11th ANKARA INTERNATIONAL AEROSPACE CONFERENCE **AIAC-2021-095**
8-10 September 2021 - METU, Ankara TURKEY

MODELLING OF PILOT DECISION MAKING MECHANISM BY USING FUZZY LOGIC

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ABSTRACT

This study aims to model pilot behavior to provide wisely inputs to simulations in which aircraft models are tested. The pilot's age, experience and pulse are used as inputs for the model to be used and; the constant five-degree elevator angle is taken as the output. The Precision *model which is appropriate for this study used to model and analyze human behavior. The Precision model parameters were associated with the pilot behaviors and the variation of the parameters against different inputs was examined and interpreted using the fuzzy inference model. The resulting model was visualized by designing a user-friendly interface.*

INTRODUCTION

Advances in computer technologies have made it possible to simulate real situations and systems. With this development trend, tools and solutions that can be used in the preparation and analysis of complex systems and processes have started to emerge.

Today, aviation is one of the sectors where technology is used most intensively. Therefore, it is of great importance to design, model and produce these vehicles and prototypes after testing the models.

The concept of simulation can be broadly defined as the imitation of a system, process or situation. Therefore, the simulation includes a model to enable the aircraft to be tested. This model allows trials, examinations and studies related to the system represented, which are risky, expensive or time consuming to be realized in real life.

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Pilots are one of the most important components of decision and control mechanisms in aircraft. Especially when out of standard conditions or when instant decisions are needed according to sudden conditions, the roles of pilots in this mechanism can reach even more critical points.

In these situations, pilots make the best decisions based on their education and experience, so according to their pulse, age and experience, the pilot's decision-making process can be varied. In the simulations where airplane models will be tested, the simulation results are evaluated by providing different inputs.

For over 30 years the importance of aeronautical decision-making has been recognized as critical to the safe operation of aircraft. Decision-making is a complex cognitive process and is affected by situational and environmental conditions [Payne et al., 1988].

As [Li W.-C. , 2011] noted, complex systems are designed, operated, maintained and managed by human beings. As a result, it is not surprising that human decisions and actions are implicated in most accidents.

[Li & Rebok, 2001] mentioned that 38.3% of major airline crashes, 75.5% of commuter/air taxi crashes, and 85.8% of general aviation crashes are due to pilot errors. In this study, pilot error has been evaluated by considering human performance at a psychological level. There are stress factors affecting the pilot in this psychological approach. Stress factors increase the pilot's performance demand and reduce the pilot's ability, which negatively affects flight safety, and even a crash can occur if the performance demand exceeds the performance capability. In the project, factors such as pilot's age, experience and pulse have a great impact on the pilot's decision-making, as they affect the stress of the pilot.

In this study, it is aimed to guide simulations in these tests to provide inputs wisely. Since the pilots' decisions may vary due to their personal preferences, it would be better to use fuzzy analyses rather than crisp methods. Therefore, a fuzzy inference system is conducted in selecting the constraints that are effective in the pilot's decision-making and to interpret the results of this model. The user-oriented interface is created with MATLAB App Designer.

METHOD

As a part of modelling of pilot decision making mechanism, a model was designed that provides sensitive data for the inputs of flight simulators. A detailed literature survey has been conducted while determining the factors that are effective in pilots' decision-making and that will be used as inputs in the model. After examining various sources, the inputs of the model were determined as pilot age, pilot experience and pilot pulse.

An appropriate model should be used to model and analyze human behavior. Because pilot behavior is affected by constraints such as age, experience and psychological factors. In the past, many researchers have tried to describe and model human behavior.

According to the [Jirgl et al., 2017], the main purpose is to define a control loop in the interaction of the human-machine system.

Here, the human serves as a human regulator. The human regulator is an effective regulator, as it can quickly resolve unexpected situations, analyze and adapt to sudden dynamic changes/conditions. Figure 1 shows a representation of the man-machine system as a control loop.

