Digital twin-based Optimization on the basis of Grey Wolf Method. A Case Study on Motion Control Systems

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***Abstract*—Nowadays, digital twins are fostering the development of plug, simulate and optimize behavior in industrial cyber-physical systems. This paper presents a digital twin-based optimization of a motion system on the basis of a grey wolf optimization (GWO) method. The digital twin of the whole ultraprecision motion system with friction and backlash including a P-PI cascade controller is used as a basement to minimize the maximum position error. The simulation study and the real-time experiments in trajectory control are performed to compare the performance of the proposed GWO algorithm and the industrial method called Fine tune (FT) method. The simulation study shows that the digital twin –based optimization using GWO outperformed FT method with improvement of 66.4% in the reduction of the maximum position error. The real-time experimental results obtained show also the advantage of GWO method with 18% of improvement in the maximum peak error and 16% in accuracy.**

Keywords—digital twin, optimization, grey wolf optimizer, controller tuning, CNC machine tools

I. INTRODUCTION

Nowadays, a set of modeling and control methods for Industrial cyber-physical systems (ICPS) is available to enable new cooperation and coordination levels for achieving better efficiency short time-to-market solutions and more flexibility [1-3]. Several gaps and research challenges in ICPS should be addressed in short terms [4, 5]. Digital twins (DT) have emerged as a powerful strategy to deal with multiphysical, multiscale and heterogeneity of systems [6, 7]. Key aspects of DTs in relation to big data applications and a pathway to integrate them according to Industry 4.0 paradigm to foster smart manufacturing solutions were carefully analyzed in [8]. Certainly, the use of big data tools and methods in ICPS to deal with product lifecycle is not straightforward. Some contemporary studies have shown how efficient methods can be designed and deployed to address this hot topic on the basis of a DT-based procedure [9]. New research working towards shop-floor DT systems was reported in the literature as well as key components ranging from physical to DT data [10]. Nowadays, dozens of scientific and technical reports have demonstrated the wide range of DT applications in ICPS such as design of sensoring systems [11, 12], system integration and diagnostics [13], smart prediction and promising web services [14]. Recently, swarm intelligence and gradient free optimization methods have received more attention due to better computational framework and more efficient computing resources [15-18]. Soft-computing and machine learning have also demonstrated high potential in ICPS [19-21], but still few solutions based on DT. One challenging issue is related with the accuracy and exploitability of DTs in smart manufacturing. Indeed, manufacturing data and sensory data can be integrated into DTs of virtual systems to improve the overall behavior of the physical system [22, 23]. DTs in ICPS are lacking:

- clear engineering procedures for systematic application of Artificial Intelligence, mainly machine learning methods, for designing and implementing DTs,

- focus on feedback systems including human-in the-loop and closed-loop control system performance,

- procedures for considering real-time constraints and real time issues in AI-based DTs and,

- systematic procedures for DT-based optimization and adaptation procedures for smart manufacturing.

From the viewpoint of modeling and control, traditional and AI-based modeling and control strategies have been explored in laboratories [24-26] but technology transfer is still cumbersome [27]. Therefore, DT are essential to address the unsatisfactory behavior of industrial systems due to poor tuning of controllers. For example, the calibration of cascade control systems is a cumbersome task for nonlinear systems, specifically before hard nonlinearities [28]. In the last two decades, nature-inspired metaheuristic algorithms were designed and implemented to tackle complex optimization problems and to provide a set of quasi-optimal solutions [29]. The advantages of swarm intelligence motivated the use of these methods in order to improve the tuning of P-PI cascade controllers' parameters on the basis of DT. In this paper, a population-based metaheuristic method called grey wolf optimizer (GWO) is re-designed and tailored in a digital twin procedure shown in Fig. 1 to optimally set control and compensation parameters of motion system. The cost function or main figure of merit is maximum position error. Therefore, it is necessary to yield a set of parameters able to decrease as much as possible this error keeping the overall accuracy

without remarkable increase in the control effort. The performance of the presented GWO method is evaluated by means of a simulation study and real-time experiments.

