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Optimized Fuzzy Control and Simulation for Vibration Mitigation in Fighter Aircraft Landing Gear Using Magnetorheological Dampers

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Abstract-- This paper explores the simulation and control of interval Type-1 and Type-2 fuzzy systems for mitigating vibrations in a fighter aircraft's landing gear, aiming to minimize the transmission of vibrations to the airframe and pilots. A ten-degree-of-freedom vibration model, derived using the Lagrange method, is employed, incorporating the dynamics of the landing gear, airframe, seats, and pilots. To address the vibrations caused by wheel-ground contact during landing, optimally designed Type-1 and Type-2 fuzzy controllers are implemented in conjunction with intelligent magnetic damper actuators. These controllers are developed using metaheuristic optimization techniques, eliminating the reliance on expert knowledge for rule table design. The proposed methodology is evaluated by comparing the performance of the optimized fuzzy controllers with one another and with a conventional fuzzy controller designed based on expert-defined rules. Simulation results confirm the effectiveness of the proposed approach, showing substantial improvements in vibration control performance. Notably, the Type-2 fuzzy controller

outperforms the Type-1 controller, demonstrating superior capabilities in managing nonlinear dynamics and uncertainties in the landing gear system.

Keywords-- Fuzzy Control Systems, Landing Gear Vibration, Type-1 and Type-2 Fuzzy Logic, Metaheuristic Optimization, Smart Magnetic Dampers.

1. Introduction

Damping is an inherent property of vibratory systems that reduces vibration amplitude by dissipating vibrational energy. This characteristic is a key factor in the analysis of vibrational phenomena, as it enables vibrations to cease and the system to return to a state of equilibrium in the absence of external excitation [1]. The landing gear, as a critical component of an aircraft, plays a pivotal role in ensuring stable landings, minimizing fuselage vibrations caused by impact forces transferred from the ground during touchdown, enhancing passenger comfort, and improving flight safety [2]. Equipping the landing gear with shock absorbers capable of effectively dissipating landing impact energy is a fundamental requirement for achieving stable landings. In this context, magnetorheological (MR) dampers have garnered significant attention due to their ability to adjust damping force by varying the intensity of an external magnetic field, their high shock absorption efficiency, and their excellent stability under diverse landing conditions [3-5].

Various methods have been proposed for controlling the vibrations of fighter aircraft landing gear systems, each with its own advantages and limitations. In [6], the control of a magnetorheological damper system in the landing gear was investigated using an intelligent controller based on supervised neural networks. This approach, by simulating the behavior of a hybrid controller derived from precise mass and force data, significantly reduces dependency on

direct system information. In [7], a novel robust controller for landing gear equipped with a magnetorheological damper was introduced, combining model reference sliding mode control with adaptive hybrid control. This controller improves impact energy absorption efficiency by considering variables such as aircraft weight and landing speed while addressing uncertainties like ambient temperature and damping coefficients. In [8], to enhance the performance of landing gear systems with magnetorheological dampers facing challenges such as nonlinear behavior, disturbances, and time delays, two control approaches were utilized: a model predictive controller and an intelligent neural network-based controller. The model predictive controller was designed using a mathematical description of the system, allowing precise system tuning, while the intelligent controller, leveraging a greedy algorithm, was specifically trained to optimize impact absorption efficiency under various mass and landing speed scenarios. In [9], a fault-tolerant adaptive sliding mode control algorithm was developed to enhance the performance of the landing gear shock absorption system. This algorithm, by performing online identification of system parameters and applying an adaptive control law, enables compensation for damper failures and ensures the optimal performance of the system. In [10], the design of an adaptive fault-tolerant controller for unmanned aircraft landing gear equipped with magnetorheological dampers was presented. This adaptive approach, utilizing advanced control laws, maintains the functionality of the shock absorption system even in scenarios where the damper experiences partial failure or jamming. The proposed robust controller is designed to manage existing faults effectively, sustain high system performance, and prevent failure from adversely affecting overall functionality. In [11], an optimized control approach based on a generalized Bingham number was proposed to improve soft landing accuracy in magnetorheological shock absorption systems.

Analyses demonstrate that this method, incorporating second-order damping, offers superior performance compared to linear damping in achieving precise control for soft landings.

Although significant progress has been made in reducing landing gear vibrations, further advancements are essential to improve the performance of control systems utilizing intelligent dampers. This research focuses on enhancing the vibration reduction capabilities of aircraft landing gear equipped with intelligent dampers through a fuzzy control strategy based on a ten-degree-of-freedom aircraft model. The proposed approach uses metaheuristic optimization to fine-tune the fuzzy control system by minimizing a cost function, effectively removing the reliance on expert knowledge. A detailed comparison with conventional fuzzy controller design methods demonstrates the clear advantages of the proposed method, supported by comprehensive graphs and performance curves. Developing fuzzy control systems for landing gear with three inputs and nonlinear actuators is a critical step forward, and the results of this study highlight the method's high precision and effectiveness in addressing vibration challenges.

In Section 2, the vibrational model of the fighter aircraft is examined, and the dynamic model of the landing gear is presented in detail. Section 3 focuses on the design of a fuzzy controller using optimization algorithms to enhance the system's performance. Section 4 is dedicated to the simulation results of the proposed method for the fighter aircraft, demonstrating its effectiveness and performance. Finally, Section 5 concludes the study, summarizing the findings and highlighting the significance of the proposed approach.

2. The vibrational model of the fighter aircraft

In this study, the vibration modeling of the aircraft is conducted under the assumption of a discrete system with rigid bodies, which is considered an effective approach for analyzing the dynamics of complex systems. This modeling employs two primary methods: the Newton-Euler

method and the Lagrange method. The Newton-Euler approach, an extension of vibration analysis for single-degree-of-freedom systems, uses Newton's equations for translational motions and Euler's equations for rotational motions to analyze the positions and velocities of system components. While this method is suitable for simple systems, it becomes less efficient for systems with higher degrees of freedom due to extensive computational requirements and the inclusion of unnecessary reaction forces. In contrast, the Lagrange method considers the entire system as a unified whole without requiring the separation of components. By utilizing the total kinetic and potential energy of the system as scalar quantities and incorporating the virtual work of non-conservative forces, this approach provides a more comprehensive and efficient framework for modeling complex systems. For this reason, the Lagrange method has been adopted in this study to derive the vibrational model of the fighter aircraft.

In this research, the vibration modeling of the aircraft assumes a discrete system comprising rigid bodies, an effective approach for analyzing the dynamics of complex systems. Two primary methods are utilized in this modeling: the Newton-Euler method and the Lagrange method. The Newton-Euler approach, an extension of vibration analysis for single-degree-of-freedom systems, employs Newton's equations for translational motion and Euler's equations for rotational motion to determine the positions and velocities of system components. While effective for simple systems, this method becomes less practical for systems with higher degrees of freedom due to its computational complexity and the inclusion of superfluous reaction forces. Conversely, the Lagrange method considers the entire system holistically, eliminating the need to separate components. By leveraging the total kinetic and potential energy of the system as scalar quantities and incorporating the virtual work of non-conservative forces, it offers a more robust and efficient framework for modeling complex systems. Consequently, this study employs the Lagrange method to develop the vibrational model of the fighter aircraft.

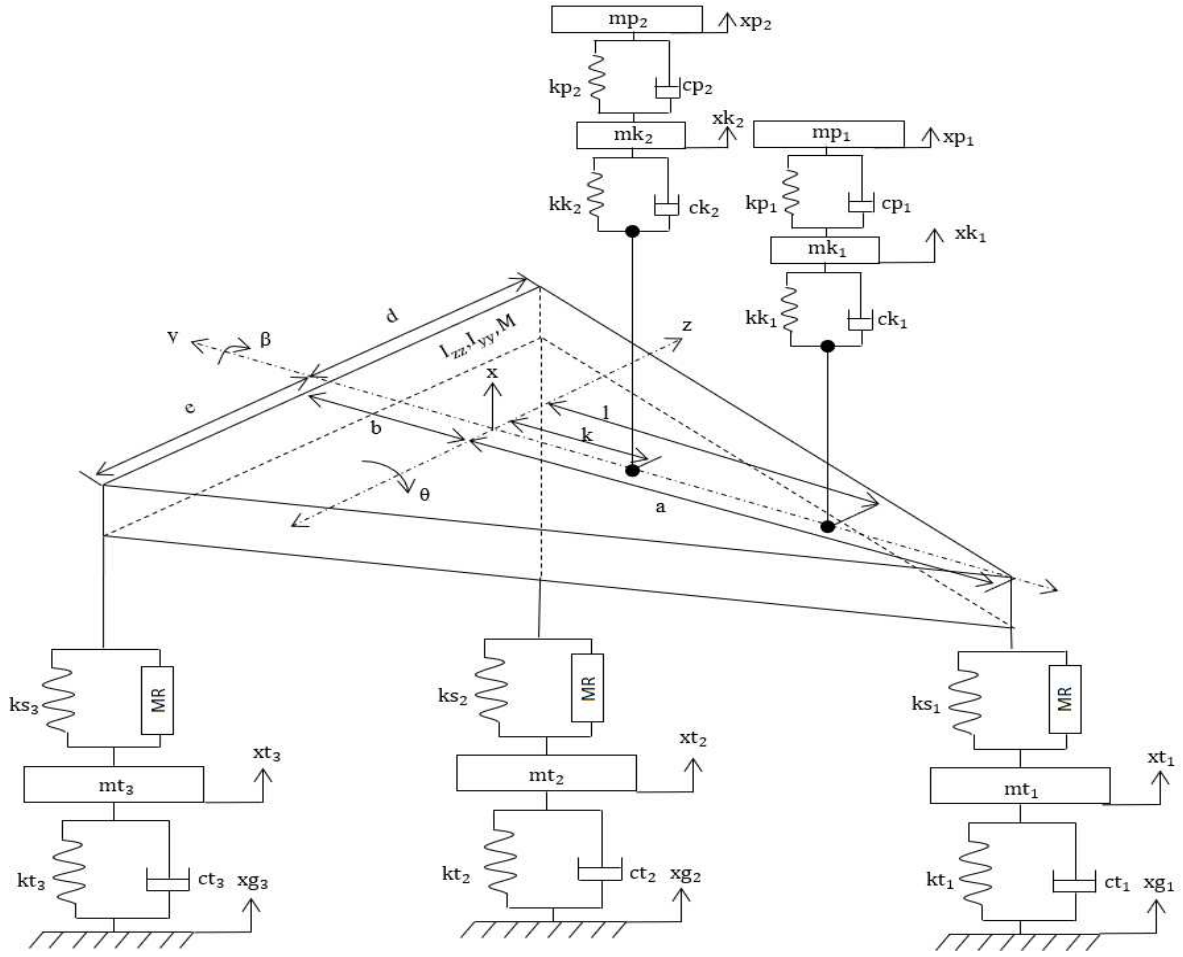


Fig. 1. The vibrational model of the fighter aircraft

As shown in Fig. 1, the generalized variables include 8 absolute translational displacement variables, xt_i , representing the positions of the aircraft tires; x , describing the translational position of the aircraft fuselage; xk_i , representing the positions of the seats; and xp_i , describing the translational positions of the pilots, where $i = 1, 2, 3$. Additionally, two angular variables, β and θ , are used to describe the rotational positions of the aircraft fuselage along the longitudinal and lateral axes, respectively. Based on Figure 1, the mathematical equations for the fighter aircraft are given by (1) to (10).

