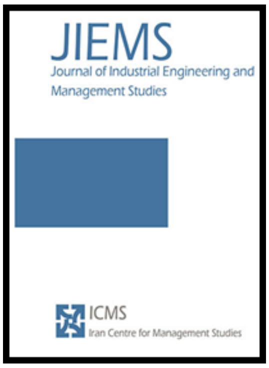
JIEMS
Journal of Industrial Engineering and Management Studies

Vol. 6, No. 2, 2019, pp. 196-213

DOI: 10.22116/JIEMS.2019.94158

www.jiems.icms.ac.ir



A novel multi-objective model for two-echelon green routing problem of perishable products with intermediate depots

Erfan Babaee Tirkolaee[1,*], Shaghayegh Hadian[1], Hêriş Golpîra[2]

Abstract
Multi-echelon distribution mechanism is common in supply chain design and logistics systems in which freight is delivered to the customers through intermediate depots (IDs), instead of using direct shipments. This primarily decreases the cost of the chain and consequences of environmental (energy consumption) and social (traffic, air pollution, etc.) logistic operations. This paper develops a novel multi-objective mixed-integer linear programming model (MOMILP) for a two-echelon green capacitated vehicle routing problem (2E-CVRP) in which environmental issues and time windows constraints are considered for perishable products delivery phase. To validate the proposed mathematical model, several numerical examples are generated randomly and solved using CPLEX solver of GAMS software. The ε-constraint method is applied to the model to deal with the multi-objectiveness of the proposed model. Finally, the best Pareto solution for each problem is determined based on the reference point approach (RPA) as one of the most effective techniques to help the decision-makers.

Keywords: Two-echelon green routing problem; Intermediate depots; ε-constraint method; Perishable product distribution; Reference point approach.

Received: July 2019-11

Revised: August 2019-31

Accepted: October 2019-19

1. Introduction

A supply chain is a network of facilities organized to acquire raw materials, convert them to finished products, and distribute the products to consumers. Organizational relationships and strategic alliances and partnerships are crucial for supply chain management success (Golpîra, 2016; Golpîra et al., 2017a). So, supply chain network coordination is a vital decision affecting the future success of the business (Khan et al. 2019a). In today's competitive environment, minimizing the operational cost plays an important role for companies along the coordinated supply chains. Industrialization, on the other hand, makes pollutions a serious issue. Dealing with such contradiction, transportation should be more considered along the supply chain (Khan et al., 2019b). Hence, constructing optimal routes to

* Corresponding author; e.babaee@ustmb.ac.ir
[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran.
[2] Department of Industrial Engineering, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran.

serve customers to minimize the total cost and emissions is of interest for academicians and practitioners. In this way, a classical vehicle routing problem (VRP) was introduced by Dantzig and Ramser (1959) to determine an optimal set of routes for a fleet of vehicles to serve a given number of the customers and minimize total traveled distance. Besides, each customer should be served by exactly one vehicle that starts its trip from a depot and ends in the depot. VRP problems considering vehicles' capacity constraints are called Capacitated Vehicle Routing Problem (CVRP), which has been studied by many researchers in many industries (Mandziuk and Swiechowski, 2017). Managers have to make some limitations on heavy vehicles moving in urban areas. However, large vehicles are used for transferring cargos from the depot located on the outskirts of the cities to the Intermediate Depots (IDs). And, small vehicles are used to transfer cargos from IDs to the customers located in the metropolitan areas. So, forming a two-echelon distribution system has been proposed by Wang et al., (2017). Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) is a well-known distribution system in which IDs are located between suppliers and customers (Gonzalez-Feliu et al., 2008). Direct shipments from suppliers to customers are not allowed in this system (Jabali et al., 2012; Kritikos and Ioannou, 2013). This transportation network consists of two-echelons. 1) The 1st echelon routing including determining the optimal routes of vehicles, which start from the central depot (supplier) and end at the IDs. 2) The 2nd echelon routing as the determination of optimal routes, which start from IDs and ends at the customers' nodes. In each echelon, a homogeneous vehicle fleet is used. It is because of the fact that by using optimization approaches, only a few designs need to be assessed, hence the necessary computational time to achieve an optimal design is dramatically decreased (Golpîra, 2019). 1st echelon vehicles are located in the central depot and only fulfill the IDs demands, whereas 2nd echelon vehicles have lower capacities and provide customers' demands through IDs. The unloading of the 1st echelon vehicles and loading of the 2nd echelon vehicles at the IDs contain a proportion of operational costs to the quantity loaded/unloaded additional to the vehicles' usage costs. The 2E-CVRP aims to find a set of routes in each echelon to minimize the total vehicles usage and routing cost considering the assumption that each customer can only be visited once (Perboli et al., 2011; Baldacci et al., 2017).

Recent growing attention to the environmental issues, on the other point of view, is an important perspective in transport systems (Khan et al., 2018, 2019c). In this way, reducing CO_2 emissions is the best way in building an environmental-friendly society (Yu et al., 2018). And, different speeds of the vehicles, as well as the number of carrying loads, are directly related to the fuel consumption and CO_2 emissions (Franceschetti et al., 2013; Soysal et al., 2015).

Crainic et al. (2012) examined total routing costs minimization of the overall two-echelon network in a 2E-CVRP. They considered more realistic assumptions in urban cargo delivery where the travel costs depend directly on the distances, fixed cost of arcs usage, operational costs, and environmental costs. However, they didn't consider the diversity of the arcs' travel cost over time periods in the planning horizon. Soysal et al. (2015) presented a Mixed Integer Linear Programming (MILP) model for a time-dependent 2E-CVRP considering different vehicle types, vehicle speed, load, and emissions as well as multiple time zones. They solved a small real-world instance by CPLEX to show the applicability of their model for economies of environmentally friendly vehicle routing.

Another critical issue in a distribution system, especially in the case of perishable products is customers' satisfaction. The quality and freshness of the products depend on the delivery process and environmental temperature during the delivery phase. Hence, perishable goods must be delivered within acceptable delivery time windows, or a penalty should be incurred for early/late deliveries (Chen et al., 2009). Song and Ko (2016) proposed a nonlinear mathematical model to maximize the total level of customer satisfaction, which depends on the freshness of deliverables, where each vehicle has a maximum allowable delivery time. Esmaili and Sahraeian (2017) presented a 2E-CVRP model with the aim of minimizing customers' waiting time and total travel cost considering environmental issues for perishable goods. They used a Single Additive Weighting (SAW) method to solve the problem. Tirkolaee et al. (2017) developed a novel model for the robust multi-trip vehicle routing problem with intermediate depots and time windows in order to determine the optimal routes in a single-echelon supply chain for perishable products. They solve the model using CPLEX solver and demonstrated the validity of their proposed model by generating and illustrating different problems. Developing an Integer Linear Programming (ILP), Marandi (2017) developed an approach for solving an integrated production-distribution scheduling problem for perishable products and solved it using a graph-based heuristic method. More recently, Shahparvari and Bodaghi (2018) proposed a MIP model to support tactical decision making in assigning and distribution of perishable rescue items. They solved a VRP using time windows (VRPTW) by CPLEX solver for multiple perishable products distribution using historical data related to a case study. A two-echelon Inventory-Routing Problem (IRP) for perishable items was investigated by Rohmer et al. (2019). They designed three metaheuristic algorithms to solve the problem and could compare the obtained results against CPLEX. Rahbari et al. (2019) proposed two robust bi-objective mathematical models for VRP with cross-docking for perishable products with the aims of cost minimization and freshness maximization. The Lp metric method was used to provide single-objective models. Finally, they implemented the model using CPLEX solver of GAMS software and performed comparative analyses. In terms of greenness consideration, Golpîra (2016) and Golpîra (2017b) introduced a new model to formulate a green supply chain network through a MILP formulation. Yavari and Zaker (2019) designed a resilient-green supply chain for perishable products considering environmental concerns. They formulated the problem using a bi-objective MILP model and could investigate a real case study in a dairy company. A heuristic approach was developed by Yavari and Geraeli (2019) for designing a green closed-loop supply chain network of perishable products. They implemented their proposed algorithm to solve a real case study problem considering multiple products and multiple periods.

