Operational transport planning in an automobile supply chain: an interactive fuzzy multi-objective approach
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Abstract: - We propose a novel fuzzy multi-objective linear programming model (FMOLP) for the supply chain transport planning problem at the operational level that considers various conflicting objectives simultaneously as well as the imprecise nature of some critical parameters such as capacity levels. The proposed model enables improved procurement process optimizing the use of transport resources and inventory levels. We also present an interactive solution methodology to convert this FMOLP model into an auxiliary crisp single-objective linear model and to find a preferred compromise solution in an interactive fashion. We validated the proposed model and the solution methodology in a real-world automobile supply chain. The computational results indicate that the proposed approach outperforms 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
Supply chain (SC) management deals with planning and coordinating bidding, production, sourcing and procurement activities across the multiple organizations involved in the delivery of one or more products [1]. In this context, the transport planning plays a very important role. The transport can be defined as the physical link connecting the fixed points in a logistics supply chain [2] and hence, the transport planning is a key integral process in contributing to: the overall goal of a successful SC management; the effective planning and control of material flows [3]; and, in definitive, the delivery of superior value to the end consumer [4].

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 [5].

In the literature, several authors have analyzed SC operational transport planning from a deterministic point of view [6-8]. Moreover, according to Peidro et al. [9] and [10], the literature provides several models for SC planning under uncertainty conditions. Among them, the fuzzy programming approaches for transport planning are being increasingly applied [11-14]. 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. [9] for a literature survey on supply chain planning under uncertainty conditions). Finally, there are several methods in the literature for solving multi-objective transport planning problems in a fuzzy environment [15-20].

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 [21] 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 [22].

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 [23].

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. Firstly, the procedure begins by obtaining the initial stock of each product at the beginning of the planning period and the daily demand of each given reference. As we cannot allow a delay in demand, should the inventory of any part at the end of the any 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 the considered periods. Trucks load in accordance with both the space available (approximately 13 meters with a FTL) and the number of days that the available stock may cover the demand in the following periods. Hence, vehicles are filled with products lot by lot in order of increasing coverage to complete its capacity, updating the stock level and coverage after each addition.

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 [24] and Evans et al. [25], 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).

<table>
<thead>
<tr>
<th>Sets of indices</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I:</strong> Set of products (i =1,2,...,I).</td>
</tr>
<tr>
<td><strong>J:</strong> Set of trucks (j =1,2,...,J).</td>
</tr>
<tr>
<td><strong>T:</strong> Set of planning periods (days) (t =1, 2…T).</td>
</tr>
</tbody>
</table>

| Decision variables |

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3.1 Objective functions

The formulation of FMOLP is as follows:

Minimize the total number of trucks utilized

\[ \text{Min } z_1 \equiv \sum_{j=1}^{J} \sum_{t=1}^{T} Y_{jt} \]  

(1)

Minimize the total inventory amount generated.

\[ \text{Min } z_2 \equiv \sum_{i=1}^{I} \sum_{t=1}^{T} I_{it} \]  

(2)

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 \( z_1^U(z_2^U) \) [26]. Accordingly, Eq. (1) and (2) are fuzzy and it is necessary for the DM to simultaneously optimize these conflicting objectives in the framework of imprecise aspiration levels [11].

3.2 Constraints

\[ I_{it} = I_{i(t-1)} - D_{it} + \sum_{j=1}^{J} Q_{ij}t \quad \forall i, t \]  

(3)

\[ Q_{ij}t = K_{ij} \cdot I_{i} \quad \forall i, j, t \]  

(4)

\[ I_{it} \leq W_{i} \quad \forall i, t \]  

(5)

\[ \sum_{i=1}^{I} Q_{ij}t \cdot u_{i} \leq M \cdot Y_{jt} \quad \forall j, t \]  

(6)

\[ \sum_{i=1}^{I} Q_{ij}t \cdot u_{i} \geq m \cdot Y_{jt} \quad \forall j, t \]  

(7)

\[ I_{it} \geq D_{i(t+1)} \quad \forall i, t \]  

(8)

\[ I_{it}, K_{it}, Q_{ij}t \geq 0 \quad \forall i, t \]  

(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.

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 [5].

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 [12,27,28] is used for the defuzzification process and converting this fuzzy parameter into a crisp number. So, if the minimum acceptable degree of feasibility ($\beta$) is given, then the equivalent auxiliary crisp constraint can be represented as follows:

$$\sum_{i=1}^{I} Q_{ij} \cdot u_i \leq (w_1 M_p^a + w_2 M_p^b + w_3 M_p^c) \cdot Y_p \quad \forall j,t$$

(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. Based on the concept of the most likely values proposed by Lai and Hwang [28] and considering several relevant works [12,27], we set these parameters as: $w_2=4/6$, $w_1=w_3=1/6$ and $\beta = 0.5$.

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.

