especially two-echelon systems, have drawn increasing attention of researchers as a consequence of damaging effects of freight distribution, including environmental pollution, traffic, etc. In two-echelon distribution networks, freights are delivered from the depot to the customers through intermediate points (Belgin et al., 2018).

The two-echelon capacitated vehicle routing problem (2E-CVRP) is in fact a two-echelon distribution network in which goods are first delivered to capacitated intermediate depots (satellites) and then, from there to the customers. The first echelon includes routes starting and ending at the depot and delivering the freights to a subset of satellites. In this case, satellites have limited capacity and could be served by more than one first-level route. The second echelon contains routes starting and ending at the same satellite and supplying to all consumers. By default, the first-level

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homogeneous fleet is located at the depot. Besides, the capacity of each second-level vehicle is smaller than that of each first-level vehicle. Loading the first- or second-level vehicles at their origin depots has a cost proportional to the quantity loaded or unloaded. The objective of 2E-CVRP is finding two sets of first- and second-echelon routes in a way that each consumer is served just once by a second-level route and the overall cost of routing and handling is minimized (Baldacci et al., 2013). As stated in the previous research, the 2E-CVRP is NP-hard. Fig. 1 demonstrates a feasible solution to 2E-CVRP.

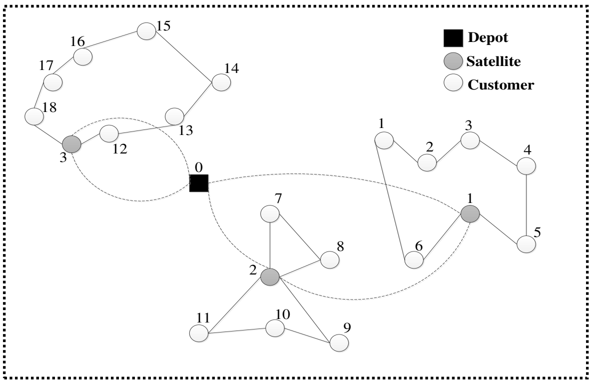

Fig. 1. A feasible solution to 2E-CVRP

As stated, Baldacci et al. (2013) and Feliu et al. (2007) explained a commodity flow problem and introduced problems solved through the branch-and-cut approach with at most 32 consumers and two satellites. Perboli & Tadei (2010) and Perboli et al. (2011) improved this algorithm by augmenting some valid inequalities. Jepsen et al. (2013) attended to some fixed costs for the routes and satellite usage of both levels; they described an exact method (branch-and-cut) for the new problem formulation and extended valid inequalities that operated better than the strategy of Perboli et al. (2011).

In another research, a two-echelon routing problem and a review of two-echelon distribution systems were presented by Cuda et al. (2015). They considered three versions of the problem: the two-echelon Location Ruting Problem (2E-LRP), the two-echelon Vehicle Routing Problem (2E-VRP), and the Truck and Trailer Routing Problem (TTRP). In the review, heuristic and exact methods were surveyed to the same extent in the literature. According to Hemmelmayr et al. (2012), one of the finest performing heuristics for the 2E-CVRP is the ALNS; also, one of the best exact approaches was provided by Baldacci et al. (2013). Song et al. (2017) proposed a dynamic (adaptive) two-echelon capacitated vehicle routing problem (A2E-CVRP), which was a variant of the classical 2E-CVRP. A2E-CVRP includes multiple depots and the vehicles are allowed to serve consumers without deviation from the depots. They introduced a novel mathematical formulation and a good lower bound for the problem, which led to implementation of a new procedure for modeling and solving 2E-CVRP by Sitek & Wikarek (2014). This new approach was a combination of constraint linear programming (CLP) and mixed-integer linear programming (MILP) along with problem transformation. A two-echelon multiple-trip vehicle routing problem with satellite synchronization (2E-MTVRP-SS), a variant of the 2E-CVRP, was addressed by Grangier et al. (2016). They suggested a dynamic or adaptive large neighborhood search for solving the problem.

Green transportation deals with dispatching items in a sustainable way. In recent years, with increase in carbon dioxide (CO_2) emissions, logistics service providers, researchers, practitioners, and transportation carriers have paid more attention to these operations (Dabia et al., 2014). A sheer review of GVRP and a taxonomy of it were published by Lin et al. (2014). They divided these problems into three classes of Green-VRP, Pollution-Routing Problem (PRP), and VRP in reverse logistics. According to Dabia et al. (2014), the PRP originates in the study of Bektas & Laporte (2011). This category deals with the whole amount of energy on a route, transformed into the fuel consumption and GHG emissions. The objective function minimizes fuel consumption, emissions, and driver costs on one arc. Sadegheih et al. (2011) took carbon emission costs under scrutiny in total cost of the supply chain. The model decreased total costs and yielded the best solutions, which were both cost-effective and eco-friendly. Esmaili & Sahraeian (2017) represented a novel bi-objective 2-ECVRP model minimizing (1) total travel cost and (2) total waiting time of customers. A restriction on maximum allowable carbon dioxide (CO_2) emissions from transport in each route was considered as an environmental issue in the problem. The sensitivity analysis performed on the model showed that less restrictive policies on carbon emissions could lead to more total emissions with less total traveling cost and waiting time of customers.

Over recent years, delivering perishable goods to consumers as soon as possible with the minimum cost has been a considerable challenge for practitioners and producers. This challenge has been emphasized for mitigating global costs. In a paper by Angel-Bello et al. (2013), service time in demand points (clients) was taken into account in routing problem, aiming at minimizing the sum of waiting time of clients while receiving service. The VRP with simultaneous pickup and delivery accounting for consumer satisfaction in a time window at each customer node was proposed by Fan (2011). It is clear that customer demand fulfillment is proportional to the waiting time calculated from the lower bound of the time window. The goal is to minimize the distance in order to reduce the cost and maximize satisfaction of the sum of all customers, which results in total service quality improvement.

