Modelling and solving the bi-objective production-transportation problem with time windows and social sustainability

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Abstract

This paper deals with modelling and solving the production-routing problem (PRP) with time windows, product deterioration and split delivery. A bi-objective PRP model for a single perishable product, which is subject to deterioration, is presented. The two objectives represent the economic and social aspects of sustainability, whereas the environmental impact is enforced through incorporating ad-hoc constraints. The economic dimension of sustainability consists of minimizing the costs related to the production, setup, holding, transportation and lateness penalty. The social responsibilities are modelled through maximizing the total freshness of the delivered products at all nodes over the planning horizon. The outcomes of our formulation are represented by the lot-sizes and the amounts of product to be delivered, as well as the routing at each planning period. To solve the resulting problem, we develop an interval robust possibilistic approach and we carry out an experimental study and a sensitivity analysis. Finally, we further validate our optimization model and solution method using a real-life case of a food factory producing a product that is subject to perishability and deterioration.

Keywords: Production-transportation planning; Time windows; Environmental and social responsibility; Robust possibilistic optimization.

1. Introduction

The production-routing problem (PRP) includes the integration and coordination of the lot-sizing and the vehicle routing problems (VRP). Often, the production decisions within the PRP involve also inventory management both in the factory and at the customers (Adulyasak et al., 2014). The advantages of integrating the production planning and the vehicles routing within the same optimization framework have been highlighted in Fu et al. (2017), Triki et al. (2020) and Gharaei and Jolai (2020). Furthermore, while defining the optimal routes of the vehicles, it is often important to take into account the time limitations related to the deliveries. In this case, it is necessary to consider time windows to get closer to reality and to increase the customers' satisfaction.

Recently, the awareness of modern society towards sustainability has increased remarkably. However, most of the available studies just focused on the economic and environmental pillars of sustainability and ignored the social factor, despite its importance. The most quoted definition of sustainability has been proposed by Brundtland (1987): "development that meets the needs of the present without compromising the ability of future generations to meet their own needs". Unfortunately, the movement of products within the supply chain has often a negative impact on the environment. In the PRPs, besides the greenhouse gas (GHG) emission due to transportation activities, factory emissions have also an undesirable effects on environment that should be controlled and reduced. This study will focus on reducing the emissions during the production process, which will also have desirable impact on reducing the energy consumption during production. Moreover, besides the economic and environmental impacts of sustainability we also consider here, the social aspect related to both customers' satisfaction and manpower planning. For this purpose, we incorporate in this study the time windows in deliveries to enhance the customer's satisfaction. Also, we consider the manpower planning by increasing the freshness related to the production and transportation activities.

This research presents a novel sustainable model for the PRP in the supply chain design with split delivery alongside the time windows for the specific case of a single supplier and a single product. Each customer has certain storage for holding inventories. The products after one period start to deteriorate at a certain rate. The proposed model investigates the trade-off between achieving the social objective (i.e., maximizing the freshness) and the objective regarding economic factors (i.e., minimizing total cost). The environmental aspect is controlled through side constraints incorporated into the model. Therefore, by considering all three aspects of sustainability, we can ensure a complete foundation of the sustainability concept, a fact that has been done only in few studies. The first objective of this problem is to minimize the total cost that includes the setup, manufacturing, human resource, stock holding, transportation and lateness penalty costs for customers and drivers. The second objective of this problem is to maximize freshness. Several studies have considered freshness as criteria of social responsibility since it will reduce the waste of products (see Perrini et. al., 2010; Reich et. al., 2010; Weteling, 2013; Samant and Seo, 2016; Ghezavati et al., 2017; Jackson et. al., 2019; Ghaffarkadhim et.al., 2019) It is worth noting that considering the freshness to endorse the social responsibility impact is one of the novel contributions of this study. Likewise, considering the cost of tardiness and earliness simultaneously, and the effect of deterioration on the products is an original approach of this study that has never been proposed in advance.

This paper is structured as follows. In Section 2, the literature related to the problem under exam is reviewed. In Section 3, the problem is formally described and a bi-objective mixed-integer programming (MIP) model is presented. A novel robust possibilistic optimization method to solve the PRPs with time windows is developed in Section 4. In Section 5 our experimental results and numerical analysis on a real case instance are presented. Finally, some conclusions and possible future studies conclude the paper in Section 6.

2. Literature review

A VRP is one of the well-known problems in the academic literature that had a lot of attention during the past decades. It determines the vehicle routes to answer the demand of customers, who are placed at different nodes of a supply chain network. It considers the objective of minimizing the total transportation cost of vehicles. Dantzig and Ramser (1959) first introduced a truck dispatching problem to find routes of gas and oil trucks from a central depot to customer zones for optimization of the travelled distances and satisfy customers. This initial problem was developed by Clarke and Wright (1964) who generalized it to a linear problem. This problem became a VRP that is one of the most reputable study fields in Operations Research in the past years. An extensive review on a classical VRP, definitions, formulations of it in problems and its solution approaches can be seen in Laporte (1992), Toth and Vigo (2002), Berbeglia et al. (2007) and Parragh et al. (2008). In recent years, some researchers tried to develop a VRP with real-life cases and complexities, such as considering time windows for delivery and pickup, multiple vehicles, backhauls and uncertain as well as dynamic parameters (Ghiani et al., 2007). By considering a VRP with restriction of time windows while trying to include the minimum and maximum waiting times, this limitation is very effective for time-dependent problems, especially in those cases in which time is a key factor, such as perishable goods. The general VRP was studied as the concern of pollution and PRP considering time windows by Bektas and Laporte (2011). The goal of this extension is to minimize the total operational cost including the cost of the drivers' wages and that of the fuel. Many studies have modelled VRPs in a multi-objective structure, such as Ghoseiri and Ghannadpour (2010), Baños et al. (2013), Amorim and Almada-Lobo (2014), and Braekers et al. (2014). Kuznietsov et al. (2017) considered the food distribution logistics to minimize the transportation cost and find the best route for food delivery. They presented a mathematical model for a real case study. Ambrosino and Sciomache (2007) presented a mixed-integer programming model for delivering perishable food products. They considered this model for a capacitated vehicle routing problem with split delivery.

Besides the importance of VRPs, focus on sustainability is a novel approach that has attracted more attention than in the past, both in academic fields and in real-world markets. An introduction of sustainability in the context of supply chain management (SSCM) is proposed by Linton et al. (2007). Seuring (2013) and Brandenburg et al. (2014) reviewed quantitative models in SSCM. They covered a large part of the SSCM literature and also considered environmental and social aspects simultaneously. In another study, Kim et al. (2011) introduced a multi-depot vehicle-routing method to minimize the total distance travelled between local recycling centers (RCs) and major manufacturers considering reverse logistics for recycling end-of-life electronic commodities. Varsei (2016) reviewed sustainable development in SCM and determined various factors of three aspects of sustainability in different categories and sub-categories that determines a transparent view of these three dimensions. Rajeev et al. (2017) reviewed trends on sustainable SCM issues in academia and industries. The economic factors are the most classic measurement metric in a supply chain, which is mostly measured in terms of minimizing the cost (Fledelius and Mayoh, 2008) or maximizing the profit (Shen, 2006). The most frequently used metric for measuring the environmental influence is the carbon emissions, provoked by the different activities in the supply chain, such as production and transportation (Sundarakani et al., 2010). Asgari et al. (2016) surveyed a good literature review of SC models and tools considering different issues (e.g., sustainability).

Millet (2011) analyzed the main factors in providing a sustainable supply chain, which considers economic, social, and environmental aspects simultaneously. Mjirda et al. (2014) considered inventory and transportation of multiple products in an SC and solved the problem by a variable neighborhood search method. Zhalechian et al. (2016) studied a network design problem for a closed-loop location-routing-inventory supply chain considering three objectives, namely minimizing the total cost, minimizing the environmental negative effects and maximizing the social responsibility. A queuing system and game theory approach is applied in their model. Soleimani et al. (2017) studied a closed-loop supply chain network design problem along with the sustainability. Also, Cimen and Soysal (2017) worked on a time-dependent capacitated VRP model with a focus on the green aspect by considering the vehicle's carbon emissions. This model is formulated and solved by applying a dynamic programming approach. Jeong and Illades Boy (2018) studied a model that considers routing and refueling plans for minimizing the transportation time in alternative-fuel vehicles. Mirmohammmadi et al. (2017) worked on a robust multi-trip VRP in the case of perishable goods and supposed intermediate depots and time windows. In their model, the demand was uncertain without considering the sustainability. More recently, Chernykh and Lgotina (2020) dealt with a 2-machine routing open shop problem and developed a decomposition algorithm based on the instance reduction method. The most related study with our work is due to Kumar et al. (2016) who developed a sustainable VRP model that considers production-routing and pollution-routing problems concurrently. In their model, they considered a time window and two objectives that minimize the total cost and total emissions. They just focused on the "green aspect" of sustainability and did not include social factors in their problem.

Pishvaee et al. (2012) suggested a novel approach based on a combination of robust optimization and stochastic planning to solve the bi-objective model by minimizing costs and maximizing social factors. Midya and Roy (2014) investigated a stochastic distribution problem through three objectives. They used fuzzy programming to meet uncertainty. Fazli Khalaf et al. (2017) studied a robust fuzzy stochastic model for designing a closed-loop supply chain. This model also has been employed to manage greenhouse gas emissions and prevent air pollution by considering a second objective function that minimizes carbon emissions. Govindan et al. (2017) published a comprehensive review on supply chain network design problems under uncertainty and analyzed the solution methods are applied to these problems, such as recourse-based stochastic programming, risk-averse stochastic programming, robust optimization and fuzzy mathematical programming to evaluate their performance.

In another research, Soleimani et al. (2018) worked on a VRP model with a focus on the delivery of original products and pickup of end of life products. They also considered environmental factors to minimize air pollution. Zahiri et al. (2018) worked on the pharmaceutical supply chain network design with consideration of vague demands and costs. To solve this model, they presented an innovative robust possibilistic programming (IRPP) approach and analyzed its performance by applying this model in a real case study.

