An interactive fuzzy multi-objective approach for operational transport planning in an automobile supply chain

DAVID PEIDRO, MANUEL DÍAZ-MADROÑERO, JOSEFA MULA
Research Centre on Production Management and Engineering (CIGIP)
Universidad Politécnica de Valencia
Escuela Politécnica Superior de Alcoy, Plaza Ferrándiz y Carbonell, 2, 03801 Alcoy (Alicante)
SPAIN
dapeipa@cigip.upv.es, fcodiama@cigip.upv.es, fmula@cigip.upv.es

Abstract: - A novel supply chain operational transport planning model is developed in this paper. The goals of the model are to minimize the number of used trucks and the total inventory levels. Because of somewhat imprecise nature of vehicle capacities and decision makers' aspiration levels for the goals, a fuzzy multi-objective linear programming (FMOLP) modeling approach is adopted. Moreover, an interactive solution methodology is proposed to determine the preferred compromise solution. An industrial case from a real-world automobile supply chain demonstrates the feasibility of applying the proposed model and the solution methodology to a realistic operational transport planning problem. The computational results indicate that the proposed approach improves the results obtained by the heuristic decision-making procedure spreadsheet-based which is actually applied in the automobile supply chain under study.

Key-Words: - Supply chain planning, transport planning, fuzzy multi-objective linear programming, uncertainty.

1 Introduction

Transport processes are essential parts of the supply chain. They perform the flow of materials that connects an enterprise with its suppliers and with its customers. The integrated view of transport, production and inventory holding processes is characteristic of the modern supply chain (SC) management concept [1]. Crainic and Laporte [2] classify transportation problems according to three planning levels. Some typical examples of decisions at the strategic level are the design of the physical network and its evolutions, the location of main facilities, resource acquisition, etc. Tactical decisions about the design of the service network, i.e., route choice and type of service to operate, general operating rules for each terminal and work allocation between terminal and traffic routing, are all necessary. At the operational level, important decisions include the scheduling of services, maintenance activities, routing and dispatching of vehicles and crews, and resource allocation.

Nevertheless, the complex nature and dynamics of the relationships among the different actors in a SC implies an important degree of uncertainty in SC planning decisions. In such environments, where transport decisions involve resources and data that are owned by different entities within the SC, there are two main characteristics of the transport planning problems that a decision maker (DM) will be faced with: (1) conflicting objectives that may arise from the nature of operations (e.g., to minimize costs and at the same time to increase customer service) and the structure of the SC where it is often difficult to align the goals of the different parties within the SC; (2) lack of knowledge of data (e.g., cost and lead time data) and/or presence of fuzzy parameters (e.g., demand fuzziness). Thus, it's important that models addressing problems in this area should be designed to handle the foregoing two complexities [3].

In the literature, several authors have analyzed supply chain operational transport planning from a deterministic point of view. Jansen et al. [4] describe the operational planning of a multimodal transportation system developed for a merger of Deutsche Post Transport. The objective of the planning is to provide a cost-efficient transportation plan for a given set of orders by taking a large number of constraints into account. Sarkar and Mohapatra [5] 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 maximizing the utilization of vehicles capacity. Pan et al. [6] develop a mixed integer programming model to synchronize inventory and transportation planning in a distribution network with vehicles outsourced from a 3rd party logistic company.

According to Peidro et al. [7] and [8], the literature provides several models defined for SC planning under uncertainty. Among them, the fuzzy programming approaches for transport planning are being increasingly applied. Chanas et al. [9] consider several assumptions on the supply and demand levels for a given transportation problem in accordance with the kind of information the decision maker has. Liu and Kao [10] develop a procedure to derive the fuzzy objective value of the fuzzy transportation problem with fuzzy cost coefficients and fuzzy supply and demand quantities. Liang [11] and [12] develop an interactive multi-objective method for solving transportation planning problems using fuzzy linear programming and a piece-wise linear membership function in the second.

Other authors have studied transport planning decisions as a part of supply chain production-distribution planning or procurement-production-distribution planning problems (see Peidro et al. [7] for a literature survey on supply chain planning under uncertainty conditions)

Moreover, there are several methods in the literature for solving multi-objective linear programming models, by adopting fuzzy programming approaches. In this sense, Bit et al. [13] and [14], Bit [15], Jimenez and Verdegay [16], Li and Lai [17] and Lee and Li [18] presented the fuzzy mathematical programming approach to solve multi-objective transportation problem corresponding to numerical examples.

However, in most of the aforementioned works, (especially those with fuzzy multi-objective programming models), the authors have applied their approaches to case studies and not in real cases.

In this paper we propose a novel fuzzy multi-objective operational transport planning model applied in a real SC of the automobile industry. The SC transport planning (SCTP) problem at the operational level, considered here, deals with optimizing the use of transport resources and the inventory levels determining the amount of each product to procure under certain warehousing and transport constraints (see Section 3 for a detailed definition). An interactive solution methodology to solve the fuzzy multi-objective SCTP problem for the purpose of finding a preferred compromise solution has been applied. We compared the results obtained by this approach with a heuristic decision-making procedure which is actually applied in the automobile SC being analyzed.

