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A New PID Tuning Technique Using Ant Algorithm

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Abstract --- In this paper, ant algorithm (AA) which is a new nature-inspired optimization technique, was used to tune a PID controller. In the tuning process, the following cost functions were employed: i) Integral Absolute Error (IAE), ii) Integral Squared Error (ISE), iii) a new proposed cost function called reference based error with minimum control effort (RBEMCE). The results obtained from ant algorithm PID tuning process were also compared with the results of Ziegler-Nichols (ZN), Internal Model Control (IMC) and Iterative Feedback Tuning (IFT) methods. The PID controllers optimized with ant algorithm and the new proposed cost function gives a performance that is at least as good as that of the PID tuning methods mentioned above. With our method, a faster settling time, less or no overshoot and higher robustness were achieved. Moreover, the new tuning process is successful in the presence of high noise.

I. INTRODUCTION

The PID controllers are the best known controllers for industrial control processes since they have a simple structure and their performance is quite robust for a wide range of operating conditions. After the three parameters have been tuned or chosen in a certain way, control parameters of a standard PID are kept fixed during control process. There are many tuning techniques based on several methods. These methods can be classified as: i) empirical methods such as the Ziegler-Nichols (ZN) method [1] and the Internal Model Control (IMC) [1], ii) analytical methods such as root locus based techniques [1], iii) methods based on optimization such as the iterative feedback tuning (IFT) [2] and genetic algorithm tuning technique [3].

A fundamental closed-loop control system shown in Fig. 1 contains a controller and a plant. In this paper, the PID controller was used as controller. It is comprised of three components: a proportional part, a derivative part and an integral part. The PID controller uses the following control equation.

$$C(s) = k_p + \frac{k_i}{s} + k_d s \qquad (1)$$

where the k_p is the proportional constant, k_i integral constant and the k_d is the derivative constant. In the design of a PID controller, these three constants must be selected in such a way that, the closed loop system has to give desired response. The desired response should have minimal settling time with a small or no overshoot in the step response of the closed loop system.

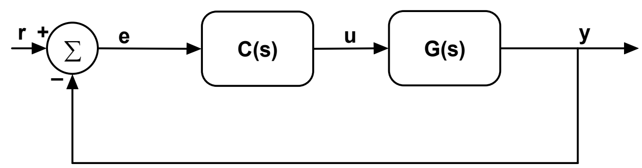

Fig. 1 Closed-Loop System

In this work ant algorithm (AA) was applied to optimize the constants of the PID controller. To show the effectiveness of our method, the step responses of closed loop system were compared with that of the existing methods (ZN, IMC and IFT). Next, the method was tested for the robustness to model errors. In the robustness test, the used model is slightly changed by adding delay to the model, varying the steady state gain and changing a pole. At last, the ant algorithm was used to tune the PID controller in the presence of noise with different variances.

II. ANT ALGORITHM

Ant algorithm is a new nature-inspired optimization technique used especially in combinatorial optimization problems (COP). In ant algorithm, there is an iterative process in which a population of simple agents (ants) repeatedly creates candidate solutions of the given problem. There are two mechanisms in probabilistically guided solution creation process of AA. These are heuristic information on the given problem and memory containing experience gathered by ants in the previous iterations (the pheromone trails). The communication between the ants is mediated by the deposition of pheromone to the elements of good solutions. Then the elements with a higher quantity of pheromone become more attractive for the other ants. The quantity of pheromone deposited on each element is a function of the quality of the solution. The algorithm was applied to the traveling salesman problem (TSP) and as well several quadratic assignment problems (QAP) [4,5]. In TSP, an artificial ant is considered as an agent that moves from city to city on a TSP graph. The agents traveling strategy is based on a probabilistic function that considers two facts. Firstly, it counts the edges it has traveled accumulating their lengths and secondly it senses the trail (pheromone) left by other agents (ants). Ants select the next city j among a candidate list based on the following transition rule [4] :

$$j = \begin{cases} \arg\max_{u \in J_i^k} \{[\tau_{iu}(t)][(\eta_{iu}(t)]^{\beta}\} & \text{if } q \le q_0 \\ J & \text{if } q \ge q_0 \end{cases}$$

