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Adaptive Control and Enhanced Algorithm for Efficient Drilling in Composite Materials

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ABSTRACT

Due to their inexpensive cost and superior qualities compared to conventional metals, Glass Fibre Reinforced Plastic (GFRP) composites are frequently used in engineering applications. Despite the development of numerous non-traditional drilling methods, traditional mechanical drilling methods based on CNC machines are still utilized as the primary applications for composites due to their financial advantages. Damage in the composite materials during the drilling process due to delamination often happens. The delamination has directly related to the drilling force. A dynamic model of the drilling force is a function of the feed rate. Due to the unpredictable nature of the composite material's physical and chemical properties, it may be challenging to realize the dynamics of the drilling process in this material. In this paper, the mathematical model of the drilling process is obtained experimentally based on system identification. Then, to address the problem of controlling the drilling force of composite materials, this paper proposes a Model Reference Adaptive Control (MRAC) based on the Enhanced Flower Pollination Algorithm (EFPA) to handle the uncertainties and time-varying dynamics of the drilling process. The performance of the proposed controller is evaluated based on the Integral Time of Absolute Error (ITAE) index. The simulation results show that the proposed controller is effective in avoiding drilling-induced delamination in composite under different operation conditions.

1. INTRODUCTION

Due to the requirement for connecting components, drilling is regarded as the secondary machining method that is used the most frequently [1]. Although many non-traditional drilling techniques have been developed, such as laser machining, water-jet machining, electrochemical, electro-discharge, and electrochemical discharge to create holes, traditional mechanical drilling techniques based on CNC machines are still used as the primary applications because of their financial benefits [1].

For a very long time, humans have employed traditional materials including glassware, polymers, ceramics, and metal alloys. Overall, composite materials have revolutionized many industries by providing uncommon combinations of properties not found in conventional materials alone. Through advancements in material science and manufacturing techniques, engineers continue to develop new composite materials with enhanced properties to meet the ever-growing demands of modern technology [2]. Composite materials can also exhibit other desirable properties, such as high thermal resistance, chemical resistance, electrical conductivity or insulation, and even tailored thermal expansion coefficients. These characteristics make composites versatile and enable their use in a wide range of applications across various industries [3]. Glass Fibre Reinforced Plastic (GFRP) is extensively used in appliances, printed wiring boards, machine tool components, etc. because of its electrical insulating capabilities [3].

It can be challenging to realize the mechanism of the drilling process because the constituents' physical and chemical properties fluctuate. However, a dynamic model of the drilling force is primarily based on the feed rate. Besides, drill geometry, depth of the process, temperature, and tool material are just a few examples of the variables that might affect the thrust force in GFRP composites [4]. A composite construction may be harmed by delamination, fibre pull-out, and extreme thrust force, though. The drilling operation produces heat, and too much heat may harm the GFRP composite material. The temperature rise during drilling is influenced by factors like cutting speed, feed rate, drill shape, and cooling/lubrication methods. Surface roughness, delamination, fibre degradation, and other variables are used to evaluate the quality of holes in GFRP composites [4].

Adaptive control techniques can be applied to drilling machines to improve their performance and adapt to varying drilling conditions. Model-based adaptive control involves developing a mathematical model of the drilling machine and the drilling process. This model is used to estimate the system dynamics and predict the behaviour of the drilling machine [5]. Besides, adaptive control techniques can help in compensating for disturbances that affect the drilling process, such as changes in material properties, tool wear, or variations in drilling conditions. By continuously monitoring the drilling performance and adapting the control parameters, adaptive control algorithms can mitigate the impact of disturbances and maintain the desired drilling performance [6].

There are several types of adaptive control methods that can be used in various applications. The selection of the appropriate adaptive control method depends on the specific application, system dynamics, available information, and control objectives. Each method has its own advantages and limitations, and the choice should be based on a thorough analysis of the system and the requirements of the control problem at hand [5].

Model Reference Adaptive Control (MRAC) strategy is used to design an adaptive controller that works on the principle of adjusting the controller parameters so that the output of the actual plant tracks the output of the reference model having the same reference input. MRAC can be applied to a wide range of systems and processes, including industrial control systems, robotics, aerospace applications, and more. Its adaptability makes it suitable for various control tasks and scenarios [6].