We arranged the rest of the paper as follows. Section 2 describes the SCTP problem at the operational level and also presents the heuristic decision-making procedure that the SC under study currently uses. We propose the FMOLP model for the SCTP problem in section 3 and in section 4 we describe its solution methodology. Next, we evaluate the behavior of the proposed model in a real-world automobile SC in section 5. Finally, we provide conclusions and directions for further research.

2 Problem Description

The SCTP problem considered herein refers to a dyadic-type SC [19] belonging to the automobile sector. This SC is made up of an assembler and a first-tier supplier whose replenishment process of materials is the full truck load (FTL) pick-up method [20].

Transport planning is usually the responsibility of the supplier. But there are important exceptions, e. g. in the automobile industry, where the manufacturer controls the transports from his suppliers. In this case, transport planning occurs on the procurement side as well [1].

Thus we state the SCTP problem at the operational level, in the automobile SC considered, as follows:

Given: (1) product data, such as unitary dimensions, the number of units which composes the lot of each order; (2) transportation data, such as transport capacity, the number of trucks available in each period, the minimum percentage of truck occupation to complete, etc.; (3) warehouse information: the maximum number of stored containers of each product; (4) initial inventory; and (5) assembler demand over the entire planning periods.

To determine: (1) the amount of each product to order; (2) the inventory level of each product; and (3) the number of trucks required in each period and their occupation.

The main goals of this work are: (1) to minimize the number of trucks; and (2) to minimize the necessary inventory levels to satisfy the assembler's demand without incurring delays in demand.

Moreover, the following assumptions have been made: (1) Assembler demand is considered to be firm along the entire planning horizon. As this is an operational level problem, planning horizons are short (only lasting a few days); therefore, in this case, demand does not tend to vary; and (2) this problem does not consider the supplier's transportation times; it merely indicates the period to receive the amounts to transport irrespectively of when they must be ordered.

2.1 Heuristic procedure

In the SC studied, the current decision-making procedure for the previously presented SCTP problem is a heuristic procedure based on the use of a Microsoft Excel sheet with an associated macro VBA with which the staff in charge of the first-tier supplier's replenishments may calculate short-term net requirements to satisfy the assembler's demand, minimize the inventory level and improve the utilization of the transport resources without allowing for a delay in demand.

Firstly, the procedure begins by obtaining the initial stock of each product at the beginning of the planning period by using the data stored in the corporate ERP, along with the daily demand of each given reference. The stock and demand values for each part in each time period determine the decision as to requesting a new full truck load. As we cannot allow a delay in demand, should the inventory of any part at the end of the first period be lower than its demand level in the next period, then the planner will execute the macro VBA to automatically calculate the inclusion of loading a new truck in period 1.

Trucks load in accordance with both the space available (approximately 13 meters with a FTL) and the coverage value of each product along the planning horizon. The coverage value corresponds to the number of days that the available stock may cover the demand in the following periods. In this way, the loading process begins by calculating the coverage of all the parts in the corresponding period. The coverage calculation works according to the products availability in accordance with the product spreadsheet. Having selected the item with less coverage, the procedure then calculates the space occupied by a lot of the given product. Next, we check whether there is enough space available in the truck to load the selected item by finalizing the loading procedure should there be no space available. If there is enough space on the truck to load the selected product lot, we then update the inventory value of this product in the corresponding period by calculating its new coverage and by restarting the described loading process to load the truck as much as possible by incorporating the lots of those products with less coverage.

Once we have updated the stock values in terms of the amounts to be ordered for the new truck, and should the inventory of a certain part be, once again, lower than the demand level of the next period, we will then repeat this process by adding the number of trucks required until the stock values of all the parts are higher than the demand levels of the subsequent period. Subsequently, we will run this process for all the periods until we come to the end of the planning horizon. Figure 1 is a graphical representation of the heuristic procedure.

The spreadsheet used to conduct this heuristic procedure is that shown in Figure 2. The *Order* parameter corresponds to the amounts to be ordered on each truck. We calculate the space occupied by the amounts to be ordered in the lower part of *Daily* (which corresponds to the demand values) and *Order* using an orange color when we execute the macro VBA. Then we update the Stock columns for the amounts to be ordered and in accordance with the daily demand. We repeat this structure in accordance with the length of the desired planning horizon.

The staff in charge of replenishments review the results obtained by this heuristic procedure, and occasionally modify the amounts obtained to meet the set objectives. According to Allen and Liu [21] and Evans et al. [22], in real practice, logistics managers often rely entirely on their personal judgment and experience to choose the transportation mode, to consolidate shipments and to select the carrier. Thus, sub-optimal choices may result.

3 Model formulation

In order to improve the results obtained by the heuristic procedure, we propose a new fuzzy multi-objective linear programming (FMOLP) model for the SCTP at the operational level. The proposed model considers the fuzzy goals and the fuzzy data related to the transport capacity levels. The nomenclature defines the sets of indices, parameters and decision variables for the FMOLP model (Table 1).

