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Decision Support System for Aircraft Takeoff and Landing Using Mamdani Fuzzy Logic Based on Weather Parameters

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Abstract−Aviation safety is highly influenced by weather conditions, particularly during take-off and landing, necessitating an accurate feasibility assessment. Traditional manual methods rely on subjective judgment, making them prone to inconsistencies and errors. This study proposes a decision support system utilizing Mamdani fuzzy logic to process real-time meteorological data from the Radin Inten II station and assess take-off and landing feasibility. The system evaluates key weather parameters, including wind speed, wind direction, visibility, precipitation, and cloud height. Testing 31 data samples from BMKG, the system achieved an accuracy of 96.77%, with 30 out of 31 outputs matching standard aviation criteria. These results indicate that the system significantly improves decision-making reliability. The Mamdani fuzzy logic approach proves effective in interpreting complex weather data and generating consistent, data-driven recommendations to support safe aircraft operations.

Keywords: Mamdani Fuzzy Logic; Decision Support System; Weather; Flight Safety; Takeoff and Landing

1. INTRODUCTION

Airplanes are currently the main means of transportation for people and goods. Compared to land or sea transportation, aircraft allow movement between locations in a much shorter time [1]. Air traffic activity in Indonesia has continued to grow, with the number of aircraft movements rising from 1,527,743 in 2015 to 1,735,788 in 2019 [2]. This rapid increase in flight operations elevates the risk of accidents, highlighting the critical need to prioritize safety in aviation operations. Safety in air transportation is a crucial aspect, especially during takeoff and landing, as it involves the transition of the aircraft between land and air. Boeing data (1959-2017) shows that 63% of fatal accidents occur in these two phases, with 14% during takeoff and 49% during landing [3]. This indicates that the takeoff and landing phases require special attention in flight safety design, including navigation systems, pilot training, and other supporting technologies [4].

The aircraft take-off and landing process is heavily influenced by various weather parameters affecting flight safety and success [5]. The International Civil Aviation Organization (ICAO) states that weather forecasts for aviation safety must include parameters such as wind, visibility, weather, clouds, and temperature [6]. These parameters are in line with those mandated by Indonesia's Civil Aviation Safety Regulation (CASR), issued under Ministry of Transportation Regulation No. 95 of 2018, which requires the provision of standardized meteorological information containing surface wind, visibility, weather phenomena, and cloud conditions for aviation safety purposes [7]. In response to these weather factors, pilots and Air Traffic Control (ATC) officers work together to ensure a safe takeoff, supported by the latest weather information from the local Meteorology, Climatology and Geophysics Agency (BMKG) station. Based on the weather data received, the pilot assesses whether the conditions meet the safety limits set for the aircraft to be flown [8]. However, the manual or rule-based method of assessing aircraft takeoff feasibility has several limitations, especially when faced with dynamic and complex weather conditions [9]. In addition, manual decision-making relies heavily on individual experience and intuition, which can lead to inconsistencies and potential human error.

A decision support system capable of processing large volumes of data in real time, identifying complex patterns, and generating accurate recommendations is essential, particularly in environments characterized by uncertainty and imprecise information. In such cases, conventional binary logic may be insufficient, as it limits reasoning to two absolute values: true (1) or false (0). Fuzzy logic offers a more flexible approach by allowing truth values to exist on a continuous scale between 0 and 1. This enables systems to handle vague, uncertain, or subjective data more effectively. For instance, rather than simply classifying a condition as "safe" or "unsafe," a fuzzy logic system can assess it as "less safe" or "fairly safe," assigning a specific degree of membership to each category. This approach better reflects human reasoning in complex decision-making scenarios [10]. To implement fuzzy logic in such systems, several methods have been developed. One widely used method is the Mamdani approach, introduced by Ebrahim Mamdani in 1975. This method applies a set of linguistic rules to translate input data into output decisions. It is particularly suitable for decision support systems, as it mimics the way humans reason under uncertainty [11].

Previous research by Dagal *et al.* [12], Siahaan [13] , and Pratiwi [14] have demonstrated the effective use of fuzzy logic to assess runway suitability for landing or takeoff by analyzing weather parameters such as visibility, wind direction, and wind speed. While these studies have provided important insights, the scope of weather variables considered remains relatively narrow. Building on these previous studies, the present research introduces additional parameters specifically, rainfall and cloud height to enhance the decision-making process. These two additional parameters are crucial. Cloud height is used to determine the 'ceiling,' which refers to the lowest altitude at which clouds cover more than half of the sky. This is especially important for flight operations, particularly during approach

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and landing. Meanwhile, heavy rainfall can significantly affect visibility, aircraft performance, and operational safety [15]. For instance, intense rain can reduce visibility, interfere with the electronic systems of light aircraft, and create water accumulation on runways, which may impair braking effectiveness [16]. By integrating these variables, this study aims to offer a more comprehensive and adaptive analysis of real-time weather dynamics. This extended approach represents a novel contribution, as it allows for a more detailed and realistic assessment of runway conditions without disregarding the foundational work of earlier research.