Numerous strategies have been adopted using adaptive control, for example, Sheng and Tomizuka [7] and Shekhar and Sharma [8] presented an approach based on the adaptive control for drilling composite materials. Mikolajczyk and Olaru [9] proposed adaptive predictive control (APC) for drilling of composite materials. Recently, Gai [10] developed a MRAC Based on PID controller for CNC machine tools.

This work proposes a MRAC for many reasons, including it provides robustness against uncertainties and variations in the system, can adapt to changing conditions and disturbances, and ensures stable and reliable control even in the presence of unknown or varying system parameters.

Compared the present work with the works presented in [7-9], the present work proposes MRAC as control strategy as compare to adaptive control [6, 7], and APC [8]. Besides, the work [10] improves the performance of MARC by incorporate the PID controller. The present work enhances the performance of MRAC by utilizing the Enhanced Flower Pollination Algorithm (EFPA) to handle the tuning process of the adaptive gain of the MRAC. This integration of optimization and MRAC control is a novel approach that can potentially enhance the performance and efficiency of the proposed controller for drilling process.

2. SYSTEM MODELING

The link between drilling force and feed rate represents the mathematical model of the drilling process in this study [11]. In general, the mathematical model between the feed rate as the drilling process's input and the drilling force as the drilling process's output is represented by a first-order system, as shown in Eq. (1).

$$G(s) = \frac{F(s)}{u(s)} = \frac{k}{\tau s+1} \quad (1)$$

where,

s: Laplace operator
$G(s)$: Drilling-process transfer function
F: Cutting force
u: Feed rate
k: Gain of the process
τ: Time constant of the process

The gain (k) and the time constant (τ) of the process can be obtained experimentally under various cutting conditions [12]. Singh and Sharma [12] developed a mathematical model of the drilling process of GFRP composite. The specifications of the drilling process are listed in Table 1. The thrust forces generated during drilling are recorded. The response of the thrust force is shown in Figure 1. First order transfer function as given in Eq. (2) is obtained as the dynamics model between the thrust force as an output and feed rate as an input [12].

$$G(s) = \frac{F(s)}{u(s)} = \frac{1.1884}{0.4172s+1} \quad (2)$$

Table 1. Drilling specification [12]

Parameters	Specification
Piece-work thickness	12 mm
Drilling tool diameter	8 mm
Drilling tool coating	Tungsten carbide
Feed rate	212.8 mm/min

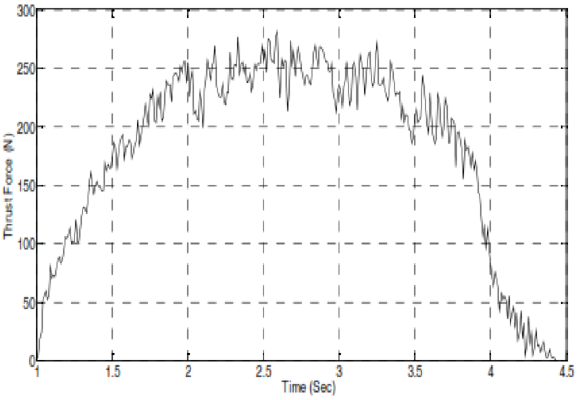

Figure 1. Experimental thrust force response at feed rate of 212.8 mm/min [12]

3. CONTROLLER DESIGN

In general, adaptive control is a control strategy used to control a system has uncertainty in its parameters and/or its parameters change with time. In this direction, the Model Reference Adaptive Control (MRAC) is an approach to designing the adaptive control based on a standard reference model. As a result, the output of the actual plant follows the output of the reference model response to make the system adapt to any change in the system dynamics, the MRAC has adaptive parameters that can be adjusted based on a mechanism of adjustment [6]. This mechanism of adjustment is developed based on mathematical equations named the adaptive law [12]. The basic block diagram of MRAC system is shown in Figure 2.

In the MRAC, the controller transmits the reference input to the plant. The states of the plant and the reference model are contrasted. To alter the controller parameters, the adjustment mechanism receives the plant states and the error signal. As the dynamics of the drilling process is modeled as first order system, the state space of the first-order system is given as follows:

$$\dot{x}(t) = ax(t) + bu(t) \quad (3)$$

where, x is the state of the plant, a and b are unknown coefficient of the plant. Consider the reference model has the following first-order state space model:

$$\dot{x}_m(t) = a_m x_m(t) + b_m r \quad (4)$$

where, x_m is the state of the reference model, a_m and b_m are coefficients of the reference model. Define the control law u as:

$$u(t) = \hat{k}_1(t)x(t) + \hat{k}_2(t)r \qquad (5)$$

where, $\hat{k}_1(t)$ and $\hat{k}_2(t)$ are an estimation of the controller gains k_1 and k_2 respectively.

