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Original paper

Proper process selection during flight schedule disruption using a fuzzy multi-criteria decision-making expert system

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Abstract

The aviation industry is a complicated, sensitive, and challenging phenomenon. One of the major issues in the operation of streamlined processes in this industry is the management of proper decisions during the disruption of flight schedules. Such disruptions commonly reduce customer satisfaction and the profitability of the airlines. Since there are multiple reasons for the disruption of the flight schedules along with the different possible decisions, a correct decision is very difficult to make requiring the opinions of the specialist staff. In this research, an expert model using a "fuzzy multi-criteria decision-making" method is proposed to provide a correct decision during the disruption of the flight schedules. The results show that the most important factors that make disruption of flight schedules are arrival delays and technical failure of the airline fleet. Besides, the most important possible decisions are the announcement of the delay and canceling of the flight. Thanks to utilizing the fuzzy analytical network process, the outcomes of the proposed expert model are in good alignment with the opinions of the specialist staff. The fuzzy analytical network process determines the values of 0.5124 and 0.2621 for the magnitude of the arrival delay and technical defect respectively. This method also determines the values of 0.7042 and 0.2076 for flight delay and flight canceling as the two most important possible decisions.

Keywords: Flight schedules disruption, expert system, fuzzy system, multi-criteria decision making.

1 Introduction

Today, the aviation industry is one of the most effective industries in the global economy and transport management. However, this industry has faced different issues in recent years [19]. One of these main issues is the disruption of flight schedules. Generally, the schedule of the flights involves four flight phases including fleet assignment, route allocation, flight network, and flight allocation [20]. The most important goal of the flight schedule is to reduce the operational and human costs and to increase the profits of the airlines which is determined primarily by the airline's facilities and limitations [3]. Statistic studies show that many airlines, despite their comprehensive efforts, lose much of their budget because of the multiple disruptions of their flight schedules [23]. Most of these disruptions are due to the weather conditions and limitation of resources of airlines [9] among many other factors. Therefore, specialists in transport science are trying to find the reasons for the disruption of the flight schedules for each region to reduce its negative impacts as well as to increase the efficiency of the airlines and the satisfaction of the customers [13]. Achieving these targets is complicated because of the high number of effective parameters in the disruption of the flight schedules and corresponding possible decisions [2]. The main goal of this research is to provide a solution for optimizing the decision-making process by the directors of airline companies. To achieve this target a two phases analysis containing two subsystems is utilized. First, according to Morgan's table, 250 specialists have been selected to answer an open survey

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form and a comparative questionnaire as the sample size. The data obtained from the open survey forms are criteria for the disruption of the flight schedule and further possible decisions. This data has been presented to the specialists in comparative forms. The obtained data have been analyzed and resolved using the fuzzy analytical network process and Chang Extended method analysis. The output of this part has been presented again as a comparative survey form to the specialists. The results of this comparison have been inputted into the first subsystem. The outcomes of this step are presented again as a comparative survey form to the specialists and the results of this comparison are imported into the second-level subsystem. The output of this step is the proposed decision of the model when a disruption in the flight schedules occurs by considering the reasons for it. Accordingly, we propose a fuzzy multi-criteria decision-making expert system for the management of disruption of flight schedules. The suggested model is based on the most important reasons for such disruptions and the most important possible decisions. This modeling approach allows the airlines to react properly to the changes and disruptions of the flight schedules and make the most appropriate decisions to minimize their negative effects on the profits of the company and the satisfaction of the passengers. The paper is structured as follows; section 2 contains a literature review concerning the topic of this research. In section 3, the research method consisting of pre-design and decision-making phases are described. In section 4 the suggested expert model that contains two expert subsystems for disruption of the flight schedules is presented. In the end, the main findings are discussed.

2 Literature review

The main task of an expert system is the transfer of knowledge from human to computer. Such knowledge is stored by rules in the system, and then users can access these rules and deduce them with their help. In other words, the computer can deduct from the stored knowledge and rules, draw conclusions, and advise the person [1]. (see Figure 1)

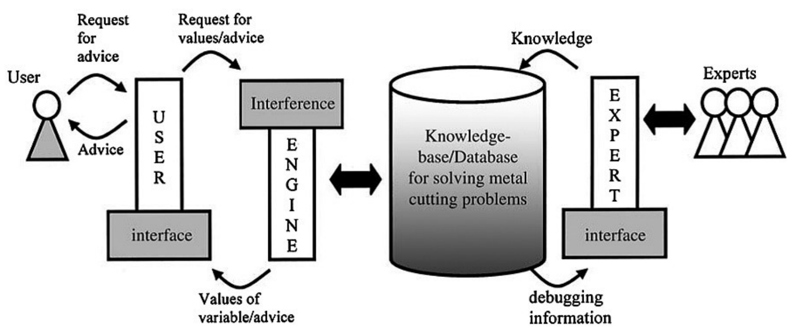


Figure 1: Example of an expert system [14].

