A fuzzy optimization approach for procurement transport operational planning in an automobile supply chain

Abstract: We consider a real-world automobile supply chain in which a first-tier supplier serves an assembler and determines its procurement transport planning for a second-tier supplier by using the automobile assembler's demand information, the available capacity of trucks and inventory levels. The proposed fuzzy multi-objective integer linear programming model (FMOILP) improves the transport planning process for material procurement at the first-tier supplier level, which is subject to product groups composed of items that must be ordered together, order lot sizes, fuzzy aspiration levels for inventory and used trucks and uncertain truck maximum available capacities and minimum percentages of demand in stock. Regarding the defuzzification process, we apply two existing methods based on the weighted average method to convert the FMOILP into a crisp MOILP to then apply two different aggregation functions, which we compare, to transform this crisp MOILP into a single objective MILP model. A sensitivity analysis is included to show the impact of the objectives weight vector on the final solutions. The model, based on the full truck load material pick method, provides the quantity of products and number of containers to be loaded per truck and period. An industrial automobile supply chain case study demonstrates the feasibility of applying the proposed model and the solution methodology to a realistic procurement transport planning problem. The results provide lower stock levels and higher occupation of the trucks used to fulfill both demand and minimum inventory requirements than those obtained by the manual spreadsheet-based method.

Keywords: Fuzzy multi-objective integer linear programming; uncertainty modeling; supply chain planning; transport planning; procurement; automobile.

1. Introduction

The supply chain (SC) encompasses all the activities associated with moving goods from the raw materials stage to the end user, including sourcing and procurement, production scheduling, order processing, inventory management, transportation, warehousing and customer service (Quinn 1997). Transport processes are essential parts of the SC as they perform the flow of materials by connecting an enterprise with its suppliers and customers (Fleischmann 2005). Hence, transport planning contributes to: the overall successful SC management goal, the planning and control of material flows

(Ellram 1991), and the delivery of superior value to end consumers (Christopher and Towill 2001).

Frequently, real-world transport planning problems have two main properties; first, there are conflicting objectives in the problem structure; second, fuzziness at the aspiration levels of planners, and/or the epistemic uncertainty or lack of knowledge of some data. Fuzziness is modeled by fuzzy sets and may reflect the fact that goals or constraints are linguistically formulated, and that their satisfaction is a matter of tolerance and degrees or fuzziness (Bellman and Zadeh 1970). Epistemic uncertainty is concerned with ill-known parameters modeled by fuzzy numbers in the possibility theory setting (Zadeh 1978; Dubois and Prade 1988). Fuzziness and vagueness related to uncertain epistemic parameters can be found in Bhattacharya and Vasant (2007), Elamvazuthi et al. (2012), Vasant (2006), Vasant et al. (2010a, 2010b, 2010c) and Vasant el al. (2011), among others. The multi-objective nature and the existence of fuzzy goals, constraints or parameters make the mathematical expression of problems harder to solve with traditional approaches. In order to overcome this difficulty, the fuzzy set theory (Zadeh 1965; Bellman and Zadeh 1970) and the possibility theory have been applied to fuzzy multi-objective linear programming (FMOLP), and many approaches have been developed (Baykasoğlu and Göçken 2008; Cadenas and Verdegay 2000; Bhattacharya et al. 2007; Díaz-Madroñero et al. 2010; Ganesan et al. 2013; Vasant et al. 2007).

The SC procurement transport operational planning (SCPTOP) problem is used as a manual process based on planners' personal judgment and experience. Furthermore, manual processes consider a short or myopic time perspective when planning instead of an entire view of the whole horizon planning at any time, which could generate suboptimal plans. Given the motivation of providing optimal solutions to the SCPTOP problem, we propose a novel fuzzy multi-objective integer linear programming (FMOILP) model for the SCPTOP problem in a three-level, multi-product and multi-period SC network. The model's fuzzy goals are to minimize the number of used trucks and total inventory levels by determining the amount of each product to procure, which also contemplates the fuzzy data related to the transport maximum capacity levels and the minimum percentages of demand in stock. The fuzzy parameter of the FMOILP model is, firstly, defuzzified based on the possibility approach proposed by Lai and Hwang (1992), which is used in Liang (2006) and Wang and Liang (2005). Then, the FMOILP model, with fuzzy objective functions, is adapted to a mixed-integer linear programming (MILP) model by using the two fuzzy solution approaches provided by Selim and Ozkarahan (2008), based on Werners (1987), and Torabi and Hassini (2008), which we compare.

Moreover, an interactive solution methodology by Liang (2008) based on the previous works of Bellman and Zadeh (1970) and Zimmermann (1975, 1978) is adopted as the basis to solve the fuzzy multi-objective SCPTOP problem for the purpose of finding a preferred compromise solution. To illustrate the validity of the proposed solution method, we applied the FMOILP model to a real-world automobile SC and compared the results obtained with the manual procedure currently applied.

The rest of the paper is arranged as follows. Section 2 presents a literature review about supply chain transport planning at the operational level under uncertain conditions. Section 3 proposes the FMOILP model for the SCPTOP problem. Section 4 and Section 5 describe the solution methodology. Next, Section 6 evaluates the behavior of the proposed model in a real-world automobile SC. Finally, Section 7 provides conclusions and directions for further research.

2. Literature review

The scope of this work is the procurement transport operational planning problem based on mathematical programming approaches. Along these lines, several authors have analyzed supply chain operational transport planning from a deterministic point of view. Cisheng et al. (2008) analyze the model of load matching. An effectual truck stowage planning model is proposed by equilibrating truck cargo weight and volume. Moreover, Sarkar and Mohapatra (2008) describe a case of an integrated steel plant where the plant engages a third-party transporter to bring a large number of items from its suppliers by maximizing the utilization of the vehicles capacity.

In our previous works (Mula et al. 2010; Peidro et al. 2009a; 2009b; 2010b), we review and provide several approaches for SC planning under uncertainty conditions. Among them, the fuzzy mathematical programming for transport planning is being increasingly applied. Chanas et al. (1993) consider several assumptions on the supply and demand levels for a given transportation problem in accordance with the type of information the decision maker has. On the other hand, Shih (1999) addresses the cement transportation planning problem in Taiwan by using fuzzy linear programming with three different approaches (Zimmermann 1975; Chanas 1983; Julien 1994). Bilgen and Ozkarahan (2006) present a distribution planning problem in an uncertain environment with a fuzzy linear programming approach. Bilgen (2007) proposes a possibilistic linear programming model for solving the blending and multi-mode, multi-period distribution planning problem with uncertain transportation, blending and storage costs. Moreover, Aliev et al. (2007) present an integrated multi-period multi-product production-distribution aggregate planning model in the SC in which customer demand and capacities in production environment are uncertain. More recently, Bilgen (2010) proposes a model which addresses the production and distribution planning problem in a SC system that involves allocation of production volumes among the different production lines in manufacturing plants, and the delivery of products to distribution centers under uncertain conditions. Kumar et al. (2011) and Kumar and Kaur (2012) present new methods to find the fuzzy optimal solution of fuzzy transportation with transshipment and unbalanced problems occurring in real life situations. On the hand, Vinotha et al. (2012) propose an algorithm for solving total time minimization in fuzzy transportation problem where the transportation time, source and destination parameters have been expressed as exponential fuzzy numbers by the decision maker.

With regard to multi-objective linear programming (MOLP) models, some works (for instance, Bit et al. (1993a), Bit et al. (1993b), Bit (2005), Jiménez and Verdegay (1998), Li and Lai (2000), and Lee and Li (1993)) provide fuzzy programming approaches to solve multi-objective transportation problems in a fuzzy environment. Besides, Liang (2006) and Liang (2008) develop an interactive multi-objective method for solving transportation planning problems by using fuzzy linear programming and a piece-wise linear membership function. Moreover, Peidro and Vasant (2011) consider the transportation planning decision problem with fuzzy goals, available supply and forecast demand represented by modified S-curve membership functions which is solved by using an interactive fuzzy multi-objective approach. On the other hand, Jolai et al. (2010) and Torabi and Hassini (2009) present MOLP models for SC planning, solved by using fuzzy mathematical programming approaches.

After a review process, we highlight the following issues relating to the SCPTOP problem:

- There is a need for multi-objective models to optimize conflicting objectives simultaneously and to manage the use of the constrained resources within organizations.
- Transport capacities are expressed in general terms without specifying the transport mode or the type of vehicle used.
- The consideration of uncertainty in procurement transport models is scarce.

- Shortage of validated transport planning models applied to real supply chains.

These aspects are taken into account to address the SCPTOP problem in this work.

3. Problem description

The SCPTOP problem considered herein refers to a three-level SC of the automobile industry sector (see Figure 1). This SC consists of an automobile assembler, a first-tier supplier and a second-tier supplier. The procurement process of materials at the first-tier supplier level considers different pick-up methods: load form or full truck load, partial load or less than load and pick-up at the suppliers, or milk-round (see Hernández et al. (2008) for an explanation of the different material pick-up methods).

Transport planning is usually the supplier's responsibility, but there are important exceptions, e.g., in the automobile industry, where the manufacturer controls transport from suppliers. In this case, transport planning also occurs on the procurement side (Fleischmann 2005). The SCPTOP problem refers to a specific problem related to the associated procurement stage and transport in the automobile industry. A similar problem for the full truck load method was previously studied by Peidro et al. (2010a) for a first-tier supplier's procurement transport planning. Here we consider product groups, order lot sizes and vehicle capacities, which are expressed in terms of numbers of containers.

The current decision-making procedure for the considered SCPTOP problem is based on the use of a Microsoft Excel spreadsheet, which the first-tier supplier is in charge of. The second-tier supplier establishes product groups. Each product group consists of 3 items determined by the different options that the car assembler offers to end customers. The second-tier supplier requires orders to be released by these product groups and their associated order lot size, which implies a high cost to penalize those additional parts ordered in an unbalanced way. However given the product characteristics, which can easily deteriorate once stored, unbalanced inventory levels among the different product groups parts could exist.

The procedure initiates by obtaining the initial stock of each product at the beginning of the planning period by using the data stored in the company information system, along with the daily demand of each given reference. The stock and demand values for each part in each time period determine the decision of requesting a new full truck load. The second-tier supplier supplies its products at the beginning of each period, but only once the first-tier supplier has started production. As the car assembler does not allow delays in demand by the first-tier supplier, should the inventory of any part at the end of the first period be lower than 40% of the demand level in the next period, then the first-tier supplier will include a new truck in period 1.

