ANALYZING AIRCRAFT LANDING DECISION-MAKING THROUGH FUZZY LOGIC APPROACH: A COMPARATIVE STUDY

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ABSTRACT

Due to the importance of weather in people's lives, various groups have advocated for accurate climate information. However, weather predictions can often be unclear or ambiguous. Weather advice and information are crucial in determining the safety of landing an aircraft in aviation. To address this, Mamdani Fuzzy Logic will be used to compare two scenarios: one with three inputs (wind direction, wind speed, and visibility) and another that includes the pilot's experience to assess its impact on the landing process. A fuzzy logic-based intelligent system generates three decisions: feasible, careful, and not feasible for landing an aircraft on a runway. The difference rate between the two experiments was 68%, indicating that the pilot's experience played a significant role and forced its importance in the results.

KEYWORDS

Mamdani Fuzzy Logic; decision making; prediction; airplane; landing; Pilot experience Weather

1. INTRODUCTION

The earth's rotation and sunlight-based energy cause the climate to constantly change, which has a significant impact on human activity. For instance, weather information is crucial for agricultural purposes, particularly in countries that heavily rely on agriculture. Additionally, tourism and aviation industries also require weather updates [1]. Knowing the upcoming weather conditions is essential for human safety in air travel as factors such as wind direction, pressure, wind speed, and cloud ceiling height can affect flight safety. According to data from the Federal Aviation Administration (FAA), human factor, fleet factor, and weather factor are the top three causes of accidents in aviation [2]. The World Meteorological Organization has established regulations regarding weather and flight safety, as weather conditions can affect aircraft taking off, flying, and landing. If the weather is bad, these activities can be disrupted and passengers' safety may be compromised. Accurate and timely forecasts of airport weather are crucial for air transport to operate safely and efficiently. Pilots rely on these forecasts to determine how much reserve fuel to load before takeoff, especially if poor weather is predicted at their destination airport. In such cases, pilots may need to divert the flight enroute to an alternate airport, which requires extra fuel. The Meteorological Service (MS) is responsible for providing precise and up-to-date information on cloud ceiling height, visibility, precipitation, wind direction, and speed. Forecasters use all relevant data to ensure the accuracy of these forecasts [3]. The term "Weather" pertains to the atmospheric conditions on the surface of the earth. Meteorologists use various tools, observational data, science, and technology to predict weather at a specific time and place. In the past, weather forecasting was done through observation alone until the first computer-generated forecast was produced in 1955. Weather forecasting is essential for both short-term and long-term planning. The process involves recording ongoing measurements of

DOI: 10.5121/ijsea.2023.14502

temperature, pressure, precipitation, and wind speed and using them to predict future weather conditions. Accurate forecasting is crucial for hazardous and severe weather conditions as it can potentially save lives, property, and crops. Meteorologists use various tools such as outdoor thermometers, barometers, anemometers, hygrometers, radar, and radiosondes to measure data accurately. Computer models are used to process all of this information to produce forecasts for scientists [4].

This paper focuses on the significant challenge faced by pilots in weather forecasting as they play a vital role in flying and need to make decisions about flying feasibility in adverse weather conditions based on their experience. Accurate weather information about their destination and enroute is crucial for them. Inexperienced pilots may make incorrect decisions that could result in fatal accidents during takeoff or landing. Our research motivation is to investigate how pilot experience impacts the feasibility of flying, with a focus on understanding the weather conditions that pilots may encounter during their flight. Accurate knowledge of weather conditions is critical for pilots to ensure safe flights and reduce accidents. The aim and objectives of our research are to apply the Mamdani methodology to analyze how pilot experience affects weather prediction. The aims of this study are as follows: firstly, to train the Mamdani methodology on three factors (wind speed, wind direction, and visibility); secondly, to train the same methodology on these factors with the addition of a fourth factor (pilot experience); thirdly, to evaluate and compare the results of both experiments; and finally, to apply Matlab to a real dataset in order to observe how increasing pilot experience affects the results. The ultimate aim of this research is to improve weather prediction accuracy and reduce aviation accidents by focusing on landing prediction. The scope of this study will be centered around comparing the two experiments and examining how increasing pilot experience influences landing prediction. The rest of this paper is organized as follows. In Section 2, we highlight the background knowledge and related works. The research methodology will be introduced in Section 3. Section 4 presents the results. Finally, Section 5 concludes the paper and presents future work.

