Abstract— In this paper, a new approach has been proposed to identify and model the dynamics of a highly maneuverable aircraft through fuzzy logic algorithm. In general, aircraft flight dynamics is considered as a nonlinear and coupled system whose modeling through fuzzy logic algorithm can be done using a few experimental flight test data. In this study, for identification and modeling of the aircraft dynamics, the Takagi-Sugeno fuzzy system has been used. For this purpose, three different methods including recursive least squares (RLS), batch least squares (BLS), and Levenberg-Marquardt (LM) algorithms were applied to simultaneously train and optimize the parameters of the fuzzy logic algorithm. The results of this study show that the proposed algorithm, trained with experimental flight test data, is able to model the dynamical behavior of a highly maneuverable aircraft with acceptable accuracy. Therefore, a mathematical model of aircraft nonlinear dynamics without using aerodynamic and engine data, and without solving complex equations of aircraft motion can be precisely obtained. On this account, this approach can be an effective substitute for the conventional methods in aircraft modeling and identification.

Keywords— fuzzy logic algorithm; flight dynamics; modeling and identification; experimental flight data;

I. INTRODUCTION

Modeling and simulation are widely applied as essential tools to predict and analyze complex systems in almost all areas of science and technology. Over the last decades modeling and simulation of vehicle dynamics, particularly for aircraft and helicopters, has become an inseparable part of the various levels of vehicle design, simulation, development, verification of performance predictions, production, and optimization process. Aircraft modeling can be done in two different methods. The first approach is the physics-based dynamical model which uses Newton laws in order to describe the aircraft dynamical behavior [1, 2]. The second approach is based on the experimental identification of aircraft dynamics using wind tunnel and flight test data. The theoretical modeling of aircraft requires some types of data including the aerodynamic, inertial, and structural properties of various elements of the airframe. These data are not always accurate enough and their computations are often costly and, even in some cases, unavailable. These models are also linearized or only valid in a limited domain around a specific point. Furthermore, when the degree of nonlinearity increases, the modeling process becomes even more difficult.

System identification refers to an experimental approach which is able to determine complicated system models such as aircraft more quickly and accurately by fitting experimental data into a suitable model structure [3]. So far, various methods for system identification have been applied, some of which are introduced in the references [3-6]. The frequency domain analysis [7, 8], the state space identification [9, 10], the artificial neural networks (ANNs) [11-13], and fuzzy logic -based aerodynamic modeling with continuous approximation and generalization capabilities, fuzzy logic

modeling and identification of fighter aircraft nonlinear flight dynamics, by using fuzzy logic algorithm
algorithms are potentially applicable to offline nonlinear modeling of aircraft dynamics.

In the present study, a new fuzzy logic algorithm approach has been proposed to model the coupled nonlinear six-degree-of-freedom dynamics of a highly maneuverable aircraft based on flight tests data. For this purpose, Takagi-Sugeno fuzzy system has been extended and applied. RLS, BLS, and LM algorithms have been used to identify and explain how they can be used to train and tune Takagi-Sugeno fuzzy algorithm parameters. In order to examine fuzzy logic algorithms ability in modeling and identification of the aircraft nonlinear dynamics at a specific Mach and altitude, two series of data, i.e., experimental and simulation data, have been used. The simulation data have been generated from linear and decoupled dynamics of the F-4D fighter aircraft. The experimental data have been obtained from the flight tests of a highly maneuverable 4th generation fighter aircraft called X-craft in this paper.

II. FUZZY ALGORITHM IN NONLINEAR SYSTEMS IDENTIFICATION

Aircraft system identification is a highly versatile procedure which is used to extract aircraft mathematical models based on the measured response to specific control inputs [3]. Depending on the type of the system being identified (linear, nonlinear, or multi input multi output), there are various methods such as linear/nonlinear classic or non-classic and intelligent or non-intelligent identification methods. Three main methods used in system identification include white-box method, grey-box method, and black-box [4, 5, and 6].

The fuzzy logic algorithm can be considered as a black-box model [23] which, due to general approximation and generalization capabilities, has potential applicable to offline nonlinear modeling of the aircraft dynamics.

