Carbon Pollution Removal in Activated Sludge Process of Wastewater Treatment Systems Using Grey Wolf Optimization-Based Approach

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***Abstract*—Managing wastewater to effectively remove water pollution is inherently difficult. Ensuring that the treated water meets stringent standards is a main priority for several countries. Advances in control and optimization strategies can significantly improve the elimination of harmful substances, particularly in the case of carbon pollution. This paper presents a novel optimization-based approach for carbon removal in Activated Sludge Process (ASP) of Wastewater Treatment Plants (WWTPs). The developed pollution removal algorithm combined the concepts of Takagi-Sugeno (TS) fuzzy modeling, Model Predictive Control (MPC) and Grey Wolf Optimization (GWO), as a parameters-free metaheuristics algorithm, to boost the carbon elimination in terms of standard metrics, namely Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD5) and Total Suspended Solids (TSS). To enhance such a pollution removal, the proposed fuzzy predictive control for all wastewater variables, i.e. effluent volume, concentrations of heterotrophic biomass, biodegradable substrate and dissolved oxygen, is formulated as a constrained optimization problem. The MPC parameters' tuning process is therefore performed to select appropriate values for weighting coefficients, prediction and control horizons of local TS sub-models. To demonstrate the effectiveness of the proposed parameters-free GWO algorithm, comparisons with homologous state-of-the-art solvers such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), as well as the standard commonly used Parallel Distributed Compensation (PDC) technique, are carried out in terms of key purification indices COD, BOD5, and TSS. Additionally, an ANOVA study is conducted to evaluate the reported competing metaheuristics using Friedman ranking and post-hoc tests. The main findings highlight the superiority of the proposed GWO-based carbon pollution removal in WWTPs with elimination efficiencies of 93.9% for COD, 93.4% for BOD5, and 94.1% for TSS, in comparison with lower percentages for PSO, GA and PDC techniques.**

Keywords—Wastewater treatment systems; carbon pollution removal; fuzzy predictive control; metaheuristics optimization; Grey Wolf Optimizer; ANOVA tests

I. Introduction

Wastewater is a major environmental problem that poses a threat to ecosystems and human health [1]. Contaminants in untreated wastewater, including organic pollutants, pathogens, and heavy metals, can lead to serious health risks and disrupt the balance of ecosystems [2]. To address the critical issue of water pollution and ensure a sustainable future, a wide range of strategies and regulations are being implemented to improve water quality, safeguard public health and protect the environment [3]. The modeling [4] and control [5] of WWTPs are gaining growing attention, with considerable efforts dedicated to improving their performance. Advanced automatic control, artificial intelligence and soft computing approaches have led to the development of various models aimed at enhancing the overall effectiveness of WWTPs [6].

Wastewater treatment involves several stages each aimed at removing different contaminants. The secondary treatment, which is biological, is the most crucial phase in the overall process, aimed at removing organic matter from the water, as well as nitrogen and phosphorus. Biological treatment through ASPs is the most widely adopted solution for addressing pollution and removing toxicity from wastewater [7]. In an ASP, wastewater is aerated in a tank where bacteria break down organic pollutants in the presence of oxygen. After aeration, the treated water flows to a clarifier, where the activated sludge settles out. Some of the sludge is re-circulated into the aeration tank to maintain microorganism concentration. The primary goal of ASP is to produce treated wastewater that meets regulatory standards for effluent quality, mainly in terms of BOD5, TSS, and COD [8]. It also aims to maintain appropriate dissolved oxygen levels to avoid anoxic conditions. However, achieving these objectives is challenging due to several factors. Variability in influent characteristics, such as changes in flow rate and pollutant concentrations, requires constant adjustments to maintain consistent effluent quality. The behavior of microbial communities is influenced by numerous factors, including temperature, pH, and nutrient availability, making it difficult to maintain an optimal balance. Furthermore, the interactions between various biological, chemical, and physical processes within the system are highly complex and difficult to model accurately [9]. As a result, ensuring optimal treatment performance demands the use of sophisticated modeling and advanced control strategies, making the management of ASPs a persistent and significant challenge.

Over the years, numerous control strategies have been proposed for WWTPs. These techniques differ in their targeted objectives, which are typically defined in terms of optimizing dissolved oxygen and enhancing harmful substances removal. In study [10], a comprehensive framework is proposed for evaluating various control techniques of WWTPs. Feedback

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strategies for simultaneous evaluation of economics, energy, and removal of nutrients are addressed. In study [11], a two-stage linear control scheme is developed to regulate the effluent substrate concentration. Static inner-loop controller is designed using a metaheuristic algorithm for parameters selection. Strategies of static feedback with pole placement [12] and model predictive control [13] are investigated based on an established TS fuzzy representation for ASPs. In study [14], authors examined the design of fuzzy controllers for dissolved oxygen and nitrate dynamics under varying conditions. In [15], a PDC technique is designed under linear matrix inequalities (LMI) constraints of stabilization. In study [16], model predictive control, PID regulation, data-driven and neural networks are investigated to optimize nitrogen removal offering a flexible and adaptive approach to process control. In [17], authors implemented cascaded PI and event-based control strategies for WWTPs using the nitrogen-to-energy index as a performance indicator. In study [18], various artificial intelligence-based strategies are explored with a particular focus on aeration control. In study [19], authors developed deep learning-based simulators to improve the control of phosphorus removal processes. In study [20], authors proposed a nonlinear predictive control strategy to manage the nonlinear dynamics inherent in WWTPs and enhancing the control performance and stability. In study [21], a neuro-fuzzy based MPC controller is designed to estimate key process variables and adjust aeration levels for cost-effective nutrient removal. In [22], authors proposed an economic-oriented MPC ensuring ammonia concentration within specified limits.

In addition to these aforementioned state-of-the-art control strategies, the application of metaheuristics algorithms has become increasingly significant in addressing the complexities inherent in WWTPs. In study [23], a dynamic multi-objective PSO algorithm is proposed for dissolved oxygen and nitrate dynamics. In study [24], a GA optimizer is used to modify the set-point of PI controller for dissolved oxygen variables. Two levels are used: at the higher one, GA determines the optimal dissolved oxygen set-point based on operational conditions and at the lower, a PI controller adjusts the aeration to reach the set-point. In study [25], various metaheuristics are integrated with a fuzzy inference system to enhance the modeling accuracy of WWTPs. The achieved prediction capabilities guarantee more effective management and compliance with environmental standards. In study [26], a coyote optimization algorithm is employed to optimize the adaptive controller parameters for dissolved oxygen concentration in a biological sequential batch reactor. In [27], authors proposed a framework to optimize the aeration in WWTPs. A neural network predicts energy consumption and dynamically adjusts PI controllers. In [28], an extreme learning machine with metaheuristic algorithms is designed for the modeling of water quality parameters in Nigeria.

In this context, advanced optimization strategies are crucial to effectively manage WWTPs. Metaheuristics have emerged as powerful tools for controlling complex systems, offering competing solutions to the challenges inherent in biological processes [29]. Due to the strict quality requirements set by international standards as well as the increasing complexity of WWTPs, it becomes essential to optimize all biochemical variables involved in the purification process to ensure more effective pollutant removal and guarantee the compliance with increasingly stringent water quality standards. Indeed, there are few contributions in the literature that address the enhancement of all pollutants removal. Most proposed optimization strategies focus on economic objectives, and many studies often limit their scope to the dynamics of dissolved oxygen to minimize energy consumption, neglecting other critical variables such as wastewater influent volume, biomass growth, substrate concentration, and others. On the other hand, most metaheuristics of the literature suffer from the problem of choosing and tuning their control parameters. The efficiency of such algorithms is strongly linked to the tuning of parameters of the algorithm itself, often tedious and time-consuming in design. Thus, the use of a metaheuristic with a reduced number of algorithmic parameters, or even without parameters, can circumvent such a design problem and offers more simplicity in the optimization process. GWO algorithms as a parameters-free metaheuristics thus present an interesting and justified choice for optimizing the wastewater treatment. Therefore, the use of a GWO algorithm combined to a nonlinear multi-input multi-output model, which accounts for all state variables of ASPs, as well as an efficient automatic control strategy, is essential to further enhance the purification challenges and the carbon pollution removal. In this paper, an intelligent carbon pollution removal strategy, based on an established TS fuzzy modeling and MPC combined with a GWO metaheuristic tuning policy is proposed to manage all intervening variables in WWTPs and enhancing the performance of purification in terms of BOD5, COD and TSS metrics. The uniqueness and main contributions of this work are summarized as follows: (1) A powerful and parameters-free GWO metaheuristic is proposed to adjust the many effective gains of the designed fuzzy MPC controllers and consequently boost the carbon pollution removal in WWTPs. (2) The enhancement of overall purification variables is aimed and the commonly used BOD5, COD and TSS indices are considered to quantify the carbon removal efficiency. (3) Performance is evaluated in terms of reproducibility, algorithmic convergence, and solution quality. (4) Comparisons to the most commonly used state-of-the-art algorithms, i.e. PSO and GA optimizers, as well as the PDC technique are performed. (5) An ANOVA based on Friedman ranking and post-hoc tests is carried out.