2. BACKGROUND KNOWLEDGE AND RELATED WORK

In 2009, the United States spent approximately $5.1 billion on weather forecasting, which is considered a part of the economy [5]. Machine learning algorithms have been successfully used to forecast weather conditions by integrating data from multiple sources and identifying patterns in a set of data [6]. Deep Learning is a subfield of machine learning that uses artificial neural networks inspired by the structure and function of the brain. Researchers have developed a new method of weather prediction called Deep Learning Weather Prediction (DLWP), which uses historical weather data to make predictions for the next 2-6 weeks for the entire world [7]. Data Mining can be applied to relational databases to search for patterns, hidden relations, and validate datasets based on input conditions [8]. In prediction, a classification system is commonly used to forecast data occurrences by collecting dynamic data related to the current state of weather [9] Production rules, which are condition action statements, are the most typical representation of knowledge and expertise in expert systems [10] and were used in weather forecasting.

Fuzzy system refers to a system based on fuzzy logic theory developed by Lotfi Zadeh in 1965. Fuzzy Logic allows something to be partially true and partially false, considering the influence of different input values on the system's output. Its main characteristic involves representing symbolic knowledge through fuzzy conditional rules [11]. Predictions are specific future expectations estimated or grounded in several variables and presumptions. However, statistical methods are difficult to handle in many situations in weather forecasting, even decision trees and flow charts based on traditional logic. Fuzzy logic can consider how various input values affect the output of a system [12]. There are numerous variations of fuzzy systems, including Mamdani and Sugeno. Mamdani's rules are derived from human experience, and in this system, each fuzzy if-then rule's consequence is represented by a fuzzy set. In contrast, Sugeno uses a mathematical function of the input variable instead of a fuzzy set. The Sugeno fuzzy model takes the form of "IF x is A and y is B THEN z = f(x, y)," where A and B are fuzzy sets in the antecedent and z = f(x, y) is a crisp function in the consequent.

Weather prediction is not just limited to rainfall and forest-fire smoke, but also extends to aviation. According to Wijaya et al. [2], a study was conducted to create a decision-making tool that aids Air Traffic Control (ATC) officers and pilots in determining whether the weather conditions are appropriate for an aircraft to fly or land. The variables used in the research include visibility, wind speed, and wind direction, and Mamdani fuzzy logic was utilized. The decision results are classified into three output factors: feasible, careful, and not feasible. The study's findings demonstrate that this system can assist ATC personnel and pilots in determining the possibility of takeoff and landing. In other study conducted by Pratiwi et al. [13], Mamdani's fuzzy logic was employed to address issues related to weather and pilot experience during aircraft landings. The inputs for this research include wind speed, wind direction, visibility, and pilot experience, while the output is the feasibility of the landing process. The study suggests that the system should attempt to imitate human behavior. In [14], Ramli et al. presented a method for predicting weather and making decisions about whether an aircraft can land or take off at an airport with inadequate weather conditions. The output is generated by combining environmental parameters, turbulence parameters, and fog parameters. The study's findings demonstrate that the output is highly accurate in weather forecasting. As per [15], a thesis was conducted to determine whether an airport is suitable for landing or taking off based on weather conditions. The study utilized three parameters: wind speed, wind direction, and visibility. The decision regarding airport conditions with specific weather is categorized as suitable, careful, or not suitable in terms of percentage. The study's results can assist in making informed decisions about landing and taking off. Zadeh [16] utilized a Microsoft Flight Simulator to determine the feasibility of landing or taking off an aircraft based on specific weather conditions and pilot experience. The study employed three parameters: wind speed, visibility, and pilot experience. The findings of the research can determine the success rate of landing and takeoff based on the system's results. The purpose of this paper is to use the Mamdani to predict aircraft landing and test the impact of pilot experience as an extra factor.