For aircraft flight identification, the aircraft nonlinear dynamics can be considered as an indistinct function:

\[ f(x(n), x(n-i),..., x(n-i+j)) \]

where \( f \) is an unknown function which needs to be identified, \( u \) and \( x \) are the aircraft control inputs and outputs respectively, and \( i \) and \( j \) are positive integers. The main purpose of fuzzy algorithms is to identify \( f \) function. Figure 1 shows a fuzzy-modeling, in which optimization algorithm sets the parameters to reach the minimum error by using the error between the measured output and the fuzzy system output during a recursive process.

A. Batch Least Squares

One of the optimization algorithms which minimizes the cost function for all input/output pairs is BLS. In other words, the goal of designing fuzzy system is identifying or obtaining \( f(x) \) which minimizes the cost function.

Let's assume that \( g \) represents the system's physical equations that should be identified, which can be a vector of aircraft state variables:

\[ x = \begin{bmatrix} x_1 & x_2 & \ldots & x_n \end{bmatrix}^T \]

(2)

The training set \( G \) is defined by the experimental input/output data that is generated from this system. The input/output data for training, which is generated from the aircraft, is considered as \( G \); and the following model can be used in system identification model:

\[ y(k) = \sum_{i=1}^{n} \theta_i y(k-1) + \sum_{i=0}^{n} \theta_i u(k-1) \]

(3)

In this model, \( u(k) \) and \( y(k) \) are system input and output at the time \( k \). In this case, \( f(x) = \theta^T x(k) \), and vector \( x(k) \) \( \theta \) can be defined as:

\[ x(k) = \begin{bmatrix} y(k-1),..., y(k-q), u(k),..., u(k-p) \end{bmatrix}^T \]

(4)

\[ \theta = [\theta_1, ..., \theta_q, \theta_{q+1}, ..., \theta_{q+p}] \]

(5)

where \( x(k) \) is the regression vector, and \( \theta \) values are set by using system input/output information or \( G \) information. In this case:

\[ f(x) = \theta^T x(k) \approx g(x) \]

(6)

If the cost function is chosen as:

\[ V(\theta) = \frac{1}{2} E^T E \]

(7)

which \( E = y - \theta \), the output data vector \( Y(M) = [y^1, y^2, ..., y^M]^T \), and \( \varphi(M) \) vector is an \( M \times N \) matrix which is defined below:

\[ \varphi(M) = \begin{bmatrix} (x^1)^T, (x^2)^T, ..., (x^M)^T \end{bmatrix} \]

(8)

Therefore, the purpose of this algorithm is to obtain a minimum value for the cost function. Since this function is a second order function of \( \theta \), its minimum is global and it is \( \hat{\theta} = (\varphi^T \varphi)^{-1} \varphi^T Y \).

B. Recursive Least Square Algorithms

The BLS approach has proven to be very successful for a variety of applications. In this approach, all the data are collected and then the processing is done (called a “batch”). Therefore, this is an appropriate process for small numbers of data (M). Since the domain and dimension of \( \varphi \) and \( Y \) depend on \( M \), when \( M \) increases, the calculation of inverse of \( \varphi^T \varphi \) will get costly due to an increase in dimension. In order to compensate for it, the BLS algorithm can be used. This method enables \( \hat{\theta} \) estimation to be updated for each new input without calculating the inverse of \( \varphi^T \varphi \) and using all the old data.

To carry out this method, by considering \( k = M \) and also \( 0 \leq i \leq k \), \( P(k) \), which is called covariance matrix will be defined as:
\[ P(k) = (\phi^T \phi)^{-1} = \left( \sum_{i=1}^{r} x_i^r \right)^{-1} \]  
(9)

\[ P^{-1}(k) = \sum_{i=1}^{r} x_i^r \phi^T = P^{-1}(k-l) + x^T(k) \]  
(10)

In the obtained BLS algorithm \( \hat{\theta} = (\phi^T \phi)^{-1} \phi^T Y \); this estimation is as follows:

\[ \hat{\theta}(k) = (\phi^T \phi)^{-1} \phi^T Y = P(k) \left( \sum_{i=1}^{r} x_i^r y_i^r + x^T(k) \right) \]  
(11)

Therefore, to estimate parameter \( \hat{\theta}(k) \) based on previous estimations when the last pair of data \( (x^k, y^k) \) is received:

\[ \hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x^k(y^k - (x^k)^T \hat{\theta}(k-1)) \]  
(12)

