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Decision-Making Model for Aircraft Landing Based on Fuzzy Logic Approach

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ABSTRACT

An aircraft's landing stage involves inherent hazards and problems associated with many factors, such as weather, runway conditions, pilot experiences, etc. The pilot is responsible for selecting the proper landing procedure based on information provided by the landing console operator (LCO). Given the likelihood of human decisions due to errors and biases, creating an intelligent system becomes important to predict accurate decisions. This paper proposes the fuzzy logic method, which intends to handle the uncertainty and ambiguity inherent in the landing phase, providing intelligent decision support to the pilot while reducing the workload of the LCO. The fuzzy system, built using the Mamdani approach in MATLAB software, considers critical inputs like wind speed, wind direction, visibility, and runway condition to determine the landing's feasibility. The connection between the fuzzy rules is shown in the plotted curves, which indicate the smoothness and absence of overlap of decision-making rules for various input scenarios. A study employing data from Baghdad International Airport found that the proposed fuzzy approach predicted landing feasibility with an outstanding more than 85% accuracy across 20 different real-world scenarios. This level of reliability demonstrates how well the system can assess varied weather and runway conditions and identify the best landing decisions.

1. INTRODUCTION

The landing of an aircraft is considered the most important and dangerous phase of flight due to the risks associated with the approach and landing phases. The safe landing necessitated high precision in the pilot's cognitive task performance, which was dependent on several factors. The factors were runway condition, weather, aircraft traffic, and visibility [1]. To achieve a safe and smooth landing, the pilot must have a high level of skill and instant response [2]. After analyzing the information provided by the landing console operator (LCO), the pilot makes a landing choice. This information was improved by using special instruments that collect data on weather and runway conditions [3, 4].

According to statistics on the causes of 1,805 aircraft accidents from 1950 to 2019, weather was responsible for 10% of these incidents, while pilot error accounted for 50% of them [5]. Several inherent uncertainties can influence the decision-making process, including uncertainties in weather conditions such as unpredictable changes in wind speed and direction, uncertainties in instrument landing system (ILS) sensors that are subject to distortion, error, or delay, and runway conditions, which have a significant impact on the decision of an airplane landing to apply appropriate braking action. Due to the nature and complexity of landings, it is impossible to achieve human decision-making that combines high precision and speed. In situations where information about landing ability is vague or confusing, artificial intelligence plays a crucial role in tackling these challenges effectively [6].

Fuzzy logic is an artificial intelligence method and a mathematical theory that distinguishes itself from binary logic, which relies on precise true or false values. In the fuzzy logic method, every input and output are classified into separate fuzzy sets. Each set is assigned membership values ranging from 0 to 1, which quantify the degree of relationship with a certain set [7, 8]. Fuzzy logic excels in handling uncertainty and imprecision by processing unclear or linguistic data, making it perfect for real-world applications. Unlike standard binary systems, it employs straightforward (if-then) logic, which improves clarity and trust. In contrast to machine learning, it requires less computer power and no big datasets, ensuring practicality and adaptability to new conditions without costly retraining. These characteristics make fuzzy logic a dependable option for uncertain and complex decision-making engineering systems.

Several studies used fuzzy logic approaches to handle the landing decision-making challenges of an aircraft. One of them, Zadeh [9] discussed the importance of uncertainty and ambiguity in the flight environment and established a Fuzzy Inference System (FIS) that uses visibility, pilot experience, and airspeed as input variables to calculate the landing success rate. The suggested fuzzy logic results are compared to flight simulation results to demonstrate that it can forecast landing success probability under the inputs used. The Adaptive Neuro-Fuzzy Inference System (ANFIS), which determines whether or not a touchdown will occur, is both effective and beneficial in model computations.

Ramli et al. [10] offered a practical weather forecasting model for air traffic control systems based on a fuzzy hierarchical method. The model generates weather forecasts, for airports by combining factors and data from online sources with a structured knowledge model called Mamdani. The input factors include weather conditions, turbulence, and fog each of which is made up of components that work together to produce a result. Weather data takes into account factors such as visibility, wind speed, and barometric pressure. Turbulence is affected by sky conditions the presence of thunderstorms and the occurrence of precipitation. The fog component is dew point, temperature, and relative humidity. The study suggested that this prediction technique can generate accurate forecasts for air traffic controllers because it was based on online information.

Wijaya et al. [11] conducted a fuzzy logic method to evaluate if an aircraft is suitable, for takeoff and landing. This approach considers various factors like visibility, wind speed, and wind direction to predict precipitation. The study utilized Mamdani fuzzy logic to classify the outcome as feasible, careful, or if it was not feasible. It highlights the importance of fuzzy logic in air traffic control, for supporting aircraft operations during bad weather conditions.