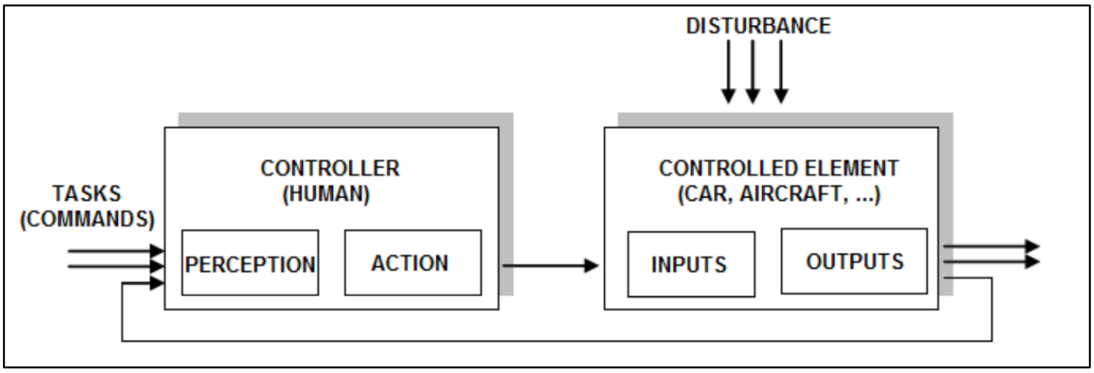

Figure 1: Man-Machine System as a Control Loop [Jirgl et al., 2017]

One of the eminent scientists in the field of modeling of pilots' behavior was Robert McRuer, whose argument is based on the assumption that pilots' behavior can be described via the theory of linear dynamic systems after accepting several simplifying hypotheses. According to this concept, a human being (a pilot) adjusts his/her control actions to comply with the controlled element [Bradac et al., 2014].

Various functions have been developed for modeling pilot behavior. In this project, the Precision Model was used for pilot modelling.

The Precision Model

According to the Crossover Law, the Eq. 1 is defined by McRuer including the human neuromuscular system dynamics,

$$F_H(s) = K \frac{(T_L * s + 1)}{(T_I * s + 1)} \frac{1}{\frac{s^2}{{W_N}^2} + \frac{2 * \zeta}{W_N} * s + 1} exp(-\tau * s),$$

(Eq. 1)

Here, K is the pilot's gain, T_L, denotes the time lead constant [s], T_I is the time lag constant [s], W_N represents the natural frequency of the neuromuscular system, ζ denotes the damping for the neuromuscular system, τ indicates the pilot response delay [s], and s represents the Laplace operator [Wang, 2018].

In order to interpret the effect of the Precision model parameters on pilot behavior, different values of each parameter were compared [Dikbaş, 2020]. The response of the real pilot and model corresponding to these parameters is shown in Figure 2.

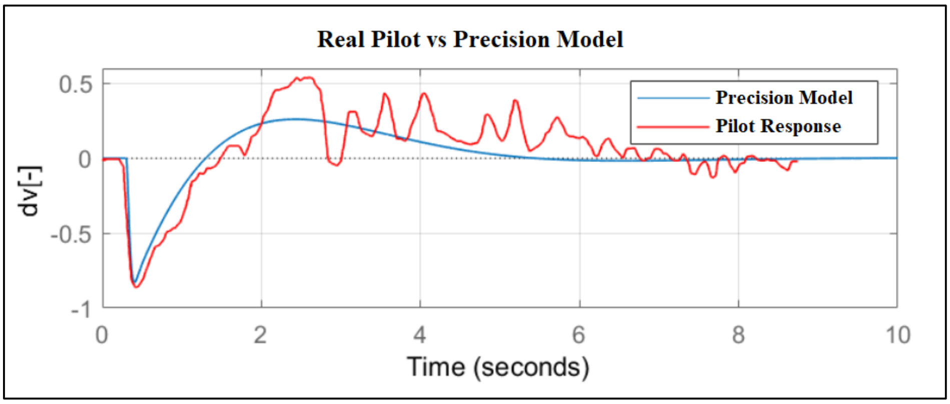

Figure 2 : The Real Pilot's Response vs the Precision Model

Generally, aircraft contains three transalation motions (vertical, horizontal and tranverse) and three rotational motion (pitch, yaw and roll) by controlling aileron, rudder and elevator. In longitudinal control, the elevator controls pitch or the longitudinal motion of aircraft system. The pitch of aircraft is control by elevator which usually situated at the rear of the airplane running parallel to the wing that houses the ailerons [Wahid & Hassan, 2012].