A group of expert systems uses production rules to display knowledge [12]. The rules of production have the benefits of simplicity, the unit of validity, and the possibility of description. However, if the number of production rules increases, the degree of transparency of the system and its response can be significantly reduced. Therefore, in such cases, the establishment of successful communication between the rule-based expert systems and the databases is really difficult [14]. Similarly, rule-based systems have an inherent limitation in learning and cannot change themselves, while this feature is essential for any knowledge display system [1]. The major challenge to solving such problems is the weakness of the classical zero and one logic principle Boolean" in understanding the natural language variables due to the ambiguity in this language [2]. Despite the advantages of the analytical network process for assigning priority to the criteria and problem decisions based on paired comparisons and decision-making judgments, they cannot take into account the uncertainty in their linguistic variables and their mental judgments. Fuzzy sets are one of the most appropriate decision-making methods in such situations due to their ability to deal with uncertainty [9]. The fuzzy analytical network process itself is derived from changes in the process of the fuzzy analytical hierarchical process [2]. Cagman et al. [5] also define a fuzzy soft set theory and its related properties. They then define fuzzy soft aggregation operator that allows constructing more efficient decision making method. In research articles such as Jangizehi et al. [9], Asfe et al. [2] and Jangizehi et al. [8] have investigated the problem of making the right decision when there is a disruption in the flight schedule of airlines with the processes of analytical network, analytical hierarchical and fuzzy analytical network. The results of these studies indicate some differences in the prioritization of disorder criteria and proposed decisions. These differences are due to the consideration of internal relationships in the analytical network process and the disambiguation of the opinions of experts and respondents to the questions of the problem from the fuzzy perspective. Zhang et al. [24] focused on the propagation of flight delays in air transportation networks (ATNs) by considering both network structures and airport operation performance and Ohi and Kim [17] explored the application of count models to represent the relationship between flight disruptions and the weather. Another piece of research concerning the issue at hand was done by Serrano-Hernandez et al. [20] who proposed a stochastic optimization model for the airline fleet management problem, considering uncertainty in the demand, operational costs, and fares. In another study, Pei et al. [19] described a data-driven approach to the irregular flight recovery problem and developed a quantitative mechanism to evaluate the disrupted flight providing easily adopted recovery suggestions. Regarding the issue of passengers baggage disrupting the smoothness of flight schedules, Skorupski and Uchroski [21] focused on that and proposed a fuzzy theory-based model for solving the passenger timetable issue at the airport. The results of the proposed model showed that the distribution of the load screening devices in different locations increases the passengers safety. Also, this solution increases the speed of the baggage controlling process and pre-flight operations thus reducing the number of disruptions in the flight schedules. In another research presented by Bruno et al. [4] an optimal decision under different flight conditions was made. In their work, an approach that combines the analytical hierarchical process and fuzzy theory is used to carry out the proposed evaluation. This hybrid approach utilizes the strengths and weaknesses of both methods in solving the problem. Additionally, Patel et al. [18] reviewed the issue of planning and scheduling flights in unmanned systems under the ambient multi-objective environment. examining their proposed model in a defined scenario. The results revealed that multi-objective fuzzy programming is a practical method for solving the flight schedule problem in uncertain conditions. Jarrah et al. [10] explored the reasons for flight canceling by airline companies and proper decision-making solutions in such a situation. The findings of this study indicated that the use of networked and deployed models in the planning of airline companies makes more efficient solutions. Furthermore, Dunbar et al. [7]. have reviewed the issue of programming and scheduling in airlines and presented a new perspective for accurate calculation and reduction of the cost of delays in a complex framework, including aircraft routing and crew scheduling. Sohoni et al. [22]. studied methods that help airlines to carry out a timetable when uncertain conditions occur, while Karels et al. [11]. concentrated on the risk management process under a fuzzy expert model pointing out that there is a significant difference between trained officers/soldiers and untrained ones in the level of perceived risk, which helps leaders of an army to make systematic planning to reduce the risk of their organization. In another study, NG et al. [16] introduced an expert system to support past events to predict possible future events. This system, as an intelligent agent, identifies similar events and provides possible effective factors. This intelligence is based on the expert system's ability to learn from past event data using the combined inference technique of the fuzzy logic system. Li and Jing [15] have proposed a new prediction framework (ST-Random Forest) to predict flight schedule delay as one of the disruption factors from a temporal and location perspective. To predict flight delays, they have used network and forest theory in the context of fuzzing systems to resolve the ambiguity of the degree of influence of delay factors expressed in the form of verbal variables. Lastly, Arias-Aranda et al. studied the basic parameters of business issues and the basics to make them expertise [1]. proposing a fuzzy expert system for managing business issues. They concluded that such a model in a predefined scenario represented an increase in the precision and quality of knowledge for decision making.