Some scholars have compared the effectiveness of 2E-CVRP delivery policy with the single-echelon one (Cuda et al., 2015). In one case, the impact of instance alterations, e.g., the number and site of the satellites and the customers, on the total distribution cost was investigated (Crainic et al., 2010). Also, Crainic et al. (2012) investigated how the coverage of constituents other than the distance affected the optimal solution. Both articles showed that the functioning of a distribution system pursuing a 2E-CVRP strategy was better than the one adopting a CVRP strategy. The main benefit of the paper published by Eitzen et al. (2017) was formulating a multi-objective multi-commodity heterogeneous vehicle 2E-VRP. They presented good demonstrations and instructive examples, which differed in several characteristics. The most significant difference in examples concerned whether the location of the satellites was outside the area of clients or within it. The main objective of the work was the minimization of environmental effects. The results demonstrated that a 2E-VRP would have less CO_2 emissions, although the total traveled distance was more.

The current paper compares the performances and results of the multi-objective 2-echelon CVRP, which was proposed by the authors in 2018, and the single-echelon CVRP. The novelty of this paper is proposing mathematical formulations for multi-objective single-echelon Capacitated Vehicle Routing Problem and comparing them with those for the two-echelon one. The objectives are minimizing 1) total travel cost, 2) the sum of customers waiting times, and 3) total CO_2 emissions. The proposed formulations are Mixed-Integer Non-Linear Programming (MINLP); thus, some linearization methods are used. By applying these methods, the model changes to Mixed-Integer Linear Programming (MILP). Different sizes of the problem are solved by NSGA-II meta-heuristic algorithm in both distribution systems. The parameters of the considered algorithm are calibrated using the Taguchi method. The results of the 2-echelon distribution system are compared with those of the single-echelon one.

The remaining of this manuscript is organized as follows: in Section II, an abstract introduction to the two-echelon CVRP and the proposed formulations for the single-echelon CVRP and its linearization are presented. The solution for the model and the suitable algorithm are addressed in Section III. In Section IV, the results obtained from the computational experiments are presented for different sizes of the problem. Finally, the conclusion of the paper and several topics for future research are discussed in Section V.

II. PROBLEM DESCRIPTION

A. Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP)

The fundamental type of 2E-VRP often referred to is 2E-CVRP in which one depot and a set of satellites are the entities. The first- and second-echelon fleets are settled at the depot and satellites, respectively. Every satellite has a specified capacity determined by the maximum number of the secondary vehicles allowed to be routed from it. In both echelons, primary and secondary vehicles have the same capacity and they are homogeneous within the same echelon. There is not any direct shipment between depot and customers. Each primary vehicle is permitted to serve more than one satellite on the same route. On the other hand, each secondary vehicle is permitted to supply exactly one customer. This means that on the second tier split, deliveries are not admissible. A handling cost is rewarded for loading/unloading operations in each satellite. The 2E-CVRP tends to find a set of routes for each level to meet the demands of all customers; it should not violate the satellite and vehicle capacity constraints, but minimize the total distribution cost. The total distribution cost is composed of two components named the cost of applying primary and secondary paths, and the handling cost on satellites (Cuda et al., 2015).

The 2E-CVRP multi-objective formulation is derived from the previous work of the authors (i.e., Sahraeian & Esmaeili, 2018). The objectives are minimizing 1) total travel cost, 2) customers total waiting time, and 3) total CO_2 emissions. This research accounts for the customers waiting time from depot in the first echelon, so the formulation of the model is MINLP.

The main contribution of the current research is proposing a mathematical model for multi-objective SE-CVRP and comparing it with those for 2E-CVRP.

The 2E-CVRP mathematical model, including its sets, parameters, and variables, and the linearization of the proposed mixed-integer nonlinear programming (MINLP) model have been described by Sahraeian & Esmaeili (2018).

B. Single-Echelon Capacitated Vehicle Routing Problem (SE-CVRP)

Dantzig & Ramser (1959) introduced the vehicle routing problem for the first time. They explained a problem in the real world dealing with the distribution of gasoline between a bulk terminal storage and too many fueling stations by tanker trucks. When there are a significant number of service stations, the size of the set of possible paths increases sharply in a way that an improved path is needed to yield the optimal solution. They suggested a procedure dependent on integer linear programing to attain an acceptable solution (not necessarily the optimal solution). All assumptions of the proposed multi-objective single-echelon CVRP mathematical model are as follows:

1. Freight shipments are direct and there is not any satellite.
2. The vehicles are the same first-level vehicles in 2E-CVRP.
3. Speed of the vehicles is equal to v_1 for incoming and outgoing arcs of the depo, but it is equal to v_2 in other arcs. Due to city congestion, vehicle speed in city roads is lower.
4. Vehicles have the same capacity and speed.
5. Fixed costs are not considered for the vehicles.
6. Each customer receives its freight from one vehicle.
7. There is just one perishable product type which has to be distributed.
8. The traveling cost of each unit of distance is equal to 1 ($\acute{c}_{ij}$= 1).

