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Designingan Adaptive PID Controller for Dissolved Oxygen Control of the Activated Sludge Wastewater Treatment using Hedge Algebras

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Abstract—In this paper, we present the design methodology of the coefficients of adjustment of classical PI controller based on hedge algebras approach (HA - Hedge Algebras) to improve the quality of operation of the system. The adjustment works online with a wide range of adjustment enough around the value calculated by empirical methods Ziegler - Nichols. Subjects selected for trial is the controller method for dissolved oxygen in the wastewater treatment system by activated sludge method. Through system simulation in Matlab or Simulink environment at some different reference values, the results have been evaluated for quality control shows that the response time and overshoot reduce significantly, static deviation level is small. Through these results, it can be tested on the control system for more complex subjects to evaluate the effectiveness of methods and practical applications on the industrial control systems.

Keywords*--Dissolved Oxygen control; Wastewater treatment system;Hedge Algebra; Adaptive PID Controller;*

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I. INTRODUCTION

PI controller is characterized by simple, sustainable and economic structure, so it should be used very popularly in the industry. Control quality depends on the calculations to determine the coefficients K_P, K_I of the controller. Since these coefficients are just calculated for a specific mode certain work during the system should work in the different working points, the output of the controller should be reacted with other factors for the input components. Therefore, to suit the working mode of the system, the controller needs to work efficiently by always updating the coefficient K_P, K_I, at different working points.At this time, the coefficients K_P, K_I are no longer constants but depend on the input components.

Hedge algebras have been developed for the semantic modeling based on the order of linguistic values of linguistic variables. Through orderly natural relations of that semantics, NC Ho & W. Wechler [1], [2] has built an algebraic structure called hedge algebras which allows computing the value of semantic domain linguistic variables. Thus, solving the problem of inference based on HA will make the control problem become optimal [3], [4], [5], [6], [7], [8].

Based on the above analysis, in this study, we propose a design method which works online to adjust the coefficients K_P, K_I of the PI controller according to the hedge algebras approach. Control structure includes a PI controller that plays a role as the main controller and generate the control signal objects and a set of parameters adjustment for the PI controller appropriately according to the current state of subjects. The parameters of the set of adjustment have also been optimized by genetic algorithm (GA - Genetic Algorithm).

It is difficult for the activated sludge wastewater treatment process to be controlled due to its complex, time-varying and non-linear behavior. During this process, the control of the dissolved oxygen (DO) concentration in the reactors is very essential in the operation of the facility

DO control process will create aerobic conditions which are favorable for the development of a variety of microorganisms, including heterotrophic bacteria, thereby contributing substrate removal in wastewater. Therefore, DO control is the problem that is widely studied in wastewater treatment. This is a difficult task and a central stage of the process of biological wastewater treatment [9]. Currently, in fact, most of the control systems DO use the classic PI controller.

Therefore, in this paper, the researchers selected the dissolved oxygen controller in the wastewater treatment system using activated sludge method. It is also the subject to prove the effectiveness of the method of adjusting the parameters of PI controller based on hedge algebras approach. The system was simulated on the environment Matlab/Simulink. The results showed that the control quality is significantly improved through analysis and evaluation of indicators such as response time, supercontrolling and static bias.

