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Original Research Article

A Fuzzy Inference System for Predicting Air Traffic Demand based on Socioeconomic Drivers

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Abstract

The past ten years have seen significant expansion in the aviation sector, which during the previous five years has steadily pushed emerging countries closer to economic independence. It is crucial to accurately forecast the potential demand for air travel to make long-term financial plans. To forecast market demand for low-cost passenger carriers, this study suggests working with low-cost airlines, airports, consultancies, and governmental institutions' strategic planning divisions. The study aims to develop an artificial intelligence-based methods, notably fuzzy inference systems (FIS), to determine the most accurate forecasting technique for domestic low-cost carrier demand in Bangladesh. To give end users real-world applications, the study includes nine variables, two sub-FIS, and one final Mamdani Fuzzy Inference System utilizing a Graphical User Interface (GUI) made with the app designer tool. The evaluation criteria used in this inquiry included mean square error (MSE), accuracy, precision, sensitivity, and specificity. The effectiveness of the developed Air Passenger Demand Prediction FIS is assessed using 240 data sets, and the accuracy, precision, sensitivity, specificity, and MSE values are 90.83%, 91.09%, 90.77%, and 2.09%, respectively.

Keywords: Aviation industry, Fuzzy Inference System, Membership Function, Graphical User Interference.

1. INTRODUCTION

Accurate forecasts significantly influence decision- making processes and are essential for managerial decisions on time, resource allocation, and production [1–4]. Using machine learning for forecasting and prediction has been highly recommended [5–8]. Even a slight increase in forecast accuracy can significantly impact the overall process [9]. This demonstrates how crucial accurate projections are for enabling informed choice and operational optimization.

Precise forecasting of air traveler demand is crucial for airlines in the aviation sector [10–12]. It forms the basis for route extension, fleet planning, and the overall annual operating plan [13]. Airlines can efficiently manage resources, organize operations, and increase revenue by precisely estimating passenger demand [14]. Additionally, by objectively assessing the demand side of the company, analysis and projecting travel demand helps airlines reduce risks. This allows airlines to decide strategically, such as choosing routes and adjusting. capacity, based on a thorough understanding of market dynamics and passenger preferences [15]. Airlines can reduce the risks associated with underutilization or overcapacity by aligning services to predicted demand [16]. Forecasting accurate passenger demand is much more crucial in developing nations like Bangladesh. Reliable forecasts help decision-making and planning processes as the aviation industry grows in these locations [17]. By using them, airline experts can predict future expenditures related to changes in the number of passengers and make wise choices regarding the development of capacity, the purchase of a new fleet, and the provision of services [18–20].

Li *et al*., [21], presented a comparison between commercial forecasting software and a developed Web-based Intelligent Forecasting System (WIFS). The WIFS was developed using a hybrid neural model that merged standard statistical methods with network and fuzzy logic techniques. Stakeholders must consider market competitiveness and business operations in today's competitive business environment. Over time, various forecasting techniques, such as AI, ML, deep learning, and regression models, have created data-based and knowledge-based forecasting models. The User Forecaster, Target Configurator, Method Configurator, Adjuster & Analyzer, Data Manager, and Report Generator comprise the WIFS. While the database system is continuously updated with input data, these components take user commands and provide the desired output. Compared to conventional forecasting techniques, the study found that the WIFS displayed enhanced forecasting accuracy and the capacity to handle a more extensive range of data.

Profillidis *et al.*, [22], proposed econometric and fuzzy methods to predict air passenger numbers at Rhodes's airports. The study analyzed different parameters to choose the best forecasting model. The researchers examined the connection between economic activity and transportation before reviewing the airport's high seasonal demand. The next step was constructing a computational relationship between the airport and anticipated passenger demand using statistical, fuzzy, and economic methodologies. For long-term strategic planning to be successful, accurate forecasting is essential. This holds for big investment projects like new runways, terminal expansions, and ramp expansions that rely on data on future demand. Using the same variables as the econometric model, the research mainly used fuzzy linear regression to forecast international travelers at the airport of Rhodes. Although it was noted that predicting changes in human behavior is not always possible, the study's findings were regarded as satisfactory.

Mehmood *et al*., [23], conducted an empirical study to investigate the aviation-led growth hypothesis in Bangladesh. Using information from 1973 to 2012, they examined the causal connection between aviation and economic growth. The researchers used modified entirely Ordinary Least Square (OLS), dynamic OLS, and conical co-integration regression analysis to examine the relationship between economic growth and aviation demand. Visual techniques like the Cholesky Impulse Response Function and variance decomposition increased the study's robustness. All three estimating approaches' findings similarly indicated the aviation demand's beneficial impact on economic growth. The Granger causality test also demonstrated a causal link between GDP and passenger (PAX) traffic, highlighting the importance of the aviation sector in promoting economic progress in a developing nation like Bangladesh.

Sultana *et al*., [24], provided an analysis of the aviation sector in Bangladesh, highlighting its economic and social growth within the country. The article emphasizes how vital domestic airlines are in promoting economic growth and bringing about a variety of positive economic and social outcomes. The study outlines local airlines and discusses Bangladesh's trend of increasing passenger traffic. It also highlights that handling the significant rise in passenger numbers could be difficult due to a lack of long-term planning. The study also links Bangladesh's GDP and passenger growth rates.

