ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp.161-178, DOI: 10.18038/estubtda.1674259

RESEARCH ARTICLE

AIRCRAFT SEQUENCING WITH FUZZY LOGIC METHOD

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Abstract

The growth in the demand for air transport causes an increase in air traffic. In this case, more air traffic needs to be carried out safely, regularly and quickly. It is important to correctly and fairly order the landing traffic in order to reduce the delaying, especially in the air due to heavy traffic.

In this study, it is aimed to sequence the arrival traffic with fuzzy logic method. Speed, distance, altitude parameters were used for sequencing. Traffic data was collected from the Air Traffic Simulation Laboratory at Eskişehir Technical University's Air Traffic Control Department.

A comparative analysis was conducted between the current arrival traffic sequencing within the simulation area and the sequencing results derived from the fuzzy logic method. The findings indicate a significant overlap between both traffic ranking outcomes. This research contributes to the existing literature by demonstrating the application of the fuzzy logic method in the field of air traffic control.

Keywords

Aircraft,
Sequencing,
Fuzzy Logic,
Real Time Simulation

Time Scale of Article

Received : 11 April 2025
Accepted : 14 June 2025
Online date : 25 June 2025

1. INTRODUCTION

The demand for air transportation is continuously increasing due to technological advancements and globalization. According to estimates by the European Organization for the Safety of Air Navigation (EUROCONTROL), the number of daily Instrument Flight Rules (IFR) flights in European airspace is projected to reach 53,600 in the high scenario by 2050 (EUROCONTROL, 2023). This increase results in the concentration of air traffic within the Terminal Control Area (TMA) and issues such as delays, conflicts, and disruptions in flight operations. To address these challenges, air traffic controllers provide instructions and recommendations to ensure the safe, orderly, and efficient management of traffic. However, there is an increasing need for automation systems to reduce the workload of controllers and provide more effective sequencing under heavy traffic conditions.

Sequencing arrival traffic within the TMA is crucial for minimizing airborne waiting times, optimizing fuel consumption, and reducing environmental impacts such as emissions and noise pollution. One of the traditional sequencing methods, the First Come, First Served (FCFS) approach, although simple to apply, is insufficient in heavy traffic scenarios and can lead to delays. In this context, the fuzzy logic method emerges as an effective tool for modeling complex systems that involve uncertainty.

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The aim of this study is to present a new approach for sequencing arrival traffic within the TMA using the fuzzy logic method. In the study, the traffic was ordered by considering the distance, altitude, and speed from the entry points of the TMA to the final approach point using the fuzzy logic method. The traffic sequencing derived from the fuzzy logic method was comparatively assessed against the sequencing executed within a real-time simulation (RTS) environment at the Department of Air Traffic Control, Eskişehir Technical University. The findings demonstrate a strong consistency between the aircraft arrival sequencing determined by real-time simulation's estimated arrival times and the sequencing generated via the fuzzy logic method.

2. LITERATURE REVIEW

The aircraft sequencing problem is one of the fundamental research areas of air traffic control and has been studied for a long time in order to increase operational efficiency and reduce delays. Numerous methods have been developed in the literature for this problem; these methods can be generally classified as deterministic, stochastic and metaheuristic approaches. While deterministic methods include static and dynamic models, stochastic methods include techniques such as genetic algorithms and tabu search. Metaheuristic approaches include innovative solutions such as ant colony optimization, particle swarm optimization and artificial bee colony algorithms.

Studies on single-runway landing problems have formed the basis of sequencing models. Moser developed a hybrid algorithm combining stochastic and deterministic elements to solve the single-runway aircraft landing problem and showed that this method is effective even in chaotic scenarios with up to 24 aircraft [1].

Brentnall and Cheng compared the scheduling algorithms using discrete event simulation at a single-runway airport; they analyzed the effects of delay sharing strategy, arrival rate and turbulence category mix with statistical methods [2]. Çeçen et al. managed to minimize the total aircraft delay by proposing a stochastic model for mixed aircraft operations and demonstrated the superiority of this model over deterministic approaches [3]. For multi-runway scenarios, Dönmez (2022) developed a stochastic model that takes into account the runway exit point and occupancy period uncertainties; they proved the applicability and robustness of this model on runways with multiple exits [4].

The First Come, First Served (FCFS) approach, one of the traditional sorting strategies, is widely used in the world due to its simplicity and applicability. However, Liang stated that FCFS does not produce optimum results in high-density operations and can lead to excessive delays [5]. To overcome this problem, the Constrained Position Shift (CPS) method proposed by Dear aims to shorten the sorting time by optimizing the positions of the aircraft according to operational constraints [6]. Ikli et al. showed that CPS significantly reduces the total landing time compared to FCFS through an example scenario; for example, the total landing time, which is 452 seconds in a four-aircraft FCFS sorting, decreases to 238 seconds with CPS [7].

Fuzzy logic is increasingly gaining attention in air traffic control as a powerful tool for modeling systems with uncertainty. Ören and Koçyiğit successfully applied the fuzzy logic model to the landing sequence of unmanned aerial vehicles and proved the effectiveness of the system in real-time scenarios [8]. Pratiwi used the fuzzy logic method to automate the landing decision processes of Boeing aircraft; reliable results were obtained by processing parameters such as speed, distance and altitude with fuzzy rules [9]. Ntakolia and Lyridis presented an n-dimensional optimization model by integrating fuzzy logic with ant colony optimization in air traffic flow management and reported that this approach was successful in managing traffic density [10]. Bongo and Seva used fuzzy DEMATEL and fuzzy BWM methods to examine the factors affecting the performance of air traffic controllers. The case study conducted at the Mactan Control Tower determined the cause-effect relationships and priority ranking of the factors;

While communication stood out as the highest priority factor, factors such as situation awareness were included in the effect factors group [11].

