Optimization of PID Parameters Using Ant Colony Algorithm for Position Control of DC Motor

Enes Can Şimşek
Department of Electrical and Electronics Engineering
Gazi University
Ankara, Turkey
enescansimsek@gmail.com

Ali Köse
Technical Sciences Vocational Colleague,
Gazi University,
Ankara, Turkey
alikose@gazi.edu.tr

Murat Şahin
Roketsan
Ankara, Turkey
msahin@roketsan.com.tr

Erdal Irmak
Department of Electrical and Electronics Engineering
Gazi University
Ankara, Turkey
erdal@gazi.edu.tr

***Abstract*— Instead of standard techniques, intelligent ones are more preferred for motor control applications. Since the most important factor to execute the control process in the shortest time without causing any instability issue is the control parameters, this study presents the optimization of PID parameters for position control operation of a DC motor. Ant Colony Optimization (ACO) algorithm, which is one of the most popular techniques, is used in the proposed control approach. Thanks to the method developed, while the rise time and the settling time are considerably shortened, the overshoot percentage is successfully decreased.**

***Keywords*— Position Control, PID, Ant Colony Algorithm**

I. INTRODUCTION

DC motors have been popular in the industry and robotic applications for a long time because of their control characteristics and high performance such as high start torque characteristic, high response performance, easy to be linear control [1]. In recent literature, DC motors are usually modeled as a linear system and thereby linear control strategies such as PID, genetic algorithm based PID, pole-placement approach, incremental motion control are applied to them [2-8].

Among several control techniques, PID controller is highly preferred recently due to its useful structure for position control. In PID, there are three parameters as proportional (K_p), integral (K_i) and derivative (K_d) and the success of the controller depends on the optimum selection of them [9-11]. Although the Ziegler-Nichols method is very popular for determining these parameters, it is unable to serve sufficient performance in some sensitive applications. Therefore, some more complex and specific methods are used such as analytical methods, frequency response methods, heuristic methods and optimization methods [12]. Furthermore, multi-population based evolutionary computation methods improve the solution quality [13-14].

As an intuitive intelligent algorithm based on population, ant colony algorithm proposed by Marco Dorigo is characterized by strong robustness and easy usage with its parallel computing mechanism [15]. Ants live in colony and have important behavioral characteristics that can be sampled in problem solving. Although ants are not fully capable of seeing, they have the ability to find the shortest distance between their nests and food. Moreover, even in changing environmental conditions, this feature is successfully maintained. When an obstacle is placed on the path between their food and their nest or the path is completely disrupted, ants can find the shortest path again [16]. Ants leave pheromone secretion on their way and help other ants coming after them to find the shortest path. Ants prefer the path with a large amount of pheromones. As more ants pass through the preferred route, the amount of pheromone also increases with time. This behavior explains how they found the shortest path. Because there is no pheromone around the ant when it encounters the obstacle, so the possibility of new direction selection is equal. In this case, if the choice of ant colony is not the shortest path, they will quickly find a new path. The ants moving on this simple principle can find the best way in a short time [17].

Considering above features, this study aims to optimize the parameters of a PID control system used for position control of a DC motor by ACO algorithm. In order to examine the results comparatively, the parameter optimization is achieved by using the PID Tuner function in MATLAB/Simulink at first. Thus, for the position control of DC motor, the results of the parameters calculated in ACO and PID Tuner are compared.

II. MODELING OF DC MOTOR

Equivalent circuit model of a permanent magnet DC motor is shown in Fig 1.

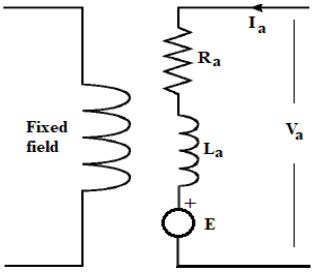


Fig. 1. Electrical model of the DC motor.

Applying Kirchhoff's laws, the following electrical equation can be obtained [18]:

$$V_a = R_a.I_a + L_a.\frac{dI_a}{dt} + E \quad (1)$$

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIV. Downloaded on October 23,2023 at 10:15:53 UTC from IEEE Xplore. Restrictions apply.