II. APPROXIMATE REASONING BASED ON HEDGE ALGEBRA APPROACH

A. Hedge Algebras

Hedge algebras (HAs) are aimed at showing that the inherent ordered-based structures of term-domains of linguistic variables are useful to discover order-based semantic properties of terms and term-domains[1], [2].On this viewpoint, every term-domain of a linguistic variable X can be considered as an HA, AX = (X, G, C, H, $\leq$), where X is a term-set of X; $\leq$ is an order relation on X, which is regarded as to be induced by the inherent order-based semantics of the terms of X; $G = \{c^-, c^+\}$, where c^- (or, c^+) is called the *negative* (or, *positive*) primary term, is the set of generators that satisfy $c^- \leq c^+$; $C = \{\mathbf{0}, W, \mathbf{1}\}$ is the set of constants satisfying $\mathbf{0} \leq c^- \leq W \leq c^+ \leq \mathbf{1}$, whose meanings state that $\mathbf{0}$ and $\mathbf{1}$ are, respectively, the least and the greatest term in X, W is the neutral term; $H = H^- \cup H^+$, where $H^- = \{h_j : -1 \leq j \leq -q\}$ is the set of *negative* hedges $h \in H$ satisfying $hc^+ \leq c^+$ (written as $sign(h) = -1$) and $H^+ = \{h_j : 1 \leq j \leq p\}$ is the set of *positive* hedges h satisfying $hc^+ \geq c^+$ (written as $sign(h) = +1$). Since h_j's are regarded as unary operations, every term of AX, except from the constants, is of the form $h_n h_{n-1} \ldots h_1 c$, $c \in G$. Many inherent semantics properties of terms and, especially, hedges can be discovered in the structure of AX. For instance, hx and x are always comparable, for every $x \in X$ and $h \in H$; Assuming that $hx \geq x$, the comparability of hx and khx implies that either $khx \geq hx \geq x$, which is indicated by $sign(k, h) = +1$, or $hx \geq khx \geq x$, which is indicated by $sign(k, h) = -1$. E.g. we can check that $sign(V,L) = +1$, as $VL\ big \leq Lbig \leq big$, while $sign(V,R) = -1$, as $Rbig \leq VRbig \leq big$. Then, every $x \in X \backslash C$ has a sign defined by $Sgn(x) = sign(h_n, h_{n-1}) \ldots sign(h_2 h_1) sign(h_1) sign(c)$, where $x = h_n h_{n-1} \ldots h_1 c$, for $c \in G$. It is proved that $Sgn(hx) = -1 \Rightarrow hx \leq x$ and $Sgn(hx) = +1 \Rightarrow hx \geq x$.

The semantic structure of AX discovered in the algebraic approach to the term semantics implies that the set $H_I(x) = \{x = h_n h_{n-1} \ldots h_1 c\colon c \in G,\ h_j \in H\} \cup \{x\}$, for every $x \in X$, can be considered as the model of the fuzziness of x. The structure of the set of all such sets, $H(x)$, $x \in X$, induces a fuzziness measure fm of the terms of X, which is equal to the "diameter" of $H(x)$ and can be calculated by given fuzziness measure of the primary terms, $fm(c^-)$ and $fm(c^+)$, and the fuzziness measure of hedges, $\mu(h)$, $h \in H$, called commonly the fuzziness parameters of X. We have that for every $x \in X, x = h_n h_{n-1} \ldots h_1 c$

$$fm(h_n h_{n-1} \ldots h_1 c) = \mu(h_n) \ldots \mu(h_1)\, fm(c), c \in G \quad (1)$$

In turn, a given fuzziness measure fm of X induces numeric term semantics, defined by the so-called Semantically Quantifying Mapping (SQM) υ_{fm}, which is also calculated by the given fuzziness parameter values as follows:

$$\begin{aligned} &\upsilon_{fm}(W) = \theta = fm(c^-), \upsilon_{fm}(c^-) = \theta - \gamma\, fm(c^-) = \delta\, fm(c^-) \\ &\upsilon_{fm}(c^+) = \theta + \gamma\, fm(c^+) \\ &\upsilon_{fm}(h_j x) = \upsilon_{fm}(x) + Sgn(h_j x)\left\{\left[\sum\nolimits_{i=sign(j)}^{j} fm(h_i x)\right] - \zeta(h_j x)\, fm(h_j x)\right\}, \end{aligned} \quad (2)$$

Where: $\zeta(h_j x) = \frac{1}{2}\left[1 + Sgn(h_j x) Sgn(h_p h_j x)(\delta - \gamma)\right] \in \{\gamma, \delta\}$

For all integers $j \in [-q\text{^}p] = [-q, p] \backslash \{0\}$.

The concept of SQMs is very important, in particular in the field of fuzzy control, as it can immediately map the terms to their relevant numeric values without the need for defuzzification. In relation with the vague terms, SQMs must be defined in a close relation with the fuzziness measure and preserve the term order, i.e. they are order-isomorphism. Hence, the order-based relationships between variables, e.g. directly or inversely proportional relationships mentioned above, are preserved under SQMs. So, simulating human reasoning methods with SQMs, one can maintain the essential term meaning[3].