Chikha and Skorupski developed a fuzzy logic-based expert system to assess the risk of accidents in airport ground traffic. The study focused on the performance and training level of ground handling personnel (GSE operators) and emphasized the importance of human factors in preventing accidents. Using fuzzy inference systems, personnel reactions and the severity of possible consequences were modeled [12].

Kolotusha et al. proposed fuzzy logic methods together with expert evaluation methods to evaluate the conformity of air traffic control (ATC) simulators to the real system. Fuzzy logic was used in processing uncertain and imprecise data, quantitatively classifying the adequacy of simulators (e.g. ‘low conformity’, ‘medium conformity’, ‘best fit’) and formalizing expert opinions through membership functions in the analysis of practical tasks such as ‘Vectoring’. This approach provided reliable results in evaluating the accuracy of simulators in reproducing the professional environment (high, typical, basic, low) [13]. Chang and Wong used the fuzzy Delphi method to assess human-induced risk factors in runway incursion incidents [14]. Pacheco et al. presented a fuzzy logic methodology to determine the risk of airport accidents [15] and considered the perceptions of pilots operating in airport traffic [12].

A review of the literature reveals that research in the field of air traffic control remains limited. Also, existing efforts often lack integration with real-time simulation (RTS) environments, which are essential for assessing the practical applicability and operational performance of sequencing models. To address this gap, this study proposes a fuzzy logic-based sequencing approach for arrival traffic. Moreover, the proposed model, which relies on speed, distance, and altitude parameters, is validated in real-time air traffic simulation and offers an alternative approach to existing sequencing methods.

3. METHODOLOGY

The generic TMA and scenario required for the fuzzy logic-based model were provided through the real-time simulator which supports the basic training of air traffic controllers. Moreover, it plays a significant role in airspace and procedural development. The design and implementation of the proposed fuzzy model were carried out systematically by taking into account the basic components of fuzzy logic. The details of the method are presented in the following parts.

3.1. Fuzzy Logic

Fuzzy logic, in contrast to classical (binary) logic, is a mathematical approach that handles uncertainty and gradation rather than relying on strict boundaries. Introduced by Lotfi Zadeh in 1965, this methodology is specifically designed to address complex and imprecise data encountered in real-world systems [16]. While classical logic dictates that an element either fully belongs to a set (1) or does not belong at all (0), fuzzy logic allows for degrees of membership, represented by continuous values within the interval [0, 1]. This characteristic makes fuzzy logic particularly suitable for dynamic and uncertain systems such as air traffic control. For instance, an aircraft’s speed is not rigidly categorized as “slow” or “fast”; instead, a specific speed value may simultaneously belong to multiple fuzzy sets to varying degrees [17].

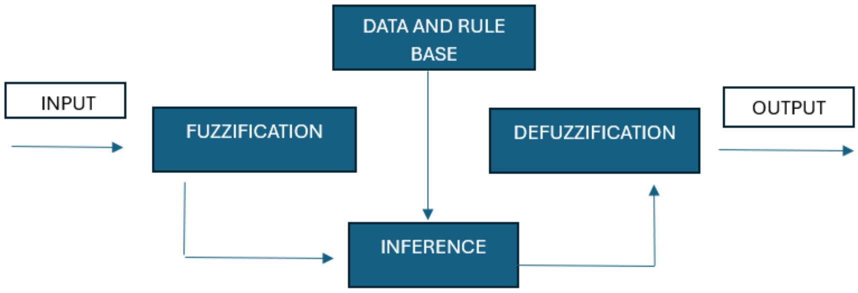

Figure 1. Fuzzy Logic System. [18].

3.2. Fuzzy Set

A fuzzy set is a concept that defines the degree of belonging of elements to a set in the range [0, 1]. Unlike classical sets, the belonging of an element in fuzzy sets is determined not by sharp boundaries but by a continuous function. In fuzzy logic; the graph that changes with the values of the set members is called a membership function. The x-axis of this graph indicates the member values, and the y-axis indicates the membership degrees [19].

3.3. Membership Functions

Membership functions mathematically express the degree of belonging of an element to a certain fuzzy set. The most commonly used membership functions are triangular, trapezoidal and Gaussian types.
Triangle Membership Function: Triangle membership function can be explained with three parameters, a left side point, b center point, c right side point, the graphic of the triangle membership function is shown in Figure 2 and Equation 1 [20].