Radin Inten II Airport in South Lampung serves as the main gateway for air transportation in Lampung Province. The surrounding area frequently experiences extreme weather conditions such as heavy rainfall and strong winds, which can significantly impact flight safety, particularly during takeoff and landing operations. However, current decision-making in such situations still heavily relies on manual judgment. This study fills the gap by designing a decision support system based on Mamdani fuzzy logic, which analyzes real-time weather data from the Radin Inten II meteorological station to provide recommendations on the feasibility of takeoff and landing. Furthermore, the system is evaluated to assess its performance and reliability in enhancing flight safety.

2. RESEARCH METHODOLOGY

2.1 Research Stages

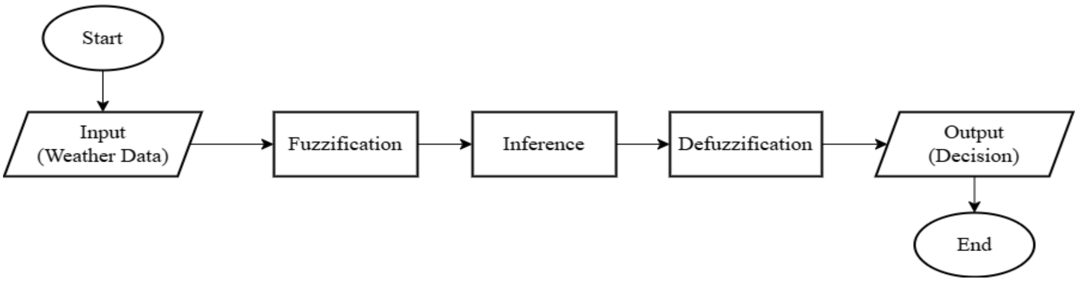

Figure 1. Flowchart of Research Methods

Figure 1 presents the flowchart of this research. This decision support system operates by analyzing five weather parameters: wind direction, wind speed, visibility, rainfall, and cloud height. The system's workflow consists of two main stages, namely data acquisition and data processing using Mamdani fuzzy logic. In the first stage, weather data is collected and stored in Excel format (.xlsx) after being retrieved from the database of the Class I Meteorological Station Radin Inten II Lampung in March 2023. In the second stage, the data is processed using fuzzy logic, which includes fuzzification, inference, and defuzzification. The output of the system is a decision indicating whether an aircraft is suitable for takeoff or landing.

2.2 Fuzzification

In assessing the feasibility of aircraft take-off, several input variables are used, such as wind speed, wind direction, visibility, rainfall, and cloud height. Each fuzzy variable in the input data is divided into several sets. All fuzzy sets and each fuzzy variable in the input data are represented using membership functions, that is in the form of a decreasing linear curve, trapezoid, and an increasing linear curve. The end result is a decision regarding aircraft take-off, where the linguistic variable values for each parameter category are described in Table 1.

Table 1. Variables and Categories of Each Parameter

No	Parameter	Criteria	
1	Wind Speed (knots)	0 – 5	Slow
		3 – 13	Medium
		10 – 30	Strong
2	Wind Direction (degrees)	0 – 70	Danger 1
		60 – 90	Moderately Safe 1
		80 – 180	Safe
		170 – 200	Moderately Safe 2
		190 – 360	Danger 2
3	Visibility (km)	0 – 5	Near
		4,5 – 8	Medium
		>7,5	Far
4	Rainfall (millimeters)	0 – 5	Mild
		3 – 10	Medium
		>8	Heavy
5		0 – 2000	Low

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No	Parameter	Criteria	
	Cloud Height (m)	1800 – 7000	Medium
		6000 – 13000	High
6	Decision (%)	0 – 40	Feasible
		30 – 70	Caution
		60 – 100	No Feasible

2.2 Inference

After the fuzzification process, the data is processed using a predetermined model, namely Mamdani to generate basic rules in the fuzzy inference model. At this stage, the system processes the relationship between the input value (crisp input) and the expected output value (crisp output) with rules. In this study, the decision-making model for determining aircraft takeoff feasibility is constructed using the Mamdani fuzzy logic system, which incorporates five meteorological input variables: wind speed, wind direction, visibility, rainfall, and cloud height. Each variable is discretized into linguistic categories, among which certain values are defined as critical: high wind speed, danger 1 and danger 2 wind directions, low visibility, heavy rainfall, and low cloud height, as decribed in Table 2.