Stathopoulos *et al.*, [25], utilized a fuzzy rule-based system (FRBS) to enhance the accuracy of traffic predictions by effectively integrating estimates derived from multiple independent predictors. Fuzzy logic is used by the FRBS to convey many types of problem-related information and to define the relationships between its variables. A database (DB) that describes the quantity, kind, and shape of membership functions (MFs) and a rule base (RB) made up of fuzzy IF-THEN rules that reflect the properties of the system make up the knowledge base (KB) components of the FRBS. The different input states of the system are connected to the corresponding output states by each rule. The center of gravity (CoG) defuzzification method converts fuzzy numbers into crisp values, and the resulting crisp value (output) represents the CoG of the area described by the fuzzy number.

In evolving nations, projecting traveler demand is necessary for scheduling and decision-making. However, limited studies have explored intelligence-based models using all the mentioned socio-economic parameters mentioned in this study for predicting air passenger demand in these developing nations. Rather most of the study in the literature confined within 3 to 4 economic parameters for predicting air traffic demand in the emerging nations. By developing and analyzing a Mamdani Fuzzy Inference System, an artificial intelligence-based model, to predict domestic low-cost carrier demand, this study attempts to fill this research gap. The study specifically focused on developing a trustworthy and appropriate intelligent method for forecasting domestic air passenger demand, considering nine socioeconomic factors, including Gross Domestic Product (GDP), Labor Force Participation (LFP), Population (POP), Industrial Production Index (IPI), Jet Fuel Price (JFP), Exchange Rate (ER), Unemployment Rate (UR), Inflation Rate (IR), and Time of the Year (TY). Our model has two sub-FIS systems with four socioeconomic factor inputs each, one primary fuzzy system with three inputs (eight inputs from each of the two sub-FIS systems, and the ninth one is the season/time of the year), and the predicted number of air passengers and volume status of passengers as an output. The development of user-interactive software in this study can help airline industry experts make well-informed decisions by forecasting future costs related to changes in passenger numbers. Additionally, it assists stakeholders and investors in determining the viability of upcoming projects.

2. METHODS

The most effective technique for forecasting air passenger demand was the fuzzy inference system after carefully examining the body of earlier literature and the most recent trends in developing nations. Before choosing the input and output parameters for the forecasting job, the target country's socioeconomic context had to be considered.

2.1 Fuzzy Logic

Fuzzy logic is a decision-making method like how people make decision [26, 27]. It accommodates ambiguous and imperfect information and offers a more accurate representation of real-world problems than traditional Boolean logic. Instead of using binary or 1/0 numbers that are strictly true or false, fuzzy logic uses degrees of truth [28, 29]. To better understand the topic, consider the example in Fig. 1. This example demonstrates how fuzzy systems assign values between 0 and 1, unlike Boolean methods, which only use true/yes/1 or false/no/0. In fuzzy logic, the absolute truth is represented by 1.0, while the absolute falsity is represented by 0.0. The number assigned in fuzzy systems is the truth value [30–32].

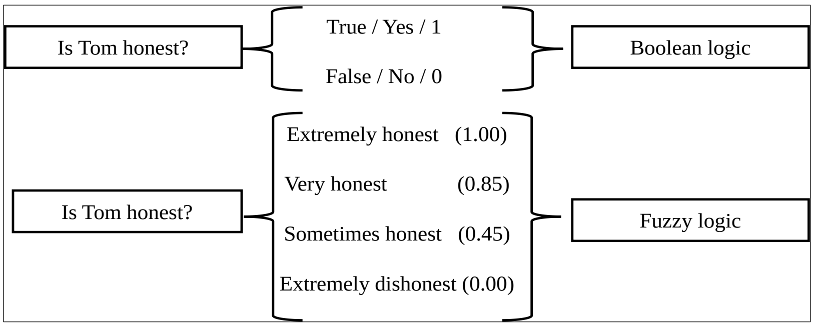

Fig. 1: Perception of Fuzzy logic vs. Boolean logic [16]

The objective of developing our model involves the following tasks:

- Fuzzy "if-then" rules are employed to govern the output.
- The process of fuzzification, which turns crisp input into fuzzy input, uses membership functions.
- To evaluate the model's effectiveness, the output membership functions, and rule intensity are combined.
- To provide smooth or accurate output results based on the output distribution, defuzzification is used. In

Fig. 2, each task has nine inputs and one output.

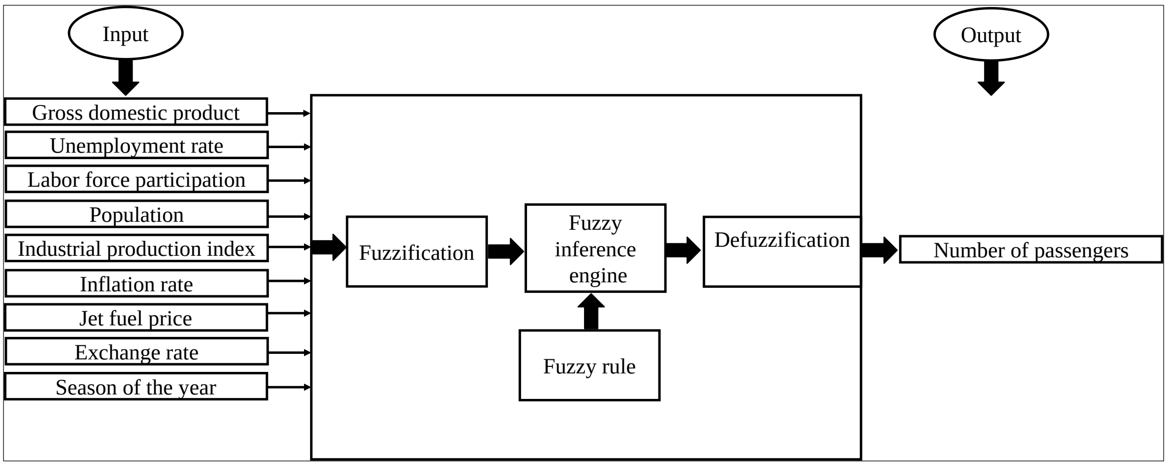

Fig. 2: Developed fuzzy inference system schematic diagram.

