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A design of higher-level control based genetic algorithms for wastewater treatment plants

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ABSTRACT

A wastewater treatment plant facilitates various processes (e.g., physical, chemical and biological) to treat industrial wastewater and remove pollutants. This topic recently encourages much attention in different fields to explore suitable methods to be able to remove chemical or biological elements from wastewater. This paper presents a novel genetic based control algorithm for biological wastewater treatment plants, intending to improve the quality of the effluent, and reduce the costs of operation. The proposed controller allows adjusting the dissolved oxygen in the last basin, $S_{O,5}$, according to the operational conditions, instead of maintaining it at a constant value. genetic algorithm (GA) is used in the higher-level control design to verify the desired value of the lower level based on the Ammonium and ammonia nitrogen concentration in the fourth tank, $S_{NH,4}$, concentration values in the fourth tank. In order to modify the tuning parameters of the higher level, an adjustment region is determined. Consequently, the effluent quality is improved, help to decrease the total operational cost. Simulation results demonstrate the advantages of the proposed method.

1. Introduction

Wastewater is water that is discharged after being used, or created in a technological process, and is no longer directly useful for that process. Wastewater can originate from activities of households, industry, commerce, agriculture, surface runoff, stormwater, and flows into underground sewers or seepage. All wastewater must be treated before being put into the environment. One of the methods of wastewater treatment is the use of bio-activated sludge treatment methods. Wastewater treatment plants (WWTP) are complex nonlinear systems. It is a challenge to control the effluent quality due to the complexity of biochemical, biological processes, and fluctuations of input wastewater flow.

For decades, the main goals of treating either municipal or industrial wastewater are to reduce contents of suspended solids, oxygen-demanding materials, dissolved inorganic compounds, harmful bacteria etc. Advanced biological methods of nitrogen removal, chemical and physical methods, such as granular filtration and activated carbon absorption, are employed in different fields. Control also take a very important place at the point of generation in WWTPs. Different control strategies to the WWTPs are modelled the actual systems [1–3].

The Benchmark Simulation Model No.1 (BSM1) has been considered widely in different research in different fields [4–6]. BSM1 is utilized as a standard model for modeling, performance assessment, and evaluation of control strategies [5–8]. This is based on the most popular Activated Sludge Model No.1 (ASM1) expanded by the International Association on Water Pollution Research and Control [3]. The simulation model of Benchmark 1 has determined the wastewater treatment system layout, inlet flow, testing process, and evaluation criteria. The diagram of BSM1 is given in Fig 1. There are five basins in the biological reactor: two anoxic sections (pre-nitrification) followed by three aerated ones (nitrification). To maintain the microbiological population, the sludge is fed back from the settler.

Abbreviations: ASM1, Activated Sludge Model No.1; BSM1, Benchmark Simulation Model No.1; DO, Dissolved Oxygen, GA, Genetic Algorithm; EQI, Effluent Quality Index; IAE, Integral of the Absolute Error; ISE, Integral of the Squared Error; OCI, Operating Cost Index; WWTP, Wastewater treatment plants.

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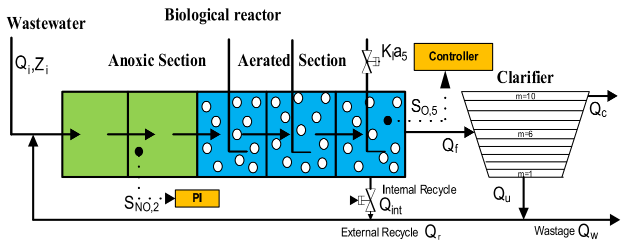

Fig. 1. Benchmark Simulation Model 1 (BSM1).

The Dissolved Oxygen (DO) concentration is an important control variable, which significantly influences many microbiological processes occurring in the system. To maintain the desired aeration in the biological tank, a DO controller is implemented. Besides, DO level in the last tank is controlled that manipulates the aeration coefficient for this basin K_{La}^{5}. Besides, an outer control loop is used to verify the nitrate removal by manipulating the internal recycle flow-rate. This project implements a DO controller to maintain the desired aeration in the biological tank is mainly focus.