The mechanical equation of the DC motor is given as [18]:

$$J\frac{d^2\theta}{dt^2} = T_m - f\frac{d\theta}{dt} - T_L \quad (2)$$

where:

$$E = K_e\frac{\theta}{dt} \quad (3)$$

$$T = K_e.I_a \quad (4)$$

Using Laplace transform, the current equation is as follow:

$$I_a = \frac{V_a - sK_e\theta}{R_a - sL_a} \quad (5)$$

$$\theta = \frac{K_e.I_a - T_L}{f + sJ} \quad (6)$$

From (5) and (6), we obtain the block diagram of the DC motor as seen in Fig 2 and the transfer function is obtained as follow [19]:

$$\frac{\theta_{(s)}}{V_{a(S)}} = \frac{K_e}{s[(L_af + R_aJ)s + R_af + {K_e}^2]} \quad (7)$$

DC coreless AM-CL1643MB-1809 brushed motor produced by Assun Motor Corp., parameters of which are given in Table I, is selected for the perform the simulations.

After obtaining the electrical and mechanical parameters, motor is modeled in Simulink as seen in Fig 2. The output of this model gives the speed value.

TABLE I. PARAMETERS OF DC MOTOR

Symbol	Quantity	Value
R	Armature Resistance	8.3 Ω
L	Nominal Inductance	0.47 mH
J	Moment of Inertia	3.02x10^{-5} kgm^2
K_E	Voltage Constant	0.0178 V/(rad/s)
K_T	Torque Constant	0.0178 Nm/A
V	Rated Voltage	18 V
I	Rated current	280 mA
f	Coefficient of friction	5.65x10^{-6} N.m.s/rad

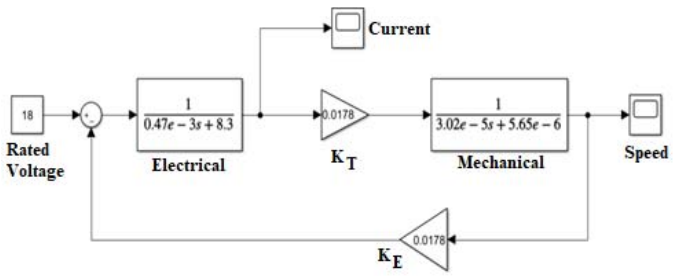


Fig. 2. Simulink model of the DC motor.

III. CONTROLLER DESIGN

A. PID Controller

The general purpose of a control system is to bring the system to the reference value in a short period, to provide fast response and stable operation. Therefore, the design of the controller is important so optimization techniques based on intelligent algorithms are preferred to obtain the most suitable PID parameters [20]. Since the parameters of the controller are selected optimally, the rise time, settling time and overshoot values become better.

The PID controller enables the output of the system to approach the reference value by using the error value that results from the difference between the given reference value and the real value from the output of the system. The error value is sent to the PID block and multiplication with K_p, integration with K_i and derivation with K_d processes are realized. Continuous and discrete time mathematical expressions of the error signal at the input and the control signal at the output of the PID controller are as following:

$$d(t) = K_p\left(e(t) + \frac{1}{T_i}\int_0^t e(\tau).d\tau + T_d\frac{d}{dt}e(t)\right) \quad (8)$$

$$d[n] = K_c\left(e[n] + \frac{T_s}{T_i}\sum_{i=0}^{n} e[i] + \frac{T_d}{T_s}(e[n] - e[n-1])\right) \quad (9)$$

In above equations, T_s is the sampling time. In the time domain:

$$d(t) = K_p.e(t) + K_i\int_0^t e(\tau).d\tau + K_d\frac{d}{dt}e(t) \quad (10)$$

Transfer function in the s-domain of the PID controller is defined as:

$$C_{(s)} = K_p + \frac{K_i}{s} + K_ds \quad (11)$$

Each parameter has different effects on the operation of the system. *P* coefficient increases the overshoot value while decreasing the rise time. *I* coefficient reduces the steady state error but increases the settling time. *D* coefficient reduces the overshoot and the settling time. The effects of parameters on the system response is given in Table II.

TABLE II. P, I, D EFFECTS ON SYSTEM RESPONSE

	Rise Time	Overshoot	Settling time	Steady State Error
P	decrease	increase	little changes	decrease
I	decrease	increase	increase	decrease
D	little changes	decrease	decrease	little changes

B. ACO-PID Controller

ACO is a metaheuristic idea used to discover high-quality solutions for difficult problems in a reasonable time. When ant behavior is used to find solutions to existing problems, artificial ants are created by making some assumptions [21]. The main principle of this algorithm is that the ant has an ability to store pheromone on the ground amid their trips and create a fragrant track that can be trailed by other ants to approach the best arrangement [22]. There are many ants working in parallel in the colony.