Table 2. Definition of Input Parameters and Their Critical Categories

Parameter	Total Number of Categories (n)	Number of Critical Categories (c)
Wind Speed	3	1 (High)
Wind Direction	5	2 (Danger1, Danger 2)
Visibility	3	1 (Low)
Rainfall	3	1 (Heavy)
Cloud Height	3	1 (Low)

The total number of input combinations is calculated by multiplying the number of linguistic terms (categories) for each parameter:

$$N_{total} = n_1 \times n_2 \times n_3 \times n_4 \times n_5 = 3 \times 5 \times 3 \times 3 \times 3 = 405$$

Let c be the number of critical categories for each parameter, and C be the total number of critical categories present in a specific combination. To determine the output classification for each combination, the number of critical categories present is counted. The output decision function D is defined as :

$$D = \begin{cases} Feasible, & if\ C = 0 \\ Caution, & if\ C = 1\ or\ C = 2 \\ Not\ feasible, & if\ C \geq 3 \end{cases}$$

A complete enumeration over the 405 combinations was performed, classifying each according to its value of C . The resulting distribution was:
$D_{feasible} = 48$, for combination with $C = 0$
$D_{caution} = 269$, for combination with $C = 1\ or\ C = 2$
$D_{not\ feasible} = 88$, for combination with $C \geq 3$
Table 3 presents examples of fuzzy rules derived from sample data used in this study. These examples represent a subset of the full 405 possible parameter combinations. Specifically, the table showcases 31 selected rules that were formulated based on observed data values during the research.

Table 3. Fuzzy Rules Example

No	Wind Speed (knot)	Wind Direction (Degree)	Visibility (km)	Rainfall (mm)	Cloud Height (m)	Output
1	Medium	Danger 2	Low	Heavy	Low	Not Feasible
2	Slow	Danger 2	Far	Heavy	Heavy	Caution
3	Medium	Danger 2	Far	Medium	Low	Caution
4	Medium	Danger 1	Far	Medium	Low	Caution
5	Medium	Danger 1	Far	Medium	Low	Caution
6	Medium	Danger 2	Far	Heavy	Low	Not Feasible
7	High	Danger 2	Far	Heavy	Low	Not Feasible
8	Medium	Danger 2	Far	Heavy	Heavy	Caution
9	Medium	Danger 1	Far	Heavy	Low	Not Feasible
10	Medium	Safe	Far	Medium	Low	Feasible
11	Slow	Danger 2	Far	Medium	Heavy	Caution

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No	Wind Speed (knot)	Wind Direction (Degree)	Visibility (km)	Rainfall (mm)	Cloud Height (m)	Output
12	High	Danger 1	Far	Medium	Heavy	Caution
13	Medium	Danger 2	Far	Medium	Low	Caution
14	Medium	Danger 2	Medium	Medium	Low	Caution
15	Medium	Danger 2	Far	Medium	Low	Caution
16	Medium	Danger 2	Far	Medium	Heavy	Caution
17	Medium	Danger 2	Far	Medium	Low	Caution
18	Medium	Danger 1	Far	Medium	Low	Caution
19	Slow	Danger 1	Medium	Medium	Low	Caution
20	Medium	Danger 1	Far	Medium	Heavy	Caution
21	Medium	Danger 1	Far	Medium	Low	Caution
22	High	Danger 1	Far	Medium	Low	Caution
23	Medium	Moderate Safe 1	Far	Medium	Heavy	Feasible
24	Medium	Safe	Far	Heavy	Low	Caution
25	Medium	Safe	Far	Medium	Heavy	Feasible
26	Medium	Moderate Safe 2	Far	Medium	Heavy	Feasible
27	Medium	Safe	Far	Medium	Light	Feasible
28	Medium	Danger 2	Far	Medium	Low	Caution
29	Medium	Danger 2	Medium	Heavy	Heavy	Caution
30	Slow	Danger 1	Far	Medium	Low	Caution
31	High	Danger 1	Medium	Medium	Heavy	Caution

In this fuzzy logic system, five parameters can be included in the critical category, such as wind speed (strong), wind direction (danger 1 or danger 2), visibility (Slow), rainfall (heavy), and cloud height (low). The rules used to determine the output are as follows: if there are at least three parameters in the critical category, then the output is categorized as “Not Feasible.” If there are one or two parameters in the critical category, then the output is categorized as “Caution.” Meanwhile, if there are no parameters in the critical category, then the output is categorized as “Feasible.”

2.3 Defuzzification

Finally, the results of the inference process using the Mamdani method are in the form of fuzzy numbers, which are subsequently converted into crisp values through the defuzzification process. In fuzzy systems, after fuzzy rules are applied and inference is carried out, the results are still in the form of membership degrees in several fuzzy sets. Since this result is still in an uncertain form or cannot be directly used by deterministic systems, a defuzzification process is needed to convert it into a single value that can be interpreted more clearly. In this study, the defuzzification method used is the Centroid or Center of Gravity (CoG), which calculates the center of the area under the aggregated membership function curve to produce a representative crisp output.

3. RESULT AND DISCUSSION

3.1 Design of Fuzzy System

In this study, the data was analyzed using fuzzy logic by taking 31 random samples from the data set representing each criterion in the aircraft flight decision variable. In this study, MATLAB was utilized to implement the fuzzy inference system due to its robust and versatile environment for fuzzy logic development. The Fuzzy Logic Toolbox in MATLAB offers integrated functionalities for constructing Mamdani-type systems, including the specification of input and output variables, the design of membership functions, and the formulation of fuzzy rules. One of MATLAB’s notable strengths lies in its user-friendly graphical interface, which enables researchers to intuitively define fuzzy sets and rules, perform simulations of the inference process, and visualize defuzzification outcomes in real time [17]. Furthermore, MATLAB supports a variety of membership function shapes that are essential for accurately modeling uncertainty and smooth transitions between linguistic terms. The first step in building this application is to enter the initial data into the Fuzzy toolbox, which includes five input variables and one output variable. Figure 2 shows the design of the fuzzy system designed.