There have been various control strategies successfully improved control quality indexes: differential integration method (IAE) and integrating the square of control deviation (ISE), compared to the classical PI controller, such as model predictive controller (MPC) [9–11], fuzzy controller [12,13] and Iterative Learning Control (ILC) [14]. These methods, however, almost did not improve the system performance indexes: operating cost index (OCI) and output wastewater quality index (EQI). Thanks to the good work in [15] that addresses many control technologies for wastewater treatment processes. In ref. [16], some common techniques are compared among the bee colony optimization (BCO), differential evolution (DE), harmony search (HS) algorithms, type-1 fuzzy logic system (T1FLS) and show the promissing point related to fuzzy controller. The type 1 fuzzy parameter applying in genetic algorithms (GA) to optimize the parameters of the membership functions for a type 2 fuzzy aggregation module is proposed in [17] that improves GA to the problem of flight control. Fuzzy controller and GA techniques support each other and provide different ways for wastewater treatment plants [18–20].

Genetic algorithms (GA) have been deployed in different ways in WWTPs [21–23]. An intelligent controller design using neural network and GA is proposed to control pH and Phosphorus concentration [21]. A design for multiobjective control and auto tuning fuzzy controller is proposed to change the control rules and focus on Nitrate concentration and flow rate [22]. Genetic algorithm and Neural Network in fuzzy logic control are combined to control the combustion temperature and air pollution [23]. Techniques based on GA and the others show promising points for WWTPs. Along with these methods, there are also many techniques focus on such variables, Dissolved oxygen, Airflow rate, Biogas concentration, Sludge concentration, Nitrate concentration, etc. [24–27]. These work provide significant references to motivate WWTPs ahead.

Some of existing work focus on the strategies applied constant setpoints for the dissolved oxygen (DO) concentration. Different to the other work, in this paper, the authors apply WWTP utilizing GA into the Benchmark Simulation Model 1 (BSM1). We realize that variable setpoints at different times in a cycle (14 days) will certainly affect the quality of the system. Therefore, a two-level control is proposed, in which the GAs based higher-level stage is designed to adjust the setpoint for the lower-level one. Consequently, EQI and OCI indexes will be minimized according to the different objectives: (1) Maintain EQI, and minimize OCI; (2) maintain OCI, and minimize EQI; and (3) minimize both OCI and EQI. The system is modelled and analyzed following the GA's steps.

The remainder of this paper is addressed as follows. The system description is introduced in Section 2. Then, the proposed approach is presented in Section 3. Simulation results and discussion are provided in Section 4. Finally, Conclusions and future work in Section 5.

2. System description

2.1. Modeling

The total zero-lift drag coefficient of the body is usually considered to be of three components; friction drag, wave drag, and base drag as shown in Eq. (1). These different components are further discussed in the following sub-sections.

The ASM1 describing the biological phenomena is shown in Fig. 2 [29]. There are eight stages in the process, in which connections between layers vertically is modelled according to the model of settling velocity double-exponentially [30].

Control of the concentration of DO from the conversion rate of oxygen (r_O). It is represented as follows [7].

$$r_O = -\frac{1 - Y_H}{2.86 Y_H}\rho_1 + \frac{1}{Y_A}\rho_3, \tag{1}$$

where ρ_1, ρ_3 are two processes defined in ASM1.

ρ_1 is the aerobic growth of heterotrophs:

$$\rho_1 = \mu_H\left(\frac{S_S}{K_S + S_S}\right)\left(\frac{S_O}{K_{O,H} + S_O}\right)X_{B,H}, \tag{2}$$

ρ_3 is the aerobic growth of autotrophs as:

$$\rho_3 = \mu_A\left(\frac{S_{NH}}{K_{NH} + S_{NH}}\right)\left(\frac{S_O}{K_{O,A} + S_O}\right)X_{B,A} \tag{3}$$

where μ_A, μ_H, K_S, $K_{O,\ H}$, K_{NH} and $K_{O,A}$ are the stoichiometric parameters are listed in Table 1 and the kinetic parameters in Table 2. S_O is the dissolved oxygen concentration, S_S is the readily biodegradable substrate, S_{NH} is the NH_4 + and NH_3 concentration, $X_{B,H}$ is the active heterotrophic biomass and $X_{B,A}$ is active autotrophic biomass.

