Asynchronous bio-inspired tuning for the DC motor speed controller with simultaneous identification and predictive strategies

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***Abstract*—One of the main issues in the control system is the online tuning of its gains. The use of bio-inspired algorithms (BA) is gaining more attention in the control tuning task because they are less sensible to system uncertainties. Nevertheless, the computational time of BA must be reduced to be used in practice. In this work, an event condition is stated to reduce the computational cost of the optimization process in the online bio-inspired tuning approach. This condition activates the tuning approach only when it is required, i.e., when the regulation error tends to increase. Also, in this approach, an identification process and a predictive strategy are simultaneously optimized to find the more suitable control parameters that handle more efficient the parametric uncertainties. The proposed online Asynchronous Bio-inspired Tuning Approach with Simultaneous Identification and Prediction (ABioTASIP) is validated in the study case of the velocity regulation of a DC motor considering dynamic parametric uncertainties. The comparative analysis with an approach where the control parameters are periodically tuned indicates that the proposal decreases the tuning process without considerably increase the regulation error.**

***Index Terms*—Optimum tuning, DC motor, Event based tuning, bio-inspired algorithms**

I. Introduction

The DC motor is one of the most used electro-mechanical actuators in the industry. Since the control theory emerges in the 1940s [1], one of the main issues is to provide an efficient control system under parametric uncertainties. The proposal on a new control system that guarantees the closed-loop control system stabilization has been addressed for many decades [2], [3]. Nevertheless, satisfying a set of control specifications and requirements is the other important issue in industrial applications. This issue is handled by using controller tuning methods since the Proportional-Integral-Derivative (PID) controller tuning rules were introduced by Ziegler and Nichols in 1942 [4]. Since that time, several tuning strategies have been proposed for linear systems [5].

However, for nonlinear systems with uncertainties, the adaptive tuning methods [6] are the most effective approach to handle uncertainties [7]. These methods periodically update the control parameters at each fixed period. One proposal is to find such parameters based on the solution of an optimization problem to accomplish a desired control design trade-off. Recently, controller tuning is one of the most crucial problems in Intelligent Control [8], which integrates the computational intelligence and soft computing to formulate methodologies based on the knowledge and rules.

Among computational intelligence techniques, evolutionary algorithms have been widely accepted in the tuning methods which require an optimization process to find the most suitable control gains [9]–[11]. The above because they are robust, find solutions near the global one in non-convex and discontinuous design space, and do not require specific problem characteristics such as the continuity in the performance functions and constraints. For instance, the type-1 fuzzy logic controller for the water tank regulation control and the mobile robot trajectory tracking (benchmark control problems) is tuned in [12] by adopting the Bee Colony Optimization (BCO) algorithm with a fuzzy dynamic adaptation of the BCO parameters. With a similar idea but with the use of Firefly Algorithm (FA) is investigated in [13]. The results statistically indicate that the fuzzy dynamic adaptation of the bio-inspired algorithms improves the exploitation and exploration of the search mechanism and then, provides an outstanding design in the fuzzy controller. In [14], the PID control gains are designed by considering robustness in the obtained solution. The design is done by including sensitivity function constraints into the optimal tuning problem and solving by the Particle Swarm Optimization (PSO). The simulation results indicate that the unmodeled dynamics or uncertainties, which are not taken into account into the optimal tuning process, can significantly

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affect the controller performance. Still, with the proposal, this is reduced.

Another controller tuning procedure which includes the robustness specification is given in [15], where the fractional order proportional integral speed controller for a Permanent Magnet Synchronous Motor (PMSM) is tuned by using Differential Evolution (DE) algorithm. Different types of electric motors have utilized the Proportional-Integral (PI) controller tuning for improving speed regulation. The obtain controller parameters is based on the use of different optimization techniques such as Bacteria Foraging Optimization Algorithm (BFOA) and the FA in [16], the Ant Colony Optimization (ACO) in [17], the Imperialist Competitive Algorithm (ICA) in [18] and the Differential Evolution (DE) algorithm [7]. Other control tuning proposals as in [19]–[24] relate the diverse set of trade-off among several indicators of control performance to provide a collection of alternatives to the designer. Then, multi-objective optimization problems are stated and solved by using different Multi-Objective algorithms such as Non-dominated Sorting Genetic Algorithm II and III (NSGA-II and NSGA-III), Multi-objective Particle Swarm Optimization (MOPSO), Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D), the third evolution step of Generalized Differential Evolution (GDE3), Strength Pareto Evolutionary Algorithm II (SPEA-II) among other multi-objective optimizers. In [25] the PI control gains of a linear induction motor are dynamically tuning by using Genetic Algorithms. In [26], the use of diverse bio-inspired algorithms such as Differential Evolution (DE), Particle Swarm Optimization (PSO), Bat Algorithm (BAT), Firefly Algorithm (FFA), Wolf Search Algorithm (WSA) and Genetic Algorithm (GA) are studied for the optimal tuning of the DC motor speed controller. The (1+1)-Dynamic Evolution Strategy is used in [27] for tuning PI controller in a real single-degree-of-freedom robotic mechanism. The study of different Pareto-front approximation search approaches in multi-objective evolutionary algorithms in the controller tuning of the four-bar mechanism is presented in [28].