2.2 Fuzzy Rule for the Developed Model

In 1973, Zadeh *et al.*, [33], proposed using fuzzy rules to include human knowledge in an innovative approach to analyzing complex systems. In its simplest form, fuzzy control is a conditional statement stated as "if...then," where the rules are defined in terms of fuzzy ideas [34].

Our fuzzy inference system (FIS), which specifies the "if" and "then" conditions for the proposed fuzzy system, consists of a total of 662 rules (256+256+150). The fuzzy system consists of two subsystems and a final system. While each sub-system has 256 rules, the final design only utilizes 150 rules [10].

2.3 Fuzzy Inference System Developed Procedure

Fuzzy logic uses fuzzy inference to create mappings between input and output variables [35]. Fuzzification is converting crisp input values into fuzzy values using membership functions—conversely, defuzzification results in reliable and insightful output [36]. In artificial intelligence and fuzzy systems, multi-objective genetic fuzzy systems have become more well-liked for optimization goals [37]. Fuzzy systems are beneficial when traditional methods fall short, for as when developing non-linear models, controlling time-variable elements, or working with untested mathematical models [38]. Some applications include pattern recognition, decision support systems, plant control, problems with electromagnetic fields, aviation flight control, genetic learning of databases, and telecommunications [39].

Mamdani's inference method created the FIS for forecasting domestic aviation passenger demand in Bangladesh. A technique was developed to prevent complex rule overfitting criteria by analyzing nine variables that impact the prediction's effectiveness. Because Mamdani's inference approach is well-suited to handle intricate, non-linear relationships within the dataset, it was chosen for this study's purpose of estimating domestic aviation passenger demand in Bangladesh. Mamdani's methodology excels in handling inaccurate, real-world data, which is consistent with the inherent uncertainties and changes in the socio-economic aspects that impact the demand for air travel. After a thorough analysis of the nine selected factors, Mamdani's technique was shown to be suitable for capturing the complex interactions between these variables. It is well-suited for the complex and context-dependent nature of socioeconomic factors influencing domestic air travel in emerging economies like Bangladesh because of its capacity to handle linguistic variables and fuzzy rules.

The FIS comprises two subsystems that act as inputs to the final system and one central system. The nine inputs were split into three fuzzy systems, where four inputs had a positive impact on the output variable, four inputs had a negative effect, and one input had an impact that changed over time. GDP, labor force participation, population, and the industrial production index are some of the inputs used in the positive effect evaluation approach. Contrarily, the negative impact is considered when factors like the price of jet fuel, the exchange rate, the unemployment rate, and the inflation rate.

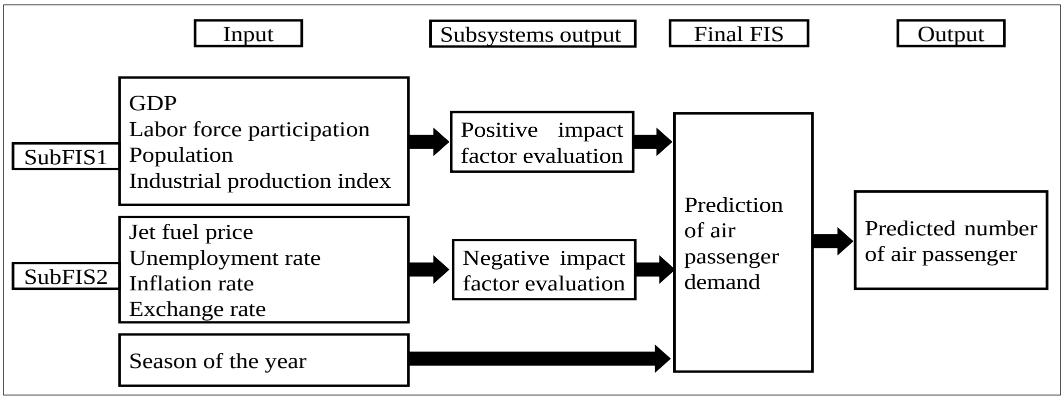

Fig. 3: Developing procedure of fuzzy inference system [10]

The study's nine socio-economic variables—GDP, Labor Force Participation, Population, Industrial Production Index, Jet Fuel Price, Exchange Rate, Unemployment Rate, Inflation Rate, and Time of Year—were chosen based on how much of an impact they were thought to have on the demand for air travel among developing countries, especially Bangladesh. Each variable is considered crucial in reflecting various aspects of economic, cost-related, and seasonal factors affecting aviation, even though possible interdependencies among them are acknowledged. It is recognized that certain factors, such as the price of jet fuel and inflation and the rate of unemployment and labor force participation, may be associated. These parameters consider the intricate dynamics of a developing economy such as Bangladesh, wherein the demand for air travel can be greatly influenced by variables such as inflation, fuel prices, labor dynamics, and economic growth.