3. RESEARCH METHODOLOGY

In 2009, the United States spent approximately $5.1 billion on weather forecasting, which is considered a part of the Fuzzy Logic is a type of soft computing that deals with the imprecision of the real world. It is an extension of multivalued logic that aims for approximate reasoning rather than exact solutions. Unlike traditional crisp logic, which only allows for true or false values represented by 1 or 0 respectively, fuzzy logic allows variables to have truth values ranging from 0 to 1. These values indicate the degree of truth rather than absolute yes or no answers. Fuzzy Logic is closely related to human language and prediction (Wang, 20165). This study focuses on fuzzy inference, which involves passing input variables through a system of If-Then rules and fuzzy logical operations to reach an output space. The If-Then rules are expressed in human language and each word is considered a fuzzy set defined by membership functions before being used in building the rules. Classical crisp set theory operates on a binary logic where an element either belongs to the set or does not. Unlike having a clear boundary, fuzzy set theory allows elements to have a degree of membership between complete belonging and complete non-belonging. Membership functions are used to assign values between 0 and 1 to each element in the input space, determining their degree of membership in the fuzzy collection. The membership function curve shows the range where an input variable will have a non-zero membership value, with the core representing the range where it will have full membership. This is illustrated in

Figure 1, where $\mu(x) \neq 0$ for any point between a and d, and $\mu(x) = 1$ for any point within the interval [b, c].

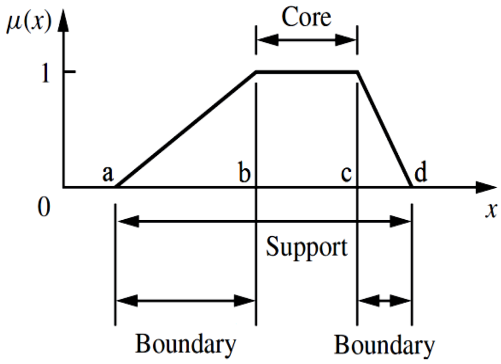

Figure 1. A sample of membership function

The equation (1) evaluates linguistic expressions for variables and their membership functions, where membership function "u" is defined by lower limit "a," upper limit "d," and value "b," with "a" being less than "b" which is less than "d."

$$\mu(b) = \frac{d - b}{d - a} \quad \dots\dots\dots\dots\dots\dots\dots (1)$$

To maintain consistent logical operations, fuzzy logic must adhere to the same principles as standard binary logic. However, in fuzzy logic, operands A and B are membership values within the range of 0 to 1, rather than being limited to fully true or totally false values. The basic logical operations of AND, OR, and NOT are still used, but they are expressed differently in fuzzy logic. For example, the function min is used to express logical AND. If-Then rules are utilized in fuzzy inference processes to map input variables onto the output space. These rules follow a specific format where x is an input variable and y is an output variable. Both A and B in these statements are linguistic values that work with human judgment. A can be defined by a specific membership function while B can be either a fuzzy set or a polynomial depending on the specific method used for fuzzy inference. The antecedent of these statements aims to determine the membership value of input variable x corresponding to fuzzy set A, while the consequent provides a precise value for output variable y.

Mamdani believes that fuzzy sets should be used as output membership functions for complex systems and decision processes. Once the aggregation process is complete, there will be a fuzzy set for each output variable that requires defuzzification. A fuzzy logic method experiment is conducted to identify a plane landing on a runway under specific weather conditions and pilot experience, with three parameters (wind speed, wind direction, and visibility) being examined. Then the same method is implemented with four parameters, including the pilot's experience, which has been found to have a relationship with aircraft landing decisions based on previous research. All variables in each criterion are processed using fuzzy logic through a Mamdani-type inference process consisting of fuzzification, rule evaluation, aggregation, and defuzzification. The fuzzification process involves mapping crisp input values to fuzzy set membership functions derived from controlled system data. The system inference process uses fact data from experts or institutions presented in logical sentences as rules to determine the fuzzification output. After calculating each variable, the final step is defuzzification. All combinations of variables or parameters are compared by evaluating existing rules resulting in decisions on landing aircraft. The AIRNAV Ahmad Yani Airport in Semarang provides the training and testing data for this study on fuzzy logic.