The rest of the paper is organized as follows. Section II presents the modeling part as well as a preliminary survey on the nonlinear ASP model for carbon removal, along with its equivalent TS fuzzy representation and the MPC strategy. The main indices and measures for quantifying carbon removal efficiency, namely BOD5, COD and TSS, are also provided. In Section III, the MPC gains tuning problem is introduced and formulated as an optimization problem under operational constraints. The proposed parameters-free GWO algorithm is presented in Section IV. Section V provides demonstrative results and discussions to assess the effectiveness of the proposed GWO-based approach in enhancing carbon removal in WWTPs. Finally, Section VI concludes the paper.

II. Modeling and Preliminaries

A. Activated Sludge Process

As shown in Fig. 1, a typical architecture of ASP consists of a bioreactor, a decanter/clarifier, and a sludge recycling pipe [8]. The wastewater is mixed with activated sludge in the bioreactor, where dissolved oxygen is supplied to support the growth of microorganisms that degrade organic pollutants. Following the aeration phase, the mixture flows into the decanter, where the sludge settles to the bottom, allowing the clarified water to rise to the top. The treated water is then separated for further processing or discharge, while a portion of the settled sludge is recycled back into the bioreactor via the sludge recycling pipe, maintaining the optimal concentration of microorganisms for continuous treatment.

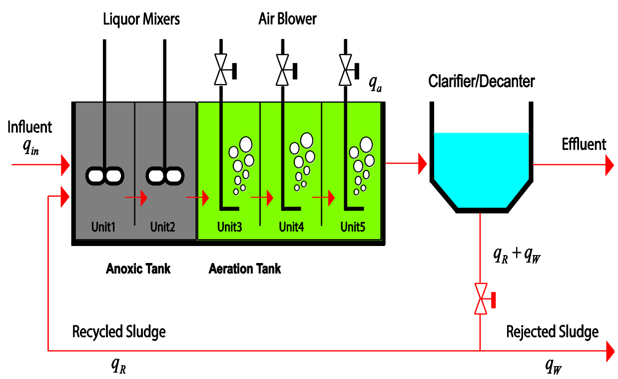

Fig. 1. Layout of an activated sludge treatment procedure.

Focusing on the carbon removal, a reduced dynamic model based on the commonly used Activated Sludge Model N°.1 is retained to describe all the nonlinear dynamics of the plant. It is assumed that the purified water is free of particulate substances and the concentrations of soluble components are equal at inlet and outlet of the decanter:

$$\dot{V} = q_{in} + q_R - q_{out} = \kappa_V \left(V_{ref} - V \right) \tag{1a}$$

$$\begin{aligned}\dot{X}_{BH} &= \frac{q_{in}}{V} X_{BH,in} - \frac{q_{in}}{V} \frac{f_W (1+f_R)}{(f_R + f_W)} X_{BH} \\ &+ \mu_H \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} X_{BH} - b_H X_{BH}\end{aligned} \tag{1b}$$

$$\begin{aligned}\dot{S}_S &= \frac{q_{in}}{V} S_{S,in} - \frac{q_{in}}{V} S_S - \frac{\mu_H}{Y_H} \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} X_{BH} \\ &+ (1-f) b_H X_{BH}\end{aligned} \tag{1c}$$

$$\begin{aligned}\dot{S}_O &= -\frac{q_{in}}{V} S_O - \frac{1-Y_H}{Y_H} \mu_H \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} X_{BH} \\ &+ \kappa_O q_a \left(S_{O,sat} - S_O \right)\end{aligned} \tag{1d}$$

where κ_V is a regulation gain, V_{ref} is the volume reference, f_R and f_W are the fraction rates of recycling and extraction flows, respectively, κ_S is the half-saturation rate of substrate, κ_{OH} is the oxygen saturation rate for biomass, κ_O is the oxygen regulation gain, $S_{O,sat}$ is the saturation concentration of oxygen, b_H is the heterotrophic biomass mortality rate, μ_H is the biomass growth rate, f is the fraction of particulate products, and Y_H is the substrate/biomass conversion rate.

B. TS Fuzzy Modeling

From the nonlinear model (1) of ASP system, an equivalent quasi-LPV form can be derived as follows [30, 31]:

$$\begin{cases} \dot{\boldsymbol{X}}(t) = \boldsymbol{A}(\vartheta(\boldsymbol{X},\boldsymbol{u}))\boldsymbol{X}(t) + \boldsymbol{B}(\vartheta(\boldsymbol{X},\boldsymbol{u}))\boldsymbol{u}(t) \\ \boldsymbol{y}(t) = \boldsymbol{C}(\vartheta(\boldsymbol{X},\boldsymbol{u}))\boldsymbol{X}(t) \end{cases} \tag{2}$$

where $\vartheta(\boldsymbol{X},\boldsymbol{u})$ is a parameters vector of the system state variables $\boldsymbol{X} \in \mathrm{R}^n$ and control inputs $\boldsymbol{u} \in \mathrm{R}^m$, $\boldsymbol{A}(\vartheta(\boldsymbol{X},\boldsymbol{u}))$ and $\boldsymbol{B}(\vartheta(\boldsymbol{X},\boldsymbol{u}))$ are non-constant state-space matrices given by the following Eq. (3) and Eq. (4) expressions:

$$\boldsymbol{A}(\vartheta(\boldsymbol{X},\boldsymbol{u})) = \begin{bmatrix} -\kappa_V & 0 & 0 & 0 \\ 0 & \mu_H \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} - \frac{f_W(1+f_R)}{(f_R+f_W)} \frac{q_{in}}{V} - b_H & 0 & 0 \\ 0 & -\frac{\mu_H}{Y_H} \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} + (1-f) b_H & -\frac{q_{in}}{V} & 0 \\ 0 & \frac{Y_H - 1}{Y_H} \mu_H \frac{S_S}{\kappa_S + S_S} \frac{S_O}{\kappa_{OH} + S_O} & 0 & -\kappa_O q_a - \frac{q_{in}}{V} \end{bmatrix} \tag{3}$$

$$\boldsymbol{B}(\vartheta(\boldsymbol{X},\boldsymbol{u})) = \begin{bmatrix} 0 & 0 & 0 & \kappa_V \\ \frac{q_{in}}{V} & 0 & 0 & 0 \\ 0 & \frac{q_{in}}{V} & 0 & 0 \\ 0 & 0 & \kappa_O S_{O,sat} & 0 \end{bmatrix} \tag{4}$$