As a result of the literature studies, it was decided to use the pilot's age, experience and pilot's pulse as inputs in the project. The range values of these inputs were determined as a result of the literature research. In the decision-making modelling, it is accepted that the pilot will always determine the airplane elevator angle taken as output as 5 degrees in response to different input values. Here, the parameters in the Precision model affect the change in the time the pilot should give the output as 5 degrees.

Table 1 shows the algorithm table created with specified inputs and outputs.

Table 1: Algorithm Inputs, Outputs and the Precision Model Parameters

Inputs	Pilot Age
	Pilot Experience
	Pilot Pulse
Precision Model Parameters	K
	T_L
	T_I
	W_N
	τ
	ζ
Outputs	Elevator Angle

Different factors such as pulse, age, gender, physical build and emotional change cause may differ from person to person.

The resting pulse in healthy adults is, on average, in the range of 60-80 per minute. Normal pulse values differ from person to person but should be within a certain range. However, a continuous pulse of 90 or more poses a risk to the heart [Devor, 2006]. As a result of the pulse measurement, the heart that beats 40 or less per minute cannot pump enough blood and the tissues are damaged because the body is not sufficiently oxygenated.

The maximum annual flight time of a pilot has been determined as 1800 hours by the General Directorate of Civil Aviation. It is assumed that a person can be a pilot at the age of minimum 25 and have a maximum of 35 years of experience, as he will retire at 60. As a result, when the pilot experience is expressed in hours, the maximum experience is determined as 63000 hours [Directorate General of Civil Aviation of Turkey, 2021]. According to the literature review, if the average age of 18 is accepted as the age for a pilot to start training, a pilot completes his training in 7 years. For this reason, while the minimum age was 25 in the study, 60, which is considered as the retirement age of the pilots, was taken as the upper limit.

Fuzzy Logic

The idea of fuzzy logic was introduced in 1965 by Zadeh of the University of California at Berkeley [Zadeh, 1965]. The main inspiration behind the theory of fuzzy sets has been the necessity of modeling real-world phenomena that are inherently uncertain. Human knowledge of complex problems can be successfully represented using imprecise terms of natural language. Fuzzy sets and fuzzy logic provide formal tools for mathematical presentation and efficient processing of such information [Prokopowicz et al., 2017].

Fuzzy logic has emerged in recent years as a useful tool for modeling processes that are too complex for traditional quantitative techniques, or when the information obtained from the process is qualitative, imprecise, or uncertain [Konstandinidou et al., 2006].

Fuzzy inference has been adopted as a method in many studies such as aviation, engineering, and human behavior [Sharma, 2020], [Singh, 2017], [Babuska, 1995].

In this study, fuzzy logic was used because expert opinions and qualitative determinants are used as constraints in the decision support system. In addition, fuzzy inference, which can process qualitative information at a high level, has been adopted as a tool in this project because it resembles human emotions, the way people make inferences and decisions.

The variables were defined using membership functions in order to model uncertainties in the experience, age and pulse variables of the pilot. It added flexibility to variable uncertainties.

The Precision model parameters to be used in the model represent some interactions between the pilot and the vehicle, such as learned moves, delays, and experiences. It also describes the pilot's neuromuscular system.

Three inputs were determined in the model created to examine the behavior of a pilot with certain characteristics. These inputs are pilot age, pilot experience and pilot pulse. According to the changes in the determined inputs, the relationship between the possible changes in the Precision model parameters and the model inputs was interpreted with expert opinion.

The number of categories determined for the model inputs took different values for different inputs in order to create the appropriate sensitivity on the Precision model. For each input combination, the model parameters are interpreted. In the interpretation of the parameters, some rules based on expert opinion have been determined. According to these rules, T_L parameter is less affected by the pulse than its other inputs. The pilot experience affects the parameter the most. K pilot habit is more related to the pilot's experience and age. The pulse effect is low on the K parameter. The T_I parameter is highly correlated with pulse, affected by age and experience, but not very much. The decrease in the W_N parameter value is defined as the ideal pilot behavior. τ may be less effective with pilot experience. This delay will certainly increase as the pilot age increases, causing the pulse to increase as well. The decrease in the ζ parameter is associated with pilot inconsistency, pilot experience and age. The pulse also affects this parameter.

Ideal pilot behavior in the model; defined by low K, low T_L, high T_I, low W_N, low τ, high ζ parameter values. An example of the interpretations made for different input combinations is given in Table 2 of a pilot who can be described as "young", has experience that can be defined at the "beginner" level, and has a "very low" pulse.