Truck loads are done in terms of available capacity (between 84 and 90 containers per truck), the product groups formed by those items which must be ordered together, and the ordering lot size associated with all these groups. Thus having located the first item, of which the available stock does not exceed at least 40% of demand for the next period, the amount needed to cover the rest of the demand is manually entered into the spreadsheet as an integer multiple of the lot size order. The same applies for the other items of the given product group. The inventory level is updated in the spreadsheet by incorporating the order quantities, while the total amount of supply containers to be loaded onto the truck is determined in the spreadsheet by the number of units of each product to fit in a container. Then, the operation is repeated for the following item whose current inventory is below 40% of demand in the next period, and so on. Should additional space be available, truck occupation is completed with product lots and with a more frequent demand once the necessary quantities of all the products have been determined, while maintaining the established groups and corresponding lot sizes.

After having updated the stock values, in terms of the amounts to be ordered for the new truck, the inventory of a certain part is, once again, lower than the 40% demand level of the next period, this process will then be repeated by adding the number of trucks required until the stock values of all the parts are higher than the demand levels of the following period. Subsequently, this process will be repeated for all the periods until the end of the planning horizon is reached.

At the end of this process, the staff in charge of procurement planning could modify the amounts obtained to fulfill the established objectives based on their personal judgment and experience. This practice, which is often present in the automobile industry, can generate sub-optimal solutions (Allen and Liu 1995; Evans et al. 1990).

Thus, we state the SCPTOP problem in the automobile SC considered as follows:

Given:

- A SC topology (assembler, first-tier supplier and second-tier supplier).
- Product data, such as order lot sizes, number of units that fits in a container, product groups that must be ordered together.
- Transportation data, such as transport capacities, the number of available trucks in each period, the minimum truck occupation to fill.

- Initial inventory.
- Assembler demand over the entire planning periods.

To determine:

- The amount of each product to order per period.
- The inventory level of each product per period.
- The number of trucks required in each period and their occupation.

The main goals to meet are:

- Minimize the number of trucks.
- Minimize the inventory levels to satisfy assembler demand without backordering.

Moreover, the following assumptions have been made:

- The assembler demand is considered to be firm throughout the planning horizon. Because it is an operational level problem, planning horizons are short (lasting a few days) and demand does not vary.
- This model does not consider supplier transportation times, although it indicates the period to receive the amounts to be transported.
- In general, for a transportation model the holding costs at customers and/or suppliers are parameters that have direct effect on inventory levels. Most of the time the holding costs are deterministic, also in the same way if the truck cost is available. However, holding costs and truck costs are not managed by the company in this operational decision level for this specific problem, so that they were not available have not been estimated.

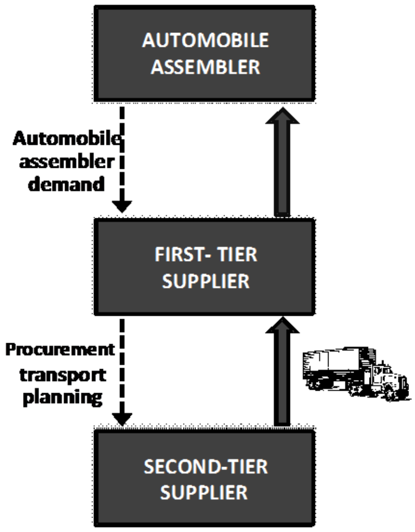

Figure 1. Automobile SC considered in the SCPTOP problem

4. Model formulation

In this section, we propose a new FMOILP model for the SCPTOP problem in order to improve the results obtained by the manual procedure described in the previous section. The model, based on the full truck load material pick method, provides the quantity of products and number of containers to be loaded per truck and period. The main novelty of this model is the optimization of truck loads by ensuring the minimum stock coverage at an operational level. The model considers fuzzy parameters in nature and fuzzy aspiration levels, which can be prioritized through two fuzzy programming solution methods based on weight assignments. The proposed model considers fuzzy objectives and fuzzy data relating to both the transport capacity levels and the minimum demand in stock percentages. The nomenclature defines the sets of indices, parameters and decision variables for the FMOILP model (Table 1).

Table 1. Nomenclature (a tilde ~ denotes the fuzzy parameters)

Sets of indices	
I:	Set of products (i =1, 2,…,I).
J:	Set of groups composed of products that must be ordered together (j =1,2,…,J).
K:	Set of trucks (k =1, 2,…,K).
T:	Set of planning periods (days) (t =1, 2…T).
Decision variables	
Q_{ikt}:	Units transported of i by k in period t (units).
G_{ijkt}:	Units transported of i corresponding to group j by k in period t (units).
C_{kt}:	Amount of containers transported by k in period t (units).
I_{it}:	Inventory amount of i at the end of period t (units).
K_{jkt}:	Number of lots to order of products of group j by k in period t.
Y_{kt}:	Binary variable indicating whether a truck k has been used in period t.
Objective functions	
z_1:	Total number of trucks utilized.
z_2:	Total inventory amount generated.
Parameters	
u_i:	Amount of product i that fits in a container (units).
l_j:	Number of units of each group lot j (units).
b_{ij}:	1 if product i belongs to group j, and 0 otherwise
D_{it}:	Demand of product i in t (units) (*considered firm*).
$\tilde{M}$:	Fuzzy maximum capacity of the available truck (in containers)
m:	Minimum truck occupation (in containers).
$\tilde{\eta}$:	Fuzzy minimum percentage of demand in period $t+1$ in stock at the end of period t
$I0_i$:	Inventory amount of i in period 0.

The formulation of the FMOILP model is as follows:

There are two objectives to simultaneously optimize:

Minimize the total number of trucks utilized

$$\mathrm{Min}\, z_1 \cong \sum_{k=1}^{K}\sum_{t=1}^{T} Y_{kt} \tag{1}$$

Minimize the total inventory amount generated.

$$\mathrm{Min}\, z_2 \cong \sum_{i=1}^{I}\sum_{t=1}^{T} I_{it} \tag{2}$$

subject to

$$I_{it} = I_{i(t-1)} - D_{it} + \sum_{k=1}^{K} Q_{ikt} \qquad \forall i,t \tag{3}$$

$$Q_{ikt} = \sum_{j=1}^{J} G_{ijkt} \qquad \forall i,k,t \tag{4}$$

$$G_{ijkt} = K_{jkt} \cdot l_j \cdot b_{ij} \qquad \forall i,j,k,t \tag{5}$$

$$C_{kt} = \sum_{i=1}^{I} Q_{ikt} / u_i \qquad \forall k,t \tag{6}$$

$$C_{kt} \leq \tilde{M} \cdot Y_{kt} \qquad \forall k,t \tag{7}$$

$$C_{kt} \geq m \cdot Y_{kt} \qquad \forall k,t \tag{8}$$

$$I_{it} \geq \tilde{\eta} \cdot D_{it+1} \qquad \forall i,t \tag{9}$$

$$Y_{kt} \leq 1 \qquad \forall k,t \tag{10}$$

$$I_{it},\, Q_{ikt},\, G_{ijkt},\, C_{kt},\, K_{jkt},\, Y_{kt} \geq 0 \text{ integer} \qquad \forall i,j,k,t \tag{11}$$

For each objective function, the decision maker has fuzzy objectives. Symbol "≅" is the fuzzified version of "=" and refers to the fuzzification of the aspiration levels. Accordingly, Eqs. (1) and (2) are fuzzy, and the decision maker needs to simultaneously optimize these conflicting objectives within the fuzzy aspiration levels framework. Constraint (3) is the inventory balance constraint. Constraint (4) determines the amount of each product to be transported per truck and period. Constraint (5) establishes the order lot size for all the items in each product group. Constraint (6) calculates the containers placed in each truck in accordance with both the quantities of each product ordered and the number of units of each product that fits in a container. Constraint (7) limits the maximum number of containers per truck loaded. Constraint (8) ensures that the occupied capacity on each truck is over *m* containers by avoiding trucks with slack. Next, Constraint (9) ensures the minimum inventory level for each product in each period. Finally, Constraints (10) and (11) define Y_{kt} as a binary variable and establish the non negative and integrality conditions of the decision variables , respectively.

In this SCPTOP problem, $\tilde{M}$ and $\tilde{\eta}$ are fuzzy in nature. To a great extent, truck storage capacity (in containers per truck) depends on the exact combination of the loaded

products and in such a way that, despite us theoretically knowing the meters occupied by a single product on the truck when combined with other products, the total occupied truck capacity does not exactly match the arithmetical sum of what each loaded product occupies. On the other hand, the minimum percentage of demand in period t+1 in stock at the end of period t, $\tilde{\eta}$, should be considered a fuzzy parameter since its estimation could not be done precisely in practice. We consider that the rest of the parameters are crisp because the related information is well-known over the planning horizon. We also assume that demand data are certain because we use firm orders in this operational decision-level problem with short (a few days) planning horizons.
Figure 2 provides an overall block diagram for the proposed method.

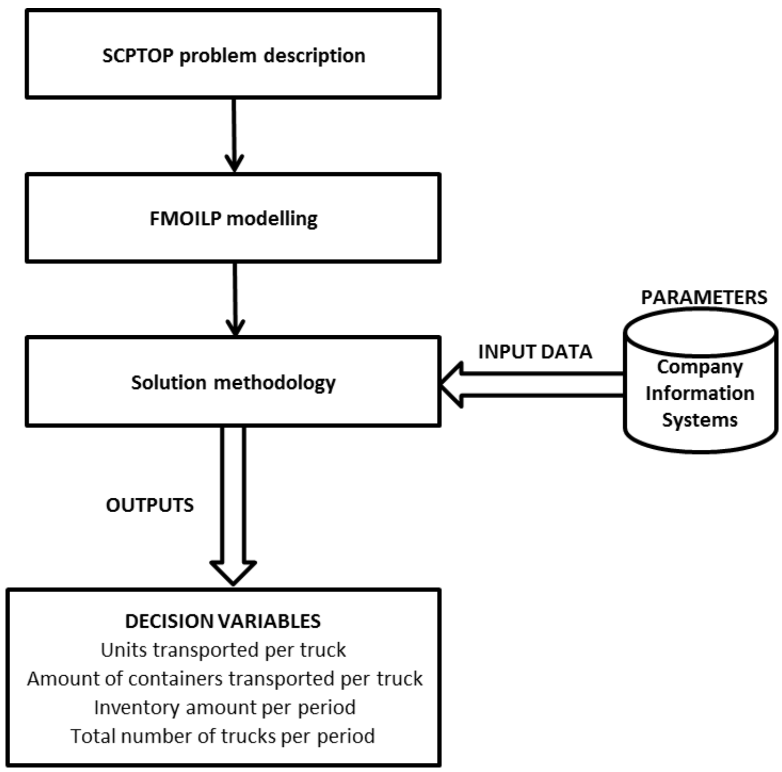

Figure 2. Overall block diagram

5. Solution methodology

In order to reach a preferred solution for the SCPTOP problem, the uncertain parameters, $\tilde{M}$ and $\tilde{\eta}$, are firstly defuzzified by using triangular fuzzy numbers. Then, the fuzzy programming solution methods of Selim and Ozkarahan (2008) and Torabi and Hassini (2008) are adopted to transform the FMOILP model, with fuzzy objective functions, into a MILP model. Furthermore, an interactive solution procedure based on Liang (2008) is proposed to solve the SCPTOP problem.