$$\begin{aligned}
M\ddot{x} + ks_1(x - a\theta - xt_1) + ks_2(x + b\theta - d\beta - xt_2) + ks_3(x + b\theta + e\beta - \\
xt_3) - kk_1(xk_1 - x + l\theta) - kk_2(xk_2 - x + k\theta) - ck_1(\dot{x}k_1 - \dot{x} + l\theta) - \\
ck_2(\dot{x}k_2 - \dot{x} + k\theta) = -F_{MR}^f - F_{MR}^{rr} - F_{MR}^{rl}
\end{aligned} \tag{1}$$

$$\begin{aligned}
mk_1\ddot{x}k_1 + kk_1(xk_1 - x + l\theta) + ck_1(\dot{x}k_1 - \dot{x} + l\theta) - kp_1(xp_1 - xk_1 \\
- cp_1(\dot{x}p_1 - \dot{x}k_1) = 0
\end{aligned} \tag{2}$$

$$\begin{aligned}
mk_2\ddot{x}k_2 + kk_2(xk_2 - x + k\theta) + ck_2(\dot{x}k_2 - \dot{x} + k\theta) - kp_2(xp_2 - xk_2) \\
- cp_2(\dot{x}p_2 - \dot{x}k_2) = 0
\end{aligned} \tag{3}$$

$$mp_1\ddot{x}p_1 + kp_1(xp_1 - xk_1) + cp_1(\dot{x}p_1 - \dot{x}k_1) = 0 \tag{4}$$

$$mp_2\ddot{x}p_2 + kp_2(xp_2 - xk_2) + cp_2(\dot{x}p_2 - \dot{x}k_2) = 0 \tag{5}$$

$$mt_1\ddot{x}t_1 + kt_1(xt_1 - xg_1) - ks_1(x - a\theta - xt_1) + ct_1(\dot{x}t_1 - \dot{x}g_1) = F_{MR}^f \tag{6}$$

$$mt_2\ddot{x}t_2 + kt_2(xt_2 - xg_2) - ks_2(x + b\theta - d\beta - xt_2) + ct_2(\dot{x}t_2 - \dot{x}g_2) = F_{MR}^{rl} \tag{7}$$

$$mt_3\ddot{x}t_3 + kt_3(xt_3 - xg_3) - ks_3(x + b\theta + e\beta - xt_3) + ct_3(\dot{x}t_3 - \dot{x}g_3) = F_{MR}^{rr} \tag{8}$$

$$\begin{aligned}
I_{zz}\ddot{\theta} + a \cdot ks_1(x - a\theta - xt_1) + b \cdot ks_2(x + b\theta - d\beta - xt_2) + b \cdot ks_3(x + b\theta \\
+ e\beta - xt_3) - l \cdot kk_1(xk_1 - x + l\theta) - k \cdot kk_2(xk_2 - x + k\theta) \\
- l \cdot ck_1(\dot{x}k_1 - \dot{x} + l\theta) - k \cdot ck_2(\dot{x}k_2 - \dot{x} + k\theta) \\
= a \cdot F_{MR}^f - b \cdot F_{MR}^{rr} - b \cdot F_{MR}^{rl}
\end{aligned} \tag{9}$$

$$\begin{aligned}
I_{yy}\ddot{\beta} - d \cdot ks_2(x + b\theta - d\beta - xt_2) + e \cdot ks_3(x + b\theta + e\beta - xt_3) \\
= d \cdot F_{MR}^{rr} - e \cdot F_{MR}^{rl}
\end{aligned} \tag{10}$$

F_{MR}^f , F_{MR}^{rr} and F_{MR}^{rl} represent the forces generated by the intelligent actuators at the front axle, and the right and left sides of the rear axle, respectively. MR dampers, with adjustable damping

capabilities, can operate over a wide force-displacement range and function as passive dampers in the absence of an electric current. The modeling of these dampers encompasses various approaches, ranging from simplified models to more complex ones that account for friction forces, gas chambers, and magnetic field effects.

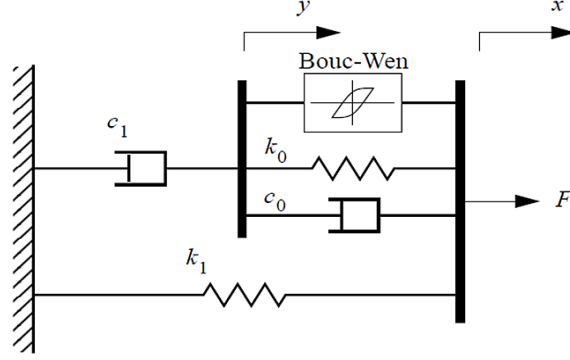


Fig. 2. Modified Bouc-Wen Damper Model

Fig. 2, illustrates the modified Bouc-Wen damper model. The system components include springs, dampers, and external forces applied to it, which are utilized for vibration analysis and control in complex systems such as aircraft landing gear.

The rigid rod forces on both sides of the damper are expressed by,

$$c_1 \dot{y} = a_h z + c_0 (\dot{x} - \dot{y}) + k_0 (x - y) \quad (11)$$

where z , the hysteretic variable, is defined as,

$$\dot{z} = -\gamma |\dot{x} - \dot{y}| |z|^{n-1} z - \beta (\dot{x} - \dot{y}) |z|^n + A (\dot{x} - \dot{y}) \quad (12)$$

using (11) and (12), (13) is derived:

$$\dot{y} = \frac{1}{c_0 + c_1} [a_h z + c_0 \dot{x} + k_0 (x - x_0)] \quad (13)$$

The total force of the damper can be expressed as,

$$F = a_h z + c_0 (\dot{x} - \dot{y}) + k_0 (x - y) + k_1 (x - x_0) = c_1 \dot{y} + k_1 (x - x_0) \quad (14)$$

Here, k_l represents the stiffness coefficient of the reservoir spring, c_0 denotes the damping coefficient at high velocities, c_l accounts for the attenuation effect at low velocities, k_0 is the spring stiffness at high velocities, and x_0 is the initial displacement due to accumulated stiffness defined as k_l .

$$\begin{aligned} a_h &= a_{ha} + a_{hb}u \\ c_1 &= c_{1a} + c_{1b}u \\ c_0 &= c_{0a} + c_{0b}u \end{aligned} \tag{15}$$

Here, u is a first-order filter calculated by,

$$\dot{u} = -\eta(u - V) \tag{16}$$

where V is the voltage applied to the damper.

3. Design and Optimization of the Fuzzy Controller

This study investigates the control of complex nonlinear aircraft landing gear systems using Type-1 and Type-2 fuzzy systems. Due to the inherent nonlinear characteristics, disturbances, and modeling complexities of landing gear systems, advanced control methods are essential. To address these challenges, fuzzy systems are designed using metaheuristic optimization techniques aimed at minimizing the sum of squared errors, thereby enhancing vibration control accuracy and impact absorption. Type-1 fuzzy systems are composed of four main components: the fuzzy rule base, fuzzy inference engine, fuzzification, and defuzzification. Input values are fuzzified and processed in the inference engine based on predefined fuzzy rules, and the results are defuzzified into actionable control signals. Type-2 fuzzy systems extend Type-1 systems by addressing uncertainties in membership functions, where each membership function is represented as a fuzzy set within the range $[0,1]$. These systems are particularly effective in scenarios involving

uncertainty about the degree of membership or ambiguity in the parameters of the membership function. The membership functions in Type-2 systems are modeled as two-dimensional functions, resulting in three-dimensional surface representations, with upper and lower membership functions defining the uncertainty bounds. When uniform uncertainty is assumed between these bounds, the system is referred to as an interval Type-2 fuzzy system. This approach allows for improved handling of uncertainties and enhances the overall precision and robustness of the landing gear control system.