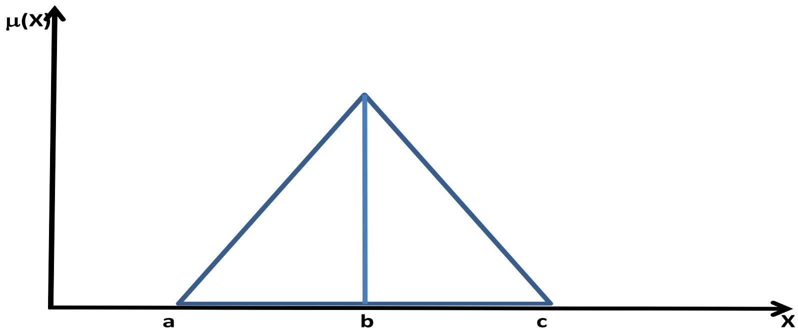

Figure 2. Triangle Membership Function. [20].

$$\text{Triangle } \mu A(x;,a,b,c,) = \begin{cases} (x-a)/(b-a) & a \leq x \leq b \\ (c-x)/(c-b) & b \leq x \leq c \\ 0 & x > c \text{ veya } x < a \end{cases} \tag{1}$$

Trapezoidal Membership Function is defined by four parameters a, b, c and d, the distance between b and c represents the highest membership value that the element can have. And if x is between (a, b) or (c, d), then it will have a membership value between 0 and 1. The trapezoidal membership function is shown in Figure 3 and the equations belonging to this membership function are shown equation 2, 3. [21].

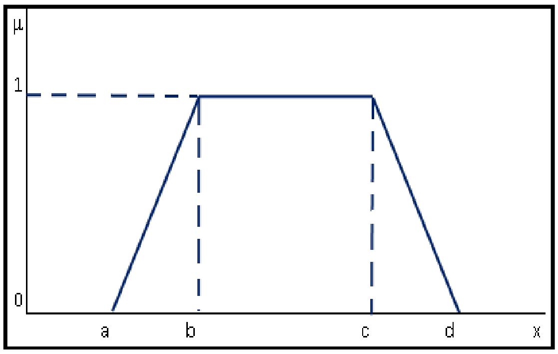

Figure 3. Trapezoidal Membership Function [21].

$$\text{Trapezoid } \mu(x) = (x;, a, b, c, d) = \begin{cases} 0, & x < a \\ (x-a)/(b-a) & a \leq x \leq b \\ 1 & b \leq x \leq c \\ (d-x)/(d-c) & c \leq x \leq d \end{cases} \tag{2}$$

$$\mu(x) = \mathrm{Max}(\min(x-a)/(b-a),\ 1, (d-x)/(d-c) \quad , 0) \tag{3}$$

Gaussian Membership Function:

The Gauss membership function, σ, consists of two parameters, the function is shown in Figure 4 and Equation 4.

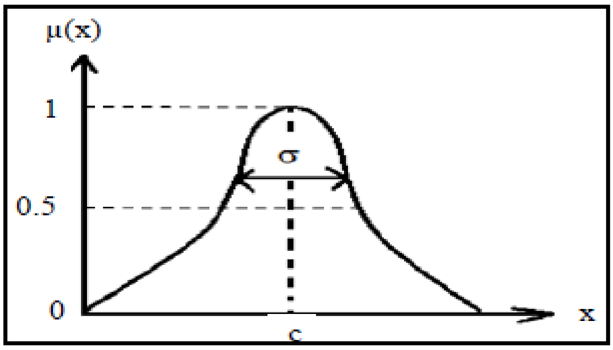

Figure 4. Gaussian Membership Function [22].

$$\text{Gauss } \mu(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{4}$$

In this function, c represents the mean, center, of the Gaussian curve and σ represents the distribution of the curve. This is a natural way to represent the distribution of data, but is not often used in fuzzification methods due to its mathematical complexity [22].

3.4. Fuzzification

The stage of converting the data input, which is taken from the outside world to the computer through measurement and has a definite numerical value, into verbal expressions by the membership functions in the knowledge base and into membership degrees that show to what extent the input data supports this expression is called fuzzification. The verbal expressions obtained at the end of fuzzification are compared with the propositions in the rule base, as in the decision-making process of humans, and verbal judgment results are reached, and the extent to which these results are valid is determined by the membership degrees in the input [19].

3.5. Data and Rule Base

Data base is where the membership functions of the fuzzy system are located. All the rules that transform the inputs obtained from here into output variables, which can be written in the if-then type, are located in the knowledge base. Thus, each rule logically connects a part of the input space to the output space. All of these contexts constitute the rule base [18].

VSlow: Very Slow, Slow: Slow, M: Medium, F: Fast, VF: Very Fast, VFar: Very Far, Far: Far, C: Close, VC: Very Close, VL: Very Low, L: Low, H: High, VH: Very High, VVL: Very Very Low, VL: Very Low, L: Low, VVH: Very Very High are expressed as and are given in Table 1.

Table 1. Rule Matrix

Speed	**Distance**	**Altitude**				
		Very Low	**Low**	**Medium**	**High**	**Very High**
VSlow	VFar	VL	VL	VVL	VVL	VVL
VSlow	Far	L	VL	VL	VVL	VVL
VSlow	M	L	L	VL	VL	VVL
VSlow	C	M	L	L	VL	VL
VSlow	VC	H	M	L	VL	VL
Slow	VFar	L	VL	VL	VVL	VVL
Slow	Far	L	L	VL	VL	VVL
Slow	M	M	L	L	VL	VL
Slow	C	H	M	L	L	VL
Slow	VC	VH	VH	H	H	M
M	VFar	L	L	VL	VL	VVL
M	Far	M	L	L	L	VL
M	M	H	H	M	M	L
M	C	VH	VH	H	H	M
M	VC	VVH	VH	VH	H	H
H	VFar	M	L	VL	VL	VL
H	Far	H	H	H	H	L
H	M	VH	H	H	H	M
H	C	VVH	VH	VH	H	H
H	VC	VVH	VVH	VH	VH	H
VH	VFar	VH	H	H	M	L
VH	Far	VH	VH	H	H	M
VH	M	VVH	VH	VH	H	H
VH	C	VVH	VVH	VH	VH	H
VH	VC	VVH	VVH	VVH	VH	VH

3.6. Inference Procedures

Inference is the process of deriving fuzzy outputs from fuzzy inputs. In this study, the Mamdani inference method is preferred (Figure 5). The Mamdani method combines the fuzzy outputs obtained from the "If-Then" statements in the rule base and produces intuitive results.
The connection between linguistic variables (x, y and z) is defined using max. and min. operators based on generalized fuzzy connection. The min. operator is used in the condition (If) section of the rules, and the max. operator is used to bring two rules together [23].