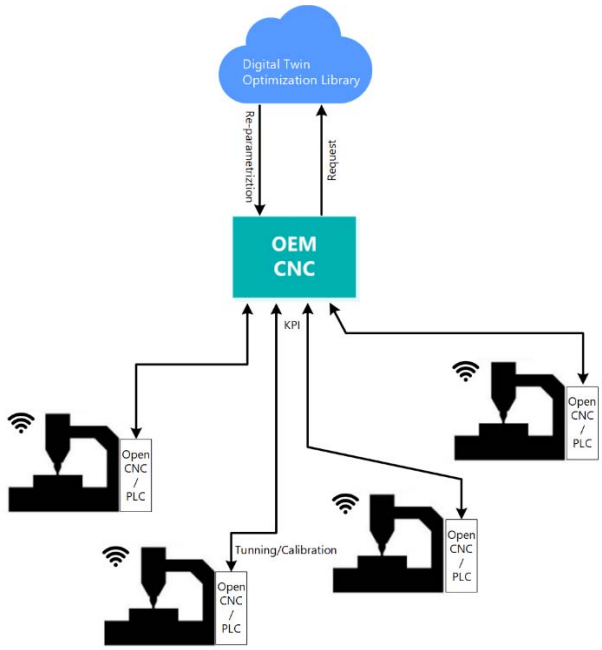

Fig. 1. Diagram of the DT-based Optimization approach

The structure of the paper is as follows. After a brief introductory overview of the physical and digital twins, Section 2 introduces the physical system and the corresponding digital twin. Section 3 presents a brief description of GWO algorithm, while Section 4 presents an industrial Fine Tune (FT) method applied for tuning of P-PI controller parameters. The simulation results and real-time experimental results are depicted in Section 5. The concluding remarks are summarized in Section 6.

II. Digital Twin

A. Physical System Description

The real case study is based on a DT of a real ultraprecision motion system commonly available in machine tools. Nowadays, open Computerized Numerical Control (oCNC) are a key element to guarantee not only accurate and fast manufacturing but also for enabling communication with other machines and devices. The experimental platform is shown in Fig. 2.

Fig. 2. Test platform.

The regulation of position and velocity is performed by a P-PI cascade controller running in the open CNC. Real-time data, the controller' parameters and key variables can be easily gathered via open CNC. The most important parameters of the whole physical system are summarized in Table I.

TABLE I Physical System

Symbol	Quantity	Value
J_M	Motor inertia	$2.9\cdot10^{-4}$ kg·m^2
J_L	Load inertia	$4.2\cdot10^{-4}$ kg·m^2
f_1, ω_{01}	Resonance frequency	70 Hz, $2\pi f_1$ rad/s
D_1	Damping coefficient	0.15
K_t	Torque constant	0.74 N·m/A
fr_H	Actual hysteresis	0.1280 rad/s
F_C	Coulomb friction	0.625 N·m
F_V	Viscous friction	0 N·m·s
	Backlash	$12.2\cdot10^{-6}$ m
K_H	Spindle Constant	0.010/(2π) m/rad
NP121	Input revolutions for coupling the motor shaft and leadscrew	3
NP122	Output revolutions, NP121/NP122 is the gear ratio	2
NP123	Feed constant for linear axis	0.02m
NP1	Reduced actuated momentum of inertia	144.61%
T_{s1},T_{s2}	Sampling time for position and velocity loops	250µs, 62.5µs