Rahim [12] introduced a fuzzy logic method to anticipate if an airport's meteorological conditions are acceptable for aircraft takeoff or landing. The fuzzy approach employed is the Mamdani method, which requires three input parameters: wind velocity, wind direction, and visibility. The system's output determines whether the weather is appropriate, cautious, or impractical. The study's findings suggested that the technique is suitable for deciding whether to fly or land an airplane in various weather circumstances.

In a separate study conducted by Pratiwi et al. [13], they utilized the Mamdani fuzzy logic technique to improve decision-making during airplane landings. They considered factors such as wind direction, wind speed, visibility, and pilot experience to assist pilots in making landing choices. By comparing the outcomes of the developed fuzzy logic system with decisions made at AirNav Ahmad Yani Airport Semarang, it was demonstrated that an intelligent system based on fuzzy logic can determine the suitable decision for airplanes to land. However, most studies frequently employ the same set of inputs without adequately explaining their findings, and they commonly do not account for all possible input scenarios.

The Mamdani FIS possesses numerous properties that render it appropriate for this study. The Mamdani fuzzy inference approach is excellent for dealing with unsupervised data since it allows for the creation of linguistic rules based on human experience. Furthermore, it employs numerous techniques in the defuzzification process, such as the center of gravity (COG) and the mean of maximum, which improves its ability to deal with a confusing system [14]. The fuzzy inference procedure comprises five steps: fuzzification of input variables, application of fuzzy operators (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of consequences across rules, and defuzzification [7]. Figure 1 shows the main diagram of the Mamdani FIS [13, 15].

In this study, the Mamdani fuzzy technique is used to develop aircraft decision-making to aid in the assessment of landing feasibility under various weather and runway circumstances. It focuses on intelligent decision support for pilots rather than actively directing aircraft dynamics. The resulting system is tested by comparing it to data on landing Boeing 733-max provided by Baghdad International Airport.

The data collected from the airport revealed that gust turbulence occurs at medium to high wind speeds with a dangerous wind direction. The gust speed is classified into three types: 'simple' reach to 24 ft/sec,' medium' reach to 48 ft/sec, and 'high' reach to 64 ft/sec [16]. The weather inputs used include wind speed, wind direction, visibility, and runway conditions. The runway condition is a new input in this study, and it has a significant impact on the decision of an airplane landing to apply appropriate braking action [17, 18].

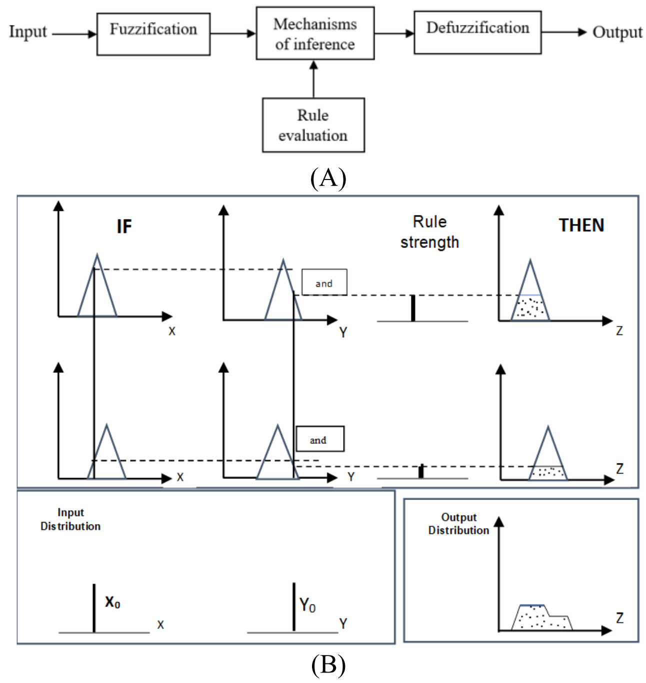

Figure 1. (A): The basic process of the fuzzy system. (B): The Mamdani fuzzy interface system block diagram

Unlike prior studies that often focus on a limited set of input factors or do not address overlapping rules comprehensively, this study introduces several novel contributions, which include taking runway conditions as a new input factor in addition to traditional inputs like (wind speed, wind direction, and visibility), in addition to incorporating all input scenarios into the rules and plotting curves ensuring smooth transitions and non-overlapping scenarios, which enhances reliability and accuracy, and finally creating a graphical user interface (GUI), for easily entering weather and runway condition data and displaying the landing decision, which supports usability in real-world applications.