2.2. Evaluation criteria

The performance of the system is assessed by the control quality and plant quality. The former one is assessed by ISE (Integral of the Squared Error) criterion [7].

where e_k is the error in between the setpoint and the measured value. The latter one uses the Effluent Quality Index (EQI) and the Operational Cost Index (OCI), in which [7]:

$$ISE_k = \int_{t_0}^{t_f} e_k^2 dt \tag{4}$$

$$EQI = \frac{1}{T.1000}\int_{t=7days}^{t=14days} B.Q_e(t)dt, \tag{5}$$

where

$$B = B_{TSS}\cdot TSS_e(t) + B_{COD}\cdot COD_e(t) + B_{NKi}\cdot S_{NKi,e}(t) + B_{NO}\cdot S_{NO,e}(t) + B_{BOD5}\cdot BOD_{5,e}(t),$$

$$TSS_e = 0.75(X_{S,e} + X_{I,e} + X_{B,H,e} + X_{B,A,e} + X_{P,e}), \tag{6}$$

$$COD_e = S_{S,e} + S_{I,e} + X_{S,e} + X_{I,e} + X_{B,H,e} + X_{B,A,e} + X_{P,e}), \tag{7}$$

$$S_{KNj,e} = S_{NH,e} + S_{ND,e} + X_{ND,e} + i_{XB}(X_{B,H,e} + X_{X,A,e}) + i_{XP}(X_{P,e} + X_{i,e}), \tag{8}$$

$$BOD_{5,e} = 0.25(S_{S,e} + X_{S,e} + (1 - f_p).(X_{B,H,e} + X_{B,A,e})), \tag{9}$$

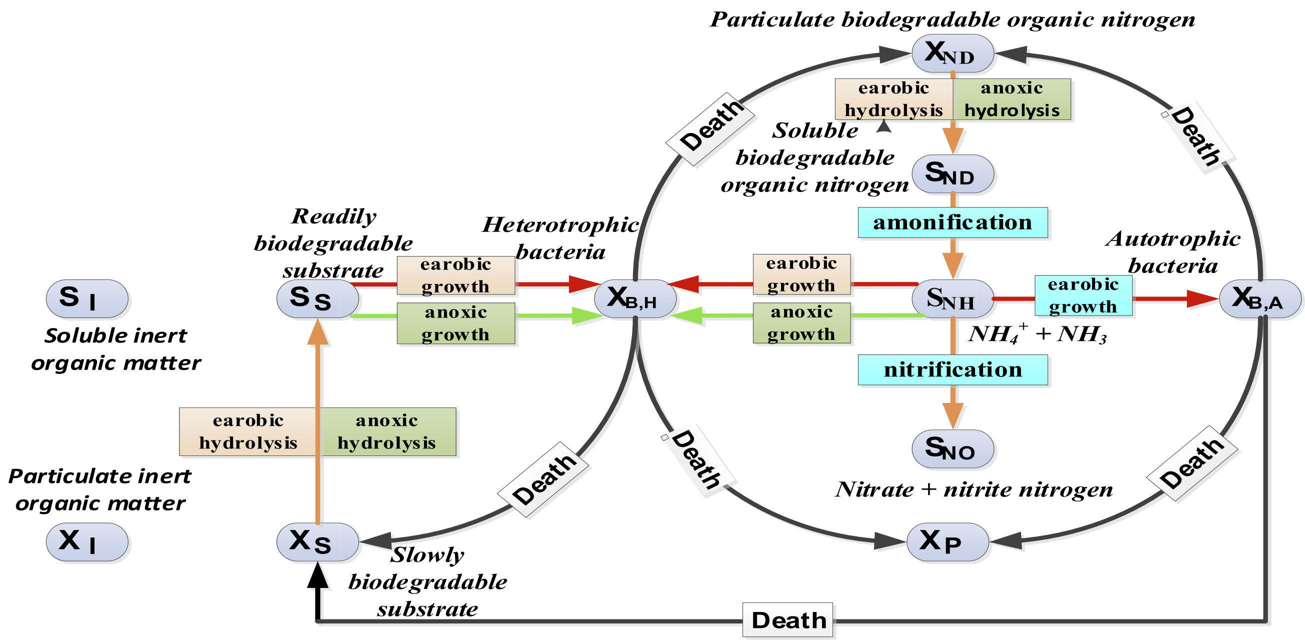

Fig. 2. Overview of ASM1.