3.1. FUZZIFICATION

Fuzzification refers to the process of converting exact input values into linguistic values represented by fuzzy associations with a membership function. The linguistic values for each variable can be classified based on data from previous research and the "Airplane Flying Handbook" issued by the Federal Aviation Administration. The inputs are obtained from a weather station in the form of METAR, which is an observation of current surface weather reported in a standard international format. Wind direction is expressed in degrees clockwise from due north, with five defined fuzzy sets representing this variable. Figure 2 illustrates the fuzzy set for wind direction. The relationship between wind direction and wind speed is significant as it affects aircraft landing or take off due to crosswinds [13].

Wind speed is a fundamental aspect of meteorology that results from the movement of air from areas of high pressure to those of low pressure, often due to temperature fluctuations. An anemometer is used to measure wind speed, which generally increases as pressure differentials become more pronounced. Wind speeds are measured in knots, with calm conditions starting at 0 knots and potentially damaging winds exceeding 30 knots. Variable wind speeds are classified into three fuzzy sets: low, average, and high. Figure 3 represents fuzzy set for the wind speed variable.

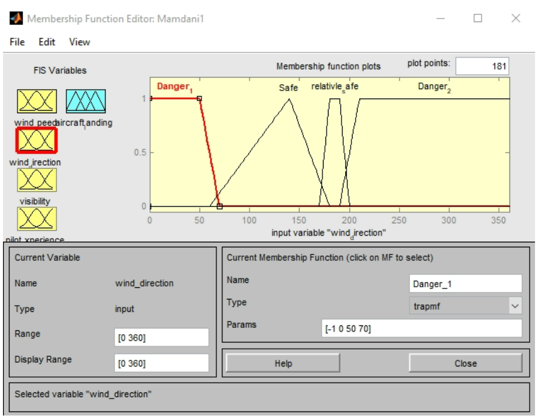

Figure 2. Fuzzy set for the wind direction variable function

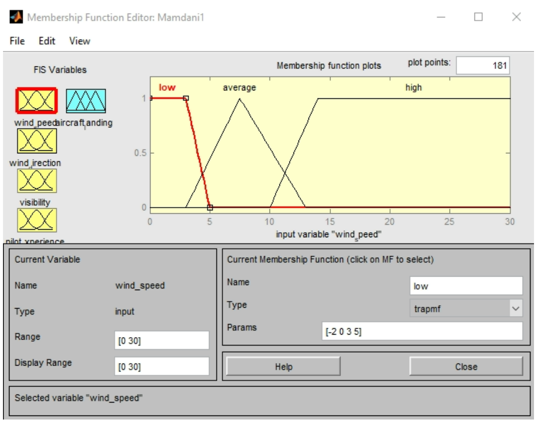

Figure 3. Fuzzy set for the wind speed variable function

Visibility is crucial for safe air travel and refers to a pilot's ability to see prominent objects during the day and night, especially during takeoff, landing, and taxiing phases of flight. Factors such as fog, clouds, haze, and precipitation can affect visibility, which is measured in statute meters ranging from 1000 m to over 100000 m. The fuzzy set for visibility variables is depicted in Figure 4.

Pilot's experience, often measured in "flight hours," indicates the total duration a pilot has spent operating an aircraft and serves as a key indicator of their level of expertise in aviation. The variable of pilot experience is divided into two fuzzy sets: low and high, as depicted in Figure 5. Flight hours are defined as the time from when an aircraft begins moving under its own power for flight until it comes to a stop after landing. This includes time spent on pre-flight inspections and taxiing while the engine is running. It typically takes two years to accumulate the required 1,500 flight hours necessary for becoming an airline pilot.