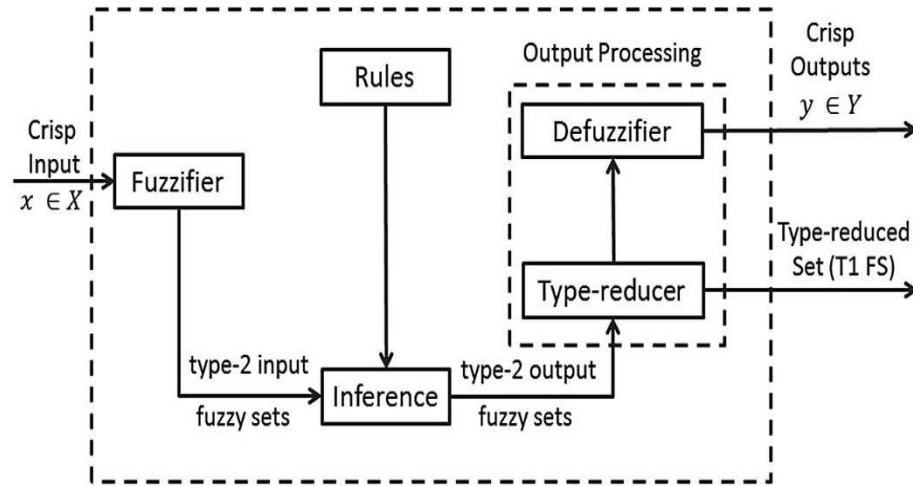


Fig. 3. The Structure of a Type-2 Fuzzy Logic System

Fig. 3, illustrates the structure of a Type-2 fuzzy inference system, highlighting the core components: fuzzifier, inference engine, rule base, type-reducer, and defuzzifier. The system processes crisp inputs into fuzzy sets via the fuzzifier, applies the fuzzy rules to generate a Type-2 fuzzy output, and subsequently reduces it to a Type-1 fuzzy set through the type-reducer. Finally, the defuzzifier converts the reduced fuzzy set into a crisp output, enabling actionable decisions.

The proposed vibration control approach for the fighter aircraft landing gear system, equipped with intelligent dampers, is implemented along three axes using Type-1 and Type-2 fuzzy control systems, as shown in Fig. 4. In this approach, the displacement and velocity at both ends of the intelligent dampers are measured and sent as inputs to the fuzzy controllers. The system operates as a closed-loop self-tuning structure, eliminating reference inputs and utilizing a feedback loop with a negative sign to ensure proper functionality. The controller's primary objective is to suppress disturbances or base excitations x_g . Input signals to the fuzzy system pass through scaling gains g_e and $g_{\dot{e}}$ while the fuzzy controller output is scaled using a gain h to adjust the control signal, which serves as the input voltage for the magnetorheological (MR) damper actuator. The MR damper generates a proportional force based on the control signal, effectively mitigating landing gear vibrations. This design leverages the tunable damping properties of MR dampers and the adaptability of fuzzy controllers, ensuring robust performance under nonlinear and uncertain operating conditions.

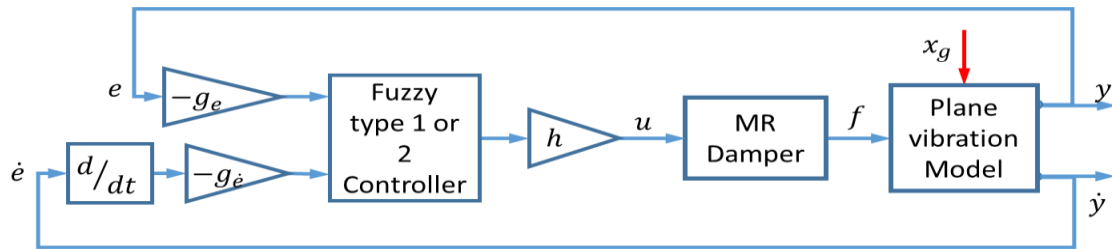


Fig. 4. Closed-Loop Block Diagram of the Aircraft Landing Gear Vibration Control System

Fig. 5, illustrates the block diagram of the fuzzy system optimization. It represents a Type-1 fuzzy control system where an optimization algorithm is employed to enhance its performance. The inputs consist of the error and its derivative, while the control signal u is processed by the fuzzy controller and optimizer to produce the output signal h . Fuzzy optimization refers to the process of adjusting the parameters of a fuzzy system, such as membership functions and fuzzy rules,

using optimization algorithms to maximize the system's performance. A compact mathematical representation of the fuzzy system rule table optimization problem is provided as,

$$\begin{aligned} \min_x J(x) &= \int_0^{t_{ss}} (w_e e^2 + w_{\dot{e}} \dot{e}^2 + w_u u^2) d\tau \\ \text{s.t. } 1 &\leq x_i (i = 1, \dots, n_{rules}) \leq n_{rules} \\ x_i (i &= 1, \dots, n_{rules}) \in N \end{aligned} \quad (18)$$

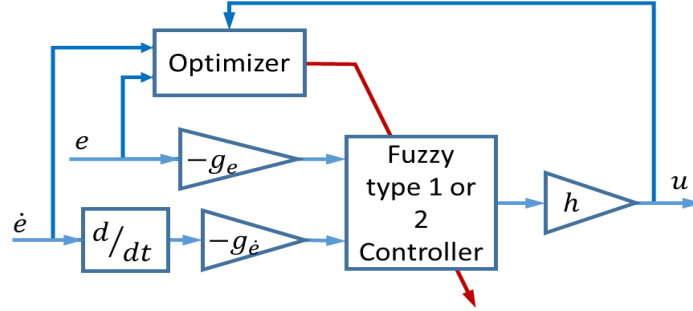


Fig.5. Optimization of Fuzzy Systems

Each element of the design variable vector x represents the index of the "then" part of the fuzzy propositions, belonging to the set of natural numbers. Considering the structure of a complete fuzzy system with n inputs and mm membership functions, these indices range from 1 to m . Additionally, t_{ss} denotes the settling time of the input tracking process, while e , $\dot{e}$, and u represent the tracking error, the rate of change of the tracking error, and the control effort, respectively. The terms w_e , $w_{\dot{e}}$, and w_u are the scaling coefficients.

4. Numerical Example

The simulations conducted for modeling the process and the intelligent magnetorheological damper require precise physical data. These data have been obtained from reliable sources, and for greater accuracy, the information provided in reference [12] has been utilized. The values of these data are fully presented in Tables 1 and 2. Using these data as the primary inputs for the

simulations enables a more accurate evaluation of the system's performance, thereby enhancing the precision and credibility of the analyses conducted in this study.

Table. 1. Vibrational Model Parameters of the Fighter Aircraft [12]

Parameter	Value	Unit	Parameter	Value	Unit
M	2200	kg	I_{ee}	6561.3	kg·m ²
I_{pp}	1001.3	kg·m ²	m_{e1}	120	kg
m_{e2}	120	kg	m_{e3}	120	kg
m_{s1}	15	kg	m_{s2}	15	kg
m_{a1}	61	kg	m_{a2}	61	kg
k_{s1}	625701.3	N/m	k_{s2}	408901.3	N/m
k_{s3}	215401.3	N/m	k_{t1}	15901.3	N/m
k_{t2}	15901.3	N/m	k_{t3}	15901.3	N/m
k_{s1}	31	N/m	k_{s2}	31	N/m
c_{s1}	144301.3	N·s/m	c_{s2}	62501.3	N·s/m
c_{s3}	62501.3	N·s/m	c_{t1}	4106.6	N·s/m
c_{t2}	4106.6	N·s/m	c_{t3}	4106.6	N·s/m
c_{a1}	2475	N·s/m	c_{a2}	2475	N·s/m
a	7.76	m	b	1.94	m
d	3.8425	m	e	3.8425	m
k	3	m	l	6	m

Table. 2. Empirical Coefficients of the Magnetorheological Damper [12]

Parameter	Value	Unit
A	58	-
k₀	3610	[N/m]
k₁	840	[N/m]
a_{ha}	14441	[N.s/V.m]
a_{hβ}	13820	[N.s/V.m]
c_{1a}	14449	[N.s/m]
c_{1β}	34622	[N.s/m]
c_{0a}	784	[N.s/m]
c_{0β}	1803	[N.s/V.m]
n	2	-

According to Fig. 6.a and Fig. 6.b, the fuzzy systems utilized are of the Mamdani type with two inputs and one output, featuring 7 membership functions for the inputs and 4 membership functions for the output. As expected, both fuzzy systems contain 49 fuzzy rules, with the main task of the optimization algorithm being the adjustment of these fuzzy rules. The input and output scaling factors for all fuzzy systems are $g_e = 1$, $g_{\dot{e}} = 0.2$ and $h = 5$ respectively.

