

Self-Tuning PID Controller based on PSO-RIW for Ultrasonic Motor

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Abstract: The characteristic changes during operation, unpredictable parameters and highly nonlinear properties may significantly affect the performance of ultrasonic motor (USM). A self-tuning scheme is necessary to overcome these effects. Additionally, this scheme can track changes in system operation and compensate for such characteristic of USM. The paper proposes a new self-tuning PID controller scheme on position control of USM using a modified particle swarm optimization with random inertia weight, called the PSO-RIW. In this scheme, an inertia weight of PSO is randomly adjusted during searching process to overcome the difficulties of the method of selecting inertia weight and to improve the performance of the standard PSO. The performance of the self-tuning PID controller based on PSO-RIW has been tested on USM servo system. Experimental results are compared with the previous methods and showing that the proposed method can improve the position accuracy of USM.

Key-Words: *PID controller, self-tuning, particle swarm optimization (PSO), ultrasonic motor (USM).*

1. Introduction

The ultrasonic motor (USM) is a non-conventional motor that is driven by the ultrasonic vibration force of piezoelectric parts. USMs have glorious features such as compactness, light-weight, no running sound, high torque even at a low speed, high retention torque within the stop condition and no emitted electromagnetic noise. Therefore, USMs are very capable of high precision actuator in many areas [1-3]. However, it is difficult to control USMs because they have no exact model, highly nonlinear properties, and characteristic changes during operation due to temperature, load, input frequency, etc. Though some models for USMs have been proposed, they were not satisfactory because the given model is not covering all properties of USMs and use parameter's simplification [4, 5]. Therefore, it is difficult to employ a modern control theory to USMs because it always begins from the expression model of the plant and based on the complex theory. Since a PID controller can be built even if there is no plant model, PID controller has been widely used

as the control method for USM [6, 7]. However, it is not easy for tuning PID gains and it is difficult for the fixed-gain PID controller to compensate for such characteristic changes and nonlinearity of USMs.

To overcome these problems, the self-tuning of PID gains using soft intelligent computation such as GA, NN and PSO has been proposed [8-12]. Recently, PSO is attractively used for self-tuning PID controller because it has superior properties such as easy implementation, simple algorithm, fast and stable convergence and efficient in time calculation. PSO gives a better result than the previous methods in terms of convergence speed and solution accuracy.

Although PSO has superior properties, they have some inherent problems such as premature convergence, possibility fall in local optima, and inefficiency or low accuracy for multiple peak problems and dynamic environment. In order to overcome those problems, many researchers have attempted to improve the PSO algorithm [13-16].

In this work, a modified PSO which employs random inertia weight was applied to self tune the PID gains for

position control of USM. To show the effectiveness of our proposed method, the experiment in USM servo system was compared with that of the previous methods (fixed-gain type PID and PSO with linear decreased inertia weight or PSO-LDW based PID).

2. Particle Swarm Optimization

PSO is a population based stochastic optimization method using the concept of cooperation inspired by the behavior of organism, such as birds flocking, in search for food. The outline for PSO is marked as follows. Let consider the optimization problem of maximizing the evaluation function $f : M \rightarrow M' \subset R$ for variable $x \in M \subset R^n$. Let there be N particles (mass point) on M dimensional space, where the position vector and velocity vector of $i(= 1,2,3,\dots,N)$ th particle for m searching number are x_i^m and v_i^m . The best position for each particle in the evaluation function $f(x)$ of $x_i^1, x_i^2, \dots, x_i^m$ searching point is represented as P_i ($Pbest$), while the best position of $f(x)$ in the searching point for the whole particle is represented as P_g ($Gbest$). The particles are manipulated according to the following recurrence equations:

$$v_i^{m+1} = w.v_i^m + c_1.r_1.\{P_i - x_i^m\} + c_2.r_2.\{P_g - x_i^m\} \quad (1)$$

$$x_i^{m+1} = x_i^m + v_i^{m+1} \quad (2)$$

where w is the inertia weight; c_1 and c_2 are cognitive and social constant; r_1 and r_2 are uniform random numbers from the interval $[0, 1]$.