The sets and parameters are the same for the proposed two-echelon SE-CVRP. But the following decision variables are different:

- Decision variables

Q_{ij} Freight flow moving through the arc (i, j)

y_{ij} A binary variable equal to 1 if the arc (i, j) is used by a vehicle

t_j Total waiting time for customer j

t_{ij} The time spent in arc (i, j)

- SE-CVRP mathematical formulation

(1)

$$\min Z_1 = \sum_{i,j \in V_O \cup V_C, i \neq j} C_{ij} \acute{c}_{ij} y_{ij}$$

$$\min Z_2 = \sum_{j \in V_C} t_j \quad (2)$$

$$\min Z_3 = \sum_{i,j \in V_O \cup V_C, i \neq j} GH_1 C_{ij} y_{ij} \quad (3)$$

$$\sum_{j \in V_C} y_{v_o j} \leq m_1 \quad (4)$$

$$\sum_{i \in V_O \cup V_C, i \neq j} y_{ij} = \sum_{l \in V_O \cup V_C, i \neq j} y_{jl} = 1 \qquad \forall j \in V_C \quad (5)$$

$$\sum_{i \in V_O \cup V_C, i \neq j} Q_{ij} - \sum_{l \in V_O \cup V_C, l \neq j} Q_{jl} = \begin{cases} \sum_{i \in V_O \cup V_C, i \neq j} d_j y_{ij} & j \text{ is not the depot} \\ \sum_{i \in V_O \cup V_C} \sum_{j \in V_C, i \neq j} -d_j y_{ij} & \text{otherwise} \end{cases} \qquad \forall j \in V_O \cup V_C \quad (6)$$

$$Q_{ij} \leq K^1 y_{ij} \qquad \forall i,j \in V_O \cup V_C, i \neq j \quad (7)$$

$$\sum_{i \in V_C} Q_{iv_o} = 0 \quad (8)$$

$$C_{ij} = \begin{cases} t_{ij} \times v_1 & \forall i \in V_O, \forall j \in V_C \\ t_{ij} \times v_1 & \forall i \in V_C, \forall j \in V_O \\ t_{ij} \times v_2 & \forall i,j \in V_C, i \neq j \end{cases} \quad (9)$$

$$t_j = \sum_{i \in V_O \cup V_C, i \neq j} (t_i + st_i + t_{ij}) y_{ij} \qquad \forall j \in V_C \quad (10)$$

$$t_j \leq T_{max} \qquad \forall j \in V_C \quad (11)$$

$$y_{ij} \in \{0,1\} \qquad i,j \in V_C, i \neq j \quad (12)$$

$$Q_{ij} \geq 0 \qquad i,j \in V_C, i \neq j \quad (13)$$

$$t_{ij} \geq 0 \qquad i,j \in V_C, i \neq j \quad (14)$$

$$t_j \geq 0 \qquad j \in V_C \quad (15)$$

The objective functions are mathematically formulated from (1) to (3). Objective function (1) minimizes the total transportation cost. Minimizing the total waiting time of customers is formulated in objective function (2), while the minimization of total carbon dioxide emissions is formulated in objective function (3). Constraint (4) ensures that the number of outgoing arcs from the depot should not exceed the existing vehicles in it. Constraint (5) expresses that each node j shoud have only one incoming and outgoing arc. Constraint (6) indicates the demand of node j; for a customer, it is equal to their demand and for depot, it is minus the demands of all customers.

Constraint (7) ensures that the flow passing arc (i,j) should not exceed the vehicle capacity. Equation (8) indicates that there should not be any flowback to the depot. Constraint (9) calculates the time duration for passing arc (i,j). The vehicle speed in the incoming and outgoing arcs of the depot is equal to v_1 and in other arcs, between the nodes, it is equal to v_2. The arrival time at customer j is calculated in Equation (10). It equals the arrival time at the previous node i plus the service time in node i plus the time duration of passing arc (i,j). Constraint (11) ensures arrival time at the upper bound of customers. Constraints (12)-(15) show binary and nonnegative decision variables.

- SE-CVRP linearization

$$t_i \times y_{ij} = Z_1(i,j) \quad (16.a) \quad (16)$$

$$Z_1(i,j) \le t_i \quad (16.b)$$

$$Z_1(i,j) \le M \times y_{ij} \quad (16.c)$$

$$Z_1(i,j) \ge t_i - M \times (1 - y_{ij}) \quad (16.d)$$

$$t_{ij} \times y_{ij} = Z_2(i,j) \quad (17.a) \quad (17)$$

$$Z_2(i,j) \le t_{ij} \quad (17.b)$$

$$Z_2(i,j) \le M \times y_{ij} \quad (17.c)$$

$$Z_2(i,j) \ge t_{ij} - M \times (1 - y_{ij}) \quad (17.d)$$

$$t_j = \sum_{i \in V_O \cup V_C, i \neq j} Z_1(i,j) + st_i \times y_{ij} + Z_2(i,j) \qquad \forall j \in V_C \quad (18)$$

$$Z_l(i,j) \ge 0 \qquad i,j \in V_O \cup V_C, l = 1,2 \quad (19)$$

According to Glover & Woolsey (1974), for linearizing constraint (10), relations (16) and (17) are added to the SE-CVRP formulation. Finally, constraint (10) is replaced by constraint (18) and the single-echelon CVRP model is linearized. Therefore, the MINLP formulation of SE-CVRP is modified into an MILP formulation and the proposed SE-CVRP is linearized.

III. SOLUTION APPROACH

The classic Vehicle Routing problem is derived from the famous Traveling Salesman Problem (TSP) of Toth & Vigo (2002). Owing to NP-hardness of TSP, VRP and its variants are NP-hard as well. Therefore, finding exact solutions for 2E-CVRP and standard CVRP is very difficult. In other words, as the size of the problem grows up, exact solutions become more unachievable. It is better to solve the mentioned problems in both 2E-CVRP and SE-CVRP by a meta-heuristic approach. We will apply the Non-dominated Sorting Genetic Algorithm II (NSGA-II) in solving large-size problems.