For a pilot whose age is categorized as “young”, experience is “beginner”, and whose pulse is “very low,” the parameter values are interpreted as high for K, very high for T_L, very low for T_I, very high for W_N, high for τ, very low for ζ.

Table 2: Parameter Values for Young, Beginner Experience and Very Low Pulse Pilot

Inputs	Pilot Age	*Y*
	Pilot Experience	*B*
	Pilot Pulse	*VL*
Precision Model Parameters	K	K – *H*
	T_L	T_L – *VH*
	T_I	T_I – *VL*
	W_N	W_N – *VH*
	τ	τ – *H*
	ζ	ζ – *VL*
Output	Elevator Degree	*5°*

For model inputs and parameters, ranges and membership functions were determined within the scope of fuzzy inference method. For instance; The three-level membership functions for pilot age are shown in Eq.2, Eq. 3 and Eq.4:

$$\mu(\text{pilot age})Y = \begin{cases} 1 & 25 \leq x \leq 30 \\ \frac{(40-x)}{(40-30)} & 30 < x < 40 \\ 0 & x \geq 40 \end{cases} \qquad \text{(Eq. 2)}$$

$$\mu(\text{pilot age})M = \begin{cases} 1 & 40 \leq x \leq 45 \\ \frac{(x-30)}{(40-30)} & 30 < x < 40 \\ \frac{(55-x)}{(55-45)} & 45 < x < 55 \\ 0 & x \geq 55 \; and \; x \leq 30 \end{cases} \qquad \text{(Eq. 3)}$$

$$\mu(\text{pilot age})E = \begin{cases} 1 & x \geq 55 \; and \; x \leq 60 \\ \frac{(x-45)}{(55-45)} & 45 < x < 55 \\ 0 & x \leq 45 \end{cases} \qquad \text{(Eq. 4)}$$

MATLAB Implementation

The algorithm was modeled with MATLAB. Since Mamdani systems have more intuitive and easier-to-understand rule bases, they are well suited to human input. Thus, Mamdani was used in the Fuzzy Inference System.

Different levels have been assigned for each input and output parameters, taking into account their sensitivities. Three or five-level fuzzy numbers were used in accordance with the value range of each level. Here, most values for classifications are given based on literature reviews.

After determining the membership functions for the inputs and outputs, rules for the data are added. Here the model has 45 rules and all of them are determined from input and output parameter values.

After creating and programming the input and output connections with fuzzy inference, it goes to the phase of plotting and testing the function that occurred after entered values to model. A MATLAB code has been created for this. The code first asks the user to enter the age, experience and pulse of the pilot. If the user does not log in within the given intervals, the code will ask the user for a new login with a warning. Then, the code displays the numeric values for the output parameters as well as the membership function graphs of the input and output parameters.

Fuzzy inference input and output graphs are shown in Figure 3 and Figure 4. With this code, it is tested whether the parameter values in the Precision model are in accordance with the rules. As a result of the tests, it was seen that the model worked correctly and it was started to create a user interface design where the capabilities of different pilots could be compared and interpreted.