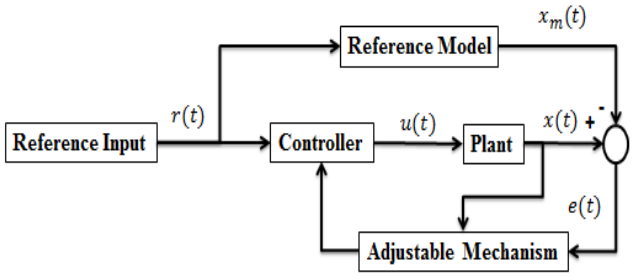

Figure 2. Basic block diagram of MRAC system

The objective of the control law u is to ensure that the states of plant $x(t)$ follows the states of the model $x_m(t)$ for arbitrary initial condition and when the reference input r is uniformly bounded. Consider the error $e(t)$ between the states of plant $x(t)$ and the model $x_m(t)$ is given by:

$$e(t) = x(t) - x_m(t) \qquad (6)$$

Taking the first derivative of the error gives:

$$\dot{e}(t) = \dot{x}(t) - \dot{x}_m(t) \qquad (7)$$

Substitute Eq. (3) and Eq. (4) into Eq. (7) gives:

$$\dot{e}(t) = ax(t) + bu(t) - a_m x_m(t) - b_m r \qquad (8)$$

Substitute the control law that is given in Eq. (5) into Eq. (8) gives:

$$\dot{e}(t) = ax(t) + b\left(\hat{k}_1(t)x(t) + \hat{k}_2(t)r\right) - a_m x_m(t) - b_m r \qquad (9)$$

Assume $\tilde{k}_1(t)$ & $\tilde{k}_2(t)$ are the estimation errors between the controller gains (k_1, k_2) and the estimation of the controller gains $(\hat{k}_1, \hat{k}_2)$ which are given by:

$$\tilde{k}_1(t) = k_1 - \hat{k}_1(t) \qquad (10)$$

$$\tilde{k}_2(t) = k_2 - \hat{k}_2(t) \qquad (11)$$

Substitute Eq. (10) and Eq. (11) into Eq. (9) gives:

$$\dot{e}(t) = ax(t) + b\left((k_1 - \tilde{k}_1(t))x + (k_2 - \tilde{k}_2(t))\, r\right) - a_m x_m(t) - b_m r \qquad (12)$$

Based on the matching condition in the MARC design, the following equations are considered:

$$a + bk_1 = a_m \qquad (13)$$

$$bk_2 = b_m \qquad (14)$$

Based on Eq. (13) and Eq. (14), rearrange Eq. (12) gives:

$$\dot{e}(t) = a_m e - b\tilde{k}_1(t)x(t) - b\tilde{k}_2(t)r \qquad (15)$$

To find the $\tilde{k}_1(t)$ and $\tilde{k}_2(t)$, the following Lyapunov function is introduced:

$$V(e, \tilde{k}_1, \tilde{k}_2) = \tfrac{1}{2}e(t)^2 + \tfrac{1}{2}\tilde{k}_1(t)^2 + \tfrac{1}{2}\tilde{k}_2(t)^2 \qquad (16)$$

Taking the first derivative of V gives:

$$\dot{V} = e(t)\dot{e}(t) + \tilde{k}_1(t)\dot{\tilde{k}}_1(t) + \tilde{k}_2(t)\dot{\tilde{k}}_2(t) \qquad (17)$$

Substitute Eq. (12) and taking the derivative of $\tilde{k}_1(t)$ and $\tilde{k}_2(t)$ gives:

$$\dot{V} = e(t)\left(a_m e(t) - b\tilde{k}_1(t)x(t) - b\tilde{k}_2(t)r\right) + \tilde{k}_1(t)\left(-\dot{\hat{k}}_1(t)\right) + \tilde{k}_2(t)\left(-\dot{\hat{k}}_2(t)\right) \qquad (18)$$