A. NSGA-II algorithm

One of the most well-appreciated and applicable meta-heuristics for solving problems in large size, which makes an exhaustive search for the optimal solution, is the genetic algorithm proposed by Holland (1975). The presented NSGA-II algorithm by Deb et al. (2002) is a development of the genetic algorithm designed for solving the multi-objective problems. The initialization step in which the initial population would be created is the starter of the algorithm. This step is interpreted in subsection B. Afterwards, crossover and mutation operators are implemented on the obtained solutions in order to attain improvement.

Before applying the algorithm, the parameters should be adjusted. The steps of the algorithm are as follows:

Step 1. Generating an initial population with the size of n.
Step 2. Evaluating and ranking the initial population according to the concept of dominance.
Step 3. Calculating the crowding distance for the same ranked solutions.
Step 4. Sorting the solutions based on the rank of each solution and crowding distance. The higher rank a solution has, the more preferred it is. However, when having two solutions with the same rank, the one with bigger crowding distance is prior.
Step 5. Choosing some solutions for performing a crossover operator to achieve improvement.
Step 6. Choosing some solutions for performing a mutation operator to improve the solutions.
Step 7. Merging the offspring of crossover and mutation operators with the initial population.
Step 8. Specifying the rank of merged solutions and calculating the crowding distance.
Step 9. Sorting the solutions based on the obtained values in step 8.
Step 10. Truncating the population to achieve the desired population size (n).
Step 11. Reporting the 1st ranked solution in the new generation as a Pareto front.
Step 12. Checking the stop criterion to understand whether it is reached. If yes, the algorithm stops; otherwise, steps 5-12 are repeated.

B. Solving the Single-Echelon CVRP

- Initial solution representation

This string consists of $n_c + m_1 - 1$ permutations. Numbers 1 to n_c represent the customers. The ones bigger than n_c are delimiters of the vehicles. For example, by considering 4 customers and 3 secondary vehicles, a feasible permutation would be as in Fig. 2.

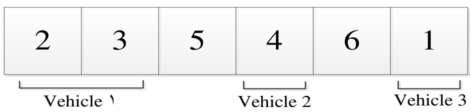

Fig. 2. String related to SE-CVRP in NSGA-II

In this permutation, customers 2 and 3 are served by the first vehicle, and customers 4 and 1 are served by the second and third vehicles, respectively. The yielded routes are 0-2-3-0, 0-4-0, and 0-1-0. Depot is shown by zero. Note that the aggregate demands of customers in each route must not overpass the capacity of the vehicle. Likewise, the maximum allowable delivery time must be considered. Therefore, all objective functions have a penalty for trespassing on the aforementioned limitations in each route.

The crossover and mutation operators in NSGA-II algorithm in order to improve the solutions to Single-Echelon Capacitated Vehicle Routing Problem (SE-CVRP) are same as those in the 2E-CVRP of Sahraeian & Esmaeili (2018).

IV. EXPERIMENTAL RESULTS

The VRP and 2E-VRP problems are NP-hard. For solving the mentioned 2E-CVRP and the proposed SE-CVRP problems, the NSGA-II meta-heuristic is implemented in the model. The results of the proposed technique for two-echelon and one-echelon models are compared with each other. The algorithms are coded in MATLAB R2015a and executed on an Intel Core i7 CPU 2.00 GHz personal computer with 8 GB RAM.

A. NSGA-II parameters setting

Taguchi method is utilized for setting the parameters of NSGA-II algorithm to apply it to the proposed distribution system. Four factors and 3 levels for each factor are considered. The factors are crossover rate (pc), mutation rate (pm), maximum iterations (MaxIt), and population (n pop). By considering these factors and levels, L9 design is recommended for NSGA-II. The response variable contains four measures of NPS, DM, MID, and SNS. The weighted sum of normalized measures (RPD) represents the response variable. Tuned parameters to apply to the SE-CVRP model are population, crossover rate, mutation rate, and iteration, which, based on Sahraeian & Esmaeili (2018), are set to 90, 0.9, 0.2, and 500, respectively.

B. Small-size problems

Three small-size problems are considered. In these problems, 10, 11, and 12 nodes of the E-n13-k4-62 instance in Christofides & Eilon (1969) datasets, which are presented on the OR-Library website, are considered. In two-echelon capacitated vehicle routing problems, we have 2 satellites and 1 depot. But, in standard CVRP problems, satellites are not considered and it is assumed that the vehicles are the same in the first level of the 2E-CVRP. NSGA-II results for both distribution systems are reported in Table Ⅰ. f_i^{best} is the best amount of the ith objective function in pareto front of the related problem. The values in Table Ⅰ are the averages for five runs of the algorithm.

According to Table I, in small-size problems, having single-echelon CVRP system is more desirable, because all three objective values would increase by having 2E-CVRP system.