Based on the aforementioned literature review, this paper would cover the research gaps by developing a novel bi-objective model for green 2E-CVRP with intermediate depots for delivering perishable products. Two types of time windows are considered to define the applicability of the perishable products in the proposed approaches. The first objective is defined to minimize total travel costs including routing costs, usage costs of the vehicles, loading/unloading operations costs, and earliness and tardiness penalties of IDs/customers deliveries in the $1^{st}/2^{nd}$ echelon, and the second objective is devoted to minimize the total CO_2 emissions along the supply chain. Hence, a multi-objective MILP (MOMILP) model is developed to formulate the problem with regards to the real-world assumptions. Then, the exact ε-constraint method is applied to the model in order to deal with bi-objectiveness. Finally, reference point approach (RPA) is implemented as one of the best techniques to find the best Pareto solution.

The remainder of this paper is organized as follows. Section 2 describes problem assumptions and mathematical model, Section 3 introduces the proposed solution method, Section 4 represents the computational results, and finally, the conclusions and research outlook are presented in Section 5.

2. Problem Definition

In this section, a bi-objective model is developed and explained for the green 2E-CVRP with intermediate depots of perishable product distribution in order to determine the optimal routes for the vehicles in each echelon concerning economics and environmental aspects. The main characteristics applicable to the problem are to consider hard and soft time windows representing the nature of perishable products distributions. Serving the customers out of soft time windows may cause some penalty cost, but it is impossible out of hard time window. Serving out of hard time windows would lead to perished products.

Figure 1 shows this two-echelon planning for the proposed supply chain design. In this example, 1 central depot (supplier), three IDs, and 12 customers are distributed within the supply chain network. The central depot covers all the IDs using two first-type vehicles. ID number 1 (ID1), ID2 and ID3 cover 4 customers, 3 customers, and 5 customers, respectively. Note that, ID3 uses two second-type vehicles to cover all of its allocated customers. Each vehicle in each echelon has different capacity but all have equal maximum available time.

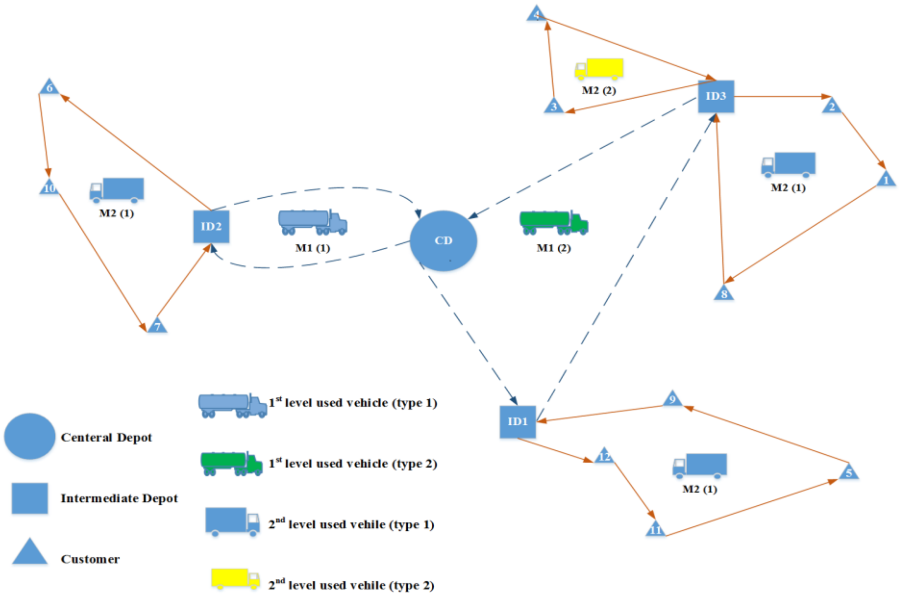


Figure 1. The schematic scheme of the proposed two-echelon supply chain.

The main assumptions of the model are as follows:

1. The defined supply chain network consists of a central depot and a set of IDs and customers. Products flow passing through the 1st echelon is from the depot to IDs and in the 2nd echelon is from IDs to customers,
2. Vehicles in the same echelon have the same speed, capacity and usage cost,
3. Each ID receives its freight from one or more 1st echelon (first-type) vehicles, but each customer receives its freight from one of the 2nd echelon (second-type) vehicles,
4. Each 1st echelon vehicles will return to the depot after ending their tour and each 2nd echelon vehicles will return to IDs to complete their tour after their last service,
5. Vehicles have a constant maximum allowable service time,
6. Multiple perishable products are considered in the supply chain,
7. IDs have a limited capacity for each type of product,
8. A time planning horizon is considered in the supply chain,

9. Each customer has a hard and soft time window of service during each period. Serving out of a hard time window is not possible, but serving out of a soft time window is possible with the acceptance of penalty cost.

2.1. Sets

V_O	Set of central depots ($v \in V_O$),
V_S	Set of IDs ($k \in V_S$),
V_C	Set of customers ($j \in V_C$),
P	Set of products ($p \in P$),
T	Set of periods ($t \in T$),
M_1	Set of 1st echelon vehicles ($m_1 \in M_1$),
M_2	Set of 2nd echelon vehicles ($m_2 \in M_2$),
i, j, k, v	Index of nodes.

2.2. Parameters

Ca_{m_1p}	Capacity of vehicle m_1 for product *p*,
Ca'_{m_2p}	Capacity of vehicle m_2 for product *p*,
IC_{kpt}	Capacity of intermediate depot *k* for product *p* in period *t*,
C_{ij}	Distance between nodes *i* and *j*,
d_{jpt}	Demand of customer *j* for product *p* in period *t*,
λ	Coefficient factor of distance to cost ($/km),
CV_{m_1}	Usage cost of vehicle m_1,
CV'_{m_2}	Usage cost of vehicle m_2,
S_{kp}	Cost for loading/unloading operations of a unit of freight for product *p* in intermediate depot *k*,
S'_{jp}	Cost for unloading operations of a unit of freight for product *p* in the place of customer *j*,
S''_{vp}	Cost for loading operations of a unit of freight for product *p* in depot *v*,
GH_{m_1}	Carbon emissions in each distance unit for vehicle m_1 (kg/km),
GH'_{m_2}	Carbon emissions in each distance unit for vehicle m_2 (kg/km),
v_1	Speed of 1st echelon vehicles (km/h),
v_2	Speed of 2nd echelon vehicles (km/h),
L_{jt}	Lower bound of hard time window for customer *j* in period *t*,
U_{jt}	Upper bound of hard time window for customer *j* in period *t*,
LL_{jt}	Lower bound of soft time window for customer *j* in period *t*,
UU_{jt}	Upper bound of soft time window for customer *j* in period *t*,
Pe	Penalty cost of earliness in delivery time,
Pl	Penalty cost of tardiness in delivery time,
$st1_{jp}$	Unloading time of a unit of product *p* at the node of customer *j*,
$st2_{kp}$	Loading time of a unit of product *p* at the node of intermediate depot *k*,
$st3_{kp}$	Unloading time of a unit of product *p* at the node of intermediate depot *k*,
$st4_{vp}$	Loading time of a unit of product *p* at the node of central depot *v*,
T_{max}	Maximum available time considered for each vehicle,
A	Optional large number.