(2)

$$P_{iJ}^k(t) = \frac{[\tau_{iJ}(t)].[\eta_{iJ}(t)]^{\beta}}{\sum_{l \in J_i^k} [\tau l(t)].[\eta_{il}(t)]^{\beta}} \quad (3)$$

Where τ is the pheromone, η is the inverse of the distance between the two cities, q is a random variable uniformly distributed over [0, 1], q_0 is a tunable parameter in the interval [0, 1], and J belongs to the candidate list and is selected based on the above probabilistic rule as in (3). Each ant modifies the environment in two different ways:

i) Local trail updating: As the agent moves between cities it updates the amount of pheromone on the edge by the following equation:

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t-1) + \rho.\tau_0 \quad (4)$$

where ρ is the evaporation constant. The value τ_0 is the initial value of pheromone trails and can be calculated as $\tau_0 = (nL_{nn})^{-1}$, where n is the number of cities and L_{nn} is the length of the tour produced by one of the construction heuristics.

ii) Global trail updating: When all agents have completed a tour the agent that finds the shortest route updates the edges in its path using the following equation:

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t-1) + \frac{\rho}{L^+}. \quad (5)$$

where L^+ is the length of the best tour generated by one of the agents.

A. Application of Ant Algorithm to PID Tuning

In order to optimize the parameters of a PID controller with ant algorithm, the PID tuning has to be transformed into a COP problem. Firstly, the maximum and minimum values for the PID parameters are chosen in such a way that the search space of optimization is not too large. In our work, the search space is divided into 100 values for each PID parameter ranging from 0 to 1.5 times that of the ZN method. However, if short computation time is not a must, a wider search space can be selected. All of the values for each parameter are placed in three different vectors. In order to create a graph representation of the problem (Fig. 2), these three vectors and the values in these vectors can be considered as three caves and the paths between the caves, respectively. In the tour, the ant must visit all three caves by choosing one path between the each cave. The objective of optimization in ant algorithm is to find the best tour with the lowest cost function among the three caves. The ants deposit pheromone to the beginning of each path. The pheromones in our ant algorithm were updated in two ways: Local pheromone updating and global pheromone updating.

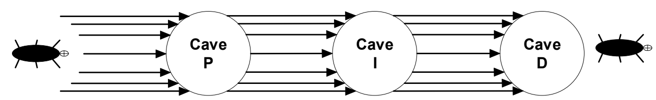

Fig 2 Graphical representation of AA in PID tuning process.

In local pheromone updating (6), each ant updates the pheromones deposited to the paths it followed after completing one tour.

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \frac{0.01\, a}{C_{nn}} \quad (6)$$

where a is the general pheromone updating coefficient, n is the number of paths and caves, C_{nn} is the calculated cost function for the tour traveled by the ant.

In global pheromone updating, there are positive (7) and negative (8) pheromone updating. The pheromones of the paths belonging to the best tour and worst tour of the ant colony are updated as given in the following equations:

$$\overset{best}{\tau}_{ij}(t) = \overset{best}{\tau}_{ij}(t) + \frac{a}{C_{best}} \quad (7)$$

$$\overset{worst}{\tau}_{ij}(t) = \overset{worst}{\tau}_{ij}(t) - \frac{0.3\, a}{C_{worst}} \quad (8)$$

where $\overset{best}{\tau}$ and $\overset{worst}{\tau}$ are the pheromones of the paths followed by the ant in the tour with the lowest cost value *(C_{best})* and with the highest cost value *(C_{worst})* in one iteration, respectively. The pheromones of the paths belonging to the best tour of the colony are increased considerably, whereas those of the paths belonging to the worst tour of the iteration are decreased. After each iteration some of the pheromones evaporate. Pheromone evaporation (9) allows the ant algorithm to forget its past history, so that AA can direct its search towards new directions without being trapped in some local minima.

$$\tau_{ij}(t) = \tau_{ij}(t)^{\lambda} + \Delta \quad (9)$$

where λ is the evaporation constant and Δ is the sum of the (7) and (8).