This forms a formalized basis to develop a methodology for constructing HA controllers and to solve some control problems[4],[7].

B. Application of Hedge Algebras in approximate reasoning

Considering the Linguistic Rule Base System (LRBS) of the set of approximate reasoning with the type MISO as follows:

$$\begin{aligned} &R1\colon If\ X_1 = A_{11}\ and\ X_2 = A_{12}\ and \ldots and\ X_m = A_{1m}\ then\ Y = B_1 \\ &R2\colon If\ X_1 = A_{21}\ and\ X_2 = A_{22}\ and \ldots and\ X_m = A_{2m}\ then\ Y = B_1 \\ &\ldots \\ &Rn\colon If\ X_1 = A_{n1}\ and\ X_2 = A_{n2}\ and \ldots and\ X_m = A_{nm}\ then\ Y = B_n \end{aligned} \quad (17)$$

(3)

With $X_1, X_2, \ldots X_m$ are linguistic variables, each one X_j belongs to background space U_j and linguistic variable Y belongs to the background space V, A_{ij}, B_i are the linguistic values of corresponding background space. With every rule "If ... then" we can determine one "fuzzy point" in the space $Dom(X_1)xDom(X_2)x \ldots xDom(X_m)xDom(Y)$. There, (3) can be seen as a "hypersurface" S_{fuzz}^{m+1} in this space. According to the theoretical approach HA, HA structure is built for linguistic variables using SQMs function to convert each above fuzzy point into one real point in semantic space $[0,1]^{m+1}$.

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Meanwhile, (3) can be respectively represented as a real “hypersurface” " S_{real}^{m+1}. The "hypersurface" S_{real}^{m+1} can be seen as a mathematical representation of LRBS which each fuzzy concept (linguistic value) of the fuzzy valuables (linguistic variables) are quantified as its semantic value (QRBS – Quantified Rule Base System).

Considering the inputs which belong to corresponding background space are the input values of the controller $X_{01}, X_{02}, ...X_{0m}$,, using normalization for those values to the domain of values of HA we have $X_{01s}, X_{02s}, ...X_{0ms}$, respectively. After carrying out the problem of approximation inference by interpolation method on S_{real}^{m+1}, we received the interpolation value in the range $[0,1]$ as semantically quantifying value of output linguistic variable Y which is converted to real variable domain (background space of variableY)) of the control value at the output by the denormalization.

Model of the controller based on HA approaching is described as in Fig. 1.

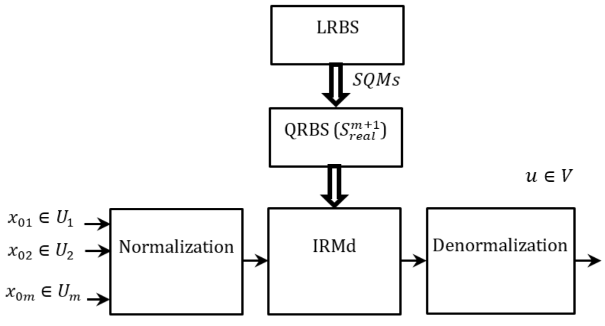

Figure 1. The diagram of the approximate reasoning set MISO based on HA approaching

- LRBS: Linguistic rule based system of the controller.
- QRBS: Quantifying rule based system of linguistic values which is computed by mapping function SQM (S_{real}^{m+1}).
- Normalization: standardize values of the variables in the semantic domain.
- IRMd (Interpolation ReasoningMethod): Interpolation on the “hypersurface” S_{real}^{m+1}.
- Denormalization: convert semantic control value to the domain of variable real value of the output variable.

Note that: the approximate reasoning set MIMO can be seen as several approximate reasoning sets MISO.