From the studies reviewed above, we can identify some gaps in the field of PRPs. Most of the works related to the sustainable area just focus on economical and green aspects of sustainability without taking into account the social factors. It is one of the serious gaps in sustainable literature, especially in routing problems. Thus, to include sustainability with all its pillars, it is important to consider simultaneously all the three dimensions of sustainability. Another gap is not to consider more than one stop for vehicles in the PRPs. For example, the option of allowing any node to be served more than once in the same period is known as “split delivery”. With this respect, applying time windows limitations and penalty costs of tardiness and earliness to be close to real-world cases is helpful. Also, the related literature does not completely address the uncertainty in the PRPs (that has been studied in other contexts, such as maritime transportation, Pantuso et al., 2015). So, the goal of this work is to cover a further gap in the present literature by considering uncertain parameters and by solving the stochastic variant of this problem by applying the novel approach introduced by Zahiri et al. (2018).

Thus, to fulfill these gaps, a new sustainable PRP model with time windows and split delivery is presented. Our main contributions can be summarized as follows:

- Including the total freshness to endorse the social responsibility impact.
- Considering the possibility of performing several stops at any node and introducing, thus, the split delivery in PRPs with time windows alongside the sustainability.
- Including all the three aspects of sustainability to have a complete foundation of this concept.
- Considering the cost of tardiness and earliness simultaneously and also the effect of deterioration on the products.
- Applying a novel robust possibilistic optimization method to solve PRPs problem with time windows.

Also, the proposed mathematical model has been successfully applied to solve a case study that shows the value of our contributions.

3. Problem description and optimization model

In this section, a mathematical model for determining an optimum production and routing planning from the factory to its customers is described. In this problem, a single factory and n customers are considered. Any of the customers can have a demand that exceeds the vehicle's capacity, so more than one vehicle may be needed to meet the customers’ demand. Each vehicle has a known CO_2 emission quantity when travels from node i to j. Furthermore, the concept of the social dimension of sustainability is included in the proposed model by maximizing the total freshness of the delivered products to customers over the planning horizon. In the food industry, ensuring the freshness of the products delivered to the customers is important, to increase customer satisfaction. On the other hand, maximizing the freshness of products ensures social responsibility since it leads to waste reduction. Given that the freshness of products decreases over time, three states can be observed for its quantification:

State I: some products are transferred from the previous period and the vehicles will visit the concerned node at the same period;

State II: a fraction of the products available at node *i* during period *t*-1 is consumed and after deterioration starts, still part of the products remains in good condition which will be transferred to next period and, thus, no need at the next period of any vehicle visit to node *I*;

State III: all delivered products at node *i* during period *t* are consumed during the same period *t*.

The environmental aspect related to the production and transportation CO_2 emissions is controlled by keeping them under the allowed threshold.

Each of the customers has a certain demand, as well as a given holding capacity to store the products (see Figure 1). In this model, the optimal production and freight delivery of each vehicle, as well as the customer's order quantities per period should be determined. One of the objectives of the model is the minimization of total cost by considering all types of cost: (production, setup, driver, worker, holding, transportation, earliness, and tardiness costs (see also Shu et al., 2012). This objective represents the economic goal. The social side of sustainability is considered by maximizing the total freshness of products at all nodes over the planning horizon. The third dimension of sustainability (i.e., environmental factor) will be included as constraints to express the CO_2 emissions due to vehicle transportation and supplier's production.

{Please insert Figure 1 about here.}

The assumptions, notation and mathematical modelling are presented below.

3.1. Assumptions

- If some products remain with the customer at the end of the period, a fraction will be excreted.
- Split delivery can be considered at each node.
- CO_2 emissions produced by vehicles transportation and supplier production are taken into account
- Initial customers and supplier inventories are not zero.
- At the end of each period, product deterioration happens.

3.2. Notation

Indices:

t	Time period over the planning horizon $t = (1,2,\dots,T)$
i	0 indicates plant node and $N_0 = N - \{0\}$ is the customers nodes set $i = 0,1,2,\dots,n$,
$E(S')$	Set of routs (i,j) and $i \neq j$ such as $i,j \in S'$, where $S' \subseteq N$ is a given subset N
k	Index of vehicles $k = (1,2,\dots,K)$

Parameters:

C	Capacity of production
Q	Capacity of vehicle
M	Big number
I_{i0}	Primary inventory at node *i*
L_i	Maximum level of stocked inventory at node *i*
S	Fixed production cost (setup)
u	Unit production cost
α	Rate of deterioration at each period
A	Labor cost
SP	Unit sale price
fn	Coefficient of product freshness
e_{ij}^k	CO_2 emissions produced by vehicle k when travelling from node i to node j
K	Number of units per worker per period
θ_t	CO_2 emission associated with manufacturing the product at period t
AL	Allowed amount of CO_2 emission associated with the manufacturing activities
TE	Allowed amount of CO_2 emission associated with the transportation phase
c_{ij}	Unit shipment cost (each item shipped from node *i* to node *j*)
D_{it}	Demand at node *i* in time period *t*
v_{ijkt}	Speed of vehicle k when traveling between nodes *i* and *j* at period *t*
d_{ij}	Distance between nodes *i* and *j*
V_{it}	Number of vehicles that can visit node *i* at time period *t*
h_i	Unit holding cost per time period at node *i*
ut_{ikt}	Time of unloading vehicle *k* at node *i* in time period *t*
ur_{kt}	Rate of unloading vehicle *k* in period *t*
$[a_{it}, b_{it}]$	Time window at node *i* in time period *t*
wd_{it}	Penalty cost of driver waiting at node *i* in time period *t* (per time period)
wc_{it}	Penalty cost of late arrival at node *i* in time period *t* (per time period)

Decision variables

p_t	Quantity of production in time period *t*
I_{it}	Quantity of inventory at node *i* in time period *t*
q_{ikt}	Quantity of production delivered to node *i* by vehicle *k* in time period *t*
fl_{ijtk}	Material flow of vehicle *k* during traveling from node *i* to node *j* in time period *t*
fr_{it}	Freshness of product at node $i \in N_0$ in period *t*
W_t	1 if the plant produces in period *t*; 0 otherwise
X_{ijkt}	1 if the vehicle *k* passes arc (i, j) in time period *t*; 0, otherwise
Z_{ikt}	1 if vehicle *k* visits node *i* in time period *t*; 0, otherwise
ar_{ikt}	Arrival time of vehicle *k* at node *i* in time period *t*

3.3. Optimization model

$$\text{Min} \quad \sum_{t=1}^{T}\{(up_t + Apr_t + SW_t + \sum_{i=0}^{n} h_i I_{it} + \sum_{i=0}^{n}\sum_{j=0,j\neq i}^{n}\sum_{k=1}^{K} c_{ij}X_{ijkt} + \sum_{i=1}^{n}\sum_{k=1}^{K}(wd_{it}\,[\,a_{it} - ar_{ikt}]^{+}Z_{ikt}) + \sum_{i=1}^{n}\sum_{k=1}^{K}(wc_{it}\,[ar_{ikt} - b_{it}\,]^{+}Z_{ikt}))\} \tag{1}$$

$$\text{Max} \quad \sum_{i=1}^{n}\sum_{t=1}^{T} fr_{it} \tag{2}$$

s.t.

$$fr_{it} = \max\{(1-\alpha), fn\frac{1}{\max\limits_{k} ar_{ikt}}\} \qquad \forall t \in T, \forall i \in N_0, Z_{ikt} > 0. I_{i,t-1} > 0 \tag{3}$$

$$fr_{it} = (1-\alpha) \qquad \forall t \in T, \forall i \in N_0, Z_{ikt} = 0, I_{i,t-1} > 0 \tag{4}$$

$$fr_{it} = fn\frac{1}{\max\limits_{k} ar_{ikt}} \qquad \forall t \in T, \forall i \in N_0, Z_{ikt} > 0, I_{i,t-1} = 0 \tag{5}$$

$$[\,a_{it} - ar_{ikt}]^{+} = \max\{0,\, a_{it} - ar_{ikt}\} \qquad \forall i \in N_0, \forall k \in K, \forall t \in T \tag{6}$$

$$[\,ar_{ikt} - b_{it}\,]^{+} = \max\{0, ar_{ikt} - b_{it}\,\} \qquad \forall i \in N_0, \forall k \in K, \forall t \in T \tag{7}$$

$$(1-\alpha)I_{0,(t-1)} + p_t = \sum_{i=1}^{n}\sum_{k=1}^{K} q_{ikt} + I_{0t} \qquad \forall t \in T \tag{8}$$

$$(1-\alpha)I_{i,(t-1)} + \sum_{k=1}^{K} q_{ikt} = D_{it} + I_{it} \qquad \forall i \in N_0, \forall t \in T \tag{9}$$

$$p_t \leq \min\{C, \sum_{i=1}^{n} D_{it}\}w_t \qquad \forall t \in T \tag{10}$$

$$I_{0t} \leq L_0 \qquad \forall t \in T \tag{11}$$

$$(1-\alpha)I_{i,t-1} + \sum_{k=1}^{K} q_{ikt} \leq L_i \qquad \forall i \in N_0, \forall t \in T \tag{12}$$

$$q_{ikt} \leq QZ_{ikt} \qquad \forall i \in N_0, \forall k \in K, \forall t \in T \tag{13}$$

$$\sum_{k=1}^{K} Z_{ikt} \leq V_{it} \qquad \forall i \in N_0, \forall t \in T \tag{14a}$$

$$V_{it} - 1 < \frac{D_{it}}{Q} \leq V_{it} \qquad \forall i \in N_0, \forall t \in T \tag{14b}$$

$$\sum_{k=1}^{K} q_{ikt} \leq \text{M}\sum_{k=1}^{K} Z_{ikt} \qquad \forall i \in N_0, \forall t \in T \tag{15}$$