Looking at the state-space form given in Eq. (2)-(4), three non-constant terms, known as model nonlinearities, which constitute the set of TS fuzzy premise variables are expressed as follows:

$$z_1(\vartheta(\boldsymbol{X},\boldsymbol{u})) = \frac{S_S(t)}{\kappa_S + S_S(t)} \frac{S_O(t)}{\kappa_{OH} + S_O(t)} \tag{5a}$$

$$z_2(\vartheta(\boldsymbol{X},\boldsymbol{u})) = \frac{q_{in}(t)}{V(t)} \tag{5b}$$

$$z_3(\vartheta(\boldsymbol{X},\boldsymbol{u})) = q_a(t) \tag{5c}$$

A global state-space TS fuzzy model of the WWTP carbon removal dynamics is therefore obtained by defuzzification of local LTI sub-models as given in Eq. (6):

$$\begin{cases} \dot{\boldsymbol{X}}(t) = \sum_{i=1}^{r} \mu_i(\boldsymbol{z}(t)) \{ \boldsymbol{A}_i \boldsymbol{X}(t) + \boldsymbol{B}_i \boldsymbol{u}(t) \} \\ \boldsymbol{y}(t) = \sum_{i=1}^{r} \mu_i(\boldsymbol{z}(t)) \boldsymbol{C}_i \boldsymbol{X}(t) \end{cases} \tag{6}$$

where $\boldsymbol{X} \in \mathrm{R}^4$, $\boldsymbol{u} \in \mathrm{R}^4$ and $\boldsymbol{y} \in \mathrm{R}^4$ are the system state, input and output vectors, respectively, $\boldsymbol{A}_i \in \mathrm{R}^{4\times4}$ and $\boldsymbol{B}_i \in \mathrm{R}^{4\times4}$ denote the constant state-space matrices, $\boldsymbol{z} = (z_1, z_2, z_3) \in \mathrm{R}^3$ is the vector of premise variables, $\mu_i(.) \geq 0$ is the i^th activation function, and $r = 2^3 = 8$ is the number of local sub-models.

The convex polytopic transformation of premise variables of Eq. (5) yields the following expression of all fuzzy activation functions:

$$\begin{aligned} &\mu_1(\boldsymbol{z}(t)) = F_1^1(z_1(t)) F_1^2(z_2(t)) F_1^3(z_3(t)); \mu_2(\boldsymbol{z}(t)) = F_1^1(z_1(t)) F_1^2(z_2(t)) F_2^3(z_3(t)) \\ &\mu_3(\boldsymbol{z}(t)) = F_1^1(z_1(t)) F_2^2(z_2(t)) F_1^3(z_3(t)); \mu_4(\boldsymbol{z}(t)) = F_1^1(z_1(t)) F_2^2(z_2(t)) F_2^3(z_3(t)) \\ &\mu_5(\boldsymbol{z}(t)) = F_2^1(z_1(t)) F_1^2(z_2(t)) F_1^3(z_3(t)); \mu_6(\boldsymbol{z}(t)) = F_2^1(z_1(t)) F_1^2(z_2(t)) F_2^3(z_3(t)) \\ &\mu_7(\boldsymbol{z}(t)) = F_2^1(z_1(t)) F_2^2(z_2(t)) F_1^3(z_3(t)); \mu_8(\boldsymbol{z}(t)) = F_2^1(z_1(t)) F_2^2(z_2(t)) F_2^3(z_3(t)) \end{aligned} \tag{7}$$

where $F_{1,2}^j(.)$ denote the convex partition terms expressed as function of upper and lower bounds of the premise variables $\overline{z}_j$ and $\underline{z}_j$, respectively:

$$F_1^j(z_j) = \frac{z_j - \underline{z}_j}{\overline{z}_j - \underline{z}_j}, \; F_2^j(z_j) = \frac{\overline{z}_j - z_j}{\overline{z}_j - \underline{z}_j} \tag{8}$$

where $\overline{z}_j = \max_{\boldsymbol{X},\boldsymbol{u}} \{z_j\}$ and , $\underline{z}_j = \min_{\boldsymbol{X},\boldsymbol{u}} \{z_j\}$ are the upper and lower bounds of premise variables, respectively.

A complete TS fuzzy model as given in Eq. (6) is therefore established by computing the constant state-space matrices (3)-(4) with all possible combinations of the bounds of premise variables (5) and activation functions (7). On the other hand, the validity of the established TS fuzzy model is evaluated using the well-known Variance Accounted For (VAF %) metric defined as follows [15]:

$$VAF_i = \left(\frac{1 - \mathrm{var}(y_i - \hat{y}_i)}{\mathrm{var}(y_i)} \right) 100\,\% \tag{9}$$

where y_i and $\hat{y}_i$ are the outputs of the nonlinear and TS fuzzy models, respectively, $\mathrm{var}(.)$ is the mathematical variance function, $i \in \{V, X_{BH}, S_S, S_O\}$.

C. Model Predictive Control Design

To achieve an efficient carbon pollution removal in the WWTP, a fuzzy Model Predictive Control (MPC) approach is proposed. The principle aims to compute a sequence of TS fuzzy local control laws where only the first element is applied to the process [32, 33]. Such a control sequence is updated at each sampling time to minimize the following quadratic cost function:

$$J(t) = \sum_{l=1}^{N_p} e^T(t+l \mid t) \boldsymbol{Q} e(t+l \mid t) + \sum_{l=0}^{N_c-1} \left[\Delta u^T(t+l \mid t) \boldsymbol{R} \Delta u(t+l \mid t) \right] \tag{10}$$

where $N_p \in \mathrm{N}$ and $N_c \in \mathrm{N}$ are the prediction and control horizons, respectively, $\boldsymbol{Q} = \boldsymbol{Q}^T > 0$ and $\boldsymbol{R} = \boldsymbol{R}^T > 0$ are the weighting matrices, $e(t+l\,|\,t)$ is the tracking error between the desired and predicted system outputs.

Based on the established TS fuzzy representation (6) of the WWTP carbon removal model, a distributed MPC strategy is proposed. The local predictive controllers are designed using the same fuzzy sets and activation functions as those in the TS fuzzy model. The defuzzification of the overall MPC laws is then performed and applied to the nonlinear model (1) of the studied WWTP.

III. Optimization Problem Formulation

The removal of organic carbon is a crucial step to ensure the effluent water quality and compliance with environmental regulations. Three primary metrics are commonly used to evaluate and measure the efficiency of carbon removal in wastewater: Chemical Oxygen Demand (COD), Biochemical Oxygen Demand over five days (BOD5), and Total Suspended Solids (TSS). Each of these metrics serves as an indicator of organic material and pollutants in the water, providing essential information about the performance of the treatment process. These quality indicators are quantified using the ASP's purification variables such as biodegradable substrate (S_S), particulate inert organic matter (X_I), slowly biodegradable substrate (X_S), active heterotrophic biomass (X_{BH}), active autotrophic biomass (X_{BA}), and particulate byproducts from biomass decay (X_P).

For both the influent and effluent, the calculation of these performance metrics is performed using the following formula [8]:

$$COD = \left(S_S + X_S + X_I + X_{BH} + X_{BA} + X_P\right) \tag{11}$$

$$BOD_5 = 0.25\left(S_S + X_S + (1-f)\left(X_{BH} + X_{BA}\right)\right) \tag{12}$$

$$TSS = 0.75\left(X_S + X_I + X_{BH} + X_{BA} + X_P\right) \tag{13}$$

The closed-loop performance of WWTPs in terms of COD, BOD5 and TSS metrics is clearly dependent on the appropriate choice of MPC design parameters controlling the purification variables. Up to now, no efficient tuning technique exists to select optimal MPC parameters, i.e. weighting coefficients $\lambda \in \mathrm{R}_+$ and horizons $\left(N_p, N_c\right) \in \mathrm{N} \times \mathrm{N}$, under complex and time-varying operational conditions. The selection of optimal values for these gains is often done by time-consuming and tedious trials-errors based procedures. The hardness of such a tuning problem increases further with the complexity and dimensionality of the system. To overcome this hard challenge, the idea to formulate such a tuning task as an optimization problem is proposed as follows:

$$\begin{cases} \underset{\boldsymbol{W} \in \boldsymbol{D}^{d} \subseteq \mathrm{R}^d}{\text{Minimize}}\ f(\boldsymbol{W}) \\ \text{subject to:} \\ g_j(\boldsymbol{W}) = 0;\ \ \forall j = 1, \ldots, n_{con-eq} \\ h_j(\boldsymbol{W}) \le 0;\ \ \forall j = 1, \ldots, n_{con-ineq} \end{cases} \tag{14}$$

where $\boldsymbol{D}^{d} = \left\{\boldsymbol{W} \in \mathrm{R}^d; \boldsymbol{W}_{low} \le \boldsymbol{W} \le \boldsymbol{W}_{up}\right\}$ denotes the initial bounded d-dimensional search space and $\boldsymbol{W}$ is the vector of decision variables, unknowns of the problem.