Table 1
Stoichiometric parameters.

Parameter	Unit	Value
Y_A	g N oxidized)$^{-1}$	0.24
Y_H	(g COD oxidized)$^{-1}$	0.67

Table 2
Kinetic parameters.

Parameter	Unit	Value
μ_H	d^{-1}	4.0
K_S	g COD.m-3	10.0
$K_{O,\ H}$	g (–COD).m-3	0.2
μ_A	d^{-1}	0.5
K_{NH}	g NH_3-N.m^{-3}	1.0
$K_{O,\ A}$	g (–COD).m^{-3}	0.4

in which Q_e is the rate of output effluent flow and T is time (14 days in simulation). In BMS1 model, the reaction coefficients are given as follows: $B_{TSS} = 2,\ B_{COD} = 1,\ B_{TKN} = 30,\ \ B_{NO} = 10$, and $B_{BOD5} = 2$ are coefficients.

$$OCI = AE + PE + 5.SP_{total} + 3.EC + ME \tag{10}$$

In which AE is the aerating energy calculated according to the formula [7]:

With $V_{as,k}$ is the tank's volume, K_La_k is the oxygen transferring coefficient at 15 °C and $S_O^{sat,15} = 8\ mg/l$ is the concentration of the oxygen saturation at 15 °C.

$$AE = \frac{S_O^{sat,15}}{T.1,8.1000}\int_{t=7day}^{t=14day}\sum_{k=1}^{5} V_{as,k.K_La_k(t)dt} \tag{11}$$

PE is the pump's energy:

$$PE = \frac{1}{T}\int_{t=7day}^{t=14day}(0.004.Q_{int}(t) + 0.008.Q_r(t) + 0.05.Q_w(t))dt \tag{12}$$

SP_{total} is the total sludge production:

$$SP_{total} = \frac{1}{T}(TSS(14day) - TSS(7day) + 0.75\int_{t=7\ days}^{t=14\ days}(X_{S,w} + X_{I,w} + X_{B,H,w}X_{B,A,w}).Q_w(t).dt) \tag{13}$$

EC the cost of the carbon source:

$$EC = \frac{COD_{EC}}{T.1000}\int_{t=7\ days}^{t=14\ days}(\sum_{k=1}^{k=n} Q_{EC,k})dt \tag{14}$$

The mixing energy (ME) provided to the tanks when the aeration process was not enough to maintain the activated sludge operating condition is calculated as follows [7]:

$$ME = \frac{24}{T}\int_{t=7days}^{t=14days}\sum_{k=1}^{k=5}\left[0,005.V_{as,k}\ if\ K_La_k(t) < 20d^{-1}\right].dt \tag{15}$$

3. Proposed approach

3.1. Brief Introduction to GA

Genetic algorithm (GA) is a global random searching method that simulates natural evolution. GA begins without knowledge of the correct solution and it is completely dependent on environmental responses by exploiting evolutions (reproduction, crossover, and mutation) to obtain the best solution. By starting at some standalone searching points and searching parallel, GA avoids local extremes as well as convergence to substitute optimal solutions. Therefore, GA has been proven to be able to search with high performance in complicated spaces without the hassles associated with the dimensionality of space. It differs from gradient techniques or optimizing search methods based on information of the derivative. Due to the WWTP systems are highly nonlinear, GAs could be used as soft-calculation tools for such systems.

Genetic algorithms are founded upon the principle of evolution and are applicable to many hard optimization problems, soon to be applied widely [28]. The algorithm includes 6 steps: (1) Creating populations of chromosomes; (2) Find the adaptive function and determine the adaptive value of each chromosome; (3) Selective; (4) Crossover; (5) Mutation; and (6) Converging. The maximum number of evolutionary generations (Gmax) is chosen as the stopping condition. The optimization process will end when the current generation number exceeds the Gmax value.