Rearrange Eq. (18) gives:

$$\dot{V} = a_m e(t)^2 - b\tilde{k}_1(t)x(t)e(t) - b\tilde{k}_2(t)re(t) - \tilde{k}_1(t)\dot{\hat{k}}_1(t) - \tilde{k}_2(t)\dot{\hat{k}}_2(t) \qquad (19)$$

Selection the adaptive law as:

$$\dot{\hat{k}}_1(t) = -bx(t)e(t) \qquad (20)$$

$$\dot{\hat{k}}_2(t) = -bre(t) \qquad (21)$$

As b is unknown, Eq. (20) and Eq. (21) can be rewrites as:

$$\dot{\hat{k}}_1(t) = -\gamma x(t)e(t) \qquad (22)$$

$$\dot{\hat{k}}_2(t) = -\gamma re(t) \qquad (23)$$

where, γ is the positive quantity that represents the controller's adaption gain to compensate the effect of the unknown b of the plant. In some industrial applications, larger values of γ can cause the instability of the system. The choice of this parameter is therefore crucial. This paper uses a swarm optimization technique to determine the best value of the controller's adaption gain.

4. SWARM OPTIMIZATION

Swarm optimizations are search methods or techniques for addressing problems that are meant to find ideal or nearly ideal solutions. These methods are motivated by natural or abstract concepts to efficiently explore and exploit the search space, in contrast to traditional optimization approaches that rely on mathematical modelling and analytical methodologies.

Swarm optimization algorithms typically work by exploring and exploiting candidate solutions iteratively to improve the results. Swarm optimizations are used to solve problems such as large-scale, non-linear, and multi-objective optimization problems which are difficult for classical optimization approaches to solve because of computational complexity or informational constraints [13].

The Flower Pollination Algorithm (FPA) is a swarm optimization algorithm inspired by the pollination behaviour of flowering plants. It was introduced by as a novel approach to solving optimization problems [14].

FPA has demonstrated promising performance in solving various optimization problems, including continuous, discrete, and constrained problems. It benefits from its simplicity, robustness, and ability to handle multimodal optimization problems. However, like other swarm optimization algorithms, the performance of FPA can be influenced by parameter settings and problem-specific characteristics, requiring careful tuning and customization for specific applications [15].

FPA aims to find the optimal or near-optimal solution by iteratively updating the candidate solutions. The algorithm uses fitness evaluation to assess the quality of solutions, and based on this evaluation, it adjusts the agent' positions (candidate solutions) using a combination of randomization, exploration, and exploitation strategies [16].

A flower's main job is to reproduce through pollination. Transport of pollen is frequently associated with flower pollination, and pollinators such as insects, birds, bats, and other animals play a vital role in this process. Abiotic and biotic pollination are the two main forms. Biological pollination is used by about 90% of flowering plants, which implies that pollinators like insects and animals distribute pollen. Abiotic pollination, or pollination without pollinators, accounts for around 10% of all pollination.

The two mechanisms that result in pollination are self-pollination and cross-pollination. Cross-pollination is the technique of using pollen from a flower on a separate plant to nourish a single blossom [15].

On the other hand, self-pollination happens when a single flower is fed by pollen from another flower on the same plant or from the flower itself [16]. An N-flower population is first distributed randomly over the search space by the algorithm. Two probability-based search algorithms are used in the strategy. Use a round number (Rand). If >Rand, the FPA performs a world-wide search. The position of the optimal response affects each agent's position in the population's pollination search, as demonstrated.

$$p_i(k+1) = p_i(k) + \sigma\left(p_g - p_i(k)\right) \tag{24}$$

where,

P	Position of individual solution
σ	Step size
p_g	Best position found by the population

If $\beta \leq Rand$, the FPA performs a local search. Each agent in the population has its position altered in the local pollination search by choosing two random solutions from the population, as shown below [17]:

$$p_i(k+1) = p_i(k) + \epsilon\left(p_j - p_q\right) \tag{25}$$

where,

ϵ	Random value between [0,1]
p_j, p_q	Position of two solutions selected randomly from the population

In order to speed up the search phase of the algorithm, a revised version of the FPA is used in this study.