When starting to solve the problem, each ant is placed in different places or in the same point. At which neighboring point the ants will be in time *t* is determined by the probability formula shown in Eq. 12 where the ant *k* moving from node *i* to node *j*. Alpha (α) and beta (β) are two parameters, which determine the relative influence of the trail pheromone (τ_{ij}), and the heuristic information called visibility (η_{ij}).

$$P_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha[\eta_{ij}(t)]^\beta}{\sum_{k\in A_k}[\tau_{ik}(t)]^\alpha[\eta_{ik}(t)]^\beta} & (if\ k\ is\ allowed) \\ 0 & (if\ k\ is\ not\ allowed) \end{cases} \quad (12)$$

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIV. Downloaded on October 23,2023 at 10:15:53 UTC from IEEE Xplore. Restrictions apply.

To prevent the algorithm from running over a wide range and from failing to determine the exact parameters, the minimum and maximum values of the optimization and the search area should not be selected too large at the beginning. Depending on the model, successful results cannot be achieved if the search area is selected smaller. Similarly, if it is selected too much, a very long time passes for the solution.

As shown in Fig 3, ants are placed at the starting point. The minimum and the maximum values of each parameter (K_p, K_i, K_d) are represented as vectors. In each tour, ants should visit all three nodes by selecting a path between the starting and the ending node.

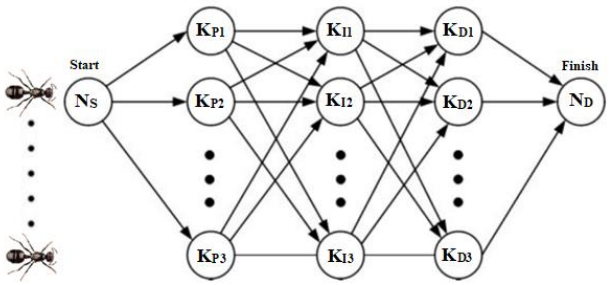


Fig. 3. Graphical representation of ACO for PID tuning [23]

After the completion of a tour, each ant left pheromone on the roads crossed and it is updated using local pheromone update rules as given Eq. 13.

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \frac{0.01\alpha}{C_{nn}} \tag{13}$$

Global pheromone update includes positive and negative pheromone updates. At the end of each round of colony pheromones of the best and the worst are calculated as given Eq. 14 and Eq. 15.

$$\tau_{ij}^{best}(t) = \tau_{ij}^{best}(t) + \frac{\alpha}{C_{best}} \tag{14}$$

$$\tau_{ij}^{worst}(t) = \tau_{ij}^{worst}(t) - \frac{0.3\alpha}{C_{worst}} \tag{15}$$

The pheromone ratios of the routes belonging to the best round of the colony are significantly increased, while the pheromone ratios of the routes belonging to the worst round are decreased. Some pheromones evaporate after each iteration. Pheromone evaporation is expressed as in Eq. 16 and allows the algorithm to forget its history.

$$\tau_{ij}(t) = \tau_{ij}(t)^{\lambda} + \Delta \tag{16}$$

$$\Delta = \tau_{ij}^{best}(t) + \tau_{ij}^{worst}(t) \tag{17}$$

A node represents a solution value of the parameters K_p, K_i and K_d. Thus, as the number of nodes used increases, the paths are updated more precisely. Optimum ACO parameters α and β are obtained from many trials. The flowchart in Fig 4 shows the calculation steps of the ACO method:

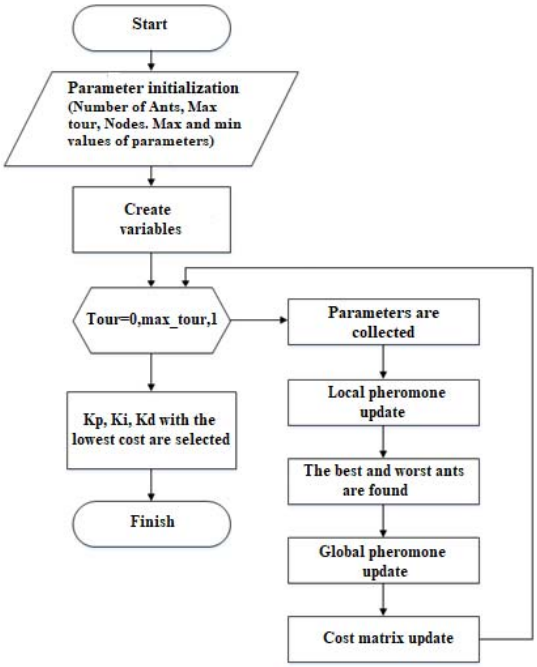


Fig. 4. Flowchart of ACO

IV. Simulation Studies

In order to test the proposed method comparatively, the model given previously in Fig 2 is created in Simulink for performing the parameter optimization using PID Controller/Tuner function of MATLAB/Simulink. The output of the model in Fig 2 gives the speed. However, the PID parameters will be determined according to the position of the motor. Therefore, an integrator is added to the model to obtain the position information from the output. Thus, the position feedback taken from the output is subtracted from the reference to obtain the error. This error value is given to the PID block as seen in Fig 5. Once the required processes in PID block are completed, optimum overshoot, rise time and settling time parameters for the motor are determined.

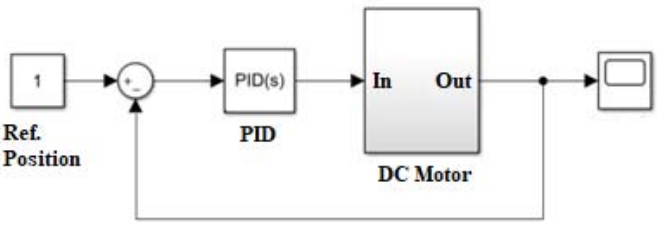


Fig. 5. PID controlled DC motor.

The PID Tuner is used to automatically adjust the parameters of the selected controller type (P, PI, PID) to provide a good balance between the system performance and robustness. The algorithm chooses a transition frequency based on the model dynamics, and designs for a target phase margin of 60°. PID coefficients are recalculated when values such as response time and transient response are desired to change. Fig 6 presents a sample screen that is captured while the parameters are being set and Figures 7 and 8 are illustrate the results obtained by using PID Tuner function.

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIV. Downloaded on October 23,2023 at 10:15:53 UTC from IEEE Xplore. Restrictions apply.