The main characteristics of the previous works are 1) The optimum tuning process is based on bio-inspired algorithms. 2) In the control tuning approaches given in [7], [13]–[24], the optimum control gains remains fixed through the dynamic simulation of the closed-loop system i.e., the control gain parameters do not change through the time, and then, those works do not adequately handle uncertainties that are not considered in the control optimal tuning formulation. 3) The optimum tuning process is executed online (adaptive bio-inspired tuning approach) in [25]–[28] and hence, the control gain parameters are changed through time (dynamics control gains) which provide more robustness under the effects of uncertainties than those where optimum control gains remain fixed all the time. 4) Identification and predictive strategies are not simultaneously used in the adaptive bio-inspired tuning approach.

Consequently, the adaptive bio-inspired tuning approach results in a high computational cost due to the high computational complexity in the optimization process or the plant. Then, the experimental evaluation in a real system or a Hardware in the Loop (HiL) platform or embedded devices may be prohibitive [29] because of the requirement of high-performance computational resources. This periodic computation of the control gains is a waste of system resources, computational power, and even of network bandwidth and energy in the data broadcast when the tuning process is in a network as in Industry 4.0. Then new methodologies must be proposed to reduce the computational burden in the controller tuning, and to the best author knowledge, this is an unexplored area.

In this paper, an online Asynchronous Bio-inspired Tuning Approach with Simultaneous Identification and Prediction (ABioTASIP) is proposed to reduce the computational cost of the tuning process. The execution of the tuning strategy is based on an event function proposal which provides an asynchronous update of the controller gain parameters. The proposed event function is derived from the rate of change of the Lyapunov function [30], [31]. Besides, the proposed ABioTASIP is based on the simultaneous identification and predictive processes when the event function is activated. It concurrently estimates the system parameters and predicts the future system behavior at the current time to provide the suitable control gains to the next time intervals. The proposal is numerically validated in the speed regulation of the Direct Current (DC) motor under static and dynamic uncertainties. Simulation results show that the proposal reduces the computational time and provides a suitable regulation control performance concerning the adaptive tuning approach where periodic activation of the tuning process is considered, and also the identification and predictive strategies are considered in separated stages.

The rest of the paper is organized as follows: Section II described the design of the event function for the activation of the DC motor controller tuning. The description of the ABioTASIP is detailed in Section III. The comparative analysis between the proposal with a Synchronous Bio-inspired Tuning Approach with Independent Identification and Prediction (SBioTAIIP) is discussed in Section IV. Finally, the conclusions are drawn in Section V.

II. Design of the event function

Let's consider the null stabilization and the system dynamics (1) in the state vector $x(t) \in \mathbb{R}^n$ with the input vector $u \in \mathbb{R}$, where $A \in \mathbb{R}^{n \times n}$ and $B, C(t) \in \mathbb{R}^n$ are constant matrix and vectors, respectively.

$$\dot{x}(t) = Ax(t) + Bu(t) + C(t) \tag{1}$$

As the proposed controller tuning process requieres the update of the controller parameters only when is needed, an event function $\bar{e}(x(t), x(t-\Delta t)) : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ is proposed to inform about the suddenly changes in the current state vector $x(t)$ (changes where the system stabilization is perturbed), where $t \in \mathbb{R}^+$ is the current time, $t - \Delta t$ is the previous time and $x(t-\Delta t)$ is the state vector in a previous sampling time Δ. This event function $\bar{e}(x(t), x(t-\Delta t))$ must be computed at each sampling time $\Delta t > 0$ in order to monitor if the controller parameters needs to be updated ($\bar{e} \leq 0$) with the ABioTASIP or continue as in the last update.

To apply the proposed event function $\bar{e}$, the assumption that the controller u asymptotically stabilize the closed-loop system to the origin must be considered. Then, there will be a Lyapunov function $V(x(t))$ where the definite negative of the derivative of V is guaranteed. Considering this fact, the difference of the rate of change of the Lyapunov function at the current time t and the previous one $t-\Delta t$ is proposed as the event function $\bar{e}$ (2).

$$\bar{e}(x(t), x(t-\Delta t)) = \dot{V}(x(t)) - \dot{V}(x(t-\Delta t)) \tag{2}$$

Consider a system expressed in the form (1) with the control strategy u as in (3) and the control gain vector $K \in \mathbb{R}^n$,

$$u = -Kx - \frac{B^T C(t)}{\|B\|} \tag{3}$$

and the function $V : \mathbb{R}^n \to \mathbb{R}$ given by

$$V(x(t)) = x^T P x \tag{4}$$

Then, a sufficient condition for using $\dot{V}(x(t))$ in the event function is that there exist two symmetric positive definite matrices $P \in \mathbb{R}^{n\times n}$ and $Q \in \mathbb{R}^{n\times n}$ [32], such that the matrix $A^T P + PA + Q$ is negative definite.