B. Digital twin description.

The DT is composed of two key virtual modules, one for representing the electromechanical system and another one for emulating the control systems. The two masses and spring system serves as basement for representing the motion system including the motor, the shaft, and the load. [26]. If the resonance and antiresonance frequencies, ω01 and ω02, are defined as:

$$\omega_{01} = \sqrt{K / J_L}$$
$$\omega_{02} = \omega_{01}\sqrt{1 + (J_L / J_M)}\ ; \qquad (1)$$

and, the damping coefficients, D_1 and D_2, are:

$$D_1 = \frac{B}{2\omega_{01}J_L}$$
$$D_2 = D_1\sqrt{1+\frac{J_L}{J_M}} = \frac{B(J_M + J_L)}{2J_M J_L \omega_{02}} \qquad (2)$$

The transfer function that relates motor speed and torque is:

$$H_{\omega_M / M_M}(s) = \frac{1}{J_M s}\cdot\frac{s^2 + 2D_1\omega_{01}s + \omega_{01}^2}{s^2 + 2D_2\omega_{02}s + \omega_{02}^2}\ ; \qquad (3)$$

By using the previously defined values of, ω_{02}, D_1, and D_2, the transfer function relating motor and load velocities becomes:

$$H_{\omega_L / \omega_M}(s) = \frac{2D_1\omega_{01}s + \omega_{01}^2}{s^2 + 2D_1\omega_{01}s + \omega_{01}^2}\ . \qquad (4)$$

Moreover, an electric model that relates electric current to the torque developed by the motor is also considered in the DT. Friction, backlash and noise are also considered in the DT, through computationally efficient models. Friction is represented by a viscous friction component, FV, relies on the relative velocity between the surfaces, v, depicted in (5):

$$F = F_{\mathrm{C}}\,\mathrm{sgn}(v) + F_{\mathrm{V}}\,v \,. \tag{5}$$

The backlash compensation is also represented by virtual element. The backlash peak amplitude PP2 and peak time PP3 are essential for increasing motor speed during a time period making possible the exponential compensation due to movement reversal peak, can be:

$$R_P = PP_2\, \mathrm{e}^{-t/PP_3} \tag{6}$$

The sixth parameter is the hysteresis amplitude, fH. The compensation of these non-linearities requires to face the zero cross discontinuity problem, solved by appropriately set of the hysteresis amplitude.

Therefore, on the basis of the relevance of the six parameters previously explained, the DT-based optimization method for an ultraprecision motion system sets the following parameter's vector:

$$K = \left[K_{\mathrm{p}}^{\mathrm{pos}}\ K_{\mathrm{p}}^{\mathrm{vel}}\ K_i^{\mathrm{vel}}\ PP_2\ PP_3\ f_{\mathrm{H}} \right] \tag{7}$$

where, $K_{\mathrm{p}}^{\mathrm{pos}}$ is the proportional gain of the position controller; $K_{\mathrm{p}}^{\mathrm{vel}}$, K_i^{vel} are the proportional and integral gain, respectively, of the speed controller. PP_2 and PP_3 are the peak amplitude and peak time for compensating the backlash and, f_H is the compensator for the friction hysteresis.

III. Grey wolf optimization algorithm

The Grey Wolf Optimization (GWO) algorithm, initially proposed by Mirjalili et al. in [30], belongs to class of novel swarm-based meta-heuristics inspired from the social leadership and hunting technique of grey wolves in nature. According to GWO algorithm, the grey wolves are classified into four levels of social hierarchy: alpha (α), beta (β), delta (δ), and omega (ω). The alphas are the leaders of the group responsible for hunting process and making decisions. The betas belong to the second level of hierarchy and they assist the alphas in making decisions, while deltas belong to the third level and dominate the wolves of the last level omega. The omegas are the lowest ranking grey wolves on the pyramid of social hierarchy.