3 Research method

The research method consists of two phases pre-design and decision-making. In the pre-design phase, the basic criteria for disruption of the flight schedules, along with the decisions made to manage it are achieved. This phase includes two steps:

1. Finding the reasons for the disruption of the flight schedules as well as further possible decisions by using the library data and opinions of specialists obtained from an open-ended questionnaire.

2. Analysis of the results of the previous step by using the paired comparison questionnaires with the help of the fuzzy analytical network process.

In the decision-making phase, an expert system has been developed that includes two subsystems for making the final decision. For this target, by using the paired comparison questionnaires, six steps are followed:

1. Designing fuzzy fogging agents for the disruption of the flight schedules and the possible decisions

2. Extracting rules of the fuzzy expert system

3. Fuzzing the inputs

4. Fuzzy Inference
5. Decaying
6. Making the final decision

In the first phase by using the library data [19, 20, 2, 24, 17, 22] , observations, and opinions of specialists extracted from the survey forms, different criteria for the disruption of the flight schedules were obtained. These criteria include delay arrival (DA), technical defect (TD), weather conditions (WC), airport traffic (TR), internal problems (IP), and specific causes (SC). Accordingly, the possible decisions during the flight disruption were obtained as flight delay (FD), flight cancelation (FC), aircraft replacement (AR), and route replacement (RR). In this questionnaire matrix, the elements in the main diagonal are one, and therefore the preference of each criterion is the same itself. If the preference of criterion X over criterion Y is A, then the preference of Y over X is 1/A. Consequently, in the as matrix of comparisons, the top of the main diameter should be completed by the specialists, the elements on the main diagonal are 1 and the elements below the main diagonal are inverse of the corresponding elements above the main diagonal. For Fuzzing, the numbers obtained from the paired comparison forms filled by the specialists are converted to the fuzzy form triangular fuzzy numbers as shown in Table 1.

Table 1: Paired comparison forms [9]

Types of preferences (language variables)	**Definitive number**	**Triangular fuzzy number**
Very high important or desirable	9	(9,9,9)
High important or desirable	7	(6,7,8)
More important or desirable	5	(4,5,6)
Medium preference, which is more favorable than average	3	(2,3.4)
The same preference or the same importance or the same utility	1	(1,1,1)
Preferences between the above intervals	2,4,6,8	(1,2,3),(3,4,5),(5,6,7),(7,8,9)

The opinions of the specialists obtained from the paired comparison questionnaire forms are replaced with fuzzy numbers according to Table 1. In other words, for each number obtained from the paired comparison, there is a three-part number by converting the paired comparison questionnaire of each specialist into a fuzzy form. In this step, the geometrical mean method is used to combine the opinions of the specialists. The final fuzzy paired comparison table is illustrated in Table 2.

Table 2: The final fuzzy paired comparison table

G	**DA**			**TD**			**WC**			**TR**			**IP**			**SC**		
DA	1	1	1	2.5198	3.5569	4.5789	2.2894	3.3019	4.3089	5.7388	6.6039	7.3986	3.9791	5.0397	6.0822	7.6127	8.3203	9
TD	0.2185	0.2810	0.3969	1	1	1	2.1124	3.1454	4.1561	6.2573	7.2685	8.2868	1.1003	1.7100	2.6207	4.6416	5.6462	6.6494
WC	0.2321	3.0265	00.3217	0.2500	0.3330	0.5000	1	1	1	2.7144	3.9149	5.0133	1.0014	2.1547	2.2167	4.2172	5.2416	6.2573
TR	0.1356	0.1514	0.1742	0.1208	0.1377	0.1599	0.1996	0.2556	0.3684	1	1	1	0.2232	0.2924	0.4366	0.6929	1.1735	1.7100
IP	0.1644	0.1984	0.2512	0.3817	0.5848	0.9086	0.3330	0.5000	1.1570	2.2894	3.4200	4.4814	1	1	1	5.2415	6.2573	7.2685
SC	0.1110	0.1201	0.1314	0.1506	0.1773	0.2154	0.1599	0.1910	0.2370	0.5848	1.1721	1.4418	0.1377	0.1599	0.1910	1	1	1

The degree of influence of each criterion on the disruption of the flight schedules is illustrated in Table 3.