III. ABioTASIP in the DC motor

The dynamic model of the brushed DC motor is provided in (5)-(6) [3], where the involved variables describe the angle q, the angular speed $\dot{q}$ and the angular acceleration $\ddot{q}$ of the shaft , the armature current i_a, the rotor inertia moment J_0, the torque constant k_m, the viscous friction coefficient b_0, the load torque τ_L, the armature resistance R_a, the armature inductance L_a, the back-electromotive force constant k_e and the input voltage V_{in}.

$$L_a \frac{di_a}{dt} + R_a i_a + k_e \dot{q} = V_{in} \tag{5}$$

$$J_0 \ddot{q} + b_0 \dot{q} = k_m \left(i_a - \frac{\tau_L}{k_m} \right) \tag{6}$$

Using the transformed dynamics of the DC motor $z = [\dot{q}, \ddot{q}]^T$ given in [7] and considering the load torque as $\tau_L = 0$, the motor dynamics in the error state $x = z - \bar{x}^T$ is provided in (7), where $\bar{x} = [\bar{x}_1, 0]^T$ represents the velocity and acceleration desired reference, and the DC motor parameters are grouped in $\theta_0 = k_e + \frac{R_a b_0}{k_m}$, $\theta_1 = \frac{J_0 R_a}{k_m} + \frac{L_a b_0}{k_m}$, $\theta_2 = \frac{J_0 L_a}{k_m}$.

$$\dot{x}_2 = \frac{1}{\theta_2} u - \frac{\theta_0}{\theta_2} x_1 - \frac{\theta_1}{\theta_2} x_2 + \frac{\theta_0}{\theta_2} \bar{x}_1 \tag{7}$$

According to Section II, the controller u in (8) asymptotically regulates the speed of the DC motor whether $\tilde{\theta}_0 = \theta_0$.

$$u = -Kx + \tilde{\theta}_0 \bar{z}_1 \tag{8}$$

Then, considering the matrix P as an identity matrix, the event function $\bar{e}$ is proposed as in (9).

$$\bar{e} = \underbrace{\sum \left({}^{n}_{i=1} x_i^2 (t-\Delta t) \right)}_{-\dot{V}(x(t-\Delta t))} - \underbrace{\sum \left({}^{n}_{i=1} x_i^2 (t) \right)}_{-\dot{V}(x(t))} \tag{9}$$

It is important to point out that the controller parameters includes the control gain vector $K = [k_1, k_2] \in \mathbb{R}^{1\times 2}$ and the parameter $\tilde{\theta}_0$ which results of the estimation of the DC motor parameter θ_0.

With the event function, the proposed Asynchronous Bio-inspired Tuning Approach with Simultaneous Identification and Prediction (ABioTASIP) can be implemented. In Fig. 1 such approach is schematically represented. In the ABioTASIP, an emulation approach [33] is adopted to apply the ABio-TASIP into a computer, and the procedure is given next:

1) Divide the continuous time $t \in \mathbb{R}^+$ into the discrete time sequence $\{t_l\}_{l\in\mathbb{N}}$ with $\mathbb{N} := \{1, 2, ...\}$ and $t_{l=0} = 0$. The interval between two discrete-time sequences is referred to as the sampling time $\Delta t = t_l - t_{l-1} > 0$. On the other hand, the sequence of time related to the event activation (when $\bar{e} \leq 0$) is specified by $\Sigma_e = \{t_k\}_{k\in\tilde{\mathbb{N}}\subseteq\mathbb{N}}$, where $n_s \Delta t = t_{k+1} - t_k > 0$ and $n_s \geq 1$ are the time interval and the number of sampling instants Δt elapsed between two events, respectively.
2) Regulate the motor velocity with the controller u (8) and arbitrarily choose the parameters $K(t) = K(t_{k=0} = 0)$ and $\tilde{\theta}_0(t) = \tilde{\theta}_0(t_{k=0} = 0)\ \forall\ t \in [0, \Delta w]s$. The term $\Delta w = n_w \Delta t$ is related to the time horizon with $n_w > 1$ samples. The time horizon Δw is used next for the simultaneous estimation and prediction stages.
3) Compute the event function $\bar{e}$ (9) at each sampling time Δt once $t > \Delta w$.
4) Verify the event function $\bar{e}$:
   - If $\bar{e} \leq 0$ (event activation), then update the controller parameters $K(t) = K^*(t_k)$ and $\tilde{\theta}_0(t) = \tilde{\theta}_0^*(t_k)$ with the obtained parameters given by the adaptive controller tuning approach which considers simultaneous identification and prediction.
   - On the contrary, if the event function is not activated ($\bar{e} > 0$), the controller parameters are not changed. Then, the controller is computed according to the parameters obtained in the last time when the controller parameter tuning was performed, i.e., $K(t) = K^*(t_{k-1})$ and $\tilde{\theta}_0(t) = \tilde{\theta}_0^*(t_{k-1})$.