2.3. Decision variables

x_{m_1t}	A binary variable equal to 1 if the vehicle m_1 is used in period *t*; 0 otherwise,
x'_{m_2kt}	A binary variable equal to 1 if the vehicle m_2 is used in intermediate depot *k* in period *t*; 0 otherwise,

y'_{ijm_1t}	A binary variable equal to 1 if arc (*i*, *j*) in 1st echelon is traversed by vehicle m_1 in period *t*; 0 otherwise,
$y^k_{ijm_2t}$	A binary variable equal to 1 if arc (*i*, *j*) in 2nd echelon is traversed by vehicle m_2 in period *t*; 0 otherwise,
z_{kjm_2t}	A binary variable equal to 1 if the customer *j* is served by intermediate depot *k* and vehicle m_2 in period *t*; 0 otherwise,
z'_{vkm_1t}	A binary variable equal to 1 if intermediate depot *k* is served by central depot *v* and vehicle m_1 in period *t*; 0 otherwise,
O_i	Auxiliary integer variable for the elimination of 1st echelon sub-tours,
O'_i	Auxiliary integer variable for the elimination of 2nd echelon sub-tours,
D_{kpt}	Positive variable indicating the amount of product *p* received from intermediate depot *k* in period *t*,
Fe_{jt}	Positive variable indicating earliness in delivery times in node *j* in period *t*,
Fl_{jt}	Positive variable indicating tardiness in delivery times in node *j* in period *t*,
tt_{it}	Presence time in node *i* to deliver service in period *t*.

2.4. Mathematical model

$$Min\ z_1 = \lambda\left(\sum_{m_1\in M_1}\sum_{m_2\in M2}\sum_{t\in T}\sum_{k\in V_S}\sum_{i,j\in V_0\cup V_C\cup V_{S,i\neq j}} c_{ij}\left(y'_{ijm_1\,t}+y^k_{ijm_2t}\right)\right) + \sum_{t\in T}\sum_{m_1\in M_1} CV_{m1}x_{m_1\,t} + \sum_{k\in V_S}\sum_{t\in T}\sum_{m_2\in M_2} CV_{m_2}\,x'_{m_2kt} + \sum_{p\in P}\sum_{t\in T}\sum_{k\in V_S} S_{kp}D_{kpt} + \sum_{m1\in M1}\sum_{p\in P}\sum_{t\in T}\sum_{k\in V_S}\sum_{v\in V_O} S''_{vp}z'_{vkm_1t}D_{kpt} + \sum_{j\in V_c}\sum_{t\in T}\sum_{p\in P} S'_{jp}d_{jpt} + \sum_{t\in T}\sum_{j\in V_S\cup V_c}(Pe\ Fe_{jt}+Pl\ Fl_{jt}) \quad (1)$$

$$Min\ z2 = \sum_{m1\in M1}\sum_{t\in T}\sum_{i,j\in V_0\cup V_S} GH_{m_1}c_{ij}\,y'_{ijm_1\,t} + \sum_{m_2\in M2}\sum_{t\in T}\sum_{k\in V_S}\sum_{i,j\in V_S\cup V_c} GH'_{m_2}c_{ij}\,y^k_{ijm_2t} \quad (2)$$

$$D_{kpt} = \sum_{m2\in M_2}\sum_{j\in V_c} d_{jpt}\,z_{kjm_2t} \qquad \forall k\in V_S, p\in P, t\in T, \quad (3)$$

$$\sum_{m2\in M_2}\sum_{k\in V_S} z_{kjm_2t} = 1 \qquad \forall j\in V_C, t\in T, \quad (4)$$

$$\sum_{m1\in M1}\sum_{v\in V_O} z'_{vkm_1t} = 1 \qquad \forall k\in V_S, t\in T, \quad (5)$$

$$\sum_{i\in V_O\cup V_S} y'_{ikm_1\,t} \geq z'_{vkm_1t} \qquad \forall\ v\in V_O, k\in V_S, m_1\in M_1, t\in T, \quad (6)$$

$$\sum_{k\in V_S} z'_{vkm_1t} \leq M\sum_{k\in V_S} y'_{vkm_1\,t} \qquad \forall\ v\in V_O, m_1\in M_1, t\in T, \quad (7)$$

$$\sum_{i\in V_S\cup V_c} y^k_{ijm_2t} \geq z_{kjm_2t} \qquad \forall k\in V_S, j\in V_c, m_2\in M_2, t\in T, \quad (8)$$

$$\sum_{j\in V_c} z_{kjm_2t} \leq M\sum_{j\in V_c} y^k_{kjm_2t} \qquad \forall k\in V_S, m_2\in M_2, t\in T, \quad (9)$$

$$\sum_{j\in V_0\cup V_S, i\neq j} y'_{ijm_1t} = \sum_{j\in V_O\cup V_S, i\neq j} y'_{jim_1t} \qquad \forall m_1\in M_1, i\in V_o\cup V_s, t\in T, \quad (10)$$

$$\sum_{j \in V_S \cup V_C, i \neq j} y_{ijm_2t}^{k} = \sum_{j \in V_S \cup V_C, i \neq j} y_{jim_2t}^{k} \qquad \forall m_2 \in M_2, i \in V_S \cup V_C, t \in T, k \in V_C, \tag{11}$$

$$\sum_{m1 \in M1} \sum_{v \in V_O} D_{kpt}\, z'_{vkm_1t} \leq IC_{kpt} \qquad \forall p \in P, t \in T, k \in V_C, \tag{12}$$

$$\sum_{i,j \in V_O \cup V_S, i \neq j} y'_{ijm_1t} \leq M\, x_{m_1t} \qquad \forall m_1 \in M_1, t \in T, \tag{13}$$

$$\sum_{i,j \in V_S \cup V_C, i \neq j} y_{ijm_2t}^{k} \leq M\, x'_{m_2kt} \qquad \forall m_2 \in M_2, t \in T, k \in V_C, \tag{14}$$

$$\sum_{k \in V_S} \sum_{i \in V_O \cup V_S, i \neq k} D_{kpt}\, y'_{ikm_1t} \leq Ca_{m_1p} \qquad \forall m_1 \in M_1, p \in P, t \in T, \tag{15}$$

$$\sum_{k \in V_S} \sum_{i,j \in V_S \cup V_C, i \neq j} d_{jpt}\, y_{ijm_2t}^{k} \leq Ca'_{m_2p} \qquad \forall m_2 \in M_2, \forall p \in P, t \in T, \tag{16}$$

$$tt_{jt} = \sum_{m1 \in M1} \sum_{i \in V_O \cup V_S, i \neq j} \left(tt_{it} + \frac{C_{ij}}{v_1} \right) y'_{ijm_1t} \qquad \forall j \in V_S, t \in T, \tag{17}$$

$$tt_{jt} = 0 \qquad \forall j \in V_O, t \in T, \tag{18}$$

$$L_{kt} \leq tt_{kt} \leq U_{kt} \qquad \forall k \in V_C, t \in T, \tag{19}$$

$$Fe_{kt} \geq LL_{kt} - tt_{kt} \qquad \forall k \in V_C, t \in T, \tag{20}$$

$$Fl_{kt} \geq tt_{kt} - UU_{kt} \qquad \forall k \in V_C, t \in T, \tag{21}$$

$$tt_{jt} = \sum_{m2 \in M2} \sum_{k \in V_S} \sum_{i \in V_S \cup V_C, i \neq j} \left(tt_{it} + \frac{C_{ij}}{v_2} \right) y_{ijm_2t}^{k} \qquad \forall j \in V_C, t \in T, \tag{22}$$