Table 3: The influence of each criterion on the disruption of the flight plan

DA	TD	WC	TR	IP	SC
0.5124	0.2621	0.1231	0.0021	0.1003	0

After the formation of the final fuzzy paired comparison matrix, it is necessary to examine the compatibility of the opinions of the specialists. One of the effective methods for determining this compatibility is to examine the degree of compatibility of the middle-number matrix derived from the paired comparison matrix. Based on the accepted rule in the analytical network process, if the obtained number is less than 0.1 it means that the opinions of the specialists are compatible. Otherwise, it is necessary to review the opinions of experts and the forms of paired comparisons because of the possibility of contradictions and inconsistencies in the opinions [9, 6]. Due to the large numbers of comparative matrices in this work, the described process for examination of the compatibility of all opinions by using the middle-number matrix method is time-consuming. Therefore, Super Decision software has been used to ensure that the opinions of the specialists are compatible. Figure 2 shows a preview of the effect of each criterion on the disruption of the flight schedule provided by specialist staff. In this preview, the degree of each criterion is given along with the consistency of the opinions, which is approximately 0.06. Considering that this value is less than 0.1, the consistency of the opinions is acceptable and allows us to take them into the next step of our analysis.

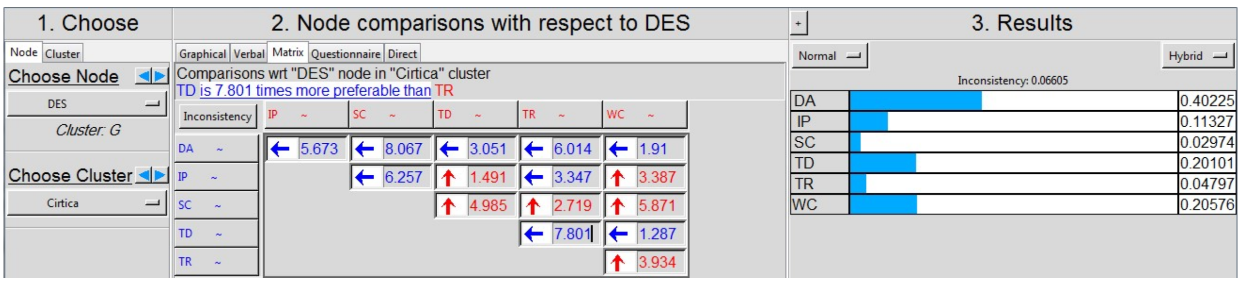


Figure 2: Effect of each criterion on the disruption of the flight plan.

Since reviewing the matrices of opinions of all specialists shows that all comparison matrices have acceptable compatibility (less than 0.1), there is no requirement to re-evaluate the comparisons and therefore the next steps can be taken to Non-fuzzing these opinions. At this step, Chang's developmental analysis method is used, which is one of the proposed methods for obtaining the weight of decision-making criteria by fuzzy analytical hierarchical/analytical network process [6]. For this purpose, the following steps have been taken for each pair of comparison matrices:

1. The summation of the corresponding cells for each table (matrix)
2. Collecting cells of each column
3. Reversing the response cells
4. Multiplying the inverse of each cell in the total row matrix
5. Determining the preference of each fuzzy number obtained over the other numbers using Chang's development method
6. Minimizing the preferred values obtained for each criterion and its normalizing

Due to the time-consuming nature of these steps for all comparison matrices, the implementation of the Chang method in MATLAB software has been used. The final status of the disruption criteria and the decision options using Chang's method are shown in Table 4.

The priority of each decision option is shown in Table 5.

4 Modeling and results

In this section, the developed models and their obtained results are discussed.

Table 4: Summary of the pairwise comparisons and effect of each criterion on the decision options

Preference	0.5124	0.2621	0.1231	0.0021	0.1003	0
	DA	**TD**	**WC**	**TR**	**IP**	**SC**
FD	0.7633	0.5321	0.6002	0.7082	0.4560	1
FC	0.1452	0.2583	0.3428	0	0.3166	0
AR	0.0915	0.2096	0	0	0	0
RR	0	0	0.0570	0.2918	0.2274	0