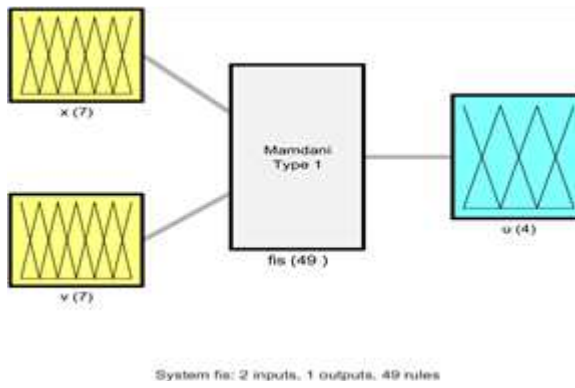


Fig. 6. a. Structure of a Type-1 Fuzzy System

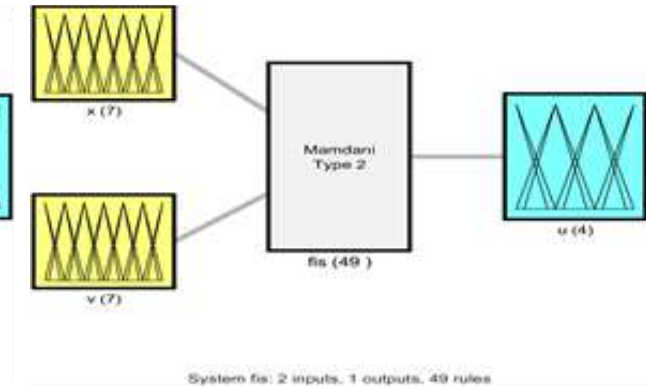


Fig. 6. b. Structure of a Type-2 Fuzzy System

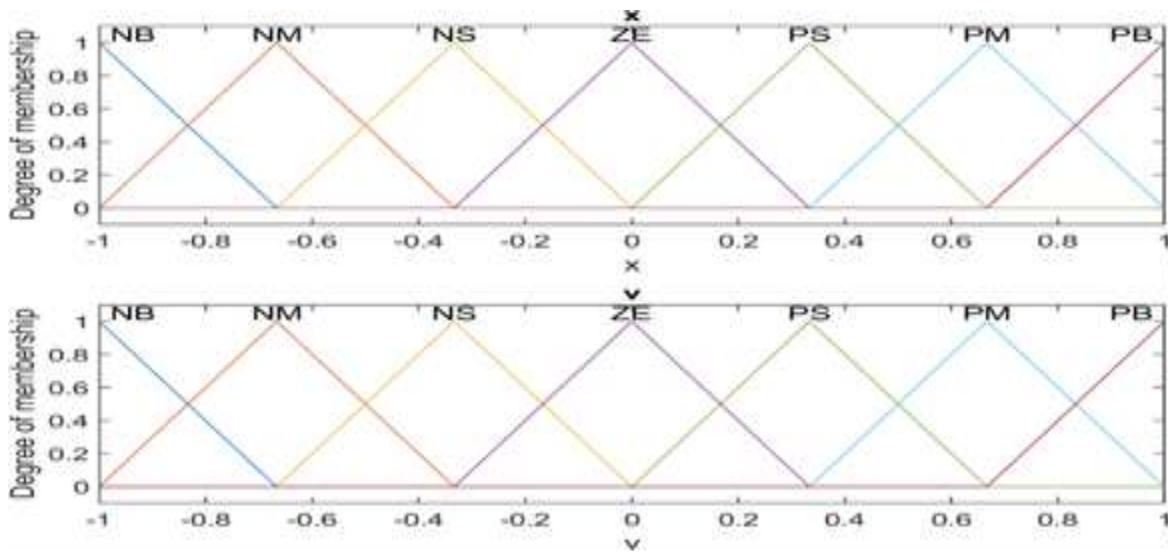


Fig. 7. a. Input Membership Functions of Type-1 Fuzzy Systems

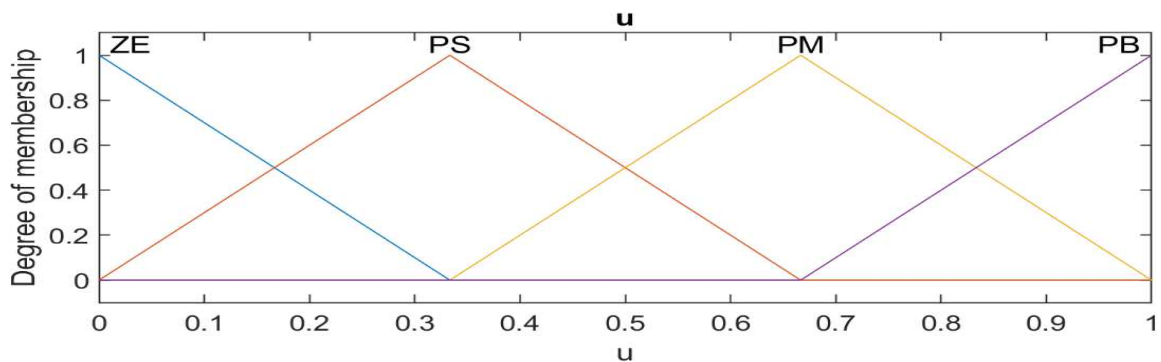


Fig. 7. b. Output Membership Functions of Type-1 Fuzzy Systems

Fig. 7.a, demonstrates the membership functions of a Type-1 fuzzy logic system. The upper plot represents the input variable x , while the lower plot corresponds to the input variable v , both

featuring seven triangular membership functions evenly distributed over the range $[-1,1]$, ensuring comprehensive coverage and smooth transition between linguistic terms. Fig. 7.b, illustrates the membership functions of the output variable in a Type-1 fuzzy logic system. The output is represented by four triangular membership functions (ZE, PS, PM, PB) distributed across the range $[0, 1]$, ensuring a smooth and precise mapping for the fuzzy inference process.

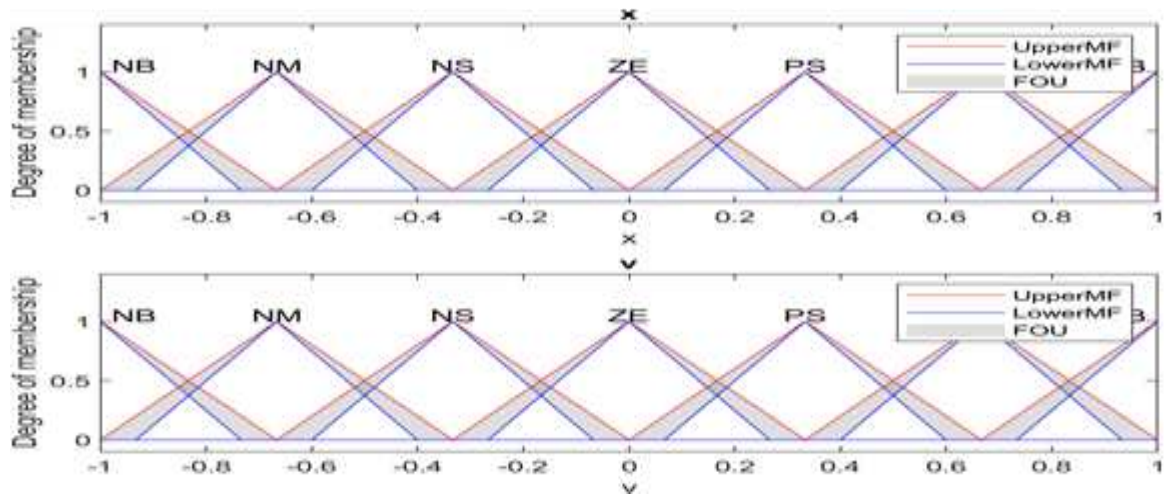


Fig. 8. a. Input Membership Functions of Type-2 Fuzzy Systems with [12] method

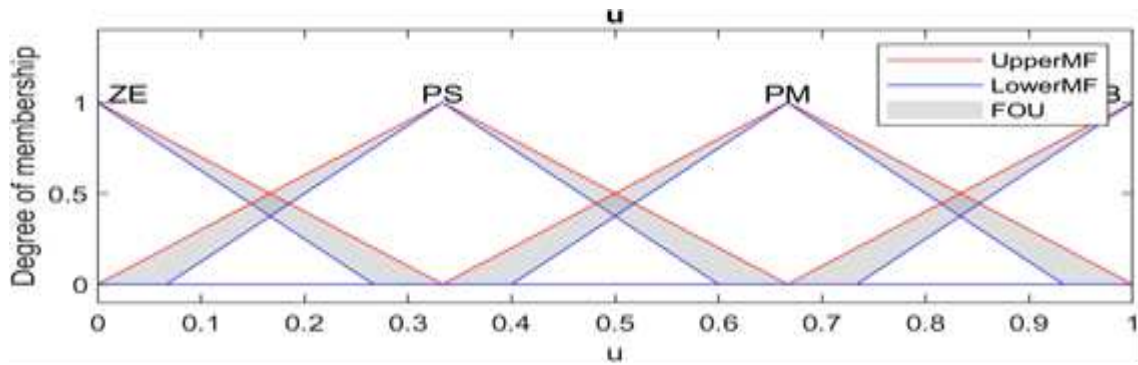


Fig. 8. b. Output Membership Functions of Type-2 Fuzzy Systems with [12] method

Fig. 8.a, presents the input membership functions for variables x and v , each characterized by seven triangular membership functions defined by Upper Membership Functions (Upper MF) and Lower Membership Functions (Lower MF). The shaded region between these boundaries, known as the Footprint of Uncertainty (FOU), captures the range of uncertainty, enhancing

robustness and precision over the input range $[-1,1]$. Similarly, Fig. 8.b, illustrates the output membership functions for variable u , featuring four triangular membership functions (ZE, PS, PM, PB) with a corresponding FOU, ensuring reliability in handling imprecision across the output range $[0, 1]$. Together, these figures underscore the critical role of FOU in providing flexibility, adaptability, and enhanced decision-making capabilities in uncertain environments.

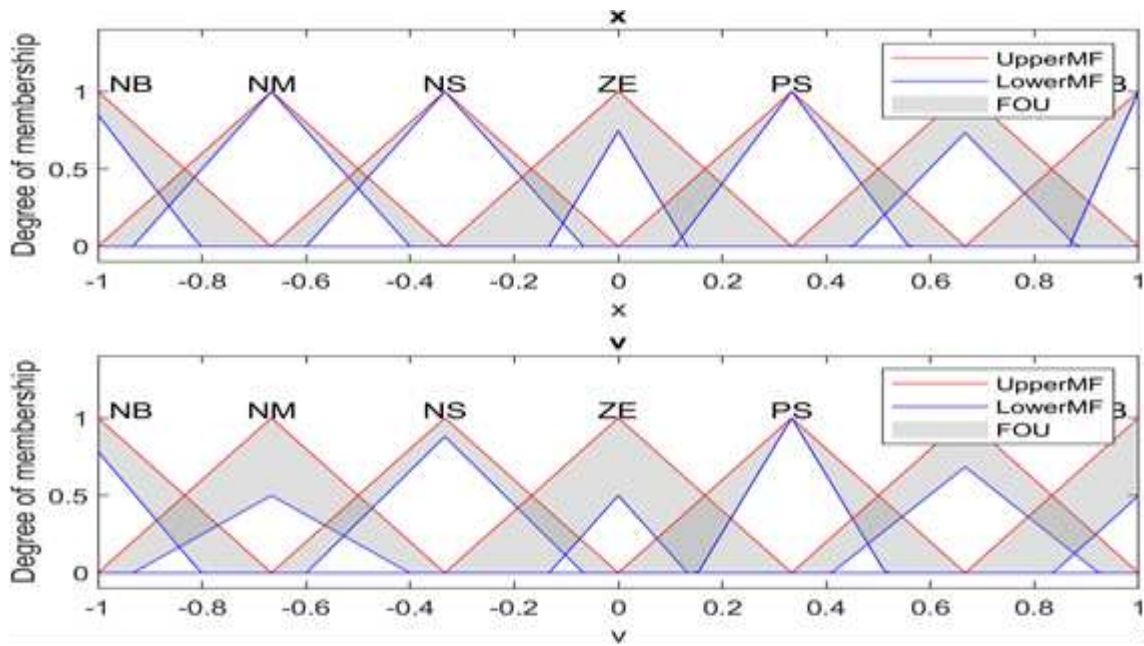


Fig. 9. a. Input Membership Functions of Type-2 Fuzzy Systems with proposed method