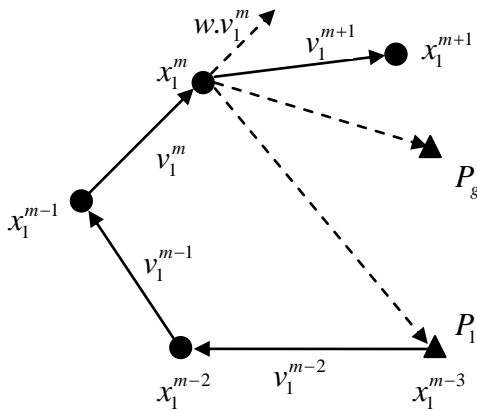


Fig. 1. Search example of PSO

The example for optimized solution search using PSO is shown in Fig. 1. Now, x_1^{m-3} searching point is $Pbest$, and $Pbest$ for the individual number g is assumed to be the $Gbest$. The velocity vector of v_1^{m+1} is formed based on three vectors as shown in Eq. (1). The first one is inertia vector, which is the vector from weighting factor w and the velocity vector v_1^k . The remaining two are vectors for each P_i and P_g , which formed from weighting factors c_1 as well as c_2 , and also $[0, 1]$ of uniform random numbers r . From those interactions, velocity vector v_1^{m+1} acts so that the particle comes closer to optimum value [13].

3. Modified PSO

The experiments indicate that inertia weight is most important parameter to balance the global search ability (exploration) and local search ability (exploitation), when inertia weight is higher, the global search ability is strong, but the local search ability is low; whereas the local search ability is strong, but global search ability is low. This balancing is a key role to improve the performance of PSO. However, the method of selecting inertia weight is not easy and need to be further investigated. The linear and nonlinear decreasing inertia weight can make PSO adjust global search ability and local search ability, but it has shortcomings: firstly, due to the lack of local search ability at beginning of iteration and global search ability at the end of iteration, there is a possibility to get stuck in local optima; secondly, improper selected initial inertia weight (w_{max}), final inertia weight (w_{min}) and nonlinear index number can decrease the performance of PSO [13,14]. Moreover, major experiments show that particles can accumulate at point in searching area, but it is not a global optimum solution. The particles have stagnated and lost the ability to find the global optima solution. Especially, in dynamic environment, so the particles will often fall in local optima.

To overcome those problems, the inertia weight employing a random number uniformly distributed in $[0,1]$ was introduced to improve the performance of PSO. In this

method, global search ability and local search ability can be processed in the same time. Thus, the proposed method is capable of escaping from the local optima. During iteration, the value of inertia weight is randomly varying according to the following equation:

$$w = \alpha_1 + \alpha_2 \cdot \text{rand}() \quad (3)$$

where $\text{rand}()$ is a random number in $[0, 1]$; α_1 is the lower limit of w ; α_2 is the upper limit of $\text{rand}()$.

4. Implementation PSO-RIW in PID Controller

Design of the self-tuning PID controller based on PSO-RIW for USM is shown in Fig. 2. In this system, three PID parameters (K_p , K_i , K_d) will be tuned automatically by PSO-RIW algorithm. The reference signal $r(k)$ is a rectangular signal. The amplitude is set from +45 [deg] or clockwise (CW) rotation to -45 [deg] or counter clockwise (CCW) rotation. The period is 4 [sec]. Because of the sampling time of 1 [ms], there are 4000 cycles of sampled-data in discrete-time. The error signal $e(k)$ will be entered for PSO-RIW and subsequently evaluated in the fitness function to guide the particles during the optimization process. The fitness function for the proposed method is given as:

$$\text{Fitness} = \frac{1}{1 + e(k)^2} \quad (4)$$

Fitness shows the following-up of evaluation function for the object input. The purpose is to decrease the steady-state error by maximizing the function. The fitness is updated by each millisecond according to the value of $e(k)$. The fitness calculation is started from $k = 0$ and stopped at $k = 2000$ for +45 [deg] and the next calculation is started from $k = 2001$ and stopped at $k = 4000$ for -45 [deg].