The final system for projecting the number of air passengers receives the outputs from these sub-systems and the ninth input, which stands for the year's season. Based on the literature analysis, it was determined that the Gaussian membership function is appropriate when there are 3 or 5 variables. However, the triangle membership function performs better when there are seven or more variables. As a result, all variables were employed with the triangle membership function. Defuzzification uses the "Centroid of Area" approach to produce the final output. Based on definitions of language concepts provided by specialists and a literature review, appropriate fuzzy if-then rules were allocated. The proposed models' membership functions were likewise created using these language words. An overview of the fuzzy inference system is described in Fig. 3.

3. RESULTS DISCUSSION

3.1 Positive Influence Elements Evaluation in the System

The positive Fuzzy based Inference System has one output and four inputs. Gross domestic product, participation rate of labor force, people of the country, and production index of the industry all have a favorable impact on demand for air travel. This implies that a rise in these inputs' values is associated with increased airplane passengers traveling on airplanes. Each input has a very high, high, medium, and low membership function. TABLE I demonstrates that the output variable is differentiated by five membership functions: very high, high, medium, low, and very low. The Positive Impact Factors Evaluation FIS is made up of triangular membership functions. An example of the design is shown in Fig. 4's system block diagram.

Altogether conceivable fuzzy if-then conditional declarations were judged when creating the positive impact factor evaluation FIS. For each input variable, these conditional statements consider various membership function combinations. There are 256 fuzzy conditional statements, or 4 * 4 * 4 * 4.

Table I: Positive factors input and output membership function with numerical ranges

Parameters	Membership functions	Ranges
Labor Force Participation Ref: 40-90.00	Very high	>66.90
	High	61.51-66.90
Unit: Million	Medium	52.4 -61.50
	Low	< 52.4
GDP Ref: 50-365.00 Unit: USD Billion	Very high	>251.60
	High	188.01-251.60
	Medium	118.9-188.00
	Low	< 118.9
Production index of Industry Ref: -5-40.00 Unit: Percentage (%)	Very high	>25.90
	High	15.61-25.90
	Medium	6.25-15.60
	Low	<6.25
Population Ref: 125-190.00 Unit: Million	Very high	>155
	High	144.01-155
	Medium	134-144.00
	Low	<134
SUBFIS_1 Output Ref: 0-50.00	Very high	>40
	High	30.01-40
	Medium	20.01-30
	Low	10-20
	Very Low	<10

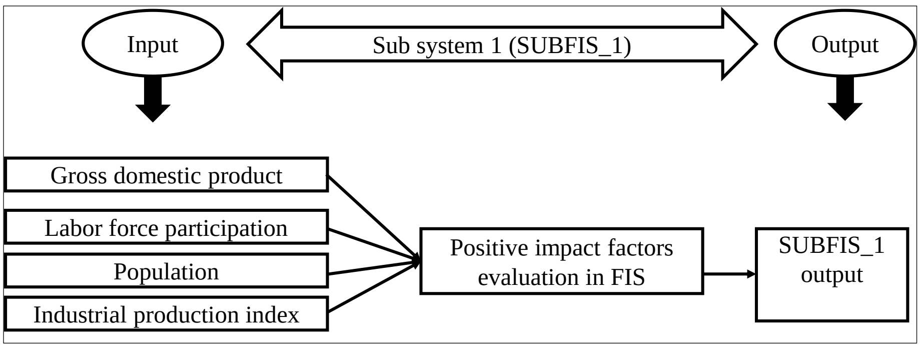

Fig. 4: Positive influence elements evaluation in the fuzzy system

3.2 Negative Impact Factors Evaluation in FIS

The second fuzzy inference subsystem, which has one output and four inputs, assesses the negative characteristics of FIS. The system is represented in Fig. 5. The inputs for this sub-system include the cost of jet fuel, unemployment, inflation, and exchange rates relative to the US dollar. The quantity of travelers by air is inversely correlated with all these factors. In other words, it is expected that if these inputs have a high value, fewer individuals will fly. The four membership functions for each input are very high, high, medium, and low. As demonstrated in TABLE II, the output, on the other hand, has five membership functions: very high, high, medium, low, and very low.

Triangular membership functions are used in this FIS's inputs and outputs. All possible fuzzy if-then conditional expressions are considered, like when looking for positive impact factors FIS. There are 256 fuzzy or 4 * 4 * 4 * 4 rules.