Such a problem is solved to found optimal values of MPC parameters $\boldsymbol{W}_i^* = \left(N_{p,i}^*, N_{c,i}^*, \lambda_i^*\right)$. In this optimization process, the Integral of Absolute Error (IAE) and Integral of Square Error (ISE) are considered as performance criteria. An appropriate external penalty technique is proposed to handle the MPC constraints $N_c - N_p \le 0$ as follows:

$$f_{IAE,i}(\boldsymbol{W}) = \int_0^{+\infty} \left|e_i(\boldsymbol{W})\right| dt + \exp\left(1000\frac{N_c - N_p}{N_p}\right) \tag{15}$$

$$f_{ISE,i}(\boldsymbol{W}) = \int_0^{+\infty} e_i^2(\boldsymbol{W}) dt + \exp\left(1000\frac{N_c - N_p}{N_p}\right) \tag{16}$$

where $e_i(.), \forall i \in \left\{V, X_{BH}, S_S, S_O\right\}$ denotes the tracking error between the desired set-point and system's output for each ASP dynamics.

IV. Proposed Grey Wolf Optimizer

The proposed Grey Wolf Optimization (GWO) algorithm is a parameters-free metaheuristic method inspired by the social behavior and hunting mechanism of grey wolves in nature [34]. In the social hierarchy of wolves, there is a leader known as the α-wolf, who is responsible for making decisions related to hunting, food distribution and resting areas. The β-wolves, who are at the secondary level, assist the α-wolf in decision-making. The δ-wolves, take on roles such as scouting and sentry duties. Finally, the ω-wolves occupy the lowest level in the hierarchy and are responsible for maintaining a balanced relationship within population.

In a d-dimensional search space, each wolf is characterized by its position $\boldsymbol{x}_k^i = \left(x_{k,1}^i, x_{k,2}^i, \ldots, x_{k,d}^i\right)$. The position of the prey is denoted as $\boldsymbol{x}_k^p = \left(x_{k,1}^p, x_{k,2}^p, \ldots, x_{k,d}^p\right)$. The best solution of GWO is considered as α. The second and third best ones are respectively considered as β and δ. The rest of the wolves have their positions updated randomly around the prey. Hunting process includes the following three main steps [34]:

1) Encircling: The grey wolves' encircling behavior to hunt for a prey can be expressed as follows:

$$\boldsymbol{x}_{k+1}^{i} = \boldsymbol{x}_{k}^{p} - \Delta_k \vartheta_k \tag{17}$$

$$\Delta_k = \left| \eta_k \boldsymbol{x}_k^p - \boldsymbol{x}_k^i \right| \tag{18}$$

$$\vartheta_k = 2\upsilon_k U\left(0,1\right) - \upsilon_k \tag{19}$$

where η_k is a random number between 2 and 0, υ_k is linearly decreased from 2 to 0 over the iterations courses, and $U\left(0,1\right)$ is a uniformly random number in $\left[0,1\right]$.

2) Hunting: The best candidate solutions α, β and δ wolves, have the better recognition of the prey's potential position. The top three solutions $\boldsymbol{x}_k^{best,1}$, $\boldsymbol{x}_k^{best,2}$, $\boldsymbol{x}_k^{best,3}$ are stored to guide the other wolves toward the prey's potential location by updating their positions as follows:

$$\boldsymbol{x}_{k+1}^{i} = \frac{\boldsymbol{x}_k^{best,1} + \boldsymbol{x}_k^{best,2} + \boldsymbol{x}_k^{best,3}}{3} \tag{20}$$

where $\boldsymbol{x}_k^{best,1} = \boldsymbol{x}_k^{\alpha} - \Delta_k^{\alpha} \vartheta_{1,k}$, $\boldsymbol{x}_k^{best,2} = \boldsymbol{x}_k^{\beta} - \Delta_k^{\beta} \vartheta_{2,k}$, $\boldsymbol{x}_k^{best,3} = \boldsymbol{x}_k^{\delta} - \Delta_k^{\delta} \vartheta_{3,k}$, the coefficients vectors $\vartheta_{1,k}$, $\vartheta_{2,k}$ and $\vartheta_{3,k}$ as well as Δ_k^{α}, Δ_k^{β} and Δ_k^{δ} are computed as follows:

$$\begin{cases} \vartheta_{1,k} = 2\upsilon_{1,k} U\left(0,1\right) - \upsilon_{1,k}, \vartheta_{2,k} = 2\upsilon_{2,k} U\left(0,1\right) - \upsilon_{2,k} \\ \vartheta_{3,k} = 2\upsilon_{3,k} U\left(0,1\right) - \upsilon_{3,k}, \Delta_k^{\alpha} = \left| \eta_{1,k} \boldsymbol{x}_k^{\alpha} - \boldsymbol{x}_k^i \right| \\ \Delta_k^{\beta} = \left| \eta_{2,k} \boldsymbol{x}_k^{\beta} - \boldsymbol{x}_k^i \right|, \Delta_k^{\delta} = \left| \eta_{3,k} \boldsymbol{x}_k^{\delta} - \boldsymbol{x}_k^i \right| \end{cases} \tag{21}$$

3) Attacking: Grey wolves finish the hunting process by attacking the prey until it stops moving. In order to model the attacking process, the value of υ_k is linearly decreased from 2 to 0 over iterations and involves the reduction of the fluctuation rate of ϑ_k which is a random value in the range $\left[-2\upsilon_k, 2\upsilon_k\right]$.

A pseudo-code for the proposed GWO algorithm is given in Algorithm 1 [35, 36].

Algorithm 1: Grey Wolf Optimizer

Randomly initialize the grey wolves' population.

Initialize $\vartheta_{j,0}$, $\upsilon_{j,0}$ and $\eta_{j,0}^{i}$.

Evaluate the objective function for each search agent and select $\boldsymbol{x}_0^{\alpha}$, $\boldsymbol{x}_0^{\beta}$ and $\boldsymbol{x}_0^{\delta}$.

Update the position of the current search agent.

Update $\vartheta_{j,k}$, $\upsilon_{j,k}$ and $\eta_{j,k}^{i}$.

Evaluate the objective values of all GWO search agents.

Update the positions $\boldsymbol{x}_k^{\alpha}$, $\boldsymbol{x}_k^{\beta}$ and $\boldsymbol{x}_k^{\delta}$.

Check the termination criterion and repeat iterations.

V. Simulation Results and Discussion

A. Numerical Experimentations

In this study, the most commonly used state-of-the-art metaheuristics, such as Genetic Algorithm (GA) [37] and Particle Swarm Optimizer (PSO) [38] are considered for the performance evaluation and comparison. All competing metaheuristics are independently executed on an AMD Ryzen 5 CPU, 3.3 GHz, and 8.0 GB of RAM. Population cardinality of $n_{pop} = 100$ and maximum iterations of $n_{iter} = 500$ are set. Specific control parameters of GA and PSO algorithms are given as follows:

- GWO [35, 36]: parameters-free algorithm.
- GA [37]: mutation rate 0.02, crossover probability 1.
- PSO [38]: inertial factor 1, coefficients of cognitive and social accelerations 1.5 and 2, respectively.

Numerical parameters of the WWTP system are derived from literatures [8]. All reported algorithms are independently executed 10 runs. Results are summarized in Table I, Table II and Table III where STD and ET metrics denote the standard deviation and elapsed time, respectively. Convergence histories and data distribution for the metaheuristics optimization are depicted in Fig. 2 and Fig. 3, respectively.