The USM control for clockwise (CW) rotation and the counter clockwise (CCW) rotation use the different PSO in tracking the object input. Since the characteristics of USM are different depends on the rotation direction, we evaluate both rotations separately.

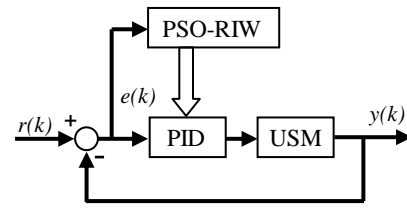


Fig. 2 PSO-RIW based PID controller

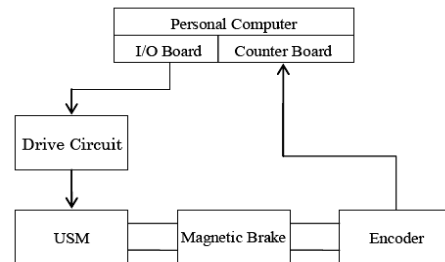


Fig. 3 USM servo system

5. Experimental Result

The USM servo system constructed in this study is shown in Fig. 3. USM, the electromagnetic brake and the encoder (resolution = 0.0011 [deg]) are connected on a same axis. The position information from an encoder is transmitted to the counter board embedded into a Personal Computer (PC). Meanwhile, according to error resulted from the comparison between the output and reference signal, the control input signal which is calculated in PC is transmitted to the driving circuit through the I/O board and oscillator. In each experiment, the load is added or not is discussed to observe the changes of the USM's characteristics. While the voltage of 12 [V] is imported, the force of 0.25 [N.m] could be loaded to the shaft of the USM. The specifications of USM as follows: rated rotational speed = 100 [rpm], rated torque = 0.5 [N.m], holding torque = 1.0 [N.m].

5.1 Tuning PID Controller using Conventional Approach

Firstly, we used the conventional method for tuning PID controller on USM servo system. This method is introduced by Ellis [17] and called the zone-based tuning. It means that the low and high frequency parts of the controller can be tuned separately, starting with the high frequency part. For a PID controller, this means that first the P- and D-action are

tuned and then the I-action. The procedure with steps to follow to tune a PID controller is given as follows:

1. Set K_p low, while $K_i = 0$ and $K_d = 0$
2. Apply square wave reference at about 10% of the desired bandwidth. Use large amplitude, but avoid saturation.
3. Raise K_p for approximately 10% overshoot.
4. Raise K_d to eliminate most overshoot.
5. Raise K_i to eliminate steady-state

We found that $K_p = 0.3692$, $K_i = 12.175$ and $K_d = 0.000085$, for the best performance after many experiments. Then, we started on USM servo system with 10 runs of clockwise (CW) direction (i.e., +45 deg) and 10 runs of counter clockwise (CCW) direction (i.e., -45 deg) for no-load condition. After that, we repeat again for with load condition, i.e., 0.25 [N.m].

The relationship between reference signal and output of system is shown in Fig. 4. The output of system is position of USM in +45 [deg] (CW rotation) and -45 [deg] (CCW rotation). Figure 5 and 6 present the position accuracy of USM in histogram for no-load and with load condition. We can say that the position accuracy of USM using a hand-tuned PID is good and reliable in no-load condition, but becomes poor and inaccurate in with load condition. The gains have been determined previously only applicable to no-load condition. If the plant's behavior is changed (i.e., due to the loading), it is necessary to re-tune PID and it is drawback of the fixed-gain PID.