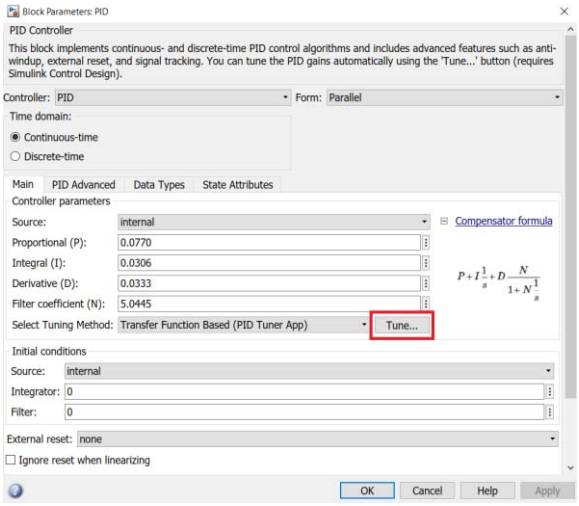


Fig. 6. Simulink PID block

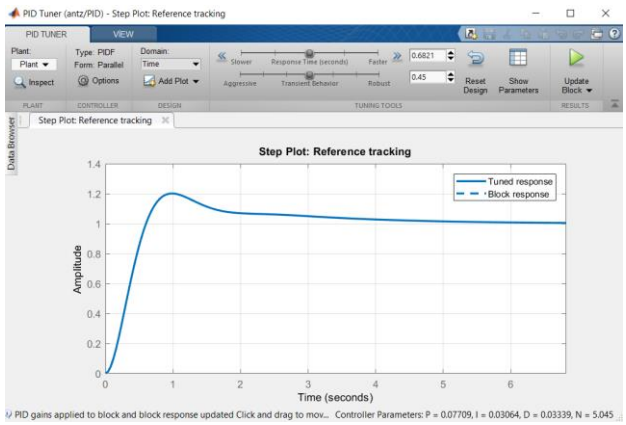


Fig. 7. Step plot of reference tracking in PID Tuner

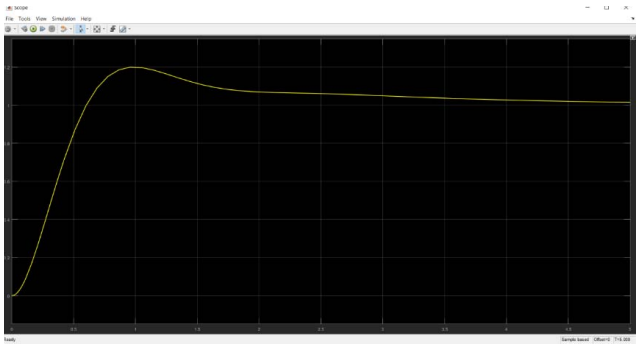


Fig. 8. Motor output graph obtained by using PID Tuner

As the second step of simulation study, a Simulink model shown in Fig 9 and script files including optimization algorithm are used together to set PID parameters with the proposed ACO based method.

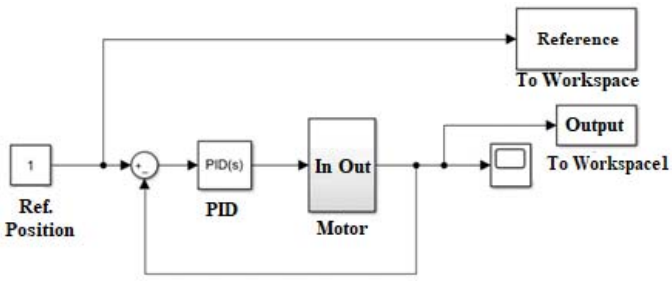


Fig. 9. Model for setting PID parameters with ACO

Two script files have been created in MATLAB workspace. One is the main script called *ant.m* that performs such processes as making the default settings, creating the pheromone, cost functions and index matrices, updating the pheromones locally or globally according to the number of ants and rounds, and selecting the lowest cost coefficients. The second one called *ant_cost.m* assigns the obtained values to coefficients, transfers the coefficients to the Simulink, and determines the cost value according to the reference and output values.

To start the optimization algorithm, script files *ant.m* and *ant_cost.m* and also the Simulink model are activated. According to the model, main settings such as the most suitable ant number, maximum number of turns, pheromone amount, evaporation, the number of parts are determined. Furthermore, the minimum and the maximum PID coefficient vectors are created. The value matrix is determined according to the smallest and maximum values generated for the coefficients and the number of parts specified in the settings. Then a loop is created and runs until the maximum number of turns.

All subsequent program parts are recalculated for each cycle. The pheromone values are assigned to a matrix, where the maximum value in the columns of this matrix indicates the location of the index. Each ant replaces the pheromones of the tracks it follows in a round with the local pheromone update, and global pheromone update is performed by finding positive and negative update values relative to the best and the worst ants. Pheromone evaporation is also carried out to allow ants to move in new directions. PID parameters and cost values are determined by means of the best ant. After completing the cycle by reaching the maximum number of turns, the lowest cost coefficients are obtained. Values with the lowest cost indicate the best parameters.

Resulting from ACO execution, K_p, K_i, K_d values and cost value are shown in Command Window as shown in Fig 10, respectively. The obtained data is transferred to the Simulink and as shown in Fig 11, the overshoot, rise time and settling time are improved considerably compared to the PID Tuner. Table III and Table IV also presents some comparative data between ACO based and PID Tuner based optimizations. Graphical comparison of two PID control techniques is given in Fig 12.

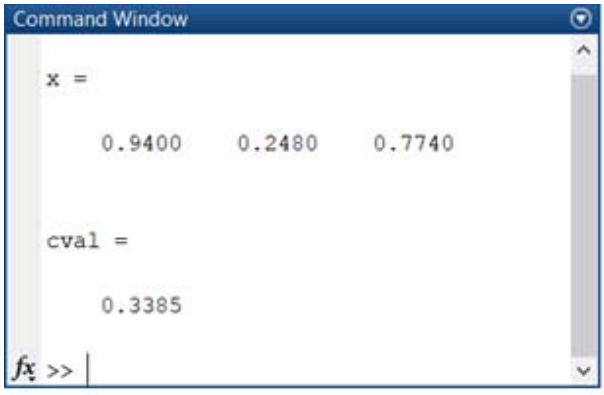


Fig. 10. Parameters and cost value obtained with ACO

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIV. Downloaded on October 23,2023 at 10:15:53 UTC from IEEE Xplore. Restrictions apply.