Torabi and Hassini [5] proposed a new single-phase fuzzy approach as a hybridization of the previous methods of Lai and Hwang [29] and Selim and Ozkarahan [30]. According to Torabi and Hassini [5], a multi-objective model could be transformed in a single-objective model as follows:

Max $\lambda(x) = \gamma \lambda_0 + (1-\gamma) \sum_k \theta_k \mu_{z_k}(x)$

s.t. $\lambda_0 \leq \mu_{z_k}(x) \quad k = 1, ..., n$

$x \in F(x)$

$\lambda_0, \gamma \in [0,1]$

(11)

where $\mu_{z_k}$ and $\lambda_0 = \min \{\mu_{z_k}(x)\}$ denote the satisfaction degree of the $k$th objective function and the minimum satisfaction degree of the objectives, respectively. Moreover, $\theta_k$ and $\gamma$ indicate the relative importance of the $k$th objective function and the coefficient of compensation, respectively. The $\theta_k$ parameters are determined by the decision maker based on her/his preferences so that $\sum_k \theta_k = 1, \theta_k > 0$. Besides, $\gamma$ 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 $\gamma$ [5].

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 $M$ and specify the corresponding non-increasing continuous linear membership functions for all the fuzzy objective functions as follows.

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

(12)

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

Step 3. Determine the minimum acceptable degree of feasibility ($\beta$) for the fuzzy constraint and specify the corresponding relative importance of the objective functions ($\theta_k$) and the coefficient of compensation ($\gamma$).

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 $(\beta, \theta_k, \gamma, (z_k^l, z_k^c)$ and $M$).

5 Application to an automobile supply chain

In this section, we validate the proposed model as a tool for making decisions related to operational transport planning in a dyadic 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. Due to space limitations, the details of the basic item data and item demand are not presented here, but can be made available upon request.

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: \( \theta = (0.2, 0.8) \). 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.

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 2 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 2 shows the results obtained by the proposed method which adds the minimum satisfaction degree of the objectives (\( \lambda_0 \)), 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 2 the proposed method is clearly superior to the heuristic procedure. The proposed method, for the different \( \gamma \) 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 \( \gamma \) value is lower (unbalanced solution). As mentioned before, a low \( \gamma \) 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 \( \gamma \) 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 \( \gamma \) decreases the satisfaction degree of the objective function \( z_2 \) (whose assigned weight is higher) increases. On the other hand, when \( \gamma \) increases the inventory levels are higher and hence the satisfaction degree \( \mu_{z_2} \) is lower. Moreover, when the values of the coefficient of compensation \( \gamma \) increase the distance between \( \mu_{z_1} \) (setting the minimum satisfaction degree of objectives) and \( \mu_{z_2} \) is lower. Finally, the value of the objective function \( \lambda(x) \) is decreasing when \( \gamma \) increases. This is because the weight of the minimum satisfaction degree of the objectives, whose value is always \( \lambda_0=0.9 \), is higher in Eq. (11). For this reason, when \( \gamma=0.9 \) \( \lambda(x) \) is practically equal to \( \lambda_0 \).

![Figure 1: Total stock evolution (units)](image)

Figure 1 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 \( \gamma=0.1 \) and \( \gamma=0.3 \)) 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.
<table>
<thead>
<tr>
<th>Item</th>
<th>Heuristic</th>
<th>Proposed method ($\gamma=0.1$)</th>
<th>Proposed method ($\gamma=0.3$)</th>
<th>Proposed method ($\gamma=0.5$)</th>
<th>Proposed method ($\gamma=0.7$)</th>
<th>Proposed method ($\gamma=0.9$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trucks ($z_1$)</td>
<td>12</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Inventory ($z_2$)</td>
<td>132,797 units</td>
<td>124,773 units</td>
<td>125,431 Units</td>
<td>125,475 units</td>
<td>126,411 units</td>
<td>127,101 units</td>
</tr>
<tr>
<td>Truck occupation</td>
<td>12,9150 m</td>
<td>13,0767 m</td>
<td>13,0792 m</td>
<td>13,0792 m</td>
<td>13,0759</td>
<td>13,0792 m</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>0.9855</td>
<td>0.9835</td>
<td>0.9834</td>
<td>0.9806</td>
<td>0.9806</td>
<td>0.9785</td>
</tr>
<tr>
<td>$\mu(x)$</td>
<td>0.9616</td>
<td>0.9468</td>
<td>0.9334</td>
<td>0.9193</td>
<td>0.9063</td>
<td>Not applicable</td>
</tr>
<tr>
<td>$[z^l_1, z^u_1]$</td>
<td></td>
<td>$z^l_1 = 10$; $z^u_1 = 20$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$[z^l_2, z^u_2]$</td>
<td></td>
<td>$z^l_2 = 120,000$; $z^u_2 = 450,000$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$M_\beta^p$</td>
<td></td>
<td>$M_\beta^p = 12.85; M_\beta^m = 13; M_\beta^o = 15$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: A comparison of the heuristic and proposed method solutions.

### 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. For this reason, future studies may apply the use of evolutionary computation to solve fuzzy multi-objective SCTP problems more efficiently.

### 7 Acknowledgments

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