The adaptive controller tuning approach requires simultaneous stages in the identification and also in the prediction to find the most suitable control parameters and hence, to reduce the regulation velocity error. The two-objective optimization problem (identification and prediction) is formulated as a weighted sum approach. In this, one objective is related to the fulfilment of the parameter identification to provide a more realistic estimated motor behavior and the other involves the predictive strategy to know its future behavior. The identification objective (first term in (10)) minimizes the error among

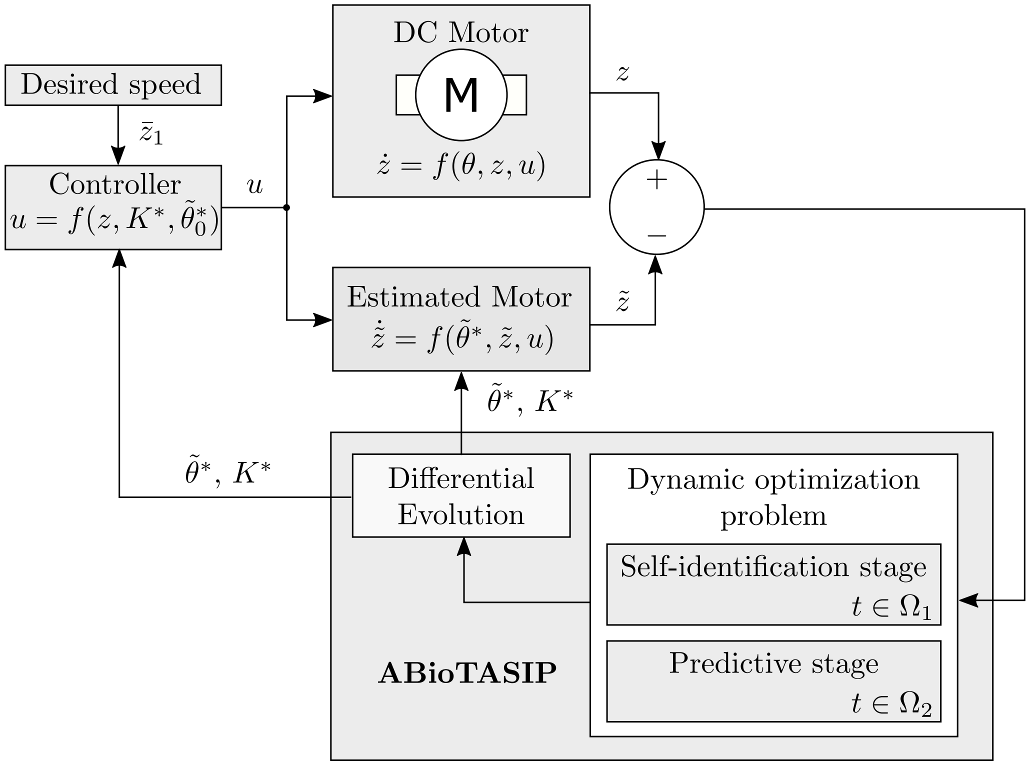

Fig. 1. Schematic diagram of the proposed Asynchronous Adaptive Controller Tuning

the current states $z(t)$ and the estimated ones $\tilde{z}(t)$ in the time interval $\Omega_1 \in [t - \triangle w, t]$, i.e., the time horizon Δw is used as a backward time window. The prediction objective (second term in (10)) minimizes the velocity error of the state predictor $\hat{x}$. The state predictor computes the future system behavior in the time interval $\Omega_2 \in [t, t+\triangle w]$, i.e., the time horizon Δw is used as a forward time window. With the simultaneous minimization of both objective functions, the optimal estimated DC motor parameter vector $\tilde{\theta}^*(t_k) = [\tilde{\theta}_0^*(t_k), \tilde{\theta}_1^*(t_k), \tilde{\theta}_2^*(t_k)]^T$ and the optimal control gains $K^*(t_k)$ are obtained to the next time interval Δt. The constraints related to the optimization problem are the dynamics of the estimated DC motor (11) with its initial condition (12), the dynamics of the predictor $\hat{x}$ (13) with the corresponding initial condition (14), and the lower $l_b \in \mathbb{R}^5$ and upper $u_b \in \mathbb{R}^5$ bounds in the design variable vector (15). The mathematical programming problem is formally stated in (10)-(15).