The three cost functions for PID tuning optimized with ant algorithm in our study are: i) Integral Absolute Error (IAE), ii) Integral Squared Error (ISE), iii) reference based error with minimum control effort (RBEMCE). In reference based error with minimum control effort, a desired response is approximated as an exponential function (first order system response) (10).

$$y_d(t) = 1 - e^{-ct} \tag{10}$$

where *1/c* can be taken as the time constant of the system. The system is forced to trace this desired response using minimum control effort. Based on this assumption, the cost function used in our optimization has the form as follows:

$$I(\rho) = \frac{1}{N}\sum_{i=1}^{N}\left|y[i] - y_d[i]\right| + \frac{k}{N}\sum_{i=1}^{N}u[i] \tag{11}$$

where N is the number of data points, k is the weight of minimal control effort and ρ is a vector containing the PID parameters.

III. RESULTS AND DISCUSSION

A. Analysis of the Cost Functions in AA

In order to illustrate the differences between the PID tuning process with AA and the other methods (ZN, IMC and IFT), the following model (12) is taken from [6].

$$G(s) = \frac{(1-5s)}{(1+10s)(1+20s)} \tag{12}$$

Using three different cost functions (IAE, ISE and RBEMCE), tuning process with ant algorithm is applied to the model (12). Because of the probabilistic nature of the ant algorithm, ant algorithm was run five times with 5 ants and 1000 iterations. Among five runs for each cost function, the best result with the lowest cost for step input is shown in Fig. 3. The corresponding control signals are illustrated in Fig 4. As can be seen from Fig. 3 and Fig 4, RBEMCE outperforms the other two cost functions. In RBEMCE cost function, the desired response defined by the user is traced with the use of minimum control effort. For comparison, the maximum overshoot (*OS%*), rise time (T_r) and %2 settling time (T_s) of the controllers which were optimized with respect to three different cost functions are summarized in Table 1. However, the rise time of RBMCE method is higher than the other methods. It has almost the same settling time with IAE method and has no overshoot. The other two methods, IAE and ISE, have higher overshoots.

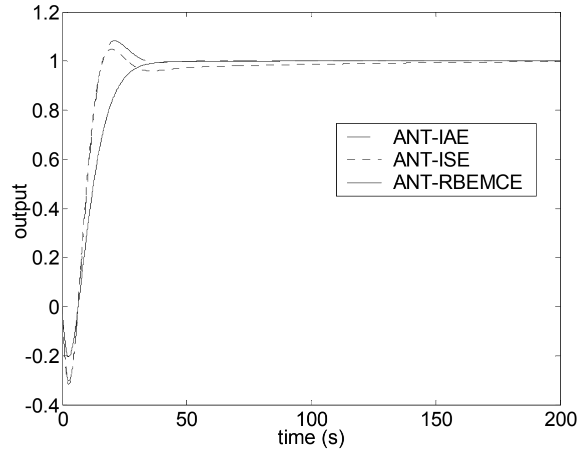

Fig 3 Step responses for the closed-loop systems with G(s) and the PID controllers tuned with the three different cost functions.