5.2 Self-Tuning PID Controller using Intelligent Soft Computation

The used parameters in PSO-RIW algorithm are as follows: particles number, $n = 5$; cognitive constant, $c_1 = 1.0$; social constant, $c_2 = 1.0$; $\alpha_1 = 0.3$; and $\alpha_2 = 0.3$. Using the same test condition as before, the PSO-RIW algorithm will tune automatically to determine the optimal gains of PID controller. For comparison, we also used the common PSO method, called the PSO with linear decreasing inertia weight or PSO-LDW, with maximum inertia weight, $w_{max} = 0.8$ and minimum inertia weight, $w_{min} = 0.3$.

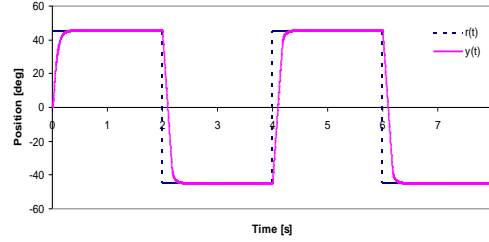


Fig. 4 Output response of USM

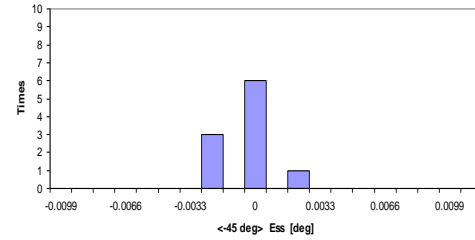
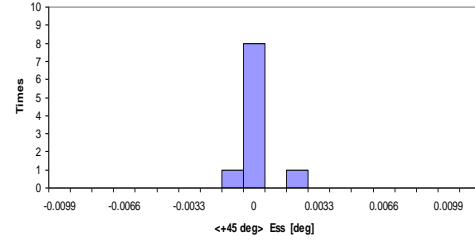


Fig. 5. Position error of USM using PID controller (no-load)

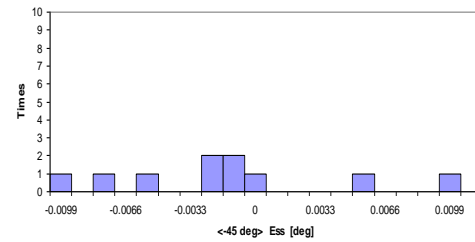
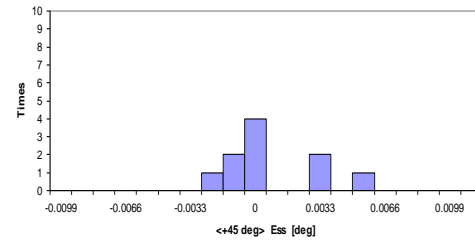


Fig. 6. Position error of USM using PID controller (load 0.25 N.m)

Figures 7-10 show the position accuracy of USM in histogram for no-load and with load condition. It can be seen clearly that self-tuning PID controller can compensate the characteristic changes of USM due to the loading effect.

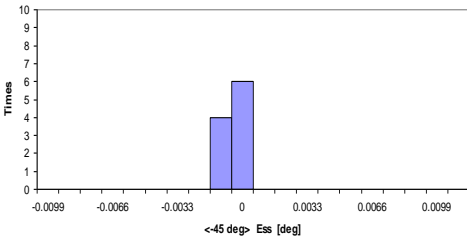
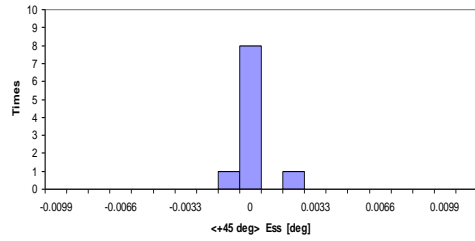


Fig. 7. Position error of USM Using PSO-LDW PID controller (no-load)