3.2. Two-level control for WWTPs

To improve the system performance indexes, a hierarchical control structure is proposed, as depicted in Fig 4.

In the lower-level control (LLC), DO is fed through the aeration system, by manipulating the oxygen transfer coefficient, $K_{La,5}$ to achieve the desired DO concentration. In this project, we applied Iterative Learning Control combined with a PI regulator for this stage due to this method gives the best control tracking performance. Detail of this method can be found in [14]. In particular, the energy for aeration (AE) accounts for most of the system's power consumption, approximately 50% [31]. Therefore, to minimize the OCI, it is necessary to provide enough oxygen according to the current needs of the microbiological system, avoiding overproduction (increasing costs) or lack of oxygen (reduction of the water treatment quality).

Eq. (1) shows that oxygen is used by both autotrophic and heterotrophic bacteria in aerobic tanks to create biomass, to remove carbon and nitrogen in wastewater. Substituting the parameters in Table 2 into Eq. (1) gives:

$$r_o = -0.4925.\rho_1 - 18.0417.\rho_3 \tag{16}$$

However, due to the structure of BSM1 with the first two non-aerated tanks (anoxic tanks), most organic matter is used by bacteria in these two tanks, the concentration of organic substrates SS in the remaining tanks is very low, less than 2 [gCOD/m3]. As a result, the heterotrophic growth rate in Eq. (2) is very small. The most dissolved oxygen is used by autotrophic biomass with speed given by Eq. (3).

Autotrophic biomass using ammonia (NH) as an energy source, combined with oxygen to convert ammonia to nitrate according to the reaction equation [32]:

$$NH_4^+ + 1.86O_2 + 1.98HCO_3^- = 0.02C_5H_7NO_2 + 0.98NO_3^- + 1.88H_2CO_3 + 1.04H_2O \tag{17}$$

Thus, the oxygen demand of the biomass is determined mainly by the amount of ammonia in the reactor. As ammonia level rises, microorganisms need more oxygen to oxidize to nitrate, and vice versa when the ammonia level reduces, the necessary amount of oxygen also reduces. From the above analysis, it can be seen that the amount of oxygen supplied to the tank must be calculated according to the ammonia concentration of the wastewater. This is impossible with a default PI set.

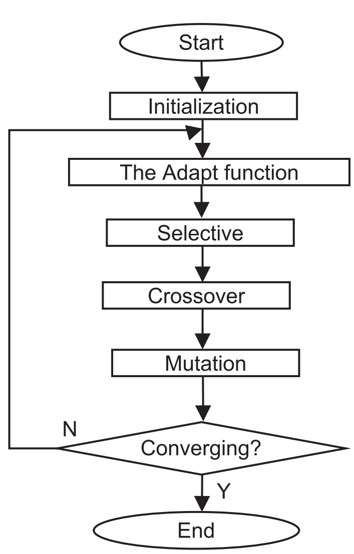

Fig. 3. Genetic Algorithm applying for WWTPs.

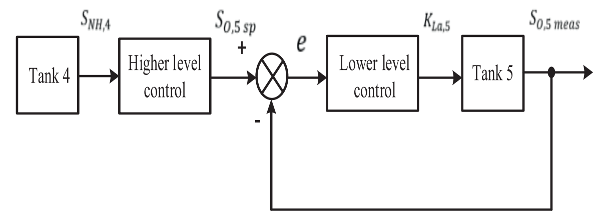

Fig. 4. A hierarchical control structure is proposed.

From Eq. (17), the author finds that the relationship between NH4 and O2 is linear. So, a higher-level control to manipulate the desired value for the lower-level control is proposed as follows:

$$S_{O,5sp} = K.S_{NH,4} + B,$$

where K and B are parameters of higher-level controller.

3.3. Genetic algorithms applying into BSM1

To find the value of K and B in Eq. (18), genetic algorithm (GA) is utilized. This is the optimal search method based on natural selection, genetic and evolutionary mechanisms. They select genes that have a string structure that adapts to the natural selection process, exchanging information about genetic structure randomly to create a generation that is more adaptive than the previous one under a specific condition. GA uses natural selection as a navigation tool and harnesses past information to forecast new search points in the hope of improving the string structure.