Sets of indices	
I:	Set of products (i =1,2,…,I).
J:	Set of trucks (j =1,2,…,J).
T:	Set of planning periods (days) (t =1, 2…T).
Decision variables	
Q_{ijt}:	Units transported of i by j in period t (units).
I_{it}:	Inventory amount of i at the end of period t (un
K_{ijt}:	Number of lots to order of i by j in period t.
Y_{jt}:	Binary variable indicating whether a truck j has been used in period t.
Objective functions	
z_1:	Total number of trucks utilized.
z_2:	Total inventory amount generated.
Parameters	
u_i:	Dimensions of product i (meters/unit).
l_i:	Number of units that make up each product lot i (units).
W_i:	Maximum warehouse space available for product i (units).
D_{it}:	Demand of product i in t (units).
$\tilde{M}$:	Maximum length of the available truck (in linear meters)
m:	Minimum truck occupation (in linear meters).
$I0_i$:	Inventory amount of I in period 0.

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

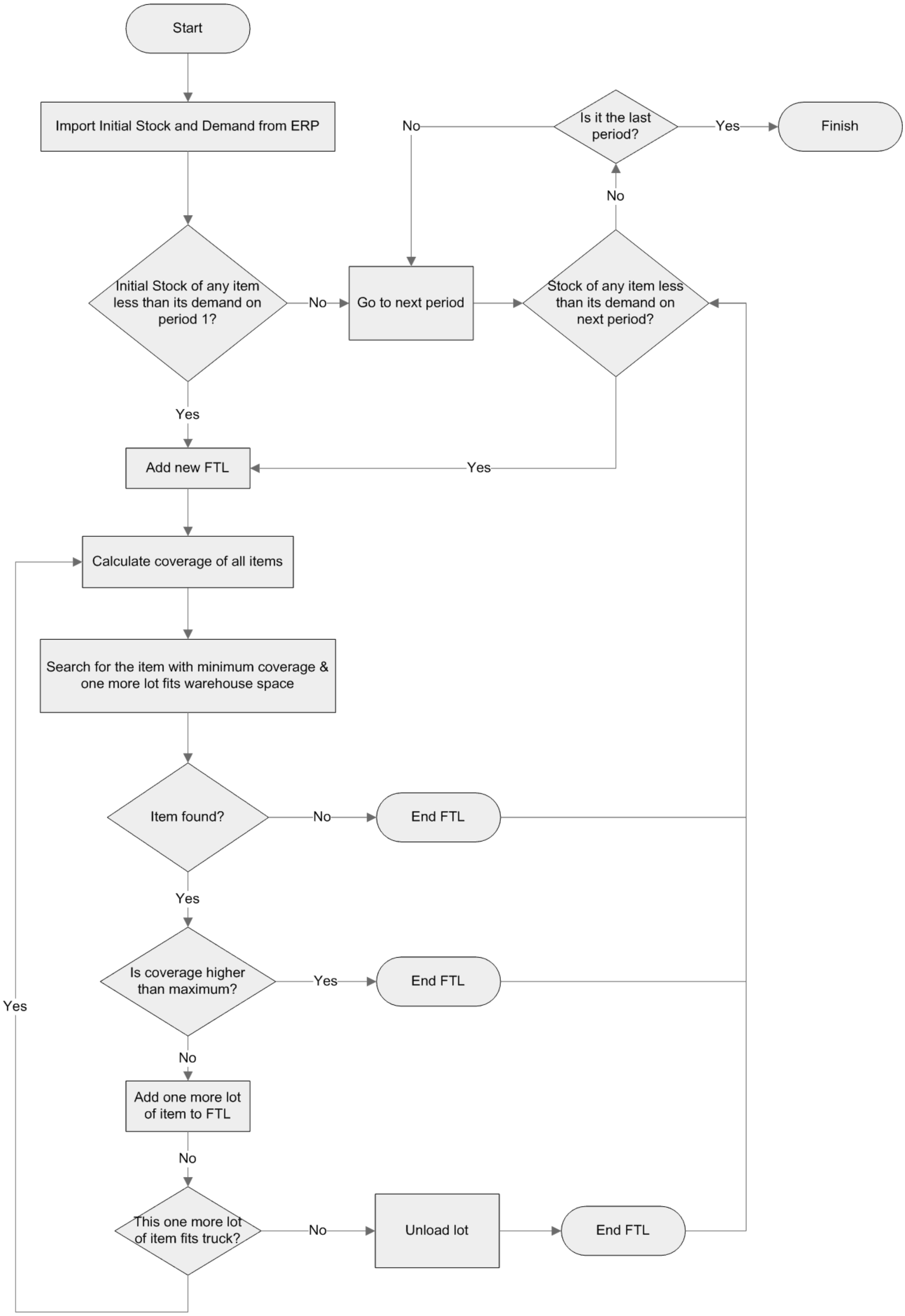

Figure 1. Heuristic procedure

REFERENCE	StockERP	Coverage	DIF	Stock	Order	Order	Daily	Stock	Order	Daily	Stock	Order	Daily	Stock	Order	Daily	Stock
ID ITEM 1	69	3		69			14	55		16	39	72	16	95		16	79
ID ITEM 2	45	3		45			0	45		0	45		0	45		0	45
ID ITEM 3	160	3	-18	142			96	46		16	30	90	6	114		18	96
ID ITEM 4	346	1	-60	286	180	90	230	326	90	146	270	90	164	196	180	122	254
ID ITEM 5	79	3	-9	70			48	22		8	14	90	3	101		9	92
ID ITEM 6	175	1	-25	150	90	90	115	215		73	142	90	82	150	90	61	179
ID ITEM 7	170	2	-66	104			28	76		14	62	72	8	126		22	104
ID ITEM 8	108	3		108			0	108		0	108		0	108		4	104
ID ITEM 9	156	3		156			96	60		16	44		6	38	72	18	92
ID ITEM 10	349	1		349	144	144	230	407	72	146	333	144	164	313	72	122	263
ID ITEM 11	365	1	-5	360	180	180	241	479	180	199	460	180	206	434	180	198	416
ID ITEM 12	71	3		71			1	70		6	64		5	59		4	55
ID ITEM 13	265	1	-10	255	180	90	164	361	180	145	396	90	141	345	90	141	294
ID ITEM 14	802	1	-30	772	360	360	482	1010	360	398	972	360	412	920	240	396	764
ID ITEM 15	162	1		162			2	160		12	148		10	138		8	130
ID ITEM 16	461	1	-72	389	360	240	328	661	240	290	611	240	282	569	240	282	527
ID ITEM 17	1364	1	-200	1164	432	288	396	1488	576	570	1494	432	426	1500		498	1002
ID ITEM 18	65	3		65	72		20	117		10	107		2	105		0	105
ID ITEM 19	715	1		715	360	216	482	809	360	398	771	360	412	719	360	396	683
ID ITEM 20	147	2		147			2	145		12	133		10	123		8	115
ID ITEM 21	423	1	-30	393	216	288	328	569	288	290	567	216	282	501	288	282	507