Table 5: Summary of the impact of each criterion on decision options

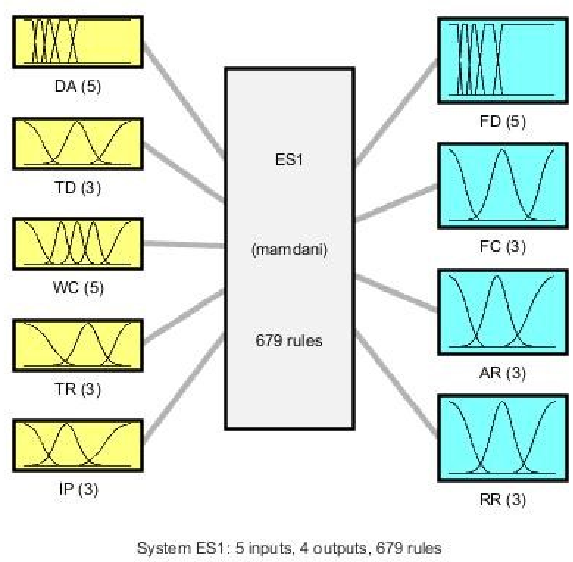
FD	**FC**	**AR**	**RR**
0.7042	0.2076	0.0784	0.0098

4.1 Modeling the first expert subsyste

According to the results obtained from the criteria, the specific causes (SC) criterion was ignored in the analysis because of its zero preference. Then, the first subsystem is made by the MaIPani method and the Fuzzy toolbox of MATLAB using other criteria as inputs and decision options as outputs. The overall design of the first subsystem is shown in Table 6.

Table 6: Overall design of the first subsystem

Parameter	**Value**
Name	ES1
Type	MaIPani
And Method	max
Or Method	min
Defuzz Method	Centroid
Imp Method	Min
Agg Method	max
Input	[1x5 struct]
Output	[1x4 struct]
Rule	[1x675 struct]



The methods of introduction of the input and output variables of the first subsystem are shown in Tables 7 and 8 respectively.

Table 7: Input variables of the first subsystem

Variable name	**Condition**	**Introducing function**	**Amounts**
DA	VL	trapmf	[-15 0 30 45]
	L	trapmf	[30 45 60 75]
	Med	trapmf	[60 80 90 120]
	H	trapmf	[90 120 150 180]
	VH	trapmf	[150 180 Inf Inf]
WC	VG	zmf	[0 0.3]
	G	gaussmf	[0.05 0.35]
	Med	gaussmf	[0.05 0.5]
	B	gaussmf	[0.05 0.65]
	VB	smf	[0.7 1]
TD	L	zmf	[0 0.35]
	Med	gaussmf	[0.1 0.5]
	H	smf	[0.6 1]
TR	L	zmf	[0 0.5]
	Med	gaussmf	[0.1 0.6]
	H	smf	[0.7 1]
IP	L	zmf	[0 0.35]
	Med	gaussmf	[0.1 0.4]
	H	smf	[0.5 1]

Table 8: Output variables of the first subsystem

Variable name	**Condition**	**Introducing function**	**Amounts**
FD	VL	trapmf	[-15 0 30 45]
	L	trapmf	[30 45 60 75]
	Med	trapmf	[60 80 90 120]
	H	trapmf	[90 120 150 180]
	VH	trapmf	[150 180 Inf Inf]
FC	L	zmf	[0 0.3]
	Med	gaussmf	[0.1 0.5]
	H	smf	[0.7 1]
RR	L	zmf	[0 0.35]
	Med	gaussmf	[0.1 0.45]
	H	smf	[0.5 1]
AR	L	zmf	[0 0.35]
	Med	gaussmf	[0.1 0.45]
	H	smf	[0.5 1]

After defining the inputs and outputs of the first subsystem, the rules governing the variables must be entered into the system. The number of these rules is obtained by multiplying the number of input variables by each other, which is equivalent to 675. To gain the rules, a survey form similar to Table 9 is given to the specialists.

Table 9: Survey form of the first subsystem

Rules	**Criterion**					**Decision**			
#	**DA**	**TD**	**WC**	**TR**	**IP**	**FD**	**FC**	**AR**	**RR**
1	VL	L	VG	L	L	?	?	?	?
...	...	...	...	...	...	...	...	...	...
675	VH	H	VB	H	H	?	?	?	?

Then the rules have been imported into the first expert system. For example, one of the rules is as follows:

if (DA is VL) and (TD is L) and (WC is VG) and (TR is VL) and (IP is VL) **then**
(FD is VL) (FC is L) (AR is L) (RR is L)

Since the surface section of the designed model shows a maximum of three dimensions and the number of input and output variables is greater than this value, only the behavior of the input variables can be seen pairwise with each of the output variables.
For example, the behavior of the input variables of DA and WC relative to the output variable FC is shown in Figure 3.