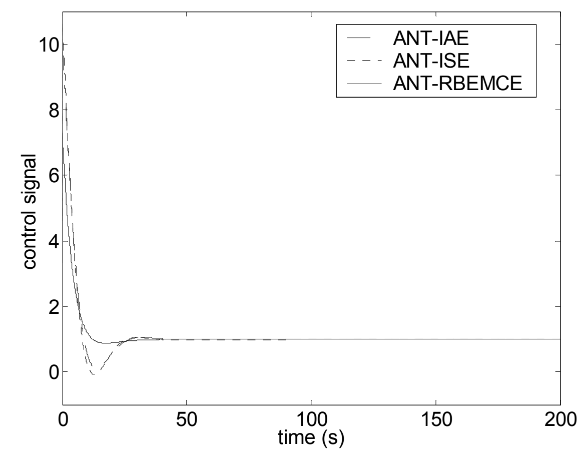

Fig 4 Corresponding control signals for the closed-loop systems with G(s) and the PID controllers tuned with the three different cost functions.

B. Comparison with Other Tuning Methods

In this section, the PID controller tuned with ant algorithm using RBEMCE cost function is compared with that of ZN, IMC and IFT methods. The results are given in Table II.

TABLE I.
PID PARAMETERS FOR DIFFERENT COST FUNCTIONS AND THEIR CONTROL CHARACTERISTICS.

	Ant - IAE	**Ant – ISE**	**Ant RBMCE**
K_p	4.606	4.7655	3.3358
K_i	0.0913	0.0725	0.0661
Kd	21.7854	22.23	21.7854
OS(%)	8.2	4.7	0
T_S	29.95	72.3	31.7
T_R	7.17	7.07	14.97

TABLE II.
PID PARAMETERS FOR DIFFERENT METHODS AND THEIR CONTROL CHARACTERISTICS.

	ZN	**IMC**	**IFT**	**Ant RBMCE**
K_p	3.5294	3.3926	3.0279	3.3358
K_i	0.2101	0.1074	0.0654	0.0661
Kd	14.8235	13.2247	18.4075	21.7854
OS(%)	54	23.5	0.5	0
T_S	86	45.1	28.55	31.7
T_R	6.83	8.54	14.69	14.97

From Table II, the best settling time is obtained by IFT method with a small overshoot and ANT-RBEMCE has nearly same settling time with no overshoot. Fig. 5 and Fig. 6 show the step responses and the corresponding control signals for closed-loop systems with the PID controllers tuned with four different methods, respectively. From Fig. 5, IFT and ANT-RBEMCE methods have the best output characteristics (lower overshoot and faster settling time), which are almost indistinguishable. The control signal characteristics of IFT and ANT-RBEMCE methods behave also in a similar fashion.

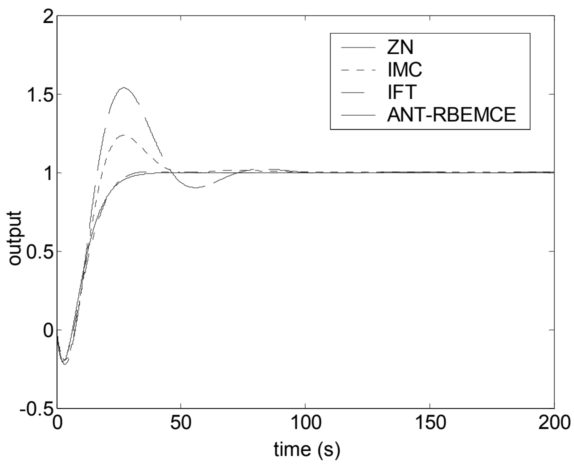

Fig 5 Step responses for the closed-loop systems with G(s) and the PID controllers tuned with different methods.

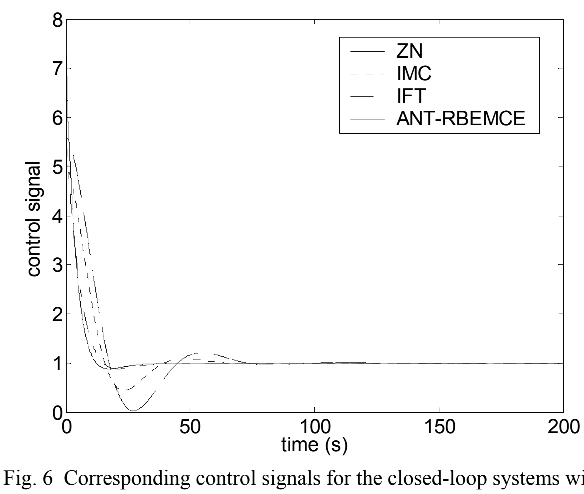

Fig. 6 Corresponding control signals for the closed-loop systems with G(s) and the PID controllers tuned with different methods.