2. MATHEMATICAL MODEL OF THE SYSTEM

In the Mamdani inference method, often called the Min-Max method, fuzzy rules are combined to produce a final decision. Here's how it works:

In the fuzzification, each input is converted into fuzzy values using membership functions. Figures 2 and 3 represent the graph of the triangular curve's membership functions and the L-shape used in this study [19].

Eqs. (1) and (2) demonstrate the usage of the triangle and L-membership functions for the fuzzification of this system, respectively [20, 21]. A membership function on X is any function that maps X to the real unit interval [0, 1]. The membership function for a fuzzy set A is typically denoted by μA. The value μA(X) represents the x's membership degree in the fuzzy set A. The membership degree μA(X) measures an element's membership in the fuzzy set A.

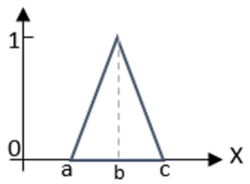

Figure 2. Tringale membership function

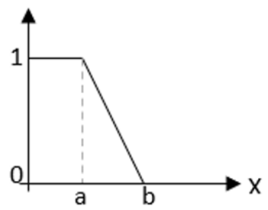

Figure 3. L-shape membership function

$$\mu A(x) = \begin{cases} 0 & if\ x \le a \\ \dfrac{(x-a)}{(b-a)} & if\ a < x \le b \\ \dfrac{(c-x)}{(c-b)} & if\ b < x \le c \\ 0 & if\ \ x \ge b \end{cases} \tag{1}$$

$$\mu A(x) = \begin{cases} 1 & if\ \ x \le a \\ \dfrac{(b-x)}{(b-a)} & if\ \ \ a < x \le b \\ 0 & if\ x > b \end{cases} \tag{2}$$

In rule evaluation (inference), each rule is assessed to determine how well the inputs match the conditions of the rule. The minimum value among the inputs (min) is used to represent the degree of truth (or activation level) for that rule. Eq. (3) represents the mathematical representation of the minimum operator.

$$\mu_{rule} = min\big(\mu A_1(X_1), \mu A_2(X_2), \ldots, \mu A_n(X_n)\big) \tag{3}$$

After that, the result of all rules is aggregated using the maximum operator (max). This results in producing a single fuzzy set accounting for all the influences of all rules in the Fuzzy Control System. The mathematical representation of the aggregation step is represented in Eq. (4):

$$\mu B(y) = max\big(\mu Bi(y)\big) \tag{4}$$

where, $\mu Bi(y)$ represents the membership function of each output individual rule.

After that, the output variables are defuzzified using the center of gravity approach of Eq. (5) [22, 23]. The center of gravity technique is utilized in this decision-making system because it produces a balanced, steady, and intuitive result that takes into account the influence of all contributing fuzzy rules.

$$a = \frac{\sum \mu A(xi).xi}{\sum \mu A(xi)} \tag{5}$$

3. FUZZY METHOD PROCEDURES

This work uses four input parameters for the Mamdani fuzzy system: wind speed, wind direction, visibility, and runway condition. The linguistic values of each input can be classified using classification data based on the value of each variable.

Table 1 displays the factors used in this investigation. The first three variable values were classified using a previous study with the same range [9-13], where these ranges were taken based on wind description in the study [24].

Table 1. Range criteria of the linguistic input parameters

Input Parameters	Range Criteria and Its Name	
	0 - 5	Low
Wind Speed/ Knots	3 - 13	Moderate
	10 - 30	High
	0 - 70	Danger1
	60 - 90	Relatively safe 1
Wind Direction/ Degree	80 -180	Safe
	170 - 200	Relatively safe 2
	190 - 360	Danger2
	0 - 5000	Close
Visibility/ Meters	4500 - 8000	Medium
	7500 - 10000	Far
	0 - 4	Slush
Runway Condition	3 - 7	Wet
	6 - 10	Dry