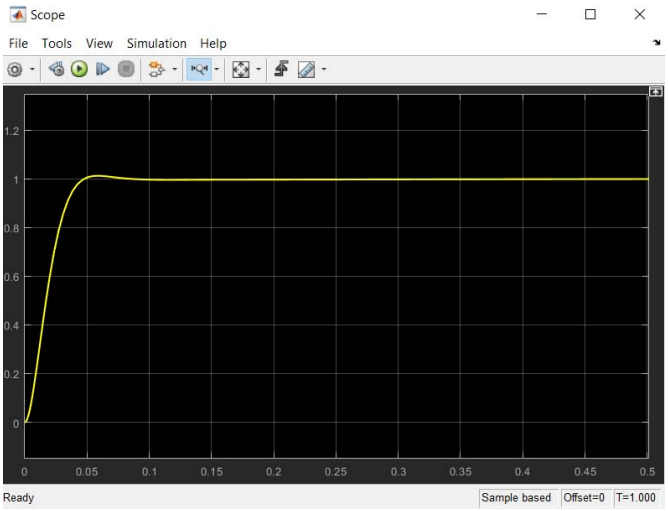


Fig. 11. Motor output graph formed by ACO-PID

TABLE III. PARAMETERS DETERMINED BY ACO-PID AND PID TUNER

	ACO-PID	PID Tuner
K_P	0.9400	0.0770
K_I	0.2480	0.0306
K_D	0.7740	0.0333
N	140	5.0445

TABLE IV. PERFORMANCE VALUES OF PARAMETERS DETERMINED BY ACO-PID AND PID TUNER

Criteria	ACO-PID	PID Tuner
Rise time	0.0279 s	0.41 s
Settling time	0.9326 s	4.52 s
Overshoot	1.29 %	20.1 %
Peak	1.01	1.2

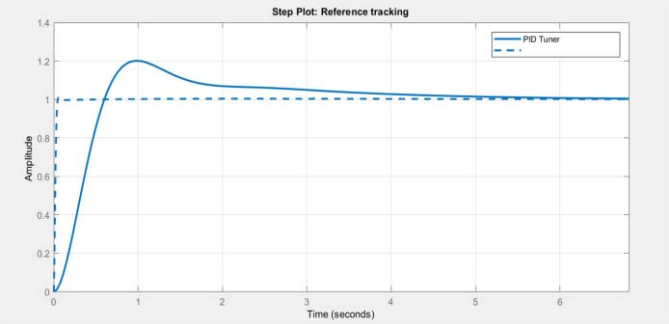


Fig. 12. Comparison of output performance graphs of ACO and PID Tuner

V. CONCLUSION

Considering the ACO algorithm serves effective and successful results for optimization problems, this paper deals with the use of ACO for determining the PID parameters for position control of a DC motor. In order to perform a comparative study, the parameters determined by proposed ACO based method are compared with the results of parameter determination process using PID Controller/Tuner function of MATLAB/Simulink. It is observed that the ACO based method provides better results in respect of rise time, settling time and overshoot values.

REFERENCES

[1] A. P. Singh, U. Narayan, A. Verma, “Speed control of DC motor using PID controller based on matlab”, Innovative Systems Design and Engineering, vol. 4 (6), pp. 22-28, 2013

[2] J. Chotai, K. Narwekar, “Modelling and position control of brushed DC motor”, Int. Conf. on Advances in Computing, Communication and Control, India, 2017

[3] D. Rawat, K. Bansal, A.K. Pandey, “LQR and PID design technique for an electric furnace temperature control system” Proceeding of Int. Conf. on Intelligent Comm., Control and Devices. Advances in Intelligent Systems and Computing, vol. 479, pp. 561-567, Springer, 2017

[4] N. Saqib, M. Rehan, N. Iqbal, K.S. Hong, "Static antiwindup design for nonlinear parameter varying systems with application to DC motor speed control under nonlinearities and load variations", IEEE Trans. on Control Systems Technology, vol. 26(3), pp. 1091-1098, 2018