TABLE I. Results of NSGA-II algorithm for small-size problems

row	nodes	n_s	n_c	SE-CVRP				2E-CVRP			
				f_1^{best}	f_2^{best}	f_3^{best}	Time(s)	f_1^{best}	f_2^{best}	f_3^{best}	Time(s)
1	10	2	7	92	4.145	82.8	355.89	265.66	14.10	149.2	460.04
2	11	2	8	106	5.483	95.4	363.36	282.37	15.98	155.68	448.25
3	12	2	9	114	7.179	102.6	351.34	286.38	17.75	155.33	465.18

TABLE II. Relusts of CPLEX and NSGA-II algorithms for small-size problems of SE-CVRP

row	nodes	n_c	f_1^{best}		f_2^{best}		f_3^{best}		CPU time(s)	
			NSGA-II	CPLEX	NSGA-II	CPLEX	NSGA-II	CPLEX	NSGA-II	CPLEX
1	8	7	92	92	4.145	4.195	82.8	82.8	355.89	0.33
2	9	8	106	106	5.483	5.483	95.4	95.4	363.36	0.51
3	10	9	114	114	7.179	7.179	102.6	102.6	351.34	0.92

The time columns in Table I show that solving a two-echelon problem takes more time than the single-echelon one. Feasible solutions to instance 3 in Table I for both two-echelon and single-echelon CVRPs are depicted in Figs. 3 and 4, respectively. Pareto fronts for both two-echelon and single-echelon CVRP strategies are shown in Figs. 9 and 10, respectively.

The efficiency of the algorithm for 2E-CVRP is expressed in Sahraeian & Esmaeili (2018) and for SE-CVRP is depicted in Table II.

It can be observed that NSGA-II is capable to find near optimal solutions for SE-CVRP. Therefore, this algorithm performs efficiently.

C. Medium-size problems

We consider instances covering up to 51 nodes (1 depot, 50 customers, and 5 satellites), which are categorized in 4 sets as medium-size problems. The first 3 sets are made from the existing instances for VRP by Christofides & Eilon (1968) denoted as E-n13-k4, E-n22-k4, E-n33-k4, and E-n51-k5, while the fourth set is adopted from Crainic et al. (2010), which is comprised of randomly generated instances simulating different geographical distributions, including customers distribution in urban and zonal areas. All datasets can be downloaded from OR-Library website (Beasley, 1990).