$$\min_{[\tilde{\theta}^*, K^*]^T \in \mathbb{R}^5} \quad J = \int_{\tilde{t} \in \Omega_1} \left(z(\tilde{t}) - \tilde{z}(\tilde{t})\right)^T \left(z(\tilde{t}) - \tilde{z}(\tilde{t})\right) d\tilde{t} + \int_{\tilde{t} \in \Omega_2} \hat{x}^T \hat{x} \; dt \tag{10}$$

Subject to :

$$\dot{\tilde{z}} = \frac{1}{\tilde{\theta}_2} u(\tilde{t}) - \frac{\tilde{\theta}_0}{\tilde{\theta}_2} \tilde{z}_1 - \frac{\tilde{\theta}_1}{\tilde{\theta}_2} \tilde{z}_2 \tag{11}$$

$$\tilde{z}(\tilde{t}_0) = z(\tilde{t}_0) \tag{12}$$

$$\dot{\hat{x}}_2 = \frac{1}{\tilde{\theta}_2} u(\hat{x}, K) - \frac{\tilde{\theta}_0}{\tilde{\theta}_2} \hat{x}_1 - \frac{\tilde{\theta}_1}{\tilde{\theta}_2} \hat{x}_2 + \frac{\tilde{\theta}_0}{\tilde{\theta}_2} \bar{x}_1 \tag{13}$$

$$\hat{x}(\tilde{t}_0) = x(\tilde{t}_0) \tag{14}$$

$$l_b \leq [\tilde{\theta}, K]^T \leq u_b \tag{15}$$

The solution of the above optimization problem is provided by the Differential Evolution (DE) algorithm [34]. This finds the optimal parameters $[\tilde{\theta}^*(t_k), K^*(t_k)]^T$ at each event activation. Hence, once the event function is activated ($\bar{e} \leq 0$) and the tuning process is done, the optimum controller gains $K^*(t_k)$ with the optimum parameter $\tilde{\theta}_0^*(t_k)$ are set in the controller (8) for the next time t_{l+1}.

IV. Results

This section presents the behavior of the proposed Asynchronous Bio-inspired Tuning Approach with Simultaneous Identification and Prediction (ABioTASIP) through two test

TABLE I
BOUNDS OF THE CONTROL PARAMETERS USED FOR THE OPTIMIZATION.

Parameter	Lower Bound l_b	Upper Bound u_b
$\tilde{\theta}_0$	0.1	5.0
$\tilde{\theta}_1$	1.0e−3	5.0e−2
$\tilde{\theta}_2$	1.0e−5	5.0e−4
k_1	5.0e−2	0.5
k_2	1.0e−3	1.0e−2

TABLE II
MOTOR PARAMETERS.

Nominal parameters	Disturbed parameters
$\bar{R}_a = 9.665\ (\Omega)$	$R_a(t) = \bar{R}_a\left(1 + \frac{1}{10}\sin(2\pi t)\right)$
$\bar{L}_a = 102.44\text{e}{-3}\ (H)$	$L_a(t) = \bar{L}_a\left(1 + \frac{1}{10}\sin(3\pi t)\right)$
$\bar{k}_m = 0.3946\ (Nm/A)$	$k_m(t) = \bar{k}_m\left(1 + \frac{1}{10}\sin(\frac{3}{2}\pi t)\right)$
$\bar{k}_e = 0.4133\ (Vs/rad)$	$k_e(t) = \bar{k}_e\left(1 + \frac{1}{10}\sin(2\pi t)\right)$
$\bar{b}_0 = 5.85\text{e}{-4}\ (Nms)$	$b_0(t) = \bar{b}_0\left(1 + \frac{1}{10}\sin(\frac{5}{3}\pi t)\right)$
$\bar{J}_0 = 3.45\text{e}{-4}\ (Nms^2)$	$J_0(t) = \bar{J}_0\left(1 + \frac{1}{10}\sin(\frac{7}{5}\pi t)\right)$
$\bar{\tau}_L = 0\ (Nm)$	$\tau_L(t) = \begin{cases} 0.15, & \textbf{when } 5 \le t \le 10 \\ \bar{\tau}_L, & \textbf{otherwise} \end{cases}$

scenarios. As a reminder, ABioTASIP updates the control parameters asynchronously depending on the value of the activation function in (9). Only when necessary, ABioTASIP calculates the control parameters through a single optimization process through Differential Evolution (DE) that simultaneously performs an identification, to obtain the model parameters of the DC motor, and a prediction, to estimate the most appropriate control gains.