Rule 1: If x = A1 and y = B1 then z = C1
Rule 2: If x = A2 and y = B2 then z = C2

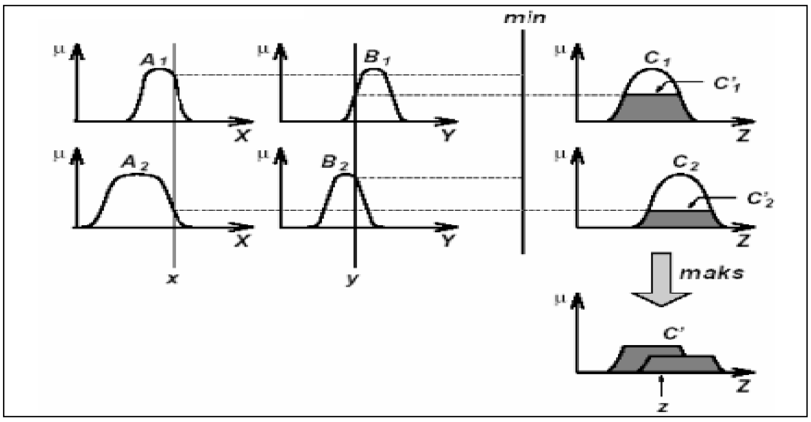

Figure 5. Mamdani Inference Method [23]

Alternative methods are Takagi-Sugeno and Tsukamoto Figure 5 among inference methods. While Takagi-Sugeno produces linear outputs with mathematical functions, Tsukamoto works with monotonic membership functions. However, in this study, the Mamdani method was chosen due to its interpretability and suitability for intuitive requirements in air traffic control [23].

3.7 Defuzzification and Methods

The results obtained as a result of the inference process are a fuzzy set containing linguistic expressions. Defuzzification process is required to transform this set system into the required numerical data [17]. For defuzzification, the centroid method, the largest membership (maximum) method, the weight average method, the Mean-Max membership method, the smallest of the largest method, the largest of the largest method are among the most commonly used methods.

In center of gravity method, the center of gravity of the areas obtained as a result of the inference process is found and calculated as a defuzzification process as a definite value. In this method, the integral process is applied in the conversion of fuzzy numbers to classical numbers. The centre of gravity is shown in Figure 6 and Equation 5 [24].

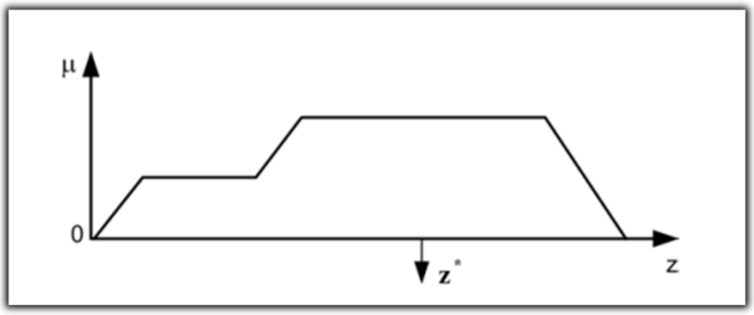

Figure 6. Center of Gravity Method [25]

$$z^* = \frac{\int \mu_z z \, dz}{\int \mu_z z \, dz} \quad (5)$$

4. APPLICATION OF THE FUZZY LOGIC METHOD TO THE AIRCRAFT SEQUENCING PROBLEM

In this study, the membership functions, inference method and defuzzification processes used in fuzzy logic are modeled with the MATLAB program.

The assumptions made in the fuzzy logic modeling in the study can be listed as follows:

• All aircraft entering TMA follow their current arrival routes and perform point-to-point navigation.

• Meteorological conditions (wind etc.) are not taken into account.

• Longitudinal separation is not used between traffics.

• Speed restriction is not applied.

•No delay method (waiting, vector etc.) is used in sequencing traffics.

• Ground speed is used in the model.

• The altitude range of traffics in TMA is 4000 ft-10000ft.

• Traffic entering TMA will complete their landing sequence based on the specified report point (called as Imren) at a distance of 23 NM on the final approach route and it is assumed that they will land according to the determined landing sequence.

In this study, the fuzzification, rule base and inference, defuzzification and system integration stages of the fuzzy logic system are systematically applied to model the traffic sequence in TMA as follows, respectively.

4.1. Fuzzification

In this phase, numerical inputs such as speed, distance and altitude are converted to fuzzy values by means of defined membership functions. For example, 180 kt speed is fuzzified with a degree of belonging to the “Medium” cluster of 0.6 and to the “Fast” cluster of 0.4. In this study, real-time data obtained from the simulator (for example, Speed: 200 kt, Distance: 10 NM, Altitude: 3000 ft) are fuzzified in the MATLAB/FIS interface and provided as input to the model.