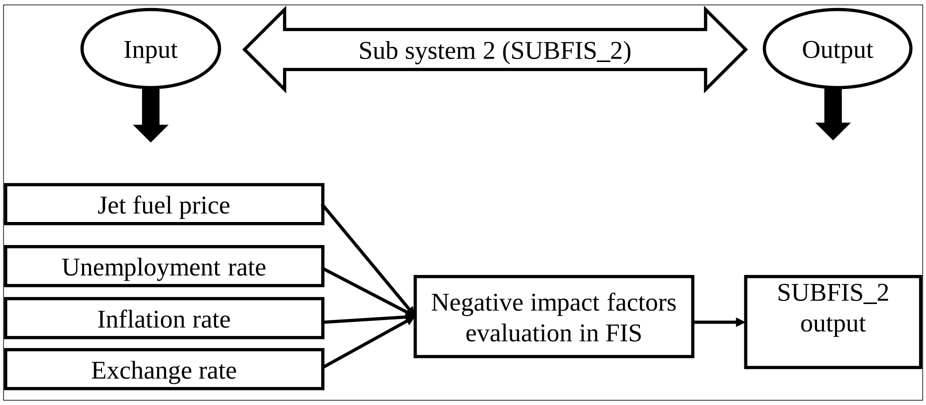

Fig. 5: Negative impact factors evaluation in FIS

3.3 Air Passenger (pax) Demand Prediction through FIS

Air passengers' number and the volume status of the passenger are the last and main predictions made by the fuzzy inference system. This system uses three inputs: the outputs of subsystems 1 and 2, as well as the season of the year. The two inputs and the outputs of subsystems one and two share the same membership functions (MF) configuration. The six seasons of the year, observed in Bangladesh, are represented by six MFs: summer, monsoon, autumn, late autumn, winter, and spring. Two months of the year are devoted to each season. As shown in TABLE III, the fuzzification procedure involves normalizing the linguistic variable for the season into numerical values. The development of the air passenger demand prediction FIS uses triangular membership functions. Additionally, Fig. 6 illustrates the structure of the system block diagram.

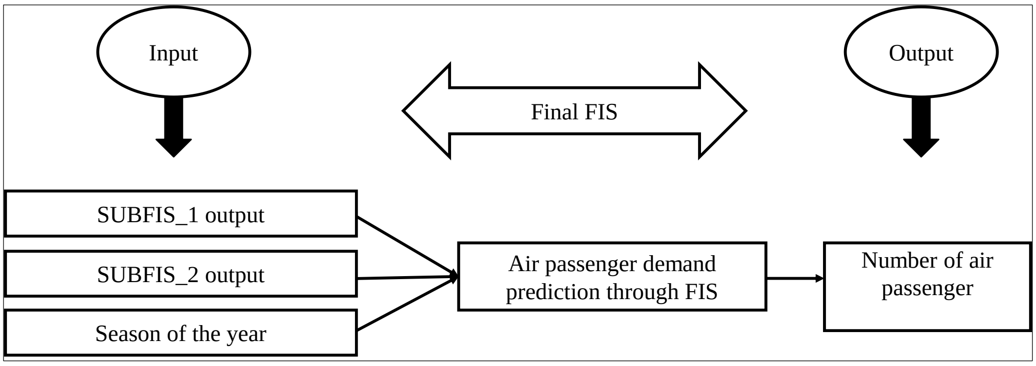

Fig. 6: Air customer demand forecast in the system.

Table II: Negative factors input and output membership function with numerical ranges

Parameters	Membership functions	Ranges
Rate of unemployment Ref: 1.50-5.50 Unit: Percentage (%)	Very high	>4.58
	High	4.06-4.58
	Medium	3.40 -4.05
	Low	<3.40
Fuel price of the jet Ref: 0.20-4.50 Unit: USD per gallon	Very high	>3.40
	High	2.66-3.40
	Medium	1.38-2.65
	Low	<1.38
Rate of exchange Ref: 45-95.00	Very high	>82.50
	High	70.01-82.50

Parameters	Membership functions	Ranges
Unit: USD to BDT	Medium	57.50-70.00
	Low	<57.50
Inflation rate Ref: 0-13.00 Unit: Percentage (%)	Very high	>9.75
	High	7.21-9.75
	Medium	4.70-7.20
	Low	<4.70
SUBFIS_2 Output Ref: 0-50.00	Very high	>40
	High	30.01-40
	Medium	20.01-30
	Low	10-20
	Very Low	<10

Table III: Season (month) of the year with the respective numerical element

Period	Numerical Element	Month
Spring	11	Mar -Apr
Winter	9	Jan-Feb
Late autumn	7	Nov-Dec
Autumn	5	Sept-Oct
Monsoon	3	July-August
Summer	1	May-June

We utilized 150 fuzzy rules in total for this study. Based on the judgments of specialists and information obtained from published materials, the passenger volume status in Bangladesh is split into six distinct categories: Extremely high, high, close to high, medium, low, and extremely low. Four classes with corresponding names represent each of the six seasons of the year. As a result, 24 membership functions (MFs) are included in the output parameters of the final inference system.

3.4 Development of Graphic User Interface

The objectives of this study were achieved by applying the app designer tool of MATLAB to develop graphical user inference software. The function offers a user-friendly interface for quick results. Each of its five significant screens serves a different purpose.

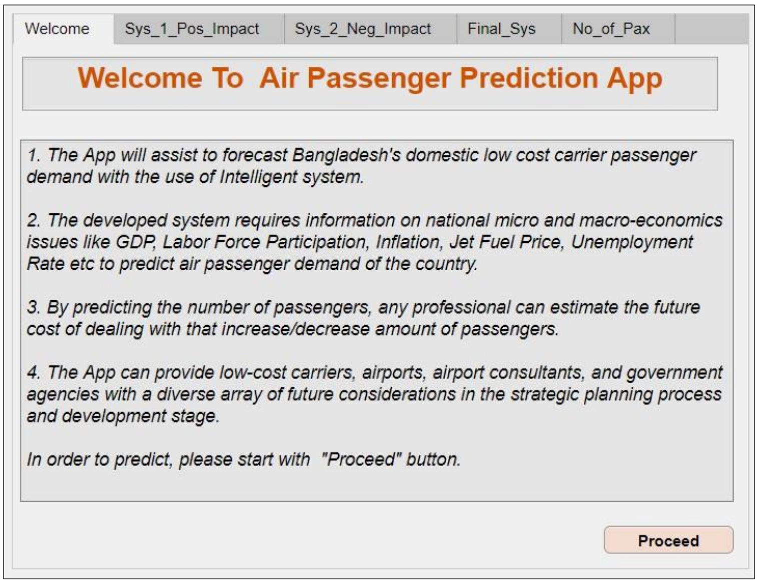

Fig. 7: Welcome tab of air passenger demand app

The first screen, the “Welcome Screen,” depicted in Fig. 7, briefly summarizes the application's objectives and system operations. The descriptions are intended to make it easier for users to understand how the software works and to ensure smooth system navigation. To progress, the user must click the 'proceed' button on the welcome screen.