A Synchronous Bio-inspired Tuning Approach with Independent Identification and Prediction (SBioTAIIP) is also considered to perform comparisons. Unlike ABioTASIP, SBioTAIIP lacks an asynchronous activation mechanism, and then, updates the control parameters periodically, i.e., the tuning is carried out at each sampling interval Δt. Additionally, SBioTAIIP obtains the control parameters through two sequential and independent optimization processes, the first for estimation and the second for prediction.

The rand/1/bin variant of Differential Evolution (DE) is adopted in both tuning approaches. The chosen DE parameters are: the number of generations $G_{max} = 200$, the population size $NP = 25$, the crossover rate $CR = 0.5$, and the scaling factor $F = 0.5$. Regarding the search space for DE, Table I shows the upper and lower bounds of the control parameters.

The test scenarios require the DC motor to track the profile $\bar{x} = [52.35, 0]^T$ during the time interval $t \in [0, 15]$. For both scenarios, the sampling interval is $\Delta t = 0.005\ (s)$, the initial condition is $z(0) = [0, 0]^T$, and the backward/forward time window for identification/prediction is $\Delta\omega = 0.05\ (s)$. Each of the scenarios, from now on referred to as T1 and T2, considers different operation conditions of the DC motor. For T1, the motor parameters do not vary from the nominal ones as is given in the first column of Table II. In the case of T2, variations up to 10% from the nominal values are injected in the motor parameters, and a disturbance load is included in a given interval, as observed in the second column of Table II.

Thirty independent runs of ABioTASIP and SBioTAIIP are carried out under the conditions of T1 and T2. The performance of each approach is studied in this work.

Table III summarizes the performance of ABioTASIP and SBioTAIIP for the tests T1 and T2, through the results of each set of runs. The test and the name of the tuning approach are shown in the first and second columns, respectively. The mean Integral Square Error (ISE) can be observed in the third column. For each run, ISE is obtained from the settling time of $0.5\ (s)$. The fourth column presents the mean number of activations, i.e., the mean of times that the control parameters are updated through the optimization process. Finally, the last column indicates the mean complexity of the tuning approach regarding the times that DE performs the optimization of the control parameters. Results in boldface denote the best values of the performance indicators for each test.

According to the $\overline{ISE}$ in Table III, SBioTAIIP has a better performance than ABioTASIP when regulating the desired profile for both test scenarios, i.e., in cases when the motor parameters present or not uncertainties or disturbances. The above is attributed to the lack of an asynchronous activation mechanism in SBioTAIIP, which consequently always optimizes the control parameters that achieve a lower value of ISE. Nevertheless, the cost of this improvement in ISE for SBioTAIIP is a higher computational complexity compared to the one of ABioTASIP. Since ABioTAIIP activates the parameter tuning only when necessary, and also performs the parameter identification and prediction in a single optimization process, the number of computations is reduced.

Due to the above, there is a trade-off between the tracking performance and the computational complexity. Depending on the application, the designer must determine a suitable preference level of both performance indicators (ISE and complexity). If a high-precision task is performed and the available equipment can handle the computational complexity, SBioTAIIP can be a suitable alternative. Otherwise, if some precision loss is allowed for a given task or the computational resources are limited (or distributed among other important computational tasks such as communication, estimation, data acquisition, and general processing), ABioTASIP can be the best choice.

Table IV shows the improvement rates between the performance indicators of ABioTASIP and SBioTAIIP. The symbol $\uparrow$ indicates that the performance of the tuning approach overcomes the performance of the other one, and the symbol $\downarrow$ indicates the opposite.

If an equitable trade-off between the performance indicators is taken into account, the rates in Table IV show that SBioTAIIP is the best alternative for the T1 test. Although the number of activations for SBioTAIIP is considerably larger than the one of ABioTASIP, the error is huger in ABioTASIP. In the T2 test, the gap between the tracking performance is significantly reduced, and the number of activations for ABioTASIP is still under the half of the activations for

TABLE III

RESULTS IN SIMULATION OF THE ABIoTASIP AND SBIoTAIIP STRATEGIES FOR THE TESTS T1 AND T2.

test	Control strategy	$\overline{ISE}$	$\overline{Activations}$	$\overline{Complexity}$
T1	SBioTAIIP	$\mathbf{7.1894e-7}$	2990	5980
	ABioTASIP	$5.0328e-5$	$\mathbf{184.9}$	$\mathbf{369.8}$
T2	SBioTAIIP	$\mathbf{7.6105}$	2990	5980
	ABioTASIP	12.8641	$\mathbf{1235.33}$	$\mathbf{2470.66}$

TABLE IV

PERFORMANCE RATES OF THE ABIoTASIP AND SBIoTAIIP STRATEGIES FOR THE TESTS T1 AND T2.

test	Control strategy	$\overline{ISE}$	$\overline{Activations}$	$\overline{Complexity}$
T1	SBioTAIIP	98.57% (↑)	1517.09% (↓)	1517.09% (↓)
	ABioTASIP	6900.30% (↓)	93.81% (↑)	93.81% (↑)
T2	SBioTAIIP	40.83% (↑)	142.04% (↓)	142.04% (↓)
	ABioTASIP	69.03% (↓)	58.6% (↑)	58.6% (↑)

SBioTAIIP. Then, ABioTASIP has a better performance trade-off for the T2 test.