$$tt_{jt} = 0 \qquad \forall j \in V_S, t \in T, \tag{23}$$

$$L_{jt} \leq tt_{jt} \leq U_{jt} \qquad \forall j \in V_C, t \in T, \tag{24}$$

$$Fe_{jt} \geq LL_{jt} - tt_{jt} \qquad \forall j \in V_C, t \in T, \tag{25}$$

$$Fl_{jt} \geq tt_{jt} - UU_{jt} \qquad \forall j \in V_C, t \in T, \tag{26}$$

$$\sum_{k \in V_S} \sum_{p \in P} st3_{kp} D_{kpt} + \sum_{v \in V_O} \sum_{k \in V_S} \sum_{p \in P} st4_{vp} z'_{vkm_1t} D_{kpt} + \sum_{k \in V_S} \sum_{i,j \in V_S \cup V_C, i \neq j} \frac{C_{ij}}{v_1}\, y'_{ijm_1t} \leq T_{max} \qquad \forall m_1 \in M1, t \in T, \tag{27}$$

$$\sum_{k \in V_S} \sum_{p \in P} st2_{kp} D_{kpt} + \sum_{j \in V_C} \sum_{p \in P} st1_{jp} d_{jpt} + \sum_{k \in V_S} \sum_{i,j \in V_S \cup V_C, i \neq j} \frac{C_{ij}}{v_2}\, y_{ijm_2t}^{k} \leq T_{max} \qquad \forall m_2 \in M2, t \in T, \tag{28}$$

$$O_i - O_j + A\, y'_{ijm_1t} \leq A - 1 \qquad \forall i, j \in V_S, m_1 \in M_1, t \in T, \tag{29}$$

$$O'_i - O'_j + A\, y_{ijm_2t}^{k} \leq A - 1 \qquad \forall i, j \in V_C, m_2 \in M_2, \forall k \in V_S, t \in T, \tag{30}$$

$$x_{m_1t}, x'_{m_2kt}, y_{ijm_2t}^{k}, y'_{ijm_1t}, z_{kjt}, z'_{vkt} \in \{0,1\};\ D_{kpt}, Fe_{jt}, Fl_{jt}, tt_{it} \geq 0 \qquad O_i, O'_i \in Z^+, \forall i, j \in V_O \cup V_S \cup V_C, \forall m_1 \in M_1, m_2 \in M_2, \forall k \in V_S, t \in T. \tag{31}$$

The objective function (1) minimizes total cost of the supply chain, which includes the sum of the 1st echelon and 2nd echelon vehicles routing costs, usage costs of the 1st echelon and 2nd echelon vehicles, loading/unloading operations costs in intermediate depots, loading costs of central depots, loading operation cost in customers' nodes, and finally earliness and tardiness penalties in delivery times of IDs and customers. The second objective function (2) minimizes total CO_2 emissions for the 1st and 2nd echelons' routes. Constraint (3) calculates the demand of IDs to supply the products in each period. Constraint (4) ensures that each customer's demand for products should be served in each period. Constraint (5) force that the demand of each ID should be delivered in each period. Constraints (6) and (7) lead to a relationship between 1st echelon routes variables and the allocation variables of the demand of IDs to the central depot. Constraints (8) and (9) lead to a relationship between 2nd echelon routes variables and the allocation variables of the demand of customers to the IDs.

Constraints (10) and (11) indicate the flow balance of input and output on each echelon. Constraint (12) limits the freight capacity of the IDs. Constraints (13) and (14) respectively force the use of the 1st echelon vehicles at the 1st echelon and 2nd echelon vehicles in the 2nd echelon. Constraint (15) and (16) limit the freight capacity of the 1st and 2nd echelon vehicles. Constraints (17)-(19) represent the soft time window equations for each ID. Constraint (20) and (21) respectively determine the duration of earliness and tardiness in giving service to IDs. Constraints (22)-(24) represent the hard time window equations for each customer. Constraints (25) and (26) respectively determine the duration of earliness and tardiness in serving customers. Constraints (27) and (28) set time limitation of using the 1st and 2nd echelon vehicles. Constraints (29) and (30) also lead to the elimination of sub-tours. Constraint (31) specifies the type of variables.

2.5. Linearization of the model

The 5th term of the first objective function caused to non-linearization of that function. So, the following linearization expressions are applied as follows:

$$\sum_{m_1\in M_1}\sum_{p\in P}\sum_{t\in T}\sum_{k\in V_S}\sum_{v\in V_O} S''_{vp}z'_{vkm_1t}D_{kpt} = \sum_{p\in P}\sum_{t\in T}\sum_{t\in T}\sum_{k\in V_S}\sum_{v\in V_O} S''_{vp}h_{vkm_1pt} \quad (32)$$

$$h_{vkm_1pt} \le D_{kpt} \qquad \forall p\in P, t\in T, k\in V_C, v\in V_O, m_1\in M_1, \quad (33)$$

$$h_{vkm_1pt} \le M\, z'_{vkm1t} \qquad \forall p\in P, t\in T, k\in V_C, v\in V_O, m_1\in M_1, \quad (34)$$

$$h_{vkm_1pt} \ge D_{kpt} - M(1- z'_{vkm1t}) \qquad \forall p\in P, t\in T, k\in V_C, v\in V_O, m_1\in M_1, \quad (35)$$

$$h_{vkm_1pt} \ge 0 \qquad \forall p\in P, t\in T, k\in V_C, v\in V_O, m_1\in M_1. \quad (36)$$

Constraint (27) also turns into a linear equation by replacing the variable h_{vkm_1pt} with $z'_{vkm_1t}.D_{kpt}$.

Constraint (15) is linearized as follows:

$$\sum_{k\in V_S}\sum_{\substack{i\in V_O\cup V_S\\ i\neq k}} D_{kpt}\, y'_{ikm_1 t} = \sum_{k\in V_S}\sum_{\substack{i\in V_O\cup V_S\\ i\neq k}} \delta_{ikm_1tp} \qquad \forall m_1\in M_1, p\in P, t\in T, \quad (37)$$

$$\delta_{ikm_1tp} \le D_{kpt} \qquad k\in V_S, i\in V_O\cup V_S, i\neq k, m_1\in M_1, p\in P, t\in T, \quad (38)$$

$$\delta_{ikm_1tp} \le MM\, y'_{ikm1\,t} \qquad k\in V_S, i\in V_O\cup V_S, i\neq k, m_1\in M_1, p\in P, t\in T, \quad (39)$$

$$\delta_{ikm_1tp} \ge D_{kpt} - MM(1-y'_{ikm1\,t}) \qquad k\in V_S, i\in V_O\cup V_S, i\neq k, m_1\in M_1, p\in P, t\in T, \quad (40)$$

$$\delta_{ikm_1tp} \ge 0 \qquad k\in V_S, i\in V_O\cup V_S, i\neq k, m_1\in M_1, p\in P, t\in T. \quad (41)$$

Linearization of Constraint (17) is as follows:

$$tt_{jt} = \sum_{m_1\in M_1}\sum_{i\in V_O\cup V_S, i\neq j}\left(tt_{it} + \frac{C_{ij}}{v_1}\right) y'_{ijm_1\,t} = \sum_{m_1\in M_1}\sum_{i\in V_O\cup V_S, i\neq j}\left(f_{ijm1\,t} + \frac{C_{ij}}{v_1} y'_{ijm_1t}\right) \quad (42)$$