For the IAE and ISE criteria, demonstrative results in Fig. 2 show the convergence behaviors of the reported algorithms to solve problem (14)-(16) and highlight the exploration-exploitation capabilities of each of the compared algorithms. Based on these curves, the superiority of GWO algorithm is clearly observed in terms of convergence fastness, quality of the obtained solution and the balance between global and local search capabilities. Indeed, a better exploration of the search space is shown at the first iterations of the optimization process where the GWO optimizer ensures more significant transitions between the evaluated cost function values compared to those of the reported GA and PSO ones. During last iterations, better exploitation of promising neighboring regions likely to contain the global optimum of the considered WWTPs carbon removal problem is guaranteed for the GWO solver.

The Box-and-Whisker plots of Fig. 3 display the statistical data distribution through their quartiles for the optimization results over 10 independent runs of problem (14)-(16). Tighter and symmetrical shapes are obtained for the GWO algorithm, thus showing the high performance of search reproducibility leading to minimal values of standard deviations STD, both for the ISE and IAE criteria.

All these findings from measures of Tables I to Table III as well as curves of Fig. 2 and Fig. 3 confirm the outperforming of the GWO algorithm, as a parameters-free metaheuristic, followed by the reported PSO and GA with less competitive performance and tedious process for tuning of the main control algorithmic parameters.

TABLE I. NUMERICAL OPTIMIZATION RESULTS OVER 10 INDEPENDENT RUNS OF PROBLEM (14)-(16)

Criteria		**Algorithms**		
		GA	**PSO**	**GWO**
IAE	Best	1.5244e+8	1.0259e+8	7.9002e+7
	Mean	2.1253e+8	1.5244e+8	1.0166e+8
	Worst	2.7180e+8	2.7762e+8	1.5956e+8
	STD	4.007e+7	5.3916e+7	2.3261e+7
	COD (%)	89.9	91.1	93.9
	BOD5 (%)	90.8	92	93.4
	TSS (%)	91.6	92.2	94.1
	ET (sec)	6.1458e+4	4.2635e+4	2.2441e+4
ISE	Best	1.3579e+16	3.3837e+15	2.7222e+15
	Mean	2.0811e+16	8.9913e+15	4.9479e+15
	Worst	2.9132e+16	3.2867e+16	7.4036e+15
	STD	5.730e+15	8.7072e+15	1.5908e+15
	COD (%)	89.7	90.7	93.4
	BOD5 (%)	89.2	91.1	92.8
	TSS (%)	90.6	91.8	93.3
	ET (sec)	5.0509e+4	4.7070e+4	1.6781e+04

TABLE II. DECISION VARIABLES FOR THE MEAN CASE OF OPTIMIZATION (14)-(16): IAE CRITERION

TS sub-model	**Tuning algorithms**								
	GA			**PSO**			**GWO**		
	λ^*	N_c^*	N_p^*	λ^*	N_c^*	N_p^*	λ^*	N_c^*	N_p^*
1	0.510	6	8	0.04	2	15	0.241	2	10
2	0.253	6	10	0.550	2	14	0.07	6	8
3	0.337	4	11	0.972	8	15	0.202	4	7
4	0.474	7	12	1	4	15	0.04	7	15
5	0.270	4	11	0.063	4	5	0.075	6	7
6	0.143	4	12	0.04	2	15	0.04	2	14
7	0.548	6	13	0.935	8	12	0.04	2	6
8	0.407	5	15	1	2	15	0.533	2	15

TABLE III. DECISION VARIABLES FOR THE MEAN CASE OF OPTIMIZATION (14)-(16): ISE CRITERION

TS sub-model	**Tuning algorithms**								
	GA			**PSO**			**GWO**		
	λ^*	N_c^*	N_p^*	λ^*	N_c^*	N_p^*	λ^*	N_c^*	N_p^*
1	0.886	6	10	0.390	2	5	0.091	4	12
2	0.351	7	9	0.065	5	6	0.05	4	5
3	0.529	7	10	0.709	8	15	0.075	3	10
4	0.04	4	10	0.04	8	15	0.04	4	5
5	0.316	6	9	0.127	7	8	0.182	3	6
6	0.496	6	11	0.04	2	15	0.04	2	13
7	0.04	6	11	1.00	8	12	0.04	3	8
8	0.586	6	14	0.999	2	15	0.644	2	15

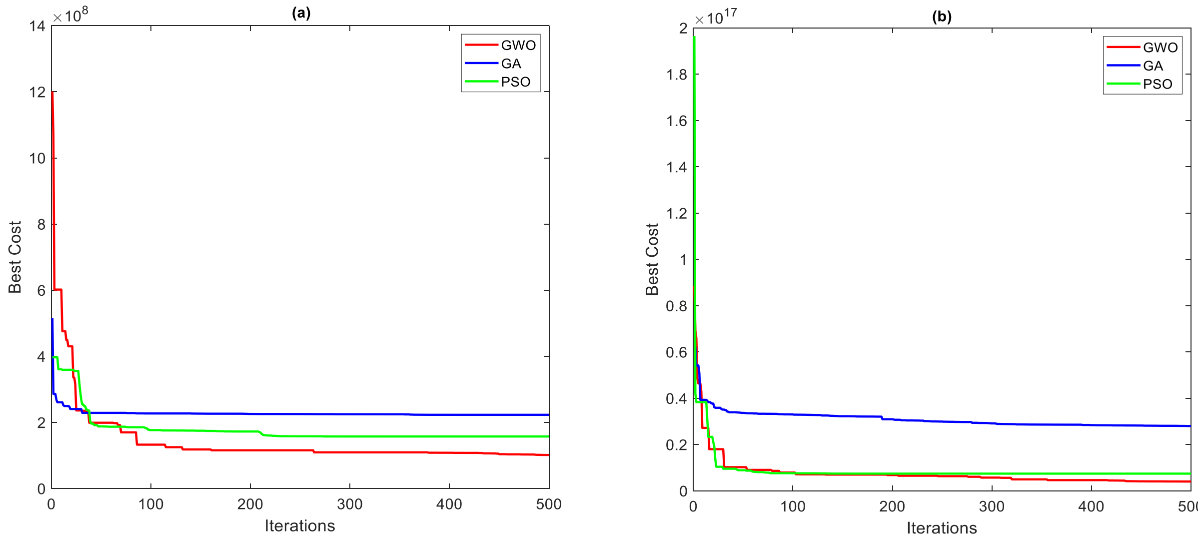

Fig. 2. Convergence histories of the reported optimization algorithms: (a) IAE criterion; (b) ISE criterion.

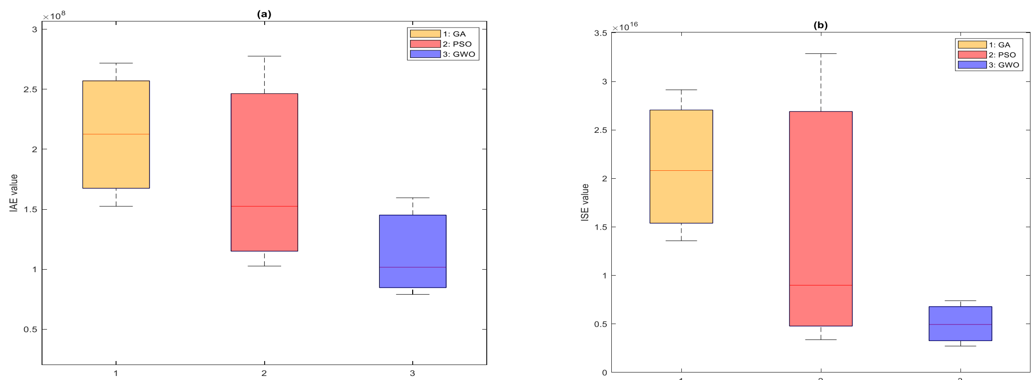

Fig. 3. Box-and-Whisker plots of the algorithms' reproducibility capacities: (a) IAE criterion; (b) ISE criterion.