$$\sum_{j=0}^{n} X_{ijkt} + \sum_{j=0}^{n} X_{jikt} = 2Z_{ikt} \qquad \forall i \in N, \forall k \in K, \forall t \in T \tag{16}$$

$$\sum_{i\in S}\sum_{j\in S, j\neq i} X_{ijkt} \leq \sum_{i\in S} Z_{ikt} - Z_{ekt} \qquad \forall S \subseteq N_0, |S| \geq 2, \forall e \in S, \forall \in K, \forall t \in T \tag{17}$$

$$\sum_{j=0}^{n} fl_{jitk} - \sum_{j=0}^{n} fl_{ijtk} = q_{ikt} \qquad \forall i \in N_0, \forall k \in K, \forall t \in T \tag{18}$$

$$\sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{j=1,i\neq j}^{n} e_{ij}^{k}\, X_{ijkt} \leq TE \qquad \forall t \in T \tag{19}$$

$$\sum_{t=1}^{T} \theta_t p_t \leq AL \tag{20}$$

$$ar_{jkt} = \left(ar_{ikt} + q_{ikt}/ur_{kt} + d_{ij}/v_{ijkt}\right)X_{ijkt} \qquad \forall i,j \in N, \forall k \in K, \forall t \in T \tag{21}$$

$$\sum_{t=1}^{t'} W_t \geq 1 \tag{22}$$

$$t' = argmin_{1\leq t\leq l} \sum_{i=1}^{n} \max\left\{0, \sum_{j=1}^{t} D_{ij} - I_{i0}\right\} - I_{00} > 0$$

$$\sum_{k=1}^{m}\sum_{t=1}^{t''} Z_{0kt} \ \geq \left\lceil\frac{\Omega}{Q}\right\rceil \tag{23}$$

$$t'': min_{i\in N_0}\left\{argmin_{1\leq t\leq l}\left\{\sum\nolimits_{j=1}^{t} D_{ij} - I_{i0} > 0\right\}\right\}$$

$$\Omega = \sum\nolimits_{i=1}^{n} max\left\{0, \sum\nolimits_{j=1}^{t''} D_{ij} - I_{i0}\right\}$$

$$I_{i,t-s-1} \geq \left(\sum_{j=0}^{s} D_{i,t-j}\right)\left(1 - \sum_{k=1}^{K}\sum_{j=0}^{s} Z_{ik,t-j}\right) \qquad \forall i \in N_0, \forall t \in T, \ \forall s = 0, 1, \dots, t-1 \tag{24}$$

$$M(u + c_{ij})(1 - X_{ijkt}) \leq SP \qquad \forall i,j \in N, \forall k \in K, \forall t \in T \tag{25}$$

$$Z_{ikt} \leq Z_{0kt} \qquad \forall i \in N_0, \quad \forall k \in K, \quad \forall t \in T \tag{26}$$

$$X_{ijkt} \leq Z_{ikt} \qquad \forall (i,j) \in E(N_0), \forall k \in K, \forall t \in T \tag{27}$$

$$X_{ijkt} \leq Z_{jkt} \qquad \forall (i,j) \in E(N_0), \forall k \in K, \forall t \in T \tag{28}$$

$$p_t \geq 0, I_{it} \geq 0, q_{ikt} \geq 0, f_{ijkt} \geq 0 \qquad \forall i,j \in N, \forall k \in K, \forall t \in T \tag{29}$$

$$W_t, Z_{ikt} \in \{0,1\} \qquad \forall i \in N, \forall k \in K, \forall t \in T \tag{30}$$

The fuzzy objective function (1) minimizes the total cost; including the production, labor, production setup, holding, transportation as well as the drivers and customers' waiting penalties. Objective (2) is to maximize the total freshness of products at all nodes over the whole planning horizon. The fuzziness of the objective functions is due to the fuzzy nature of the parameters identified in Table 1 and on their effect, as highlighted in expressions (30) and (31). Constraints (3) - (5) calculate the freshness of products at node *i* during period *t*, which increases with an arrival time reduction (state I, state II and state III), respectively. Constraints (6) define the earliness of drivers' arrival at each node in period *t*. Constraints (7) define the tardiness of arriving at customers at each node in each period. Constraints (8) balance the quantity of flow of material at the plant and inventory. Likewise, Constraints (9) balance the quantity of flow of material at the customers' nodes and inventory. Inequalities (10) are production capacity constraints and limits the quantity of production as to be the minimum between the capacity of production and the total demand of all time periods.

Moreover, constraints (11) restrict the quantities of inventory in the production plant at the end of each period. Constraints (12) restrict the quantities of inventory at the end of each time period at customers' nodes. Constraints (13) ensure that the total vehicle's load cannot be higher than its capacity. Constraints (14) ensure that at most V_i vehicles visit the customer at any time period (where V_i is obtained by dividing the customer's demand by the vehicle capacity). Constraints (15) state that one or more vehicles should visit any node whose delivered quantity is positive. Constraints (16) ensure that the number of edges incident to any node must be 2 if that node is visited by vehicle k. Constraints (17) eliminate the possibility of forming sub-tours for each of vehicles. Constraints (18) determine the arc of vehicles flow of material in each period. Constraints (19) restrict the overall CO_2 intensities emitted during each vehicles' entire route with an upper bound threshold. Similarly, Constraint (20) restricts the total carbon pollution generated by the factory to be less than the allowed amount AL. Constraints (21) set the vehicle arrival time at node j in time period t to be the sum of the time of arrival at node i, the time of unloading at node i and the time of travelling from node i to node j whenever node j is visited just after node i. Also, Constraints (22) and (23) ensure that no stock-outs can occur, where t' and t'' represent the earliest period to start producing in the plant and in which replenishment start to any of the customers, respectively, and Ω is the minimum quantity to be delivered at time t''. Constraints (24) represent a set of inequalities that strengthen the replenishments to the customers. Constraint (25) ensures that customer i should not be served if his visit is not economically feasible. Constraints (26) to (28) are logical inequalities that strengthen the logical relationship between the binary variables. Constraints (29) ensure that the limitations of the quantity of production, replenishments, inventories, and material flows are non-negative, and finally, Constraints (30) define the binary nature of the decision variables.

The suggested optimization model (1) - (30) results to be a very large scale nonlinear bi-objective mixed-integer program whose size increases with the number of customers, vehicles, time periods, etc. Its solution till optimality with any state-of-the-art solver would be incompatible with the application timings.

4. Solution approach

Many fuzzy/possibilistic methods have been introduced in the literature. In a typical fuzzy approach, a novel fuzzy programming model is converted to a conventional mathematical model, then an optimization technique is used to solve the converted mathematical model (Azadeh et al. 2017; Rahimi et al. 2018; Mollanoori et al. 2019; Haghjoo et al. 2020; Kaveh et al. 2021). At the end, if the determined optimal solution is not acceptable, the fuzzy model is rebuilt based on the improved interpretation (Inuiguchi and Ramık, 2000).

An interval robust possibilistic programming approach is proposed, to consider the uncertain parameters characterizing our IRPP model. These parameters are presented in Sections 4.1. In the sequel, the details of our proposed IRPP approach are described.

4.1. Crisp counterpart formulation

The uncertain parameters of the proposed model are illustrated in Table 1 (please refer to Section 3.2 for the meaning of each parameter).

{Please insert Table 1 about here.}

4.2. Interval-based robust possibilistic programming approach

Zahiri et al. (2018) introduced the Interval-based robust possibilistic programming approach (IRPP) through a combination of the "Me" measurement and the robust possibilistic programming concepts. Moreover, they extended their approach to solving multi-objective problems. In this paper, a bi-objective model is solved and an optimistic-pessimistic binary parameter (denoted as $\gamma_{\tau=i} \in \{0,1\}$) is considered for determining the upper or lower approximation models (UAM and LAM, respectively). If $\gamma = 1$, then the proposed model is associated with UAM, otherwise the proposed model is associated with LAM. Since objective $OFV_{LAM} \leq OFV_{UAM}$, the value of γ will always be 1 in a minimization problem (OFV is the Objective Function Value). This approach is extended to the multi-objective case by minimizing each of the f objectives to obtain the nadir solution and then by normalizing each of the objectives.

4.3. Coping the IRPP approach to the proposed model

In this section, the IRPP approach is adapted to our proposed model.

$$\begin{aligned}\text{Min } & E[Z] + \eta\, [Z_{max} - E[Z]] \quad + M\, [\left((1-\gamma_{\tau=1})(AL_{(2)} - AL_{(1)}) + \gamma_{\tau=1}(AL_{(3)} - AL_{(2)} + \varepsilon)\right) \\ & + \left((1-\gamma_{\tau=2})(u_{(2)} - u_{(1)}) + \gamma_{\tau=2}(u_{(3)} - u_{(2)} + \varepsilon)\right) \\ & + \pi y[(1-\gamma_{\tau=1})(AL_{(2)} - \psi_{\tau=1}(AL_{(2)} - AL_{(1)}) - AL_{(1)}) \\ & + \gamma_{\tau=1}(AL_{(3)} - AL_{(2)} - (1-\psi_{\tau=1})(AL_{(3)} - AL_{(2)})] \\ & + \pi'[(1-\gamma_{\tau=2})\left(u_{(3)} - u_{(2)} - \psi_{\tau=2}(u_{(3)} - u_{(2)})\right) \\ & + \gamma_{\tau=2}(u_{(2)} - (1-\psi_{\tau=2})(u_{(2)} - u_{(1)}) - u_{(1)})]\end{aligned} \tag{31}$$