GWO algorithm is based on the aforementioned social behavior of the grey wolves. Optimization (hunting) process is initialized with randomly generated candidate solutions (grey wolves) in a multi-dimensional search space. This phase of searching for prey is also known as exploration. The best fitness solution is defined as alpha (α), the second and third best solutions are beta (β) and delta (δ), and the rest of the solutions are assumed to be omega (ω). In order to catch the prey, the α, β, and δ grey wolves firstly encircle the victim. During the optimization (hunting) process, they estimate the victim position and update their positions randomly around the victim according to the mathematical model given by the following equations (8) and (9):

$$D = \left| \vec{C} \cdot \vec{X}_p(\mathrm{t}) - \vec{X}(\mathrm{t}) \right| \tag{8}$$

$$\vec{X}(\mathrm{t}+1) = \vec{X}_p(\mathrm{t}) - \vec{\mathrm{A}} \cdot \vec{\mathrm{D}} \tag{9}$$

where t represents iteration, $\vec{X}_p$ is the position vector of the prey, $\vec{X}$ is the position vector of a grey wolf, $\vec{A}$ and $\vec{C}$ are coefficient vectors calculated by (10), (11):

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{10}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{11}$$

The components of vector $\vec{a}$ linearly decrease from 2 to 0, and r_1 and r_2 are random vectors in [0,1].

Furthermore, hunting behavior of the grey wolves can be mathematically modeled by equations (12), (13) and (14):

$$D_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right| \tag{12}$$

$$D_\beta = \left| \vec{C}_1 \cdot \vec{X}_\beta - \vec{X} \right| \tag{13}$$

$$D_\delta = \left| \vec{C}_1 \cdot \vec{X}_\delta - \vec{X} \right| \tag{14}$$

The positions of α, β, and δ grey wolves (the first free best solutions) are updated according to the following equations:

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1(\vec{\mathrm{D}}_\alpha) \tag{15}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2(\vec{\mathrm{D}}_\beta) \tag{16}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3(\vec{\mathrm{D}}_\delta) \tag{17}$$

$$\vec{X}(\mathrm{t}+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{18}$$

Finally, the hunting process is finished by attaching the prey (exploitation phase). The pseudocode of GWO algorithm is shown in Table II.

TABLE II. Pseudo code of GWO algorithm

Initialize the GWO algorithm (population size, maximum number of iterations, position vector X, and vectors A, a, C);
Initialize a population of grey wolves (11)-(12);
Evaluate each grey wolf's fitness function by using (10);
Identify three best wolves (the best search agent - X_α, the second best search agent - X_β, the third best search agent - X_δ) according to their fitness functions;
Repeat
  generate next population by updating each agent position (15)-(17);
  update a, A, C by using (10) and (11);
  compute each agent's fitness function (8);
  update X_α, X_β, X_δ;
Until the maximum of generation is not met
Output: the optimal parameters
$\left[K_{\mathrm{p}}^{\mathrm{pos}}\ K_{\mathrm{p}}^{\mathrm{vel}}\ K_i^{\mathrm{vel}}\ PP_2\ PP_3\ f_{\mathrm{H}} \right]_{\mathrm{OPT}}$

IV. Fine Tune Method

The Fine Tune (FT) method is a well-known method to manually tune CNC machine tools in order to improve their performance. Different experimental-based procedures combined with computational intelligence methods such as expert systems or fuzzy logic, as well as information about knowledge accumulated in databases, can be used for fine tuning of one axis or all CNC axes automatically. Finally, the tuning of servo-performance of CNC machine tools axes is carried out by combining experimental studies and frequency response diagrams. More details about FT method can be found in [31].

V. Experimental Results

A. Simulation results

This section provides information related to parameters setting of proposed algorithms. The implementation of the method is carried out Matlab R2019 software package. The personal computers has an Intel Core i7-4790 CPU 3.6GHz with 16GB RAM. The main parameters of the GWO are the size of population 20, the maximum number of iterations 100, a linearly decreasing of a parameter [2,0], and random vectors [0,1] for r_1 and r_2.