GAs is a type of evolutional algorithm used to identify and optimize parameters of an input–output map. By starting at several independent search points and parallel searching, GA will avoid local extremes and converge to optimal solutions. It differs from gradient techniques or optimizes search methods based on derivative information. GAs are computationally expensive algorithms. This method, however, can be implemented offline.

The optimizing membership function parameters using GA is shown in Fig 3. A population of 20–100 individuals is randomly chosen to initiate the GA. Each individual is chromosomes, which is a real or binary sequence. A cost function is employed to evaluate the performance of each chromosome. Through the fitness-based process, chromosomes with lower-cost value have a higher fitness, and hence have more advance to the next generation. There is a set of genetic rules, including selection, crossover, and mutation. This selection rule replicates the most successful solution found in a population, the crossover decomposes two distinct solutions, then arbitrary mix their parts to create new solutions, and the mutation changes a candidate solution randomly [28].

The fitness function is chosen as below:

$$fit_i = W_1.OCI + W_2.EQI \tag{19}$$

In which W_1 and W_2 are weighting factor. In Objective 1, to minimize OCI while maintaining EQI, we set W_1 = 1 and W_2 = 0. In Objective 2, to minimize EQI while maintain OCI, we set W_1 = 0. and W_2 = 1. In Objective 3, to minimize both *OCI* and *EQI*.

In order to find the weights of W_1, and W_2 of Eq. (19), the GA algorithm available in matlab tools is deployed with the following settings for the program to run as follows:

- Number of optimized parameters: 2 (W_1, and W_2)
- Population size: 150 (individuals).
- Generation number: 300.
- Combination probability: $P_c = 0.8$
- Mutation probability: $P_m = 0.001$

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The GA algorithm then performs the steps as described in Fig. 3 til the stop condition of the program is satisfied. This genetic algorithm has two basic stopping conditions: (i) Based on the chromosome structure, controlling the number of genes that are converged, if the number of genes converged exceeds a certain percentage of the total number of genes, then the search will end; (ii) based on the particular significance of a chromosome, measuring the algorithm's progress over a given number of generations, if this progress is less than a specified constant of ε, then the search will end. After finishing (about 24 h per algorithm), we will find the optimal values of fit_i. Because GA genetic algorithm is a random search process, each time we execute the algorithm, an optimal value of fit_i is chosen. These optimal values of fit_i are compared among the time of running implementation, until the optimal value of fit_i does not change. We finally find the appropriate weights of W_1 and W_2. These weights that are presented corresponding to different weather condition are listed in Table 3.

4. Results and discussion

Fig 5 shows the Simulink model, in which the higher-level controllers are depicted in Fig 6.

Three dynamic data input files defined in the Benchmark Simulation Model describe different weather conditions. They are considered to investigate control performance concerning disturbance rejection. The dynamic model used for the control investigations captures the main dynamic features of the biological wastewater treatment plant.

Applying genetic algorithms, $K_{SO,5}$ and $B_{SO,5}$ for the lower-level controller are found satisfying objectives of the desired problem, as illustrated in Table 4.

Table 3
Values of weighting factors.

Weather	W_1	W_2
Dry	0.28	0.72
Rainy	0.33	0.67
Stormy	0.3	0.7

These estimated values of $K_{SO,5}$ and $B_{SO,5}$ in the higher-level control are applied into the lower-level controller, as shown in Fig 6. The simulation results will be compared with the strategy that has only the lower controller, which is ILC combined a PI regulator, with the same wastewater input profile in 3 considered weather conditions. Fig. 7 illustrates the simulation results of concentrations of nitrogen and oxygen at the outlet of the tank 5 in dry weather condition.

From Fig 7, we see that the oxygen concentration always follows the change of nitrogen concentration. Besides, the average oxygen concentration when using the higher-level control is lower than when only the lower-level control is used. As a result, system quality indexes will be improved.

Tables 5–7 show the results of the system corresponding to objectives 1, 2 and 3, in all 3 different weather conditions.