5.1 Defuzzifying the fuzzy parameters

We apply the weighted average method (Liang 2006; Wang and Liang 2005; Lai and Hwang 1992). Therefore, if the minimum acceptable level of possibility, β, is given, Constraints (7) and (9) can be formulated as follows:

$$C_{kt} \leq (w_1 M_\beta^p + w_2 M_\beta^m + w_3 M_\beta^o) \cdot Y_{jt} \tag{12}$$

$$I_{it} \geq (w_1 \eta_\beta^p + w_2 \eta_\beta^m + w_3 \eta_\beta^o) \cdot D_{it+1} \tag{13}$$

where $w_1+w_2+w_3=1$, and w_1, w_2 and w_3 denote the weights of the most pessimistic, the most possible and the most optimistic value, respectively, for the fuzzy triangular number which represents the fuzzy maximum truck load. Based on the most likely values concept proposed by Lai and Hwang (1992), and considering the works by Liang (2006) and Wang and Liang (2005), we set these parameters as: w_2 =4/6, w_1= w_3 =1/6 and β = 0.5. According to Lai and Hwang (1992) the weights between M_β^p $\left(\eta_\beta^p\right)$, M_β^m $\left(\eta_\beta^m\right)$, and M_β^o $\left(\eta_\beta^o\right)$ can be changed subjectively. The reason of using the above weighted average values is that M_β^p $\left(\eta_\beta^p\right)$ is too pessimistic and M_β^o $\left(\eta_\beta^o\right)$, too optimistic. Of course these two boundary values provide boundary solutions. Besides, Lai and Hwang state that the most possible values are often the most important ones. In this sense, taking into account the simetric boundary values provided by the decision maker, we have considered a higher value of w_2, and lower and identical values of w_1 and w_3 (w_1= w_3). By considering this weight structure, same results in terms of number of trucks and total stock should be obtained, although the values of w_2, w_1 and w_3 vary. Anyway, if we consider a higher value of w_3 respect to w_1, the amount of total stock obtained will be higher than those obtained by the considered weight structure while if we consider a lower value of w_3 respect to w_1, better results could be obtained.

5.2 Transforming the FMOILP model into a MILP model

In order to solve MOLP models, several approaches have been proposed in the literature (Ehrgott and Wiecek 2005). Among them, fuzzy programming approaches are highly applied, especially in recent years because of their capability to directly measure the satisfaction level of each objective function.

There are many possible forms for a membership function to represent the fuzzy objective functions: linear, exponential, hyperbolic, hyperbolic inverse, piece-wise linear, etc. (see Peidro and Vasant (2009) for a comparison of the main types of membership functions). Among the various types of membership functions, the most feasible for constructing a membership function for solving fuzzy mathematical programming problems is the linear form, although there may be preferences for other patterns with some applications (Zimmermann 1975; Zimmermann 1978; Tanaka et al. 1984). Moreover, the main advantage of the linear membership functions is that they generate equivalent, efficient and computationally linear models.

We formulate the corresponding non increasing continuous linear membership functions for each objective function as follows (Bellman and Zadeh 1970):

$$\mu_1 = \begin{cases} 1 & z_1 < z_1^l \\ \dfrac{z_1^u - z_1}{z_1^u - z_1^l} & z_1^l < z_1 < z_1^u \\ 0 & z_1 > z_1^u \end{cases} \tag{14}$$

$$\mu_2 = \begin{cases} 1 & z_2 < z_2^l \\ \dfrac{z_2^u - z_2}{z_2^u - z_2^l} & z_2^l < z_2 < z_2^u \\ 0 & z_2 > z_2^u \end{cases} \tag{15}$$

where $\mu_1(\mu_2)$ is the membership function of $z_1(z_2)$, while $z_1^l(z_2^l)$ and $z_1^u(z_2^u)$ are, respectively, the lower and upper bounds of the objective function $z_1(z_2)$. We can determine each membership function by asking the decision maker to specify the fuzzy objective value interval (14)-(15), as well as the lower and upper bounds of the fuzzy parameters (12)-(13). Membership functions μ_1 and μ_2 are represented in Figure 3 and Figure 4, respectively.

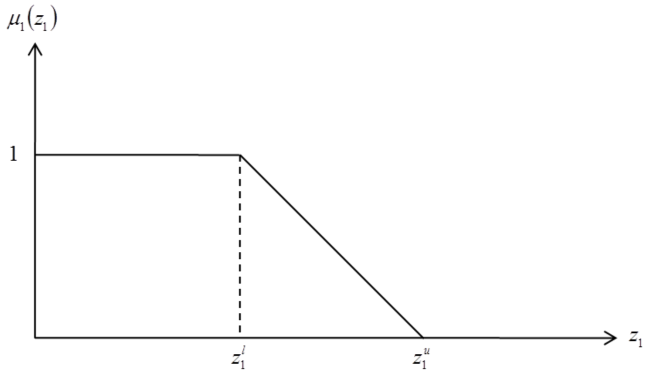

Figure 3. Membership function of z_1

Figure 4. Membership function of z_2

5.2.1 The Selim and Ozkarahan (2008) approach

Selim and Ozkarahan (2008) propose a fuzzy solution approach for solving FMOLP problems, with fuzzy objective functions, by modifying Werner's aggregation function (Werners 1988). According to these authors, a fuzzy multi-objective model can be transformed into a single objective model as follows:

$$\text{Max} \quad \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \lambda_k(x)$$

subject to

$$\lambda_0 + \lambda_k \leq \mu_h(x) \quad k = 1,...,n$$

$$x \in F(x)$$

$$\lambda_0, \lambda_k, \gamma \in [0,1] \tag{16}$$

where μ_k and $\lambda_0 = \min\{\mu_k(x)\}$ denote the degree of satisfaction corresponding to the *kth* objective function and the minimum degree of satisfaction of the objectives, respectively. Furthermore, λ_k denotes the difference between each objective's level of satisfaction and the minimum level of satisfaction corresponding to the objectives ($\lambda_k = \mu_k - \lambda_0$). Moreover, θ_k and γ indicate the relative importance of the *kth* objective function and the compensation coefficient, respectively. The θ_k parameters are determined by the decision maker based on her/his preferences so that $\sum_k \theta_k = 1, \theta_k > 0$.

Selim and Ozkarahan's aggregation function seeks a compromise value between the min operator and the weighted sum operator based on the γ value. Thus, a low γ value means that the model attempts to find a solution by focusing more on obtaining a better degree of satisfaction for the most weighted objective and by paying less attention to achieving a higher level of minimum satisfaction for the objectives. A high γ value means that the model places more importance on maximizing the minimum degree of satisfaction for the objectives, independently of the weights assigned to the objective functions. In other words, the decision makers can obtain both balanced and unbalanced compromised solutions by setting the value of parameters θ_k and γ based on their preferences (see Wang and Shu (2007) for details).

According to Selim and Ozkarahan (2008), the equivalent MILP model can be formulated as follows to solve the SCPTOP problem:

Max $\lambda(x) = \gamma\lambda_0 + (1-\gamma)(\theta_1\lambda_1 + \theta_2\lambda_2)$ (17)

subject to

$$\lambda_0 + \lambda_1 \leq \mu_1 \quad (18)$$

$$\lambda_0 + \lambda_2 \leq \mu_2 \quad (19)$$

$$I_{it} = I_{i(t-1)} - D_{it} + \sum_{k=1}^{K} Q_{ikt} \quad \forall i,t \quad (20)$$

$$Q_{ikt} = \sum_{j=1}^{J} G_{ijkt} \quad \forall i,k,t \quad (21)$$

$$G_{ijkt} = K_{jkt} \cdot l_j \cdot b_{ij} \quad \forall i,j,k,t \quad (22)$$

$$C_{kt} = \sum_{i=1}^{I} Q_{ikt} / u_i \quad \forall k,t \quad (23)$$

$$C_{kt} \leq (w_1 M_\beta^p + w_2 M_\beta^m + w_3 M_\beta^o) \cdot Y_{jt} \quad \forall k,t \quad (24)$$

$$C_{kt} \geq m \cdot Y_{kt} \quad \forall k,t \quad (25)$$

$$I_{it} \geq (w_1 \eta_\beta^p + w_2 \eta_\beta^m + w_3 \eta_\beta^o) \cdot D_{it+1} \quad \forall i,t \quad (26)$$

$$Y_{kt} \leq 1 \quad \forall k,t \quad (27)$$

I_{it}, Q_{ikt}, G_{ijkt}, C_{kt}, K_{jkt}, $Y_{kt} \geq 0$ integer $\quad \forall i,j,k,t$ (28)

$$\lambda_0, \lambda_1, \lambda_2, \gamma \in [0,1] \quad (29)$$

5.2.2 The Torabi and Hassini (2008) approach

Torabi and Hassini (2008) propose a new single-phase fuzzy approach as a combination of the previous methods of Lai and Hwang (1993) and Selim and Ozkarahan (2008). According to Torabi and Hassini (2008), a multi-objective model could be transformed into a single objective model as follows:

