FUZZY OPERATIONAL DECISION-MAKING PROCESS IN URBAN FREIGHT TRANSPORT

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ABSTRACT

This article presents a fuzzy process for operational decision-making on the freight pick-up and delivery. It allows assessing the impact of uncertainty conditions presented in urban context variables such as time windows, service time, reacting available time, on the distribution routes. We use the fuzzy decision process to assess customers' requirements on a daily urban freight. The process supports the decision-making for accepting or rejecting the requests. It considers a notable key index, the impact level on the route. This index assesses the current values of the input variables. The changes are accepted when the impact level on the route is lower than 0.25.

1. INTRODUCTION

In urban freight transport (UFT) processes, there are constant changes in customer demand, travel times, and service times, among others (Gómez-Marín, 2020). It is necessary to consider methods that assess the feasibility of reacting quickly to these online changes in terms of additional costs incurred by changing pre-established routes and the impact on the scheduled routes to visit on time for all customers.

The fuzzy inference has been implemented in distribution logistics processes to mitigate the uncertainty and risks that arise in today's business and the constant search to improve the service levels expected by customers (Adarme-Jaimes, Arango-Serna, & Cogollo-Flórez, 2012; Brito, 2011; Lin et al., 2014), to minimize cost and risk on route planning (Pamučar et al., 2016), and to reduce environmental impact of network design (Cirovic, Pamucar, & Bozanic, 2014; Soleimani et al., 2017). It can be used integrating data analysis to assess the UFT system efficiency (Bray et al., 2014; Koohathongsumrit & Meethom, 2021). By using fuzzy inference, stakeholders can make decisions and react to the dynamic context changes and improve the performance of freight transportation systems (Bray et al., 2014; Kuo, Wibowo, & Zulvia, 2016). It allows flexible behaviors or replies to each change. According to Villeta et al., (2012) it is possible to use this tool to model the attitudes and behavior of actors in different scenarios.

Simic & Simic (2011) classify the application of fuzzy inference in UFT into four types: 1) application of expert systems, 2) multi-criteria decision-making processes under uncertainty, 3) routing problems mixed with transportation modes, and 4) process actor selection process. We present an application for a multi-criteria decision-making process to assess the possibility of accepting or rejecting changes based on reached impact level on the distribution plan (route).

This paper proposes a decisional framework to assess a notable key index, the impact level on the route. It considers events of time windows changes and service time changes during the operation day. It also takes into account the moment of the day when the event occurs and the relative customer importance on the route. The paper is organized as follow: at section two, we present the fuzzy decision-making process. In section three, we discuss the results of the fuzzy inference process. Hereafter we present conclusion and propose future works.

2. FUZZY DECISION-MAKING PROCESS

We define four input variables for the fuzzy inference system. These variables represent some possible changes in customer demand conditions and the changes characteristics. The customer sends a request informing the desired changes in time windows and in the service times to the vehicles at loading or unloading activity.

The input variables are defined based on change features and customer order importance.

The output variable is the result of the fuzzy inference process that explores quantifying the impact level on the route considering the changes events to the current route. Figure 1 presents the proposed fuzzy operational decision-making process.

