Proceedings of the World Congress on Mechanical, Chemical, and Material Engineering (MCM 2015)
Barcelona, Spain – July 20 - 21, 2015
Paper No. 249

An Integrated Fuzzy Multi Criteria Approach for Robust Pairing Selection in Aviation Scheduling

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Abstract **-**Risk is present in almost every economic activity these days. The same uncertainty affects the aviation industry and requires disruption management from the airlines. With the relentless push for efficiency, aviation networks today are getting more and more optimized and hence inflexible. Even a small disturbance in such a tight network has a ripple effect which travels for long distances and hence effects a large portion of the network. Adding to the difficulty is the fact that handling disruptions has a lot of subjectivity and uncertainty involved. Most of the times there is a very little information available and also the action time window is very narrow. This makes processing the situation even more difficult. This warrants to have a proactive disruption management strategy by making the airline network more robust and hence more flexible to suitably absorb small shocks. This study is an effort towards this end by quantifying the robustness of each flight pairing and then choosing the best pairings on both the criteria of robustness and cost rather than on cost alone. An integrated fuzzy multi criteria method based on popular approach called technique for order preference by similarity to the ideal solution (TOPSIS) is used here for this purpose. A numerical example is solved to explain the workings of the methodology.

Keywords**:** Fuzzy theory, TOPSIS, Pairing selection, Aviation crew scheduling

1. Introduction

The operation of an airline requires building up an elaborate flight network and then distributing the available resources between its various components. This distribution is done in as efficient way as possible. Airlines thus hope to control their expenses, by efficient utilization of costly resources, to generate profits in an increasingly competitive fare environment (Jafari and Zegordi, 2011). This optimization to increase the efficiency of the network also renders it inflexible and making it tightly coupled within different sections of the network. This is rather dangerous in the sense that even a small disturbance in a part of the network has a ripple effect and thus affects even the far off sections. Thus although the planning is elaborate and to the minutest detail but unfortunately everything always does not go as planned. Unpredicted events such as disruptions due to problems in airports force the airlines to replan their schedules. Such events occur because it is never possible to forecast the future with complete certainty. We can use the best possible methods available for forecasting the future but there will still be uncertainty present (Samvedi *et al.*, 2013). This uncertainty is responsible for the gap between what is planned and what is needed when the time actually comes. Also this misjudgment leads to failures and subsequently losses for the firms (Lee and Kozar, 2006). Large airlines has huge networks and operate sometimes even more than a thousand flight per day. An effect carrying from one flight to another in such a huge network can cause serious problems for the management team.

Airlines usually choose flight pairings on the basis of their cost. A pairing consists of one or more duty periods, joined together sequentially, and separated by overnight rests. Similarly a duty period is a sequence of flight legs, joined together with small rest periods between them (Mercier and Soumis, 2007). This forces the airline management teams to do reactive disruption management every time any disturbance occurs. But more often than not there is very little time and also scant information available to act upon. This makes a point to go for proactive disruption management by building in a flexibility in the network and thus making them more robust. The aim of proactive decision making is partly to avoid disruptions in the first place, partly to limit the impact of disruptions when they occur (Sinclair et al., 2014). Such techniques are now becoming essential for the smooth operations of an airline network. Some airlines are now shifting towards ensuring that planned schedules are robust and allow for efficient recovery (Kohl et al. 2007). This study provides one such way of building in robustness in the schedule by choosing robust flight pairings using an integrated fuzzy multi criteria approach based on TOPSIS.

TOPSIS is a widely accepted multi-attribute decision-making technique due to its sound logic, simultaneous consideration of the ideal and the anti-ideal solutions, and easily programmable computation procedure (Chen, 2000). It is immensely popular method due to ease of application and hence has been used by a plethora of researchers. Chen and Hwang (1992) first applied fuzzy numbers to establish fuzzy TOPSIS and the method was first used for group decision making by Chen (2000). This was done by using triangular fuzzy numbers for subjective assessments and a crisp Euclidean distance was also defined between two fuzzy numbers. Agrawal *et al.* (1991) used TOPSIS for robot selection and Samvedi et al. (2013) used the method to quantify the supply chain risks.

The remainder of the paper is organized as follows. Section 2 talks about the problem at hand here. Section 3 talks in detail about the proposed methodology and describes the steps involved in the techniques used. Section 4 uses a numerical example to illustrate the proposed methodology and Section 5 concludes the paper with thoughts on future research scope.

2. Problem Description

The future is always uncertain. However good our forecasts may be, but it is not possible to accurately plan for the future. All types of industries and organizations get effected due to this uncertainty. Aviation industry is no different and is often forced to do disruption management when some unexpected event disrupts their planned schedule. Such events range from severe weather to the crew member unavailability. These inhibit the management's ability to move forward as planned and according to their set schedules. If such disruptions are not managed properly and timely, they will severely affect the airlines performance in terms of revenue, operational efficiency, and customer satisfaction (Li and Wallace, 2012).