In this study, fuzzy sets are defined for speed, distance and altitude parameters. MATLAB/FIS is used. Triangular membership functions are mainly used; this choice was made to increase the computational efficiency of the system and to facilitate the interpretability of the results. It is converted to fuzzy values by means of defined membership functions.

The parameters of the membership functions are given below:
Speed (knot-kt): Speed consists of five membership functions between 220-340 kt: Very slow, slow, medium, fast, very fast.
Distance (NM): It consists of five membership functions between 0-65 NM: Very close, close, medium, far and very far.
Altitude (feet-ft): It consists of five membership functions between 4000 ft-16000 ft: Very low, low, medium, high, very high.
Output: It consists of seven membership functions between 0-100 points under the name of score: Very very low, very low, low, medium, high, very high, very very high.

4.1.1. Speed membership function

Speed parameters are made according to the speed values of the aircraft in the scenarios run in the RTS environment. Speed values are given in terms of ground speed. Lower and upper limits and related ranges are determined according to the speed values observed at the moment of entry of each aircraft in the scenario to the TMA. The reason for taking speed values from the scenarios used in the simulator environment is to compare the traffic rankings in the scenario with the ranking values obtained with fuzzy logic. Figure 7 shows the speed ranges used in this study and the corresponding linguistic expressions.

The speed parameters between 220 kt and 340 kt are shown on the x-axis for aircraft speed, and the membership degree between 0-1 is on the y-axis. Speeds are shown as

220-245 kt very slow,
225-275 kt is slow,
255-305 kt is medium,
285-335 kt is fast,
315-340 kt is very fast.

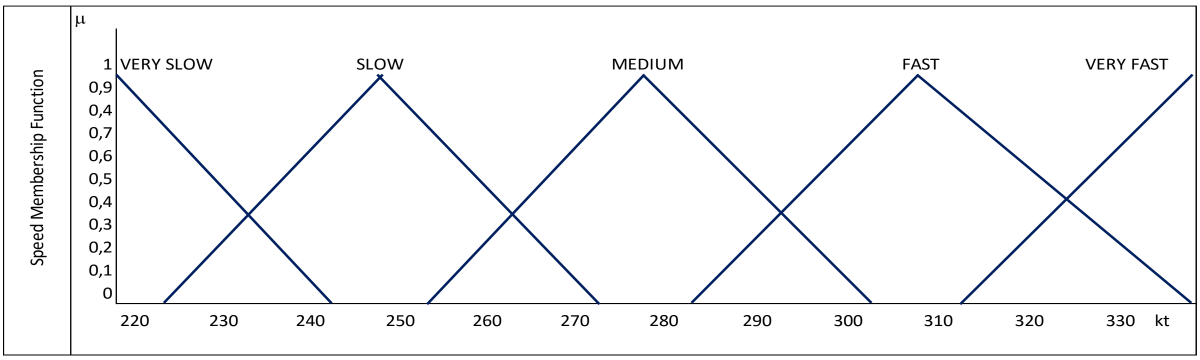

Figure 7. Airspeed triangle membership function

4.1.2. Distance membership function

In the sequencing of arrival traffics, the distance membership function is assumed that the traffics flying within the TMA will fly on the determined routes and the distance is determined between 0-65 NM. Since the study will be compared with the scenarios created in the Istanbul Terminal area where the old Ataturk Airport is located, the distance including the area where the Imren report and waiting point are located, which is 23 NM away before entering the final approach route, is taken as the basis.

The speed ranges corresponding to the verbal expressions given regarding the distance membership function shown in Figure 8 are as follows;

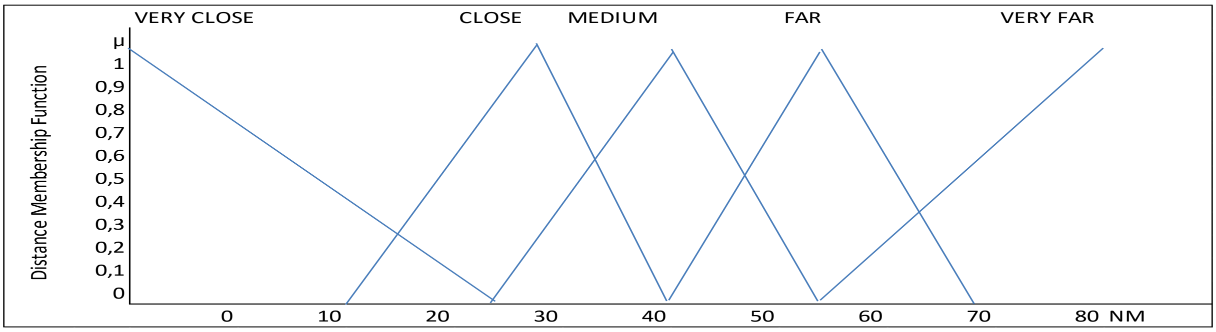

Figure 8. Distance membership function

The distance membership function is determined according to the following values:
Very close between 0-25 NM,
10-40 NM is near,
25-55 NM is medium,
40-70 NM is far,
55-85 NM is very far.

4.1.3. Altitude membership function

The altitude membership function is determined according to the values between 4000 ft-16000 ft. The altitude membership function is shown in Figure 9. The altitude membership function is determined according to the following values:
4000-9000 ft is very low,
6000-12000 ft is low,
9000-15000 ft is medium,
12000-18000 ft is high,
15000-20000 ft is very high.