B. ANOVA Tests and Comparison

Performance assessment of the metaheuristics is a crucial stage in any optimization. Various studies have been addressed for comparisons and statistical analyses of this category of algorithms [39, 40]. In this study, ANOVA tests, mainly in the form of Friedman ranking and paired comparison Fisher's LSD post-hoc test, are carried out and analyzed.

Considering the performance criteria IAE and ISE of (15) and (16), a statistical comparison based on Friedman ranking and Fisher's LSD post-hoc test is performed according to the cost functions values of 10 independent executions [41, 42]. The optimization scores-based ranking of the reported GA, PSO and GWO algorithms is performed in the sense of Friedman. For the 03 reported algorithms and 10 executions, the Friedman test leads to the computed statistics $\chi^2_{F1} = 128$ and $\chi^2_{F2} = 146$ for IAE and ISE criteria, respectively. Based on the chi-square distribution, the critical value with two degrees of freedom and 95% level of confidence is equal to $\chi^2_{2,0.95} = 62 < \chi^2_{F2} < \chi^2_{F1}$. The null hypothesis is rejected and there are significant differences between performances of the proposed optimization metaheuristics. To further explore these differences, Fisher's LSD post-hoc test is applied to determine which algorithms differ from each other. When the absolute difference of the ranks' sum of two algorithms exceeds a critical value, they are considered significantly different. Based on the statistical formula in [41, 42], the critical value is 4.9047 for the IAE criterion and 4.2476 for the ISE one. Paired comparisons are summarized in Tables IV and V where the underlined values highlight significant differences between the reported algorithms. From this ANOVA, one can conclude that the GA algorithm performs the worst according to both the IAE and ISE criteria and the GWO is the best, outperforming each one of the other algorithms.

TABLE IV. PAIRED COMPARISON OF ALGORITHMS: IAE CRITERION

	PSO	**GWO**
GA	<u>8</u>	<u>16</u>
PSO	-	<u>8</u>

TABLE V. PAIRED COMPARISON OF ALGORITHMS: ISE CRITERION

	PSO	**GWO**
GA	<u>10</u>	<u>17</u>
PSO	-	<u>7</u>

C. Carbon Removal Performance

To assess the effectiveness of the established TS fuzzy model, numerical simulations are firstly performed to represent and compare the time-domain responses of the modeled ASP dynamics, including the effluent volume and the concentrations of heterotrophic biomass, biodegradable substrate, and dissolved oxygen. Randomized input profiles are applied over a simulation horizon of 60 hours as shown in Fig. 4. The transient responses comparing the initial nonlinear model of ASP with the established TS fuzzy one are compared based on the VAF (%) metric of (9) as shown in Fig. 5. Input profiles in Fig. 4 are randomly distributed over a horizon with several transitions to well excite all dynamics. The curves of Fig. 5 quantifying the difference between time-domain responses of the system highlight the close similarity when considering its nonlinear model and its equivalent TS fuzzy model. High VAF (%) measures are achieved for all modeled ASP's dynamics with values exceeding 99% for the biomass and biodegradable substrate concentrations, and ranging from 82% to 97% for the dissolved oxygen one. The ability of TS fuzzy modeling to mimic the nonlinear dynamic behavior of the carbon removal process is guaranteed. The established TS fuzzy structure thus accurately replicates the nonlinear dynamics of the initial ASP system (1) and such a linear and time-variant (LTI) structure can be easily considered for control design purposes.

The proposed GWO-tuned MPC strategy is applied on the nonlinear model (1) of the activated sludge process over a simulation horizon of 100 hours. The time-domain responses of the control approach are illustrated and compared with those of PDC-based one as shown in Fig. 6 to Fig. 9. Curves illustrate the closed-loop performance of the controlled carbon removal variables in terms of set-point accuracy, fastness and damping of transient responses. More superior performance for effluent volume, biodegradable substrate, heterotrophic biomass and dissolved oxygen concentrations are guaranteed in comparison with the PDC-based control case [15].

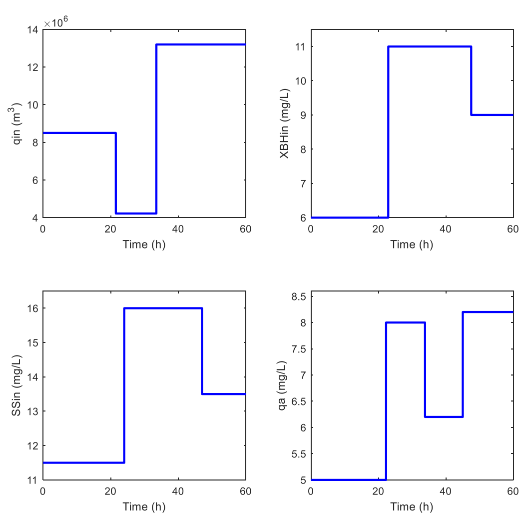

Fig. 4. Evolution of input profiles: influent flow, heterotrophic biomass and biodegradable substrate concentrations, and air flow in the bioreactor.

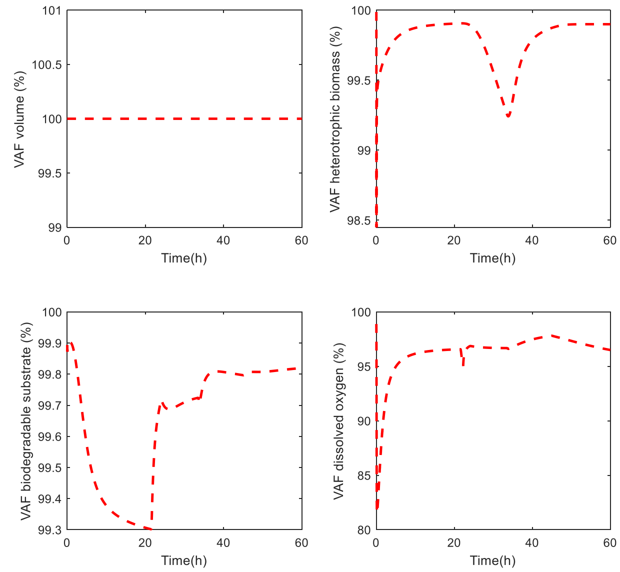

Fig. 5. VAF metrics for the TS fuzzy modeling process evaluation.

To evaluate the impact of the proposed GWO-optimization approach on purification efficiency and carbon removal, key performance indicators are compared between influent and effluent waters. In this assessment, variations in COD, BOD5, and TSS serve as critical metrics to determine the effectiveness of each method. These indicators must comply with regulatory standards with maximum permissible values of 30 mg/L for BOD5, 30 mg/L for TSS, and 125 mg/L for COD. Meeting these thresholds ensures that the treatment process is effective and aligned with environmental regulations, while any exceedance would indicate the need for further adjustments. For this purpose, results of Fig. 10, Fig. 11 and Fig. 12 depict the quantification of pollution removal efficiency.

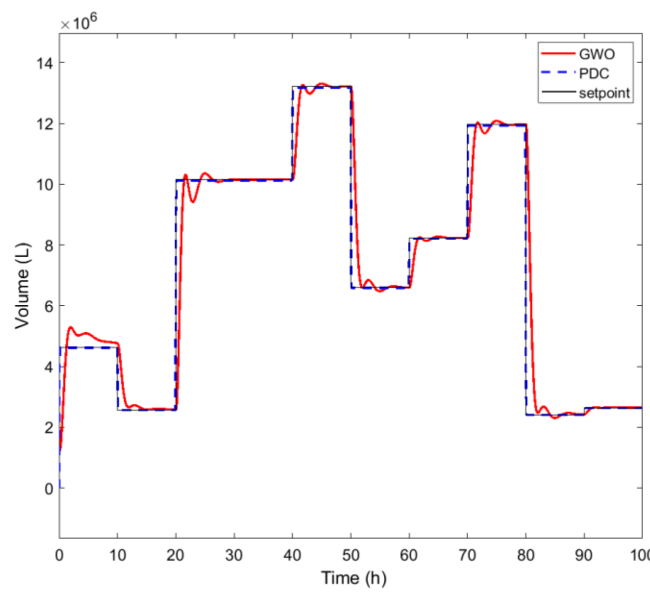

Fig. 6. Step-responses of the effluent's volume dynamics.