[5] M. Boukens, A. Boukabou, M. Chadli, “A real time self-tuning motion controller for mobile robot systems”. IEEE/CAA Journal of Automatica Sinica, vol. 6(1), pp. 84-96, 2019

[6] H. Turker., “Design optimization of interior permanent magnet synchronous machine for electric vehicle application”, 5th Int. Conf. on Renewable Energy Research and Applications, Birmingham, 2016

[7] M. Thirupathaiah “Enhancement of power quality in wind power distribution system by using hybrid PSO-firefly based dstatcom”, Int. Journal of Renewable Energy Research, 8(2), pp. 1138-1154, 2018

[8] T.R.D. Gaddam, K.K. Danduprolu, “Fuzzy logic controller based performance of SPMSM fed with improved direct torque control”, Int. Journal of Renewable Energy Research, 9(3), pp.1346-1354, 2019

[9] M. Obika, T. Yamamoto, “An evolutionary design of robust PID controllers”, Proceedings of the IEEE Int. Conf. on Mechatronics , 101-106, Canada, 2005

[10] A. Mamizadeh, N. Genc, R. Rajabioun, “Optimal tuning of PI controller for boost DC-DC converters based on cuckoo optimization algorithm”, 7th Int. Conf. on Renewable Energy Research and Applications, Paris, 2018

[11] H.W. Gomma, “Adaptive PID control design based on generalized predictive control”, Proceedings of the IEEE Int. Conf. on Control Applications, pp. 1685-1690, 2004

[12] H.E.A. Ibrahim, F.N. Hassan, A.O. Shomer, “Optimal PID control of a brushless DC motor using PSO and BF techniques”, Ain Shams Engineering Journal, 5(2), pp.391–398, 2014

[13] M. Sato, Y. Fukuyama, T. Iizaka, T. Matsui, “Total optimization of smart city by multi-population brain storm optimization with differential evolution strategies” 6th IEEE Int. Conf. on Smart Grid (icSmartGrids), pp. 228-233, Japan, 2018

[14] S. Sahoo et al., “Comparison of output power control performance of wind turbine using PI, Fuzzy Logic and Model Predictive Controllers”, Int. Journal of Renewable Energy Research, 8(2), pp.1062-1070, 2018

[15] T. Zhuo, L. Zhengding, L. Ruixuan, “A routing algorithm for riskscanning agents using ant colony algorithm in P2P network”, Wuhan University Journal of Natural Sciences, 11(5), pp. 1097-1103, 2006

[16] D. Karaboga, “Artificial intelligence optimization algorithms”, Nobel Academic Publishing, 109-133, Ankara, 2017

[17] Y. Chen, Z. Guo, J. Liu, "An improved ant colony algorithm for PID parameters optimization", 2nd Int. Conf. on Intelligent Computation Technology and Automation, pp. 157-160, 2009

[18] A.B. Yildiz, “Electrical equivalent circuit based modeling and analysis of direct current motors”, Electrical Power and Energy Systems, vol 43, pp. 1043–1047, 2012

[19] K. Boudaraia, H. Mahmoudi, M. Abbou, M. Hilal. “DC motor position control of a solar tracking system using second order sliding mode”, 5th Int. Conf. on Multimedia Computing and Systems, Morocco, 2016

[20] S. Vadi, R. Bayındır, “Optimization of PI parameters in DC motor closed loop speed control system using genetic and particle swarm algorithm”, Journal of Data Science, 2(1), pp. 51-60, 2019

[21] M. Dorigo, T. Stutzle, “Ant Colony Optimization”, Cambridge, Mass: MIT Press, 2004

[22] I. Lahlouh, A. Elakkary, N. Sefiani, “PID controller of a MIMO system using ant colony algorithm and its application to a poultry house system”, 5th Int. Conf. on Optimization and Applications, Morocco, 2019

[23] R.A. Hanifah, S.F. Toha, S. Ahmad, " PID-Ant colony optimization control for electric power assist steering system for electric vehicle", Proc. of the IEEE Int. Conf. on Smart Instrumentation, Measurement and Applications, Malaysia, 2013

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIV. Downloaded on October 23,2023 at 10:15:53 UTC from IEEE Xplore. Restrictions apply.