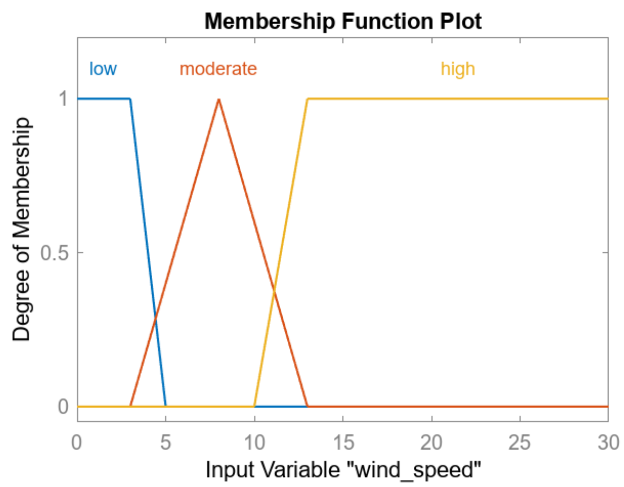

Figure 4. Wind speed membership functions

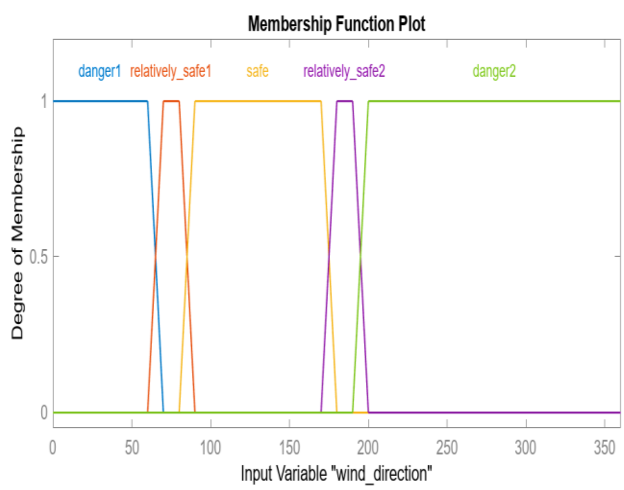

Figure 5. Wind direction membership functions

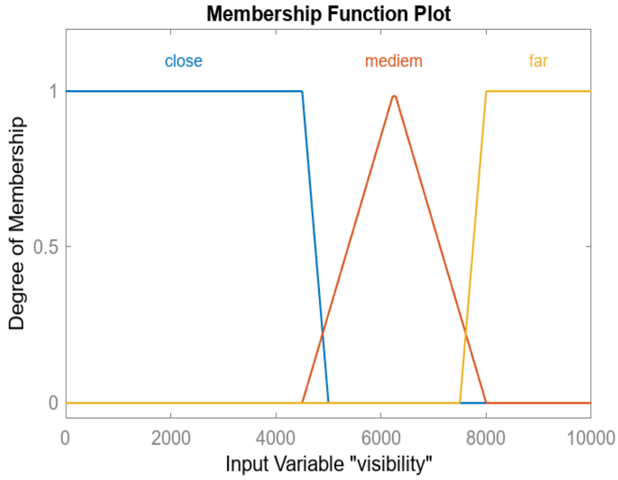

Figure 6. Visibility membership functions

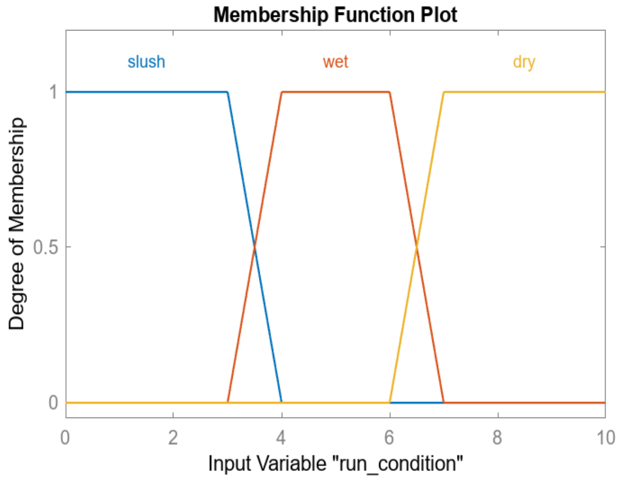

Figure 7. Runway condition membership functions

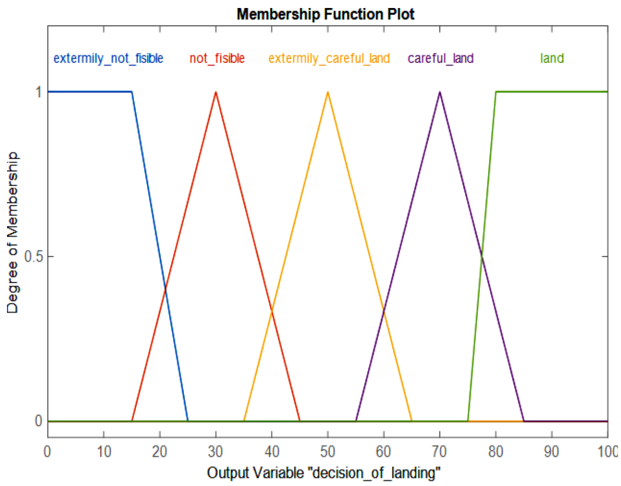

Figure 8. System evaluation membership functions

Figures 4 to 7 illustrate the representations of linguistic input parameters used in this study.