Figures 2 and 3 show the behavior of both tuning approaches for the tests T1 and T2. For both figures, the plots at the left show the speed response (outer plot) and the response error (inner plot). In the plots at the right, the activation of the tuning process during the task execution is represented by ones, while the zero value describes a state of no activation.

Considering the speed responses of both alternatives in Figures 2 and 3, they have a similar behavior from the settling time of 0.5 (s) for T1 and T2. Although the error level of ABioTASIP is higher than the one of SBioTAIIP, the differences between their speed profiles are quite imperceptible for the current task, so they are very close to the reference signal. The above must also be considered to select the correct alternative. It is important to highlight that for T2 test, both tuning approaches can successfully compensate the uncertainties and disturbances included in the motor parameters. The above is attributed to the online optimization of the control parameters in the identification and predictive stages.

The activation responses in Figures 2 and 3 highlight the different features of the tuning approaches. For SBioTAIIP, it is observed that new control parameters are calculated at every sampling instant after the backward time window $\triangle\omega$ required for identification in T1 and T2 tests. On the other hand, ABioTASIP performs optimization when necessary. In the T1 test, ABioTASIP updates the parameters several times after $\triangle\omega$, and they remain fixed when the speed response is stabilized. For T2, ABioTASIP performs the parameter optimization more frequently due to the continuous changes of the motor pa

V. CONCLUSIONS

In this work, an Asynchronous Adaptive Controller Tuning approach based on the bio-inspired algorithm of Differential Evolution is proposed where the identification and the predictive processes are simultaneously carried out. The proposal is compared with a periodic tuning approach where the tuning process is carried out at each sampling time and also, the identification and the predictive processes are sequentially optimized (in two optimization stages). The proposed event function can detect changes in the velocity regulation, and then, the proposal can be implemented when it is required. The comparative simulation results indicate that the proposal can significantly reduce the computational time. However, the asynchronous activation slightly impacts the control performance. Besides, the simultaneous optimization of the control gains and the DC motor parameters based on both the identification process and the predictive strategy also reduces the computational time. Hence, the reduction of the computational resources indicates that it can be used in an embedded system for a real application. The authors consider that the control performance can be improved by the correct setting of the bio-inspired algorithm parameters included in the ABioTASIP, but this is regarded as a future research direction.

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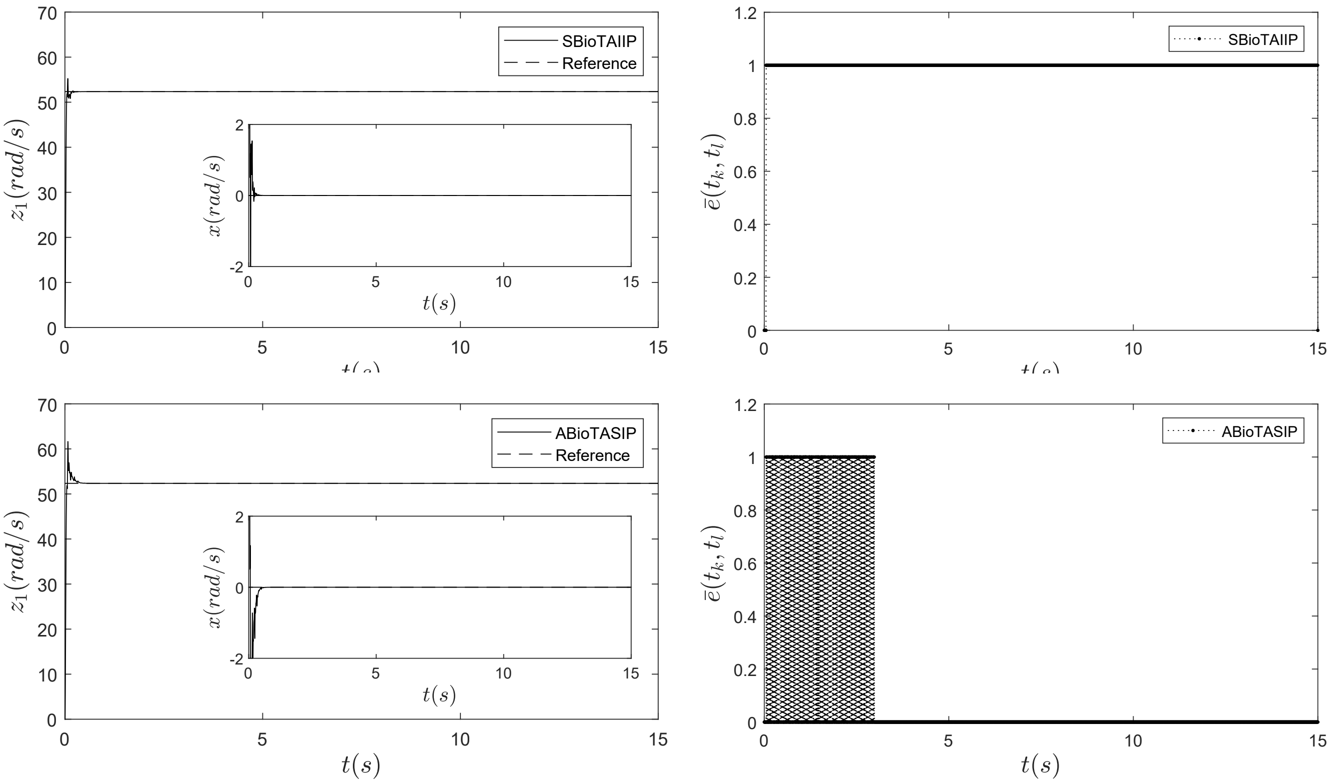