In Table 5, compared to the strategy without a higher-level controller, the EQIs are almost unchanged, while the OCIs using the GA based hierarchical control are reduced noticeably, above 1% in all three different weather conditions. In contrast, Table 6 shows a significant decrease in the EQIs, while the OCIs are kept almost constantly. In dry weather conditions, especially, the EQI is reduced by almost up to 2%. In Table 7, the results indicate that both OCI and EQI using GA based hierarchical control are all lower than those of using default PI, meeting the objective 3. In dry weather, for illustrate, the EQI is decreased by 1.46%, and the OCI is dropped 0.61%.

However, WWTPs are non-lear problems that cannot be optimized based on one or two parameters. The cost, the time consuming, and the complexity, etc. in the systems always have a trade-off. This proposed method reduce the cost but may increase the

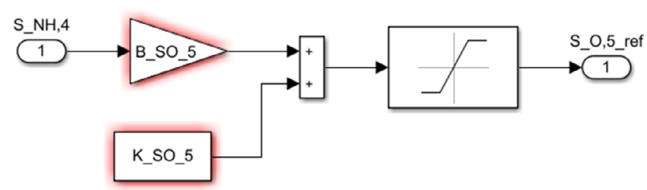

Fig. 6. Higher-level controller.

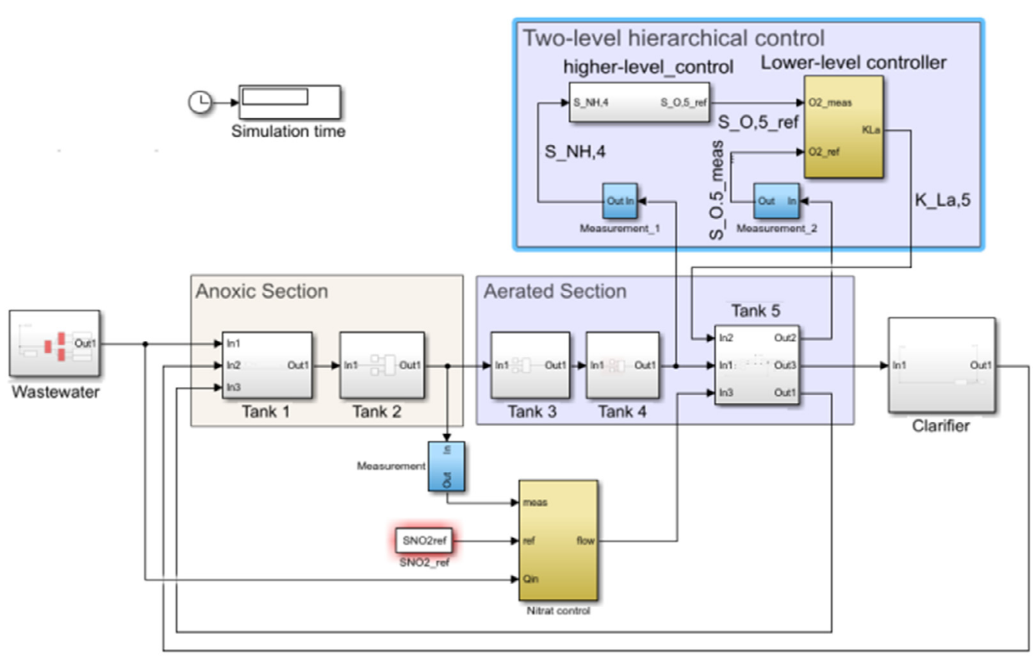

Fig. 5. Simulation model.

Table 4
Obtained parameters K_(SO,5) and B_(SO,5).