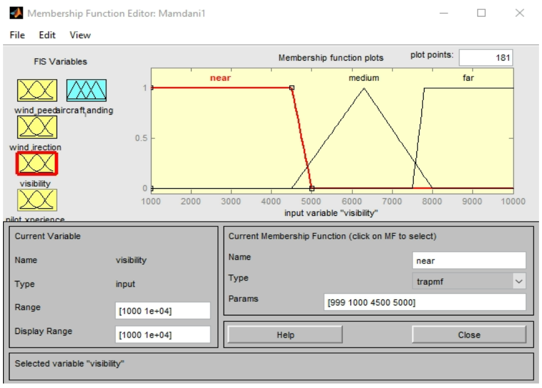

Figure 4. Fuzzy set for visibility variable

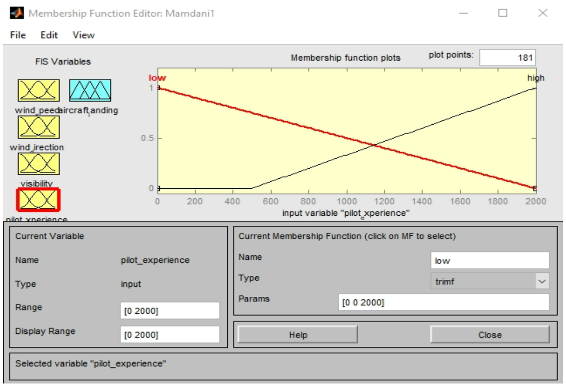

Figure 5. Fuzzy set for pilot experience variable

3.2. RULE EVALUATION

Rule evaluation is the second step that involves taking values that have been fuzzified into antecedents using the AND operator for implication processes that use the Min function $\mu A \cap B(x) = \min [\mu A(x), \mu B(x)]$. The rule base is typically defined by domain experts using evaluation rules developed based on the rule approach and correlation calculation to find variable priority. According to Pratiwi et al. [13], evaluation rules are developed into 11 rules but could be more if more data from airports were available.

Table 1. Evaluation rules

Wind	Wind	Visibility	Pilot	Aircraft
Low	Safe	Medium	Low	Feasible
Low	Danger	Medium	Low	Careful
Low	Danger	Medium	High	Feasible
Low	Safe	Medium	High	Feasible
Average	Relatively Safe	Medium	High	Feasible
Average	Danger	Medium	Low	Not Feasible
Average	Danger	Medium	High	Careful
High	Danger	Medium	High	Not Feasible
Average	Danger	Far	High	Careful
High	Danger	Far	Low	Not Feasible
High	Danger	Far	High	Careful

3.3. AGGREGATION

Aggregation involves combining all output rules into a unified whole. In order to determine the final precise deviation value using the Mamdani fuzzy inference method, all fuzzy output functions must be aggregated on the same axis, as shown in Figure 6.

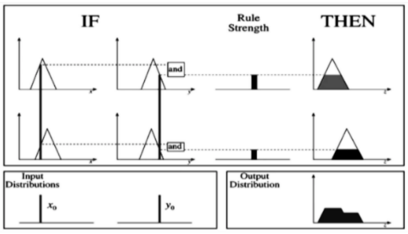

Figure 6. Aggregation phase

3.4. DEFUZZIFICATION

The motivation behind this work is to provide a method for assessing the clarity of fuzzy results in the fuzzy inference process. Defuzzification is the final step in this process, and it involves converting fuzzy sets into crisp values that can be easily understood and utilized. The authors highlight that there are various defuzzification methods available, but the Center of Gravity (COG) method is the most commonly used one. The COG method calculates the location where two equal masses of an aggregate set would be separated by a vertical line. This calculation is continuous and involves aggregating membership functions. The authors express this mathematically using equation (2), where Z represents the weighted average output that remains constant, α predicate denotes the minimum value of operating results for n fuzzy rules, and w refers to the weight assigned to each forecast in forming fuzzy rules. Overall, the motivation behind this work is to provide a clear and effective method for assessing fuzzy results in order to improve decision-making processes that rely on fuzzy inference. However, this type of rule can be potentially applicable to the study of multi-agent cooperative coordination [18]

$$Z = \frac{a2(w1) + a2(w2) + \cdots + an(wn)}{a1 + a2 + \cdots + an} \qquad \dots\dots\dots\dots\dots\dots\dots \; (2)$$