The simulation results of GWO algorithm using the digital twin are compared with the results achieved by FT method. The optimal parameters are $\mathbf{K}_{FT}$=[66.67, 0.29, 0.008 0.718, 0.008, 0.1288] and $\mathbf{K}_{GWO}$=[75.00, 0.2632, 0.0012 0.4368, 0.04393, 0.00231]. The average computing time for FT is 14.4 10^3s whereas for GWO it takes 9.75·10^3s. Fig. 3 shows the reference position and velocity used in simulation and experiments of the tracking and trajectory control in experiments that lasted 32.76 seconds. These reference values are further used for validating the proposed digital twin-based GWO methodology. Fig. 4 shows how GWO algorithm achieves the best performance index with a remarkable reduction in *maxE* quantified in 66.4% in comparison with the Fine Tune method. The simulation results of position error are presented in Fig. 5, including a zoom in, and the control signal is presented in Fig. 5. The dynamic response shown in Fig. 5 corroborates the good accuracy of the GWO for tracking the desired trajectory.

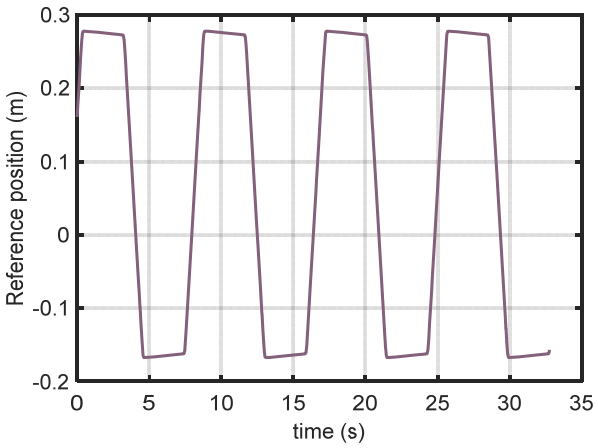

Fig. 3 The reference position for trajectory control.