ID ITEM 22	69	1		69		72	38	103		14	89	72	12	149		2	147
ID ITEM 23	2735	1	-105	2630	1800	2088	2470	4048	1800	2117	3731	1656	2278	3109	2304	2007	3406
ID ITEM 24	168	2	-15	153			38	115		14	101		12	89		2	87
ID ITEM 25	1637	1	-35	1602	1280	1408	1738	2552	1280	1461	2371	1152	1496	2027	1536	1335	2228
ID ITEM 26	1144	1	-115	1029	450	540	574	1445	540	618	1367	450	605	1212	360	585	987
ID ITEM 27	1602	1	-135	1467	960	960	1148	2239	1080	1236	2083	1080	1210	1953	1080	1170	1863
ID ITEM 28	139	1		139			10	129		30	99		20	79		6	73
ID ITEM 29	88	1		88			16	72		8	64		10	54		22	32
ID ITEM 30	89	3		89			4	85		2	83		14	69		12	57
ID ITEM 31	182	3	-11	171			14	157		16	141		17	124		16	108
ID ITEM 32	65	3		65			0	65		0	65		0	65		0	65
ID ITEM 33	128	2		128			40	88		21	67	128	12	183		29	154
ID ITEM 34	35	3		35			0	35		0	35		0	35		6	29
					12.75	12.76			12.75			12.75			12.77		

Figure 2. The spreadsheet used in the heuristic procedure

3.1 Objective functions

The formulation of FMOLP is as follows:

Minimize the total number of trucks utilized

$$\text{Min } z_1 \cong \sum_{j=1}^{J}\sum_{t=1}^{T} Y_{jt} \qquad (1)$$

Minimize the total inventory amount generated.

$$\text{Min } z_2 \cong \sum_{i=1}^{I}\sum_{t=1}^{T} I_{it} \qquad (2)$$

The symbol "≅" is the fuzzified version of "=" and refers to the fuzzification of the aspiration levels. In practical situations, most of the parameters considered in a SCTP problem are frequently fuzzy in nature because of the incompleteness and/or unavailability of the data required over the planning horizon which we may obtain subjectively [23]. For each objective function of the original FMOLP model, this work assumes that the DM has imprecise objectives, such as "objective functions should be essentially equal to some value". By considering the uncertain property of human thinking, it is quite intuitive to assume that the DM has a fuzzy goal $z_1\,(z_2)$ with an acceptable interval $[\,z_1^l(z_2^l),\, z_1^u(z_2^u)\,]$. This would be quite satisfactory as the objective value is less than $z_1^l(z_2^l)$, but unacceptable as the value is greater than $z_1^u(z_2^u)$ [24]. Accordingly, Eq. (1) and (2) are fuzzy and incorporate the variations in the DM's judgments regarding the solutions of the multi-objective SCTP optimization problem in a fuzzy environment. Moreover, it is necessary for the DM to simultaneously optimize these conflicting objectives in the framework of imprecise aspiration levels [11].