C. Robustness to Model Errors

A controller tuning method should be robust to model errors. To test the robustness of the methods, controllers tuned with methods mentioned above were applied to a model that is slightly different from the model (12). The three slightly different models used are given as follows:

$$G_a(s) = \frac{1.5(1-5s)}{(1+10s)(1+20s)} \tag{13}$$

$$G_b(s) = \frac{(1-5s)}{(1+10s)(1+25s)} \tag{14}$$

$$G_c(s) = \frac{(1-5s)}{(1+10s)(1+20s)} e^{-1.5s} \tag{15}$$

In order to evaluate the robustness of the PID controller tuned with ant algorithm and to compare it with the other tuning methods, the same PID parameters in Table II were employed. Firstly, the responses to the model (13), in which the steady state gain of (12) is increased by 50%, are shown in Fig. 7. Secondly, one pole of (12) is changed (14) and its result is shown in Fig. 8. Thirdly, a delay of 1.5 seconds has been added to G(s) (15). The responses are shown in Fig. 9.

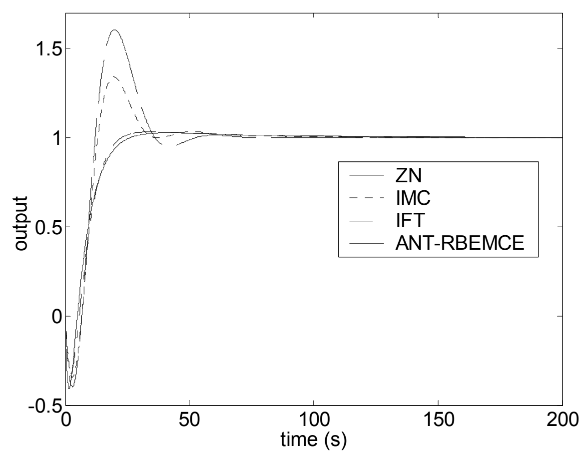

Fig 7 Step responses for the closed-loop systems with $G_a(s)$ and the PID controllers tuned with different methods

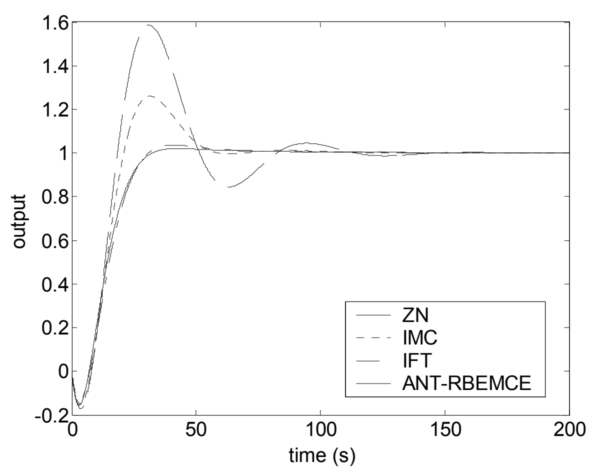

Fig 8 Step responses for the closed-loop systems with $G_b(s)$ and the PID controllers tuned with different methods