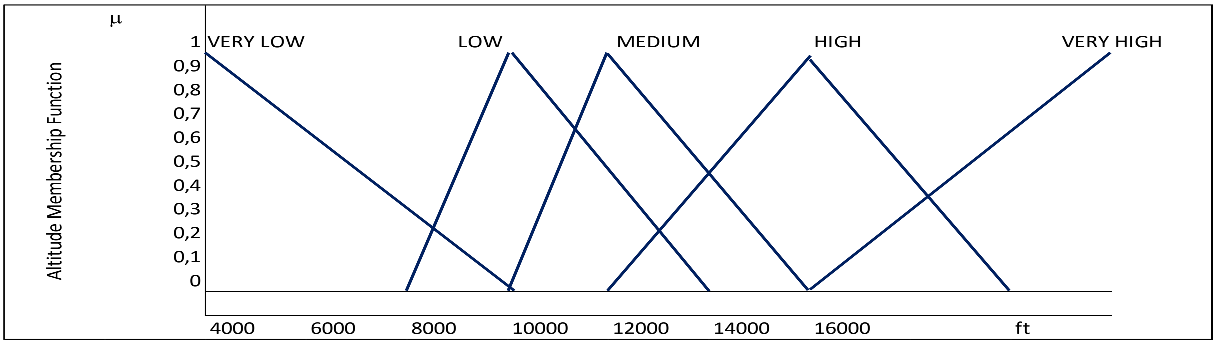

Figure 9. Altitude membership function

4.1.4. Output membership function

Based on the rule base of speed, distance, altitude membership functions, values between 0-100 points for the output membership function are shown in Figure 10. with verbal expressions.
0-20 point is very very low,
10-30 point is very low,
20-50 point is low,
40-60 point is medium,
50-80 point is high,
70-90 point is very high,
80-100 point is very very high.

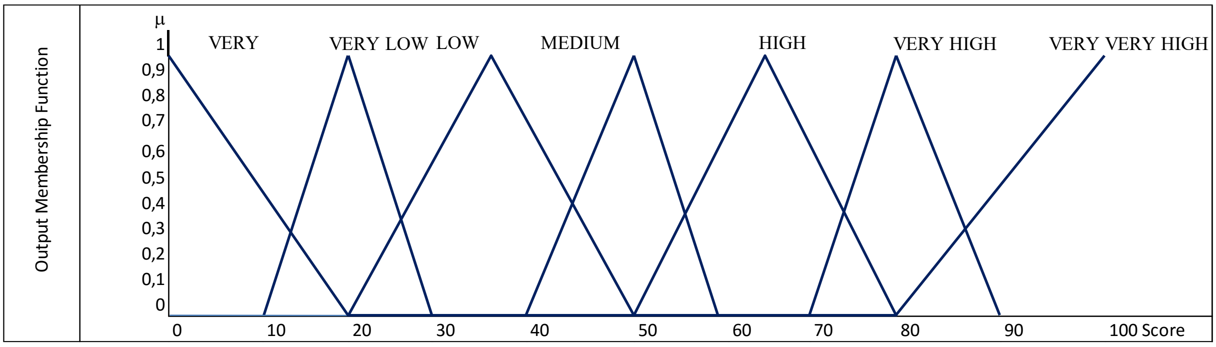

Figure 10. Output membership function

4.2. Fuzzy Database and Rule Base

Traffic data are collected from scenarios developed using aircraft performance data derived from BADA. These scenarios are implemented in the Air Traffic Simulation Laboratory of the Air Traffic Control Department at Eskişehir Technical University. The simulator is capable of running radar-free air traffic control scenarios and provides real-time data on aircraft speed, distance, and altitude at TMA reporting points. A total of ten distinct scenarios were developed based on this data.

4.3. Rule Base

The model is designed with a rule base consisting of 125 rules. The rules are defined in an "If-Then" format based on expert opinions and simulator data. It is demonstrated that when the input values of speed (280 kt), distance (32.5 NM), and altitude (10,000 ft) are entered, the resulting score is 43.7. Scores are calculated separately for each aircraft using the MATLAB.
For example, the rule base can be created according to the speed, distance and altitude of an aircraft coming in for an approach as follows;
If the aircraft is fast, the distance is medium and the altitude is very low, the score is very very high.
If the aircraft speed is slow, the distance is very close and the altitude is high, the score is high.
If the aircraft speed is fast, the distance is very far and the altitude is very low, the score is medium.
After the rule base is created, the inference process is applied.

4.4. Inference

The Mamdani fuzzy inference method is easily created and is widely used in the literature because it is closer to human behavior. In this study, since the researcher worked as an air traffic controller in active working conditions, fuzzy logic modeling was created based on his knowledge and experience and the Mamdani inference method was applied in this modeling.

4.5. Defuzzification

The centroid method was preferred in this study because the ranking scores needed to be expressed continuously and precisely, and this method provided the most accurate results.
This method produces a single numerical value by calculating the weighted average of the fuzzy output. For example, a fuzzy output consisting of the sets "High" and "Very High" was converted to a score of 0.78 by the centroid method.

5. FINDINGS

In this study, a fuzzy logic model was developed for sequencing arrival traffic within TMA, based on ten exercises conducted in the Real-Time Simulation (RTS) environment at the Air Traffic Control Simulation Laboratory of Eskişehir Technical University. Each exercise involved six aircraft, and performance data were obtained from the Base of Aircraft Data (BADA). The aircraft, all of type B738, were simultaneously displayed on the pilot screen of the simulator, with distance, speed, and altitude values provided as part of the exercise setup. The aircraft altitudes ranged between 4,000 ft and 10,000 ft, and the speeds used were those observed in the simulator. The distance values represented the aircraft's distance to the designated holding point.