3.2 Constraints

$$I_{it} = I_{i(t-1)} - D_{it} + \sum_{j=1}^{J} Q_{ijt} \qquad \forall i,t \qquad (3)$$

$$Q_{ijt} = K_{ijt} \cdot l_i \qquad \forall i,j,t \qquad (4)$$

$$I_{it} \le W_i \qquad \forall i,t \qquad (5)$$

$$\sum_{i=1}^{I} Q_{ijt} \cdot u_i \le \tilde{M} \cdot Y_{jt} \qquad \forall j,t \qquad (6)$$

$$\sum_{i=1}^{I} Q_{ijt} \cdot u_i \ge m \cdot Y_{jt} \qquad \forall j,t \qquad (7)$$

$$I_{it} \ge D_{it+1} \qquad \forall i,t \qquad (8)$$

$$I_{it}, K_{it}, Q_{ijt} \ge 0 \qquad (9)$$

Eq. (3) represents the inventory balance constraint. Eq. (4) represents the amount of each product to request in each truck for each period as a multiple integer of the packing units. Eq. (5) limits the capacity of the inventory per product and day in accordance with the maximum warehouse dimensions. Eq. (6) guarantees the approximately 13 linear meters per truck used, and not more, while Eq.

(7) ensures that the occupied space on each truck is over a specified minimum, thus avoiding trucks not making full use of any possible excess space. Next Eq. (8) ensures one day of coverage for the inventories at the end of each period. In this way, the model does not create delays in demand. Finally, Eq. (9) establishes the non negative conditions of the decision variables.

In real-world SCTP problems, Eq. (6) is fuzzy in nature. To a great extent, one truck's storage capacity (in occupied meters) depends on the exact combination of the loaded products, in such a way that, although we know the theoretical 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. We take the remaining constraints to be certain because the related information is complete and obtainable over the planning horizon. We also consider the demand data to be certain because we take demand to be firm since such data are part of this operational decision-kind problem with short (a few days) planning horizons.

4 Solution Methodology

In this section, we define an approach to transform the fuzzy multi-objective linear programming model (FMOLP) into an equivalent auxiliary crisp mathematical programming model for the SCTP problem. This approach adopts linear membership functions to represent all the fuzzy objective functions and the pattern of triangular fuzzy number to represent the fuzzy parameter, together with the Torabi and Hassini's fuzzy programming solution method [3].

4.1 Treating the soft constraint

To resolve the imprecise maximum truck load in the right-hand side of the constraint (6) the weighted average method [12,25,26] is used for the defuzzification process and converting this fuzzy parameter into a crisp number. So, if the minimum acceptable degree of feasibility (β) is given, then the equivalent auxiliary crisp constraint can be represented as follows:

$$\sum_{i=1}^{I} Q_{ijt} \cdot u_i \leq (w_1 M_\beta^p + w_2 M_\beta^m + w_3 M_\beta^o) \cdot Y_{jt} \quad \forall j,t \qquad (10)$$

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 of the fuzzy maximum truck load, respectively. The suitable values for these weights as well as β usually are determined subjectively by the experience and knowledge of the DM. However, based on the concept of the most likely values proposed by Lai and Hwang [26] and considering several relevant works [12,25], we set these parameters as: w_2=4/6, w_1=w_3=1/6 and β = 0.5.

5.2 Torabi and Hassini's fuzzy programming solution method

There are several methods in the literature for solving multi-objective linear programming (MOLP) models, among which fuzzy programming approaches are being increasingly applied. The main advantage of fuzzy approaches is that they are capable of measuring the satisfaction degree of each objective function explicitly. This issue can help the DM to make his/her final decision by choosing a preferred efficient solution in accordance with the satisfaction degree and preference (relative importance) of each objective function.

In conventional goal programming models, the DM is required to specify a precise aspiration level for each objective which is generally a difficult task for him/her. As mentioned before, fuzzy programming offers the advantage of the DM being able to specify imprecise aspirations levels that can be treated as fuzzy goals. In fuzzy goal programming, a membership function (linear o nonlinear) for each solution X should be specified. This membership function for goal kth, which considers solution X, is named $\mu_{z_k}(x)$ and denotes the satisfaction degree of this goal.

Zimmermann developed the first fuzzy approach for solving a MOLP called the max-min approach [27]. It is true that the solution yielded by a max-min operator may neither be unique nor efficient [29,30,31], so several methods have been subsequently proposed to eliminate this deficiency. Lai and Hwang [29] developed the augmented max-min approach, Selim and Ozkarahan [31] presented a modified version of Werners' approach [32], while Li et al. [30] proposed a two-phase fuzzy approach. A brief discussion of these three approaches is found in Torabi and Hassini [3].

Torabi and Hassini [3] proposed a new single-phase fuzzy approach as a hybridization of the previous methods of Lai and Hwang [29] and Selim and Ozkarahan [31]. According to Torabi and Hassini [3], a multi-objective model could be transformed in a single objective model as follows:

$$\begin{aligned} &\text{Max } \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \mu_{z_k}(x) \\ &\text{s.t.} \quad \lambda_0 \leq \mu_{z_k}(x) \quad k = 1,\dots,n \\ &\qquad x \in F(x) \\ &\qquad \lambda_0, \gamma \in [0,1] \end{aligned} \qquad (11)$$

where μ_{z_k} and $\lambda_0 = \min\{\mu_{z_k}(x)\}$ denote the satisfaction degree of the *kth* objective function and the minimum satisfaction degree of the objectives, respectively. Moreover, θ_k and γ indicate the relative importance of the *kth* objective function and the coefficient of compensation, respectively. The θ_k parameters are determined by the decision maker based on her/his preferences so that $\sum_k \theta_k = 1, \theta_k > 0.$ Besides, γ not only controls the minimum satisfaction level of the objectives, but also controls the compromise degree 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 [3].