We test the unsafe landing conditions based on three factors: Visibility, Wind Direction, and Wind Speed. Each factor has a degree of membership of 1, as shown in Figure 7.

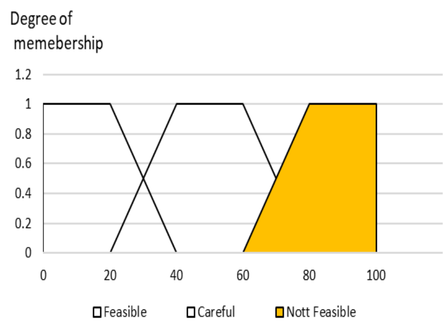

Figure 7. Result of testing unsafe landing condition

By compensating in the equation (2), we will have 85 as a result of this testing which means that if the input value follows the established rules, the fuzzy calculation process will determine that landing in position 85 is NOT FEASIBLE for the aircraft.

4. RESULTS

The study used a database of 16 cases from AIRNAV Ahmad Yani Airport Semarang to demonstrate how pilot experience affects landing feasibility. Table 2 presents the data used and results obtained in this study when considering only three inputs (Visibility, Wind Direction, and Wind Speed), as well as when Pilot's Experience was also taken into account. Data collection took place between December 2021 and June 2022 to observe variations in weather across different months. Out of the 16 cases studied, 11 showed different results due to pilot experience while five were unaffected by it. Logistic regression was used as a variation rate to predict binary response variables, with total misclassification rate being a common metric for measuring prediction error. The pilot's level of experience is a crucial factor that cannot be neglected on secure landings. Therefore, we will be increasing their experience in each instance to observe its impact on landing quality. Table 3 shows various outcomes based on changes in the pilot's hours, indicating that as they gain more experience, the predicted landing value decreases, resulting in safer landings.

Num	Weather	Visibility	Wind Direction	Wind Speed	Pilot's Experience	A	B
1		6km	280°	7 kt	1000	84.1	66.5
2		7km	230°	3kt	500	50	50
3		5km	170°	1kt	1500	18.5	18.5
4		6 km	200°	2 kt	1500	50	31.3
5		6 km	250°	4 kt	1000	57.3	46.8
6		5 km	320°	9 kt	2000	81.6	50
7		6km	280°	3kt	1500	50	28.7
8		6km	300°	8kt	1000	84.1	66.5
9		8km	300°	16kt	500	84.7	83.7
10		6km	160°	4kt	500	17.4	17.4
11		9km	300°	12kt	1500	71.1	58.1
12		6km	340°	2kt	2000	50	15.9
13		9km	210°	4kt	1500	50	50
14		6km	170°	2kt	500	18.5	18.5
15		5km	210°	2kt	2000	50	18.4
16		7km	310°	5kt	1000	81.6	62.3