Steps of designing the controller based on hedge algebra as follows:

- Step 1: Design $AX_i (i = 1,...,m)$ and AY for the variables X_i and Y
- Step 2: Determine the control rule set with linguistic items in HA.
- Step 3: Compute the semantically quantifying value for the linguistic labels in the rule set. Build the "hypersurface" S_{real}^{m+1}.
- Step 4: Select interpolation method on the "hypersurface" S_{real}^{m+1} for approximation inference

III. DISSOLVED OXYGEN CONTROL OF THE ACTIVATED SLUDGE WASTEWATER TREATMENT PROCESS

The general overview of activated sludge wastewater treatment process is shown in Fig. 2. As can be seen, the inflow is handled in the bioreactor. With the action of microorganisms, the substrate content is decreased. Then, the water flows to a settler in which the biomass sludge is recovered. At the top of the settler remains the clean water and it will be carried out of the plant. At that time, a fraction of the sludge is returned to the input of the bioreactor so that it can maintain an appropriate rate of biomass which allows the reduction of the organic matter. The rest of the sludge will be purged [10].

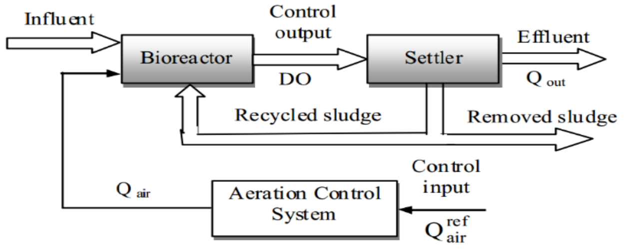

Figure 2. General overview of activated sludge wastewater treatment process

In the biological reactor, aeration plays an important part in the whole activated sludge wastewater treatment process as its conditions are useful to the growth of many different microbes such as heterotrophic bacteria. These bacteria will remove biochemical oxygen require from the wastewater, as well as nitrifying bacteria, which oxidize ammonia to nitrate. Because the effects of aeration on biomass growth are strong and fast, DO control become the most studied control problem in wastewater treatment; therefore, the deterioration of activated sludge is the result of the insufficient or excess oxygen in the aeration tank.

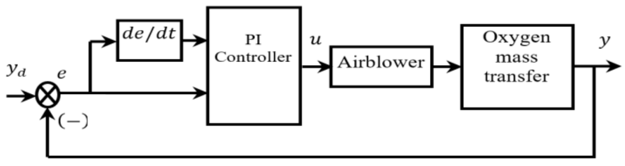

Figure 3. A block diagram of the DO control system

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A block diagram of the DO controller is shown in Fig. 2. According to [8], [9], DO transfer function is given by:

$$G(s) = \frac{K}{(T_1 s+1)(T_1 s+1)} e^{-\tau s} \quad (4)$$

Where K=0.8, T_1=12, T_2=100, τ=60.

As can be seen in Fig. 3, y_d is the set value, y is the output value and error $e = y_d - y$. The component $u(t)$ of the classical PI controller is described as follows :

$$u(t) = K_P e(t) + \frac{K_P}{T_I} \int_0^t e(t)dt \quad (5)$$

Here K_P is the proportionality factor, $K_I = K_P / K_I$ is the integration factor. Through (5), turn to the discrete domain we have:

$$u(k) = K_P e(k) + K_I \sum_{j=1}^{k} e(j) \quad (6)$$

Since the transfer function of the system has a large delay component $\tau = 60$, classical PI controller uses the diagram by Smith Predictor's method. These parameters are calculated according to Ziegler & Nichols: $K_P = 5.2$, $K_I = 0.1$.

IV. DESIGN AN ADJUST RULE SET FOR PI CONTROLLER BASED ON HA

In this part, we present a different approach which is designed as an adjust rule set for the coefficients K_P, K_I of PI controller based on HA. Then we will have an adaptive PI controller. Unlike classical PI controller, after the coefficients K_P, K_I of the adaptive PI set are calculated, they are always adjusted depending on the level of deviation$e$ and its derivative $\dot{e}$ (denoted as *ce*) during working process. The block diagram of the adaptive PI control system is shown in Fig. 4.