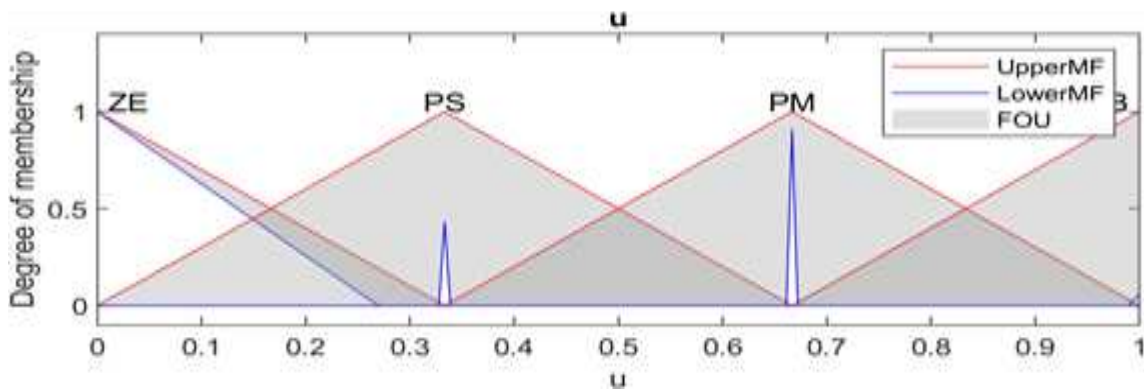


Fig. 9. b. Output Membership Functions of Type-2 Fuzzy Systems with proposed method

Fig. 9.a and Fig. 9.b, depict the input and output membership functions of the tuned Interval Type-2 fuzzy system. In Fig. 9.a, the input membership functions for variables x and v are represented

by seven triangular functions, where the upper membership functions, lower membership functions, and the footprint of uncertainty have been optimized during the tuning process. This optimization reduces uncertainty, focuses on relevant regions, and enhances the system's precision in handling uncertain input data. In Fig. 9.b, the output membership functions for the variable u are displayed with four triangular functions (ZE, PS, PM, PB), where the footprint of uncertainty and the boundaries have also been refined, improving the system's control and reliability in generating accurate outputs. The main difference between Fig. 9.a and Fig. 9.b and Fig. 8.a and Fig. 8.b lies in the tuning process, which reduces uncertainty effects, increases adaptability, and provides sharper boundaries for decision-making. These adjustments make the system in Fig. 9.a and Fig. 9.b superior in terms of precision, reliability, and performance compared to the initial system.

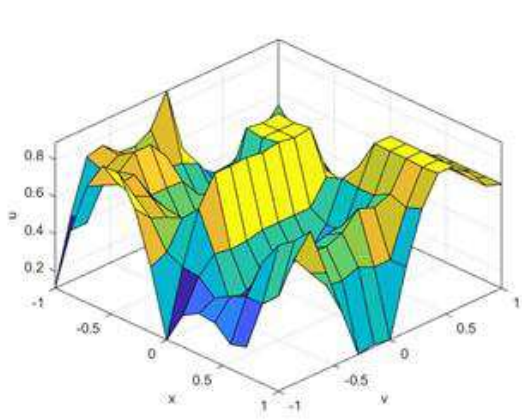


Fig. 10. A. Output Surface of a Type-1 Fuzzy System
with [12] method

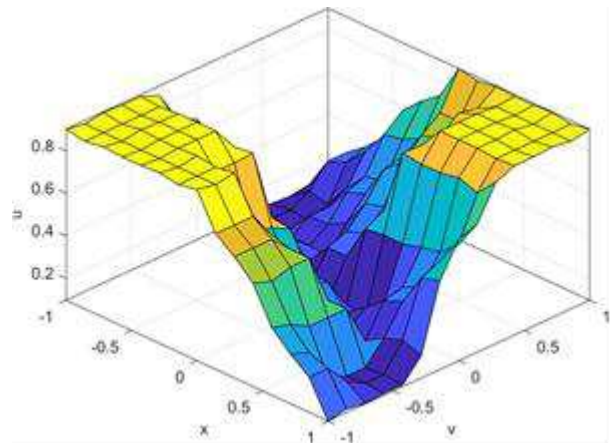


Fig. 10. b. Output Surface of a Type-1 Fuzzy System
with proposed method

Fig. 10.a and Fig. 10.b, illustrate the output surfaces of a Type-1 fuzzy system before and after tuning, respectively. Fig. 10.a shows the conventional surface, where the output u is generated based on the inputs x and v . This surface exhibits irregularities and abrupt transitions, reflecting limitations in capturing complex relationships and nonlinearities. In contrast, Fig. 10.b, depicts

the adjusted surface after tuning, which is significantly smoother and more consistent. The tuning process refines the membership functions and fuzzy rules, resulting in enhanced accuracy, better modeling of nonlinear input-output relationships, and improved robustness in handling uncertainty. Compared to the untuned system, the tuned system not only provides a more precise and reliable mapping but is also better suited for real-world applications where adaptability and precision are essential.

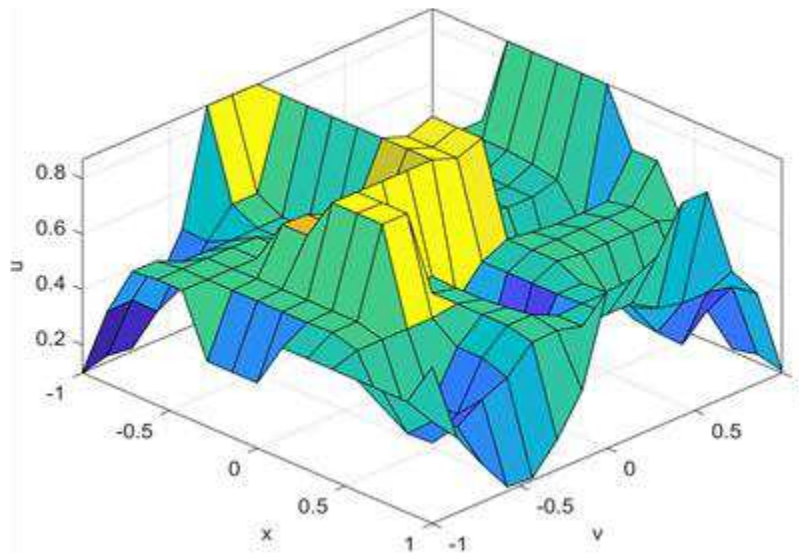


Fig. 11. Output Surface of an Interval Type-2 Fuzzy System with proposed method

Fig.11 illustrates the output surface of a tuned Interval Type-2 fuzzy system, where the output u is modeled as a function of the inputs x and v . Fig.11 highlights the system's ability to handle nonlinear relationships and uncertainties effectively. The irregularities in the output surface reflect the flexibility of the system in adapting to subtle changes and the complexities of input-output relationships. The tuning process optimizes the membership functions and fuzzy rules, enhancing the system's accuracy and adaptability. The key advantage of an Interval Type-2 fuzzy system compared to a Type-1 system lies in its ability to model and manage the footprint of uncertainty (FOU), resulting in improved precision, flexibility, and reliability in noisy and

dynamic environments. These features make it a powerful tool for complex and real-world applications.

Tables 3 and 4 both represent fuzzy rules for a tuned Type-1 fuzzy system, showcasing the mapping between the inputs and the output. While the structure is similar, the output mappings differ significantly. Table. 3, demonstrates a simpler rule set, where the output u is more focused on specific values like PB and ZE, indicating less aggressive tuning. In contrast, Table. 4, shows a more diverse rule mapping, with smoother transitions to other linguistic terms like PS and PM, reflecting a more refined tuning process. This refinement enhances the system's adaptability and precision in handling complex input-output relationships. Table. 3, may be more suitable for simpler applications prioritizing interpretability, whereas Table. 4, offers better performance in dynamic and complex scenarios requiring higher precision.

Table. 3. Fuzzy Rules of a Tuned Type-1 Fuzzy System with [12] method

	v: NB	v: NM	v: NS	v: ZE	v: PS	v: PM	v: PB
x: NB	u: PB	u: PB	u: PB	u: PM	u: ZE	u: ZE	u: ZE
x: NM	u: PB	u: PB	u: PB	u: PS	u: ZE	u: ZE	u: PS
x: NS	u: PB	u: PB	u: PB	u: ZE	u: ZE	u: PS	u: PM
x: ZE	u: PB	u: PB	u: PS	u: ZE	u: PS	u: PM	u: PB
x: PS	u: PM	u: PM	u: ZE	u: ZE	u: PB	u: PB	u: PB
x: PM	u: PS	u: ZE	u: ZE	u: PS	u: PB	u: PB	u: PB
x: PB	u: ZE	u: ZE	u: ZE	u: PM	u: PB	u: PB	u: PB

Table. 4. Fuzzy Rules of a Tuned Type-1 Fuzzy System with proposed method

	v: NB	v: NM	v: NS	v: ZE	v: PS	v: PM	v: PB
x: NB	u: ZE	u: PB	u: PM	u: PB	u: PS	u: PS	u: PS
x: NM	u: PB	u: PB	u: PB	u: PS	u: ZE	u: PB	u: PS
x: NS	u: PB	u: PM	u: PS	u: PB	u: PB	u: PS	u: ZE
x: ZE	u: ZE	u: PB	u: PB	u: PB	u: PB	u: ZE	u: PS
x: PS	u: PS	u: ZE	u: PS	u: PS	u: PB	u: PB	u: PM
x: PM	u: ZE	u: PB	u: PM	u: PB	u: PB	u: PB	u: PM
x: PB	u: PB	u: PB	u: ZE	u: ZE	u: PB	u: PB	u: PM

Table. 5, presents the fuzzy rules for a tuned Interval Type-2 fuzzy system, showcasing the relationships between the input variables x and v the corresponding output u . The linguistic terms (NB, NM, NS, ZE, PS, PM, PB) represent the membership functions of the input variables, while the output values u are determined based on these combinations. This table reflects the enhanced adaptability and precision achieved through the tuning process, which optimizes the system's rules to better handle uncertainties and nonlinear relationships. By incorporating Interval Type-2 fuzzy logic, the system gains robustness and improved decision-making capabilities, particularly in dynamic and uncertain environments.