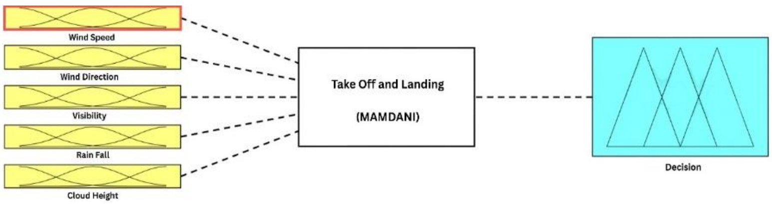

Figure 2. Fuzzy System Design

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3.2 Membership Function

To define each variable, a fuzzy set is created as described in Table 1. Then, to represent these variables, two types of membership function curves are used. A membership function is a curve that describes the mapping of input data points into their membership values, which are often referred to as membership degrees, with a range between 0 and 1 [18]. One method to determine the membership value is with a function approach. There are several types of function curves that can be used in this process, including linear curves, triangles, trapezoids, shoulders, bells, and others [19].

In this research, two types of curves are used to represent each variable which can be seen in Figure 3. In the wind speed variable, there are three fuzzy sets defined: slow, medium, and fast. Slow and fast fuzzy sets are represented with trapezoidal curves, while medium fuzzy sets use triangular curves. In the wind direction variable, five fuzzy sets are defined, namely danger 1, moderately safe 1, safe, moderately safe 2, and danger 2. All fuzzy sets in this variable are represented with trapezoidal curves. Wind direction and wind speed are closely related and affect the aircraft landing process because they can produce crosswind [20].

In the visibility variable, the three fuzzy sets defined are near, medium, and far. The near and far fuzzy sets are represented with a trapezoidal curve, while the medium fuzzy set uses a triangular curve. In the rainfall variable, the three fuzzy sets defined include light, medium, and heavy. Light and heavy fuzzy sets are represented with trapezoidal curves, while medium fuzzy sets use triangular curves. In the cloud height variable, there are three fuzzy sets, which are low, medium, and high. The low and high fuzzy sets are represented with a trapezoidal curve, while the medium fuzzy set uses a triangular curve. Finally, in the decision variable, the three fuzzy sets defined are feasible, cautious, and infeasible. The feasible and infeasible fuzzy sets are represented with a trapezoidal curve, while the cautious fuzzy set uses a triangular curve.