$\forall\, j\in V_S\ t\in T,$

$$f_{ijm_1t} \le tt_{it} \qquad \forall m_1\in M_1, i\in V_o\cup V_s, j\in V_S, t\in T, \quad (43)$$

$$f_{ijm_1t} \le M\ \ y'_{ijm_1\,t} \qquad \forall m_1\in M_1, i\in V_o\cup V_s, j\in V_S, t\in T, \quad (44)$$

$$f_{ijm_1t} \geq tt_{it} - M(1 - y'_{ijm_1t}) \qquad \forall m_1 \in M_1, i \in V_o \cup V_s, j \in V_S, t \in T, \qquad (45)$$
$$f_{ijm_1t} \geq 0 \qquad \forall m_1 \in M_1, i \in V_o \cup V_s, j \in V_S, t \in T. \qquad (46)$$

Constraint (22) is linearized as well as Constraint (17):

$$tt_{jt} = \sum_{m_2 \in M_2} \sum_{k \in V_S} \sum_{i \in V_S \cup V_C, i \neq j} \left(tt_{it} + \frac{C_{ij}}{v_2} \right) y^k_{ijm_2t} \qquad \forall j \in V_C, t \in T \qquad (47)$$
$$g^k_{ijm_2t} \leq tt_{it} \qquad \forall m_2 \in M_2, i \in V_S \cup V_C, \forall j \in V_S, \forall t \in T, \qquad (48)$$
$$g^k_{ijm_2t} \leq M\, y^k_{ijm_2t} \qquad \forall m_2 \in M_2, i \in V_S \cup V_C, \forall j \in V_S, \forall t \in T, \qquad (49)$$
$$g^k_{ijm_2t} \geq tt_{it} - M(1 - y^k_{ijm_2t}) \qquad \forall m_2 \in M_2, i \in V_S \cup V_C, \forall j \in V_S, \forall t \in T, \qquad (50)$$
$$g^k_{ijm_2t} \geq 0 \qquad \forall m_2 \in M_2, i \in V_S \cup V_C, \forall j \in V_S, \forall t \in T. \qquad (51)$$

After defining and applying the above linearization, the proposed model changes to a MILP model.
In the following, several random instances in different sizes are generated and solved by the exact ε-constraint method which is coded in CPLEX solver of GAMS optimization software to confirm the validity of the model.

3. ε-constraint method

In the literature, there are many solution methods developed in order to solve and validate the similar problems optimally including exact and approximation techniques (Alinaghian et al., 2014; Babaee Tirkolaee et al., 2016; Tirkolaee et al., 2018a, 2018b, 2018c, 2019a, 2019b, 2019c; Mostafaeipour et al., 2019; Babaee Tirkolaee et al., 2019; Goli et al., 2019a, 2019b; Sangaiah et al., 2019).
The exact approach of the ε-constraint method is used as one of the well-known approaches for modifying the multi-objective problems, which deal with this kind of issues by transferring all objective functions except one of them to the constraints (Ehrgott and Gandibleux, 2003; Golpîra et al., 2017a, 2017b).
The Pareto fronts can be generated as follows (Bérubé et al., 2009):

minimize $f_1(X)$
subject to
$x \in X$,
$f_2(X) \leq \varepsilon_2$,
…
$f_n(X) \leq \varepsilon_n$. (52)

The steps of the ε-constraint method are as follows:
1. Select one of the objective functions as the main objective function.
2. Each time, according to one of the sub-objective functions, solve the problem and obtain the optimal values of each objective function.
3. Divide the interval between two optimal values of the sub-objective functions to the predefined number and create a table of values for ε_2, ..., ε_n.
4. Each time solve the problem with each of the values of ε_2, ..., ε_n with the main objective function.
5. Report Pareto solutions findings.

In the proposed ε-constraint method, the first objective function is considered as the main objective function and the second objective function is introduced as a sub-objective function. Then, 8 breakpoints for the objective functions, and totally, up to 8 Pareto points are generated. The formulation associated with the proposed problem is shown in Problem (53):

$$\begin{aligned} &\text{minimize } f_1(X) \\ &\text{subject to} \\ &f_2(X) \leq \varepsilon_2. \end{aligned} \tag{53}$$

Therefore, the best solution for the first and second objective function is found between the Pareto fronts of the ε-constraint method.

4. Computational results

In this section, to evaluate the validity of the problem, three problems with small to large sizes are generated randomly. The input parameters are randomly generated using a uniform distribution. Then the problems are executed on a laptop with Intel Core i7 (8GB of RAM) using CPLEX solver of GAMS software. Information about the random samples generated specified in Table 1. Moreover, the value of the model's parameters is presented in Table 2. To implement the proposed solution technique, the single-objective problems are solved considering the 1st and 2nd objectives, respectively (cf. Table 3). Then, the breakpoints can be calculated using the obtained values for the 2nd objectives (cf. Table 4). Finally, the problems are solved for each breakpoint based on Problem (53). The Pareto fronts obtained for the problems are depicted in Figure 2. Decision-makers would analyze the obtained Pareto results and choose the best possible solutions according to the trade-off between objectives. To this end, an efficient method, namely, RPA is implemented to extract the best Pareto solution in each problem. The obtained objective values for each solution are represented in Table 2. We should normalize the objective values due to their unit dissimilarity.

Table 1. Information for random instance problems.

Problem No.	$\|V_O\|$	$\|V_S\|$	$\|V_C\|$	|P|	|T|	$\|M_1\|$	$\|M_2\|$
1	1	4	12	2	6	2	4
2	2	8	20	4	12	3	5
3	3	12	30	6	24	5	8

Table 2. Parameters' value of the proposed model.

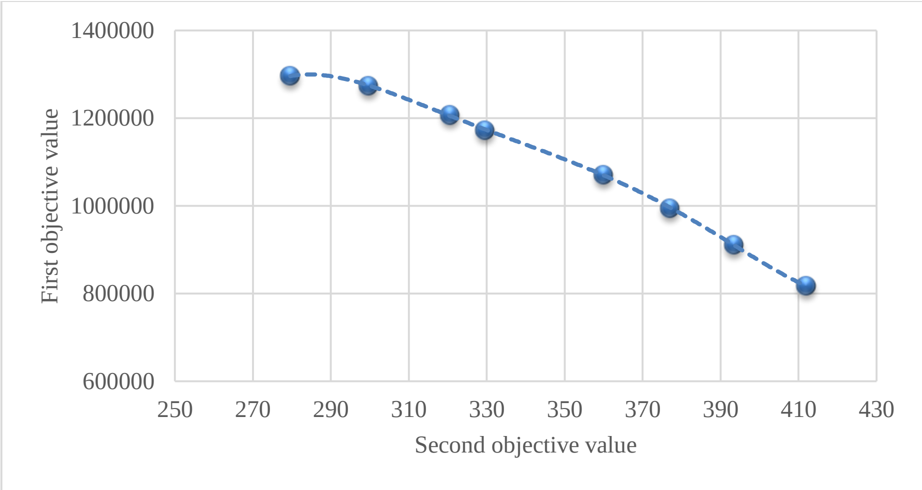
Parameter	Value	Parameter	Value	Parameter	Value
Pe	50	Ca_{m_1p}	Uniform(3000,5000)	Ca'_{m_2p}	Uniform(500,1000)
CV'_{m_1}	Uniform (300,400)	CV_{m_2}	Uniform (100,200)	IC_{kpt}	Uniform(10000,20000)
T_{max}	8	S_{kp}	Uniform(1,1.5)	C_{ij}	Uniform(2,10)
LL_{jt}	Uniform(1.5, 4)	S'_{jp}	Uniform(1,1.5)	d_{jpt}	Uniform(10,25)
UU_{jt}	Uniform(2, 8)	GH_{m_1}	Uniform(0.4, 0.45)	λ	0.5
Pe	100	U_{jt}	Uniform(3,10)	L_{jt}	Uniform(1, 6)
$st2_{kp}$	Uniform(0.01,0.05)	$st1_{jp}$	Uniform(0.01,0.05)	v_2	60
v_1	80	GH'_{m_2}	Uniform(0.4, 0.45)	S''_{vp}	Uniform(1,1.5)
$st3_{kp}$	Uniform(0.01,0.05)	$st4_{vp}$	Uniform(0.01,0.05)	A	10^8

Table 3. Computational results for single-objective problems.