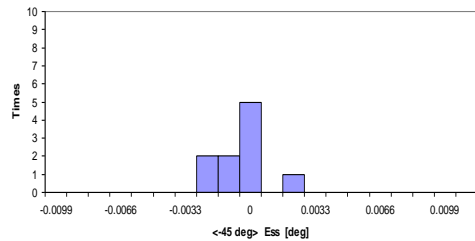
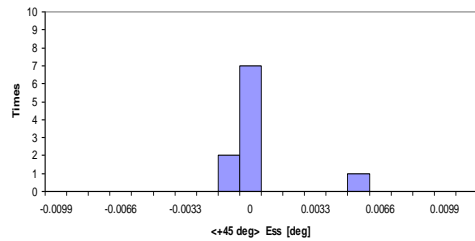


Fig. 8. Position error of USM using PSO-LDW PID controller (load 0.25 N.m)

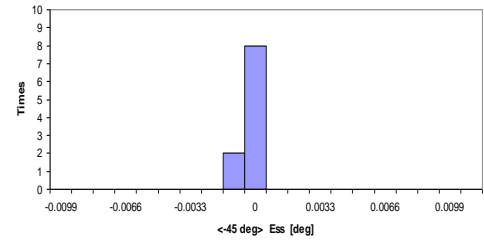
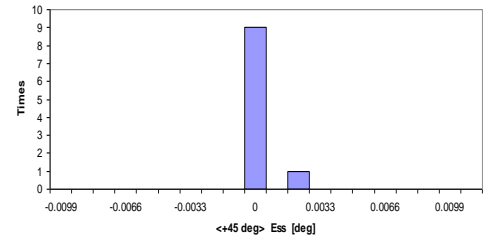


Fig. 9. Position error of USM using the PSO-RIW PID controller (no-load)

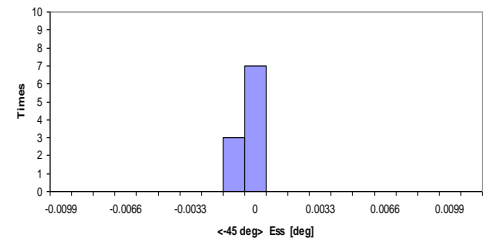
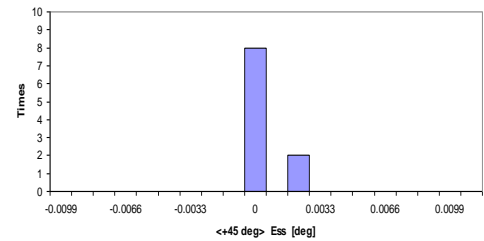


Fig. 10. Position error of USM using the PSO-RIW PID controller (load 0.25 N.m)

The gains PID are automatically adjusted according to the plant's behavior. Thus, the position accuracy of USM can be maintained still good and reliable even though there are the characteristic changes of plant. We also found that the CW direction's characteristic is slightly different from the CCW direction's characteristic. Compared to a fixed-gain PID and PSO-LDW tuned PID, the PSO-RIW tuned PID have the frequency distribution tends towards zero error.

5.3 Comparison of the Average Steady-state Error

Table 1 show the comparison of the proposed method and

Table 1 Comparison of the average steady-state error

Methods	Ave Ess		Frequency of Zero Ess in 20 runs	
	No-load	Load 0.25 Nm	No-load	Load 0.25 Nm
PID	0.000578	0.003306	14	5
PSO-LDW	0.000511	0.000894	14	12
PSO-RIW	0.000183	0.000306	17	15

other methods in term of average *Ess* and frequency of zero error in 20 runs. The self-tuned PID controller such as using PSO-LDW and PSO-RIW can outperform a hand-tuned PID or a fixed-gain PID. The average *Ess* of the PSO-RIW is smallest or 63.4% (load condition) and 64.21% (with load

condition) lower than PSO-LDW. Moreover, the frequency of zero *Ess* of PSO-RIW is more often than the previous methods. It means that the proposed method can improve the position accuracy of USM.