5.3 Solution Procedure

Here the interactive solution procedure proposed by Liang [11] is adapted for solving the SCTP problem. This procedure provides a systematic framework that facilitates the fuzzy decision-making process, enabling the DM to interactively adjust the search direction during the solution procedure to obtain the DM's preferred satisfactory solution [11].

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

Step 1. Formulate the original FMOLP model for the SCTP problems according to Eq. (1) to (9).

Step 2. Determine the appropriate triangular fuzzy number for the imprecise parameter $\tilde{M}$ and specify the corresponding non-increasing continuous linear membership functions for all the fuzzy objective functions as follows.

$$\mu_{z_k}(x) = \begin{cases} 1 & z_k < z_k^l \\ \dfrac{z_k^u - z_k}{z_k^u - z_k^l} & z_k^l < z_k < z_k^u \\ 0 & z_k > z_k^u \end{cases} \quad (12)$$

where $\mu_{z_k}(x)$ is the satisfaction degree and (z_k^l, z_k^u) are the lower and upper bounds of the *kth* objective function .

Step 3. Determine the minimum acceptable degree of feasibility (β) for the fuzzy constraint and specify the corresponding relative importance of the objective functions (θ_k) and the coefficient of compensation (γ).

Step 4. Transform the original FMOLP problem into an equivalent single-objective MILP form using the solution methodology presented before.

Step 5. Solve the proposed auxiliary crisp single-objective model by the MIP solver and obtain the initial compromise solution for the SCTP problem.

Step 6. If the DM 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, (z_k^l, z_k^u) and $\tilde{M}$).

5 Application to an automobile supply chain

The proposed model has been evaluated with data from a real SC in the automotive industry with a dyadic structure which comprises a first-tier seat supplier and an automobile assembler. In this section, we validate the proposed model as a tool for making decisions related to operational transport planning in an automobile supply chain under uncertainty.

5.1 Implementation and resolution

The proposed model has been developed with the modeling language GAMS, and has been solved by the SCIP Solver. The model has been executed for a 10-day planning time horizon with 34 different products which belong to a unique FTL supplier with a minimum truck occupation of 12'85 meters.

Furthermore, the DM provided the relative importance of objectives linguistically as: $\theta_2 >> \theta_1$, and based on this relationships we set the objectives weight vector as: θ = (0.2, 0.8). In this case, for the DM is more important to minimize inventory levels even if it means more trucks used for the procurement. Thus an unbalanced compromise solution with highest satisfaction degree for z_2 is of particular interest.

Table 2 lists the basic item data for the SC considered. Besides, Table 3 shows the item demand from the automobile assembler in each period.

Item number	u_i (meters)	l_i (units)	W_i (units)	$I0_i$ (units)
Item 1	0.0023	72	7200	69
Item 2	0.0023	72	7200	45
Item 3	0.0018	90	9000	142
Item 4	0.0018	90	9000	286
Item 5	0.0018	90	9000	70
Item 6	0.0018	90	9000	150
Item 7	0.0023	72	7200	104
Item 8	0.0023	72	7200	108
Item 9	0.0023	72	7200	72
Item 10	0.0023	72	7200	349
Item 11	0.0018	90	9000	360
Item 12	0.0018	90	9000	71
Item 13	0.0018	90	9000	255
Item 14	0.0013	120	12000	772

Item 15	0.0013	120	12000	162
Item 16	0.0013	120	12000	389
Item 17	0.0023	72	7200	1164
Item 18	0.0023	72	7200	65
Item 19	0.0023	72	7200	715
Item 20	0.0023	72	7200	147
Item 21	0.0023	72	7200	393
Item 22	0.0023	72	7200	69
Item 23	0.0023	72	7200	2630
Item 24	0.0013	128	12800	153
Item 25	0.0013	128	12800	1602
Item 26	0.0018	90	9000	1029
Item 27	0.0013	120	12000	1467
Item 28	0.0023	72	7200	139
Item 29	0.0023	72	7200	88
Item 30	0.0023	72	7200	89
Item 31	0.0013	128	12800	171
Item 32	0.0013	128	12800	65
Item 33	0.0013	128	12800	128
Item 34	0.0013	128	12800	35

Table 2. Basic item data

5.2 Evaluation of the results

This section analyzes the results obtained by the heuristic procedure and the FMOLP solution methodology proposed in this work. On the one hand, Table 4 shows the results obtained by the heuristic procedure which details the number of trucks used to meet the demand requirements, as well as the total inventory generated throughout the planning horizon.

Besides, the table also indicates the average occupation of the trucks used. On the other hand, Table 4 shows the results obtained by the proposed method which adds the minimum satisfaction degree of the objectives (λ_0), the satisfaction degree of the objectives functions, the objective value of the equivalent crisp model ($\lambda(x)$) along with the upper and lower limits specified by the DM in relation to the objectives and the parameters used to resolve the imprecise maximum truck load in the right-hand side of the constraint (6).