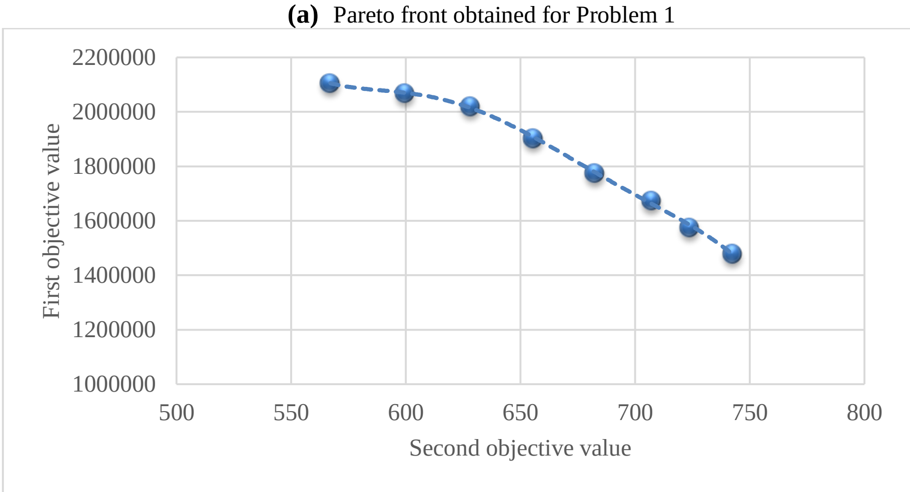
Problem No.	Min Obj. 1		Min Obj. 2		Average Run Time (second)
	Obj. 1	Obj. 2	Obj. 1	Obj. 2	
1	817310.765	419.565	1342277.642	279.614	68.504
2	1477910.497	747.114	2131605.088	566.220	497.320
3	2664148.957	1459.353	3206489.761	1076.690	3226.657

Table 4. Different breakpoints in each problem.

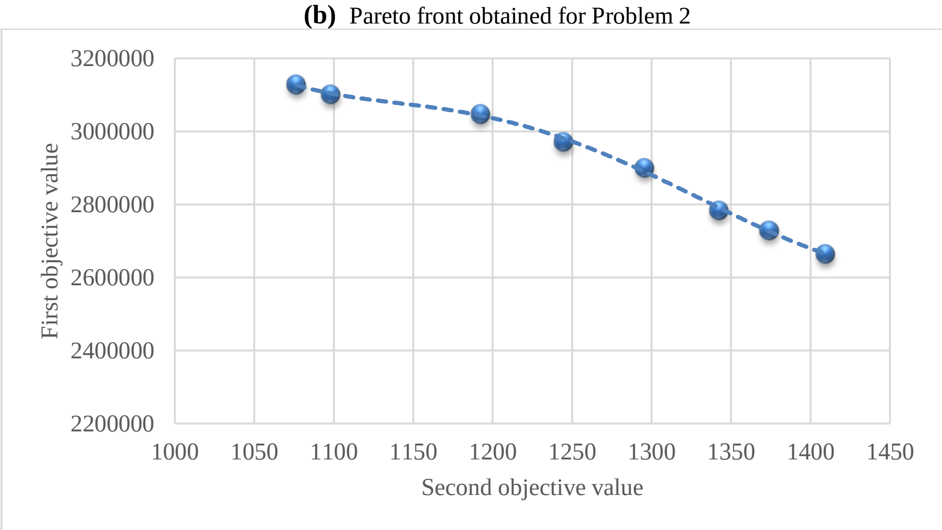
Problem No.	Breakpoints							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	279.614	299.607	319.6	339.593	359.586	379.579	399.572	419.565
2	566.22	592.062	617.904	643.746	669.588	695.43	721.272	747.114
3	1076.69	1131.356	1186.022	1240.688	1295.355	1350.021	1404.687	1459.353



(a) Pareto front obtained for Problem 1



(b) Pareto front obtained for Problem 2



(c) Pareto front obtained for Problem 3

Figure 2. Obtained Pareto fronts for different-sized problems.

As can be seen in Figure 2, there is not a direct relation between two objectives, and the Pareto fronts show a strong contradiction between two objectives. The Pareto frontier in each problem is approximately similar considering it exactness by 8 breakpoints. As it is obvious, we can’t keep both objectives in their optimal levels simultaneously. So, decision-makers should choose only one point among the existing Pareto points. Each point contains different

information for the values of decision variables and the main limitations to be institutionalized.
On the other hand, the run time comparison of the problems (cf. Figure 3) demonstrate that the problem has a high complexity such that it may not be solved using exact solution techniques in large scales. Therefore, developing heuristic/meta-heuristic algorithms can be regarded as potential future research directions.

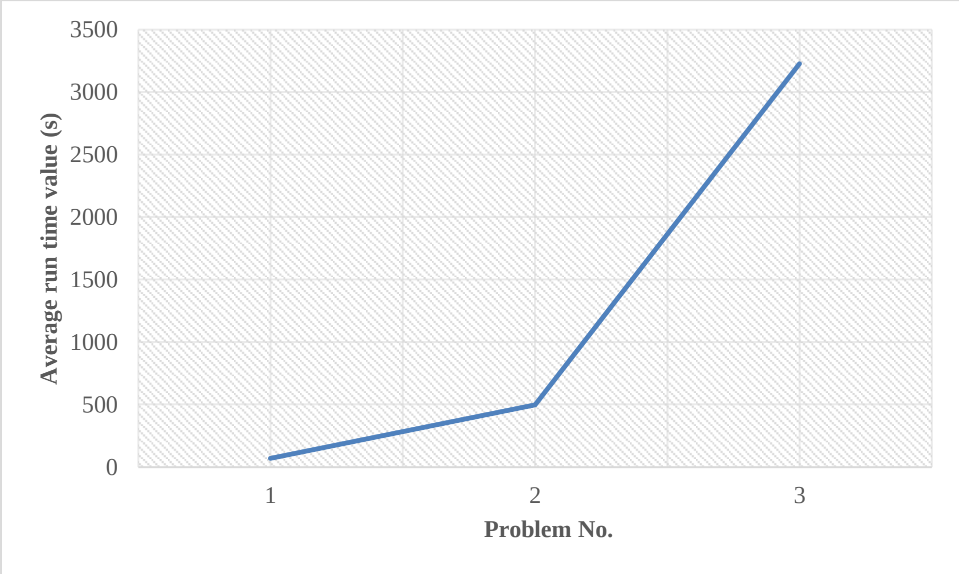


Figure 3. Run time comparison of different problems.