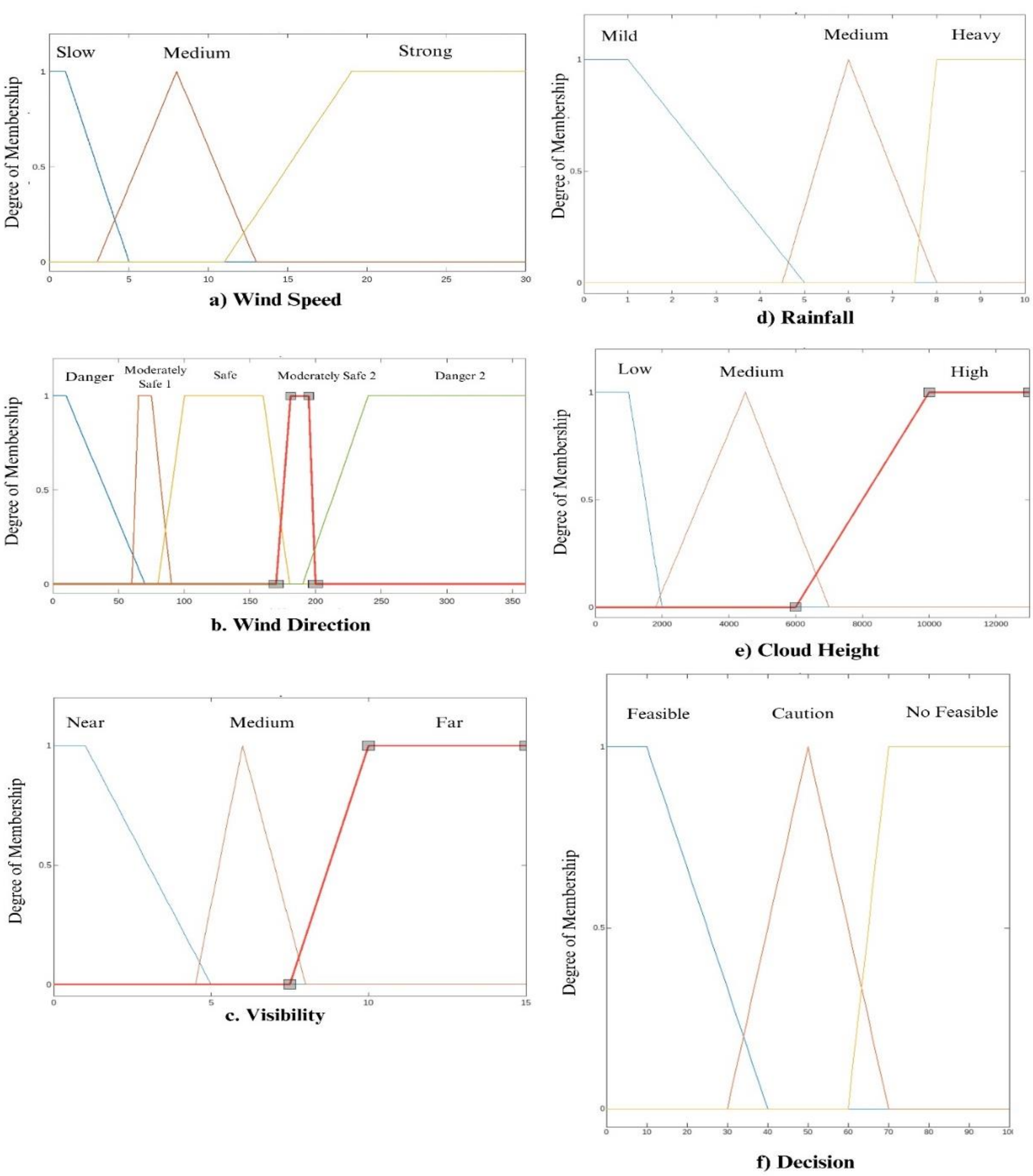

Figure 3. Membership Function Curves for All Variables

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3.3 Fuzzy System Testing

A fuzzy inference system (FIS) can be defined as a nonlinear mapping that produces outputs based on fuzzy reasoning and a set of fuzzy IF–THEN rules. The rapid development of fuzzy set theory has led to the emergence of various types of FIS, with the most commonly used systems being Mamdani, Sugeno, and Tsukamoto [21]. The Mamdani method is chosen because it mimics human decision-making processes. The process begins with fuzzification, where numerical inputs—such as weather parameter data—are converted into linguistic variables, namely weather criteria, using fuzzy membership functions. These values are then processed in the fuzzy inference stage, which uses a set of IF–THEN rules stored in a rule base. These rules connect input variables to outputs based on linguistic logic [22]. For example: "If wind speed is strong, wind direction is dangerous, visibility is low, rainfall is heavy, and cloud height is low, then the output is not suitable for takeoff/landing." The inference mechanism then combines this information to determine a fuzzy output. Afterward, defuzzification is carried out to convert the fuzzy output into a numerical value that can be used in a control system, as illustrated in Figure 2.

In this study, the accuracy level of the developed Mamdani fuzzy system was measured. Accuracy is defined as the degree to which the measurement results approach the actual value [23]. In this context, accuracy refers to how closely the output value of the Mamdani method matches the predetermined standard value. This standard value is determined based on the membership function of the output variable in the fuzzy logic system used to make aircraft takeoff decisions [24].

Next, the fuzzy system that was built was tested. Testing was carried out on 31 samples of BMKG data in the Radin Inten II Lampung Airport area. The calculation results are expected to produce fuzzy logic values that are in accordance with the standards/rules that have been made. After determining the membership function value for each variable, the next step is to test the program in MATLAB. At the end of the calculation, a Z value will be obtained, which is the result of calculations using Mamdani fuzzy logic. Figure 4 below shows the test results based on the data that has been entered into the fuzzy variables.