Max $\lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \mu_k(x)$

subject to

$$\lambda_0 \le \mu_k(x) \quad k = 1,\ldots,n$$

$$x \in F(x)$$

$$\lambda_0, \gamma \in [0,1] \tag{30}$$

where μ_k and $\lambda_0 = \min\{\mu_k(x)\}$ denote the satisfaction degree of the *kth* objective function and the minimum degree of satisfaction of objectives, respectively. Moreover, θ_k and γ indicate the relative importance of the *kth* objective function and the compensation coefficient, respectively. Besides, γ controls not only the objectives' minimum level of satisfaction, but also the degree of compromise among the objectives implicitly. That is, the proposed formulation is capable of yielding both unbalanced and balanced compromised solutions for a given problem based on the decision maker's preferences by adjusting the value of parameter γ (Torabi and Hassini 2008). By using the fuzzy decision making of Bellman and Zadeh (1970) and the Torabi and Hassini (2008) fuzzy programming method, we can formulate the complete equivalent crisp single-goal LP model to solve the SCPTOP problem as follows:

$$\text{Max} \quad \lambda(x) = \gamma\lambda_0 + (1-\gamma)(\theta_1\mu_1 + \theta_2\mu_2) \tag{31}$$

subject to

$$\lambda_0 \le \mu_1 \tag{32}$$

$$\lambda_0 \le \mu_2 \tag{33}$$

$$I_{it} = I_{i(t-1)} - D_{it} + \sum_{k=1}^{K} Q_{ikt} \qquad \forall i,t \tag{34}$$

$$Q_{ikt} = \sum_{j=1}^{J} G_{ijkt} \qquad \forall i,k,t \tag{35}$$

$$G_{ijkt} = K_{jkt} \cdot l_j \cdot b_{ij} \qquad \forall i,j,k,t \tag{36}$$

$$C_{kt} = \sum_{i=1}^{I} Q_{ikt} / u_i \qquad \forall k,t \tag{37}$$

$$C_{kt} \le (w_1 M_\beta^p + w_2 M_\beta^m + w_3 M_\beta^o) \cdot Y_{jt} \qquad \forall k,t \tag{38}$$

$$C_{kt} \ge m \cdot Y_{kt} \qquad \forall k,t \tag{39}$$

$$I_{it} \ge (w_1 \eta_\beta^p + w_2 \eta_\beta^m + w_3 \eta_\beta^o) \cdot D_{it+1} \qquad \forall i,t \tag{40}$$

$$Y_{kt} \le 1 \qquad \forall k,t \tag{41}$$

$$I_{it},\ Q_{ikt},\ G_{ijkt},C_{kt},\ K_{jkt},Y_{kt} \ge 0 \text{ integer} \qquad \forall i,j,k,t \tag{42}$$

$\lambda_0, \gamma \in [0,1]$ (43)

5.3 Interactive solution procedure

Here, the interactive solution procedures proposed by Liang (2008) are adapted to solve the SCPTOP problem. This procedure provides a systematic framework that facilitates the fuzzy decision-making process, thus enabling the decision maker to interactively adjust the search direction during the solution procedure to obtain the decision maker's preferred satisfactory solution (Liang 2008).

In summary, our proposed interactive solution procedure is as follows:

- Step 1. Formulate the original FMOILP model for the SCPTOP problem according to Eqs. (1) to (11).
- Step 2. Specify the corresponding linear membership functions for all the fuzzy objective functions and the fuzzy parameters using (14), (15) and (12) and (13), respectively.
- Step 3. Determine the minimum acceptable level of possibility, β, for Constraints (24), (26), (38) and (40) and specify the corresponding relative importance of the objective functions, (θ_k), and the compensation coefficient, γ, in (17) and (31).
- Step 4. Transform the original FMOILP problem into an equivalent MILP form by using the above-presented methodology.
- Step 5. Solve the proposed auxiliary crisp single-objective model by the MIP solver and obtain the initial compromise solution for the SCPTOP problem.
- Step 6. If the decision maker is satisfied with this current efficient compromise solution, stop. Otherwise, go back to Step 2 and provide another efficient solution by changing the value of the controllable parameters (β, θ_k , γ, $\tilde{M}$ and $\tilde{\eta}$).

Figure 5 presents the flow chart of the proposed interactive fuzzy linear programming method to solve multi-objective SCPTOP problems.

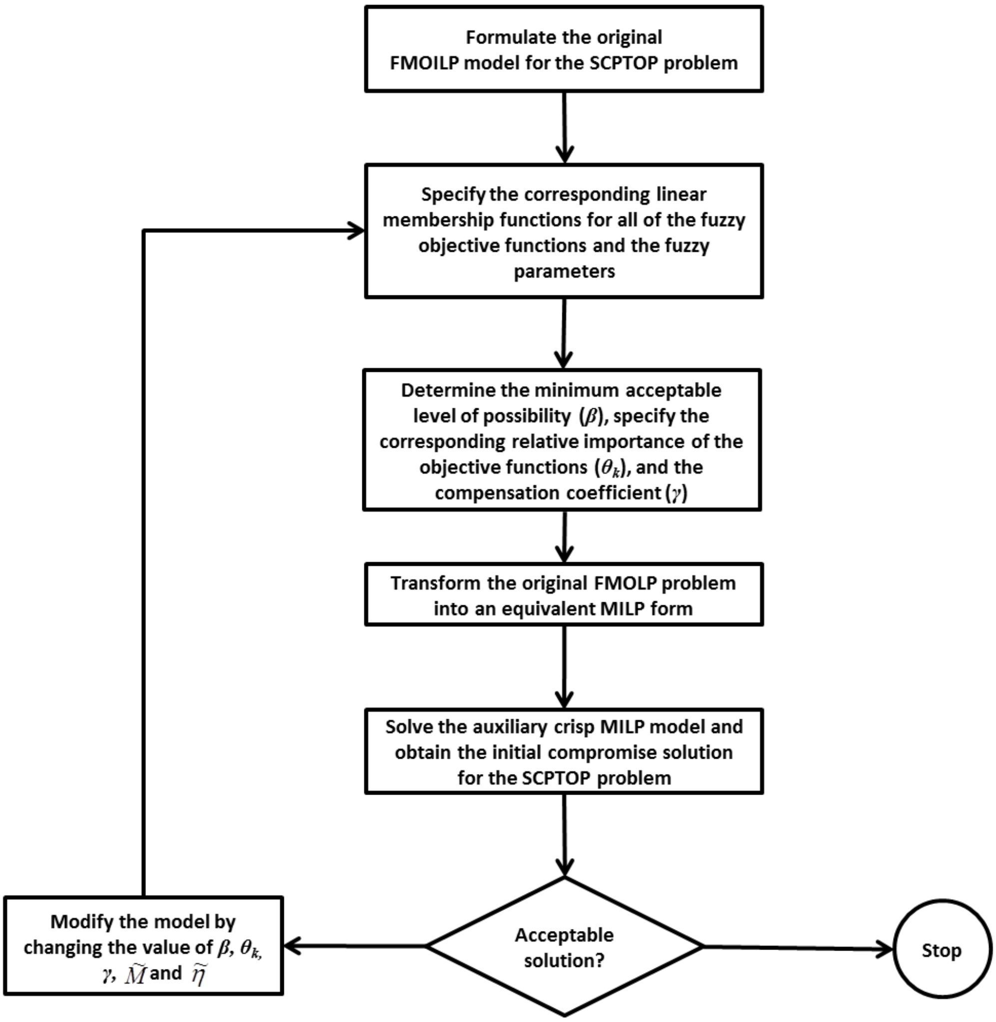

Figure 5. Flowchart of the proposed interactive solution method procedure

6. Application to an automobile supply chain

The proposed model has been evaluated with data from a real SC in the automobile industry. In this section, we validate our proposal as a tool for making decisions relating to the procurement transport operational planning in an automobile SC with epistemic uncertainty in the maximum capacity of available trucks.

6.1 Implementation and resolution

The proposed model has been developed with the modeling language GAMS and solved by the ILOG CPLEX 12.1.0 solver in an Intel Xeon, at 2.93 GHz, with 48 GB of RAM. The model has been executed for a 7-day planning time horizon with 96 different products grouped into 54 different product groups, and supplied by a unique full truck load second-tier supplier with a minimum truck occupation of 86 containers. Here, parameter $\tilde{\eta}$ is set to (0.3, 0.4, 0.5), as used in the company under study (see Section 3).

According to the relative importance of the objectives provided linguistically by the decision maker ($\theta_2 >> \theta_1$), we set the objectives weight vector as: θ = (0.1, 0.9). Therefore, an unbalanced compromise solution with the highest degree of satisfaction for z_2 is of particular interest because it is more important for the first-tier supplier to minimize inventory than the number of trucks used for procurement.

In Annex I, Table 6 lists the basic item data for the SC considered, while Table 7 shows the automobile assembler's item demand in each period. The size of the problem implemented in GAMS modeling language for each solution method is shown in Table 2.

Table 2. Data related to problem size for each solution method

	Selim and Ozkarahan (2008)	Torabi and Hassini (2008)
Blocks of equations	16	16
Single equations	38332	38332
Blocks of variables	14	12
Single variables	38032	38030
Non zero elements	78376	78372
Discrete variables	392	392

6.2 Evaluation of the results

Tables 3 and 4 show the results of the number of trucks used from the second-tier supplier to the first-tier supplier to fulfill the assembler's demand, the first-tier supplier's total inventory over the planning horizon, and the average occupation of the trucks used by the second-tier supplier obtained by the manual procedure and the FMOILP solution methodology proposed using the Selim and Ozkarahan (2008) and the Torabi and Hassini (2008) approaches, respectively. Moreover, Tables 3 and 4 add the objectives' minimum degree of satisfaction (λ_0), the objectives functions' degree of satisfaction, the objective value of the equivalent crisp model ($\lambda(x)$), the CPU time needed to solve the problem, and the upper and lower limits specified by the decision maker for the objectives, the minimum percentage of demand in the next period to remain in stock, η, and the parameters used to resolve the lack of knowledge of the maximum truck load in Constraints (24) and (38).

As seen in Tables 3 and 4, the proposed FMOILP models obtain better solutions than the manual procedure. For the different γ values analyzed, the proposed method generates lower stock levels and a higher occupation of trucks used to fulfill both demand and the minimum inventory requirements. Specifically, the best results are obtained for unbalanced solutions (lower γ values). In this sense, the degree of satisfaction of objective function z_2 (whose assigned weight is higher) increases when γ

decreases. On the other hand, the degree of satisfaction μ_2 lowers when γ increases because inventory levels are higher. Besides, the higher the compensation coefficient γ values, the lower the distance between μ_1 and μ_2 because the degree of satisfaction of the first objective is always $\mu_1=0.8750$. Therefore, 7 trucks were used for all cases to obtain a more balanced solution. Specifically in this resolved problem, the total number of trucks used is identical for both approaches, with the different values considered from the compensation coefficient. The results relating to total stock, obtained by the method of Selim and Ozkarahan (2008), are better for all the γ values, except γ=0.5. As regards computation time, both approaches use values of the same order of magnitude, except the Torabi and Hassini (2008) approach, with $\gamma=0.3$, which employs a total of 15.065 seconds. Should efficiently large-sized MILP problems need to be solved, different types of metaheuristics have been recently developed. Calvete et al. (2010) and Musa et al. (2010) propose ant colony optimization algorithms, Wang et al. (2010) and Chen and Lin (2009) present an algorithm based on particle swarm optimization (PSO), while Bard and Nanannukul (2009) present a tabu search algorithm, among others.