If the matrix inversion lemma is used, there is no need to calculate the inversion of the covariance matrix.

\[ P(k) = P(k-l) - P(k-l)x^T(k) \left( \phi^T P(k-l)x^T \right)^{-1} \phi^T P(k-l) \]  
(13)

The RLS algorithms will be:

\[ \hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x^k(y^k - (x^k)^T \hat{\theta}(k-1)) \]  
(14)

There are various methods to determine the primary values of parameters. In this project the values are \( \hat{\theta}(0) = 0 \). \( P(0) = P_0 = \alpha I \) and \( \alpha \gg 0 \).

If the parameters of the physical system \( \chi \) change slowly, weighted RLS (WRLS) can be used and V function is defined as:

\[ V(\theta, k) = \frac{1}{2} \sum_{i=1}^{r} \lambda^{k-i} (y^i - (x^i)^T \theta)^2 \]  
(15)

where \( 0 < \lambda \leq 1 \) is called a “forgetting factor”. In optimization, this factor gives the more recent data higher weight in the optimization. In this method, the equations for WRLS are given as:

\[ P(k) = \frac{1}{\lambda} (I - P(k-1)x^T) \phi^T P(k-1)x^T \phi P(k-1) \]  
(16)

\[ \hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x^k(y^k - (x^k)^T \hat{\theta}(k-1)) \]  
(17)

C. Designing Fuzzy Algorithm

There are normally two types of approach to design fuzzy algorithm based on input/output pairs. In the first approach, fuzzy algorithm is based on IF-THEN rules which are produced from input/output data. Therefore, the fuzzy system can be constructed from these rules based on certain choices of fuzzy inference engine, desirable fuzzifier, and defuzzifier. In the second approach, the fuzzy system structure is determined first and some parameters in the structure can change freely, then these parameters are specified based on input/output data.

In this study, the second method has been used to design the fuzzy system. For this purpose, Gaussian membership function, center-average defuzzification, and product for the premise and implication have been applied. Therefore the fuzzy system constructed from numerical data is given by:

\[ y = f(u|\theta) = \sum_{i=1}^{R} b_i \mu_i(u) \]  
(18)

\[ u \] which has been applied in the above equation with \( x = [x_1, x_2, ..., x_n]^T \) vector, is the input of fuzzy system. \( \mu_i(u) \) is also defined for \( i^{th} \) law as the following:

\[ \mu_i(u) = \exp \left( - \frac{1}{2} \left( \frac{u - c_i}{\sigma_i} \right)^2 \right) \]  
(19)

The values of \( b_i \) are also \( (i = 1, 2, ..., R) \) the output of centers membership function. Therefore:

\[ f(u|\theta) = \sum_{i=1}^{R} b_i \mu_i(u) \]  
(20)

Then, as a result:

\[ \xi_i(u) = \frac{\mu_i(u)}{\sum_{i=1}^{R} \mu_i(u)} \]  
(21)

If we define a function as follows:

\[ f(u|\theta) = b_1 \xi_1(u) + b_2 \xi_2(u) + ... + b_R \xi_R(u) \]  
(22)

and

\[ \xi(u) = [\xi_1, \xi_2, ..., \xi_R] \]  
(23)

If we define \( \theta = [b_1, b_2, ..., b_R]^T \), there will be

\[ y = f(u|\theta) = \theta^T \xi(u) \]. As a result, if we have \( \mu_i(u) \), we will also have \( \xi(u) \). Therefore, equation 20 is the same RLS method, and \( \xi(u) \) is the same regression vector in LS method.

Generally, the training data \( u_i \) are mapped into \( \xi_i(u_i) \) and the least squares algorithms produce an estimate of the best centers for the output membership function \( (b_i \xi_i(u)) \) is created by LS algorithm). That is, LS or BLS are reliable methods to train the fuzzy logic algorithm.