Fig. 8: Positive impact factors evaluation tab with input and output membership functions

According to Fig. 8, the program's second tab, "Sys_1_Pos_Impact," is devoted to the "Positive Impact Factors Evaluation FIS." The user enters data for the GDP, labor force participation, people of the country, and industrial output index within the permitted range. The user can decide whether these factors increase the demand for air travel by selecting "Evaluate" after entering the values. The results will be displayed on the application's fourth tab.

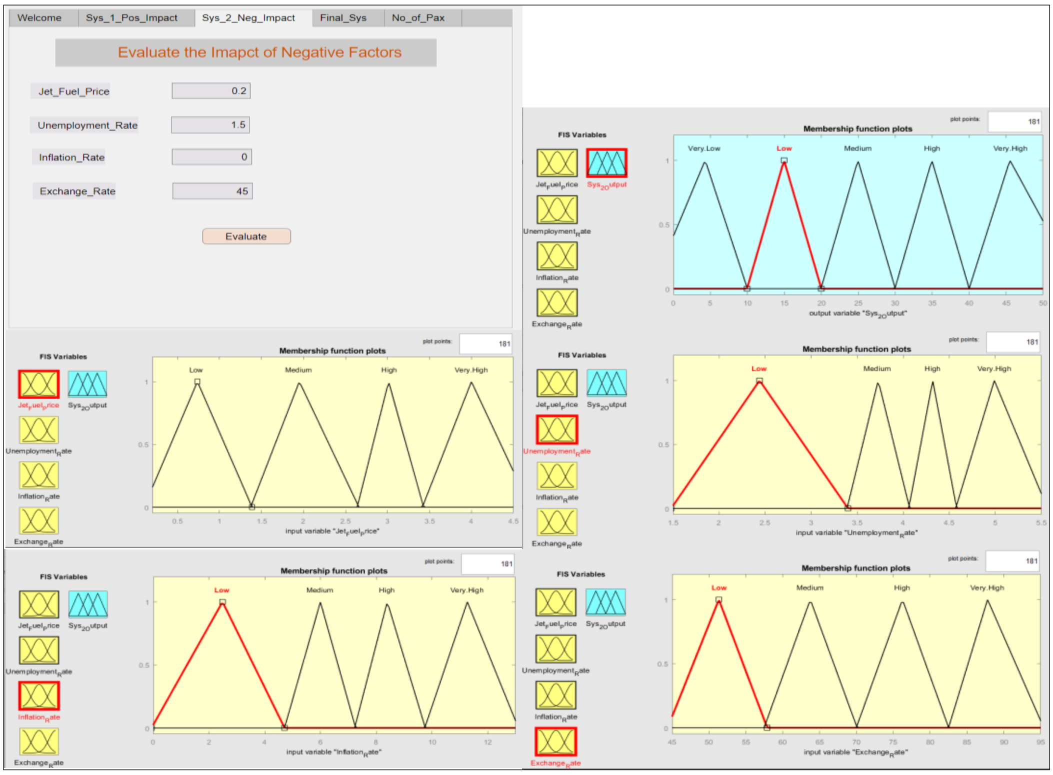

Fig. 9: Negative impact factors evaluation tab with input and output membership functions

The third screen examines variables' negative effects on the demand for air travelers, as depicted in Fig. 9. The user enters data for the price of jet fuel, unemployment, inflation, and currency rates within the defined range. After entering the settings, the user can evaluate the impact using the "Evaluate" button, which takes them immediately to the next tab.