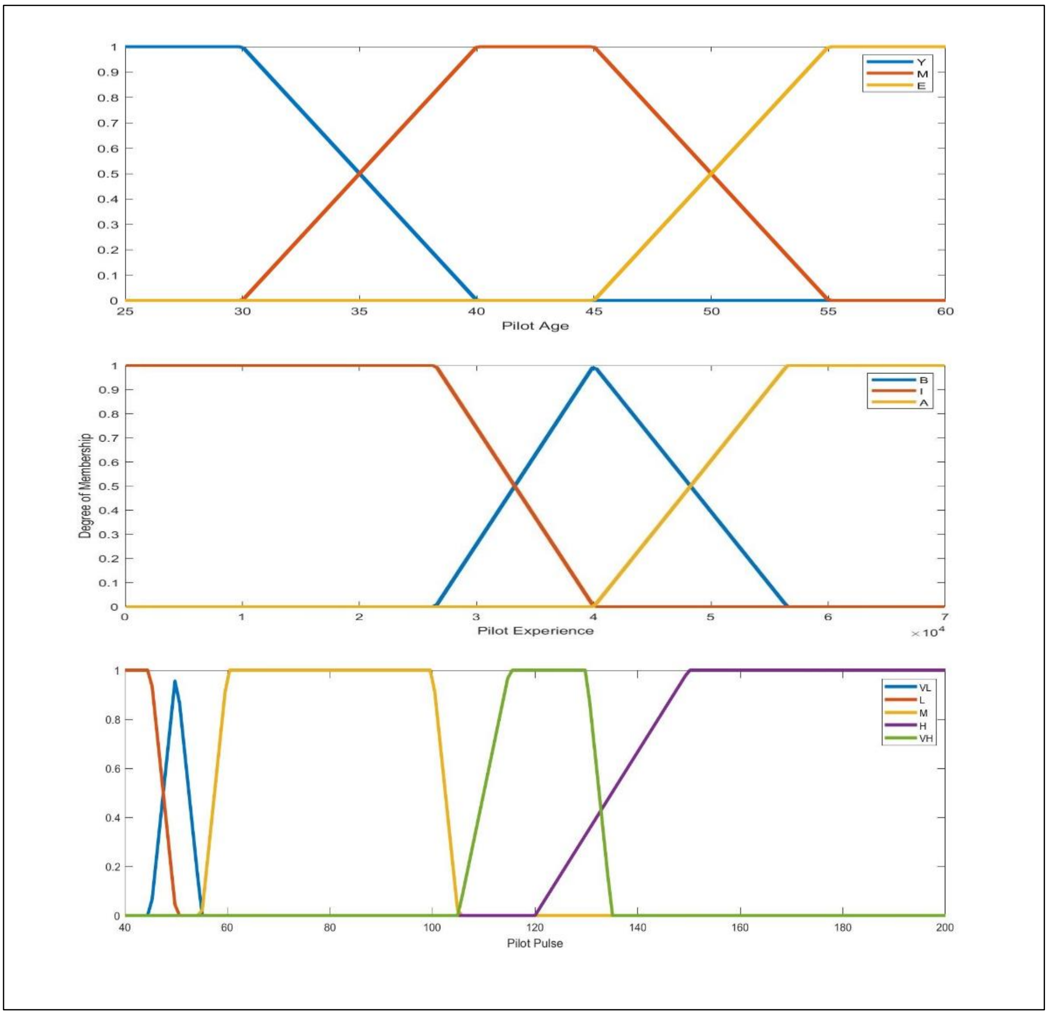

Figure 3: Fuzzy Inference Input Graphs

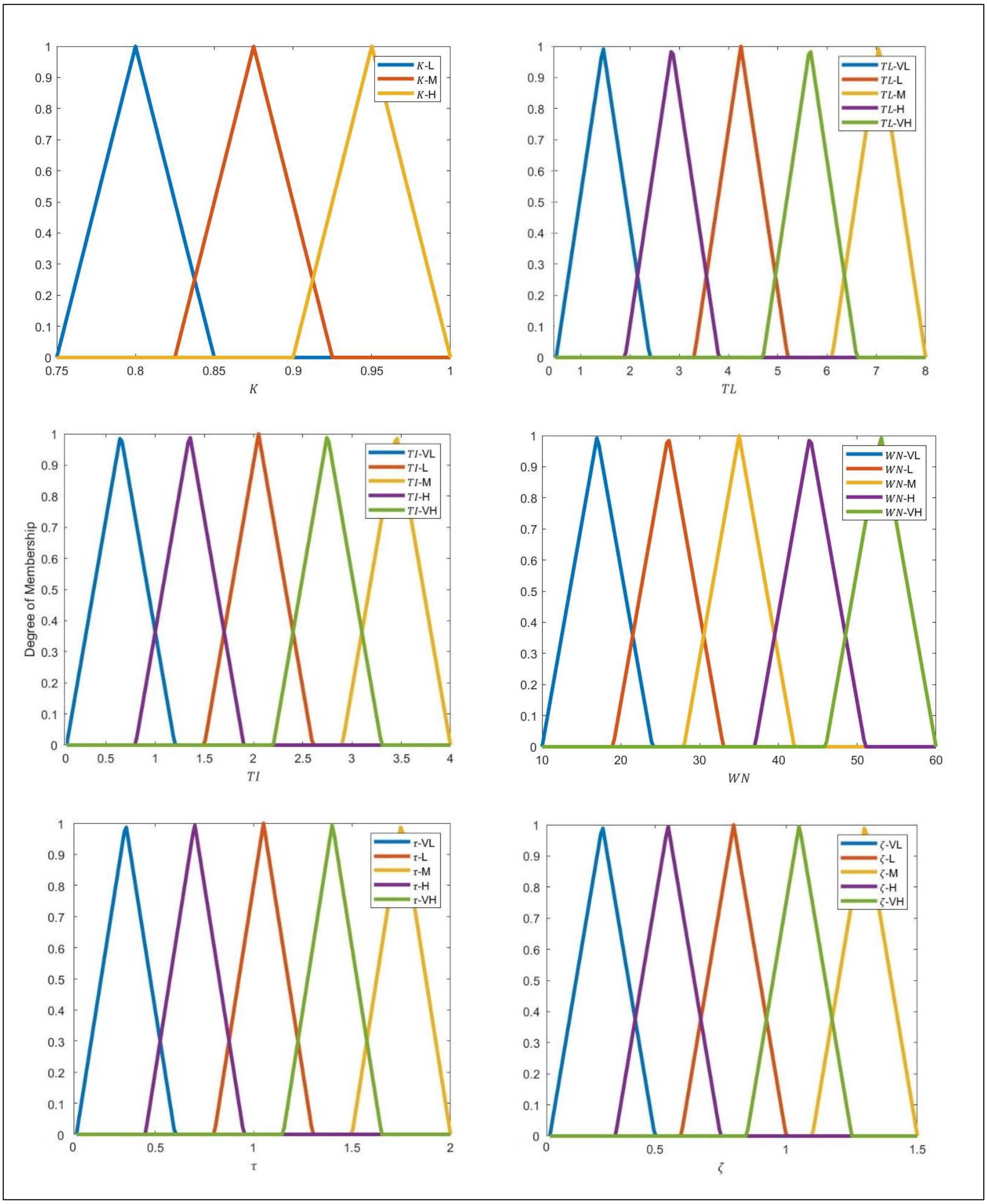

Figure 4: Fuzzy Inference Output Graphs

MATLAB Interface Design

Providing ease of use in the created MATLAB Fuzzy Logic application is of great importance for the user-friendly feature of the developed model. This ease of use has been achieved by designing an interface on MATLAB. The interface designed in MATLAB App Designer allows the use of the fuzzy inference model created in the project by entering a certain number of pilots and taking the input values of these pilots' age, experience and pulse. By substituting the obtained Precision model output values with the parameter values in the equation of the Transfer function, the Transfer function value for the pilots was obtained. Step responses were created separately by using the values of the Transfer functions calculated for each pilot. Pilots' step response curves are shown in a single graph with different colors to enable interpretation and comparison of pilots' capabilities.

The canvas is divided into two panels, considering the priority of use in the interface. A spinner is placed on the left side of the panel for the user to enter the number of pilots, while here the user is allowed to enter a minimum of one and a maximum of five pilots. After the user selects the number of pilots, the input panel is opened for each pilot with the "EXECUTE" button. After entering the age, experience and pulse values of the pilots in the input panels, it is required to click on the "START" button and then the step responses of the Transfer functions of the pilots are displayed in a single