The minimum degree of satisfaction values (λ_0) obtained by the Torabi and Hassini (2008) approach are equal for all the values considered from the compensation coefficient, and take a value of 0.8750. Yet for the Selim and Ozkarahan (2008) approach, these values are obtained only for the highest compensation coefficients, and are null for the values of γ=0.1, γ=0.2, γ=0.3, γ=0.4 and γ=0.5. What this implies is that the cited approach could obtain excessively unbalanced solutions, which only favors the optimization of those objectives with heavier weights. Nonetheless, this fact does not apply to the problem being dealt with because the values obtained for objective z_1, are equal.

The total stock evaluation throughout the considered planning horizon is shown in Figure 6 where we can it be seen that inventory levels are always above the requested amounts. In accordance with the problem description, the inventory levels at the end of each period must cover at least 40% of the demand in the next period. Nonetheless, the fact that product groups and order lot sizes exist implies that the inventory levels are above demand. In addition, the manual procedure generates higher inventory levels. Then, the proposed methods offer a better selection of truck loads which, in turn, allows lower stock.

Table 3. A comparison of the manual procedure and the Selim and Ozkarahan (2008) method solutions

Item	**Manual Procedure**	**Proposed method (γ=0.1)**	**Proposed method (γ=0.2)**	**Proposed method (γ=0.3)**	**Proposed method (γ=0.4)**	**Proposed method (γ=0.5)**	**Proposed method (γ=0.6)**	**Proposed method (γ=0.7)**	**Proposed method (γ=0.8)**	**Proposed method (γ=0.9)**
Trucks (z_1)	7	7	7	7	7	7	7	7	7	7
Inventory (z_2)	63,865 units	56,024 units	56,204 units	56,312 units	56,360 units	56,504 units	56,024 units	57,428 units	56,552 units	60,428 units
Truck occupation (Average)	86.71 containers	87.71 containers	87.71 containers	87.71 containers	87.71 containers	87.28 containers	87.71 containers	87.14 containers	87.71 containers	90 containers
λ_0		0	0	0	0	0	0.8750	0.8750	0.8750	0.8750
μ_1		0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
μ_2		0.9653	0.9643	0.9637	0.9634	0.9626	0.9650	0.9572	0.9623	0.9400
$\lambda(x)$		0.8606	0.7643	0.6684	0.5727	0.4769	0.5574	0.6347	0.7157	0.7934
T_{CPU}(s)		5.195	5.742	4.016	1.770	4.293	6.359	2.526	1.304	1.812
[z_1^l, z_1^u]		z_1^l = 6 z_1^u = 14								
[z_2^l, z_2^u]		z_2^l = 50,000 z_2^u = 223,700								
η		[0.3,0.4,0.5]								
M		$m=86$								
$\tilde{M}$		$M_\beta^p = 88; M_\beta^m = 92; M_\beta^o = 96$								

Table 4. A comparison of the manual procedure and the Torabi and Hassini (2008) method solutions

Item	**Manual Procedure**	**Proposed method (γ=0.1)**	**Proposed method (γ=0.2)**	**Proposed method (γ=0.3)**	**Proposed method (γ=0.4)**	**Proposed method (γ=0.5)**	**Proposed method (γ=0.6)**	**Proposed method (γ=0.7)**	**Proposed method (γ=0.8)**	**Proposed method (γ=0.9)**
Trucks (z_1)	7	7	7	7	7	7	7	7	7	7
Inventory (z_2)	63,865 units	56,360 units	56,264 units	56,528 units	56,444 units	56,360 units	56,792 units	57,572 units	58,592 units	62,120 units
Truck occupation (Average)	86.71 containers	87.71 containers	87.71 containers	87.71 containers	87.71 containers	87.71 containers	87.71 containers	89.43 containers	86.86 containers	89.57 containers
λ_0		0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
μ_1		0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
μ_2		0.9634	0.9639	0.9624	0.9629	0.9634	0.9609	0.9564	0.9505	0.9302
$\lambda(x)$		0.9466	0.9390	0.9301	0.9225	0.9148	0.9059	0.8970	0.8886	0.8800
T_{CPU}(s)		3.279	4.426	15.065	4.821	4.52	4.256	1.399	1.087	1.058
$[z_1^l, z_1^u]$		$z_1^l = 6$ $z_1^u = 14$								
$[z_2^l, z_2^u]$		$z_2^l = 50{,}000$ $z_2^u = 223{,}700$								
η		[0.3,0.4,0.5]								
M		$m=86$								
$\tilde{M}$		$M_\beta^p = 88; M_\beta^m = 92; M_\beta^o = 96$								

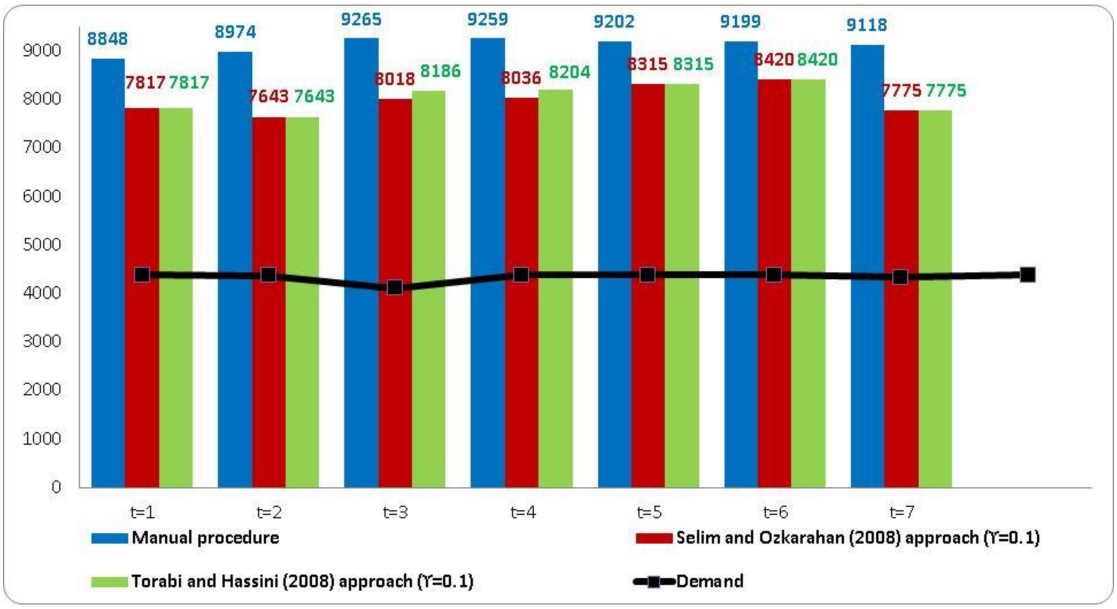

Figure 6. Total stock evolution (units)

7. Discussion

In order to explore the influence of different weight structures on the results of the problem, several problem instances are generated and solved using the Selim and Ozkarahan (2008) method. For each instance generated, the results associated with different compensation coefficient values are obtained, as Table 8 of Annex II indicates. Table 8 shows the minimum degree of satisfaction of the objectives (λ_0), the degree of satisfaction of the second objectives function (μ_2), the average occupation of the trucks used and the CPU time required to solve the problem.

Seven trucks are obtained for each generated weight vector and from the considered compensation coefficients to cover the transport between the second-tier supplier and the first-tier supplier. The minimum degree of satisfaction values are null for those compensation coefficients below 0.6, while the remaining cases take a value of 0.8750. The mean truck occupation value ranges between 86.71 containers per truck ($\theta_1=0.2$, $\theta_2=0.8$, γ=0.79) and 90.57 containers per truck ($\theta_1=0.5$, $\theta_2=0.5$, γ=0.9). As shown, and in general terms, higher occupation values are obtained for greater compensation coefficient values and for instances 8 and 9. On the other hand, calculation times range between 0.857 ($\theta_1=0.9$, $\theta_2=0.1$, γ=0.4) and 9.950 seconds ($\theta_1=0.2$, $\theta_2=0.8$, γ=0.2).

Table 5 shows the total inventory obtained for each instance generated for the different vector weights and compensation coefficients considered. In global terms, we can see how the best results are obtained for instances 1 to 4 with a heavier weight for the second objective, and lower compensation coefficients for instance 5. Meanwhile, and in general, the highest inventory results are obtained for those instances with a lower weight for the second objective, and also for higher compensation coefficients.

Table 5. Total stocks results for different weight vectors and compensation coefficients

	Problem instances								
	1	2	3	4	5	6	7	8	9
θ_1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
θ_2	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
γ=0.1	56,024	56,084	56,360	56,264	56,024	56,444	57,632	58,544	60,944
γ=0.2	56,204	56,252	56,372	56,192	56,264	56,420	57,512	57,968	58,988
γ=0.3	56,312	56,084	56,024	56,192	56,024	56,708	57,212	58,124	60,932
γ=0.4	56,360	56,192	56,360	56,264	56,504	56,864	56,372	58,412	59,012
γ=0.5	56,504	56,204	56,324	56,084	56,708	56,432	56,504	57,728	61,040
γ=0.6	56,024	56,540	56,372	57,140	56,768	56,924	58,124	59,588	65,516
γ=0.7	57,428	56,948	56,912	57,140	58,412	56,768	60,320	60,272	57,716
γ=0.8	56,552	57,848	57,092	56,384	60,212	62,396	59,744	60,296	61,088
γ=0.9	60,428	61,232	57,848	60,428	65,000	61,376	56,972	60,956	60,644

The interactive solution methodology provides a learning process about the system, whereby the decision maker can learn to recognize good solutions and the relative importance of the factors in the system. The main advantage of this interactive approach is that the decision maker controls the search direction during the solution procedure (given a weight vector θ_k and by changing the γ value); as a result, his/her preferences are accomplished by the efficient solution.

With respect to the managerial implications for an automobile supply chain, it is important to highlight the major advantages or benefits and disadvantages of the proposed methods. Thus, the FMOILP model obtains better results in terms of inventory levels and truck occupation because it makes decisions by considering all the planning periods together rather than period by period, as in the manual procedure. In this sense, we propose an effective and structured method for the SCTOP problem, which performs the automatize calculations in front of the current procedure. Moreover, there is also an improvement in the computational time needed to perform the calculations because the current manual procedure takes about 180 seconds to be completed and the proposed method always obtains optimal results or optimal results with a gap tolerance (less than 0.5% which is set as stopping criteria). Thus, this paper has shown a feasible and successful implementation of fuzzy multi-objective mathematical programming to solve an industrial procurement transportation planning problem.