The set of fuzzy inference adjusts the coefficients K_P, K_I based on HA approach has two inputs *e*, *ce* and two output K_P, K_I. This is the set of fuzzy inference for the model which has MIMO's structure. It can be considered the "2 in - 2 out" as two sets of inference "2 in - 1 out" with 2 common law systems which have input components.

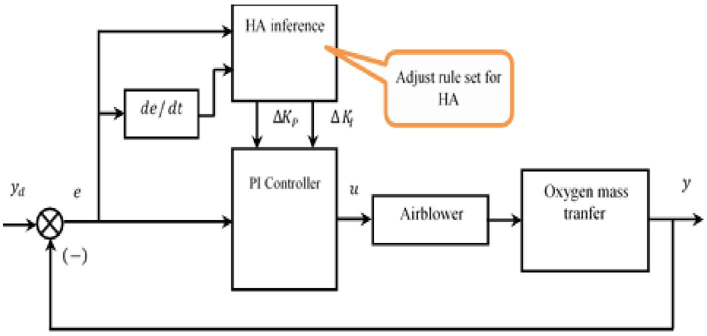

Figure 4. The block diagram of the adaptive PI control system based on HA for the DO system

Through surveying system with classical PI controller, manual adjustment of coefficients K_P, K_I accoding to e and ce we identified the variable domain of the variables, as well as their rules of changes for the adjustment rules to be constructed.

$e = [-2, 2]$, $ce = [-0.5, 0.5]$, $\Delta K_P = [-5, 5]$, $\Delta K_I = [-0.2, 0.2]$

The linguistic input and output variables contain:

The linguistic input and output variables contain:

$Le, Lce = \{VN\ (VeryNegative),$
$LN(LittleNegative), W(Zero = Neutral),$
$LP(LittlePositive), VP\ (VeryPositive)\};$
$L\Delta K_P, L\Delta K_I = \{VN\ (VeryNegative), N\ (Negative),$
$LN(LittleNegative), W(Zero = Neutral),$
$LP(LittlePositive), P(Positive),$
$VP\ (VeryPositive)\};$

- Step 1: Determine the rule set

Depending on the magnitude of the deviation e and its rate of change ce, we need to adjust coefficientsK_P, K_I properly. Rule system for adjustment is shown in Table I.

TABLE I. RULE ADJUSTMENT SYSTEM FOR THE COEFFICIENTS KP, KI

Rule set of $L\Delta K_P$						Ruel set of $L\Delta K_I$					
Lce \ Le	VN	LN	W	LP	VP	Lce \ Le	VN	LN	W	LP	VP
VN	VN	VN	N	LN	W	VN	VP	VP	P	LP	W
LN	VN	N	LN	W	LP	LN	VP	P	LP	W	LN
W	N	LN	W	LP	P	W	P	LP	W	LN	N
LP	LN	W	LP	P	VP	LP	LP	W	LN	N	VN
VP	W	LP	P	VP	VP	VP	W	LN	N	VN	VN

- Step 2: Design HA for the I/O variables

Set of generating elements:

$G = \{N\ (Negative), P\ (Positive)\}.$

Set of the selected hedges: $H^- = \{L\ (Little)\}$ and $H^+ = \{V\ (Very)\}$.

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The fuzzy parameters of hedge algebras corresponding to Le, Lce, $L\Delta K_P$ and $L\Delta K_P$ variables are optimally found by genetic algorithm and this is shown in detail in Section V

The signal relation between hedges and others and the generating ones are determined as in Table II.

TABLE II. SIGNAL RELATION OF HEDGES AND THE GENERATING HEDGE

	V	L	N	P
V	+	+	−	+
L	−	−	+	−

- Step 3: Compute semantically quantifying values for liinguistic items.
- Step 4: Interpolation method selected for the inference is bi-linear interpolation.

V. OPTIMIZING FUZZY PARAMETERS FOR ADJUSTMENT SET

During the process of finding solutions, there are the many variables needed to optimize and its searching space is usually very large. If we apply the normally exhaustive searching algorithm, it can not be feasible alternative (difficult to meet requirements in terms of time). An effective choice is using optimization algorithms which are inherited the additional information in the searching process. It's the smart optimization algorithms that modeled after the biological mechanisms such as GA, particle swarm optimization algorithm (PSO). In this study, we use GA – one of optimal algorithms that has been often used recently.