The Enhanced Flower Pollination Algorithm (EFPA) is an improved version of the FPA that incorporates additional mechanisms and enhancements to enhance its performance and optimization capabilities. EFPA builds upon the basic principles of FPA but introduces modifications to improve convergence speed, exploration-exploitation balance, and solution quality. EFPA incorporates an elite strategy that preserves the best solutions discovered during the optimization process. The elite solutions are retained to prevent their loss during the exploration or exploitation stages. This helps in preserving the most promising solutions and improves the convergence speed of the algorithm.

Instead of using an agent's current position to determine a new position, as in the original FPA for local and global search, each agent in the EFPA changed its position in accordance with the optimal position that the algorithm has discovered. As a result, for the global search, Eq. (24) becomes Eq. (26). For the local search, Eq. (25) is altered to Eq. (27) [18].

$$p_i(k+1) = p_g + \sigma\left(p_i(k) - p_g\right) \tag{26}$$

$$p_i(k+1) = p_g + \epsilon\left(p_i(k) - p_j\right) \tag{27}$$

5. SIMULATION RESULTS

In this section, the simulation of four cases of drilling operations in the GFRP composite material is presented. MATLAB is used to conduct the simulation. The proposed MRAC is utilized to control of drilling process of the GFRP composite material. The value of the parameters of the first order model reference a_m and b_m as given in Eq. (4) was set to -20 and 20 respectively. These values ensure that the drilling process as given in Eq. (1) has a process gain (k) is equal to one and time constant (τ) is equal to 0.05 sec. It also was assumed that there is a critical force where after this limit of force, the delamination problem will be occurred in the drilling process. Therefore, the reference force input to the drilling system has been set below to this critical force. Figure 3 shows both the critical force and the reference force profiles of drilling the GFRP.

Besides, the EPFA is used to find the optimal value of the adaptation gain (γ) of the MRAC control law in the Eq. (22) and Eq. (23). The Integral Time of Absolute Error (ITAE) index as given in Eq. (28) is used as cost function in the tuning process [19, 20]:

$$\mathrm{ITAE} = \int_{t=0}^{t=t_{sim}} t\left|e(t)\right|dt \tag{28}$$

where, t_{sim} is the simulation time and $e(t)$ denotes to the error between the desired and actual drilling force. The parameter of the EFPA is listed in Table 2.

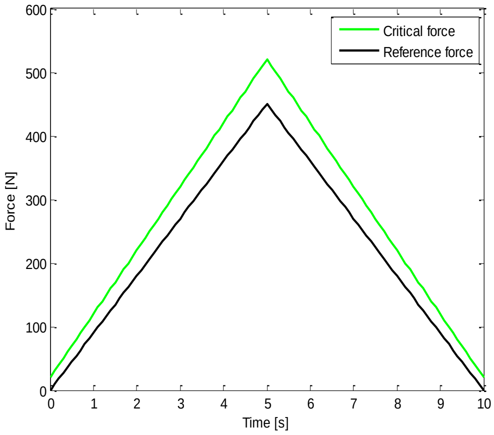

Figure 3. Critical and reference force for drilling process

Table 2. FPA parameters

Parameters	Values
Population Size (N)	25
Number of Iterations (T_{max})	40
Probability (β)	0.5
Step Size (σ)	2

In the first case, it was assumed that drill operation works normally as given in Eq. (2). Figure 4 shows the response of the open loop and the controlled system based on MRAC of the drilling force. It can be seen from Figure 4 that the delamination is occurred in the open loop system of the drilling process. However, the response of the drilling force of the system based MRAC follows the reference force and avoid the delamination.

In the second case, it was assumed that the operation condition of the drilling process such as the diameter of the drilling tool is changed. As a result, the gain of drilling process as given in Eq. (2) is changes [2]. Figure 5 shows that, by utilizing MRAC, regardless of the changes in the gain of the process, the drilling force was able to follow the reference model.

In the third case, it was assumed that the gain of the drilling operation is time varying that affected by the depth of the drilling process and the changing in the structure of composite material. Figure 6 shows that, by utilizing MRAC, regardless of the depth of drilling, the drilling force was able to follow the reference model.