The main disadvantage could be related to the required higher level of operations research training of planners. Related to the improvements of our proposal, the use of solution approaches based on metaheuristics could be convenient to solve the resulting single objective MILP model efficiently especially when solving large-sized problems (Bhattacharya et al. 2007; Ganesan et al. 2012; Tsoulos and Vasant 2009; Vasant and Barsoum 2009; Vasant et al. 2012a; Vasant et al. 2012b; Zheng and Chen 2013). Also, readers are referred to Senvar et al. (2013) for a literature review on the use of metaheuristics for solving engineering problems.

8. Conclusions

In this work, a FMOILP model has been developed to address procurement transport planning at the operational level in an automobile SC formed by a car assembler, a first-tier supplier and a second-tier supplier. The proposed model aims to minimize not only the total number of used trucks from the second-tier supplier to the first-tier supplier, but also the first-tier supplier's total inventory level to fulfill the car assembler's demand. Decision makers' fuzzy aspiration levels for the goals and lack of knowledge or epistemic uncertainty in the transport capacity levels and minimum percentages of demand in stock, are all incorporated into the model by using linear membership functions and triangular fuzzy numbers, respectively.

For the purpose of solving the corresponding FMOILP model, we propose an interactive solution methodology that has been tested in a real automobile SC. This methodology has adopted the solution methods by Selim and Ozkarahan (2008) and Torabi and Hassini (2008) to transform the FMOILP model, with fuzzy objective functions, into a MILP model. Both solution approaches have provided better results in terms of total stock levels than the manual decision-making procedure, which is currently applied in the automobile SC under study. We have also included a sensitivity analysis to show the impact of the relative importance of the objectives on the final solutions.

Some limitations in this work are related to: (i) the results obtained are subject to the data input provided; (ii) demand has been considered certain; and (iii) a static planning horizon has been considered. Thus, further research is needed to address and validate the model with other real world problems by modeling demand uncertainty and by simulating a rolling planning horizon. Furthermore, future studies could apply non linear membership functions such as exponential, hyperbolic, modified s-curve, etc., to solve the SCPTOP problem. The advantages of these membership functions are: more realistic, flexible and convenience. Among them, s-curve membership function is better in comparison with linear membership functions because its robustness in order to find an efficient solution, it avoids linearity in the degeneration problem of fuzzy linear programming, its suitability in the decision-making process for DMs given the vagueness factor alpha involved in the fuzzy problems and its flexibility in describing the vagueness of the uncertain and ill-known fuzzy problems (Vasant et al. 2003; Bhattacharya and Vasant, 2007). Finally, the application of soft computing techniques, evolutionary algorithms and metaheuristics could be applied in future studies with large-scale SCPTOP problems and with the long computation times required (Hajiaghaei-Keshteli et al. 2010; Molla-Alizadeh-Zavardehi et al. 2013; Musa et al. 2010; Zheng and Chen 2013).

9. Acknowledgments

This work has been funded partly by the Spanish Ministry of Science and Technology project: ‘Production technology based on the feedback from production, transport and unload planning and the redesign of warehouses decisions in the supply chain (Ref. DPI2010-19977) and by the Universitat Politècnica de València project ‘Material Requirement Planning Fourth Generation (MRPIV) (Ref. PAID-05-12)’.

References

Allen, W.B. and Liu, D., 1995. Service Quality and Motor Carrier Costs: An Empirical Analysis. The Review of Economics and Statistics, 77(3), 499-510.

Baykasoğlu, A. and Göçken, T., 2008. A review and classification of fuzzy mathematical programs. Journal of Intelligent and Fuzzy Systems, 19(3), 205-229.

Bhattacharya, A., Abraham, A., Vasant, P., and Grosan, C. (2007). Evolutionary artificial neural network for selecting flexible manufacturing systems under disparate level-of-satisfaction of decision maker. Int J Innov Comp Inf Con, 3(1), 131-140.

Bhattacharya, A. and Vasant, P., 2007. Soft-sensing of level of satisfaction in TOC product-mix decision heuristic using robust fuzzy-LP. European Journal of Operational Research, 177(1), pp.55-70.

Bellman, R.E. and Zadeh, L.A., 1970. Decision-Making in a Fuzzy Environment. Management Science, 17(4), B141-B164.

Bilgen, B., 2007. Possibilistic Linear Programming in Blending and Transportation Planning Problem. In Applications of Fuzzy Sets Theory, Lecture Notes in Computer Science, Volume 4578/2007, Springer, 20-27

Bilgen, B., 2010. Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem. Expert Systems with Applications, 37(6), 4488-4495.

Bilgen, B. and Ozkarahan, I., 2006. Fuzzy Linear Programming Approach to Multi-mode Distribution Planning Problem. In Knowledge-Based Intelligent Information and Engineering Systems, Lecture Notes in Computer Science, Volume 4251/2006, Springer, 37-45

Bit, A.K., 2005. Fuzzy programming with hyperbolic membership functions for multi-objective capacitated solid transportation problem. The Journal of Fuzzy Mathematics, 13(2), 373-385.

Bit, A.K., Biswal, M.P. and Alam, S.S., 1993a. An additive fuzzy programming model for multiobjective transportation problem. Fuzzy Sets and Systems, 57 (3), 313-319.

Bit, A.K., Biswal, M.P. and Alam, S.S., 1993b. Fuzzy programming approach to multiobjective solid transportation problem. Fuzzy Sets and Systems, 57 (2), 183-194.

Bard, J. and Nananukul, N., 2009. The integrated production–inventory–distribution–routing problem. Journal of Scheduling, 12(3), 257-280.

Cadenas, J.M. and Verdegay, J.L., 2000. Using ranking functions in multiobjective fuzzy linear programming. Fuzzy Sets and Systems, 111 (1), 47-53.

Calvete, H.I., Galé, C. and Oliveros, M.-J., 2011. Bilevel model for production-distribution planning solved by using ant colony optimization. Computers & Operations Research, 38(1), 320-327.

Chanas, S., Delgado, M., Verdegay, J.L. and Vila, M.A., 1993. Interval and fuzzy extensions of classical transportation problems. Transportation Planning and Technology, 17 (2), 203.

Chanas, S., 1983. The use of parametric programming in fuzzy linear programming. Fuzzy Sets and Systems, 11 (1-3), 229-241.

Chen, Y.-Y. and Lin, J.T., 2009. A modified particle swarm optimization for production planningproblems in the TFT Array process. Expert Systems with Applications, 36(10), 12264-12271.

Christopher, M. and Towill, D., 2001. An integrated model for the design of agile supply chains. International Journal of Physical Distribution & Logistics Management, 31 (4), 235 - 246.

Cisheng, C., Ying, W. and Qichao, H., 2008. Study on Truck Stowage Planning of Cargo Distribution Center in a Town. Proceedings of International Conference on Intelligent Computation Technology and Automation (ICICTA), 509-512.

Díaz-Madroñero, M., Peidro, D. and Vasant, P., 2010. Vendor selection problem by using an interactive fuzzy multi-objective approach with modified S-curve membership functions. Computers & Mathematics with Applications, 60(4), pp.1038-1048.

Dubois, D. and Prade, H., 1988. Possibility Theory, New york: Plenum.

Ehrgott, M. and Wiecek, M., 2005. Multiobjective programming. In Multiple criteria Decision Analysis: State of the art. Springer Science, 667-722.

Ellram, L.M., 1991. Supply-Chain Management: The Industrial Organisation Perspective. International Journal of Physical Distribution & Logistics Management, 21 (1), 13 - 22.

Elamvazuthi, I., Vasant, P. and Ganesan, T. 2012. Integration of Fuzzy Logic Techniques into DSS for Profitability Quantification in a Manufacturing Environment. Handbook of Research on Industrial Informatics and Manufacturing Intelligence: Innovations and Solutions, 171-192.

Evans, K., Feldman, H. and Foster, J., 1990. Purchasing motor carrier service: an investigation of the criteria used by small manufacturing firms. Journal of Small Business Management, 28 (1), 39-47.

Fleischmann, B., 2005. Distribution and Transport Planning. In Supply Chain Management and Advanced Planning, Springer, 229-244.

Ganesan, T., Vasant, P. and Elamvazuthy, I., 2012. A hybrid PSO approach for solving non-convex optimization problems. Archives of Control Sciences, 22(1).

Ganesan, T., Vasant, P. and Elamvazuthi, I., 2013. Normal-boundary intersection based parametric multi-objective optimization of green sand mould system. Journal of Manufacturing Systems, 32(1), pp.197-205.

Hajiaghaei-Keshteli, M., Molla-Alizadeh-Zavardehi, S. & Tavakkoli-Moghaddam, R., 2010. Addressing a nonlinear fixed-charge transportation problem using a spanning tree-based genetic algorithm. Computers & Industrial Engineering, 59(2), pp.259-271.

Hernández, J.E., Mula, J., Ferriols, F.J. and Poler, R., 2008. A conceptual model for the production and transport planning process: An application to the automobile sector. Computers in Industry, 59 (8), 842-852

Jiménez, F. and Verdegay, J.L., 1998. Uncertain solid transportation problems. Fuzzy Sets and Systems, 100 (1-3), 45-57.

Jolai, F., Razmi, J. and Rostami, N.K.M., 2010. A fuzzy goal programming and meta heuristic algorithms for solving integrated production: distribution planning problem. Central European Journal of Operations Research (DOI: 10.1007/s10100-010-0144-9).

Julien, B., 1994. An extension to possibilistic linear programming. Fuzzy Sets and Systems, 64 (2), 195-206.

Kumar, A. and Kaur, A., 2012. Methods for solving unbalanced fuzzy transportation problems. Operational Research, 12(3), pp.287-316.

Kumar, A., Kaur, A. and Gupta, A., 2011. Fuzzy Linear Programming Approach for Solving Fuzzy Transportation Problems with Transshipment. Journal of Mathematical Modelling and Algorithms, 10(2), pp.163-180.

Lai, Y. and Hwang, C., 1992. A new approach to some possibilistic linear programming problems. Fuzzy Sets and Systems, 49 (2), 121-133.

Lai, Y. and Hwang, C., 1993. Possibilistic linear programming for managing interest rate risk. Fuzzy Sets and Systems, 54(2), 135-146.

Lee, E.S. and Li, R.J., 1993. Fuzzy multiple objective programming and compromise programming with Pareto optimum. Fuzzy Sets and Systems, 53 (3), 275-288.

Li, L. and Lai, K.K., 2000. A fuzzy approach to the multiobjective transportation problem. Computers & Operations Research, 27 (1), 43-57.

Liang, T., 2006. Distribution planning decisions using interactive fuzzy multi-objective linear programming. Fuzzy Sets and Systems, 157 (10), 1303-1316.