As shown in Table 4 the proposed method is clearly superior to the heuristic procedure. The proposed method, for the different γ values analyzed, generates lower inventories and uses a lower number of trucks to meet demand and minimum stock requirements. The best results are obtained when the γ value is lower (unbalanced solution). As mentioned before, a low γ value means that the model attempts to find a solution by focusing more on obtaining a better satisfaction degree for the most weighted objective and by paying less attention to achieving a higher minimum satisfaction level of objectives.

A high γ value of means that the model attributes more importance to maximizing the minimum satisfaction degree of objectives independently of the weights assigned to the objective functions. For this reason, when γ decreases the satisfaction degree of the objective function z_2 (whose assigned weight is higher) increases. On the other hand, when γ increases the inventory levels are higher and hence the satisfaction degree μ_{z_2} is lower. Moreover, when the values of the coefficient of compensation γ increase the distance between μ_{z_1} (setting the minimum satisfaction degree of objectives) and μ_{z_2} is lower. Finally, the value of the objective function $\lambda(x)$ is decreasing when γ increases. This is because the weight of the minimum satisfaction degree of the objectives, whose value is always λ_0=0.9, is higher in Eq. (11). For this reason, when γ=0.9 $\lambda(x)$ is practically equal to λ_0.

Figure 3 shows the total stock evaluation throughout the planning horizon. We can see how the inventory levels of the different solutions tend to be above the requested amounts. As we have already explained, this is because the result of the stock for each period must ensure the coverage of the demand of the following period. As shown in Figure 1 the total amount of inventory generated by the proposed model (for γ=0.1 and γ=0.3) is, generally speaking, similar than that generated by the heuristic procedure for $t \leq 9$. However, in the last period there are major differences between the two approaches. The heuristic procedure (for t=10) generates higher inventory levels because it uses two trucks to meet the minimum stock requirements. The proposed method offers a better selection of truck loads which, in turn, allows a lower stock without the need for more trucks because the stock composition fulfills the aforementioned coverage requirements. This last case is one of the best advantages that the mathematical model offers as opposed to the heuristic procedure; whereas the heuristic procedure makes period-to-period truck load-type decisions, the considered mathematical model makes decisions by jointly contemplating all the planning periods and, therefore, obtains better results.

Item number	Demand									
	T=1	**t=2**	**t=3**	**t=4**	**T=5**	**t=6**	**t=7**	**t=8**	**t=9**	**t=10**
Item 1	14	16	16	16	14	14	18	18	18	14
Item 2	0	0	0	0	2	2	0	0	0	10
Item 3	96	16	6	18	16	10	2	70	40	8
Item 4	230	146	164	122	134	144	154	72	112	118
Item 5	48	8	3	9	8	5	1	35	20	4
Item 6	115	73	82	61	67	72	77	36	56	59
Item 7	28	14	8	22	74	18	50	30	4	32
Item 8	0	0	0	4	2	4	2	4	2	4
Item 9	96	16	6	18	16	10	2	70	40	8
Item 10	230	146	164	122	134	144	154	72	112	118
Item 11	241	199	206	198	209	207	222	208	247	213
Item 12	1	6	5	4	12	3	8	4	4	6
Item 13	164	145	141	141	142	147	136	152	134	115
Item 14	482	398	412	396	418	414	444	416	494	426
Item 15	2	12	10	8	24	6	16	8	8	12
Item 16	328	290	282	282	284	294	272	304	268	230
Item 17	396	570	426	498	444	450	624	556	608	694
Item 18	20	10	2	0	4	6	4	12	22	56
Item 19	482	398	412	396	418	414	444	416	494	426
Item 20	2	12	10	8	24	6	16	8	8	12
Item 21	328	290	282	282	284	294	272	304	268	230
Item 22	38	14	12	2	0	56	8	0	0	28
Item 23	2470	2117	2278	2007	2110	2175	2001	2101	2141	1876
Item 24	38	14	12	2	0	56	8	0	0	28
Item 25	1738	1461	1496	1335	1390	1413	1389	1453	1539	1356
Item 26	574	618	605	585	584	609	620	608	616	635
Item 27	1148	1236	1210	1170	1168	1218	1240	1216	1232	1270
Item 28	10	30	20	6	20	12	18	14	22	10
Item 29	16	8	10	22	4	22	22	28	24	40
Item 30	4	2	14	12	2	6	6	2	6	0
Item 31	14	16	17	16	14	16	18	18	18	16
Item 32	0	0	0	0	2	2	0	0	0	11
Item 33	40	21	12	29	83	22	73	45	6	48
Item 34	0	0	0	6	3	6	3	6	3	4

Table 3: Item demand per period

	Heuristic Procedure	**Proposed method (γ=0.1)**	**Proposed method (γ=0.3)**	**Proposed method (γ=0.5)**	**Proposed method (γ=0.7)**	**Proposed method (γ=0.9)**
Number of trucks (z_1)	12	11	11	11	11	11
Inventory level (z_2)	132,797 units	124,773 units	125,431 Units	125,475 units	126,411 units	127,101 Units
Truck occupation (Average)	12,9150 m	13,0767 m	13.0792 m	13.0792 m	13,0759	13.0792 m
λ_0	*Not applicable*	0.9000	0.9000	0.9000	0.9000	0.9000
μ_{z_1}		0.9000	0.9000	0.9000	0.9000	0.9000
μ_{z_2}		0.9855	0.9835	0.9834	0.9806	0.9785
$\lambda(v)$		0.9616	0.9468	0.9334	0.9193	0.9063
$[z_1^l, z_1^u]$		$z_1^l = 10$ $z_1^u = 20$				
$[z_2^l, z_2^u]$		$z_2^l = 120{,}000$ $z_2^u = 450{,}000$				
$\tilde{M}$		$M_\beta^p = 12.85$ $M_\beta^m = 13$ $M_\beta^o = 15$				

Table 4: A comparison of the heuristic and proposed method solutions.