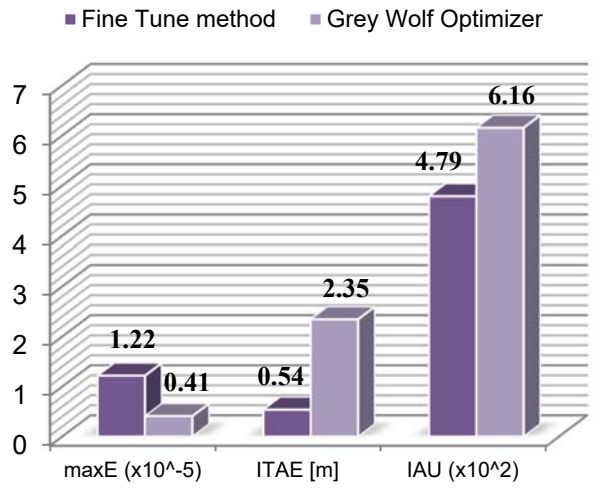

Fig. 4 Performance indices in simulation results

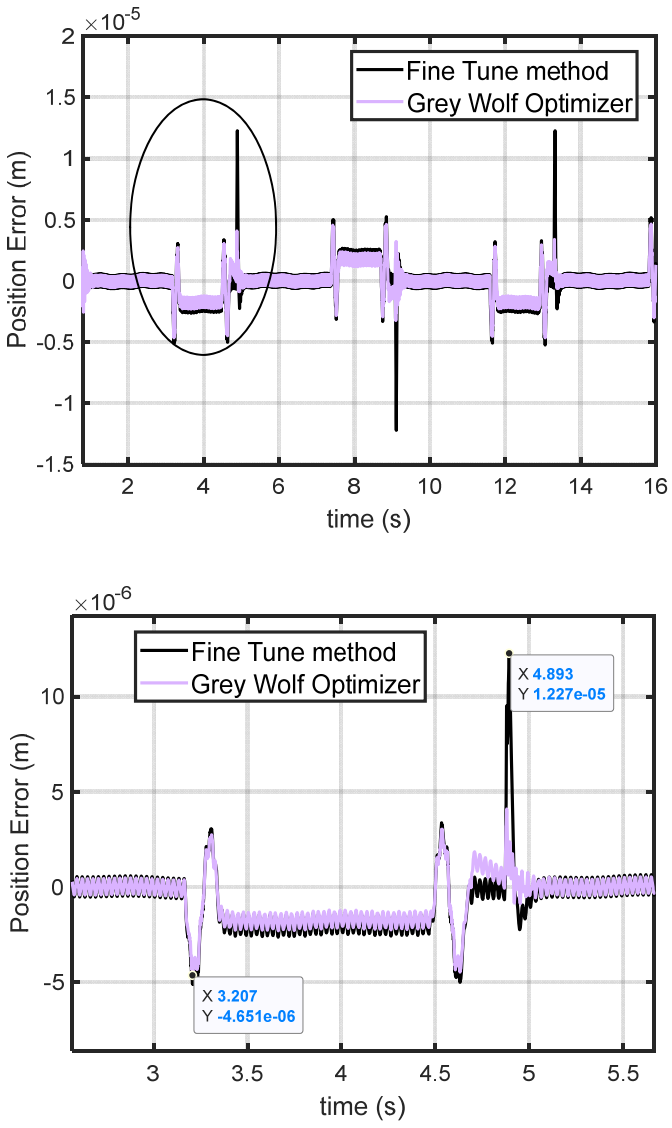

Fig. 5 Simulation results of FT and GWO for tuning cascade P-PI control system

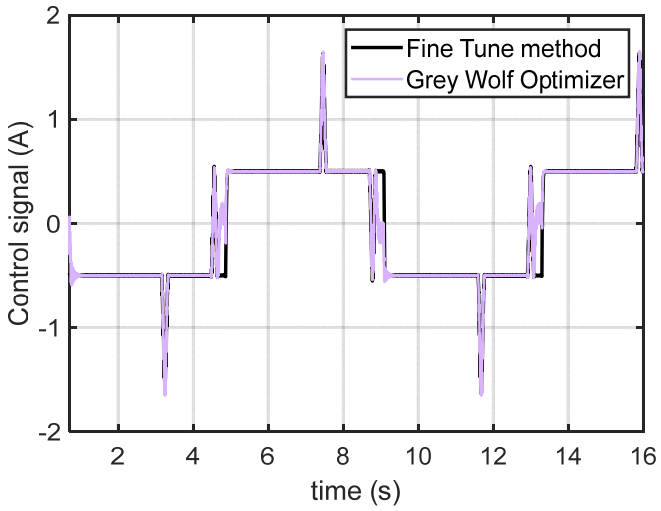

Fig. 6 Behavior of the simulated current signal for FT method and GWO algorithm

B. *Real-time experiments*

Real-time experiments for evaluating CNC machine tool positioning system with both set of parameters yielded by FT and GWO were conducted in the test platform shown in Fig. 2. The comparison of GWO and Fine Tuning method is carried out considering maxE, ITAE and IAU. Fig. 8 shows the resulting performance indices.

These experimental results are very well aligned with the simulation results, and corroborated that GWO outperforms Fine Tune Method by a remarkable reduction in the maxE with very good accuracy according to ITAE. This improvement can be quantified in 18% and 16% for maxE and ITAE, respectively. Moreover, the excellent behavior is also endorsed with a 2.42% reduction in the control effort. The obtained position error during the experiment is illustrated in Fig. 8 and the control signal is illustrated in Fig. 9.