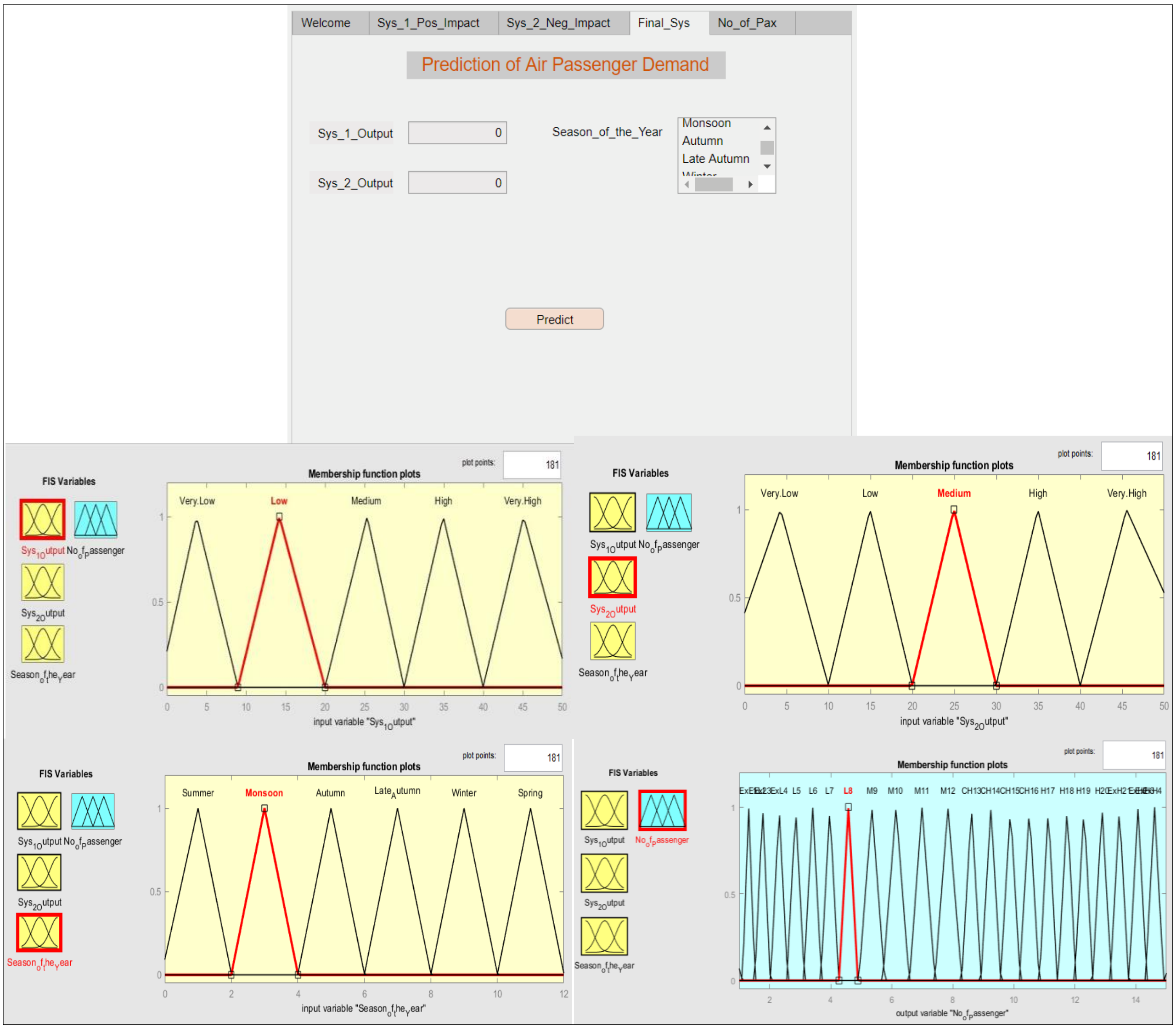

Fig. 10: Final air passenger demand prediction tab with input and output membership functions

The fourth tab, "Air Passenger Demand Prediction FIS" or "Final_Sys," is accessible by selecting the year's season from a dropdown menu, as shown in Fig. 10. The user's prior activity is used to automatically produce the other two inputs. The user can check the system's forecast on the last tab of the application after selecting the year's season and clicking the "Predict" button. The fifth and final tab, as shown in Fig. 11, corresponds to the closing screen of the application. Separate boxes display the predicted number of air travelers and the status of the existing passenger volume.

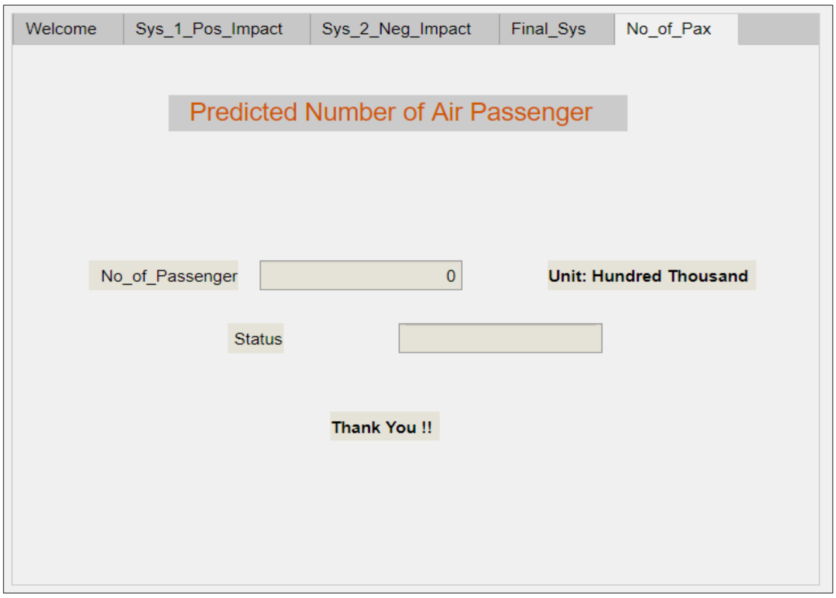

Fig. 11: Air passenger demand prediction tab

3.5 Evaluation of the Developed FIS Model

The Rule Viewer and Surface Viewer tools from MATLAB's Fuzzy Logic Toolbox assessed the generated FIS outcomes. The system was operational, but verifying its accuracy by contrasting it with test data sets was crucial. Two hundred forty groups of input data from January 2000 to December 2019 were gathered from diverse dependable sources [37]. The model was evaluated, and the result was extracted using the MATLAB function "evalfis." The correlation between the inputs and the output is also established by the model.