graphic on the right panel. In addition, the Transfer function equations of each pilot can be seen below the graph in order to make a comparison between the pilots to be compared. When the user wants to compare other pilots, the number of pilots from the spinner is selected and the user presses the "EXECUTE" button. Thus, existing plots and Transfer functions are removed. The user enters inputs again and presses the "START" button.

Figure 5 shows the interface design of model. Here, 3 pilots are selected to be compared. When we look at the step response graph of the Transfer function, we can compare these pilots. The τ parameter is related to the pilot taking action after sensing the command. If we look at the FH(s) equations, we see that pilot 3 has the highest parameter τ. Since the value of this parameter will increase as the age of the pilot increases, it is expected that the response time of the 3rd pilot, who is 60 years old, will be the longest. Then, pilot 2 has the second-longest response time and pilot 1 takes action first. The amplitude deviations in the graph are related to the K parameter. Because this parameter shows how precisely the pilot behaves and is more related to the pilot's experience and age. Here, the minimum deviation is seen in pilot 2. Because K parameter is 0.85387. It was effective that the experience of pilot 2 was more than the others. The deviation of pilot 3 is quite large, because both its age falls into the category of "elderly" and it is considered "beginner" in terms of experience. When we look at the graphs and compare the equations of the Transfer function, we can say that pilot 2 performed the best action.