D. Takagi-Sugeno Fuzzy System

Identification techniques based on Takagi-Sugeno fuzzy system have proved an effective tool in modeling complicated data-based nonlinear systems. Since inputs and outputs in engineering systems identification are real values, we have used Takagi-Sugeno method which uses real values instead of fuzzy function which has come to be known as “functional fuzzy system”. Fuzzy system is a nonlinear static mapping between inputs and outputs based on ‘If-Then’ rules. Takagi-Sugeno (or functional) fuzzy system will provide a better approximation than a standard fuzzy system for a particular application such as modeling and identification of aircraft nonlinear flight dynamics. The rules in this kind of system are:

If \( \mu_i \) is \( \mu_i \) and \( \mu_n \) is \( \mu_n \), then \( b_i = g(.) \)
\( \bar{A}_j \) is the a fuzzy collection and the ‘then’ part is a linear combination of input variables.

\[
b_j = g(. ) = a_{i,1} + a_{i,2} (u_1)^2 + \ldots + a_{i,n} (u_n)^2
\]  

Or

\[
b_j = g(. ) = \exp\left[ a_{i,1} \sin(u_1) + \ldots + a_{i,n} \sin(u_n) \right]
\]

The fuzzy system output is the average weighted \( \hat{b}_j \), that is:

\[
y = \frac{\sum_{i=1}^{k} b_i \mu_i}{\sum_{i=1}^{k} \mu_i}
\]

The regression vectors of \( \xi(u) \) and \( \theta \) will be:

\[
\xi(u) = [\xi_1(u), \xi_2(u), \ldots, \xi_k(u), u_1 \xi_1(u), u_2 \xi_2(u), \ldots, u_i \xi_k(u), \ldots, u_j \xi_1(u), \ldots, u_k \xi_k(u)]
\]

\[
\theta = [a_{1,1}, a_{1,2}, \ldots, a_{R,1}, a_{R,2}, \ldots, a_{1,n}, a_{2,n}, \ldots, a_{R,n}]
\]

Therefore, Takagi-Sugeno fuzzy algorithm which is in accordance with linear parametrical model is:

\[
f(u|\theta) = \theta^T \xi(u)
\]

### III. DATA GENERATION

In order to show the fuzzy logic algorithm abilities in modeling and identification, two sets of data have been used:

a. Linear and decoupled dynamics of the Beech M99 and F-4D fighter aircraft.

b. Experimental measurements of a highly maneuverable 4th generation fighter aircraft.

#### A. Linear and Decoupled Data

The aircraft's linearized equations are available in the form of transfer functions in Laplace space in [2]. By putting stability dimensional derivative values [24] for a specific mach and altitude, transfer functions can be obtained based on rudder input in lateral axis and elevator in longitudinal axis. At instance, the F-4D aircraft's side slip angle transfer function based on input elevator is shown as:

\[
\beta(z) = \frac{11.85 z^3 + 2403.4 z^2 + 3047.6 z + 20.60}{874.8 z^3 + 1379.5 z^2 + 4701.6 z + 6768.9 + 88.4}\delta_R (z)
\]

By converting these functions from Laplace space into state space and solving them (simulation), the necessary data for solving the fuzzy logic algorithm can be produced. These data will include angle of attack, side slip angle, linear velocities, and Euler angles.

#### B. Experimental Data

In order to obtain experimental data, a two-engine fighter aircraft has been used. Flight tests have been carried out in calm weather conditions at a specific Mach and altitude. The pilot applies suitable input to each one of the aircraft control inputs including three angles of main control surfaces (elevator, aileron, and rudder). Applying input, during flight tests for data sampling, is done by the pilot in trim conditions at a specific Mach and altitude. It is worth mentioning that due to the tested aircraft’s high maneuverability and agility, a little variation in Mach and altitude during the test can be observed.

In this type of aircraft, control commands are internally connected to one another; therefore, when only one of the commands is applied to the aircraft, there would be a little variation in other control surfaces.

The aircraft was instrumented to measure longitudinal \( (n_x) \), lateral \( (n_y) \) and normal transnational accelerations \( (n_z) \), pitch \( (\theta) \), roll \( (\phi) \), yaw angle \( (\psi) \), indicated airspeed \( (\nu) \), barometric altitude \( (h) \), and AOA. The signals were sampled at 10 Hz and stored on an on-board Flight Data Recorder (FDR).

The FDR device records both the pilot inputs applied by the stick and control surface changes.