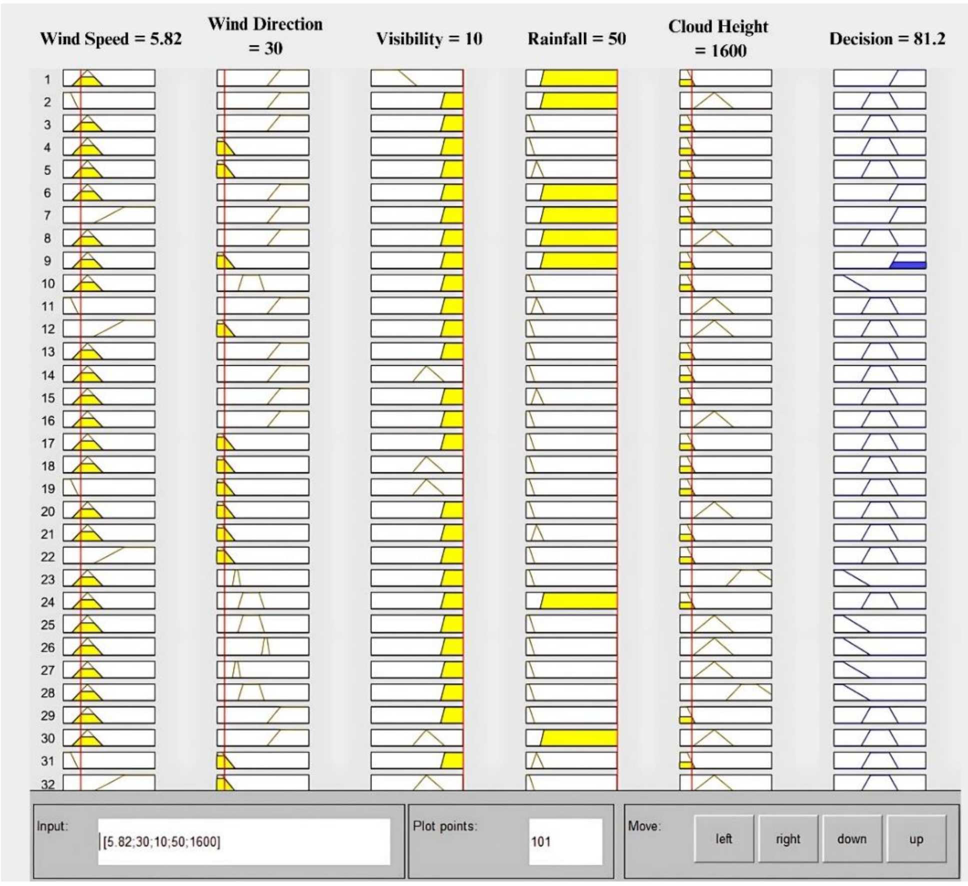

Figure 4. Fuzzy Testing Results. The decision output is 81.2% which indicates that the aircraft is not suitable for take-off/landing.

Next, the accuracy level of the fuzzy system formed is measured. Accuracy is defined as, the extent to which the measurement results are close to the true value. In this research, accuracy refers to the suitability of the output value of the Mamdani method with a predetermined standard value. The standard value is determined based on the membership function of the output variable in the fuzzy logic system used to determine aircraft take-off decisions. Next, the accuracy level of the fuzzy system formed is measured. Accuracy is defined as, the extent to which the measurement results are close to the true value. In this research, accuracy refers to the suitability of the output value

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of the Mamdani method with a predetermined standard value. The standard value is determined based on the membership function of the output variable in the fuzzy logic system used to determine aircraft take-off decisions.

Table 4. Measurement Data and Comparison of Data Results.

No	Date	Wind Speed (knots)	Wind Direction (degrees)	Visibility (km)	Rainfall (mm)	Cloud Height (m)	Rule (Standard Value)	System Output
1	01-03-2023	11.64	310	1	9	1500	Not Feasible	Not Feasible
2	02-03-2023	3.88	350	30	23.2	6000	Caution	Caution
3	03-03-2023	11.64	330	30	3.6	1500	Caution	Caution
4	04-03-2023	5.82	10	20	3.5	1500	Caution	Caution
5	05-03-2023	7.76	10	40	8	1500	Caution	Caution
6	06-03-2023	7.76	320	10	11.5	1500	Not Feasible	Not Feasible
7	07-03-2023	17.46	270	20	9.5	1500	Not Feasible	Not Feasible
8	08-03-2023	5.82	290	10	45.5	2100	Caution	Caution
9	09-03-2023	5.82	30	50	66	1600	Not Feasible	Not Feasible
10	10-03-2023	7.76	150	30	0.2	1500	Feasible	Feasible
11	11-03-2023	3.88	260	20	29.3	6000	Caution	Caution
12	12-03-2023	17.46	10	30	0	6000	Caution	Caution
13	13-03-2023	7.76	310	30	1	1500	Caution	Caution
14	14-03-2023	9.7	330	6	0	1500	Caution	Caution
15	15-03-2023	7.76	360	40	6	1600	Caution	Caution
16	16-03-2023	9.7	320	40	0	7000	Caution	Caution
17	17-03-2023	9.7	20	40	0.6	1500	Caution	Caution
18	18-03-2023	11.64	40	8	0	1500	Caution	Caution
19	19-03-2023	3.88	30	8	0	1600	Caution	Caution
20	20-03-2023	5.82	20	40	4.5	6000	Caution	Caution
21	21-03-2023	9.7	60	20	6	1500	Caution	Caution
22	22-03-2023	17.46	40	30	0	1600	Caution	Caution
23	23-03-2023	7.76	80	20	0	8200	Feasible	Feasible
24	24-03-2023	9.7	150	56	56	1500	Caution	Caution
25	25-03-2023	7.76	120	40	0.5	7000	Feasible	Feasible
26	26-03-2023	7.76	190	58	0	6500	Feasible	Feasible
27	27-03-2023	11.64	130	58	0	8100	Feasible	Feasible
28	28-03-2023	9.7	360	30	0	1500	Caution	Caution
29	29-03-2023	7.76	350	7	11.1	6000	Caution	Feasible
30	30-03-2023	3.88	10	10	7.9	1500	Caution	Caution
31	31-03-2023	17.46	70	7	1.5	6000	Caution	Caution

Determination of the accuracy level is carried out with the following criteria: a) if the fuzzy calculation result is by the predetermined standard value, it is declared accurate and, b) if the calculation result does not match, it is declared inaccurate. After the data is processed using the MATLAB toolbox, the output value of the Mamdani method can be analyzed and displayed in Table 3. The accuracy level of the Mamdani method in this study can be calculated as a percentage of the number of accurate results against the total samples tested. Of the total 31 samples analyzed, 30 data were declared accurate. Thus, the accuracy level of the fuzzy system formed is 96.77%.