Although the response time is later than pilot 1, it's deviation is less and it's settling time has a minimum value. Here, 2nd pilot's delay in response time can be negligible.

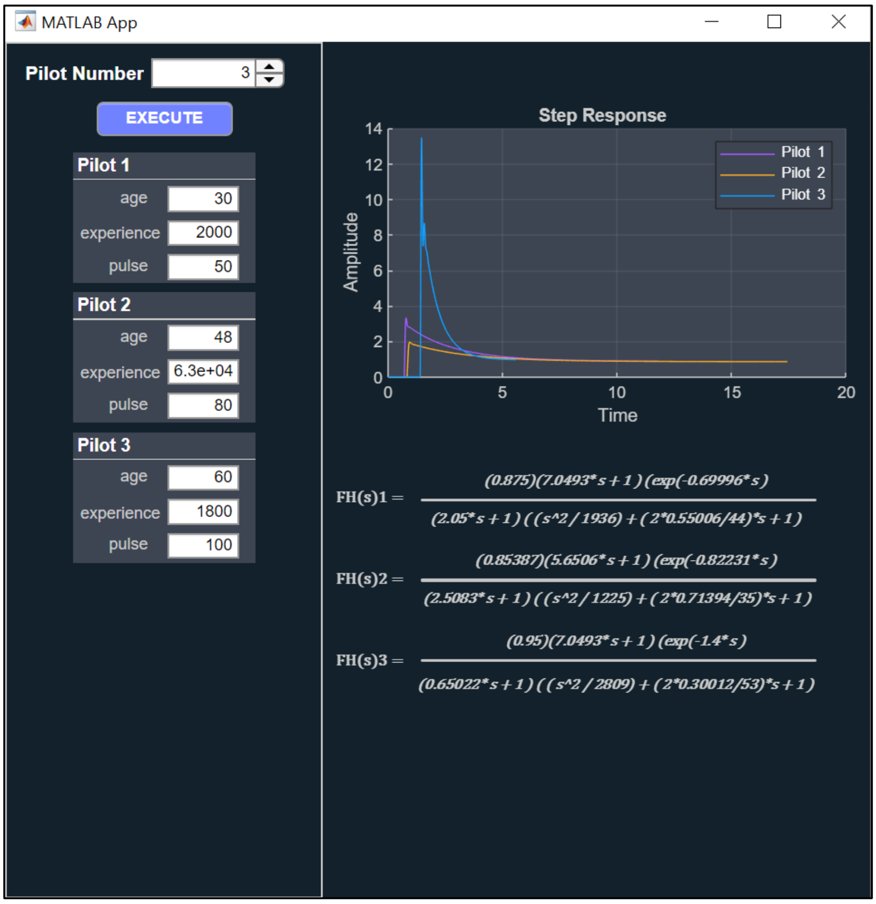

Figure 5: MATLAB App Designer Model Interface

CONCLUSION

In this study, it was decided to use fuzzy logic as a method. The input, output and variables of the model are based on a detailed literature search. As a result of expert opinions, the inputs of the model were taken as the pilot's age, experience and pilot's pulse; the output of the model is a fixed elevator angle of 5 degrees. The Precision Model, a mathematical function describing a human neuromuscular system, was used in the modeling of pilot behaviors. The change in the parameters of this model was interpreted and correlated with the pilot's age, heart rate and experience, which were determined as inputs.

The fuzzy inference model chosen as the method was created with MATLAB and the Fuzzy Logic Toolbox was used. Later, the created model was turned into a user-friendly interface with MATLAB App Designer.

As can be seen as a result of the detailed literature study, the subject of the project is new and the number of similar studies in this field is much less than in other fields. This area, which is open to development, will be an important gain for the defense industry in the future.

Although the project is open to development, it has a MATLAB application interface that can show the Transfer function step response graphs and equations comparatively according to the age, experience and pulse values of the desired number of pilots based on the fuzzy model and user convenience.

As a continuation of the project, the project can be made more comprehensive with the constraints, inputs and operations that are expanded later.

ACKNOWLEDGEMENT

The project is supported by the Turkish Aerospace Industries Lift Up Program. We would like to thank FİGES for providing technical support throughout the project.

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