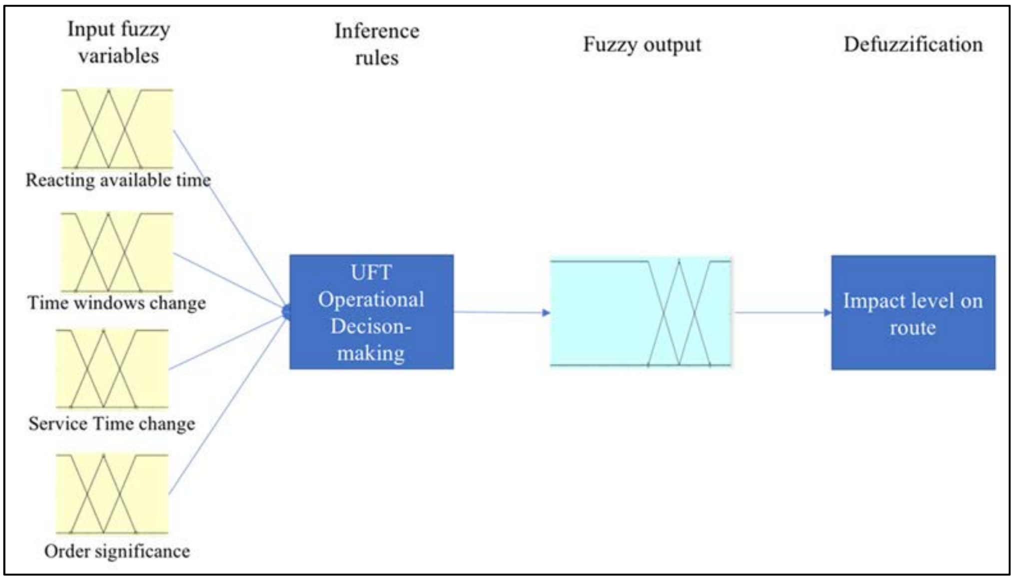


Fig. 1 – Fuzzy operational decision-making process

The selected variables in this fuzzy inference process are used to make decision-making more flexible and promptly and assess the possibility of reprogramming the initial distribution plan. These variables are:

2.1 Input variables

Reacting available time: This variable measures the time availability to react considering the moment when the customer requests the change. The available route time is the difference between the total time for the working day and the moment when the request arrives. Equation (1) shows how to calculate this variable:

$$Reacting\ available\ time = \left(\frac{Available\ route\ time\ (t)}{Total\ time\ for\ the\ working\ day}\right) \tag{1}$$

In the fuzzy parameterization process of the reacting available time, there are three fuzzy sets. Low if the reacting available time is between 0.00 and 0.25; medium, if reacting available time is between 0.125 and 0.375, and high if the reacting available time is greater than and 0.25.

Time windows change: this variable defines the time window increase or decrease, i.e., the new window size requested by the customer measured as a ratio between the change and the initial time window. We do not consider a translation of time window in a different operation time period. The fuzzy sets for the variable parameterization are three: low, when the ratio is lower than 0.25; medium, when this ratio is between 0.125 and 0.375; and high for ratios greater than 0.25. Equation (2) shows how to calculate this variable.

$$Time\ windows\ change = \left(\frac{New\ time\ window\ size}{Initial\ time\ window\ size}\right) \tag{2}$$

Service time change: We consider service time as the waiting time for be served plus the loading/unloading time**.** This variable defines the numerical value of the change in service time location with respect to an established service time, i.e., this variation just can occur when vehicle arrive to customer's location. The pre-established value for service time is 10 minutes. The fuzzy sets for the parameterization of the variable are three: low when the change in service time is negative, that is, the vehicle is served earlier than expected, and can vary between -10 minutes and 5; medium when the additional time that vehicle must wait is between 0 and 10 minutes; and high for changes greater than 5 minutes.

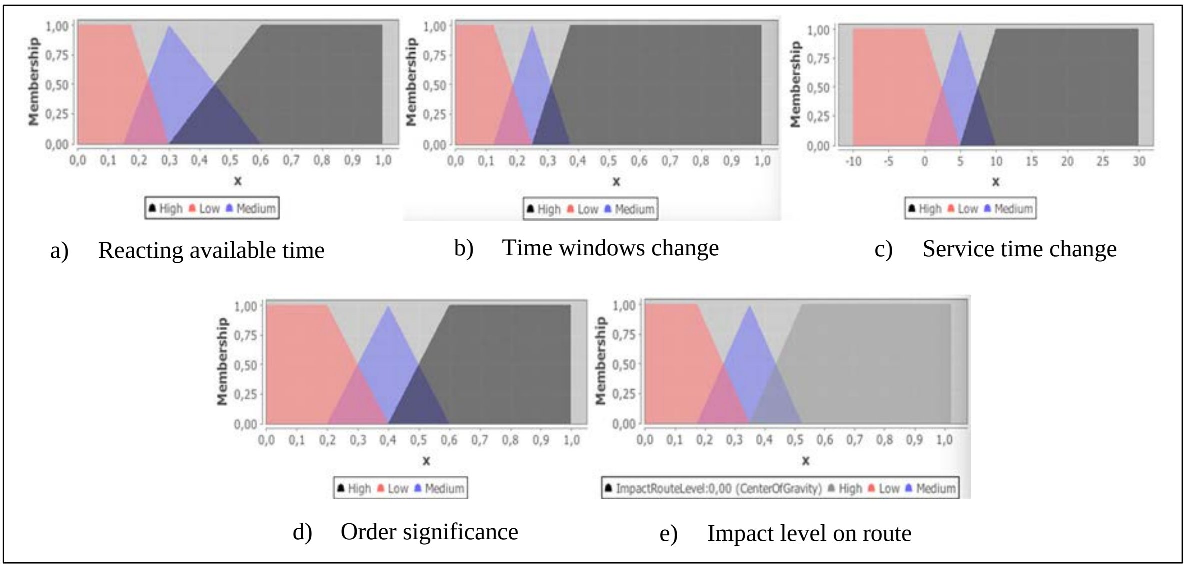
Order significance: This variable measures the ratio between the load quantity for the customer order that requires the change over the total vehicle load. Equation (3) presents the normalization for this variable.