Fig. 2. Behavior of the strategies SBioTAIIP and ABioTASIP for the test T1

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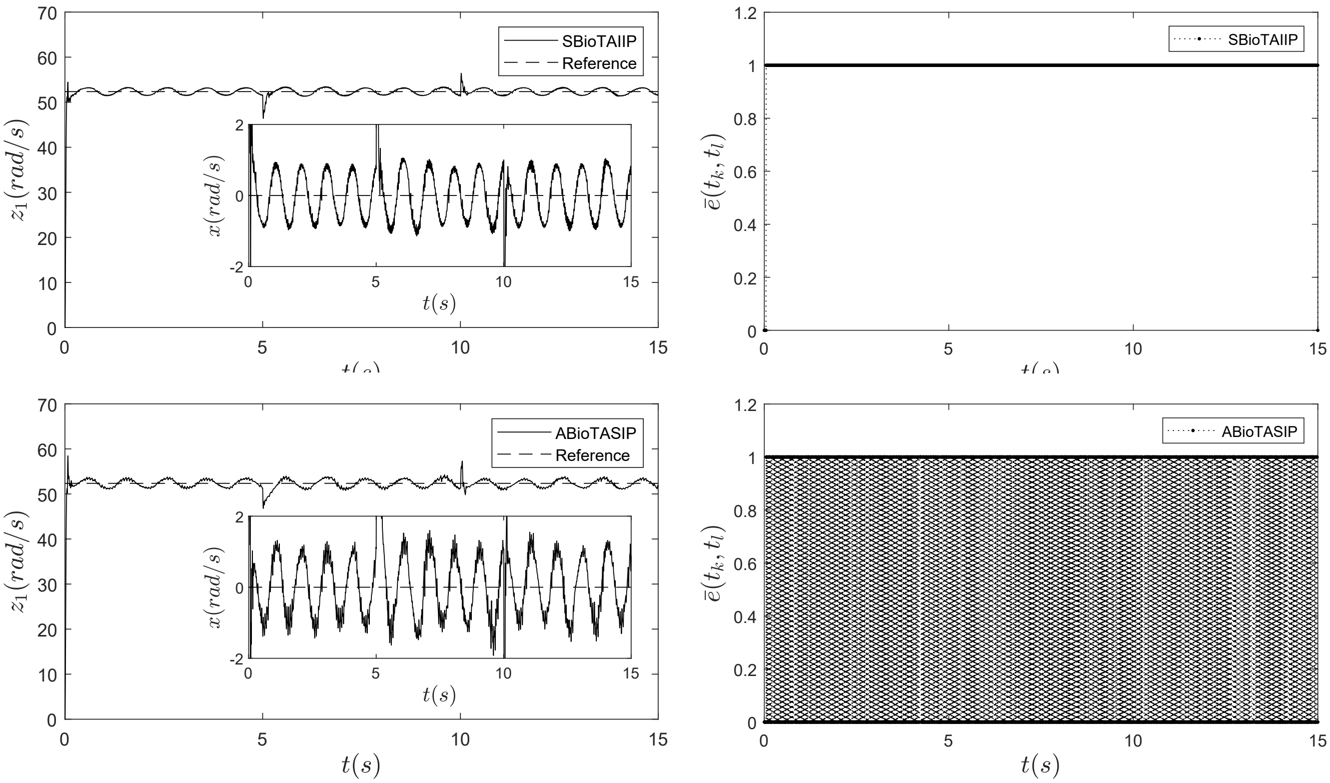

Fig. 3. Behavior of the strategies SBioTAIIP and ABioTASIP for the test T2.

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