GA is the optimal search method based on the mechanism of natural selection. It simulates the evolution process including genetics and evolution [12]. Each solution is an individual that is selected so that it can be adaptable for the process of natural selection (in the sense of being the best). The adaptation of each individual is measured through its gene sequence structure. The crossover and mutate method of evolution process are done randomly to exchange information about the gene sequence structure. The adaptation of the individuals in the next generation inherits the information in the past of the previous generation to orient new search point. Through long-term evolution process, the next generation will have a gene sequence structure that is asymptotic to the answer to the problem. Thus, the objective of the GA is just to propose the relatively optimal option, but not exactly optimal one.

A. The Fuzzy parameters need to be optimized

The fuzzy set of adjustment for the coefficients K_P, K_I for the PI controller of DO system is constructed based on the fuzzy model MIMO with 2 inputs e, ce and 2 outputs $\Delta K_P, \Delta K_I$ (Fig. 4).

Depending on the deviation degree of the input components e and ce compared to the value Zero, the coefficients K_P, K_I of PI controller will be increased or decreased. Therefore, the output components $\Delta K_P, \Delta K_I$ will be respectively negative or positive. Moreover, it is necessary to choose semantically quantifying value of the element $v(W) = fm(N) = 0.5$

There is only negative hedge in the structure of HAs ($H^- = \{L\ (Little)\}$) and one positive hedge ($H^+ = \{V\ (Very)\}$),so $\alpha = \mu(L)$ and $\beta = \mu(V) = 1 - \alpha$.

Therefore, with each HA, we just need to optimize fuzzy parameter α. 4 HAs corresponding 4 linguistic variables will offer that 4 parameters should be optimized.

B. Gene Encoding

According to the GA implementation proposal by Holland [12], we have chosen binary encoding to the solution (plan) to be searched. We carried out building the program according to the following algorithm: With each HA for each I/O respectively variable, we have a set of parameters needed to optimized. Each parameter of a set of parameters are considered as a variable to look for. Each variable will be coded by a binary string. Therefore, we will have a binary sequence for all variables which form a gene, or an. It is the answer that is based on objective function of GA.

Figure 5. Gene structure

C. Objective function

The objective function is used based on optimal standard ISE (Integral of the Square of the Error - integral of squared deviations). System model is simulated on the discrete-time domain, so the standard ISE will be transferred to the formats:

$$g = min\left(\sum_{k=1}^{l} e(k)^2\right) \quad (21)$$

Where: $e(k) = x_d(k) - y(k)$ is the deviation data sample during the simulative circle k in order, l is the total of data samples of a simulation. $x_d(k)$ is the value of the reference speed at the input, in some problems, this value is a constant, $y(k)$ is the real response subject of output in the control object.

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The evolutional calculations are used: GA's operations corresponding to the basic evolutionary processes of nature are Selection, Crossover and Mutate.

+Selection: This operation chooses the good parents individual in the populations with the sense of a high level of adaptation (fitness) in order to participate in the process of breeding the next generation. In this study, we used the selection method of roulette wheel.

+Crossover: This operation implements to generate new individual, inherited the properties from individual parents. In view of the search, this operation creates options in the vicinity of the solutions corresponding to the individual parents.

Mutate: This operation also simulate based on mutation phenomena in the nature. It can create individuals which have characteristics different from their parents. In view of the search, this operation generated plans outside the local partial area and turn towards the extremum that has adapted value better than those in the search space.

The implementation of the searching algorithm according to GA can be described as follows:

GA_param(){
Step 1: //<initialize population>;
Step 2: while (repeat condition)
{
// <evaluate fitness>;
// carry out the evolution
<selection>; //
<crossover>; //
<mutate>; //
}
Step 3: output result //
// (individual - gene) has the best objective function value}

VI. RESULT AND COMMENTS

After having implemented the searching program based on GA for the objective function as in (21), we found that:

The number of parameters needs to be optimized: 4.

Use binary coding, 10 bits gives each parameter that needs to be optimized

Population: 300 individuals

Generation: 2400.