These results indicate that the Mamdani method has a high level of accuracy in assessing aircraft takeoff and landing feasibility. However, discrepancies between the output and the actual values may be caused by various factors, such as uncertainties in the input data and imperfections in the fuzzification and defuzzification processes [25]. These two factors can be optimized to improve accuracy by using a broader data sample. Moreover, further research is needed to compare the Mamdani method with other fuzzy approaches, such as the Sugeno method, in order to provide a more comprehensive insight into the application of fuzzy logic in aircraft takeoff and landing decision-making systems. In addition to technical factors, membership function parameters and fuzzy rules also influence the final output of this decision support system [26]. Therefore, future work may focus on optimizing membership functions and fuzzy rules, comparing Mamdani with other fuzzy methods like Sugeno, and developing real-time decision support systems.

4. CONCLUSION

A fuzzy logic system built using the Mamdani method in MATLAB has been successfully used to analyze aircraft flight decisions based on weather variables. Five input variables including wind speed, wind direction, visibility, rainfall, and cloud height were successfully converted into decision variables using trapezoidal and triangular membership functions. Testing 31 samples of BMKG data at Radin Inten II Airport Lampung showed that the fuzzy

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system developed was able to produce decisions that were in accordance with the standard rules that had been set. From the comparison results, 30 out of 31 samples showed accurate results, so this system has an accuracy rate of 96.77%. This shows that the fuzzy logic approach with the Mamdani method can be an effective tool in helping decision-making related to aircraft flight feasibility based on weather conditions.

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REFERENCES

[1] K. Shirini, H. S. Aghdasi, and S. Saeedvand, "A Comprehensive Survey on Multiple-Runway Aircraft Landing Optimization Problem," *Int. J. Aeronaut. Space Sci.*, vol. 25, no. 4, pp. 1574–1602, Oct. 2024, doi: 10.1007/s42405-024-00747-z.

[2] B.-S. Indonesia, "Air Transportation Statistics 2022." Accessed: Jun. 30, 2025. [Online]. Available: https://www.bps.go.id/en/publication/2023/11/27/aec509f099371a2655c5ee0f/air-transportation-statistics-2022.html

[3] Z. Sokol, J. Szturc, J. Orellana-Alvear, J. Popová, A. Jurczyk, and R. Célleri, "The Role of Weather Radar in Rainfall Estimation and Its Application in Meteorological and Hydrological Modelling—A Review," *Remote Sensing*, vol. 13, no. 3, p. 351, Jan. 2021, doi: 10.3390/rs13030351.

[4] G.-P. Chen, T.-S. Chen, and T.-C. Chen, "Obstacle Avoidance for Flight Safety of Unmanned Aerial Vehicles Using Deep Reinforcement Learning," in *2024 IEEE VTS Asia Pacific Wireless Communications Symposium (APWCS)*, Singapore: IEEE, Aug. 2024, pp. 1–5. doi: 10.1109/apwcs61586.2024.10679316.

[5] H. Liu, R. Xie, H. Qin, and Y. Li, "Research on dangerous flight weather prediction based on machine learning," *J. Phys.: Conf. Ser.*, vol. 2870, no. 1, p. 012020, Oct. 2024, doi: 10.1088/1742-6596/2870/1/012020.

[6] I. Ostroumov and N. Kuzmenko, "Aviation Weather Data Processing with Spline Functions," in *2021 IEEE 12th International Conference on Electronics and Information Technologies (ELIT)*, Lviv, Ukraine: IEEE, May 2021, pp. 67–70. doi: 10.1109/elit53502.2021.9501065.

[7] "Permenhub No. 95 Tahun 2018." Accessed: Jun. 30, 2025. [Online]. Available: https://peraturan.bpk.go.id/Details/102846/permenhub-no-95-tahun-2018?utm_source=chatgpt.com

[8] E. Mangortey, O. J. Pinon-Fischer, T. G. Puranik, and D. N. Mavris, "Predicting The Occurrence of Weather And Volume Related Ground Delay Programs," in *AIAA Aviation 2019 Forum*, American Institute of Aeronautics and Astronautics. doi: 10.2514/6.2019-3188.

[9] J. Mihajlović, D. Burić, and M. Milenković, "Synoptic characteristics of an extreme weather event: The tornadic waterspout in Tivat (Montenegro), on June 9, 2018," *Geogr. Pol.*, vol. 94, no. 1, pp. 68–90, 2021, doi: 10.7163/GPol.0194.

[10] Y. Ardi, S. Effendi, and E. B. Nababan, "Mamdani and Sugeno Fuzzy Performance Analysis on Rainfall Prediction," *Rand. Inter. Social Sci. J.*, vol. 2, no. 2, pp. 176–192, Apr. 2021, doi: 10.47175/rissj.v2i2.240.