where,

$$\begin{aligned} Z_{max} = & \sum_{t=1}^{T}(u_{(3)}p_t + A_{(3)}pr_t + S_{(3)}W_t) + \sum_{t=1}^{T}\sum_{i=0}^{n} h_{i(3)}I_{it} + \sum_{t=1}^{T}\sum_{i=0}^{n}\sum_{j=0,j\neq i}^{n}\sum_{k=1}^{m} c_{ij}X_{ijkt} \\ & + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{k=1}^{m} wd_{i(3)}\,[a_{it} - ar_{ikt}]^{+}Z_{ikt} + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{k=1}^{m} wc_{i(3)}\,[ar_{ikt} - b_{it}]^{+}Z_{ikt}\end{aligned}$$

$$\begin{aligned}\text{Min } & (-\sum_{i=1}^{n}\sum_{t=1}^{T} fr_{it}) + M\, [\left((1-\gamma_{\tau=1})(AL_{(2)} - AL_{(1)}) + \gamma_{\tau=1}(AL_{(3)} - AL_{(2)} + \varepsilon)\right) \\ & + \left((1-\gamma_{\tau=2})(u_{(2)} - u_{(1)}) + \gamma_{\tau=2}(u_{(3)} - u_{(2)} + \varepsilon)\right) \\ & + \pi y[(1-\gamma_{\tau=1})(AL_{(2)} - \psi_{\tau=1}(AL_{(2)} - AL_{(1)}) - AL_{(1)}) \\ & + \gamma_{\tau=1}(AL_{(3)} - AL_{(2)} - (1-\psi_{\tau=1})(AL_{(3)} - AL_{(2)})] \\ & + \pi'[(1-\gamma_{\tau=2})\left(u_{(3)} - u_{(2)} - \psi_{\tau=2}(u_{(3)} - u_{(2)})\right) \\ & + \gamma_{\tau=2}(u_{(2)} - (1-\psi_{\tau=2})(u_{(2)} - u_{(1)}) - u_{(1)})]\end{aligned} \tag{32}$$

where M is a big number and ε is a very small number.

The objective function (1) is changed to objective function (31). The first term of this goal is the mean value *E(Z)*. The difference between the maximum possible value of OF1 and the related mean value is minimized in the second term with a coefficient degree of

η. The third one ensures both interval bounds of all fuzzy numbers to be respected. Finally, the last two terms consider penalty terms for the difference between the worst-case value of each uncertain parameter and the value of its chance constraint. π and π' are penalty terms related to fuzzy constraints. The objective function (2) is changed to objective function (32). The second objective function parameters are deterministic so the first term of this goal remains unaltered.

$$\theta_t p_t \leq y[((1-\gamma_{\tau=1})\left(AL_{(2)} - \psi_{\tau=1}(AL_{(2)} - AL_{(1)})\right) + \gamma_{\tau=1}(AL_{(2)} - (1-\psi_{\tau=1})(AL_{(3)} - AL_{(2)}))] \quad (33)$$

$$M\left[(1-\gamma_{\tau=2})\left(u_{(2)} + \psi_{\tau=2}(u_{(3)} - u_{(2)})\right) + \gamma_{\tau=2}\left(u_{(2)} - (1-\psi_{\tau=2})(u_{(2)} - u_{(1)})\right) + c_{ij}\right](1 - X_{ijkt}) \leq SP \quad (34)$$

$$y, \gamma_\tau \in \{0,1\}, \psi_\tau \in [0,1] \quad (35)$$

Constraints (33) and (34) replace constraints (20) and (25).

Since the presented model is a bi-objective one, the best solution can be obtained by performing the following steps:

Step 1: Minimizing every objective subject to the constraints set to derive the optimal solutions of the decision variables, and consequently the objective values $\bar{Z}_j(\vec{x}_i)$.

Step 2: Minimizing the objective function *i* by shifting the remained objective function to the constraints set such that $Z_j(\vec{x}_i) \leq \bar{Z}_j(\vec{x}_i)\ \ \forall j \neq i \in k$ to derive the nadir solutions of the decision variables, and consequently the objective value $\underline{Z}_j(\vec{x}_i)$.

Step 3: Normalizing every objective so that no objective is favored by its magnitude, also, assure that it will lie between zero and one:

$$Z_{ni}(\vec{x}_i) = \frac{Z_i(\vec{x}_i) - \bar{Z}_j(\vec{x}_i)}{\underline{Z}_j(\vec{x}_i) - \bar{Z}_j(\vec{x}_i)} \qquad , \qquad i = 1,2 \quad (36)$$

Step 4: A weighted objective function can be formulated by:

$$FC = C_1 Z_{n1}(\vec{x}_i) + (1 - C_1) Z_{n2}(\vec{x}_i) \ \ , \ \ 0 \leq C_1 \leq 1 \quad (37)$$

It minimizes the model under the presented constraints and for all combinations of the weights. To ensure that every normalized objective function will be as far away as possible from its (normalized) worst possible value of 1 ($i = 1, 2$), φ can be represented by:

$$\varphi = (1 - Z_{n1}(\vec{x}_i))(1 - Z_{n2}(\vec{x}_i)) \quad (38)$$

Then, the new objective function to find a Pareto-optimal solution is presented by:

$$F(\vec{y}) = FC - \varphi \quad (39)$$

where $\vec{y} = \{x_1, x_2, \dots, x_n, C_1\}^T\ with\ 0 \leq C_1 \leq 1$

Step 5: Minimize $F(\vec{y})$ to find $\vec{y}$, to obtain the best solution of the bi-objective model.

4.4. IRPP model linearization

Since our proposed IRPP model involves in constraint (33) a nonlinear term (related to the variables product $y\gamma_{\tau=1}$), we introduce here a new binary variable denoted as $\rho = y\gamma_{\tau=1}$ to linearize Constraint (33) as follows:

$$y + \gamma_{\tau=1} - \rho \leq 1 \tag{40}$$
$$\rho \leq y \tag{41}$$
$$\rho \leq \gamma_{\tau=1} \tag{42}$$

and constraint (33) can be replaced, thus, by the following Constraint (43):

$$\theta_t p_t \leq (yAL_{(2)} - y\psi_{\tau=1}\left(\left(AL_{(2)} - AL_{(1)}\right)\right) - \left(\rho AL_{(2)} - \rho\psi_{\tau=1}\left(AL_{(2)} - AL_{(1)}\right)\right) + \left(\rho AL_{(2)} + (\rho - \rho\psi_{\tau=1})\left(AL_{(3)} - AL_{(2)}\right)\right) \tag{43}$$

However, even constraint (43) includes two nonlinear terms (i. e. $y\psi_{\tau=1}$ and $\rho\psi_{\tau=1}$). Consequently, two new non-negative variables are introduced (namely, $\sigma = y\psi_{\tau=1}$ and $\sigma' = \rho\psi_{\tau=1}$).

$$\theta_t p_t \leq (yAL_{(2)} - \sigma\left(\left(AL_{(2)} - AL_{(1)}\right)\right) - \left(\rho AL_{(2)} - \sigma'\left(AL_{(2)} - AL_{(1)}\right)\right) + \left(\rho AL_{(2)} + (\rho - \sigma')\left(AL_{(3)} - AL_{(2)}\right)\right) \tag{44}$$
$$\sigma \leq M\rho \tag{45}$$
$$\sigma \geq M(\rho - 1) + \psi_{\tau=1} \tag{46}$$
$$\sigma \leq M\psi_{\tau=1} \tag{47}$$
$$\sigma' \leq My \tag{48}$$
$$\sigma' \geq M(y - 1) + \psi_{\tau=1} \tag{49}$$
$$\sigma' \leq M\psi_{\tau=1} \tag{50}$$
$$\sigma', \sigma \in [0,1] \tag{51}$$

Similarly, the nonlinear term in constraint (34) can be written in linearized form by introducing a new non-negative variable ($\varphi = \gamma_{\tau=2}\psi_{\tau=2}$).

$$\varphi \leq M\gamma_{\tau=2} \tag{52}$$
$$\varphi \geq M(\gamma_{\tau=2} - 1) + \psi_{\tau=2} \tag{53}$$
$$\varphi \leq M\psi_{\tau=2} \tag{54}$$
$$\varphi \in [0,1] \tag{55}$$

Finally, for the last nonlinear term (φX_{ijkt}), a new non-negative variable φ' is also introduced:

$$\varphi' \leq MX_{ijkt} \tag{56}$$
$$\varphi' \geq M\left(X_{ijkt} - 1\right) + \varphi \tag{57}$$
$$\varphi' \leq M\varphi \tag{58}$$
$$\varphi' \in [0,1] \tag{59}$$

5. Experimental results: A case study

To validate our model, a real case is illustrated here. Consider the H.M.S. factory operating in the food industry installed in Mashhad city located in the northeast of Iran.

The company produces a single perishable product that should be transferred to customers scattered around the city by a fleet of six identical trucks to satisfy customers' demands. 10 cities around Mashhad area are identified as customer nodes. Since some of the customers have high demand, so more than one ride will be needed by the trucks to serve the same customer. The problem's objective is to find the optimum routing for the truck in each period to minimize the total costs and maximize total freshness. Also, time windows are considered to limit the acceptable truck arrival time and to determine the penalty costs for earliness and tardiness service. To show the results of the model properly, 12 months are considered as a planning horizon with periods of one month each. Figure 2 shows the dispersion of the cities representing the customer nodes as well as the H.M.S. factory position. The cities' names are also detailed in Table 2.

{Please insert Figure 2 about here.}
{Please insert Table 2 about here.}

Thus, the considered scale for this case is $|t|\times|i|\times|E|\times|k|$ = 12×11×55×6. The main parameter values are described in Table 3, and the parameters related to the customers (e.g., initial inventory level, maximum storage level and unit holding cost) for each node are shown in Table 4.

{Please insert Table 3 about here.}
{Please insert Table 4 about here.}

The systematic distance matrix between each pair of cities shown in Table 5 identifies $\binom{11}{2} = 55$ arcs that our model can use to define the optimal routing that satisfies the demand of each node in every period, as detailed in Table 6.

Our model has been solved by using GAMS and the resulting solution related to the production quantity to be received by each customer in every time period is shown in Table 7. Also, the number of trucks visiting each customer i are shown in Table 8. As can be seen, in some periods, some of the nodes must be visited more than one truck, which is perfectly consistent with our initial assumptions.