#### C. Training Input Signals

The type of input (excitation) signals play the most important roles for collecting identification data in the process of training and generalization of the identified model; so, it is necessary to define suitable inputs and apply them appropriately to the aircraft. It is obvious that the identified model excited by suitable input has higher quality compared to the model identified with unsuitable inputs. Experience shows that the form of input signal can have a significant effect on the approximation accuracy of the parameter conducted by the dynamic measurements during flight. The input command form should be proportionate to the special mathematic model indicating the aircraft behavior being tested. In flying vehicles such as aircraft, the input signals should be able to excite various flight dynamic modes [25].

The best input for system identification is white noise signal which includes a wide domain of frequencies and excites all the frequencies equally [26]. This input can be used in simulation. However, the application of this input in actual flight is difficult; thus, other inputs are used in aircraft's actual dynamics identification. In this study, frequency sweep and DLR3211 multistep inputs (Figure. 2) have been used.
To obtain linear decoupled flight dynamic data, the input DLR3211 has been defined in the form of Laplace transfer function. For example, the Laplace transfer function of $\delta_R(s)$ which has been used in this study is as follows:

$$\delta_R(s) = \frac{0.1 e^{-2s} - 0.2 e^{-8s} + 0.2 e^{-20s} - 0.2 e^{-16s} + 0.1 e^{16s}}{s}$$ (33)

By applying $\delta_R(s)$ or $\delta_e(s)$ in the aircrafts' transfer functions (Eq. 1) calculating the inverse Laplace, the state variables of $\beta(t)$, $\varphi(t)$ and $\phi(t)$, $U(t)$, $\alpha(t)$ and $\theta(t)$ in longitudinal and lateral directional will be obtained.

IV. RESULTS

As it was shown, the input signal plays an important role in the identification and extraction of the system's suitable dynamic model. In order to obtain a suitable model for the aircraft, various training signals in flight test and simulated data have been used. In Figures 2 and 3, two types of training signals which have been used to obtain suitable data during flight tests are shown.

Figures 4 and 5 show the training results of AOA with multi-step and sinusoidal inputs for the simulated data. The figures for various flight parameters include three sections. In the first section of the figure, the aircraft's output (validation or training data) and the fuzzy output model have been compared. In the second section of the figure, the input applied to the aircraft has been shown. The last section of the figure shows the MSE at each instance.

As is clear in the first section of the figure, the fuzzy model has learned the aircraft's dynamics, and its output is similar to the desired data output. After training the fuzzy model and extracting its parameters, the obtained model should be able to have an appropriate response for each new input. To do this, the obtained model was evaluated by the new chirp and multi-step inputs. Figures 6 and 7 show the results of validation for the fuzzy model with these two inputs.

In order to adjust the parameters of the fuzzy model, accurate definition of fuzzy rules for the assigned functions and the selection of primary parameters play an important role in the process of model training. Figure 8 shows the amount of each rule’s activity which is dealt with in equation 19.

The number of rules and selection of parameters are determined based on the number of available data for training. On the whole, as is shown in Figure 9, an increase in the number of rules results in a decrease in the model’s average number of errors.

After the initial evaluation of the proposed fuzzy model and determination of the number of rules for the obtained fuzzy model, the fuzzy model will be evaluated by the experimental flight data. For training the fuzzy model with the experimental data, two input signals of multistep and sinusoidal have been used.

Figures 10 and 11 show the training results of aircraft’s AOA with the experimental data. The training has been done using multistep and sinusoidal signals. The training times with multistep and sinusoidal inputs are 100 and 80 seconds, respectively.

As is clear, in sinusoidal input, domains and phases for each time period are not equal. Thus, this input contains variable frequencies; therefore, it will identify a wide domain of the aircraft dynamic frequencies. The training results of AOA with the input of elevator for the aircraft using the obtained experimental data during the flight test have been shown in Figures 12 and 13. In these figures, the input type and MSE for each data have been shown. As is clear from these figures, the fuzzy model has been able to model a wide domain of the flight without the main system. This means that, the introduced sinusoidal training input is a suitable input for training.