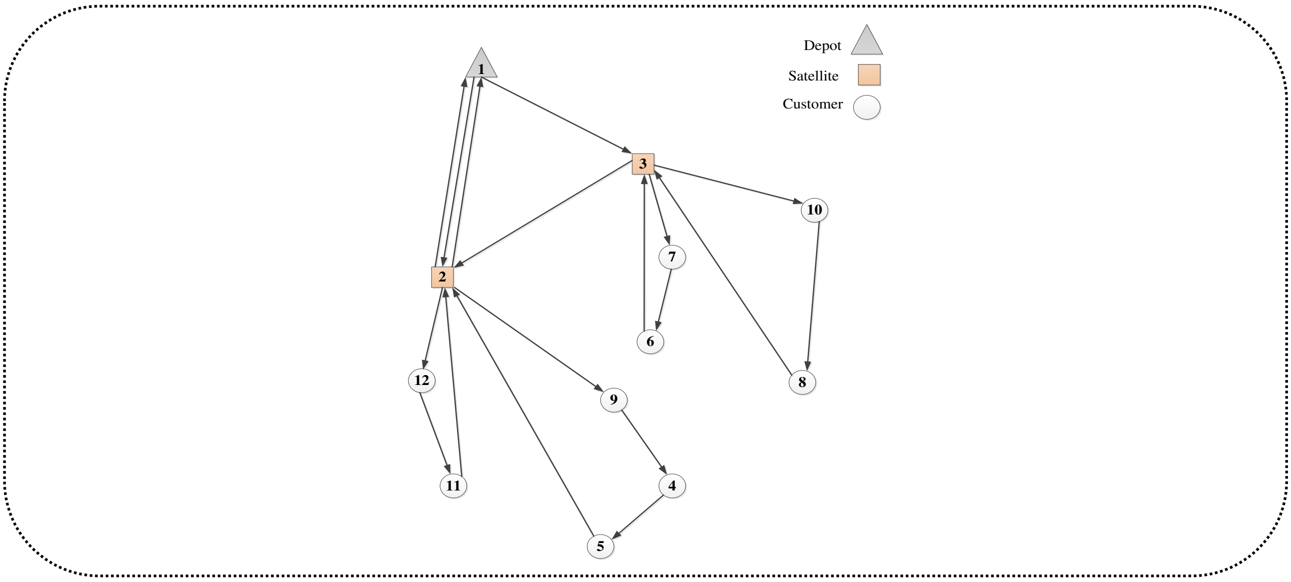

Fig. 3. A feasible solution to 2E-CVRP for the third instance in Table I

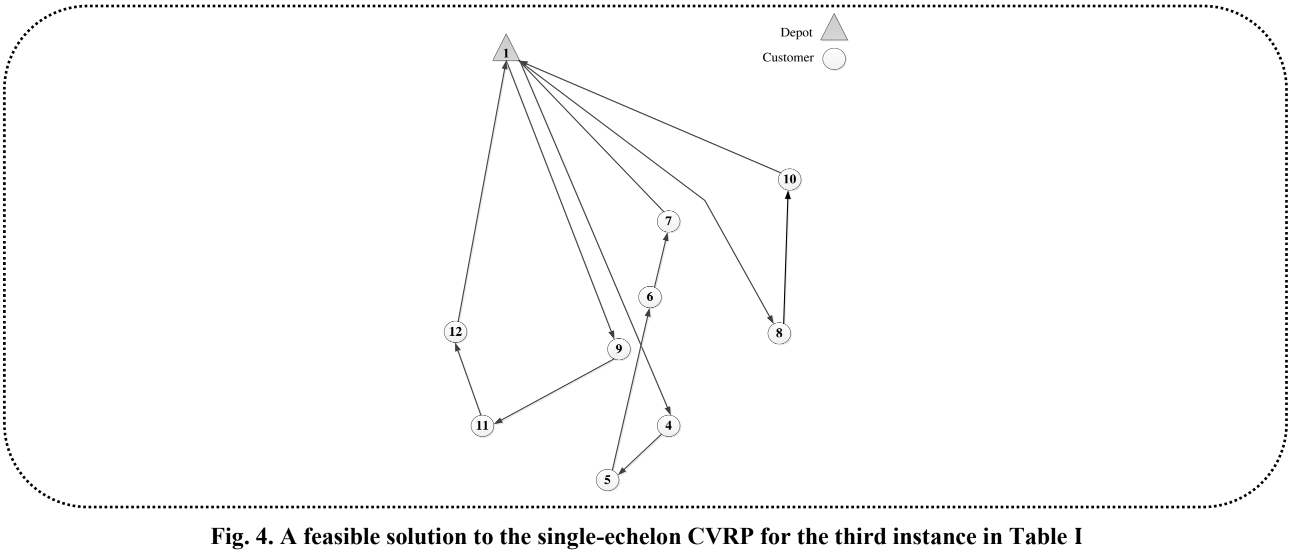

Fig. 4. A feasible solution to the single-echelon CVRP for the third instance in Table I

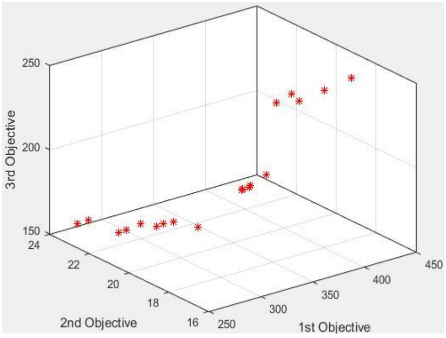

Fig. 5. Pareto front for the third instance in Table I for 2E-CVRP

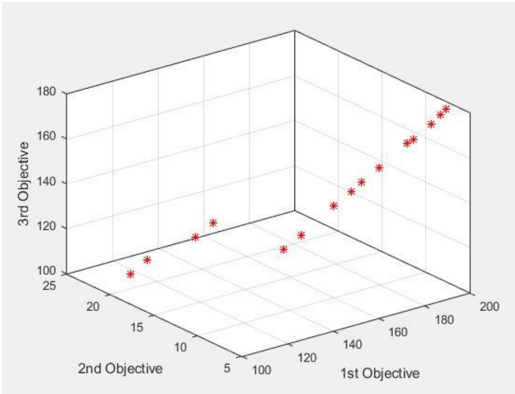

Fig. 6. Pareto front for the third instance in Table I for SE-CVRP

These instances have been presented by Perboli et al. (2011). For single-echelon Capacitated Vehicle Routing Problem, the satellites are eliminated and the first-level vehicles of the 2E-CVRP distribution system are settled in the depot. The first 4 instances in Table III, by eliminating the satellites, would be the same. Because they are different only in satellite distribution, the results are the same for SE-CVRP. These instances and the results of NSGA-II algorithm for both two-echelon and single-echelon CVRP strategies are presented in Table III.

Figs. 7, 8, and 9 compare three objective functions of both 2E-CVRP and SE-CVRP distribution systems achieved by the NSGA-II algorithm. Figs. 7 and 8 indicate that in medium-size problems and for the aforementioned datasets, the first (f_1^{best}) and second (f_2^{best}) objective functions (i.e., total travel cost and total customers waiting time) in a 2-echelon Capacitated Vehicle Routing strategy are higher than those in a standard capacitated vehicle routing strategy.

The second objective in all instances by adapting SE-CVRP distribution system is better, except in E-n51-k5-41-42. According to Fig. 8, in 96% of the medium-size instances, standard CVRP has better performance.

On the other hand, according to Fig. 9, the third (f_3^{best}) objective function (i.e., total CO_2 emissions) in 84% of medium-size instances is less by 2E-CVRP distribution system. It means that a 2E-CVRP system in these datasets is more environmentally friendly.

TABLE III. Results of NSGA-II for medium-size instances

row	Instance Name	SE-CVRP			2E-CVRP		
		f_1^{best}	f_2^{best}	f_3^{best}	f_1^{best}	f_2^{best}	f_3^{best}
1	E-n13-k4-17	170	12.76	153	255.42	19.57	131.04
2	E-n13-k4-39	170	12.76	153	250.38	20.6	117.28
3	E-n13-k4-48	170	12.76	153	265.36	21.45	132.72
4	E-n13-k4-62	170	12.76	153	321.86	24.22	167.6
5	E-n22-k4-s9-19	290.14	41.34	261.13	589.88	56.01	280.6
6	E-n22-k4-s10-14	290.14	41.34	261.13	518.63	54.09	218.38
7	E-n22-k4-s13-17	374.27	47.94	336.85	541.64	56.95	250.93
8	E-n22-k4-s19-21	374.27	47.94	336.85	600.87	59.61	248.02
9	E-n33-k4-s2-13	589.38	101.5	530.44	788.36	117.03	367.97
10	E-n33-k4-s7-25	589.38	101.5	530.44	835.72	119.06	417.98
11	E-n33-k4-s16-24	530.41	97.38	477.37	808	113.27	353.91
12	E-n33-k4-s22-26	530.41	97.38	477.37	788.4	114.14	362.40
13	E-n51-k5-13-44	527.38	168.93	474.64	936.47	179.87	416.79
14	E-n51-k5-40-42	527.38	168.93	474.64	1018.37	194.5	465.81
15	E-n51-k5-41-42	527.38	168.93	474.64	713.18	166.41	327.52
16	Instance50-3	1261.28	262.81	1135.16	1792.46	265.52	881.32
17	Instance50-11	1102.62	225.38	992.34	1674.18	291.99	834.06
18	Instance50-20	1019.85	249.11	917.85	1691.18	259.75	868.15
19	Instance50-26	884.37	225.27	795.93	1612.94	255.79	837.1
20	Instance50-31	1167	237.08	1050.31	1798.64	266.49	902.22
21	Instance50-35	1167	237.08	1050.31	892.89	278.92	1790.34
22	Instance50-40	1019.85	249.11	917.85	892.45	258.06	1747.12
23	Instance50-44	884.37	225.27	795.93	794.19	256.66	1514.32
24	Instance50-50	938.79	245.38	844.91	835.98	268.25	1625.18
25	Instance50-54	938.79	245.38	844.91	846.4	256.45	1637.1