{Please insert Table 5 about here.}
{Please insert Table 6 about here.}
{Please insert Table 7 about here.}
{Please insert Table 8 about here.}

Figure 3 shows, for each time period, the problem's solution for the specific case of customer 10. Moreover, the total amount of product delivered by the trucks in each time period is also shown in Figure 4. Note that as the demand changes from one period to another, the delivered volumes of the product adapt to the demand variations. Also, since the customers have initial inventories at the beginning of the planning horizon, the delivered quantities of the product are lower than the customers' demand.

{Please insert Figure 3 about here.}
{Please insert Figure 4 about here.}

Finally, Table 9 shows the optimal routes for each truck during every time period and Figure 5 shows an example of the truck routes for the specific case of period 3. The identified optimal solution shows, for example, that in period 4, it is not convenient for trucks 5 and 6 to deliver any product, whereas trucks 1, 2, 3 will serve one single customer each, and the optimal route of truck 4 consists in starting by node 9 and then to serve nodes 7-3-4 in this specific order. Also, some sub-problems of a case study was solved and the result is presented in Table 10.

{Please insert Table 9 about here.}
{Please insert Figure 5 about here.}
{Please insert Table 10 about here.}

6. Sensitivity analysis and managerial insights

To get some helpful managerial insights, in this section the behavior of both objective functions is analyzed when some problem's parameters are varying.

6.1. Reciprocal behavior of the objective functions

Figure 6 shows the reciprocal behavior of both the objective functions. As expected, the increase in one function increase the other. So both objective functions will increase or decrease simultaneously. This analysis shows that to achieve a high level of social factors, more investment should be spent and this is a major trade-off in this problem.

{Please insert Figure 6 about here.}

6.2. Volume of demands analysis

We focus here on investigating how the objective functions change when an increase in the demands occurs. Figures 7 and 8 show the effect of these changes. As can be seen in Figure 7 when the demand increases, the total cost will grow and more investment should be provided. Figure 8 shows how an increase in the demand when the other parameter is fixed will result in a decrease of the second objective function, which represents, as discussed above, the number of tracks that should visit one node is increased and as a consequence total freshness will decreases.

{Please insert Figure 7 about here.}
{Please insert Figure 8 about here.}

6.3. Sensitivity analysis for the number of customers

The number of customers to be served is another important parameter that has a direct impact on objective functions. Analogously to the behavior observed in the previous subsection, even here both the objective functions increase with the number of nodes characterizing the distribution network. Such an increasing trend can be seen in Figures 9 and 10 for the specific case of period 1.

{Please insert Figure 9 about here.}
{Please insert Figure 10 about here.}

6. Conclusions

In this paper, a mixed-integer programming (MIP) model was proposed for solving a sustainable production-routing problem (PRP) with time windows, product deterioration and split delivery. This model aimed to determine the optimum production plan and to select the best vehicle routes for deliveries and considered two simultaneous objectives. Firstly, all types of costs (i.e., production, labor, transportation, holding, and penalty costs) were to be minimized. Secondly, the total freshness of the delivered products over the planning horizon was maximized. The main contribution of this paper was to develop an integrated framework that, besides sustainability, considers the product deterioration and the customer's demand satisfaction splitting. Also, to mimic the real-life behavior of some of the parameters, the fuzzy nature of the production, holding and setup costs was incorporated and their values were considered as fuzzy variables. A specialized interval robust possibilistic programming method was developed to cope with the uncertain parameters within the proposed model. Both the optimization model and solution approach were validated through the use of a case study. The results of this study showed that any increase in the number of customers would lead to more total freshness but also a higher total cost. Any increase in the demands would lead to less total freshness but a higher total cost. Our sensitivity analysis of the case study recommended the necessity of performing a careful trade-off between maximizing total freshness, which led to reaching customer satisfaction and minimizing the total production-distribution cost. As future developments, it may be useful to extend the model to consider the effect of the deterioration of a fraction of the products during the transportation phase and to include the disposal cost into the objective function. Also, the multi-products and periodic variants of the problem should be investigated (as per Triki et al., 2016a and 2016b).

References

Adulyasak, Y., Cordeau, J.-F., & Jans, R. (2014). Formulations and branch-and-cut algorithms for multivehicle production and inventory routing problems. *INFORMS Journal of Computing*, 24(1), 103-120.

Ambrosino, D. & Sciomachen, A. (2007). A food distribution network problem: A case study. *IMA Journal of Management Mathematics*, 18(1), 33-53.

Amorim, P., & Almada-Lobo, B. (2014). The impact of food perishability issues in the vehicle routing problem. *Computers & Industrial Engineering*, 67, 223-233.

Asgari, N., Nikbakhsh, E., Hill, A. & Zanjirani Farahani, R. (2016). Supply chain management 1982–2015: A review. *IMA Journal of Management Mathematics*, 27(3), 353-379.

Azadeh, A., Rahimi, Y., Zarrin, M., Ghaderi, A., & Shabanpour, N. (2017). A decision-making methodology for vendor selection problem with uncertain inputs. *Transportation Letters*, *9*(3), 123-140.

Bandeira, J. M., et al. (2018). "Advanced impact integration platform for cooperative road use." *International journal of intelligent transportation systems research* 16(1), 1-15.

Baños, R., Ortega, J., Gil, C., Fernández, A., & De Toro, F. (2013). A simulated annealing-based parallel multi-objective approach to vehicle routing problems with time windows. *Expert Systems with Applications*, 40(5), 1696-1707.

Berbeglia, G., Cordeau, J. F., Gribkovskaia, I., & Laporte, G. (2007). Static pickup and delivery problems*:* a Classification Scheme and Survey. *TOP*, 15(1), 1-31.

Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, 45(8), 1232-1250.

Braekers, K., Caris, A., & Janssens, G. K. (2014). Exact and meta-heuristic approach for a general heterogeneous dial-a-ride problem with multiple depots*. Transportation Research Part B: Methodological*, 67, 166-186.

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research*, 233(2), 299-312.

Brundtland, G. H. (1987). Our common future - Call for action. *Environmental Conservation*, 14(4), 291-294.

Chernykh, I. D., & Lgotina, E. V. (2020). Two-machine routing open shop on a tree: instance reduction and efficiently solvable subclass, to appear on *Optimization Methods and Software*, DOI: 10.1080/10556788.2020.1734802.

Çimen, M., & Soysal, M. (2017). Time-dependent green vehicle routing problem with stochastic vehicle speeds: An approximate dynamic programming algorithm. *Transportation Research Part D: Transport and Environment*, 54, 82-98.

Ćirović, G., et al. (2014). "Green logistic vehicle routing problem: Routing light delivery vehicles in urban areas using a neuro-fuzzy model." *Expert Systems with Applications* 41(9), 4245-4258.

Clarke, G., & Wright, J. W. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research*, 12(4), 568-581.

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management Science*, *6*(1), 80-91.

Fazli-Khalaf, M., Mirzazadeh, A., & Pishvaee, M. S. (2017). A robust fuzzy stochastic programming model for the design of a reliable green closed-loop supply chain network. *Human and Ecological Risk Assessment: An International Journal*, 23(8), 2119-2149.

Fledelius, W., & Mayoh, B. (2008). Toward a unified framework for swarm based image analysis. In: *AISB 2008 Convention Communication, Interaction and Social Intelligence,* Vol. 1, 64.

Fu L. L., Aloulou M. A. & Triki C. (2017). Integrated production scheduling and vehicle routing problem with job splitting and delivery time windows. *International Journal of Production Research*, 55(20), 5942—5957

Ghaffarkadhim, K., Harun, A., Othman, B. A., & Raja, P. (2019). Hypermarkets in malaysia: Issues of expansion, distribution and corporate social responsibility. *International Journal of Psychosocial Rehabilitation*, 23(2), 659-670.

Gharaei, A., & Jolai, F. (2020). Two heuristic methods based on decomposition to the integrated multi-agent supply chain scheduling and distribution problem. To appear on Optimization Methods and Software, DOI: 10.1080/10556788.2020.1714615.

Ghezavati, V., Hooshyar, S., & Tavakkoli-Moghaddam, R. (2017). A Benders' decomposition algorithm for optimizing distribution of perishable products considering postharvest biological behavior in agri-food supply chain: A case study of tomato, *Central European J. of Operations Research*, 25(1), 29-54.

Ghiani G., Quaranta A. & Triki C. (2007). New Policies for the Dynamic Traveling Salesman Problem, *Optimization Methods and Software,* 22(6), 971–983.

Ghoseiri, K., & Ghannadpour, S. F. (2010). Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. *Applied Soft Computing*, 10(4), 1096-1107.

Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. *European Journal of Operational Research*, 263(1), 108-141.

Haghjoo, N., Tavakkoli-Moghaddam, R., Shahmoradi-Moghadam, H., & Rahimi, Y. (2020). Reliable blood supply chain network design with facility disruption: A real-world application. *Engineering Applications of Artificial Intelligence*, *90*, 103493.

Inuiguchi, M. and Ramık, J. (2000). Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem, *Fuzzy Sets and Systems,* 111, 3-28, 2000.

Jackson, P., Evans, D. M., Truninger, M., Meah, A., & Baptista, J. A. (2019). The multiple ontologies of freshness in the UK and Portuguese agri-food sectors. *Transactions of the Institute of British Geographers*, 44(1), 79-93.

Jeong, I. J., & Illades Boy, C. A. (2018). Routing and refueling plans to minimize travel time in alternative-fuel vehicles. *International Journal of Sustainable Transportation*, 12(8), 583-591.

Kim, H., Yang, J., & Lee, K. D. (2011). Reverse logistics using a multi-depot VRP approach for recycling end-of-life customer electronic products in South Korea. *International Journal of Sustainable Transportation*, 5(5), 289-318.