Crossover probability $Pc = 0.7$.

Mutate probability: $Pm = 0.001$.

The set of fuzzy parameters received is shown in Table 3.

TABLE III. FUZZY PARAMETERS OF HEDGE ALGEBRAS

	Le	Lce	$L\Delta K_P$	$L\Delta K_I$
$\alpha = \mu(L)$	0.2	0.387683	0.8	0.8

With set of optimal fuzzy parameters received in TableIII. and the signal relation between hedges, between hedges and the generating elements in TableII, after applying (13) – (16) we can compute the semantically quantifying value for the linguistic items of linguistic variables Le, Lce, $L\Delta K_P$ and $L\Delta K_I$ as follows:

$\nu_{Le}(W) = \theta = 0.5;$
$\nu_{Le}(N) = \theta(1-\alpha) = 0.5(1-0.2) = 0.4;$
$\nu_{Le}(VN) = \theta(1-\alpha)^2 = 0.5(1-0.2)^2 = 0.32;$
$\nu_{Le}(LN) = \theta(1-\alpha+\alpha^2) = 0.42;$
$\nu_{Le}(P) = \theta + (1-\theta)\alpha = 0.6;$
$\nu_{Le}(LP) = \theta + \alpha(1-\theta)(1-\alpha) = 0.58;$
$\nu_{Le}(VP) = \theta + \alpha(1-\theta)(2-\alpha) = 0.68;$

After do the same with other elements in Table I, we have the table QRBS (Table IV and Table V).

TABLE IV. QRBS OF LΔKP

Lce \ Le	0.3200	0.4200	0.5000	0.5800	0.6800
0.1875	0.0200	0.0200	0.1000	0.4200	0.5000
0.3813	0.0200	0.1000	0.4200	0.5000	0.5800
0.5000	0.1000	0.4200	0.5000	0.5800	0.9000
0.6187	0.4200	0.5000	0.5800	0.9000	0.9800
0.8125	0.5000	0.5800	0.9000	0.9800	0.9800

TABLE V. QRBS OF LΔKI

Lce \ Le	0.3200	0.420 0	0.500 0	0.580 0	0.680 0
0.1875	0.9800	0.9800	0.9000	0.5800	0.5000
0.3813	0.9800	0.9000	0.5800	0.5000	0.4200
0.5000	0.9000	0.5800	0.5000	0.4200	0.1000
0.6187	0.5800	0.5000	0.4200	0.1000	0.0200
0.8125	0.5000	0.4200	0.1000	0.0200	0.0200

Simulation model of the system in Matlab/ Simulink environment is shown as in Figure 6. .

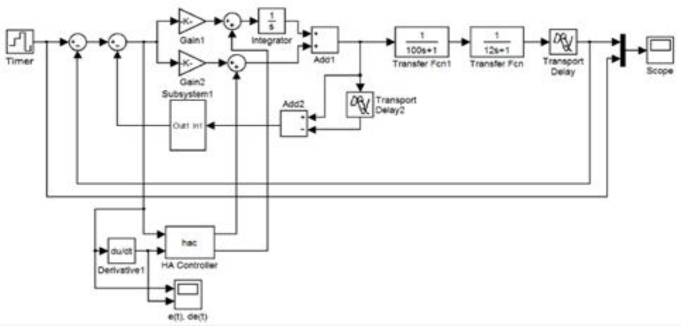

Figure 6. The simulation model of the system

Simulation of the system with the parameter of proposed values in the period is shown in Table 6. Response graph of the controllers is shown in Figure 7 and the measured values for overshoot, Rise Time and Settling time in about the first 200s and is synthesized in Table VII.