In Figures 14 to 16, the training and validation results of linear and angular accelerations for the obtained experimental data during the flight tests have been shown. The obtained data during the flight test have been sampled at a specific altitude which during the test and the application of control inputs, there were some variations in the altitude of the aircraft at about 5000 ft; so, regarding the validation data, the aircraft’s altitude around this sampling altitude should also remain constant. The increase in the data is due to moving away from altitude and the trim point. Mach variations have the same effect as altitude on the data. Figures 17 and 18 show the variations in Mach and altitude for the test and training data. The results show that if we do not go away from the initial trim condition, in testing phase; with any given input to the system, the identified model will produce acceptable output.

Table 1 shows the MSE for the data validation and training for aircraft dynamics’ different parameters. MSE is a suitable criterion for the evaluation of the fuzzy model intended to identify the system. As is clear, the MSE values for Euler angles are considerable. The reason for this can be attributed to the aircraft leaving the initial conditions of the equilibrium point. However, in fuzzy logic algorithms by increasing the number of rules, these errors can decrease.

V. CONCLUSION

In this paper, by proposing a new approach for fuzzy logic and suitable training, it was shown that the highly maneuverable fighter aircraft with nonlinear dynamics can be identified and predicted through the fuzzy logic system. It was additionally shown that fuzzy model will have suitable generalization for the new inputs without requiring any error signals from the main system. It was also found out that the proposed Takagi-Sugeno fuzzy systems are able to identify aircraft complex and nonlinear dynamics appropriately.

On the whole, fuzzy logic algorithms have enough potential for the identification of aircraft dynamics. The proposed method in this study has the advantage of having a short computation time and can estimate an acceptable model based on the flight tests. Therefore, the aircraft dynamics can be modeled without requiring any aerodynamic models or aircraft dynamics derivatives and priori knowledge about the aircraft dynamics model. Finally, it can be concluded that, the
Fuzzy logic algorithms can be applied in developing flight simulators for all types of aircraft and be acceptable for aircraft modeling and identification based on the known flight tests data.

Fig. 1 Basic scheme of the identification model for the nonlinear dynamic system using fuzzy logic algorithms.

Fig. 2. Three-channel series multistep input for training experimental flight test data

Fig. 3. Three-channel series sinusoidal input for training experimental flight test data

Fig. 4. Training results of the AOA for simulation data with sinusoidal input

Fig. 5. Training results of the AOA for simulation data with multistep input

Fig. 6. Validating results of the AOA for simulation data

Fig. 7. Validating results of the AOA for simulation data

Fig. 8. Membership functions activity for AOA in Takagi-Sugeno fuzzy system
Fig. 9. Process of minimizing error by increasing the number of rules for AOA in Takagi-Sugino fuzzy system.

Fig. 10. Results of aircraft AOA experimental data training by elevator input in Takagi-Sugino fuzzy system with multistep signal.

Fig. 11. Results of aircraft AOA experimental data training by elevator input in Takagi-Sugino fuzzy system with multistep signal.

Fig. 12. Comparing aircraft AOA experimental data by Takagi-Sugino fuzzy system with a new input.

Fig. 13. Comparing aircraft AOA experimental data by Takagi-Sugino fuzzy system with a new input.

Fig. 14. Results of aircraft linear accelerations training by experimental data in Takagi-Sugeno fuzzy system.

Fig. 15. Results of aircraft linear accelerations validating data by experimental data in Takagi-Sugino fuzzy system.

Fig. 16. Results of aircraft angular accelerations validating by experimental data in Takagi-Sugino fuzzy system.
Fig.17. Mach changes for data test

Fig.18. Altitude changes for training data

TABLE I. MSE OF TRAINING AND VALIDATING OF IDENTIFIED MODEL FOR EXPERIMENTAL FLIGHT DATA

<table>
<thead>
<tr>
<th>States</th>
<th>Training MSE</th>
<th>Validating MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>1.238</td>
<td>0.8134</td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.0060</td>
<td>0.0038</td>
</tr>
<tr>
<td>$\psi$</td>
<td>0.0038</td>
<td>0.2474</td>
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<tr>
<td>$N_x$</td>
<td>0.1137</td>
<td>0.756</td>
</tr>
<tr>
<td>$N_y$</td>
<td>0.0629</td>
<td>0.424</td>
</tr>
<tr>
<td>$N_z$</td>
<td>0.0045</td>
<td>0.0024</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>1.369</td>
<td>1.081</td>
</tr>
</tbody>
</table>

REFERENCES