Kumar, R. S., Kondapaneni, K., Dixit, V., Goswami, A., Thakur, L. S., & Tiwari, M. K. (2016). Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach. *Computers & Industrial Engineering*, 99, 29-40.

Kuznietsov, K.A., Gromov, V.A. & Skorohod V.A. (2017). Cluster-based supply chain logistics: A case study of a Ukrainian food distributor. *IMA Journal of Management Mathematics*, 28(4), 553-578.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59(3), 345-358.

Linton, J. D., Klassen, R., & Jayaraman, V. (2007). Sustainable supply chains: An introduction. *Journal of Operations Management*, 25(6), 1075-1082.

Midya, S., & Roy, S. K. (2014). Solving single-sink, fixed-charge, multi-objective, multi-index stochastic transportation problem. *American Journal of Mathematical and Management Sciences*, *33*(4), 300-314.

Mjirda, A., Jarboui, B., Mladenović, J., Wilbaut, C. & Hanafi, S. (2014). A general variable neighbourhood search for the multi-product inventory routing problem. *IMA Journal of Management Mathematics*, 27(1), 39-54.

Millet, D. (2011). Designing a sustainable reverse logistics channel: the 18 generic structures framework. *Journal of Cleaner Production*, 19(6-7), 588-597.

Mirmohammadi, S. H., Babaee Tirkolaee, E., Goli, A., & Dehnavi-Arani, S. (2017). The periodic green vehicle routing problem with considering of time-dependent urban traffic and time windows. *Iran University of Science & Technology*, *7*(1), 143-156.

Pantuso, G., Fagerholt, K., & Wallace, S. W. (2017). Which uncertainty is important in multistage stochastic programmes? A case from maritime transportation. *IMA Journal of Management Mathematics*, 28(1), 5-17.

Parragh, S. N., Doerner, K. F., & Hartl, R. F. (2008). A survey on pickup and delivery problems. *Journal für Betriebswirtschaft*, 58(1), 21-51.

Perrini, F., Castaldo, S., Misani, N., & Tencati, A. (2010). The impact of corporate social responsibility associations on trust in organic products marketed by mainstream retailers: a study of Italian consumers. *Business Strategy and the Environment*, 19(8), 512-526.

Pishvaee, M. S., Razmi, J., & Torabi, S. A. (2012). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets and Systems*, 206, 1-20.

Rahimi, Y., Tavakkoli-Moghaddam, R., Iranmanesh, S. H., & Vaez-Alaei, M. (2018). Hybrid approach to construction project risk management with simultaneous FMEA/ISO 31000/evolutionary algorithms: Empirical optimization study. *Journal of Construction Engineering and Management*, *144*(6), 04018043.

Kaveh, F., Tavakkoli-Moghaddam, R., Triki, C., Rahimi, Y., & Jamili, A. (2021). A new bi-objective model of the urban public transportation hub network design under uncertainty. *Annals of Operations Research*, 296:131–162.

Rajeev, A., Pati, R. K., Padhi, S. S., & Govindan, K. (2017). Evolution of sustainability in supply chain management: A literature review. *Journal of Cleaner Production*, 162.

Reich, A. Z., Xu, Y. H., & McCleary, K. W. (2010). The influence of social responsibility image relative to product and service quality on brand loyalty: an exploratory study of quick-service restaurants. *Hospitality Review*, 28(1), 2.

Mollanoori, H., Tavakkoli-Moghaddam, R., Triki, C., Hajiaghaei-Keshteli, M., & Sabouhi, F. (2019). Extending the solid step fixed-charge transportation problem to consider two-stage networks and multi-item shipments. *Computers & Industrial Engineering*, 137, 106008.

Samant, S. S., & Seo, H. S. (2016). Quality perception and acceptability of chicken breast meat labeled with sustainability claims vary as a function of consumers' label-understanding level. *Food quality and preference*, 49, 151-160.

Seuring, S. (2013). A review of modeling approaches for sustainable supply chain management. *Decision Support Systems*, 54(4), 1513-1520.

Shen, Z. J. M. (2006). A profit-maximizing supply chain network design model with demand choice flexibility. *Operations Research Letters*, 34(6), 673-682

Shu, J., Li, Z., & Zhong, W. (2012). A production–transportation problem with piecewise linear cost structures. *IMA Journal of Management Mathematics*, 23(1), 67-79.

Soleimani, H., Govindan, K., Saghafi, H., & Jafari, H. (2017). Fuzzy multi-objective sustainable and green closed-loop supply chain network design. *Computers & Industrial Engineering*, 109, 191-203.

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. *Journal of Cleaner Production*, 172, 960-970.

Sundarakani, B., De Souza, R., Goh, M., Wagner, S. M., & Manikandan, S. (2010). Modeling carbon footprints across the supply chain. *International Journal of Production Economics*, 128(1), 43-50.

Toth, P., & Vigo, D. (2002). Models, relaxations and exact approaches for the capacitated vehicle routing problem*. Discrete Applied Mathematics*, 123(1), 487-512.

Triki C., Piya S. & Fu L-L. (2020). Integrating the transportation procurement through auctions with the production scheduling decisions. Networks, 76, pp. 147–163.

Triki C., Al-Hinai N., Kaabachi I. and Krichen S. (2016a). An optimization framework for combining the petroleum replenishment problem with the optimal bidding in combinatorial auctions. *International Journal of Supply and Operations Management,* 3 (2), 1318-1331.

Triki C. and Al-Hinai N. (2016b). Optimization Techniques for Planning the Petrol Replenishment to Retail Stations over a Multi-Period Horizon. *International Journal of Operational Research*, 27(1-2), 341-355.

Varsei, M. (2016). Sustainable supply chain management: A brief literature review. *The Journal of Developing Areas*, 50(6), 411-419.

Weteling, R. (2013). Improving Freshness: The effects of week patterns and opening terms on outdating at Albert Heijn, https://pure.tue.nl/ws/files/46921995/752638-1.pdf.

Zahiri, B., Jula, P., & Tavakkoli-Moghaddam, R. (2018). Design of a pharmaceutical supply chain network under uncertainty considering perishability and substitutability of products. *Information Sciences*, 423, 257-283.

Zhalechian, M., Tavakkoli-Moghaddam, R., Zahiri, B., & Mohammadi, M. (2016). Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, 89, 182-214.