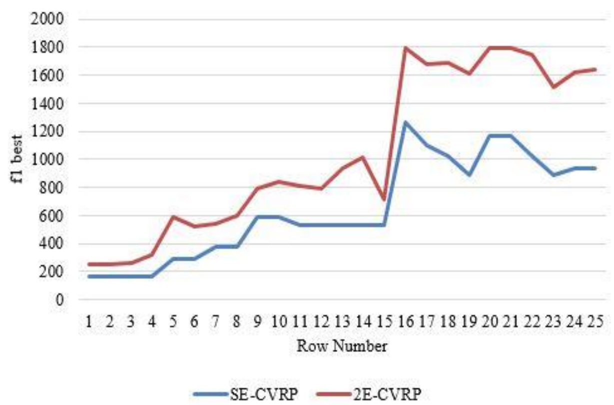

Fig. 7. Comparison of the values of f_1^{best} in 2E-CVRP and SE-CVRP for medium-size instances

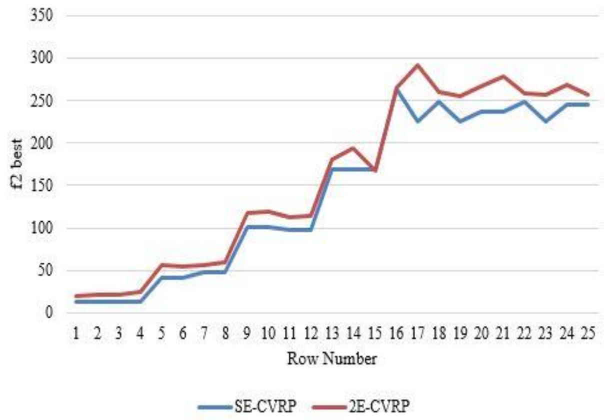

Fig. 8. Comparison of the values of f_2^{best} in 2E-CVRP and SE-CVRP for medium-size instances

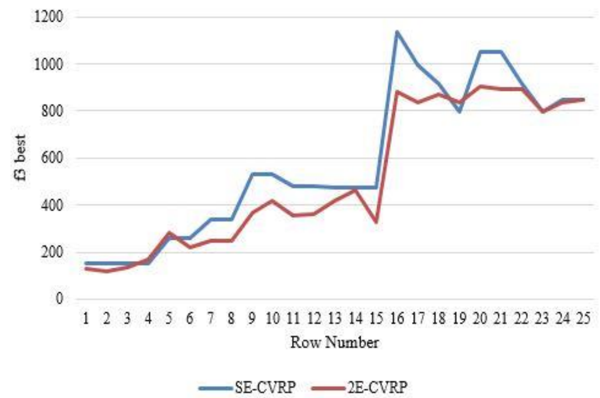

Fig. 9. Comparison of the values of f_3^{best} in 2E-CVRP and SE-CVRP for medium-size instances

D. Large-size problems

The prodhonce datasets on http://prodhonce.free.fr/ are used as large-size instances. These datasets are applicable to the Two-Echelon Location Routing Problem (2-ELRP). However, considering the capacity of vehicles, coordinates of the points, quantities of the customers and satellites, and the demand from the customers, we use these datasets for the proposed 2E-CVRP and SE-CVRP problems. They enfold up to 211 nodes (1 depot, 200 customers, and 10 satellites). These instances and the results of NSGA-II algorithm for both 2E-CVRP and SE-CVRP strategies are presented in Table IV. For Single-Echelon Capacitated Vehicle Routing Problem, the satellites and their characteristics are eliminated.

The NSGA-II algorithm is not capable of finding a feasible solution in two instances for SE-CVRP distribution system after 5 repetitions. These two instances are in rows 13 and 14 of Table IV. However, the algorithm has the capability of finding a feasible solution in all large-size instances for 2E-CVRP system. The values in Table III are the means of 5 repetitions of the algorithm for each instance. Figs. 10, 11, and 12 depict the comparison of three objective functions for the cases in which the proposed algorithm presents a feasible solution for both distribution systems.

According to Fig. 11, 2E-CVRP distribution system leads to lower total customers waiting time. Also, Fig. 12 indicates that in these large-size instances, the SE-CVRP distribution system is more environmentally friendly, because in all large-size instances, except for coord200-10-3b, it has small amounts of CO_2 emissions in comparison with 2E-CVRP distribution system.