The model was tested across ten distinct traffic scenarios. In each scenario, the sequence generated by the fuzzy logic model was compared with the current sequence produced by the procedural (baseline) approach. The analysis evaluated the impact of speed (kt), distance (NM), and altitude (ft) parameters on sequencing outcomes. The results were supported by quantitative outputs derived from both the MATLAB/Fuzzy Inference System (FIS) interface and the simulator data.

5.1. Scenario Analyses

10 scenarios were created based on the distances at the TMA report points and traffic data obtained from the simulation environment. In each scenario, the speed, distance and altitude values of more than one aircraft were given as input to the fuzzy logic model; the sequencing score (SCORE), which is the output of the model, was used to determine the landing priority of the aircraft. Detailed analyses of some selected scenarios are presented below:
The starting time of the scenarios was accepted as 00:00, and the estimated arrival time represents the time in minutes added to this hour. The traffic sequencing was designed based on Imren report point. 10 scenarios were created. The data for the traffics created in the first scenario are shown in Table 2.

Table 2. First scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
A1	293	61	8000	13	6	47,79	5
A2	262	51	6000	13	5	46,50	6
A3	292	66	7000	12	4	48,15	4
A4	292	53	7000	11	3	48,66	3
A5	260	17	5000	5	1	72,9	1
A6	292	44	9000	10	2	53,73	2

An analysis of the estimated arrival times to the Imren point in the traffic scenarios derived from the RTS reveals that the first aircraft in the traffic sequence is A5, followed by A6, A4, and A3, respectively. It is observed that aircraft A1 and A2 share the same estimated arrival time.

From the controller's perspective, when evaluating the traffic in terms of landing sequence, an aircraft at a lower altitude may be prioritized and brought forward to land earlier. Accordingly, in this example, A2 is assigned the fifth landing position, while A1 is positioned last.

When the traffic is ranked based on the scores generated by the proposed fuzzy logic method, it is observed that A5, having the highest score, is ranked first. According to the fuzzy logic-based ranking, the sequence is A6, A4, A3, A1, and A2. A comparison between the results of the simulator scenario and the traffic sequencing determined by the fuzzy logic method indicates a comparable order. In the simulator-based scenario, A1 and A2 are assigned the same rank due to their identical estimated arrival times; however, the fuzzy logic method differentiates between them based on their respective scores, thus altering the estimated ranking. The data related to the second scenario are presented in Table 3.

Table 3. Second scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
B1	262	22	6000	5	1	70,95	1
B2	292	50	9000	10	4	47,58	4
B3	293	47	8000	9	2	53,03	2
B4	293	54	8000	10	3	49,00	3
B5	292	60	9000	12	5	46,54	5
B6	288	65	7000	13	6	45,15	6

In the second scenario, the aircraft B1, B3, B4, B2, B5, and B6 arrive in the same order according to both the estimated arrival times and the fuzzy logic-based ranking. The RTS estimated arrival times for B2 and B4 are identical; therefore, it is expected that the controller would prioritize B4, which is at a lower altitude.

Table 4. Third scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
C1	282	31	7000	6	2	70,47	2
C2	260	20	6000	5	1	71,33	1
C3	291	48	9000	10	4	49,33	4
C4	292	40	8000	9	3	67,88	3
C5	285	60	8000	11	5	37,54	5
C6	280	55	9000	12	6	35	6

In the third scenario, the arrival sequence of the aircraft according to the estimated arrival times and the fuzzy logic method is as follows: C2, C1, C4, C3, C5, and C6 (Table 4). As in the previous scenario, the results indicate that the RTS and fuzzy logic methods align.

Table 5. Fourth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
D1	283	55	7000	11	6	41,03	6
D2	260	20	5000	5	1	71,33	1
D3	260	27	5000	6	2	65,82	2
D4	288	43	8000	9	4	57,83	4
D5	287	50	9000	10	5	46,53	5
D6	260	37	6000	8	3	60	3

In the fourth scenario, the estimated arrival times and the fuzzy logic method resulted in the sequence D2, D3, D6, D4, D5, and D1, with the arrival order being identical (Table 5).

Table 6. Fifth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
E1	293	60	7000	13	6	48,31	6
E2	293	61	7000	12	5	49,78	5
E3	260	20	5000	5	1	71,33	1
E4	298	47	8000	8	3	56,32	3
E5	262	30	6000	7	2	64,45	2
E6	297	54	9000	11	4	52,27	4

In the fifth scenario, the estimated arrival times and the sequencing of the aircraft according to the fuzzy logic method are the same and with the order being E3, E5, E4, E6 and E1, respectively (Table 6).

Table 7. Sixth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
F1	260	21	6000	5	1	70,66	1
F2	262	31	6000	6	2	63,82	2
F3	298	54	8000	11	5	54,38	5
F4	298	47	8000	8	3	56,32	3
F5	297	60	9000	12	6	52,27	6
F6	293	50	7000	10	4	55,02	4

According to the data presented in Table 7, the estimated arrival times of the aircraft and the arrival sequence determined by the fuzzy logic method are identical, with the order being F1, F2, F4, F6, F3, and F5, respectively.