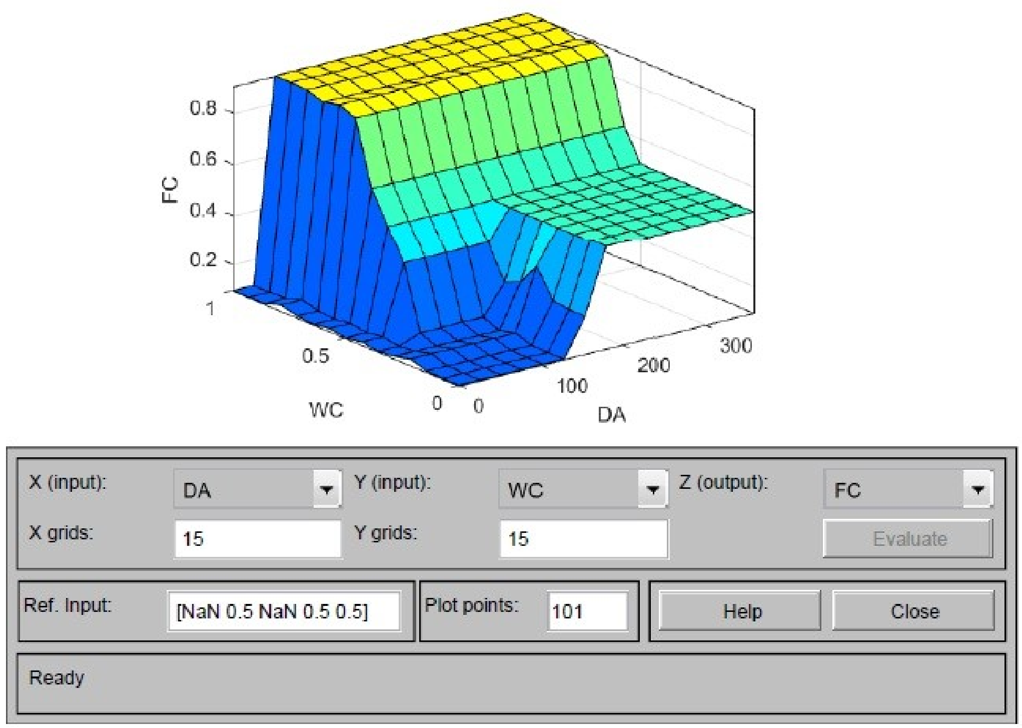


Figure 3: The behavior of the input variables of DA and WC relative to the output variable FC.

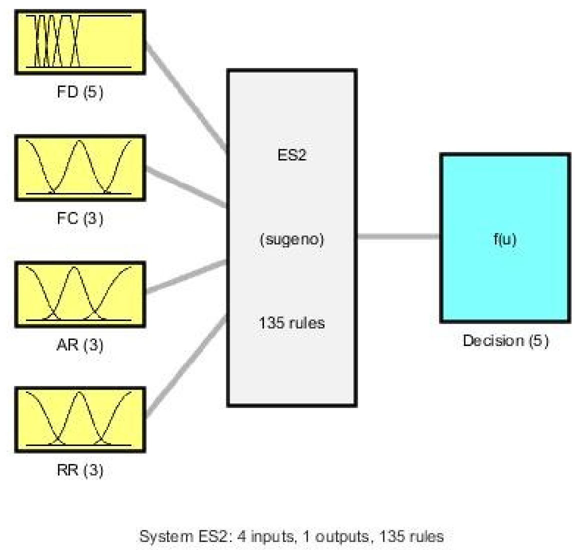
The result of the first subsystem is the non-fuzzy values of each output in terms of the values of the disruption parameters as the inputs. Such output values are not clear and the system user cannot make proper decisions.
In addition, the rules obtained through the survey forms, which reflect the network-like impact of the criteria and the incompatibility in the opinions of the specialists show overlapping.
Therefore, it is necessary to resolve the ambiguity and create a clearer context for decision-making. For this reason, the second expert subsystem was built.

4.2 Modeling the Second Expert Subsystem

This sub-system is made by the variables of the first subsystem as the input and the final decision options as the outputs by using the MATLAB fuzzy toolbox and the Sugeno method.
The overall design of the second subsystem is shown in Table 10.

Table 10: Overall design of the second subsystem

Parameter	Value
Name	ES2
Type	sugeno
And Method	Prod
Or Method	probor
Defuzz Method	Wtaver
Imp Method	Prod
Agg Method	sum
Input	[1x4 struct]
Output	[1x1 struct]
Rule	[1x135 struct]



The method of introduction of the output variables of this subsystem is shown in Table 11.