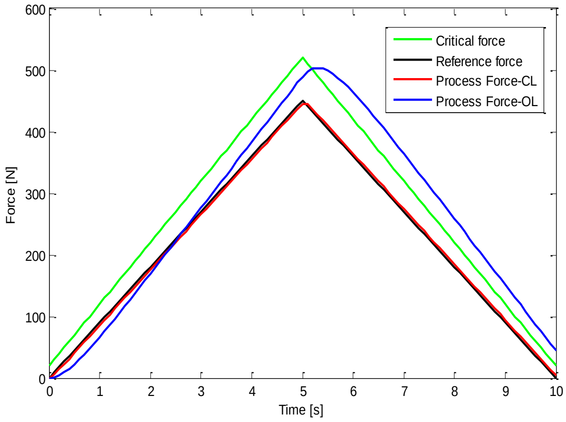

Figure 4. Drilling force response under normal operation

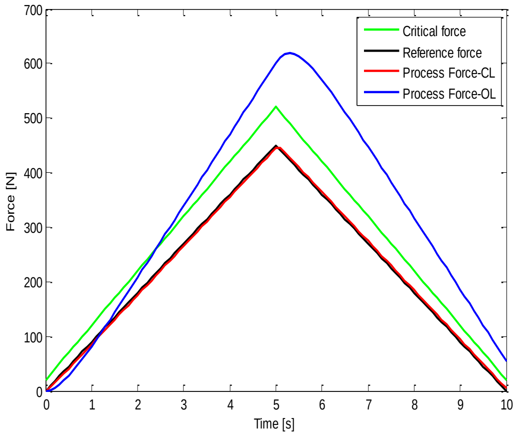

Figure 5. Drilling force response under changing of the operation condition

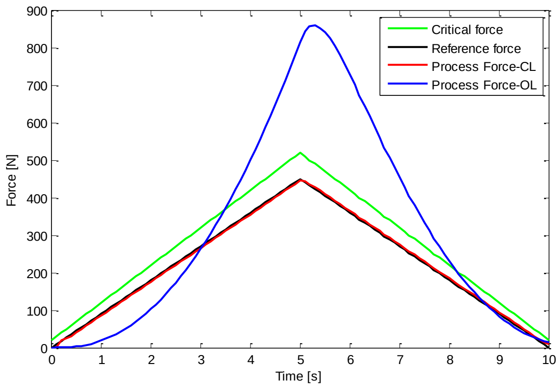

Figure 6. Drilling force response under increasing the gain of the system

To verify the role of MRAC in reducing noise, in the last case, a uniform random number within a certain range was added to the output of the dynamometer. Figure 7 shows that, MRAC could effectively reduce the impact of noise.

The aforementioned results of the simulations demonstrate that the adaptive controller is capable of effectively managing all four studied scenarios. These scenarios include the normal operation of the drilling process, variations in the drilling tool diameter which affect the drilling process, a time-varying gain of the drilling operation due to changes in drilling depth and composite material structure, as well as the influence of noise. The adaptive controller successfully handles and adjusts to these changes by determining the appropriate reference force, thereby eliminating the need to modify the controller's setup.

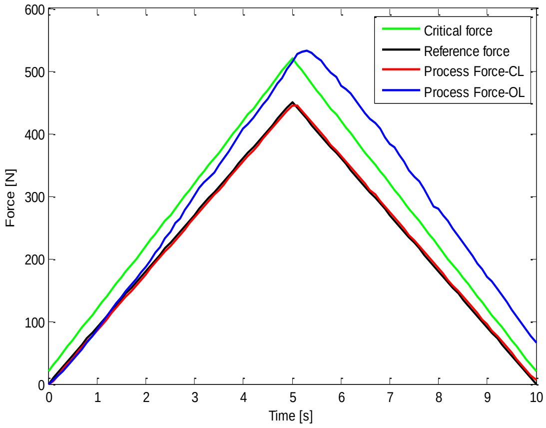

Figure 7. Drilling force response with noise in the dynamometer

6. CONCLUSIONS

Delamination during drilling composite materials is a challenging task due to the complex structure of composite materials. Delamination around the holes becomes the major reason for their poor quality and degradation of product properties. To address this problem, this paper proposes a framework of designing of Model Reference Adaptive Control (MRAC) based on the Enhanced Flower Pollination Algorithm (EFPA) to control of drilling process in composite materials. The proposed tuning algorithm used the ITAE index to improve the performance of the MRAC. The evaluation of the proposed control strategy to avoid delamination drilling has been measured under four (one normal operation and three with uncertainties) different cutting conditions. The results show the effectiveness and robustness of the proposed method to handle the uncertainties and time varying dynamics of the drilling process in composite materials.

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