5.4 Comparison of the Convergence Speed

Figure 11 shows the fitness convergence characteristics of PSO-LDW and PSO-RIW. It is seen clearly that the particles PSO-RIW achieve faster convergence than PSO-LDW. The particles of PSO-RIW achieved convergence in 0.23 seconds, while the particles of PSO-LDW achieved convergence in 0.27 seconds.

Figures 12–14 then demonstrate the convergences of PID control gains with respect to the time, respectively. Avoiding the random initial PID gains make the USM servo system unstable, we chose a group proper PID gains for initial values of PID parameters by trial and error (i.e., 0.3, 10, 0.0001). We found that the standard deviation of gain K_p , K_i and K_d of PSO-RIW tuned PID is lower than PSO-LDW tuned PID by using statistical analysis from 3 [sec] to 4 [sec] of data in steady-state condition (Table 2). In general, we can say that diversity of particles in PSO-RIW is smaller and closer to the global best solution. At the end iteration, the particles of PSO-RIW have greater local search ability with lower speed than the particles of PSO-LDW and finally almost all particles home in onto the best solution area. The particles in PSO-LDW still oscillate around a global best solution, so that its diversity is also still large. Thus, the accuracy of PSO-RIW becomes better than PSO-LDW. Moreover, these figures tell that the PSO-RIW algorithm has stable convergence with good computational efficiency.

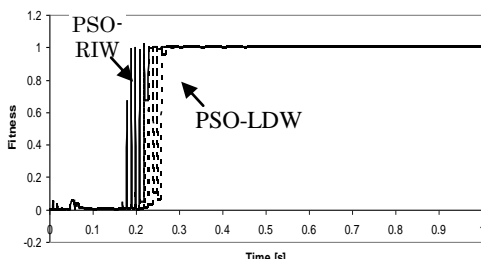


Fig. 11. Convergence of fitness

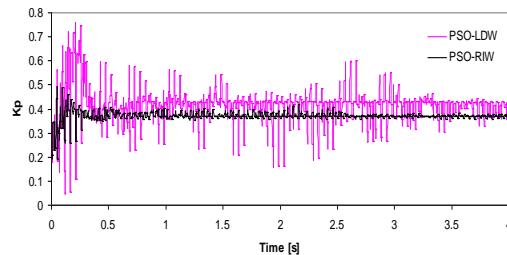


Fig. 12. Convergence of K_p

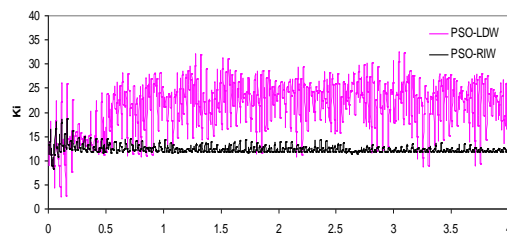


Fig. 13. Convergence of K_i

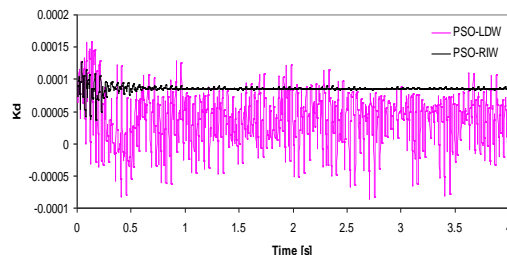


Fig. 14. Convergence of K_d

Table 2 Statistical analysis of PSO-RIW and PSO-LDW

	PSO-RIW based PID			PSO-LDW based PID		
	K_p	K_i	K_d	K_p	K_i	K_d
mean	0.3692	12.175	8.5×10^{-5}	0.4123	22.336	3.9×10^{-5}
Std	0.0051	0.3974	8.9×10^{-7}	0.0331	4.455	3.6×10^{-5}
Dev	0.0038	0.3045	6.8×10^{-7}	0.0256	3.501	2.9×10^{-5}

6. Conclusions

In this paper, a modified PSO with random inertia weight or PSO-RIW for self-tuning PID controller on position control of USM is proposed. This strategy is the simplest way to adjust the value of inertia weight. Through experiments on the USM servo system, we could conclude that the self-tuning PID using PSO-RIW is capable to compensate the characteristic changes of USM and has superiority to PSO-LDW on both convergence speed and position accuracy.