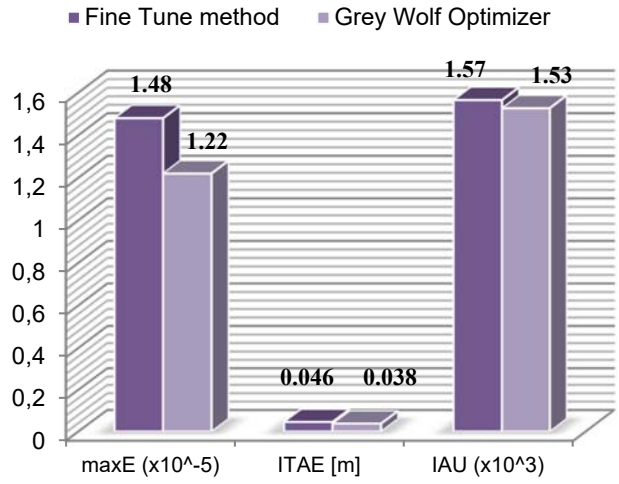

Fig. 7 Performance indices in experimental results

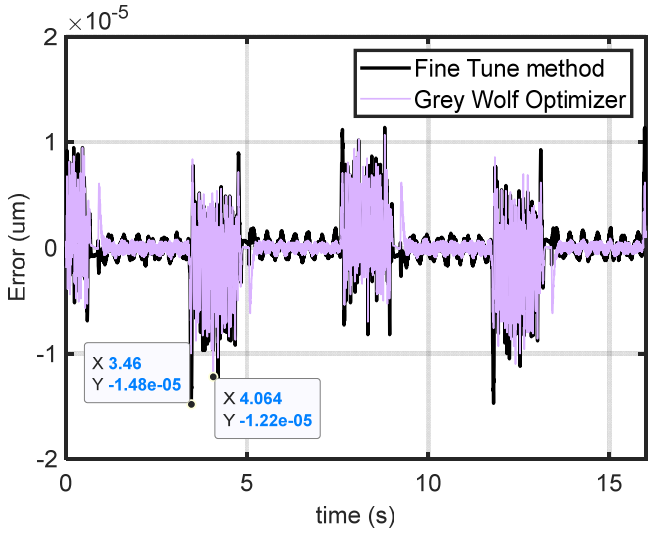

Fig. 8 Experimental results of position error when FT method and digital twin-based GWO method are applied.

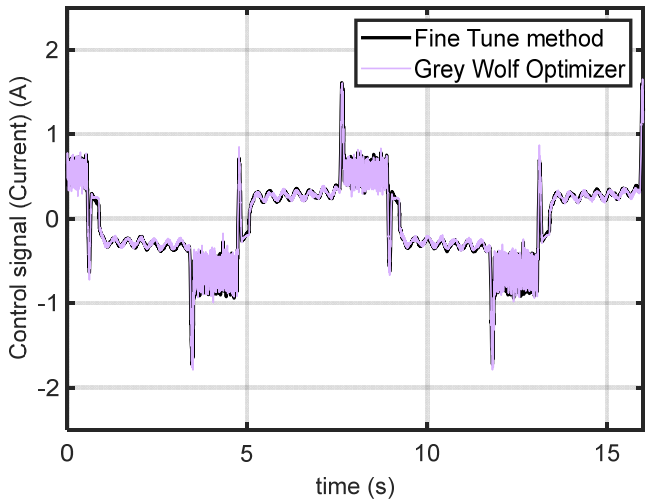

Fig. 9 Behavior of the control signal in both methods.

VI. Conclusion

This paper proposes a digital twin-based optimization method supported on grey wolf optimizer algorithm for optimally adjusting parameters in ultraprecision motion systems widely applied in machine tool positioning systems. The objective function is to reduce as much as possible the maximum position error in presence of hard nonlinearities. This optimization process results in a set of six optimal parameters. Both simulation and experimental results are compared with industry driven method called Fine Tune (FT). The simulation results show a very remarkable improvement in accuracy and good transient response. The real-time experiments carried out on a testing platform with Fagor 8070 controllers also demonstrate the advantage of the GWO over FT method on the basis of lesser maximum peak error (18%), better accuracy (16%) with almost the same or less control effort (2.42%).

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