Compute the total of control deviation according to (21) for the classical PI controller, we have:

$$g_{PI} = 7675.7574$$

And the adaptive PI controller (which has the adjustment components based on HA)

$$g_{Adaptive\ \_PI} = 1378.2656$$

TABLE VI. CHANGLE LEVEL OF PROPOSED VALUE y_d

$Time\ [s]$	0 - 200	200 - 400	400 - 600	600 - 800	800- 1000
$y_d\,[mg/l]$	2	3	4	1	2

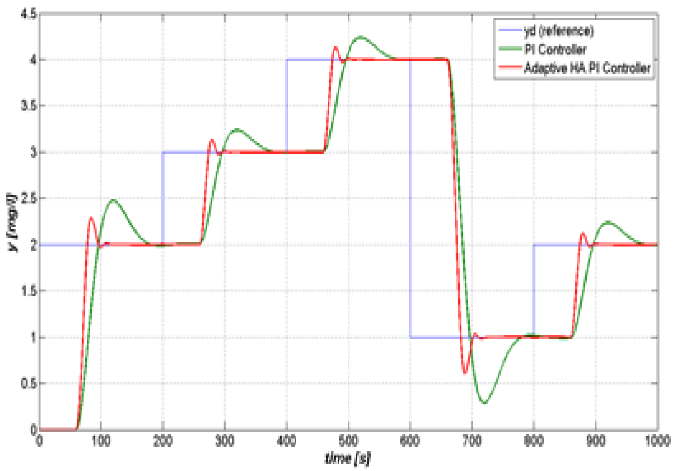

Figure 7. Responding of system

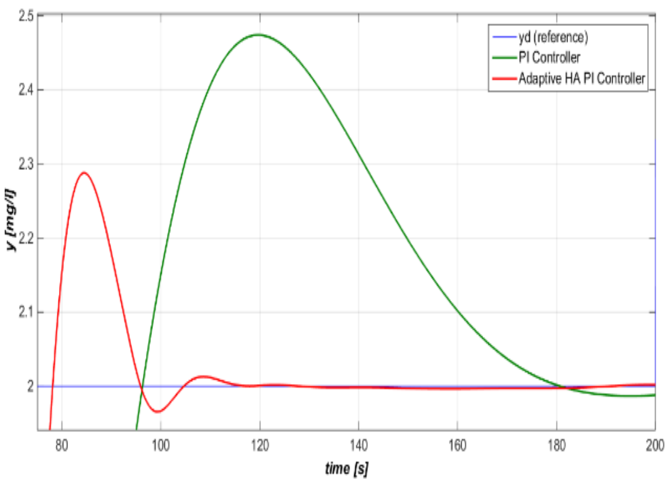

Figure 8. Overshoot và Undershoot in the first 200 s

TABLE VII. RESULTS

Time [s]		PI controller	Adaptive-HA-PI controller
0-200	Overshoot	2.474111	2.287926
	Undershoot	1.965517	1.986948
	Rise time	94.2	77.2
	Settling time	160	92.4

As can be seen in the responding diagram (Figure 7), we found that the classical PI controller has a large time responding and overshoot. When there exists the adjustment set of coefficients K_P, K_I , adaptive PI controller has a considerable decrease in terms of time responding and overshoot. This brings a fast response system and a stable working with the small static deviation at different proposed values. The most typical response of the controller is shown in the first 200 s in the simulation. The measurement results in Table VIIshows that adaptive PI controller gives the superior control quality. According to optimal standards ISE (21), the value of optimal function of adaptive PI controller versus classic PI controller fells to 17.956%.

VII. CONCLUSION

In this paper, we propose a design of a fuzzy set of adjustment for the coefficients K_P, K_I for the classical PI controller based on hedge algebras' approach. We use genetic algorithms to optimize the fuzzy parameters hedge algebras based on the objective function through optimal standard ISE. The solution proposed has been tested on the control system of the oxygen dissolved in the waste water treatment system by activated sludge method.

The simulation results are displayed by the responding diagram and measured show the set of adjustment for coefficients K_P, K_I works perfectly. It is combined with PI controller to become an adaptive PI controller to work effectively.

According to hedge algebras' approach, mathematical modeling for the linguistic rule set are correctly and semantically closely between the linguistic values appearing in the rule. That makes the process of inference reasonable. Through these results, we can see that the proposed construction of the inference to adjust the coefficients$K_P, K_I$for PI controller is a proper solution. This is a new application method of hedge algebras in control field.

Moreover, it is a new application that needs to be studied more deeply and widely applied on other complex systems in reality.

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