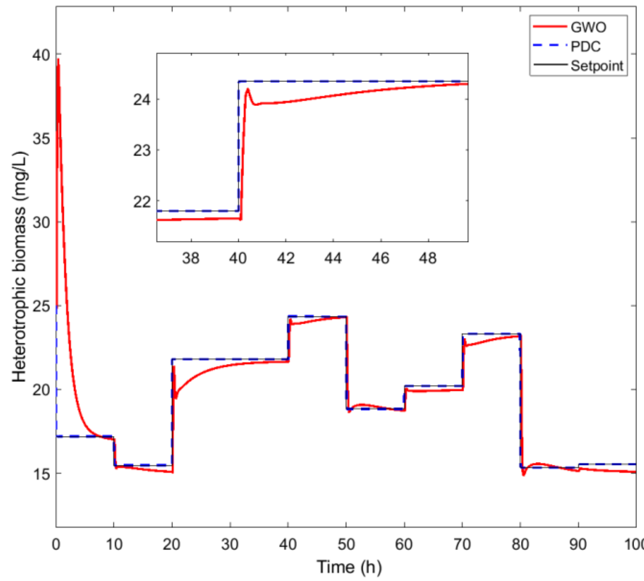

Fig. 7. Step-responses of the heterotrophic biomass concentration dynamics.

For the IAE criterion, results of Fig. 10 show that the COD removal efficiency reaches 89.9% for GA, 91.1% for PSO, and 93.9% for GWO. Similarly, the BOD5 elimination is recorded at 90.8% for GA, 92.0% for PSO, and 93.4% for GWO as shown in Fig. 11. Regarding the TSS removal of Fig. 12, GA achieves 91.6%, PSO attains 92.2%, and GWO remains the most effective with 94.1%, thus highlighting its superior performance. For the ISE case, the COD elimination rates are about 89.7% for GA, 90.7% for PSO, and 93.4% for GWO. Likewise, for the BOD5 removal, GA achieves 89.2%, PSO attains 91.1%, and GWO outperforms both with 92.8%. Lastly, for the TSS removal, GA reaches 90.6%, PSO achieves 91.8%, and GWO leads with 93.3%. For the compared PDC technique, removal efficiencies are 90.7% for COD, 90.5% for BOD5, and 91.8% for TSS remaining lower than those of the GWO-based removal case.

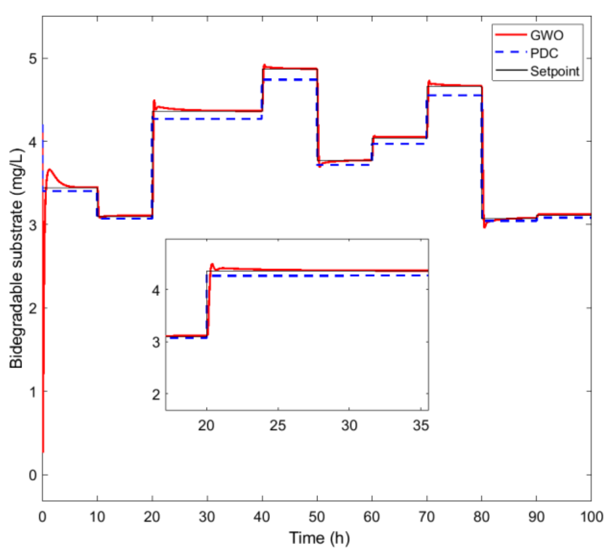

Fig. 8. Step-responses of the biodegradable substrate concentration dynamics.

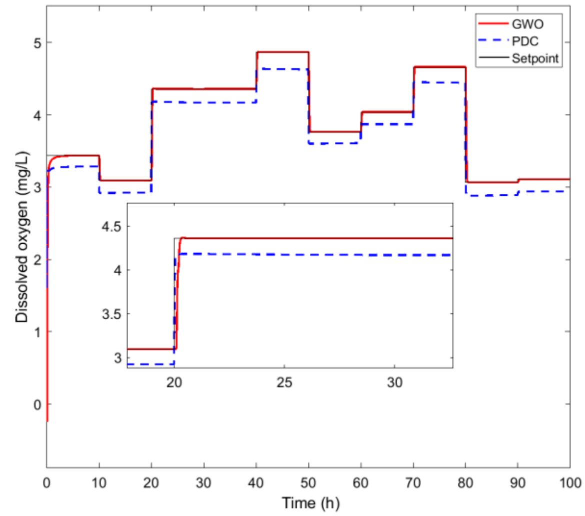

Fig. 9. Step-responses of the dissolved oxygen concentration dynamics.

D. Discussion

In this study, research findings can be summarized into three main points: numerical experimentations of optimization process, GWO-based MPC control of ASP pollutant dynamics, and quantification of carbon removal efficiency through COD, BOD5 and TSS performance metrics.

For numerical experimentations, obtained results of Table I to Table II as well as those of Fig. 2 and Fig3, show that the proposed GWO algorithm demonstrates better convergence capabilities for both the IAE and ISE criteria, confirming its efficiency in balancing the exploration and exploitation capabilities. These demonstrative results indicate that the GWO outperforms the other compared GA and PSO algorithms due to its ability to thoroughly explore the search space in the early iterations before gradually shifting to effective exploitation to refine the best solutions. This well-controlled combination enables GWO to avoid premature convergence and reach the lowest cost values efficiently. Moreover, GWO stands out for its high convergence speed, allowing it to achieve optimal solutions faster than the other algorithms. The PSO solver also performs well, maintaining a good balance between exploration and exploitation, though it is slightly less effective than GWO in fine-tuning solutions in the later stages. The GA algorithm exhibits weaker performance due to premature convergence, as it stabilizes too early and struggles to escape local optima, preventing it from reaching optimal solutions. All these findings confirm the superiority of the suggested GWO solver as parameters-free and most efficient algorithm, followed by PSO, while the GA optimizer remains the least effective due to its limited exploration and early stagnation.

Based on results of Fig. 4 and Fig. 5, one can observe that the established TS fuzzy model is valid in terms of nonlinear dynamical behavior reproduction. Time-domain responses of the modeled carbon removal variables are close since using the initial nonlinear model (1) and the TS fuzzy one (6). This demonstrates the capability of the TS fuzzy representation approach in capturing the nonlinear characteristics of the initial ASP plant. From these results, it is evident that the proposed

TS fuzzy model accurately replicates the dynamic behavior of the initial nonlinear ASP system. Based on this obtained state-space LTI representation, results on the MPC control design are carried out and compared with those of the classical PDC approach. Such a comparison clearly highlights the superiority of the TS fuzzy MPC design traduced by the high set-point tracking performance in terms of accuracy, fastness and damping. These competing performances are clearly evident to boost the carbon pollution removal in maintaining the controlled ASP dynamics around predefined set-point values. The controlled WWTP system exhibits precision, fastness and well-damping of the transient responses for the effluent volume, as well as for the concentrations of heterotrophic biomass, biodegradable substrate, and dissolved oxygen. This proposed metaheuristics-based control strategy ensures a high level of input profiles tracking, though further improvements could be considered, particularly for the biodegradable substrate concentration dynamics. For the other variables, i.e., effluent volume, biomass concentration, and dissolved oxygen concentration, the GWO-tuned MPC strategy demonstrates effective tracking, achieving convergence with minimal steady-state error and no significant overshoot. These closed-loop time-domain results highlight the effectiveness of the proposed approach, making it a highly promising solution for wastewater treatment control.

Finally, can observe that the defined regulatory standards of COD, BOD5 and TSS for effluent water quality are effectively met, demonstrating the efficiency of all proposed optimization approaches, also in comparison with the most commonly used PDC-based technique for carbon pollution removal. All these results demonstrate that while all optimization approaches ensure compliance with environmental standards, the GWO optimizer systematically achieves the highest pollutant removal rates, making it the most effective strategy for enhancing the carbon removal in wastewater treatment.