TABLE IV. Results of NSGA-II for large-size instances

Row	Instance Name	SE-CVRP			2E-CVRP		
		f_1^{best}	f_2^{best}	f_3^{best}	f_1^{best}	f_2^{best}	f_3^{best}
1	coord100-5-1	752.7	422.69	677.43	1672.74	274.74	739.56
2	coord100-5-1b	752.7	422.69	677.43	1740.42	247.9	775.5
3	coord100-5-2	592.41	372.56	533.17	2118.58	182.08	916.5
4	coord100-5-2b	592.41	372.56	533.17	1346.13	208.18	605.74
5	coord100-5-3	666.93	395.06	600.23	2212.88	188.24	954.58
6	coord100-5-3b	666.93	395.06	600.23	1536.48	236.78	677.33
7	coord100-10-1	808.14	437.82	727.33	2436.78	275.87	1146.92
8	coord100-10-1b	808.14	437.82	727.33	1826.3	329.34	852.14
9	coord100-10-2	670.47	384.39	603.42	2188.95	275.83	1013.49
10	coord100-10-2b	670.47	384.39	603.42	1649.75	308.28	783.99
11	coord100-10-3	709.53	397.16	638.58	1877.77	263.96	893.13
12	coord100-10-3b	709.53	397.16	638.58	1540.03	288.2	715.78
13	coord200-10-1	-	-	-	5692.35	650.33	2467.42
14	coord200-10-1b	-	-	-	4095.7	766.91	1764.73
15	coord200-10-2	1558.96	1777.02	1403.08	4734.44	606.69	2080.8
16	coord200-10-2b	1558.96	1777.02	1403.08	3313.37	703.32	1483.62
17	coord200-10-3	1743.2	2068.7	1568.9	4698.3	587.31	2000.08
18	coord200-10-3b	1743.2	2068.7	1568.9	3500.67	686.34	1490.52

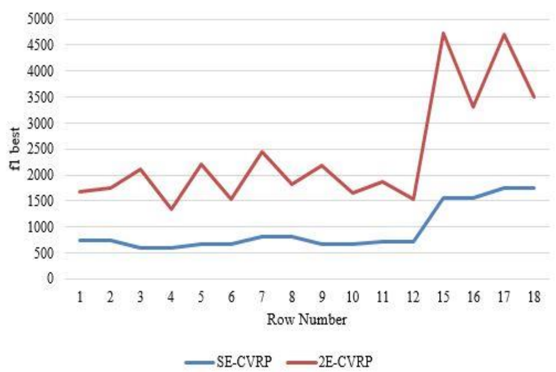

Fig. 10. Comparison of the values of f_1^{best} in 2E-CVRP and SE-CVRP for large-size instances

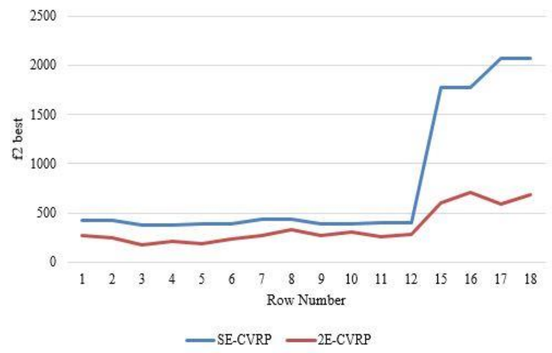

Fig. 11. Comparison of the values of f_2^{best} in 2E-CVRP and SE-CVRP for large-size instances

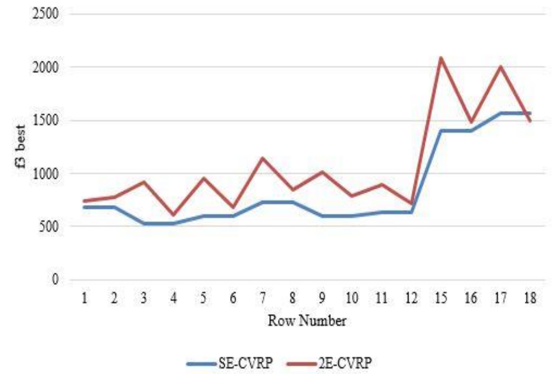

Fig. 12. Comparison of the values of f_3^{best} in 2E-CVRP and SE-CVRP for large-size instances

V. CONCLUSION AND FUTURE RESEARCH

This paper presents an equivalent Single-Echelon Capacitated Vehicle Routing Problem (SE-CVRP) formulation for the multi-objective 2-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) model introduced in a previous research by the authors and compares their results. The presented distribution system aimed at minimizing 1) total travel cost, 2) customers total waiting time, and 3) total carbon dioxide emissions in distributing perishable products. The proposed model was Mixed-Integer Non-Linear Programming (MINLP), which was changed to Mixed-Integer Linear Programming (MILP) by applying some linearization methods. To solve the problem, NSGA-II evolutionary algorithm was implemented on the model. The obtained objective functions of the two distribution systems were compared with each other. The results showed superiority of the single-echelon distribution system to the two-echelon distribution system in small-size instances. However, considering the third objective function (total CO_2 emissions) in medium-size instances and the second objective function (total customers waiting time) in large-size instances, the two-echelon distribution system outperformed the single-echelon one. That is, in medium-size instances, 2E-CVRP system was more environmentally friendly, but in large-size instances, this distribution strategy led to less total customers waiting time. The conflict between the results for different issues with different sizes was due to various distributions of the customers, satellites, and depots in various datasets. The two-echelon distribution system almost had a good performance in situations where the depot was out of the city zone and far from the customers. The difference between the results of this paper and other studies was due to the presence of SE-CVRP vehicle type and nodes distribution in this work.

In future, for better handling of the large-size problems, development of a powerful heuristic algorithm may be helpful. Because of the variation in road traffic in different hours of a day, different speeds can be considered for the vehicle. Moreover, solving the multi-product problem instead of one product is applicable. Multi-depot and time-dependent problem settings are some other possible extensions. Furthermore, introducing the 2E-VRP methodology into a location-routing strategy would improve the City Logistics systems to work more efficiently.

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