Num	Visibility	Wind		MTAR	Pilot's Experience	Landing
1	6km	280°	7 kt	WAHS 231030Z 28007KT 6000 -RA FEW013CB SCT014 29/25 Q1008 NOSIG	500 1500	83.7 57.1
2	7km	230°	3kt	WAHS 251030Z 23003KT 7000 -RA FEW013CB SCT014 27/24 Q1009 NOSIG	500 1500	50 29.9
3	6 km	200°	2 kt	WAHS 081300Z 20002KT 6000 TS FEW013CB FEW014 28/23 Q1010 NOSIG	1000 2000	37.7 18.4
4	6 km	250°	4 kt	WAHS 081200Z 25004KT 6000 FEW013CB FEW014 27/24 Q1009 NOSIG	500 1500	57.3 40.6
5	5 km	320°	9 kt	WAHS 230930Z 32009KT 5000 -TSRA FEW013CB SCT014 29/24 Q1006 NOSIG	500 1500	81.6 61.4
6	8 km	320°	11 kt	WAHS 230730Z 32011KT 8000 FEW014 31/25 Q1005 NOSIG	500 2000	81.5 50
7	6km	280°	3kt	WAHS 051400Z 28003KT 6000 SCT013 26/24 Q1008 NOSIG	500 1500	50 28.7
8	8km	300°	16kt	WAHS 060900Z 30016KT 8000 SCT014 29/23 Q1006 NOSIG	500 1500	83.7 57.1
9	9km	300°	12kt	WAHS 030900Z 31012KT 270V330 9000 FEW013CB SCT014 30/25 Q1005 NOSIG RM	1000 2000	66.5 50
10	5km	200°	2kt	WAHS 041000Z 20002KT 5000 HZ SCT014 29/25 Q1008	500 2000	50 18.4

The relationship between landing prediction and pilot experience is inverse, as demonstrated in cases 1, 5, 6, and 8 when it changes from not feasible to careful and cases 2, 3, and 10 when it changes from careful to feasible. MATLAB has been used to construct the interface for Mamdani fuzzy inference. The user inputs data such as wind speed, wind direction, visibility, and pilot experience, ensuring that each variable falls within the specified range. Figure 8 illustrates this process. After inputting rules into the rule editor, the landing prediction is generated, as shown in Figure 9.

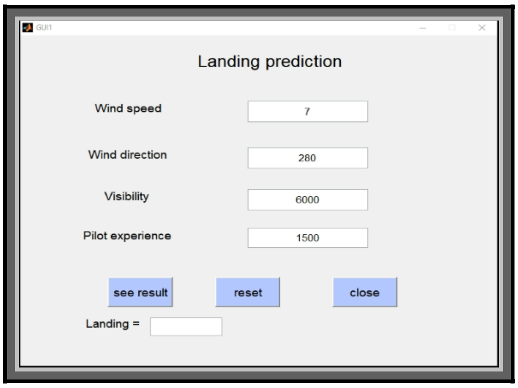

Figure 8. GUI for landing prediction inputs

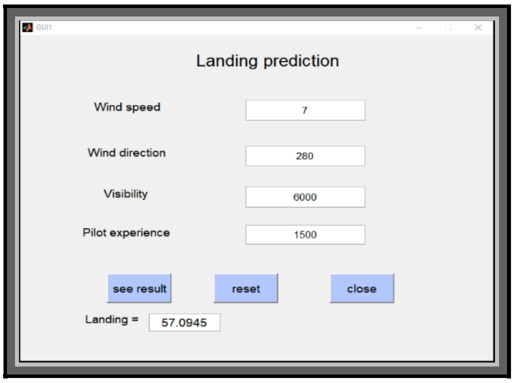

Figure 9. GUI for landing prediction inputs

5. Conclusion and Future Work

The proposed paper aimed to use the Mamdani methodology, which is a fuzzy system, to predict aircraft landing and compare the impact of pilot experience. Two experiments were conducted. The first experiment considered wind speed, wind direction, and visibility as factors while the second experiment added pilot experience as a factor. By comparing the two experiments, it was found that pilot experience had a significant impact on the landing process, accounting for over 60% of its value. Additionally, increasing pilot experience generally reduced the risk of flying in certain weather conditions. By integrating the Fuzzy Logic approach with another technique like Artificial Neural Network, we expect that our prediction can be enhanced. Additionally, incorporating additional factors such as air density, humidity, and precipitation into the regulations could enhance the precision of aircraft landing's prediction. As a future work, we plan to investigate this hypothesis by employing Fuzzy Logic in conjunction with Artificial Neural Network to determine its impact on aircraft landing prediction accuracy. Furthermore, statistical evaluations will be conducted to investigate how a pilot's age and experience influence their chances of committing errors.