Liang, T., 2008. Interactive multi-objective transportation planning decisions using fuzzy linear programming. Asia-Pacific Journal of Operational Research, 25 (1), 11-31.

Molla-Alizadeh-Zavardehi, S., Sadi Nezhad, S., Tavakkoli-Moghaddam, R., and Yazdani, M. 2012. Solving a fuzzy fixed charge solid transportation problem by metaheuristics. Mathematical and Computer Modelling.

Mula, J., Peidro, D., Diaz-Madroñero, M. and Vicens, E., 2010. Mathematical programming models for supply chain production and transport planning. European Journal of Operational Research, 204 (3), 377-390.

Musa, R., Arnaout, J.-P. and Jung, H., 2010. Ant colony optimization algorithm to solve for the transportation problem of cross-docking network. Computers & Industrial Engineering, 59(1), 85-92.

Musa, R., Arnaout, J.-P. and Jung, H., 2010. Ant colony optimization algorithm to solve for the transportation problem of cross-docking network. Computers & Industrial Engineering, 59(1), pp.85-92.

Peidro, D. and Vasant, P., 2009. Fuzzy Multi-Objective Transportation Planning with Modified SCurve Membership Function. AIP Conference Proceedings, Volume 1159, Pages 231-239. 2nd Global Conference on Power Control and Optimization, PCO'2009; Bali (Indonesia); 1-3 June 2009.

Peidro, D. and Vasant, P., 2011. Transportation planning with modified S-curve membership functions using an interactive fuzzy multi-objective approach. Applied Soft Computing, 11(2), pp.2656-2663.

Peidro, D., Díaz-Madroñero, M. and Mula, J., 2010a. An interactive fuzzy multi-objective approach for operational transport planning in an automobile supply chain. WSEAS Transactions on Information Science and Applications, 2 (7), 283-29.

Peidro, D., Mula, J., Jiménez, M. and Botella, M.M., 2010b. A fuzzy linear programming based approach for tactical supply chain planning in an uncertainty environment. European Journal of Operational Research, 205 (1), 65-80.

Peidro, D., Mula, J., Poler, R. and Lario, F., 2009a. Quantitative models for supply chain planning under uncertainty: a review. The International Journal of Advanced Manufacturing Technology, 43 (3), 400-420.

Peidro, D., Mula, J., Poler, R. and Verdegay, J., 2009b. Fuzzy optimization for supply chain planning under supply, demand and process uncertainties. Fuzzy Sets and Systems, 160 (18), 2640-2657.

Quinn, F., 1997. What's the buzz? Logistics Management, 36 (2), 43-46.

Sarkar, A. and Mohapatra, P.K., 2008. Maximum utilization of vehicle capacity: A case of MRO items. Computers & Industrial Engineering, 54 (2), 185-201.

Selim, H. and Ozkarahan, I., 2008. A supply chain distribution network design model: An interactive fuzzy goal programming-based solution approach. The International Journal of Advanced Manufacturing Technology, 36 (3), 401-418.

Senvar, O., Turanoglu, E., & Kahraman, C. 2013. Usage of Metaheuristics in Engineering: A Literature Review. In P. Vasant (Ed.), Meta-Heuristics Optimization Algorithms in Engineering, Business, Economics, and Finance (pp. 484-528), IGI Global.

Shih, L., 1999. Cement transportation planning via fuzzy linear programming. International Journal of Production Economics, 58 (3), 277-287.

Tanaka, H., Ichihashi, H. and Asai, K., 1984. A formulation of fuzzy linear programming problem bases on comparision of fuzzy numbers. Control and Cybernetics, 13, 185-194.

Torabi, S.A. and Hassini, E., 2008. An interactive possibilistic programming approach for multiple objective supply chain master planning. Fuzzy Sets and Systems, 159(2),193-214.

Torabi, S.A. and Hassini, E., 2009. Multi-site production planning integrating procurement and distribution plans in multi-echelon supply chains: an interactive fuzzy goal programming approach. International Journal of Production Research, 47(19), 5475-5499.

Tsoulos, I. G., and Vasant, P., 2009. Product mix selection using an evolutionary technique. In AIP Conference Proceedings, Volume 1159, Pages 231-239. 2nd Global Conference on Power Control and Optimization, PCO'2009; Bali (Indonesia); 1-3 June 2009.

Vasant, P., 2006. Fuzzy decision making of profit function in production planning using S-curve membership function. Computers & Industrial Engineering, 51(4), pp.715-725.

Vasant, P. and Barsoum, N., 2009. Hybrid genetic algorithms and line search method for industrial production planning with non-linear fitness function. Engineering Applications of Artificial Intelligence, 22(4–5), pp.767-777.

Vasant, P., Bhattacharya, A., Sarkar, B. and Mukherjee, S., 2007. Detection of level of satisfaction and fuzziness patterns for MCDM model with modified flexible S-curve MF. Applied Soft Computing, 7(3), pp.1044-1054.

Vasant, P., Elamvazuthi, I., Ganesan, T. and Webb, J.F., 2010a. Iterative fuzzy optimization approach for crude oil refinery industry. Scientific Annals of Computer Science, 8(2), pp.261-280.

Vasant, P., Elamvazuthi, I. and Webb, J.F., 2010b. Fuzzy technique for optimization of objective function with uncertain resource variables and technological coefficients. International Journal of Modeling, Simulation, and Scientific Computing, 01(03), pp.349-367.

Vasant, P., Ganesan, T. and Elamvazuthi, I., 2010c. Fuzzy linear programming using modified logistic membership function. Journal of Engineering and Applied Sciences, 5(3), pp.239-245.

Vasant, P., Ganesan, T., Elamvazuthi, I. and Webb, J.F., 2011. Interactive fuzzy programming for the production planning: The case of textile firm. International Review on Modelling and Simulations, 4(2), pp.961-970.

Vasant, P., Ganesan, T. and Elamvazuthi, I., 2012a. Hybrid Tabu Search Hopfield Recurrent ANN Fuzzy Technique to the Production Planning Problems. International Journal of Manufacturing, Materials, and Mechanical Engineering, 2(1), pp.47-65.

Vasant, P., Ganesan, T. and Elamvazuthi, I., 2012b. Improved tabu search recursive fuzzy method for crude oil industry. International Journal of Modeling, Simulation, and Scientific Computing, 3(1).

Vasant, P., Nagarajan, R. and Yaacob, S., 2003. Decision making using modified s-curve membership function in fuzzy linear programming problem. Journal of Information and Communication Technology, 1(2), pp.1-16.

Wang, H.S., Che, Z.H. and Wu, C., 2010. Using analytic hierarchy process and particle swarm optimization algorithm for evaluating product plans. Expert Systems with Applications, 37(2), 1023-1034.

Wang, J. and Shu, Y., 2007. A possibilistic decision model for new product supply chain design. European Journal of Operational Research, 177 (2), 1044-1061.

Wang, R. and Liang, T., 2005. Applying possibilistic linear programming to aggregate production planning. International Journal of Production Economics, 98 (3), 328-341.

Werners, B., 1987. Interactive multiple objective programming subject to flexible constraints. European Journal of Operational Research, 31(3), 342-349.

Werners, B., 1988. Aggregation Models in Mathematical Programming. In Mathematical Models for Decision Support. Springer, 295-305.

Zadeh, L., 1965. Fuzzy sets. Information and Control, 8 (3), 338-353.

Zadeh, L., 1978. Fuzzy sets as a basis for a possibility theory. Fuzzy sets and systems, 1, 3-28.

Zheng, Y. J., and Chen, S. Y., 2013. Cooperative particle swarm optimization for multiobjective transportation planning. Applied Intelligence, 1-15.

Zimmermann, H., 1975. Description and optimization of fuzzy systems. International Journal of General Systems, 2 (1), 209.

Zimmermann, H., 1978. Fuzzy programming and linear programming with several objective functions. Fuzzy Sets and Systems, 1 (1), 45-46.

Annex I. Item data and demand

Table 6. Basic item data

Item number (i)	Groups (j)	$I0_i$ (units)	u_i
Item 1	1	292	50
Item 2	2	95	50

Item number (i)	Groups (j)	$I0_i$ (units)	u_i
Item 3	3	55	50
Item 4	4	11	50
Item 5	1, 2, 3, 4	448	100
Item 6	1, 2, 3, 4	388	25
Item 7	5	286	50
Item 8	6	0	50
Item 9	5, 6	276	100
Item 10	5, 6	276	25
Item 11	7	0	50
Item 12	8	0	50
Item 13	7, 8	0	100
Item 14	7, 8	0	25
Item 15	9	148	50
Item 16	10	0	50
Item 17	9, 10	273	100
Item 18	9, 10	218	25
Item 19	11	21	50
Item 20	12	0	50
Item 21	11, 12	26	100
Item 22	11, 12	21	25
Item 23	13	55	25
Item 24	14	0	50
Item 25	13, 14	50	100
Item 26	13, 14	50	25
Item 27	15	57	25
Item 28	16	0	50
Item 29	15, 16	82	100
Item 30	15, 16	62	25
Item 31	17	61	20
Item 32	18	0	20
Item 33	17, 18	211	40
Item 34	17, 18	201	20
Item 35	19, 21	36	20
Item 36	20, 22	0	20
Item 37	19, 20, 21, 22	31	20
Item 38	19, 20	36	10
Item 39	21, 22	0	10
Item 40	23, 25	9	20
Item 41	24, 26	0	20
Item 42	23, 24, 25, 26	9	20
Item 43	23, 24	9	10
Item 44	25, 26	0	10
Item 45	27	8	20
Item 46	28	0	20
Item 47	27, 28	23	20
Item 48	27, 28	23	10
Item 49	29	93	48
Item 50	30	4	48
Item 51	29, 30	142	96
Item 52	29, 30	137	48
Item 53	31	410	48
Item 54	32	178	48

Item number (i)	Groups (j)	$I0_i$ (units)	u_i
Item 55	33	60	48
Item 56	31, 32, 33	698	96
Item 57	31, 32, 33	683	48
Item 58	34	50	48
Item 59	35	75	48
Item 60	36	50	48
Item 61	34, 35, 36	175	96
Item 62	34, 35, 36	175	48
Item 63	37	57	48
Item 64	38	0	48
Item 65	39	50	48
Item 66	37, 38, 39	102	96
Item 67	37, 38, 39	102	48
Item 68	40	78	48
Item 69	41	0	48
Item 70	42	10	48
Item 71	40, 41, 42	128	96
Item 72	40, 41, 42	118	48
Item 73	43	11	48
Item 74	44	0	48
Item 75	43, 44	51	96
Item 76	43, 44	41	48
Item 77	45	83	48
Item 78	46	0	48
Item 79	45, 46	138	96
Item 80	45, 46	138	48
Item 81	47	88	48
Item 82	48	22	48
Item 83	47, 48	120	96
Item 84	47, 48	125	48
Item 85	49	307	48
Item 86	50	23	48
Item 87	49, 50	325	96
Item 88	49, 50	360	48
Item 89	51	40	24
Item 90	52	0	24
Item 91	51, 52	40	48
Item 92	51, 52	20	24
Item 93	53	62	24
Item 94	54	0	24
Item 95	53, 54	72	48
Item 96	53, 54	57	24