The airlines approach the problem of disruption management in different ways. The various ways however can be broadly classified into two categories namely proactive and preventive disruption management. As the name suggests, proactive disruption management is done before the calamity strikes and the preventive management is done after the event occurs. The type which we are considering in this study is that of proactive management. This is done by building in flexibility in the system and trying to make the system as robust as possible. The system under consideration in this study is the flight schedule. There exist four possible disruptions

1. Aircraft disruptions: aircraft disruptions happen due to unavailability of an aircraft for a certain period of time. This can happen due to maintenance issues or breakdown of some parts of the aircraft. There are strict regulations on the duration for which an aircraft can operate before successive maintenance
2. Airport disruptions: airport disruptions happen whenever there are some problems at an airport and the efficiency of the airport comes down. This effects the number of arrivals and departures allowed at a given airport and a given period. This effects an airline by either delaying its aircraft's landing or its departure.
3. Flight delay: this can happen due to various reasons like crew unavailability, aircraft problems or airport disruptions. This is the most frequent type of disruption and happens on almost a daily basis. The only difference is the severity of disruption. Sometimes the delay is small and can be easily managed, whereas on other times this delay is sufficiently large to effect other flights.
4. Flight cancellation: this type of disruption is also related to flight disruption but is different from the previous disruption in the sense that here the flight is cancelled and hence it is required to make arrangements for the passengers. Thus the problem is different and requires other methods to deal with it.

All these types of disruptions have a ripple effect on the airlines network. As most of the network is highly optimized, mostly there is a little slack available to absorb the disruption shock. This results in long propagation of a disruption wave and thus effecting many other flights. The way out from such a situation is to make our flight schedules more robust. This is done by building in more slacks at certain nodes in the network. This is achieved by selecting those flight pairings for the network which are more robust than the others. The remaining of the paper shows how this can be done.

3. Methodology

This section proposes a methodology for quantifying the robustness of a flight schedule of an airline by assigning a robustness score for each flight pairing. The methodology consists of four steps as given in Figure 1. The first step requires the aviation expert to form all the possible feasible pairings. In the second step the expert (or sometimes more than one expert) are asked to rate each pairing for the exposure it has to the particular type of disruption. Linguistic expressions are used as it is almost impossible to assign exact scores because of the subjectivity involved in such decisions. This process is followed for all four type of disruptions defined. We use triangular fuzzy numbers for these. Once completed these inputs can then be aggregated and processed using fuzzy TOPSIS method to arrive at a numerical score, in step 3. These scores are the robustness indicators of each flight pairing. This consolidation of scores of different flight legs which form a pairing is done using the proposed formula given in equation. These pairings are then combined with the cost of each pairing to choose the best pairings.