Table. 5. Fuzzy Rules of a Tuned Interval Type-2 Fuzzy System with proposed method

	v: NB	v: NM	v: NS	v: ZE	v: PS	v: PM	v: PB
x: NB	u: ZE	u: ZE	u: PB	u: PB	u: PM	u: ZE	u: ZE
x: NM	u: PB	u: PS	u: PS	u: PB	u: ZE	u: PM	u: PB
x: NS	u: PS	u: PB	u: PM	u: PB	u: PB	u: PS	u: PB
x: ZE	u: PS	u: PB	u: PB	u: PB	u: PB	u: ZE	u: PB
x: PS	u: PM	u: PB	u: PB	u: ZE	u: PB	u: PB	u: PM
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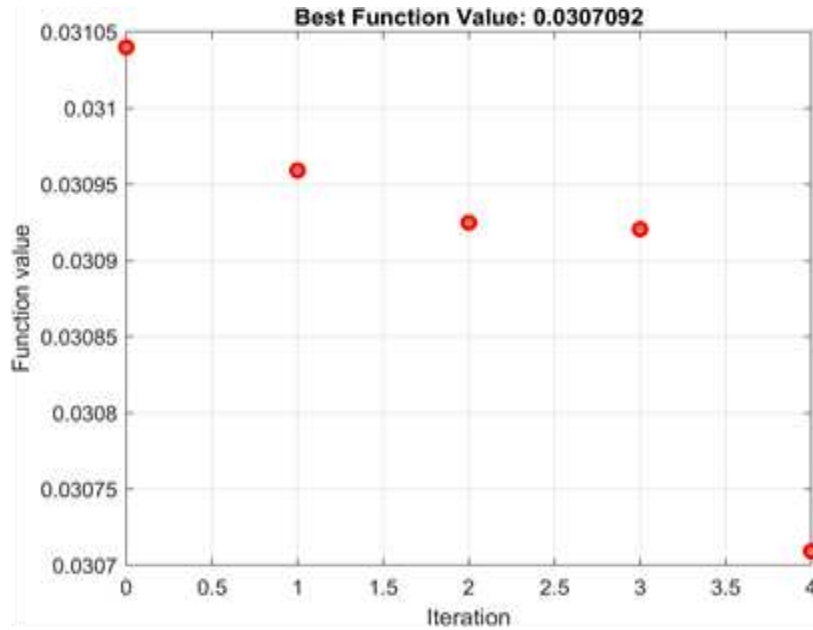


Fig. 12. Optimization Process of an Interval Type-2 Fuzzy System

Fig. 12, illustrates the optimization process of an Interval Type-2 fuzzy system. The horizontal axis shows the number of iterations, and the vertical axis represents the function value. The function value decreases with each iteration, converging to the optimal value of 0.0307092 by the fourth iteration. This trend highlights the efficiency of the algorithm in fine-tuning the system's parameters and rules, leading to improved accuracy and reduced error.

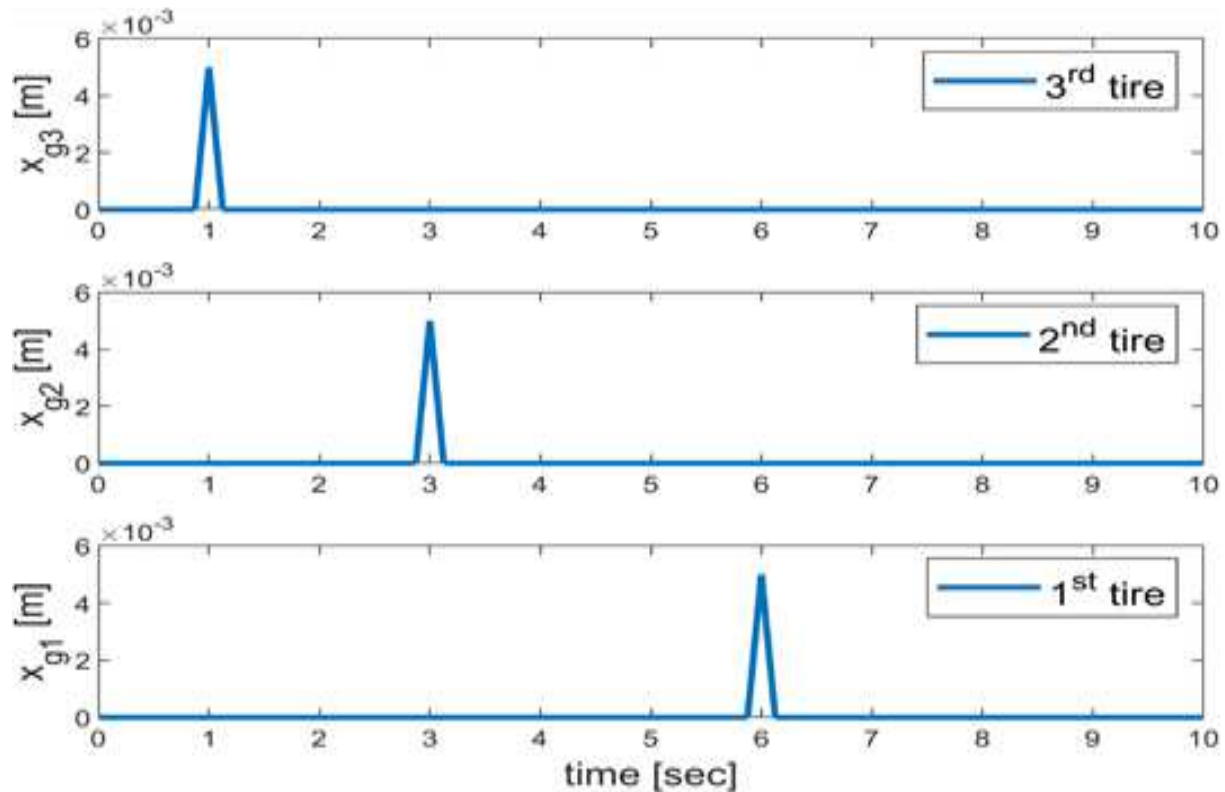


Fig. 13. Base Excitation of Aircraft Landing Gear

Fig. 13, illustrates the displacement of the tires over time during a simulated landing scenario. The simulation replicates the impact of the landing gear with the runway, applying three sharp triangular excitation waves with a maximum amplitude of 5 millimeters at different times. The graph depicts the dynamic response of each tire: the 3rd tire experiences the first excitation with a peak displacement of 4 millimeters, followed by the 2nd tire and then the 1st tire, each showing similar maximum displacements. This simulation highlights the behavior of the landing gear

under impact forces and provides valuable insights into its performance and stability, which are crucial for ensuring the safety and reliability of aircraft operations during landing.

Based on the mathematical relations presented in Section 3, the nonlinear and complex dynamics of magnetic dampers are explained. The exact solution of these relations over time plays a significant role in the performance of the control system. The damping force of magnetic dampers, as vibration control actuators, is calculated considering the base excitation of the aircraft landing gear and transmitted to the vibration model. Fig.14 to Fig.17, demonstrate the performance of the dampers in response to these excitations.

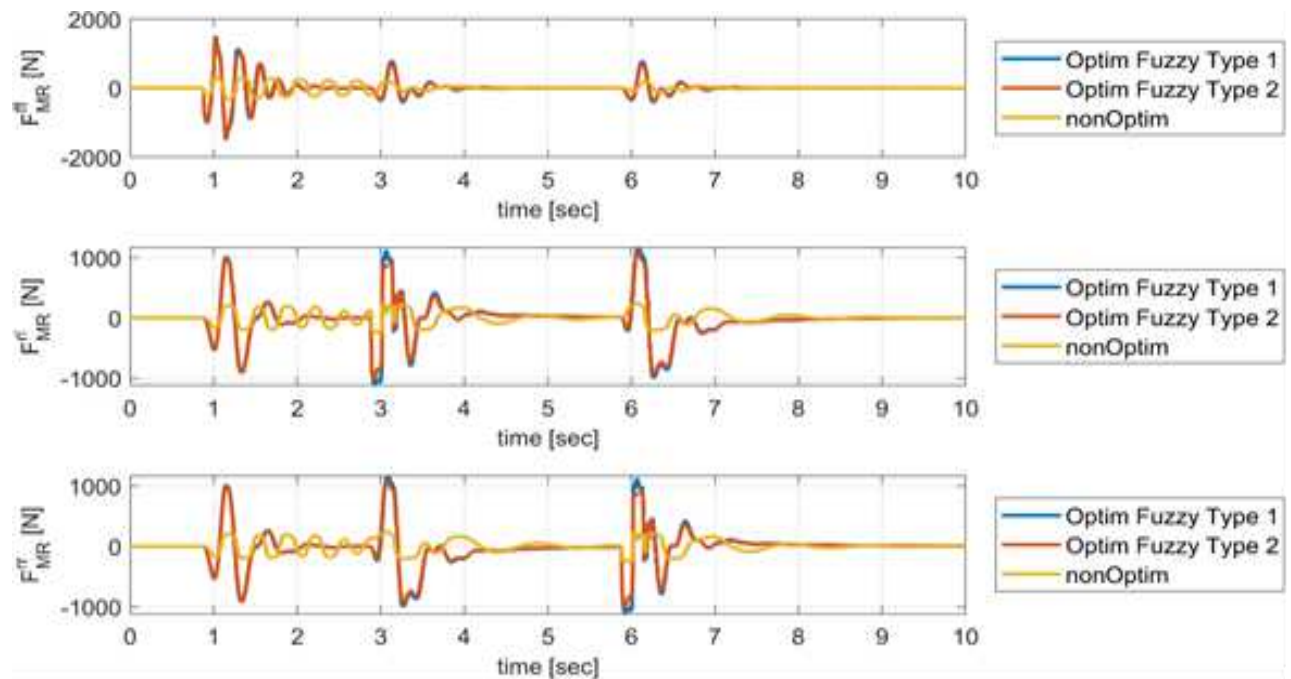


Fig.14. Comparative Force Responses of Front, Rear Left, and Rear Right Magnetic Dampers Under Base Excitations