Figures

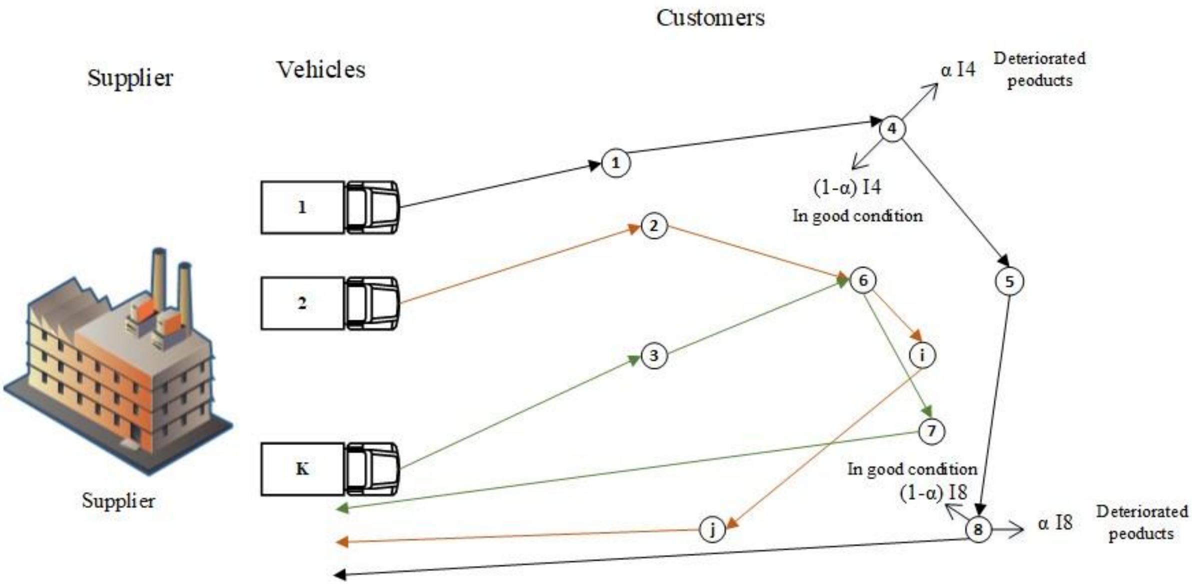

Figure 1. Vehicle routing with the split delivery and deteriorating products

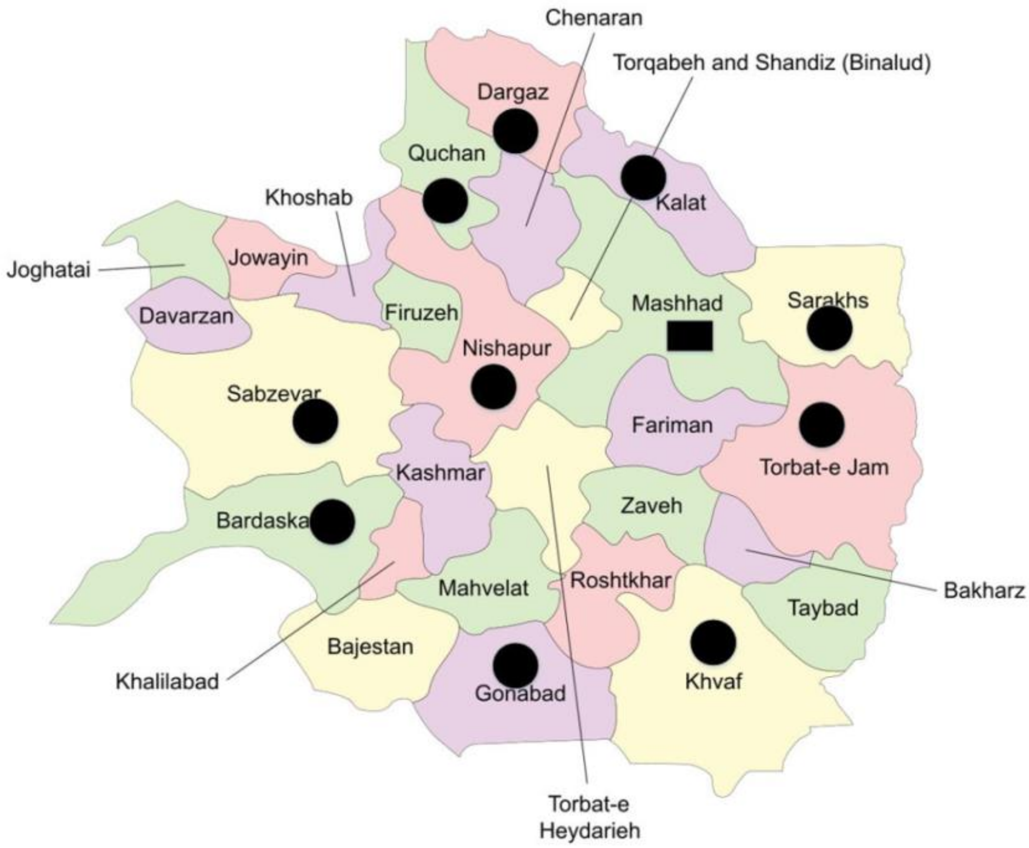

Figure 2. Locations of facilities in the Khorasan Razavi province

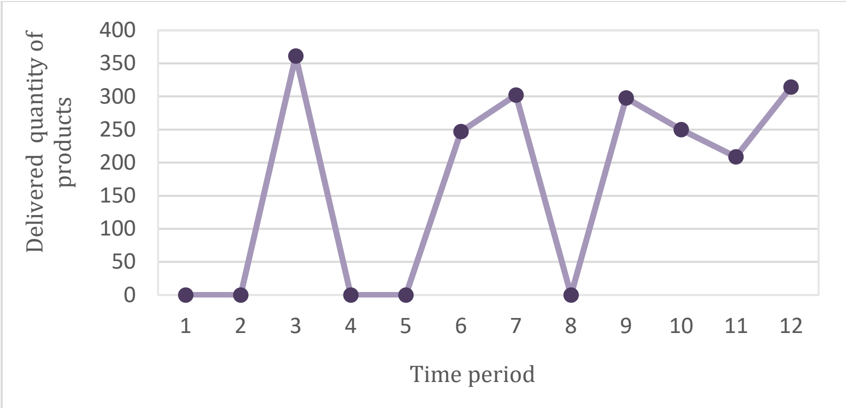

Figure 3. Amount of product delivered in each period to node 10.

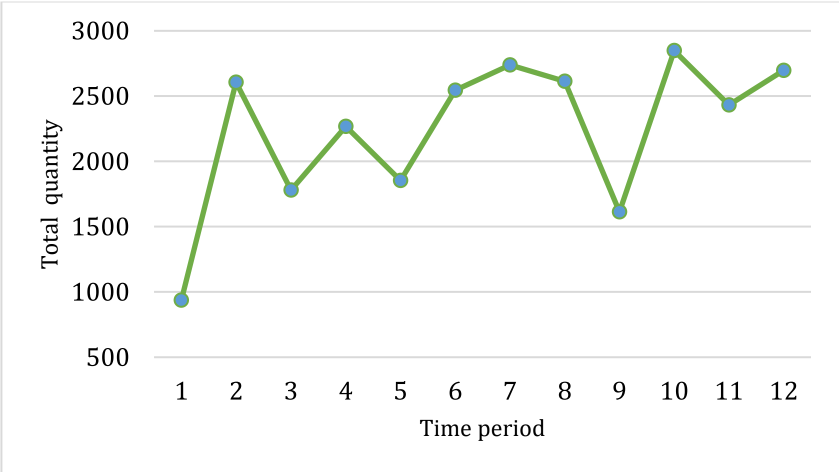

Figure 4. Amount of product delivered by the trucks in each period.

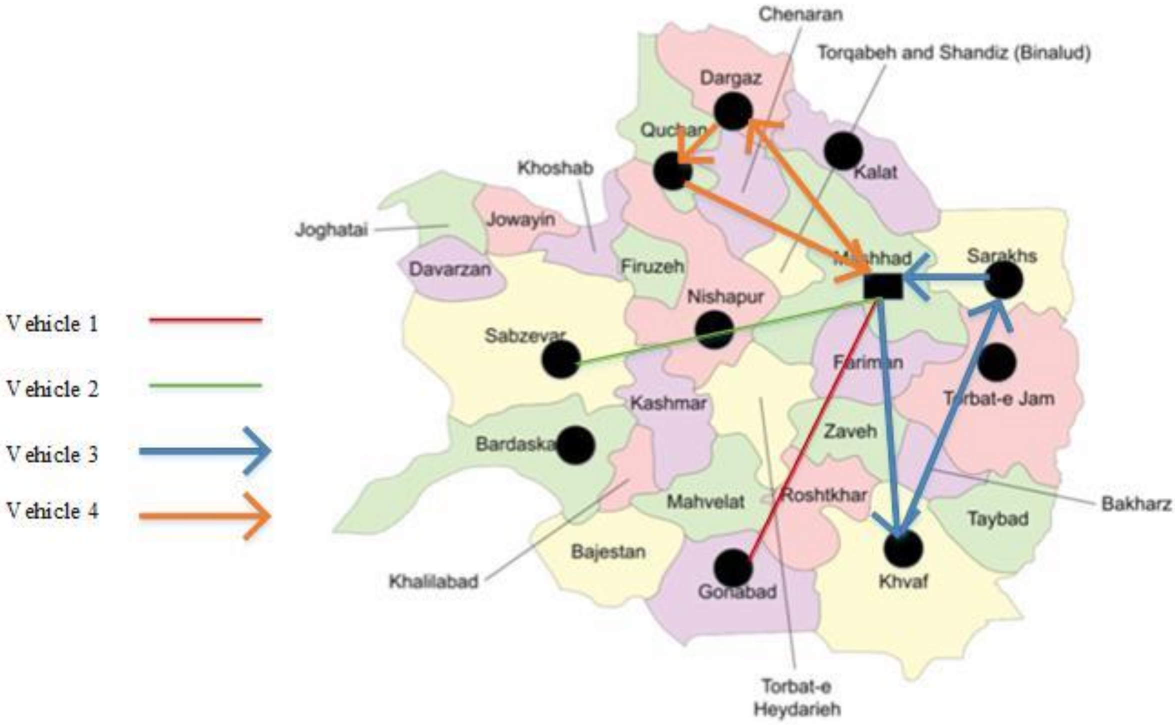

Figure 5. Trucks routes during period 9

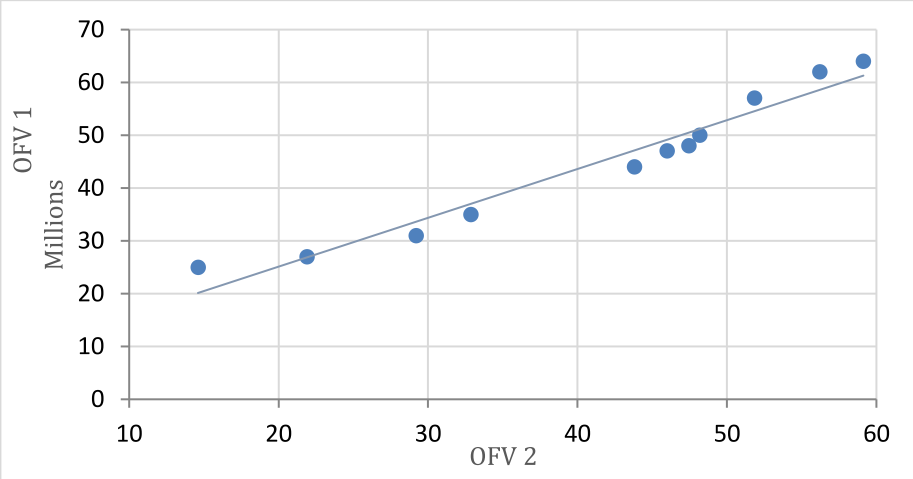

Figure 6. Reciprocal behavior of the objective functions.