4.1. Best Pareto Solution

This subsection proposes an effective technique to choose the best Pareto solution among the existing ones in the front. Eventually, the selected Pareto solution of each problem can be analyzed and implemented as the optimal planning for 2E-CVRP. Deb and Sundar (2006) introduced RPA to determine the best point or Pareto points in multi-objective problems. This method can be employed by either assigning or not assigning weights to the objectives. The main idea is to identify the solutions which are close to the reference point.
The normalized Euclidean distance (dev_b) between each non-dominated solutions and the reference point is computed using Eq. (54) so that each solution with the lowest value of dev_b has the highest priority for the decision-maker.

$$dev_b = \sqrt{\sum_{l=1}^{L} w_l \left(\frac{f_l - \bar{z}_l}{f_l^{\max} - f_l^{\min}}\right)^2} \qquad \forall b = 1, 2, \ldots, 8. \tag{54}$$

where w_l represents the weight of l^{th} objective in each Pareto solution, f_l is the value of objective *l*, $\bar{z}_l$ denotes the value of the reference objective or reference point, and $f_l^{\max}$ and $f_l^{\min}$ are the maximum and minimum values for objective *l*, respectively. Therefore, to choose the best Pareto solution for each problem, the values of the required parameters are given in Table 5. These values are tuned according to the initial importance of each objective function.

Table 5. Parameters' value in RPA

Parameters	Values
w_1	0.6
w_2	0.4
$\bar{z}_1$	$\frac{f_1^{\min}}{1.4}$
$\bar{z}_2$	$\frac{f_2^{\min}}{1.3}$
$f_1^{\max}$	Maximum value obtained for the first objective among 8 Pareto solutions
$f_2^{\max}$	Maximum value obtained for the second objective among 8 Pareto solutions
$f_1^{\min}$	Minimum value obtained value for the first objective among 8 Pareto solutions
$f_2^{\min}$	Minimum obtained value for the second objective among 8 Pareto solutions

Now, the values obtained for dev_b of each problem are represented in Table 6. The minimum value obtained for dev_b in each problem is considered as the best corresponding to its breakpoint number; i.e., Pareto solution number. Finally, Table 7 shows the best Pareto solutions.

Table 6. Values of dev_b for each problem.

Problem No.	dev_b of each breakpoint							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	1.110	1.121	1.089	**1.075**	1.077	1.082	1.099	1.143
2	1.367	1.390	1.410	1.377	**1.358**	1.375	1.380	1.407
3	1.820	1.797	1.794	1.743	1.709	1.632	1.616	**1.602**

Table 7. Best Pareto solution for each problem.

Problem No.	Minimum dev_b	Best Pareto Solution	
		Obj. 1	Obj. 2
1	1.075	1171885.783	329.641
2	1.358	1775074.114	682.419
3	1.602	2664148.957	1409.653

According to Table 7, the best Pareto solution of each problem is identified using RPA. Hereby, the decision-maker can easily provide the foundation for implementing the optimal policy.

5. Conclusion

In this paper, a novel multi-objective mixed-integer linear programming model (MOMILP) is proposed to optimize a green two-echelon capacitated vehicle routing problem (2E-CVRP) of perishable products distribution considering hard and soft time windows. The first echelon includes central depots as suppliers and intermediate depots as central warehouses. The second echelon consists of intermediate depots and customers and the aim is to determine the optimal routes for the vehicles of each echelon. The objectives are to minimize total cost and total CO_2 emissions. In order to evaluate the proposed mathematical model, several problems are generated randomly and solved using CPLEX solver of GAMS software. Moreover, the ε-constraint method is applied to the model to cope with its bi-objectiveness. Finally, the obtained Pareto solutions demonstrate an obvious contradictory between two objective functions. Furthermore, an effective technique entitled reference point approach (RPA) is then implemented to help the decision-maker for finding the best Pareto solution in each problem.

For future studies, meta-heuristic algorithms can be employed to solve the large-sized problems in reasonable run times, and we may include the other objectives such as reliability maximization, minimization of total service time. Moreover, some real assumptions can be incorporated in the model such as urban traffic conditions to make the model more close to the real-world.

References

Alinaghian, M., Amanipour, H., and Tirkolaee, E.B., (2014). "Enhancement of Inventory Management Approaches in “Vehicle Routing-Cross Docking” Problems", *Journal of Supply Chain Management Systems*, Vol. 3, No. 3.

Babaee Tirkolaee, E., Alinaghian, M., Bakhshi Sasi, M., and Seyyed Esfahani, M., (2016). "Solving a robust capacitated arc routing problem using a hybrid simulated annealing algorithm: a waste collection application", *Journal of Industrial Engineering and Management Studies*, Vol. 3, pp. 61-76.

Babaee Tirkolaee, E., Abbasian, P., Soltani, M., and Ghaffarian, S.A., (2019). "Developing an applied algorithm for multi-trip vehicle routing problem with time windows in urban waste collection: A case study. ", *Waste Management & Research*, Vol. 37, pp. 4-13.

Bérubé, J.F., Gendreau, M., and Potvin, J.Y., (2009). "An exact ϵ-constraint method for bi-objective combinatorial optimization problems: Application to the Traveling Salesman Problem with Profits", *European Journal of Operational Research*, Vol. 194, No. 1, pp. 39-50.

Chen, H.-K., Hsueh, C.-F., and Chang, M.-S., (2009). "Production scheduling and vehicle routing with time windows for perishable food products", *Computers and Operations Research*, Vol. 36, pp. 72311-2319.

Crainic, T.G., Mancini, S., Perboli, G., and Tadei, R., (2012). "Impact of generalized travel costs on satellite location in the two-echelon vehicle routing problem", *Procedia-Social and Behavioral Sciences*, Vol. 39, pp. 195-204.

Dantzig, G.B., and Ramser, J., (1959). "The truck dispatching problem", *Management Science*, Vol. 6, No. 1, pp. 80–91.

Deb, K., and Sundar, J., (2006). "Reference point based multi-objective optimization using evolutionary algorithms", *Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation*, Vol. 12, pp. 635-642.

Ehrgott, M., and Gandibleux, X., (2003). "Multiobjective combinatorial optimization-theory, methodology, and applications", In Multiple criteria optimization: State of the art annotated bibliographic surveys (pp. 369-444). Springer US.

Esmaili, M., and Sahraeian, R., (2017). "A new Bi-objective model for a Two-echelon Capacitated Vehicle Routing Problem for Perishable Products with the Environmental Factor", *International Journal of Engineering*, Vol. 30, No. 4, pp. 523-531.

Franceschetti, A., Honhon, D., Van Woensel, T., Bektaş, T., and Laporte, G., (2013). "The time-dependent pollution-routing problem", *Transportation Research Part B: Methodological*, Vol. 56, pp. 265-293.

Goli, A., Babaee Tirkolaee, E., and Soltani, M., (2019a). "A robust just-in-time flow shop scheduling problem with outsourcing option on subcontractors", *Production & Manufacturing Research*, Vol. 7, No. 1, pp. 294-315.

Goli, A., Tirkolaee, E.B., Malmir, B., Bian, G.B., and Sangaiah, A.K., (2019b). "A multi-objective invasive weed optimization algorithm for robust aggregate production planning under uncertain seasonal demand", *Computing*, Vol. 101, No. 6, pp. 499-529.

Golpîra, H., (2016). "A robust bi-objective uncertain green supply chain network management", *Serbian Journal of Management*, Vol. 11, No. 2, pp. 211-222.

Golpîra, H., (2017a). "Supply chain network design optimization with risk-averse retailer", *International Journal of Information Systems and Supply Chain Management (IJISSCM)*, Vol. 10, No. 1, pp. 16-28.

Golpîra, H., (2017b). "Robust bi-level optimization for an opportunistic supply chain network design problem in an uncertain and risky environment", *Operations Research and Decisions*, Vol. 27.