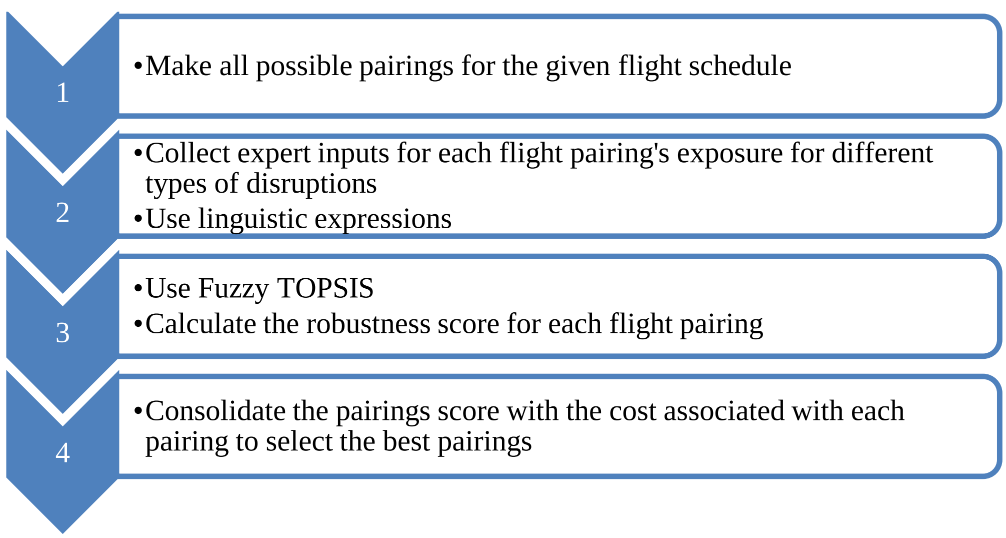

Fig. 1. Flow of the proposed methodology

3.1 Fuzzy TOPSIS

TOPSIS is a multiple criteria decision making method, which identifies the best alternative from a finite set. It was initially proposed by Chen and Hwang (1992) and uses the assessment of alternatives under different criterion as input. The theory behind TOPSIS is to identify the best possible solution and the worst possible solution. The alternatives are then compared with these two solutions and their respective distances are found. These distances are then used to evaluate a consolidated score which attaches higher scores to alternatives close to the best solution and at the same time far from the worst solution. Fuzzy TOPSIS is also quite similar to the original method with the only difference being that the numbers are changed to fuzzy values and the process now includes fuzzy mathematical techniques. Complete details about the methodology can be found in Karsak (2002). The steps important in this study have been reproduced here

a) In the first step, we normalize the given data column wise using the following equation

$$r_{ij} = (r_{aij}, r_{bij}, r_{cij}) = \left(\frac{c_j^+ - c_{ij}}{c_j^+ - a_j^-}, \frac{c_j^+ - b_{ij}}{c_j^+ - a_j^-}, \frac{c_j^+ - a_{ij}}{c_j^+ - a_j^-}\right) \quad (1)$$

Where $c_j^+ = max_i c_{ij}$ and $a_j^- = min_i a_{ij}$

b) Then we define the best and the worst possible alternative assessments. In this study best assessment is $r_j^+ = (1,1,1)$ and the worst is $r_j^- = (0,0,0)$ respectively for j = 1,…,n

c) Now the methodology calculates the distances of all alternatives from these two extreme values. To do this the following equation, which calculates the distance between two fuzzy numbers, is used.

$$D(A_1, A_2) = \frac{1}{2}\left\{\max\left(|a_1 - a_2|, |c_1 - c_2|\right) + |b_1 - b_2|\right\} \quad (2)$$

The distance of an alternative's assessments from the best and the worst assessment can be done by summing up the distances of respective parameter values from them. Equal weighting has been assumed for all parameters in this study.

d) In the last step we calculate the score for an alternative (here a pairing) by calculating their proximity to the best possible values and simultaneously it should be as far away as possible from the worst set of values. The following equation is used

$$\text{Score} = \frac{\text{Distance from the anti-ideal value}}{\text{Distance from the anti-ideal value} + \text{Distance from the ideal value}} \quad (3)$$

The scores obtained are then used with the cost of each pairing to identify the best possible pairings. The next section explains the methodology with a numerical example.

4. Numerical Illustration

For explaining the methodology clearly a small example has been picked up from the literature. The example consists of six daily flights to and fro from three airports. The departure and arrival time is also given. The example is given in Table 1.

Table. 1. An example with six flights (Yu, 1998)

Flight Leg	From	To	Departure	Arrival
1	A	B	6:30	13:30
2	B	A	14:30	21:30
3	B	C	10:15	11:45
4	C	B	12:15	13:45
5	B	C	14:15	15:45
6	C	B	16:15	17:45

The first part of the process is to enumerate all possible feasible pairings. This is actually the way even the traditional approach works, where after enumerating all possible pairings they are evaluated for their cost and the schedule with the least cost is selected. With the feasible pairings the costs are also mentioned in the Table 2. The cost is given in terms of duty periods, since mostly the pairings usually differ in the number of duty periods it has and the cost of a duty period is normally the same.

The next step in the process requires us to collect the experts input for the level of exposure the pairings have to each type of possible disruptions. The inputs being subjective in nature are taken in the form of linguistic values. There are five choices for each parameter as shown in Figure 2. Because of the subjectivity involved in collecting these inputs it is always advised to use a group of experts rather than a single expert. Then the fuzzy values are averaged using fuzzy mathematics.

Table. 2. All feasible pairings and their respective costs (Yu, 1998)

Pairing	Details	Cost (Duty Periods)
P1	1-lo-2	2
P2	1-lo-3-4-2	2
P3	1-5-lo-4-2	2
P4	1-5-6-lo-2	2
P5	3-4	1
P6	3-6	1
P7	5-6	1
P8	3-4-5-6	1
P9	2-lo-1	2
P10	2-lo-1-5-6	2
P11	3-lo-4	2
P12	3-lo-6	2
P13	3-lo-4-5-6	2
P14	3-4-5-lo-4	2
P15	3-4-5-lo-4-5-6	2
P16	5-lo-4	2
P17	5-lo-4-5-6	2