[11] N. Rajesh Mavani, C. Y. Lim, H. Hashim, N. Abd. Rahman, and J. Mohd Ali, "Fuzzy Mamdani based user-friendly interface for food preservatives determination," *Food and Bioproducts Processing*, vol. 126, pp. 282–292, Mar. 2021, doi: 10.1016/j.fbp.2021.01.012.

[12] I. Dagal, W. F. Mbasso, H. Ambe, B. Erol, and P. Jangir, "Adaptive Fuzzy Logic Control Framework for Aircraft Landing Gear Automation: Optimized Design, Real-Time Response, and Enhanced Safety," *Int. J. Aeronaut. Space Sci.*, Mar. 2025, doi: 10.1007/s42405-025-00922-w.

[13] A. P. U. Siahaan, "Take Off and Landing Prediction Using Fuzzy Logic," *International Journal of Recent Trends in Engineering & Research (IJRTER)*, vol. 02, no. 12, 2016, doi: 10.31227/osf.io/2c538.

[14] W. Pratiwi, A. Sofwan, and I. Setiawan, "Implementation of fuzzy logic method for automation of decision making of Boeing aircraft landing," *IJ-AI*, vol. 10, no. 3, p. 545, Sep. 2021, doi: 10.11591/ijai.v10.i3.pp545-552.

[15] Y.-J. Noh *et al.*, "A Framework for Satellite-Based 3D Cloud Data: An Overview of the VIIRS Cloud Base Height Retrieval and User Engagement for Aviation Applications," *Remote Sensing*, vol. 14, no. 21, p. 5524, Nov. 2022, doi: 10.3390/rs14215524.

[16] I. Gultepe *et al.*, "A Review of High Impact Weather for Aviation Meteorology," *Pure Appl. Geophys.*, vol. 176, no. 5, pp. 1869–1921, May 2019, doi: 10.1007/s00024-019-02168-6.

[17] F. Elfaladonna and I. G. T. Isa, "Uji Efektivitas Metode Fuzzy Logic Mamdani pada Penerimaan Beasiswa Menggunakan Matlab," *SINTECH (Science and Information Technology) Journal*, vol. 5, no. 1, Art. no. 1, Apr. 2022, doi: 10.31598/sintechjournal.v5i1.1043.

[18] S. Kusumadewi, L. Rosita, and E. Gustri Wahyuni, "Fuzzy linear regression based on a hybrid of fuzzy C-means and the fuzzy inference system for predicting serum iron levels in patients with chronic kidney disease," *Expert Systems with Applications*, vol. 227, p. 120314, Oct. 2023, doi: 10.1016/j.eswa.2023.120314.

[19] S. N. Putri and D. R. S. Saputro, "Construction fuzzy logic with curve shoulder in inference system mamdani," *J. Phys.: Conf. Ser.*, vol. 1776, no. 1, p. 012060, Feb. 2021, doi: 10.1088/1742-6596/1776/1/012060.

[20] H. Baomar and P. J. Bentley, "Autonomous landing and go-around of airliners under severe weather conditions using Artificial Neural Networks," in *2017 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS)*, Linkoping: IEEE, Oct. 2017, pp. 162–167. doi: 10.1109/RED-UAS.2017.8101661.

[21] G. Selvachandran *et al.*, "A New Design of Mamdani Complex Fuzzy Inference System for Multiattribute Decision Making Problems," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 4, pp. 716–730, Apr. 2021, doi: 10.1109/TFUZZ.2019.2961350.

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[22] E. Pourjavad and R. V. Mayorga, "A comparative study and measuring performance of manufacturing systems with Mamdani fuzzy inference system," *J Intell Manuf*, vol. 30, no. 3, pp. 1085–1097, Mar. 2019, doi: 10.1007/s10845-017-1307-5.

[23] D. Y. Darmawi, G. W. Nurcahyo, and S. Sumijan, "Fuzzy Sistem Fuzzy Menggunakan Metode Sugeno Dalam Akurasi Penentuan Suhu Kandang Ayam Pedaging," *jidt*, vol. 3, no. 2, pp. 72–77, 2021, doi: 10.37034/jidt.v3i2.95.

[24] R. Reynaldi, W. Syafrizal, and M. F. A. Hakim, "Analisis Perbandingan Akurasi Metode Fuzzy Tsukamoto dan Fuzzy Sugeno Dalam Prediksi Penentuan Harga Mobil Bekas," *Indonesian Journal of Mathematics and Natural Sciences*, vol. 44, no. 2, Art. no. 2, Oct. 2021, doi: 10.15294/ijmns.v44i2.32967.

[25] E. Setianingtyas, M. A. S. Yudono, and A. Erfina, "Pengambilan Keputusan Lepas Landas Pesawat Boeing Menggunakan Metode Logika Fuzzy Mamdani," *Metrik*, vol. 16, no. 01, p. 32, Jun. 2023, doi: 10.26714/me.v16i01.10930.

[26] Murugesan. G. *et al.*, "Fuzzy Logic-Based Systems for the Diagnosis of Chronic Kidney Disease," *BioMed Research International*, vol. 2022, no. 1, Jan. 2022, doi: 10.1155/2022/2653665.