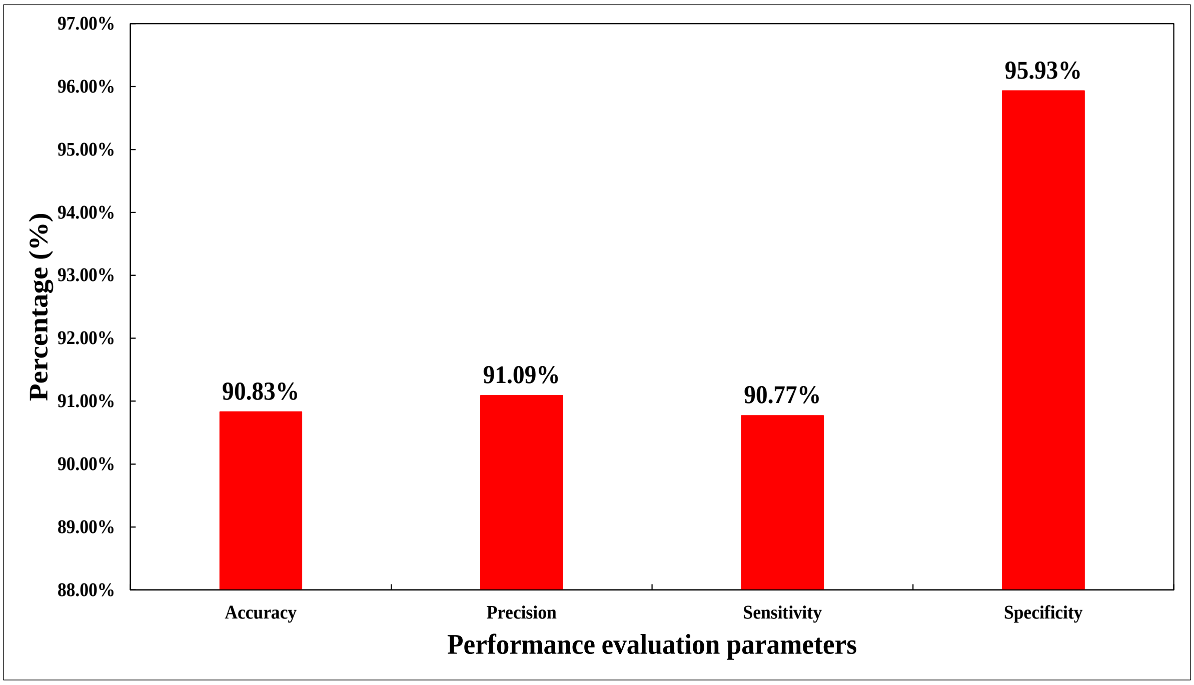

Fig. 12: Performance evaluation of developed FIS

Utilizing 240 sets of data, the effectiveness of the generated Air Passenger Demand Prediction FIS was assessed. The MATLAB "evalfis" output of the fuzzy system matched the input variables given as inputs. The system's accuracy, precision, sensitivity, and specificity are shown in Fig. 12 in a bar graph. The system demonstrated high accuracy, precision, sensitivity, and specificity, with corresponding values of 90.83%, 91.09%, 90.77%, and 95.93%, respectively. The provided values for specificity, sensitivity, accuracy, and precision show how effectively the system forecasted demand for air travel. Here, accuracy denotes the total correctness of forecasts, precision the accuracy of positive predictions, sensitivity the accuracy of positive case identification, and specificity the accuracy of negative case identification. The average squared difference between the expected and actual values is represented by the Mean Squared Error (MSE) value of 2.09%; lower MSE values indicate greater prediction ability. The average squared discrepancies between the expected and actual values are represented by the Root Mean Squared Error (RMSE), which stands at 14.45%. Predictive accuracy is improved with a reduced RMSE, just like with MSE. The model's average deviation from the actual data is 14.45%, as indicated by the RMSE value of 14.45% in this instance. Comparable to the raw MSE, it offers a more comprehensible metric by measuring the average magnitude of mistakes in the model's predictions. The high values for all these criteria indicate that the Fuzzy Inference System did a good job of predicting the demand for air travel.

3.6 Comparative Study of the Developed FIS Model

Fuzzy Inference Systems (FIS) were found to fit better than linear regression models when there are nonlinearities between the inputs and outputs. Regression is essentially a technique for handling linear relationships. FIS should therefore perform better than regression analysis if the data set contains any nonlinear interactions. Multiple linear regression analysis has been done to assess this claim or choose FIS as the study methodology. An advantage of FIS over multivariate linear analysis for this study is that it fits the nonlinearities accurately, according to the comparison of the FIS and MLR models. The results indicate that FIS is more effective in commuting non-linearities than multiple linear regression, with the mean square error and root mean square error for FIS being 2.09% and 14.45% compared to 23.11% and 48.07% for multiple linear regression.

4. CONCLUSION

To help an airline operator in emerging countries or a developing nation estimating domestic air passenger demand; this research intends to develop an intelligent system. This work is significant because it is the first to estimate low-cost domestic passenger demand using a fuzzy inference system (FIS) with nine features. The acquired findings are within a reasonable range, allowing emerging countries to use these developed models for forecasting domestic air travelers. This technology's practical use will help accomplish the research goal and promote the expansion of the aviation sector in developing nations. Making educated judgments and ensuring the success of this burgeoning industry depend on having an accurate projection of passenger demand. The sophisticated systems developed through this research could mark a crucial turning point for emerging countries' aviation sector. The main limitation of the current research is to choose nine factors specifically for passenger prediction in aircraft. Future research can be focused on applying several advanced machine learning techniques to predict air passenger demand.

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