Fig. 14, illustrates the forces generated by magnetic dampers in response to base excitations. The Type-2 fuzzy method produces the highest and smoothest forces, showcasing its superior capability in handling uncertainties and providing precise vibration control. The Type-1 fuzzy

method generates slightly lower forces, which are still stable and significantly improved compared to the reference method. In contrast, the reference method produces low and erratic forces, indicating poor performance and instability in managing the dynamic response

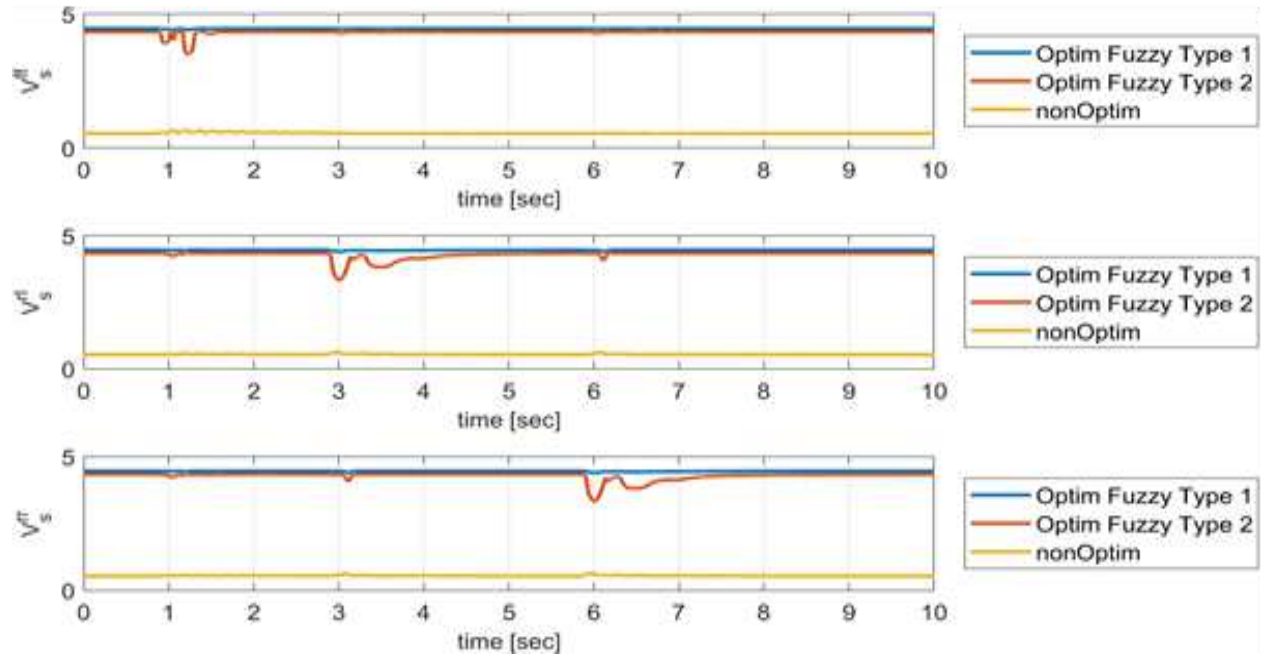


Fig. 15. Voltage Responses of Front, Rear Left, and Rear Right Magnetic Dampers in Different Control Methods

Fig. 15, depicts the applied voltage V to the dampers over time. In the Type-2 fuzzy method, the voltage is relatively high and remains stable, reflecting consistent and efficient control. The Type-1 fuzzy method exhibits slightly lower voltage levels, but it is still stable and significantly better than the reference method. The reference method shows minimal and unstable voltage levels, indicating insufficient energy for effective damper control.

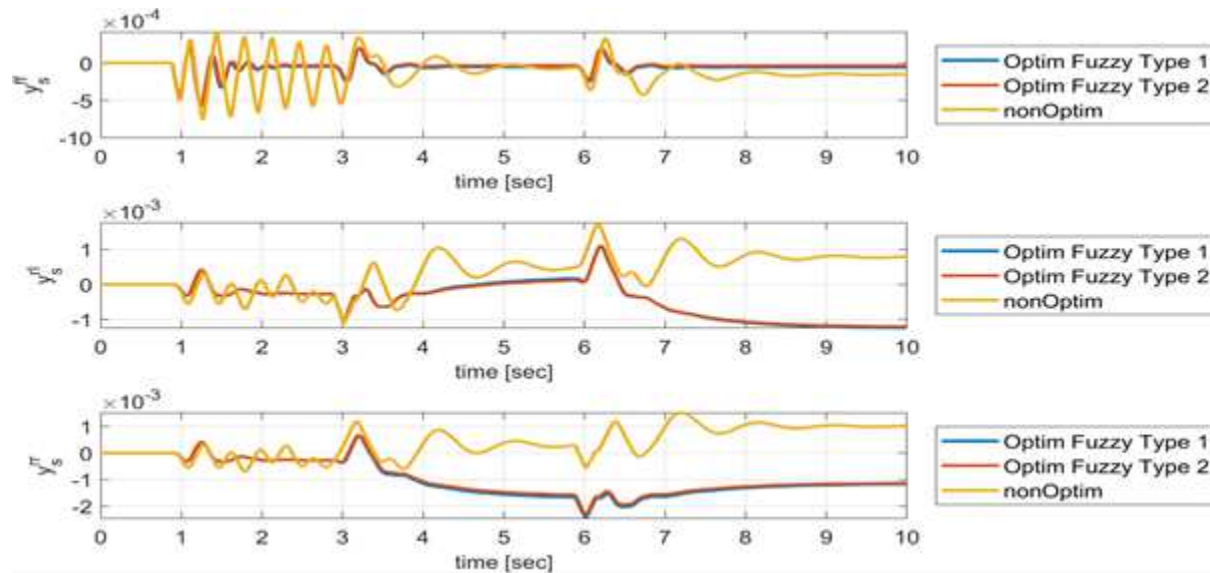


Fig. 16. Displacement y Variations of Front, Rear Left, and Rear Right Magnetic Dampers Over Time

Fig. 16, shows the variations in the internal variable y for the dampers over time. The Type-2 fuzzy method maintains smooth and uniform changes in y , demonstrating excellent control and stability in nonlinear dynamic conditions. The Type-1 fuzzy method also achieves smooth transitions, though it exhibits minor fluctuations compared to Type-2. The reference method shows highly erratic and unstable behavior, indicating poor management of the internal dynamics.

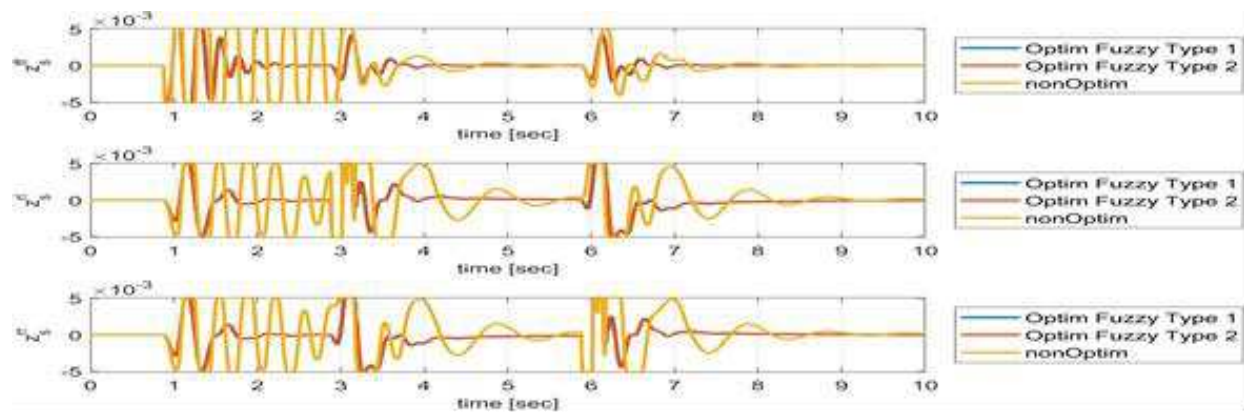


Fig. 17. Hysteresis Acceleration z Variations of Front, Rear Left, and Rear Right Magnetic Dampers in Response to Excitations

Fig. 17, presents the changes in the internal variable z over time. The Type-2 fuzzy method ensures minimal and stable fluctuations in z , highlighting its superior control over hysteresis behavior. The Type-1 fuzzy method, while stable, exhibits slightly more variability than Type-2 but still performs better than the reference method. The reference method shows erratic and highly unstable behavior, failing to manage hysteresis effects effectively.