REFERENCES

[1] Andrasto, T., & Joko, T. Simulation and design of smart clothesline using fuzzy for weather forecast. In IOP Conference Series: Earth and Environmental Science (Vol. 969, No. 1, p. 012058). IOP Publishing, 2022.

[2] Wijaya, R. F., Tondang, Y. M., & Siahaan, A. P. U. Take Off and Landing Prediction using Fuzzy Logic. Int. J. Recent Trends Eng. Res., vol. 2, no. 12, pp. 127–134, 2016.

[3] Hansen, B. A fuzzy logic–based analog forecasting system for ceiling and visibility. Weather and Forecasting, 22(6), 1319-1330, 2007

[4] Szymanski, D. Forecasting the Weather: Types & Tools Used in Forecasting. retrieved from: https://study.com/learn/lesson/weather-forecasting-types-tools.html [Accessed Aug 2022]

[5] Powers, R., & Beede, D. Fostering innovation, creating jobs, driving better decisions: The value of government data. Office of the Chief Economist, Economics and Statistics Administration, US Department of Commerce, 2014.

[6] Gagne, D. J., McGovern, A., Haupt, S. E., Sobash, R. A., Williams, J. K., & Xue, M. Storm-based probabilistic hail forecasting with machine learning applied to convection-allowing ensembles. Weather and forecasting, 32(5), 1819-1840, 2017.

[7] Weyn, J. A., Durran, D. R., Caruana, R., & Cresswell-Clay, N. Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. Journal of Advances in Modeling Earth Systems, 13(7), e2021MS002502,2021.

[8] Khan, S., Muqeem, M., & Javed, N. A Critical Review of data mining Techniques in weather forecasting. International Journal of Advanced Research in Computer and Communication Engineering, 5, 2016.

[9] Kar, K., Thakur, N., & Sanghvi, P. Prediction of rainfall using fuzzy dataset. International Journal of Computer Science and Mobile Computing, 8(4), 182-186, 2019.

[10] Collopy, F., Adya, M., & Armstrong, J. S. Expert systems for forecasting. Principles of forecasting: A handbook for researchers and practitioners, 285-300, 2001.

[11] Czabanski, R., Jezewski, M., & Leski, J. Introduction to fuzzy systems. Theory and applications of ordered fuzzy numbers: A tribute to professor Witold Kosiński, In Studies in Fuzziness and Soft Computing; Springer, 23-43, 2017.

[12] Ghosh, S., Dutta, A., Chowdhury, S., & Paul, G. Weather prediction by the use of fuzzy logic. Journal of Mechanics of Continua and Mathematical Sciences,8, 1228-1241, 2014.

[13] Pratiwi, W., Sofwan, A., & Setiawan, I. Implementation of fuzzy logic method for automation of decision making of Boeing aircraft landing. IAES International Journal of Artificial Intelligence, 10(3), 545,2021.

[14] Ramli, A. A., Islam, M. R., Fudzee, M. F. M., Salamat, M. A., & Kasim, S. A practical weather forecasting for air traffic control system using fuzzy hierarchical technique. In Recent Advances on Soft Computing and Data Mining: Proceedings of The First International Conference on Soft Computing and Data Mining, Springer International Publishing, 99-109, 2014.

[15] Rahim, R. Prediction of landing and take-off of aircraft based on the weather using fuzzy logic. International Journal of Advanced Science and Technology, 28(20), 409 – 415, 2019.

[16] Zadeh, V. T. Fuzzy logic approach to airplane precision instrument approach and landing, ARPN Journal of Engineering and Applied Sciences, 7(4), 423 – 431, 2012.

[17] Wang, C. A study of membership functions on mamdani-type fuzzy inference system for industrial decision-making. Theses and Dissertations, Lehigh University, Paper 1665, 2015.

[18] Shang, Yilun. Finite-time weighted average consensus and generalized consensus over a subset. IEEE, 2615-2620, 2016.

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