Figure 8 displays the fuzzy output membership functions used in this study, each indicating a different level of landing feasibility. The output system's evaluation is divided into "Extremely not feasible to land," "Not feasible to land," "Extremely careful land," "Careful land," and "Safe land," respectively.

4. EVALUATION RULE

The rules utilized in this study were derived from human expertise and were structured using If-Then statements. Figure 9 represents the flowchart of the fuzzy process:

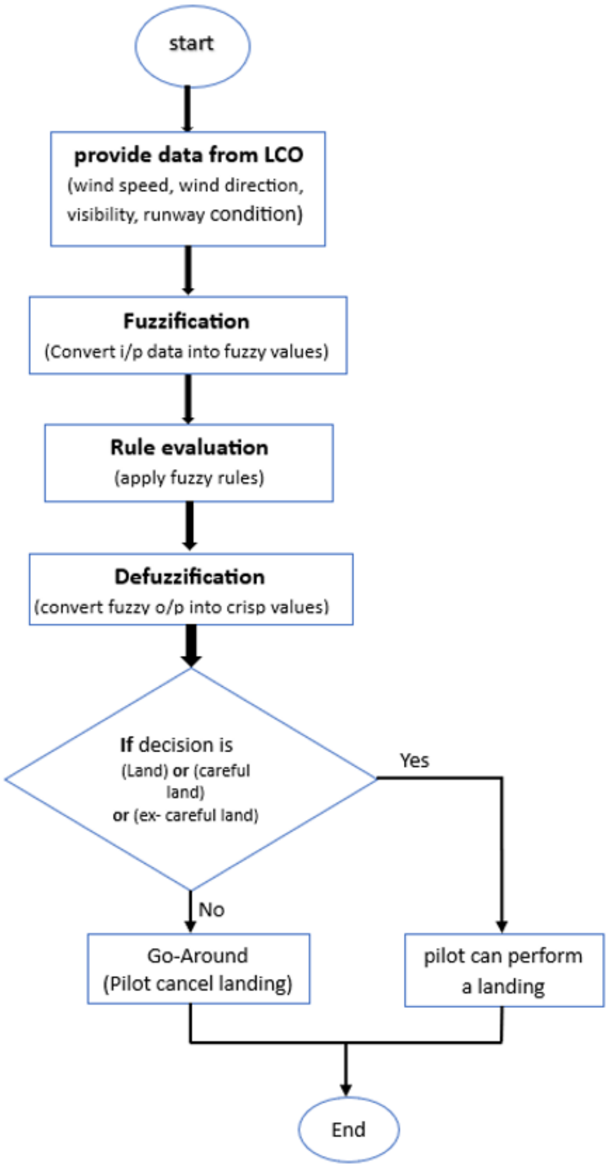

Figure 9. Flowchart of the decision-making

Figures 10-18 illustrate the Mamdani fuzzy logic system's relationship between inputs and outputs. Curves are plotted to show smoothness and non-overlapping of the rules [25, 26].

Figures 10-12 show the fuzzy system evaluation versus wind speed at each wind direction and different visibilities for various runway conditions.

Figure 10 shows how the system performs in dangerous wind directions with varying visibility conditions on three runway types.

Figure 11 illustrates the system's landing decision for different runways at various visibility levels with winds coming in "Re-safe" directions. This figure emphasizes the importance of runway conditions and visibility in the system's ability to tolerate greater winds, particularly under relatively safe wind directions.

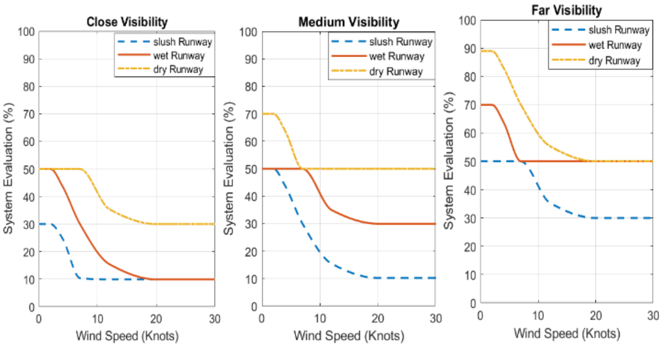

Figure 10. System evaluation versus wind speed at danger 1&2 direction for various visibility and runway conditions