$$Order\ significance\ (i) = \left(\frac{Load\ quantity\ for\ order\ (i)}{Total\ load\ quantity\ at\ vehicle}\right) \tag{3}$$

Order significance variable is bounded by three fuzzy sets. Low, when order significance takes values between 0 and 0.4; medium for significance values between 0.2 and 0.6; and high when the customer has a significance greater than 0.4.

2.2 Output variable:

Impact level on route: this variable measures the impact degree for a set of changes from a customer in the distribution route. This variable has an output range from 0 to 1 in which three fuzzy sets are determined: low, for impact route level values between 0 and 0.35; medium for values between 0.175 and 0.525; and high for impact route level values greater than 0.35. It is expected for values lower than 0.25 the changes can be accepted. Fig.2 presents the membership functions and fuzzy sets for the treatment of the variables.



a) Reacting available time
b) Time windows change
c) Service time change
d) Order significance
e) Impact level on route

Fig. 2 – Membership functions

2.3 Inference rules.

Impact level on route was evaluated on three input variables, which have three fuzzy categories. Therefore, there are $3^4 = 81$ IF-THEN rules in the fuzzy inference system. Table 1, for illustrative purpose, presents the first nine inference rules.

Rule	Service time change	Time window change	Urgency	Customer Significance	Impact level on route
1	High	High	High	High	Low
2	High	High	High	Medium	Low
3	High	High	High	Low	Low
4	High	High	Medium	High	Medium
5	High	High	Medium	Medium	Medium
6	High	High	Medium	Low	Low
7	High	High	Low	High	High
8	High	High	Low	Medium	Medium
9	High	High	Low	Low	Medium

Table 1 – First inference rules

2.4 Deffuzification method.

Since the objective of the work is to make decisions in urban freight transport to react to operational changes in the input variables, it is necessary to defuzzify the output of this inference system. For this purpose, the centroid method was used.

3. RESULTS AND DISCUSSION

The previously described fuzzy operational decision-making process allows to obtain response surface 3D graphs for modeling the relation between the input and output variables in urban freight transport (Figs. 3, 4 and 5). Figure 3 shows that the reacting available time has a greater impact level on route than the order significance. It is possible to obtain low impacts level on route and accept the changes when the reacting available time is below 0.6, regardless of the order significance values. Nevertheless, the impact level on route begins to increase when the available time to react to changes is lower than the approximately half of the total time for the working day.

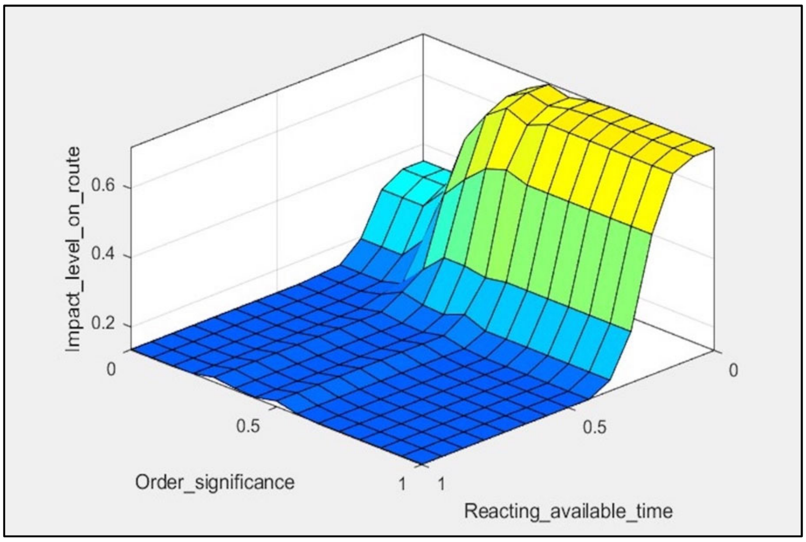


Fig. 3 – The 3D relation between order significance, reacting available time and 3.1 3.1 Impact level on route.