Table 11: Output variables of the second subsystem

Variable name	Condition	Introducing function	Amounts
Decision	On Time	Constant	1
	FD	Constant	2
	FC	Constant	3
	AR	Constant	4
	RR	Constant	5

After defining the inputs and outputs of the second subsystem, the rules governing the variables must be imported into the system. The questionnaire forms filled by the specialists have been used to make these rules. The number of these rules is obtained by multiplying the number of input variables by each other, which is equivalent to 135. To gain the rules, a questionnaire form similar to Table 12 is given to the specialists.

Table 12: Survey form of the second subsystem

Rules	Criterion				Decision
#	FD	FC	AR	RR	
1	VL	L	L	L	?
...	...	...	...	...	...
675	VH	H	H	H	?

Each specialist replied to this form and entered personal comments instead of the question marks. Then, these rules are introduced into the second subsystem. For example, one of the rules is as follows:

if (FD is VL) and (FC is L) and (AR is L) and (RR is L) **then** (Decision is On Time)

The level of the designed model represents a maximum of three dimensions; however, the numbers of input and output variables are greater than this value. Therefore, only the behavior of the input variables can be seen pairwise with the output variables. For example, the behavior of the input variables FD and AR concerning the output variable is illustrated in Figure 4.

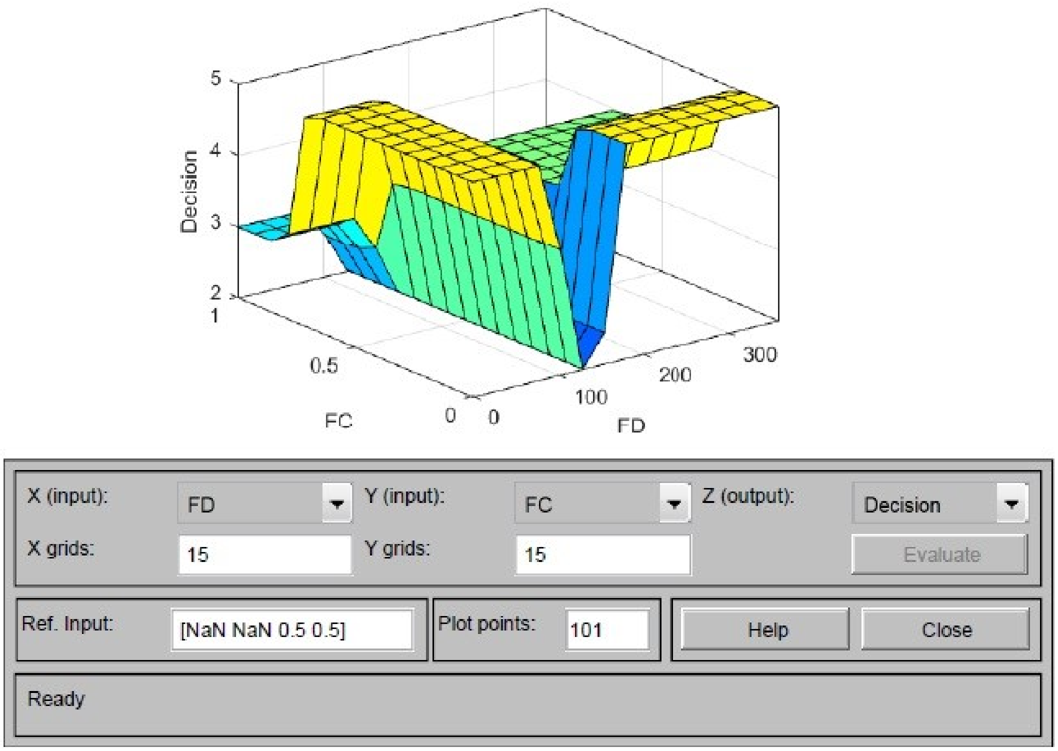


Figure 4: Behavior of the input variables FD and FC concerning the output variable.

The second expert subsystem is the non-fuzzy value of the final decision for the obtained values of the first subsystem as inputs.

5 Discussion

To ensure the accuracy and efficiency of the proposed model in comparison to the opinions of the specialists, several scenarios for the disruption of the flight schedules were selected randomly and given to the specialists. Then the suggestions of these specialists for making decisions in such situations were compared with the suggestions of the proposed model. This comparison is summarized in Table 13.