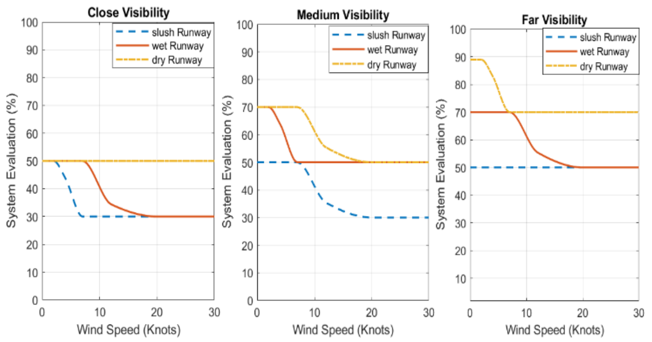

Figure 11. System evaluation versus wind speed at re-safe 1&2 direction for various visibility and runway conditions

Figure 12 illustrates how safe wind directions impact landing feasibility across different runway surfaces and visibility levels.

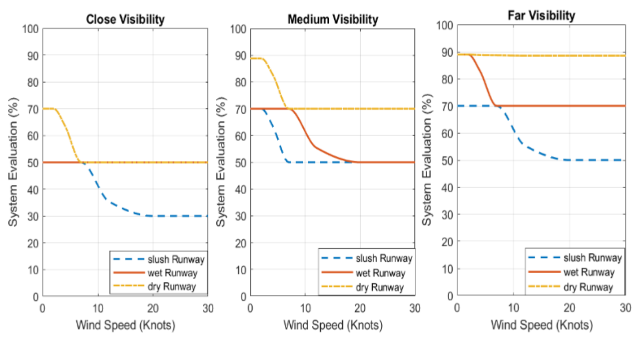

Figure 12. System evaluation versus wind speed at a safe wind direction for various visibility and runway conditions

Figures 13-15 show the fuzzy system evaluation versus wind speed at each runway condition and different visibilities for various wind directions. To explain the effect of each type of wind direction on the aircraft's landing decision for each case of the runway with different degrees of visibility in the air.

Figure 13 shows how different wind directions and visibility levels affect the safety of landing on a slushy runway. This analysis highlights how critical wind direction and visibility are for safe landings, especially on challenging surfaces like slush, where braking and steering control are compromised.

Figure 14 provides insight into how varying visibility conditions and wind directions affect landing decisions on wet runways. This figure also shows how a rise in wind speed, visibility, and wind direction can impose a much greater threat to landing on wet runways, meaning that both pilots and systems will be making progressively more conservative decisions the worse the environment gets.

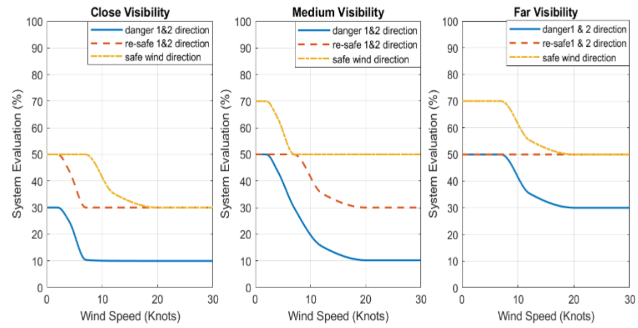

Figure 13. System evaluation versus wind speed at slush runway conditions for various visibility and wind directions

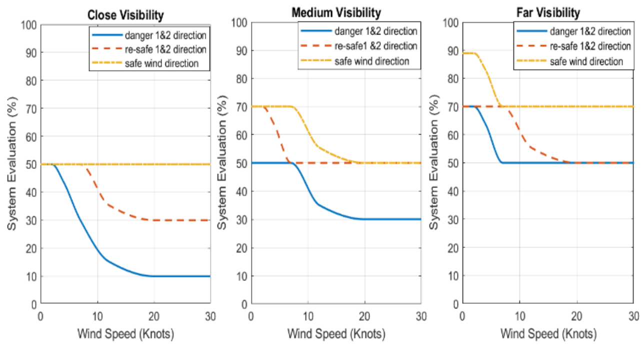

Figure 14. System evaluation versus wind speed at wet runway conditions for various visibility and wind directions

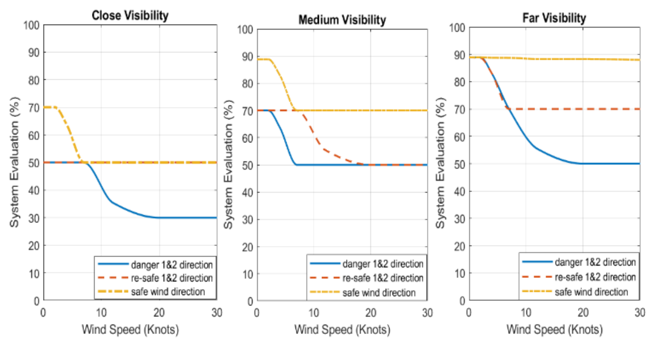

Figure 15. System evaluation versus wind speed at dry runway conditions for various visibility and wind directions