The reacting available time and service time change variables have a greater impact level on distribution route (Figure 4). With reacting available time values above 0.38 and service time change above 17 minutes, impact level on route is higher than 0.25 and the changes should be rejected. When the service time change is below 16 minutes and the reacting available time is more than 0.39, a significant decrease in impact level on route and the changes should be accepted.

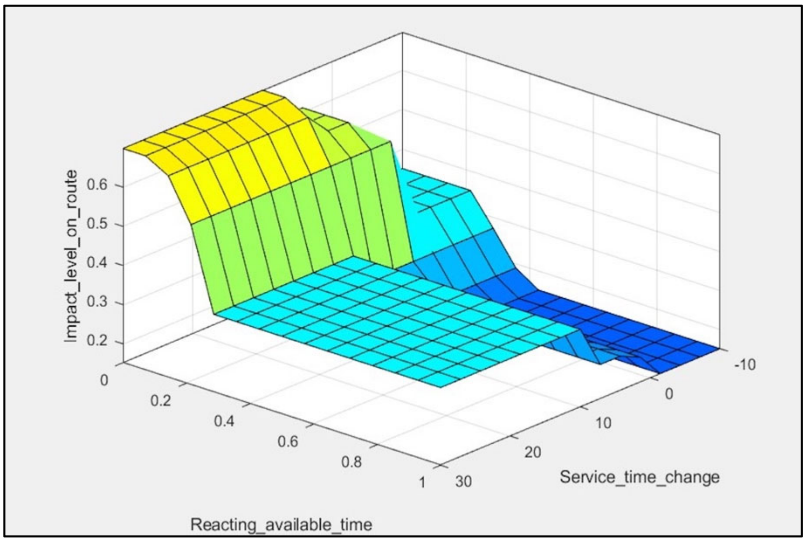


Fig. 4 – The 3D relation between reacting available time, service time change and Impact level on route

Regarding the relationship between order significance and service time change and their impact level on route (Fig. 5), it is possible to obtain high impacts level on route and reject the changes when the service time change is above + 8 minutes, regardless of the order significance values. Additionally, the impact level on route begins to decrease when the service time change is lower than the approximately +7 minutes and the change should be accepted.

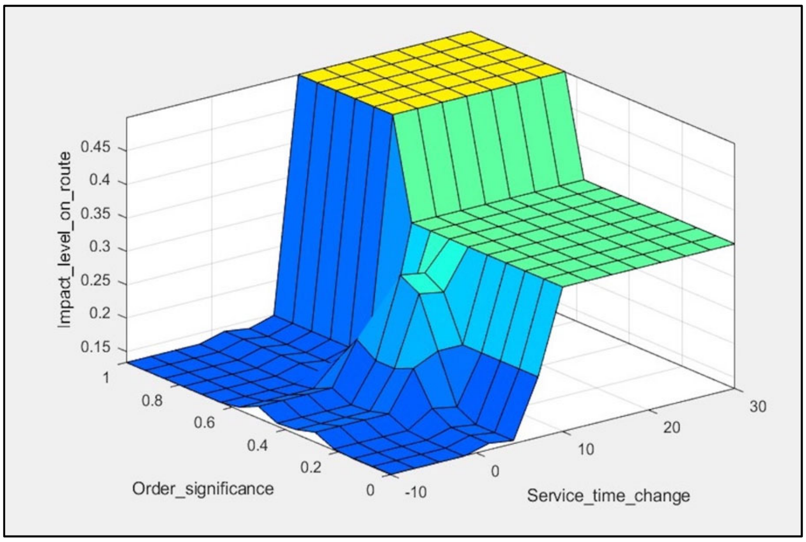


Fig. 5 – The 3D relation between order significance, service time change and impact level on route

4. CONCLUSIONS

The developed system shows that the fuzzy operational decision process is congruent with the reality of the UFT context. When there is more time to react to different changes in the operational context, it is possible to modify the distribution plan and accept the changes obtaining low impacts on routes. When the time to react to changes is relatively short, the change acceptance is affected by the low flexibility to respond to this change.

Additionally, if service times increase, it directly affects the remaining time to visit the customers and produces a higher impact level on the route, decreasing its acceptance. The variables that have a higher impact on the decision process are the reacting available time and the service time change. This work is a product of ongoing research whose objective is a model formulation for planning and evaluating urban freight distribution strategies under uncertain conditions. A future research line is the combination of this decision process integrated with the design of distribution routes and the dynamic vehicle routing problem. Also include some additional variables such as travel times and changes in demand.

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