Weather	Objective					
	Obj. 1		Obj. 2		Obj. 3	
	K_{SO5}	B_{SO5}	K_{SO5}	B_{SO5}	K_{SO5}	B_{SO5}
Dry	0.290	0.455	0.895	1.391	0.4	0.391
Rainy	0.288	0.176	0.613	0.381	0.263	0.135
Stormy	0.252	0.153	0.578	0.498	0.345	0.199

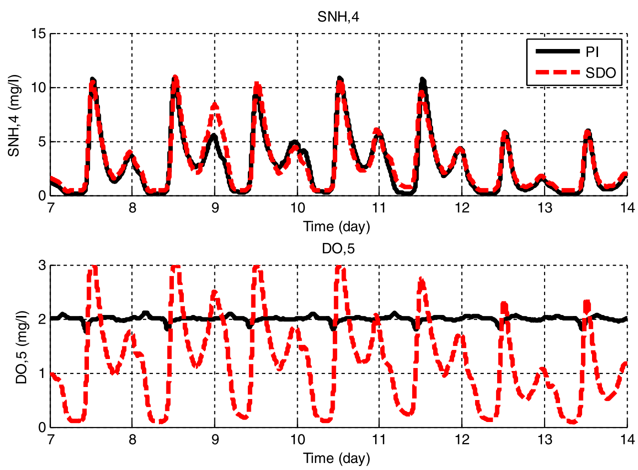

Fig. 7. Simulation results in dry weather condition

Table 5
Comparison of results using GA-based hierarchical controller with only the lower level controller (only LLC) in Objective 1.

Weather		Index		
		EQI (kg/d)	*OCI (Euro/d)*	*Reduction of OCI (%)*
Dry	Only LLC	6096.71	16366.26	
	GA based hierarchical control	6090.69	16177.90	−1.15
Rainy	Only LLC	8176.75	15994.35	
	GA based hierarchical control	8176.16	15823.17	−1,02
Stormy	Only LLC	7212.89	17248.67	
	GA based hierarchical control	7210.77	17066.77	−1,06

Table 6
Comparison of results using GA based hierarchical controller with only the lower-level controller (only LLC) in Objective 2.

Weather		Index		
		EQI (kg/d)	*OCI (Euro/d)*	*Reduction of EQI (%)*
Dry	Only LLC	6096.71	16366.26	
	GA-based hierarchical control	5979.32	16366.92	−1.93
Rainy	Only LLC	8176.75	15994.35	
	GA-based hierarchical control	8063.59	15993.14	−1,38
Stormy	Only LLC	7212.89	17248.67	
	GA-based hierarchical control	7096.76	17242.81	−1,61

complexity and also the processing time to be able to complete the algorithm as GA. Currently, there are many techniques being considered to be able to deploy in such systems to treat the parameters in different ways. Different number of tanks can be considered to apply the methods. The condition of environment to process the tanks is also considered. In this work, ony one tank is applied GA to treat the wastewater. There are still many opening space in this field to explore in our future work. We would like to optimize the problems in different conditions utilzing techniques. The trade-off could be found to provide appropriate methods for specific conditions.

Table 7
Comparison of results using GA-based hierarchical controller with only the lower level controller (only LLC) in Objective 3.

Weather		Index			
		EQI (kg/d)	*OCI (Euro/d)*	*%EQI*	*%OCI*
Dry	Only LLC	6096.71	16366.26		
	GA - based hierarchical control	6007.12	16267.14	−1.46	−0.61
Rainy	Only LLC	8176.75	15994.35		
	GA - based hierarchical control	8158.57	15834.33	−0.22	−1,00
Stormy	Only LLC	7212.89	17248.67		
	GA - based hierarchical control	7140.35	17143.25	−1.01	−0.61

5. Conclusions and future work

In this paper, a GA based hierarchical controller was proposed in which the lower-level one controls $S_{O,5}$ by manipulating $K_{La,5}$, and the higher-level controller regulates the $S_{O,5}$ setpoint of the lower-level controller according to the $S_{NH,4}$. In the higher-level control, GA is used to determine $K_{SO,5}$ and $B_{SO,5}$ to obtain three designed objectives in different weather conditions. The results obtained by applying a higher-level control are promising. That is, the overall operating cost of the system *OCI*or/and the output effluent quality index *EQI*are reduced significantly, especially in dry weather. The results show promising points for WWTPs.

The application of the proposed control has just applied at tank 5. Therefore, to further reduce the *OCI* and *EQI*, the proposed method could be used for other tanks. This is our on-going study. Theoretical or qualitative analysis of the GA could be explored. In addition, the time consuming could be reduce by utilizing PSO, DE or ACO in appropriate methods.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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