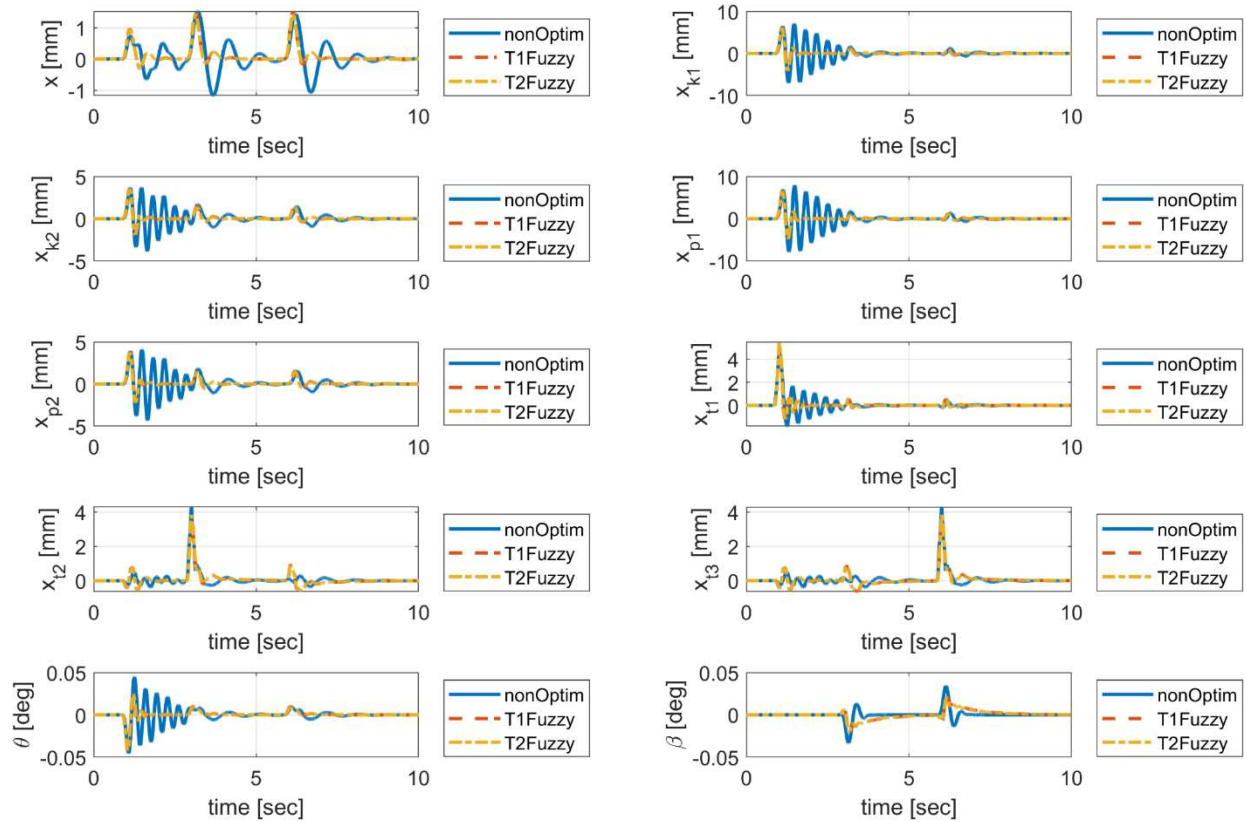


Fig. 18. Time Variations of Landing Gear State Variables Under Base Excitations

Fig. 18, shows the variations in the state variables of the landing gear system, which include eight translational movements of the masses and two rotational movements, specifically pitch and roll of the aircraft body, in response to base excitations. The immediate reaction of the dampers at the first, third, and sixth seconds, when the landing gear encounters base excitations, is evident in all state variables. The non-optimized fuzzy control system, based on the method outlined in [12],

exhibits significant oscillations across all state variables, particularly during the first excitation. In contrast, the optimized fuzzy controllers, including Type-1 and Type-2, display far smoother and more controlled behavior, with significantly reduced oscillations. The most intense response is observed during the first excitation at the first second, although for some variables, more pronounced responses are evident during the third and sixth seconds. The angular displacements in pitch and roll are negligible for all methods, remaining below 0.05 degrees, which is practically insignificant for operational concerns. Additionally, the optimized fuzzy controllers limit the displacement experienced by pilots to less than 10 millimeters in the first channel and 5 millimeters in the second channel, ensuring superior ride quality and minimal vibration transmission compared to the conventional system.

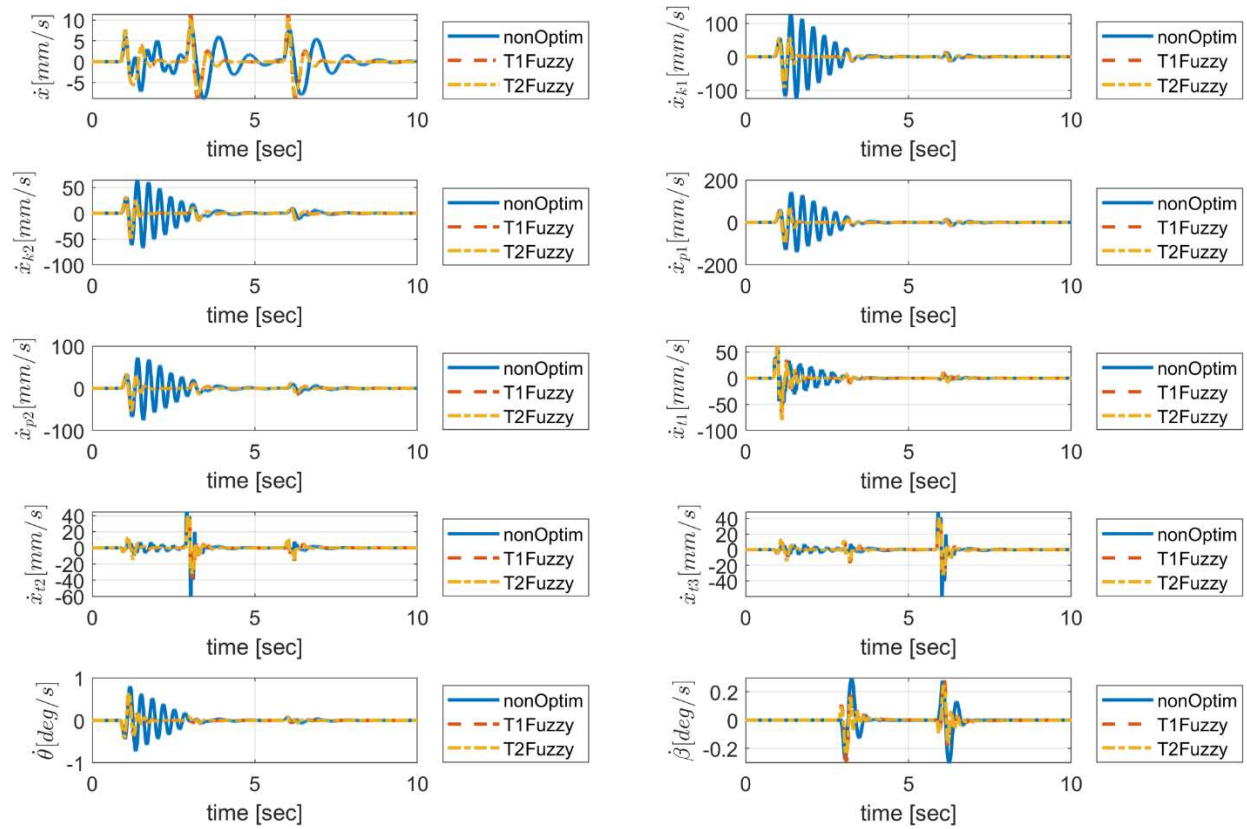


Fig. 19. Velocity Variations of Landing Gear State Variables Under Base Excitations

Fig. 19, presents the rate of change velocity of the state variables over time for the three control methods. The non-optimized fuzzy control system exhibits unstable and erratic velocities, with significant overshoots, reflecting its inability to effectively manage dynamic instabilities. The optimized fuzzy controllers, particularly the Type-2 fuzzy controller, demonstrate superior performance with smoother velocity profiles and improved stability. The aircraft body velocity under the optimized controllers is higher but remains controlled, indicating better dynamic adaptation to base excitations. The velocity experienced by pilots in the two channels is limited to approximately 100 mm/s and 50 mm/s, respectively, for the optimized controllers, which is a substantial improvement over the higher and more erratic velocities observed in the conventional method.

Based on Fig. 18 and Fig.19, the comparison between the three methods highlights clear distinctions in their performance. The Type-2 fuzzy control method outperforms both Type-1 and non-optimized systems across all metrics, delivering smoother state variable responses, reduced oscillations, and well-controlled velocities. Its ability to effectively handle uncertainties and nonlinear dynamics makes it the most reliable and efficient approach for minimizing vibrations and ensuring system stability. The Type-1 fuzzy control method shows significant improvement over the non-optimized system, with reduced oscillations and stabilized velocities, but it lacks the advanced uncertainty management capabilities of the Type-2 method. In contrast, the non-optimized fuzzy control method demonstrates the weakest performance, with significant oscillations, erratic velocity profiles, and poor stability, which lead to discomfort and higher vibration levels for the aircraft and its passengers. In conclusion, the Type-2 fuzzy control method stands out as the superior choice for managing the dynamic responses of the landing gear system,

offering enhanced stability, reduced vibrations, and greater comfort for pilots and passengers compared to the other two methods.

5. Conclusion

This article comprehensively investigates the reduction of landing gear vibrations during landing and taxiing using fuzzy control systems and intelligent magnetic dampers. The findings demonstrate that designing Type-1 and Type-2 fuzzy control systems through metaheuristic optimization methods, such as particle swarm optimization, significantly outperforms conventional approaches that rely on manual rule table tuning based on expert knowledge. The optimized fuzzy systems effectively reduce vibrations caused by landing and movement, while also providing enhanced stability and performance. Additionally, the results highlight that optimization-based methods not only improve the accuracy and efficiency of fuzzy system design but also minimize dependency on empirical models and expert knowledge. This enables the development of flexible and powerful computational frameworks for designing intelligent control systems capable of operating optimally in complex and nonlinear conditions. The article further emphasizes the positive impact of optimized fuzzy systems in mitigating oscillations and improving vibration control in closed-loop systems. Overall, the findings underscore the effectiveness of optimization-driven approaches in designing Type-1 and Type-2 fuzzy control systems and their critical role in addressing complex challenges and providing practical, efficient solutions in intelligent control applications.

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Competing Interests:

The authors declare no competing interests.

Data Availability:

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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