Table 8. Seventh scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
G1	292	54	9000	10	5	46,54	5
G2	293	50	8000	9	4	51,44	4
G3	298	44	8000	9	3	56,60	3
G4	262	34	6000	9	2	62,73	2
G5	262	16	6000	4	1	73,56	1
G6	292	60	9000	12	6	46,54	6

In Table 8, which presents the seventh scenario, the aircraft arrival sequence based on the estimated arrival times is as follows: G5 is ranked first, followed by G2, G3, and G4, which share the same estimated arrival time. Subsequently, G1 and G6 follow. According to the fuzzy logic method, the ranking is G5, G4, G3, and G2. G1 and G6 receive the same score; however, G1 is ranked ahead due to its shorter distance.

Table 9. Eighth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
H1	260	20	5000	5	1	71,33	1
H2	262	30	6000	7	2	64,45	2
H3	293	50	8000	10	4	51,44	4
H4	292	60	9000	12	6	46,54	6
H5	293	57	8000	10	5	47,79	5
H6	288	45	7000	8	3	52,93	3

In the eighth scenario, based on the estimated arrival times, the sequence is H1, H2, H6, followed by H3 and H5, which share the same estimated arrival time (Table 9). According to the fuzzy logic method, the resulting order is H1, H2, H6, H3, H5, and H4. In the fuzzy logic approach, the relatively short distance of H3 is the primary factor contributing to its higher score.

Table 10. Ninth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
I1	293	60	8000	12	5	47,79	5
I2	292	60	9000	12	6	46,54	6
I3	293	50	8000	11	4	51,44	4
I4	288	45	7000	8	3	52,93	3
I5	262	35	6000	7	1	62,53	2
I6	288	35	7000	7	2	72,17	1

In the ninth scenario, according to the estimated arrival times in the RTS, I5 and I6 are ranked first, followed by I4, I3, and then I1 and I2, which share the same estimated arrival time. In contrast, the ranking determined by the fuzzy logic method is I6, I5, I4, I3, I1, and I2, respectively, as shown in Table 10. In the fuzzy logic method, the higher score assigned to I6 is attributed to its higher altitude in combination with a higher speed compared to I5. Similarly, I1 receives a higher score than I2 due to its lower altitude.

Table 11. Tenth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
J1	293	55	8000	11	6	47,79	6
J2	288	48	7000	10	4	52,80	4
J3	262	40	6000	9	2	57,53	2
J4	262	35	6000	9	1	62,53	1
J5	288	45	7000	9	3	52,93	3
J6	293	49	8000	11	5	52,18	5

In the tenth scenario, based on the RTS estimated arrival times, the sequence is J3, J4, and J5—each with the same estimated time—followed by J2, and subsequently J1 and J6, which also share the same estimated arrival time. According to the fuzzy logic method, however, the arrival sequence is determined as J4, J3, J5, J2, J6, and J1, as presented in Table 11.

6. CONCLUSION

In air traffic management, decision making is very important for air traffic to be managed safely, quickly and regularly. Decision making must be done in a timely and most accurate way. It is especially important to be able to make a fair approach order among the traffic coming from different directions for landing within the terminal area. Controllers make decisions according to distance, level or speed parameters among multiple traffics moving within a limited time. Even in normal situations, the traffic order problem, which is very important for controllers to make decisions, leads to an increase in research every day due to the increasing traffic density in the world. In this study, the fuzzy logic method was used to determine the order of arrival traffics in order to help with decision making. The purpose of using this method is to better display human behavior compared to mathematical models and to provide an approach closer to reality by benefiting from the experience and ideas of experts.

Among the results presented by the study, the arrival order made according to the estimated arrival time in the real-time simulator can show the same time or order. However, the arrival order made according to the fuzzy logic method can give a more precise order. It is seen that the fuzzy logic method gives more accurate information, especially in cases where there is closeness or similarity in the values of parameters such as distance, speed or altitude.

In the exercises performed in the real-time simulator environment, the number of aircraft with the same estimated arrival time was 14 and constituted 23.3% of the total traffic, while the number of aircraft with the same score with the fuzzy logic method was 2 and constituted 3.3% of the total traffic. Again, no contradiction was observed between the aircraft with the same estimated arrival time and the arrival order score according to the fuzzy logic method. It was observed that the aircraft with the same estimate came after each other when the arrival order was made with the fuzzy logic score. For this reason, parallelism was observed between the data obtained in the simulator environment and the fuzzy logic method.

The findings showed that the fuzzy logic model produced consistent and reliable results in the ordering of arrival traffics in TMA. It was determined that the model provided higher accuracy in cases where speed and distance were dominant, while altitude had a secondary effect. The high agreement with the simulator supports the validity of the method for real-time applications. The study is a static model in that all data are known in advance and there are no situations that will cause changes later. In future studies, it is thought that this study will be useful in the development of ground support systems for terminal airspace optimization, aircraft ordering and aircraft landing problems by creating a dynamic model.

ACKNOWLEDGEMENTS

This study was derived from the master's thesis titled “A Fuzzy Logic Approach to Sequencing Arrival Traffic,” completed at the Graduate Education Institute, Eskişehir Technical University, 2023

This study was supported by Eskişehir Technical University Scientific Research Project Commission under grant no: 23ADP077.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Gülseren Yeşil: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Funding acquisition. **Özlem Şahin:** Supervision, Visualization, Conceptualization, Writing – Review & Editing.

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