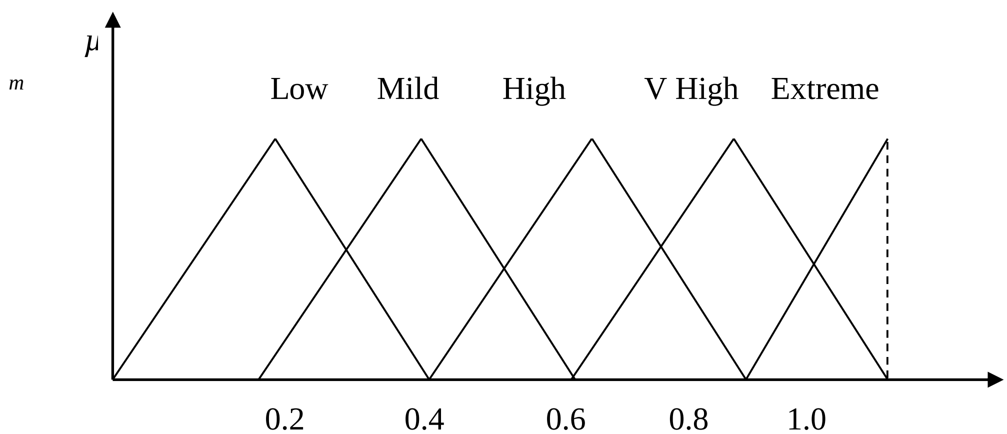

Fig. 2. Membership functions of the linguistic expressions

The assessment from the aviation experts come in the form of these linguistic expressions and are given in Table 3. Also given are the final scores calculated using the fuzzy TOPSIS method as explained in the previous section. These scores are then consolidated for the possible flight schedules. A simple way to do this is to choose the minimum from all the pairings in the schedule. This comes from the well-known saying that a chain is only as strong as the weakest link. In the Table 4, 2 of the possible best schedules are given and their cost as well as robustness score is given. From this table the management team can take the decision to whether it is advisable to cut costs at the expense of less robustness. As can be seen choice 2 is less robust but is also less expensive. So the management decision required here is that whether the extra robustness which comes by choosing choice 1, is worth expending that much extra.

Table. 3. Linguistic assessment by experts and final robustness score

Pairing	Types of disruptions				Score
	Aircraft	Airport	Flight Delay	Flight Cancellation	
1.	VH,H,H	L,L,M	E,VH,H	H,M,H	0.2781
2.	E,E,VH	M,L,H	H,VH,VH	E,E,VH	0.2545
3.	VH,VH,H	L,M,M	H,H,M	VH,VH,H	0.2961
4.	H,H,VH	L,L,L	M,M,L	M,M,H	0.3890
5.	VH,VH,E	M,H,H	H,VH,H	VH,VH,E	0.3279
6.	H,VH,H	H,M,VH	H,M,H	M,H,VH	0.2735
7.	VH,H,VH	L,M,L	H,H,H	H,H,M	0.4981
8.	L,L,M	VH,VH,H	L,L,M	M,L,H	0.3279
9.	M,L,H	H,H,VH	L,M,M	M,M,L	0.2458
10.	L,L,L	VH,H,M	M.M.H	L,M,L	0.1290
11.	VH,H,VH	M,H,M	H,M,M	M,H,H	0.3642
12.	E,VH,E	M,M,L	H,VH,H	H,M,H	0.4447
13.	L,L,M	E,VH,E	M,L,L	L,L,M	0.2001
14.	L,L,L	VH,E,H	M,M,M	M,M,L	0.1276
15.	H,H,VH	H,M,M	H,VH,H	H,H,VH	0.2650
16.	L,L,M	E,VH,H	H,M,M	M,M,H	0.1141
17.	VH,VH,H	H,H,H	M,M,H	H,H,M	0.3981

Table. 4. Consolidated scores and cost for best flight schedules

	Best Schedules	Cost (Duty Periods)	Robustness Score
1	P1 & P8	3	0.2781
2	P2, P4 & P8	2.5	0.2545

5. Conclusion

On time performance is one of the key performance measures for the aviation industry. But frequent disruptions caused by unforeseen events like crew unavailability, aircraft disruptions or problems at an airport, hinders the airlines from achieving high scores on this key metric. The airlines are forced more often than not to do disruption management so as to bring the airline network back to the laid out plan. Most of these problems can be suitably solved or at least stopped from affecting other parts of the network by making the network more robust by building in slackness and flexibility. This study is an effort in this direction and uses an integrated fuzzy multi criteria approach to help in choosing more robust pairings for the network. The methodology is illustrated using a numerical example and it can be seen from the process how a more robust network can be built by using quantified robust scores with cost values. This direction of research can be further explored by using other techniques such as fuzzy analytical network process which also has the ability to study the interactions among different criteria. As in today's world most of the criteria are interlinked, such a study can be a good extension to this research.

Acknowledgements

The work described in this paper was substantially supported by The Hong Kong Polytechnic University Research Committee with financial and technical support through an internal grant (Project Nos. G-UB03 and G-UA4F).

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