Golpîra, H., Zandieh, M., Najafi, E., and Sadi-Nezhad, S., (2017a). "A multi-objective, multi-echelon green supply chain network design problem with risk-averse retailers in an uncertain environment", *Scientia Iranica. Transaction E, Industrial Engineering*, Vol. 24, No. 1, p. 413.

Golpîra, H., Najafi, E., Zandieh, M., and Sadi-Nezhad, S., (2017b). "Robust bi-level optimization for green opportunistic supply chain network design problem against uncertainty and environmental risk", *Computers and Industrial Engineering*, Vol. 107, pp. 301-312.

Golpîra, H., (2019). "Optimal Integration of the Facility Location Problem into the Multi-Project Multi-Supplier Multi-Resource Construction Supply Chain Network Design under the Vendor Managed Inventory Strategy", *Expert Systems with Applications*.

Jabali, O., Woensel, T., and de Kok, A., (2012). "Analysis of travel times and CO_2 emissions in time‐dependent vehicle routing", *Production and Operations Management*, Vol. 21, No. 6, pp. 1060-1074.

Khan, S.A.R., Zhang, Y., Anees, M., Golpîra, H., Lahmar, A., and Qianli, D., (2018). "Green supply chain management, economic growth and environment: A GMM based evidence", *Journal of Cleaner Production*, Vol. 185, pp. 588-599.

Khan, S.A.R., Chen, J., Zhang, Y., and Golpîra, H., (2019a). "Effect of green purchasing, green logistics, and ecological design on organizational performance: A path analysis using structural equation modeling", *Information Technology and Intelligent Transportation Systems*, pp. 183-190.

Khan, S.A.R., Sharif, A., Golpîra, H., and Kumar, A., (2019b). "A green ideology in Asian emerging economies: From environmental policy and sustainable development", *Sustainable Development*.

Khan, S. A. R., Jian, C., Zhang, Y., Golpîra, H., Kumar, A., and Sharif, A., (2019c). "Environmental, social and economic growth indicators spur logistics performance: From the perspective of South Asian Association for Regional Cooperation countries", *Journal of cleaner production*, Vol. 214, pp. 1011-1023.

Kritikos, M.N., and Ioannou, G., (2013). "The heterogeneous fleet vehicle routing problem with overloads and time windows", *International Journal of Production Economics*, Vol. 144, pp. 168-75.

Mandziuk, J., and Swiechowski, M., (2017). "UCT in Capacitated Vehicle Routing Problem with traffic jams", *Information Sciences*, pp. 42–56.

Marandi, F., (2017). "A new approach in graph-based integrated production and distribution scheduling for perishable products", *Journal of Quality Engineering and Production Optimization*, Vol. 2, No. 1, pp. 65-76.

Mostafaeipour, A., Qolipour, M., Rezaei, M., and Babaee-Tirkolaee, E., (2019). "Investigation of off-grid photovoltaic systems for a reverse osmosis desalination system: A case study", *Desalination*, Vol. 454, pp. 91-103.

Perboli, G., Tadei, R. and Vigo, D., (2011). "The two-echelon capacitated vehicle routing problem: Models and math-based heuristics", *Transportation Science*, Vol. 45, No. 3, pp. 364-380.

Rahbari, A., Nasiri, M.M., Werner, F., Musavi, M., and Jolai, F., (2019). "The vehicle routing and scheduling problem with cross-docking for perishable products under uncertainty: Two robust bi-objective models", *Applied Mathematical Modelling*, Vol. 70, pp. 605-625.

Rohmer, S.U.K., Claassen, G.D.H., and Laporte, G., (2019). "A two-echelon inventory routing problem for perishable products", *Computers & Operations Research*, Vol. 107, pp. 156-172.

Sangaiah, A. K., Tirkolaee, E.B., Goli, A., and Dehnavi-Arani, S., (2019). "Robust optimization and mixed-integer linear programming model for LNG supply chain planning problem", *Soft Computing*, pp. 1-21.

Song, B.D., and Ko, Y.D., (2016). "A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery", *Journal of Food Engineering*, Vol. 169, No. 3, pp. 61-71.

Soysal, M., Bloemhof-Ruwaard, J. M., and Bektaş, T., (2015). "The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations", *International Journal of Production Economics*, Vol. 164, pp. 366-378.

Tirkolaee E.B., Goli, A., Bakhshi, M., and Mahdavi, I., (2017). "Robust Multi-Trip Vehicle Routing Problem of Perishable Products with Intermediate Depots and Time Windows", *Numerical Algebra Control and Optimization*, Vol. 7, No. 4, pp. 417-433.

Tirkolaee, E.B., Mahdavi, I., and Esfahani, M.M.S., (2018a). "A robust periodic capacitated arc routing problem for urban waste collection considering drivers and crew’s working time", *Waste Management*, Vol. 76, pp. 138-146.

Tirkolaee, E.B., Alinaghian, M., Hosseinabadi, A.A.R., Sasi, M. B., and Sangaiah, A. K., (2018b). "An improved ant colony optimization for the multi-trip Capacitated Arc Routing Problem", *Computers and Electrical Engineering*.

Tirkolaee, E.B., Hosseinabadi, A. A. R., Soltani, M., Sangaiah, A. K., and Wang, J., (2018c). "A Hybrid Genetic Algorithm for Multi-Trip Green Capacitated Arc Routing Problem in the Scope of Urban Services", *Sustainability*, Vol. 10, No. 5.

Tirkolaee, E.B., Goli, A., Hematian, M., Sangaiah, A.K., and Han, T. (2019a). "Multi-objective multi-mode resource constrained project scheduling problem using Pareto-based algorithms", *Computing*, Vol. 101, No. 6, pp. 547-570.

Tirkolaee, E.B., Goli, A., and Weber, G.W., (2019b). "Multi-objective Aggregate Production Planning Model Considering Overtime and Outsourcing Options Under Fuzzy Seasonal Demand", In Advances in Manufacturing II (pp. 81-96). Springer, Cham.

Tirkolaee, E.B., Mahmoodkhani, J., Bourani, M.R., and Tavakkoli-Moghaddam, R., (2019c). "A Self-Learning Particle Swarm Optimization for Robust Multi-Echelon Capacitated Location-Allocation-Inventory Problem", *Journal of Advanced Manufacturing Systems*.

Wang, K., Shao, Y., and Zhou, W., (2017). "Metaheuristic for a two-echelon capacitated vehicle routing problem with environmental considerations in city logistics service", *Transportation Research Part D: Transport and Environment*, Vol. 57, pp. 262-276.

Yavari, M., and Zaker, H., (2019). "An integrated two-layer network model for designing a resilient green-closed loop supply chain of perishable products under disruption", *Journal of Cleaner Production*, Vol. 230, pp. 198-218.

Yavari, M., and Geraeli, M., (2019). "Heuristic method for robust optimization model for green closed-loop supply chain network design of perishable goods", *Journal of Cleaner Production*, Vol. 226, pp. 282-305.

Yu, Z., Golpîra, H., and Khan, S. A., (2018). "The relationship between green supply chain performance, energy demand, economic growth and environmental sustainability: An empirical evidence from developed countries", *LogForum*, Vol. 14, No. 4.

Zhou, L., Baldacci, R., Vigo, D., and Wang, X., (2018). "A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution", *European Journal of Operational Research*, Vol. 265, No. 2, pp. 765-778.

This article can be cited: Babaee Tirkolaee, E., Hadian, Sh., Golpîra, H., (2019). "A novel multi-objective model for two-echelon green routing problem of perishable products with intermediate depots", *Journal of Industrial Engineering and Management Studies*, Vol. 6, No. 2, pp. 196-213.