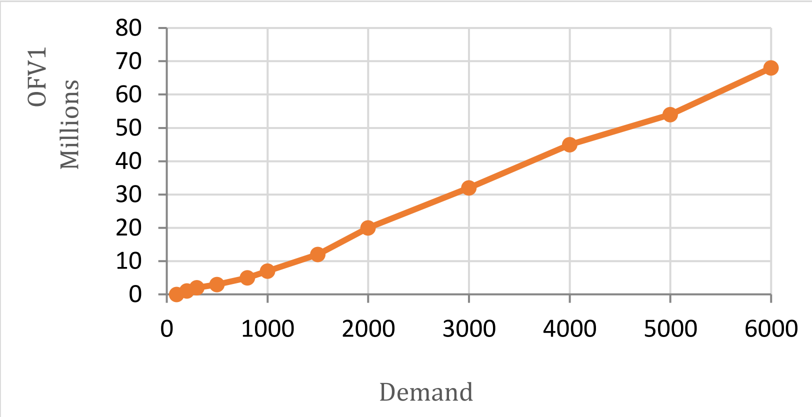

Figure 7. Behavior of objective function 1 with the demand increase

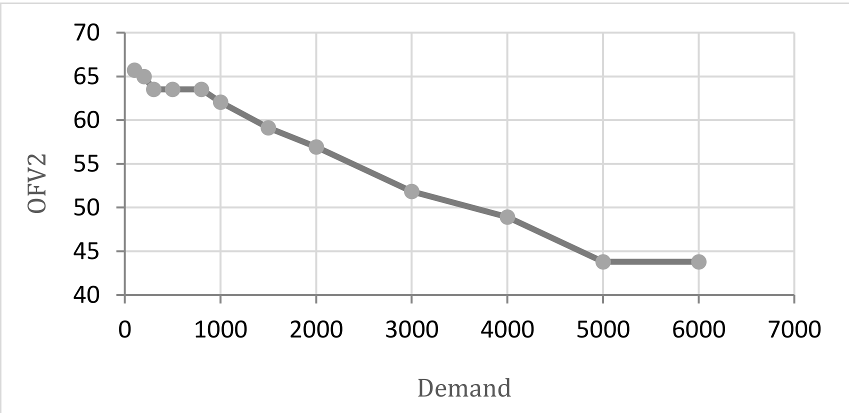

Figure 8. Behavior of objective function 2 the demand increase

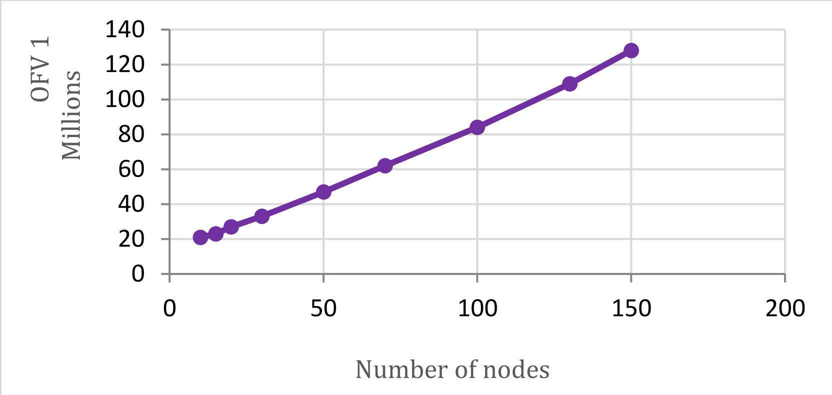

Figure 9. Behavior of objective function 1 with the number of nodes (in period 1)

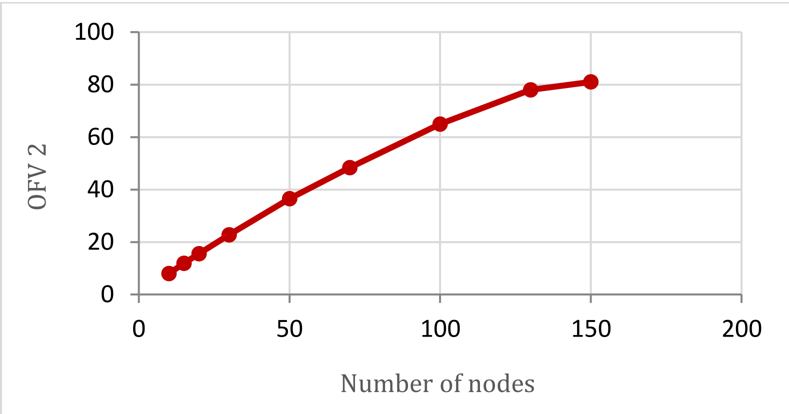

Figure 10. Behavior of objective function 2 with the number of nodes (period 1)

Tables

Table 1. List of uncertain parameters

Parameter	
u	$(u_{(1)}, u_{(2)}, u_{(3)})$
A	$(A_{(1)}, A_{(2)}, A_{(3)})$
S	$(S_{(1)}, S_{(2)}, S_{(3)})$
h_i	$(h_{i(1)}, h_{i(2)}, h_{i(3)})$
wd_i	$(wd_{i(1)}, wd_{i(2)}, wd_{i(3)})$
wc_i	$(wc_{i(1)}, wc_{i(2)}, wc_{i(3)})$
AL	$(AL_{(1)}, AL_{(2)}, AL_{(3)})$

Table 2. Number of nodes

No	0	2	4	6	8	10
Node	Mashhad	Quchan	Kalat	Dargaz	Sabzevar	Khvaf

No	1	3	5	7	9
Node	Sarakhs	Nishapur	Gonabad	Torbat-e-jam	Bardaskan

Table 3. Parameters of the H.M.S factory

α	C	Q	S	$(u_{(1)}, u_{(2)}, u_{(3)})$	A	K
0.4	6000	500	900000	(400, 600, 800)	800	50

Table 4. Initial inventory level, maximum inventory level and holding cost of each node

I	I_{i0}	L_i	$(h_{i(1)}, h_{i(2)}, h_{i(3)})$
1	100	200	(110, 130, 150)
2	420	400	(110, 130, 150)
3	130	200	(100, 115, 130)
4	370	400	(110, 125, 140)
5	145	200	(110, 125, 140)
6	280	300	(110, 120, 130)
7	190	300	(110, 120, 130)
8	287	400	(110, 120, 130)
9	80	250	(110, 125, 140)
10	364	500	(110, 130, 150)

Table 5. Distances between cities

i \ j	0	1	2	3	4	5	6	7	8	9	10
0	_	193	144	127	158	284	279	163	245	281	274
1		_	334	268	329	422	443	205	382	421	355
2			_	144	251	424	130	306	157	281	414
3				_	278	298	274	228	117	237	288
4					_	435	122	315	393	387	424
5						_	500	291	273	145	188
6							_	438	288	414	538
7								_	342	290	152
8									_	129	367
9										_	239
10											_

Table 6. Demand of customer i at period t

T \ I	1	2	3	4	5	6	7	8	9	10
1	215	204	220	145	0	207	0	0	487	0
2	602	0	508	0	643	0	567	287	157	0
3	0	0	0	219	0	320	249	0	585	492
4	467	0	510	507	452	0	96	0	254	0
5	0	195	0	0	0	293	487	587	279	0
6	527	0	471	0	517	449	165	0	168	247
7	0	429	0	396	347	0	687	204	374	302
8	645	0	591	0	478	614	157	0	128	0
9	173	206	0	0	379	217	0	357	0	298
10	0	459	497	0	397	401	278	0	467	250
11	412	0	0	0	473	339	0	377	481	209
12	0	393	521	0	516	604	468	0	0	314

Table 7. Production quantity to be received by each customer

I	I_{i0}	$t = 1$		$t = 2$		$t = 3$		$t = 4$		$t = 5$		$t = 6$	
		q_{ik1}	I_{i1}	q_{ik2}	I_{i2}	q_{ik3}	I_{i3}	q_{ik4}	I_{i4}	q_{ik5}	I_{i5}	q_{ik6}	I_{i6}
1	100	325	170	500	0	0	0	467	0	0	0	527	0
2	420	0	48	0	28	0	16	0	9	190	0	0	0
3	130	174	32	500	29	0	17	500	0	0	0	471	0
4	370	0	77	0	46	204	12	500	0	0	0	0	0
5	145	0	87	591	0	0	0	452	0	0	0	517	0
6	280	0	43	0	25	305	0	0	0	293	0	449	0
7	190	0	114	499	0	409	160	96	0	487	0	165	0
8	187	0	112	219	0	0	0	0	0	587	0	0	0
9	80	439	0	299	142	500	0	254	0	297	0	168	0
10	364	0	218	0	131	361	0	0	0	0	0	247	0

I	I_{i0}	$t = 7$		$t = 8$		$t = 9$		$t = 10$		$t = 11$		$t = 12$	
		q_{ik7}	I_{i7}	q_{ik8}	I_{i8}	q_{ik9}	I_{i9}	q_{ik10}	I_{i10}	q_{ik11}	I_{i11}	q_{ik12}	I_{i12}
1	100	0	0	645	0	173	0	0	0	412	0	0	0
2	420	429	0	0	0	206	0	459	0	0	0	393	0
3	130	0	0	591	0	0	0	497	0	0	0	521	0
4	370	396	0	0	0	0	0	0	0	0	0	0	0
5	145	347	0	478	0	379	0	397	0	500	27	500	0
6	280	0	0	614	0	217	0	500	99	454	174	500	0
7	190	687	0	157	0	0	0	278	0	0	0	468	0
8	287	204	0	0	0	358	0	0	0	377	0	0	0
9	80	374	0	128	0	0	0	467	0	481	0	0	0
10	364	302	0	0	0	298	0	250	0	209	0	314	0

Table 8. Number of trucks that visited customer *i* during time period *t*

T \ I	1	2	3	4	5	6	7	8	9	10
1	1	0	1	0	0	0	0	0	1	0
2	1	0	1	0	2	0	1	1	1	0
3	0	0	0	1	0	1	1	0	1	1
4	1	0	1	1	1	0	1	0	1	0
5	0	1	0	0	0	1	1	2	1	0
6	2	0	1	0	2	1	1	0	1	1
7	0	1	0	1	1	0	2	1	1	1
8	2	0	2	0	1	2	1	0	1	0
9	1	1	0	0	1	1	0	1	0	1
10	0	1	1	0	1	1	1	0	1	1
11	1	0	0	0	1	1	0	1	1	1
12	0	1	2	0	2	1	1	0	0	1

Table 9. Optimal routes

Truck k / Period	1	2	3	4	5	6
1	1	3-9				
2	1	3	5	7	5-9	8
3	9	7	4-10	4-6		
4	1	3	4	5	7-9	
5	7	8	9-8	6-2		
6	1	1-3	5	5-9-10	7	
7	2	4	9-8	7	10-7	5-8
8	5	3	1	6	1-7-6	9-3
9	5	8	10-1	6-2		
10	2	3	5-10	6	7-10	9
11	1-10	5	6	8-10	9	
12	2-3	3	5	6	10	7

Table 10. Objective function values for some instances

Instances	Test problem				
	k	i	t	OF1*10^6	OF2
1	2	4	4	1	7.2
2	3	5	5	1.7	10.87
3	3	6	4	1.5	10.44
4	4	6	7	3	16.8
5	5	8	6	2.5	17.4
6	4	7	5	2.1	14.6
7	6	9	8	5.8	22.7
8	5	8	7	3.9	18.1