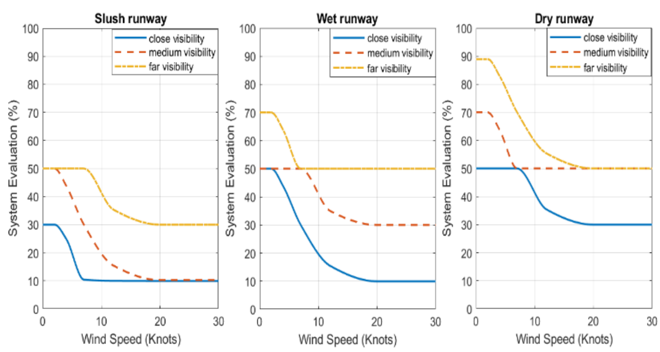

Figure 16. System evaluation versus wind speed at danger 1&2 for various runway conditions and various visibility

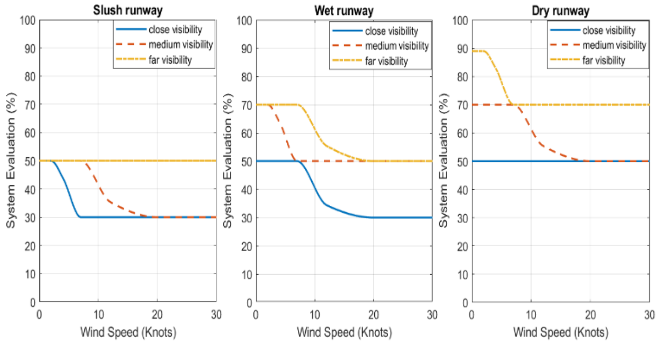

Figure 17. System evaluation versus wind speed at re-safe 1&2 for various runway conditions and various visibility

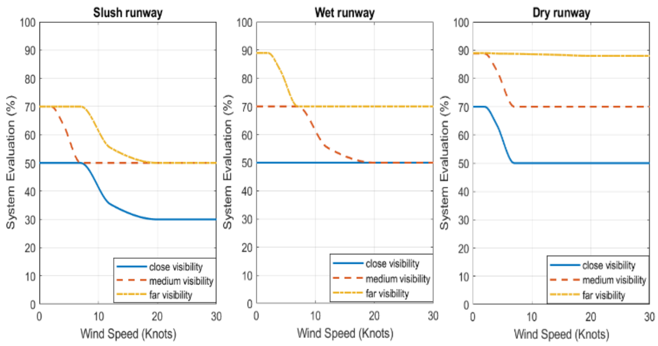

Figure 18. System evaluation versus wind speed at a safe direction for various runway conditions and visibility

Figure 15 displays the system evaluation for an airplane landing on a dry runway under varying visibility conditions.

Figures 16-18 show the fuzzy system evaluation versus wind speed at each wind direction and different runway conditions for various visibility. To explain the effect of visibility type on the aircraft's landing decision for each case of the wind direction with varying instances of runway condition.

Figure 16 displays the plotting curves of visibility cases for each runway condition in a dangerous wind direction. As wind speeds rise, reduced visibility poses significant challenges for safe landings, especially on slushy and wet surfaces.

Figure 17 demonstrates the plotting curves of visibility cases for each runway condition in relatively safe types of wind direction.

Figure 18 shows the plotting curves of visibility scenarios for each runway condition in the safe wind direction.

5. RESULTS AND DISCUSSION

This section examines how well our fuzzy logic system aligns with real-world pilot decisions, using 20 data sets from Baghdad International Airport for Boeing 737 landings. The dataset employed in this study comprises Iraqi aircraft operations at multiple international airports, ensuring a more complete picture of landing conditions and increasing the possible generalizability of the findings to varied geographic contexts. Essentially, our goal was to see if the system could replicate the judgment of a human pilot under various conditions. In a previous work [13], researchers developed fuzzy rules using real data but did not evaluate all possible rule combinations. Despite this constraint, their findings demonstrated that the fuzzy logic system could accurately simulate pilot decision-making. In contrast, our study employed all available rules to analyze different weather and runway conditions, and curves were created to show the link between inputs and outputs in the Mamdani fuzzy logic system. These plots indicated that the rules transitioned smoothly with no overlap, indicating that the decision-making process is consistent and dependable.