Table 13: Assessment of the accuracy and efficiency of the proposed model

Decision proposed by the model	**The decision made by the specialists**	**The disruption criteria and their magnitude in the example below**				
		IP	**TR**	**WC**	**TD**	**DA**
FD (135 Minute)	FD	0.7	0.1	0.2	0.6	45 Minute
FD (171 Minute)	FD	0.2	0.4	0.7	0.1	116 Minute
OnTime	OnTime	0.3	0.1	0.2	0.1	15 Minute
FC	AR	0.8	0.7	0.9	0.8	250 Minute
RR (if there is an alternative route) FC (if there is no alternative route)	RR	0.2	0.8	0.7	0.1	60 Minute

As can be seen in Table 13, the results of the proposed model provide an acceptable agreement to the opinions of specialists. Moreover, these results provide more proper decisions with more details. Therefore, specialists can make a decision using the proposed expert system with a high degree of certainty. The output of the presented model shows that the managers of the aviation industry need to change their perspective on the impact of the causes of disruption in the flight schedule in their subsequent decisions. The fuzzy method in the decision-making part of the proposed model shows that despite the emphasis of airline company managers on some of the reasons for disruption in flight schedules, the impact of these reasons is not significant. For instance, according to the results of the fuzzy analytical network process, the weather condition is the third most effective criterion in such a disorder with an impact level of 0.1231. This level of influence is not consistent with the common view of airline managers, because the process of the fuzzy analytical network process, by taking into account the internal relationships between the criteria/sub-criteria of the problem and disambiguating the opinions of experts with the use of the fuzzy theory, makes the output of the problem more realistic. On the other hand, with the advancements made in meteorology and transportation sciences and the reduction of the degree of influence of weather and traffic criteria, it would seem logical that the model presented in this study also refers to this issue. Based on the outputs obtained from the fuzzy analytical network process, the arrival delay with a magnitude of 0.5124 is the most important reason that disrupts the flight schedules. Besides, the technical defect is the second reason, with a magnitude of 0.2621. Each of the disruption criteria can lead to the arrival delay, so the fuzzy analytical network process, partly considers the impact of each disruption reason on the arrival delay due to its network nature, which increases the impact of this criterion. In their previous studies, the authors have used the analytical network process [9], analytical hierarchical process [2], in a direct way, and fuzzy analytical hierarchical process [8], in an indirect way, to find the most important criteria of disruption in the flight schedule and the main decisions ahead. Comparing the results obtained from the current study based on the fuzzy analytical network process with previous studies shows that the current results are more logical and realistic. For example, while the announcement of the flight delay is the first option in all four methods, this decision has a higher degree of impact on the fuzzy analytical network process. In addition, in this method, the degree of impact of the flight cancellation is increased and the degree of impact of the aircraft/route replacement is decreased compared to the analytical hierarchy process and its fuzzy form. All of these changes are compatible with the opinions of expert employees. The reason for this improvement is that the fuzzy multi-criteria decision-making method, unlike the process of analytical hierarchy, also considers the internal relationships between criteria and sub-criteria. In addition, it disambiguates the opinions of experts and respondents to comparative survey forms on account of using the fuzzy theory. The summary of these results is mentioned in Table 14.

Table 14: Comparison of the results of the methods

Method	**AHP [2]**		**ANP [9]**		**FAHP [8]**		**FANP**	
Options	**Weight**	**Rank**	**Weight**	**Rank**	**Weight**	**Rank**	**Weight**	**Rank**
FD	0.4031	1	0.3532	1	0.6011	1	0.7042	1
FC	0.1672	4	0.3131	2	0.0743	4	0.2076	2
AR	0.2181	2	0.1393	4	0.2192	2	0.0784	3
RR	0.2124	3	0.1951	3	0.1066	3	0.0098	4

6 Conclusion

In this study, an expert system based on fuzzy multi-criteria decision-making was presented to select the appropriate process during airline flight schedule disruption. In such conditions, decision-making is complicated due to the existence of different criteria and sub-criteria and their internal communication. The inputs were obtained as verbal variables in the form of pairwise comparison matrices. Considering that the values were less than 0.1 for all the matrices of pairwise comparisons, based on the defined rules of the fuzzy analytical network process, the compatibility of opinions was considered acceptable. The results of the proposed model, based on a fuzzy analytical network process showed that the most important reasons for flight schedule disruption, are delay arrival (DA), technical defect (TD), weather conditions (WC), airport traffic (TR), and internal problems (IP), respectively. The possible decisions during the flight disruption were obtained as the announcement of the flight delay (FD), flight cancelation (FC), aircraft replacement (AR), and route replacement (RR). In the end, the model proposes the best decision based on the degree of impact of the schedule disruption parameters. Examining the results of the model and comparing the designed subsystems with the opinions of experts show that the proposed decision of the system is highly consistent with the decision made by expert employees in such situations. In addition, the proposed model option has more details and considers realistic conditions. Consequently, it can be claimed that the proposed model performs the multi-criteria decision-making process with acceptable efficiency.

Compliance with Ethical Standards

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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