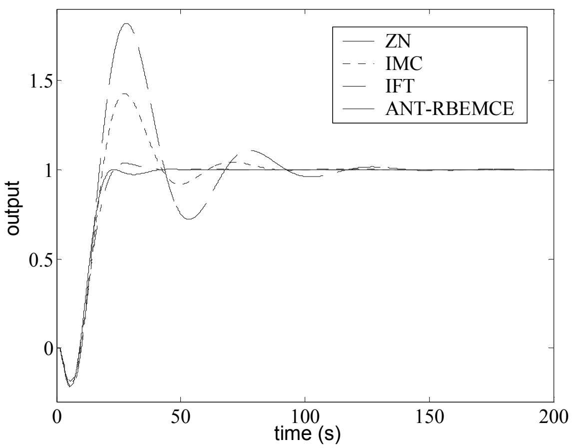

Fig. 9 Step responses for the closed-loop systems with $G_c(s)$ and the PID controllers tuned with different methods

All of the four controllers are robust to these modeling errors except for the system with the delay, which causes an increase in settling time. However, ANT-RBEMCE shows the best result with the lowest overshoot and settling time in all cases.

D. System with Gaussian White Noise

In order to test the PID tuning with ant algorithm in the presence of noise, ANT-RBEMCE is used to control the plant defined below

$$y(t)=G_2(s)u(t) + H(s)e(t), \text{with} \quad (16)$$

$$G_2(s) = \frac{1}{s^2 + 0.1s + 1}, H(s) = \frac{1}{s+1}, \quad (17,18)$$

where *e(t)* is the gaussian white noise. The above system is tested for three different variances σ^2=0.0025 σ^2=0.025, σ^2=0.25. Ant algorithm was run 5 times with 5 ants and 1000 iterations due to the probabilistic nature of AA and noise. The PID parameters are from 0 to 4.5 for k_p, 0 to 0.45 for k_i and 0 to 22.5 for k_d. General pheromone updating coefficient a is taken as 0.06 and evaporation parameter λ is taken as 0.95. The closed loop responses with the lowest cost function for different variances of gaussian white noise are illustrated in Fig. 10, 11 and 12. The corresponding PID parameters are presented in Table 3. The control parameters obtained by ANT-RBEMCE take into account the presence of the noise and the controller shows very good noise rejection feature. Even in the presence of very high noise, the system is able to trace the desired response.

TABLE III
PID PARAMETERS OF $G_2(S)$ WITH DIFFERENT GAUSSIAN WHITE NOISES

	σ^2=0.0025	σ^2=0.025	σ^2=0.25
K_p	2.6555	2.97	0.765
K_i	0.1575	0.153	0.1575
K_d	17.55	19.8	4.5