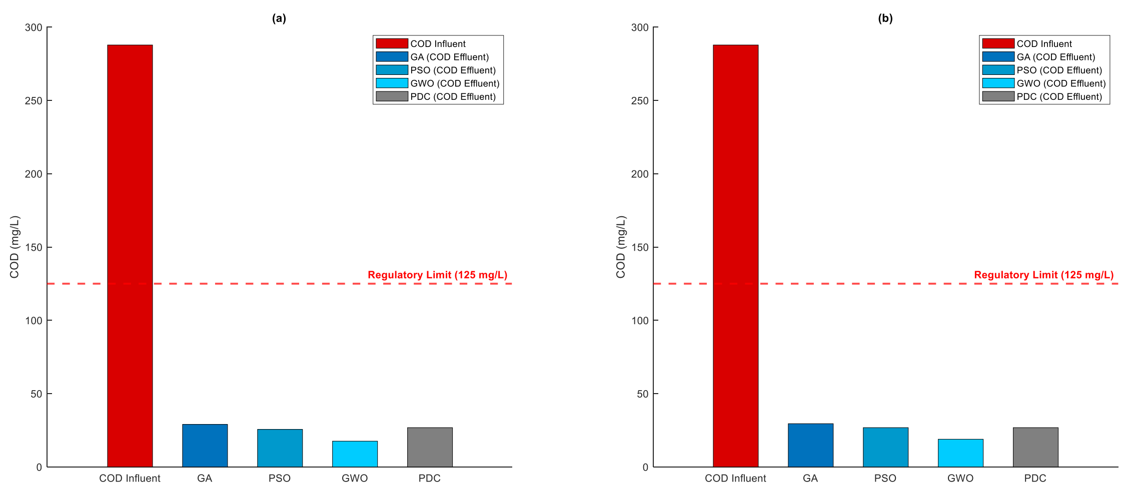

Fig. 10. Quantification of the pollution COD removal efficiency: (a) IAE criterion;(b) ISE criterion.

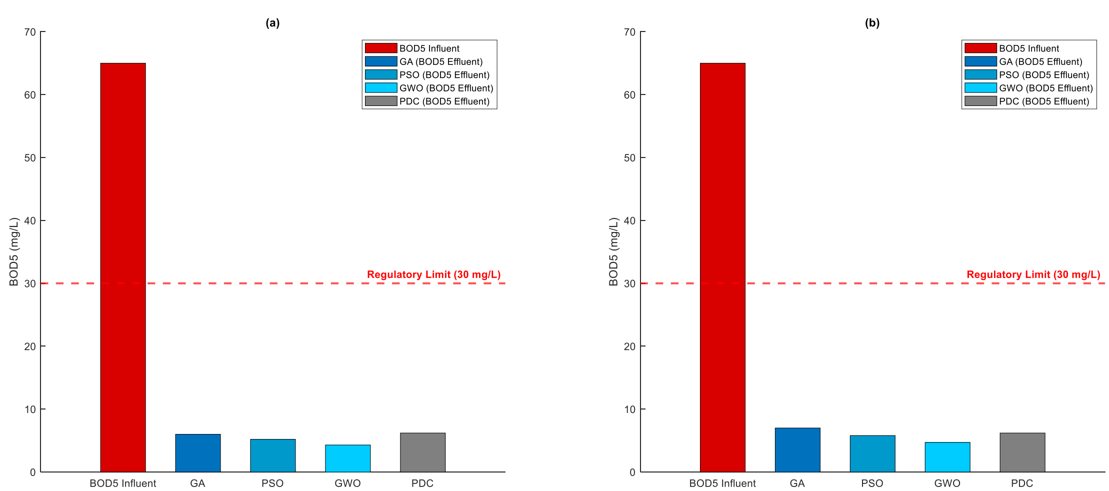

Fig. 11. Quantification of the pollution BOD5 removal efficiency: (a) IAE criterion; (b) ISE criterion.

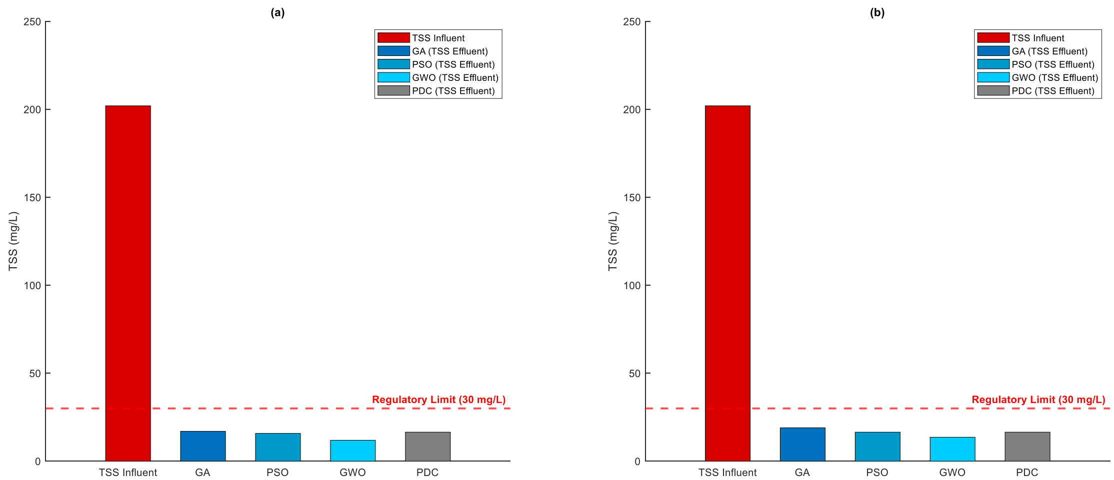

Fig. 12. Quantification of the pollution TSS removal efficiency: (a) IAE criterion; (b) ISE criterion.

VI. Conclusion

In this paper, an advanced and intelligent carbon pollution removal strategy has been proposed for an activated sludge process of wastewater treatment plants. The proposed pollution removal algorithm combined the concepts of Takagi-Sugeno fuzzy modeling, predictive control MPC and parameters-free GWO metaheuristics to boost the carbon elimination in terms of standard COD, BOD5 and TSS metrics. The performance of GWO algorithm, having the advantage of not requiring tuning parameters unlike other metaheuristics, outperformed the compared homologous solvers GA and PSO, as well as the PDC technique. The MPC-based carbon removal problem, which involves selecting the optimal prediction and control horizons as well as the weighting coefficients, has been formulated as an optimization problem with constraints and efficiently solved using the proposed GWO algorithm. The obtained results, supported by comparisons and nonparametric statistical analyses using ANOVA Friedman ranking and post-hoc tests, confirmed the effectiveness and robustness of the proposed water pollution removal strategy. Key wastewater treatment performance metrics, including COD, BOD5, and TSS, have been used to evaluate the efficiency of the proposed GWO-based control methodology. The effluent quality was significantly enhanced, achieving a purification yield of 94% for COD, 93% for BOD5, and 94% for TSS removal, thereby complying with the regulatory standards established for wastewater treatment plants. The findings of this study hold promising implications for the broader scope of wastewater treatment optimization, particularly in tackling other pollutants such as nitrogen and phosphorus. They also highlight the effectiveness of GWO in addressing the complex and nonlinear dynamics of wastewater treatment systems. By optimizing nonlinear TS fuzzy MPC parameters, the proposed strategy offers improved stability, convergence, and solution quality. This work contributes to advanced control techniques for wastewater treatment, emphasizing the importance of metaheuristics algorithms in process optimization. The proposed wastewater purification algorithm combining metaheuristics optimization and fuzzy predictive control is useful for the community of WWTPs management as a comprehensive framework modeling, control and optimization for improving pollution removal efficiency.

Future research will focus on exploring multi-objective optimization to simultaneously optimize conflicting criteria, such as pollutant removal efficiency, energy consumption, and operational costs.

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