Table 7. Item demand per period

Item number	Demand							
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=8
Item 1	170	162	107	130	111	71	140	135

Item number	Demand							
	t=1	**t=2**	**t=3**	**t=4**	**t=5**	**t=6**	**t=7**	**t=8**
Item 2	0	0	0	0	0	0	0	0
Item 3	0	0	0	0	0	0	0	0
Item 4	0	0	0	20	37	57	16	17
Item 5	170	162	107	150	148	128	156	152
Item 6	170	162	107	150	148	128	156	152
Item 7	129	130	110	94	71	31	4	0
Item 8	0	0	0	0	0	0	0	0
Item 9	129	130	110	94	71	31	4	0
Item 10	129	130	110	94	71	31	4	0
Item 11	0	0	0	0	0	0	0	0
Item 12	0	0	0	0	0	0	0	0
Item 13	0	0	0	0	0	0	0	0
Item 14	0	0	0	0	0	0	0	0
Item 15	173	178	176	205	216	270	269	281
Item 16	0	0	0	0	0	0	0	0
Item 17	173	178	176	205	216	270	269	281
Item 18	173	178	176	205	216	270	269	281
Item 19	3	2	0	11	24	6	1	5
Item 20	0	0	0	0	0	0	0	0
Item 21	3	2	0	11	24	6	1	5
Item 22	3	2	0	11	24	6	1	5
Item 23	0	0	0	0	0	0	0	0
Item 24	0	0	0	0	0	0	0	0
Item 25	0	0	0	0	0	0	0	0
Item 26	0	0	0	0	0	0	0	0
Item 27	0	1	0	0	1	1	9	0
Item 28	0	0	0	0	0	0	0	0
Item 29	0	1	0	0	1	1	9	0
Item 30	0	1	0	0	1	1	9	0
Item 31	54	55	54	65	66	82	78	81
Item 32	0	0	0	0	0	0	0	0
Item 33	54	55	54	65	66	82	78	81
Item 34	54	55	54	65	66	82	78	81
Item 35	2	2	4	1	0	2	1	0
Item 36	0	0	0	0	0	0	0	0
Item 37	2	2	4	1	0	2	1	0
Item 38	2	2	4	1	0	2	1	0
Item 39	0	0	0	0	0	0	0	0
Item 40	0	0	0	0	0	0	0	0
Item 41	0	0	0	0	0	0	0	0
Item 42	0	0	0	0	0	0	0	0
Item 43	0	0	0	0	0	0	0	0
Item 44	0	0	0	0	0	0	0	0
Item 45	0	0	0	4	5	9	10	11
Item 46	0	0	0	0	0	0	0	0
Item 47	0	0	0	4	5	9	10	11
Item 48	0	0	0	4	5	9	10	11
Item 49	38	36	32	31	39	40	39	39
Item 50	0	0	11	0	0	0	0	0
Item 51	38	36	43	31	39	40	39	39
Item 52	38	36	43	31	39	40	39	39
Item 53	320	333	382	259	379	381	363	347

Item number	Demand							
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=8
Item 54	89	57	0	155	8	15	17	10
Item 55	18	21	56	16	46	18	19	49
Item 56	427	411	438	430	433	414	399	406
Item 57	427	411	438	430	433	414	399	406
Item 58	11	5	4	6	1	7	6	2
Item 59	1	0	0	0	0	0	0	0
Item 60	10	27	0	1	10	23	23	17
Item 61	22	32	4	7	11	30	29	19
Item 62	22	32	4	7	11	30	29	19
Item 63	5	11	15	2	5	13	17	32
Item 64	0	0	0	0	0	0	0	0
Item 65	5	1	0	0	3	1	2	0
Item 66	10	12	15	2	8	14	19	32
Item 67	10	12	15	2	8	14	19	32
Item 68	3	5	8	19	3	10	2	6
Item 69	0	0	0	1	0	0	0	0
Item 70	0	0	0	0	0	0	0	0
Item 71	3	5	8	20	3	10	2	6
Item 72	3	5	8	20	3	10	2	6
Item 73	4	3	0	1	4	3	4	3
Item 74	0	0	0	0	0	0	0	0
Item 75	4	3	0	1	4	3	4	3
Item 76	4	3	0	1	4	3	4	3
Item 77	4	6	14	1	7	9	8	9
Item 78	0	0	0	0	0	0	0	0
Item 79	4	6	14	1	7	9	8	9
Item 80	4	6	14	1	7	9	8	9
Item 81	29	28	54	0	38	29	59	49
Item 82	1	0	0	0	20	0	16	57
Item 83	30	28	54	0	58	29	75	106
Item 84	30	28	54	0	58	29	75	106
Item 85	369	381	332	426	329	323	314	309
Item 86	16	6	4	3	26	60	24	0
Item 87	385	387	336	429	355	383	338	309
Item 88	385	387	336	429	355	383	338	309
Item 89	0	0	0	0	1	0	0	0
Item 90	0	0	0	0	0	0	0	0
Item 91	0	0	0	0	1	0	0	0
Item 92	0	0	0	0	1	0	0	0
Item 93	6	8	8	11	9	0	6	3
Item 94	0	0	0	0	0	0	0	0
Item 95	6	8	8	11	9	0	6	3
Item 96	6	8	8	11	9	0	6	3

Annex II. Sensivity analysis results

Table 8. Results obtained for different weight vectors and compensation coefficients

		Problem instances								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	θ_1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	θ_2	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
γ=0.1	Inventory (z_2)	56,024	56,084	56,360	56,264	56,024	56,444	57,632	58,544	60,944
	λ_0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	μ_2	0.9653	0.9650	0.9634	0.9639	0.9653	0.9629	0.9561	0.9508	0.9370
	Truck occupation (Average)	87.71	87.71	87.71	87.71	87.71	87.71	87.29	89.14	89.29
	T_{CPU}(s)	5.195	2.942	2.739	2.222	8.713	4.919	3.631	1.388	2.463
γ=0.2	Inventory (z_2)	56,204	56,252	56,372	56,192	56,264	56,420	57,512	57,968	58,988
	λ_0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	μ_2	0.9643	0.9640	0.9633	0.9644	0.9639	0.9630	0.9568	0.9541	0.9483
	Truck occupation (Average)	87.71	87.71	87.71	87.71	87.71	87.71	87.14	87.86	89.14
	T_{CPU}(s)	5.742	9.95	5.26	6.004	5.514	6.054	5.121	1.579	2.816
γ=0.3	Inventory (z_2)	56,312	56,084	56,024	56,192	56,024	56,708	57,212	58,124	60,932
	λ_0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	μ_2	0.9637	0.9650	0.9653	0.9644	0.9653	0.9614	0.9585	0.9532	0.9371
	Truck occupation (Average)	87.71	87.71	87.71	87.71	87.71	87.29	87.71	88.86	89.57
	T_{CPU}(s)	4.016	2.772	7.303	1.295	6.78	1.398	3.413	1.29	1.485
γ=0.4	Inventory (z_2)	56,360	56,192	56,360	56,264	56,504	56,864	56,372	58,412	59,012
	λ_0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	μ_2	0.9634	0.9644	0.9634	0.9639	0.9626	0.9605	0.9633	0.9516	0.9481
	Truck occupation (Average)	87.71	87.71	87.71	87.71	87.14	87.14	87.71	87.29	89.43
	T_{CPU}(s)	1.77	4.95	2.356	5.446	7.69	1.71	1.954	1.887	0.857
γ=0.5	Inventory (z_2)	56,504	56,204	56,324	56,084	56,708	56,432	56,504	57,728	61,040
	λ_0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	μ_2	0.9626	0.9643	0.9636	0.9650	0.9614	0.9630	0.9626	0.9555	0.9364
	Truck occupation (Average)	87.28	87.71	87.71	87.71	87.14	87.29	87.14	88.14	89.43
	T_{CPU}(s)	4.293	4.47	2.457	3.89	4.132	4.863	3.697	2.759	1.3
γ=0.6	Inventory (z_2)	56,024	56,540	56,372	57,140	56,768	56,924	58,124	59,588	65,516
	λ_0	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
	μ_2	0.9650	0.9623	0.9633	0.9589	0.9610	0.9601	0.9532	0.9448	0.9107
	Truck occupation (Average)	87.71	87.71	87.71	87.71	87.29	88.29	88.57	89.57	90.43
	T_{CPU}(s)	6.359	5.224	2.08	1.327	5.276	2.112	1.158	2.838	1.344

		Problem instances								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	θ_1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	θ_2	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
γ=0.7	Inventory (z_2)	57,428	56,948	56,912	57,140	58,412	56,768	60,320	60,272	57,716
	λ_0	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
	μ_2	0.9572	0.9600	0.9602	0.9589	0.9516	0.9610	0.9406	0.9409	0.9556
	Truck occupation (Average)	87.14	86.71	88.29	87.71	88.29	87.57	87.57	87.71	88.29
	T_{CPU}(s)	2.526	5.649	1.902	1.429	1.204	1.683	2.464	2.06	1.165
γ=0.8	Inventory (z_2)	56,552	57,848	57,092	56,384	60,212	62,396	59,744	60,296	61,088
	λ_0	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
	μ_2	0.9623	0.9548	0.9592	0.9632	0.9412	0.9286	0.9439	0.9407	0.9362
	Truck occupation (Average)	87.71	89.00	88.86	87.71	90.14	88.71	88.29	89.43	89.00
	T_{CPU}(s)	1.304	2.645	1.631	1.463	1.578	1.513	2.613	1.436	1.134
γ=0.9	Inventory (z_2)	60,428	61,232	57,848	60,428	65,000	61,376	56,972	60,956	60,644
	λ_0	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750	0.8750
	μ_2	0.9400	0.9353	0.9548	0.9400	0.9136	0.9345	0.9599	0.9369	0.9387
	Truck occupation (Average)	90.00	89.29	88.29	90.00	90.57	88.71	88.29	89.29	89.86
	T_{CPU}(s)	1.812	1.301	1.45	1.39	1.947	1.168	1.138	1.279	1.081