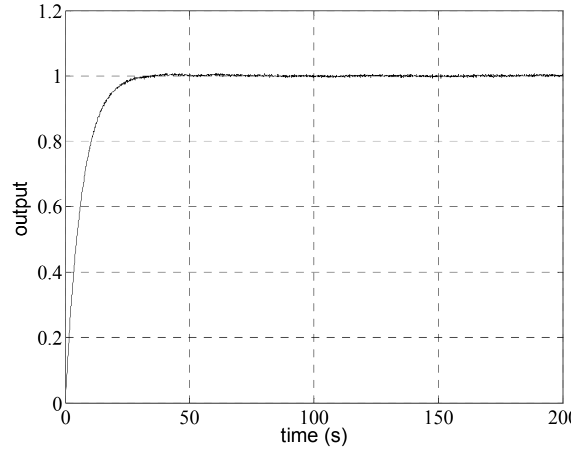

Fig. 10 The step response for σ^2=0.0025

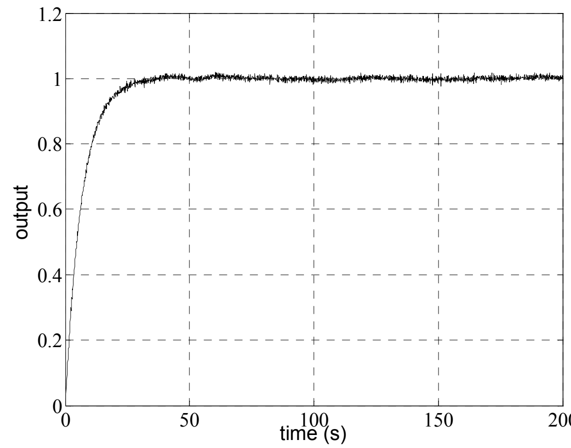

Fig. 11 The step response for σ^2=0.025

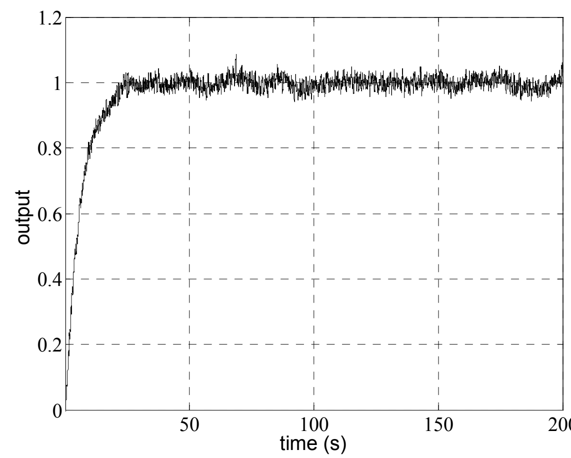

Fig. 12 The step response for σ^2=0.25

IV. CONCLUSIONS

In this study, a new PID tuning process based on ant algorithm was developed. Since ant algorithm is a powerful optimization technique, it is applied to PID tuning problem.

Firstly, AA with different cost functions was used to tune PID parameters. According to this, the proposed cost function (RBEMCE) gives a performance such that it has the optimum settling time with no overshoot. Secondly, AA using this cost function is compared with ZN, IMC and IFT methods. Based on this comparison, IFT and ANT-RBEMCE showed almost same optimal behavior (no overshoot and less settling time). Thirdly, the performance of this optimal tuning method for the tuning of PID controllers was tested in different situations (changing a pole of the system, adding time delay and varying the steady state gain). The controller tuned with ANT-RBEMCE showed high robustness in all cases compared to the other methods (ZN, IMC, IFT). Finally, the ANT-RBEMCE is applied to a model with noise. Even in the presence of very high noise, ANT-RBEMCE showed good control behavior.

There are two big advantages of ANT-RBEMCE PID tuning process: having no overshoot even if the system is perturbed in several ways and having noise rejection even if very high noise variance exists. Especially, these features are important in robotic control applications. The off-line tuning procees used in this work can be also extented to on-line tuning process.

V. REFERENCES

[1] K.J. Aström and T. Hägglund, *PID Controllers: Theory, Design, and Tuning*,. The Instrumentation, Systems, and Automation Society, 1995.

[2] H. Hjalmarsson, M. Gevers, S. Gunnarsson, O. Lequin, "Iterative feedback tuning: Theory and applications", IEEE Control Systems Magazine, vol. 18, 1998, pp 26-41.

[3] J.M. Herrero, X. Blasco, M. Martinez, J.V. Salcedo, "Optimal PID Tuning with Genetic Algorithms for Non-Linear Process Models", in IFAC 15th Triennial World Congress, Barcelona, Spain, 2002.

[4] M. Dorigo, L.M. Gambardella; "Ant colony system: a cooperative learning approach to the traveling salesman problem", IEEE Transactions on Evolutionary Computation, vol. 1, 1997, pp 53-66

[5] L.M. Gambardella, E.D. Taillard, M. Dorigo, "Ant colonies for the quadratic assignment problem", Journal of the Operational Research Society, 1999, pp 167-176.

[6] O. Lequin, M. Gevers, M. Mossberg, E. Bosmans, L. Triest, "Iterative feedback tuning of PID parameters: comparison with classical tuning rules", Control Engineering Practice, vol. 11, 2003, 1023-1033.