Table 2 demonstrates that the Mamdani fuzzy logic system predicted pilot decisions with more than 85% accuracy across 20 landing scenarios for the Boeing 737. This excellent alignment emphasizes the system's dependability throughout various conditions, including clear weather with dry runways and more difficult scenarios such as restricted visibility and wet or slushy runways. The system's evaluations, such as "Land" and "Not feasible," closely matched pilot decisions. In certain cases (lines 6, 7, 8, 9, 14, and 18), the fuzzy technique was much more conservative, advocating prudence in ambiguous situations. These findings highlight the system's dependability and potential to assist pilots in making safe landing decisions by closely mimicking pilot judgment while prioritizing safety.

Table 2. Comparison of the pilot decision to the Mamdani system landing evaluation

No.	Wind Speed/Knots	Wind Direction/Degree	Visibility/Meter	Runway Condition	Pilot Decision	System Evaluation
1	5	130	10000	dry	Land	Land
2	8	240	3000	wet	Not feasible	Not feasible
3	28	90	5000	dry	Careful land	Careful land
4	2	100	600	slush	Ex. careful Land	Ex. careful Land
5	10	10	450	slush	Ex. Not feasible	Ex. Not feasible
6	3	100	2000	dry	Land	Careful land
7	30	200	5000	wet	Ex. careful land	Not feasible
8	15	170	1000	dry	Careful land	Ex. careful land
9	18	30	800	wet	Not feasible	Ex. Not feasible
10	1	130	950	slush	Ex. careful land	Ex. careful land
11	13	280	1200	slush	Ex. Not feasible	Ex. Not feasible
12	3	120	7000	dry	Land	Land
13	8	120	550	dry	Ex. careful land	Ex. careful land
14	23	50	4000	wet	Not feasible	Ex. Not feasible
15	13	20	9000	dry	Ex. careful land	Ex. careful land
16	1	90	1000	slush	Ex. careful Land	Ex. careful Land
17	2	140	6000	dry	Land	Land
18	16	220	4000	wet	Not feasible	Ex. Not feasible
19	3	190	600	slush	Ex. careful land	Ex. careful land
20	21	120	2000	dry	Ex. careful land	Ex. careful land

A graphical user interface (GUI) was created to improve the system's usability and enable real-world deployment (see Figure 19). The GUI allows users to enter real-time environmental and runway data, which the system then processes automatically using membership functions. The interface simplifies the decision-making process and gives a clear, intuitive approach to analyzing landing feasibility under different weather circumstances. Its user-friendly design makes it accessible to operators with minimum technical skill, and its adaptability allows for simple modification. These qualities make the GUI a useful tool for making real-time decisions and integrating with pilot training or airport operations systems.

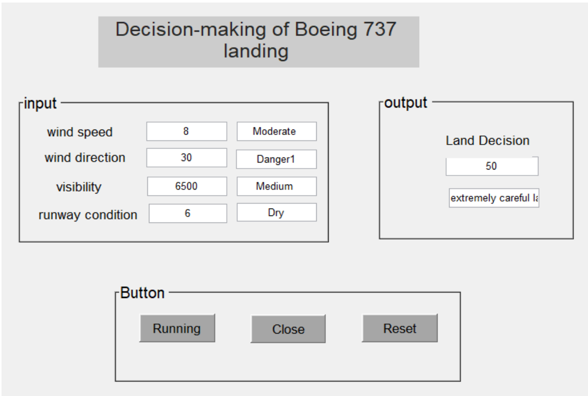

Figure 19. GUI for the landing decision process

6. CONCLUSIONS

This study aimed to examine the factors influencing landing decisions and to develop an intelligent fuzzy system that assists pilots while reducing the workload of the LCO. The system uses key inputs—wind speed, wind direction, visibility, and runway condition—to guide landing decisions. The decision-making output is divided into five stages: land, careful land, extremely careful land, not feasible, and extremely not feasible. When evaluated on 20 real landing scenarios at Baghdad International Airport, the fuzzy system demonstrated an impressive 85% accuracy in matching pilot decisions. This high reliability demonstrates the system's capacity to support safe landings in a wide range of conditions, with a minor bias toward caution. In addition, a graphical user interface (GUI) was developed to facilitate data entry and allow the system to display the final decision. These results highlight the potential of fuzzy logic to improve landing safety by reducing the role of human error and providing consistent, data-driven support in crucial decision-making scenarios. However, its application to other aircraft types is limited because it is focused on civil aircraft transport. Future studies could overcome this limitation using a wider range of datasets and operational considerations. Other approaches, including integrating hybrid methodologies like machine learning to continuously improve decision-making, or optimization algorithms to determine the safest landing paths and reduce the likelihood of strong wind or poor visibility risks, could also enhance landing safety.

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