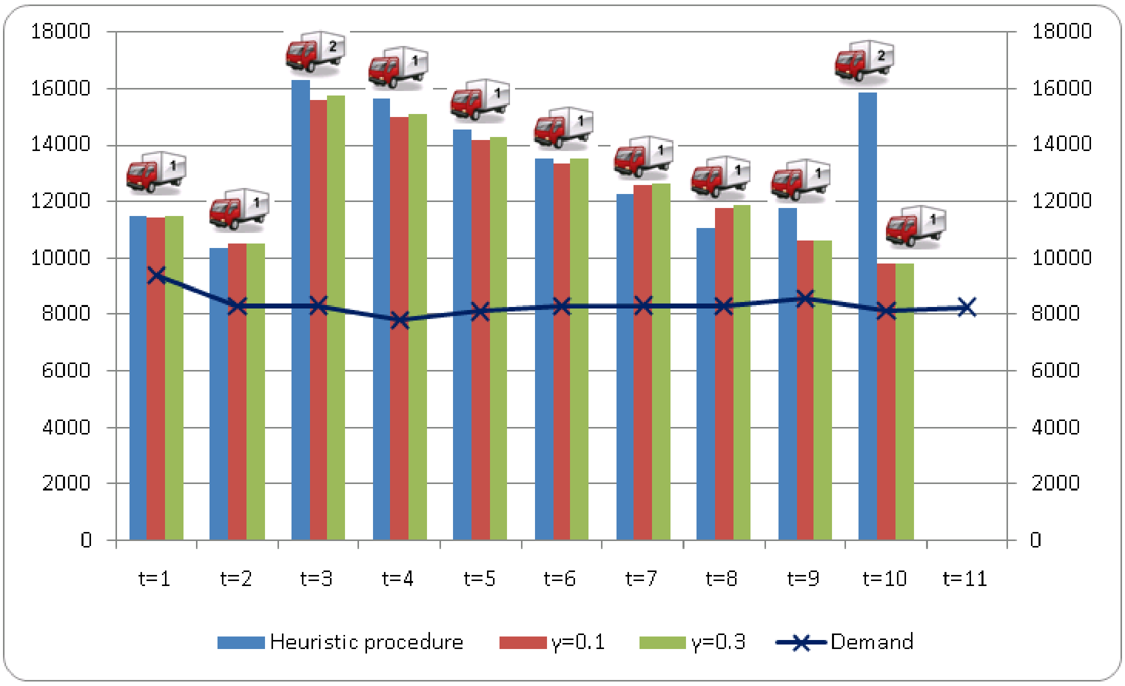

Figure 3: Total stock evolution (units)

6 Conclusions

This work proposes a new fuzzy multi-objective linear programming model for the SCTP problem at the operational level. This model considers fuzzy goals associated with the minimization of both the number of trucks used and the total inventory generated, as well as the fuzzy data related to the transport capacity levels. For the purpose of solving the FMOLP model, we propose an interactive solution methodology. This approach adopts linear membership functions to represent all the fuzzy objective functions and provides a systematic framework that facilitates the decision-making process. This approach has been tested in a real automobile supply chain. The interactive solution methodology yields an efficient compromise solution and presents the overall DM satisfaction with the determined goal values in a multi-objective SCTP problem. This approach provides solutions that are consistent with the decision maker's preferences (i.e., the consistency between weight vector θ_k and the satisfaction vector), because it is able to find different efficient solutions for a specific problem with a given weight vector θ_k by changing the γ value. Moreover, this approach has proven its efficiency by obtaining clearly much superior results than those obtained by the heuristic procedure which the SC under study is currently applying.

Although the linear membership function has been proved to provide qualified solutions for many applications [33], the main limitation of the proposed interactive approach is the assumption of the linearity of the membership function to represent the imprecise. This work assumes that the linear membership functions for related imprecise numbers are reasonably given. In real-world situations, however, the DM should generate suitable membership functions based on subjective judgment and/or historical resources. Future studies may apply related non linear membership functions to solve the multi-objective SCTP problems in fuzzy environments. Besides, the resolution times of the FMOLP model may be quite long in large-scale SCTP problems. For this reason, future studies may apply the use of evolutionary computation to solve fuzzy multi-objective SCTP problems more efficiently. Further future studies may apply the solution methodology to different problems related to supply chain planning: inventory management, vendor selection, production-distribution planning, procurement-production-distribution planning.

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