References

- [1] T. Kenjo, T. Sashida, *An Introduction of Ultrasonic Motor*, Oxford Science Publications, 1993.
- [2] K. Adachi, "Actuator with Friction Drive: Ultrasonic Motor", *Journal of the JSME*, Vol.108, No.1037, pp.4851, 2005 IEEE International Conference on Robotic and Automation, Barcelona, Spain, April 2005
- [3] Ikuo Yamano, Tadashi Maeno, "Five-fingered Robot Hand using Ultrasonic Motor and Elastic Element", *Proceeding of the 2005*
- [4] B. Nogarede, E. Piecourt, "Modelization of a Travelling Wave Piezoelectric Motor by Equivalent Electrical Circuit", *Proceedings of the International Conference on Electrical Machines*, pp.128-133, 1994.
- [5] P. Hagedorn, J. Wallaschek, "Travelling Wave Ultrasonic Motors, Part 1 : Working Principle and Mathematical Modelling of the Stator," *Journal of sound and Vibration*, Vol.155, No.1, pp.31-46, 1992.
- [6] N. Suda. *PID Control*, Asakura Publishing Co., 1992.
- [7] S. Yamamoto, N. Katou. *Base and application of PID control*, Asakura Publishing Co. 1997.
- [8] Wong-yong Han, Jin-wook Han, Chan-goo Lee, "Development of a Self-tuning PID Controller based on Neural Network for Nonlinear Systems", *Proceeding of the 7th Mediterranean Conference on Control and Automation (MED99)*, Haifa, Israel, June 28-30, 1999.
- [9] S. Kanthalakshmi, V. Manikandan, "Genetic Algorithm based Self Tuning Regulator", *International Journal of Engineering Science and Technology*, Vol. 2 (12), 2010, 7719-7728.
- [10] S.M. Giriraj Kumar, Deepak Jayaraj, Anoop R. Kishan, "PSO Based Tuning of a PID Controller for a High Performance Drilling Machine", *International Journal of Computer Application (0975-8887)*, Volume 1, No. 19, 2010
- [11] Li Xu-zhou, Yu Fei, Wang You-bo, "PSO Algorithm based online Self Tuning of PID Controller", *International Conference on Computational Intelligence and Security*, 2007.
- [12] Kennedy J, Eberhart C, "Particle Swarm Optimization", *Proceeding IEEE International Conference on Neural Networks*, pp. 1942-1945, 1995
- [13] Faridah A. Rahman, Y. Murata, K. Tanaka, Y. Nishimura, S. Uchikado, Y. Osa, "Variable Gain Type PID Control Using PSO for Ultrasonic Motor", *5th International Workshop on Computational Intelligence and Application IEEE SMC Hiroshima Chapter*, Hiroshima University, November, 2009.
- [14] Ahmad Nickabadi, M. Mehdi Ebadzadeh, Reza Safabakhsh, "A Novel Particle Swarm Optimization Algorithm with Adaptive Inertia Weight", *Journal of Applied Soft Computing* 11, pp. 3658-3670, 2011
- [15] A. Chatterjee, P. Siarry, "Nonlinear Inertia Weight variation for dynamic adaptation in particle swarm optimization", *Computer and Operation Research* 33, p.859-871, 2006.
- [16] Shi Y, Eberhart R.C., "A modified particle swarm optimization", *IEEE Int. Conf. Evol. Comput.*, Anchorage, AK, May 4-9, 1998.
- [17] G. Ellis, *Control system design guide*, Academic Press, London, 1991

