Research of Intelligent Self-Tuning PID Control using Enhanced Particle Swarm Optimization for Ultrasonic Motor

（超音波モータの改良型粒子群最適化を用いた

知的セルフチューニング PID 制御に関する研究）

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I would like to dedicate this thesis to my beloved family, supervisors and friends

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Abstract

In this dissertation, my doctoral research of intelligent self-tuning PID controller using Enhanced Particle Swarm Optimization (EPSO) for ultrasonic motor (USM) is presented. In order to get a satisfactory performance of USM servo system, a new control method based on intelligence soft computation called EPSO has been proposed and verified in this research.

The object of the research is USM. USM is new type motor that is driven by ultrasonic vibration of piezoelectric materials. USM was produced commercially at the first time by Sashida in 1980. USM has excellent features such as compactness, lightweight, high torque, high position accuracy, Electromagnetic Compatibility (EMC) compliance, silence, self-brake without power and quick response. In recent years, USM can be applied in many applications such as for auto-focus of camera, micro-robot, meal robot assistance, finger robot, MRI (Magnetic Resonance Imaging) and micro-surgical robot.

Although, USM has excellent features and offers great advantages, USM has problems. Because of no accurate mathematical model and characteristic changes during operation, the control of USM is not easy. Deriving a mathematical model of USM using physical analysis is too hard because of its strong nonlinearity, uncertainty, and complexity in working principle. Moreover, due to temperature, loading, input frequency and other disturbances, the characteristics of USM are easily changed during operation. How to control USM is the focus of our research. To overcome those problems, we proposed a new control method for USM called intelligent PID controller using Enhanced Particle Swarm Optimization (EPSO). We decided to use PID controller because of no accurate model of USM. Moreover, PID controller has superior features, such as simple, efficient, effective and robust. Then, to compensate the characteristic changes of USM and difficulties of tuning process, self-tuning scheme was used. Due to self-tuning scheme, the PID gain can be adjusted automatically and easily according to

USM's behavior. Recently, self-tuning scheme using intelligence soft computation called intelligent self-tuning is developed to avoid the difficulty and complexity in conventional self-tuning scheme. PSO is one of the intelligent self-tuning that has superior features such as simple algorithm, faster convergence and efficient in time-calculation. EPSO is a new development of PSO to overcome the shortcoming of PSO, namely premature convergence and easy to get stuck or fall into local optima. The shortcoming of PSO may lead to a poor performance, especially in loaded condition.

PSO is a population-based optimization technique inspired by behavior of birds flocking or fish schooling for finding a food. It was reported that the causes of the shortcoming of PSO are unbalance between exploration-exploitation ability, lost-diversity and lack-information due to fast rate flow in sharing information. There are three parameters in PSO, i.e., inertia weight, cognitive coefficient and social coefficient. Among them, the most important parameter is inertia weight because of its capability in control the balance between exploration-exploitation abilities.

We proposed and investigated two types of EPSO, i.e., new inertia weight approach PSO (e.g., PSO with nonlinearly decreased inertia weight or PSO-NDW and PSO with random inertia weight or PSO-RIW) and adaptive inertia weight approach PSO (e.g., adaptive PSO or APSO, adaptive PSO with random inertia weight or APSO-RIW and hybrid adaptive improved PSO or HAIPSO). PSO-NDW is proposed to control the usage period of exploration-exploitation abilities. In here, inertia weight is decreased nonlinearly from maximum value to minimum value. PSO-RIW is proposed to overcome the lack ability in PSO-NDW and PSO-LDW (PSO with linearly decreased inertia weight). In here, inertia weight is randomized from minimum value to maximum value. APSO is proposed to accelerate in obtaining a proper balance between exploration-exploitation abilities. In here, inertia weight is adjusted according to the swarm condition, i.e., fitness value of Pbest (best known position of particle) and gbest (best known position among all particles). APSO-RIW is proposed to combine the benefit of APSO and PSO-RIW. The benefit of APSO is faster in obtaining a proper balance. The benefit of PSO-RIW is high searching ability. In here, inertia weight is adjusted according to the swarm condition and then randomized. HAIPSO is proposed to overcome the causes of shortcoming simultaneously by using combination of three strategies. The first strategy called adaptive inertia weight is to accelerate in obtaining a proper balance. The second strategy called additional part is to create a new particle's movement and to compensate the lack-information and fast rate flow in sharing information. In the second strategy, a new additional part called socio-cognitive part for connecting directly between *gbest* and *pbest* is inserted into PSO algorithm. The third strategy called mutation operator is to keep the diversity of swarm and to avoid premature convergence.

To evaluate the effectiveness of the proposed control method, we tested it and compare with the previous control methods by using histogram, average error, success-rate (SR) and convergence speed. The experimental results showed that the proposed control method has a best performance in both unloaded and loaded condition. The proposed EPSO has shown faster convergence speed and higher SR. It means the proposed EPSO can reduce effectively the risk of premature convergence and fall into local optima. The proposed EPSO has proved an effective strategy for improving PSO. Due to EPSO-based PID controller, the accuracy of USM servo system can be increased significantly. The contents of the research are organized into five chapters summarized as the following.

Chapter 1 is the introduction of this research. In this chapter, the background of the research, related works, the motivation, the problem statement and target are introduced.

In Chapter 2, USM and PSO-based PID controller are provided. The basic principle of USM, PID controller, PSO algorithm, and the configuration of PSO-based PID controller for USM are explained.

In Chapter 3, new inertia weight approach PSO (PSO-NDW and PSO-RIW) is explained. Then, the effectiveness of PSO-NDW based PID and PSO-RIW based PID are investigated experimentally.

In Chapter 4, adaptive inertia weight approach PSO (APSO, APSO-RIW and HAIPSO) is explained. Then, the effectiveness of APSO based PID, APSO-RIW based PID and HAIPSO based PID are investigated experimentally.

Finally, in Chapter 5, the discussion and conclusion are summarized.

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Chapter 1
Introduction

In this chapter, the background, related works, the motivation, the problem statement and target of the research about intelligent self-tuning PID controller using Enhanced Particle Swarm Optimization (EPSO) for ultrasonic motor (USM) are introduced.

1.1 Background

The ultrasonic motor (USM) is a new type motor that has different construction, characteristics and operating principles than the common electromagnetic (EM) motors. The USM is driven by the ultrasonic vibration force of piezoelectric materials. USM was introduced at the first time by H.V. Bart and V.V Lavrinenco in 1973 and was produced commercially at the first time by Sashida in 1980. After that, USM has been widely used in many applications where the size, torque and other requirements could not be satisfied by the common EM motors. USM has excellent features, such as compact size, lightweight, high torque, high position accuracy, Electromagnetic Compatibility (EMC) compliance (unaffected by external magnetic field), silence operation, self-brake without power, and quick response. Owing to those performances, recently the USM has been used in many purposes applications. In actual applications, USM has been used as ultra-precision actuator in autofocus of camera (including camera on cellular phone), autofocus of spacecraft telescope, micro robot, finger robot, meal robot, electron beam lithography and a ’fly-bywire' of aeronautics. In the future, we expect that USM will be an important actuator in specific applications. For examples, in medical equipment and surgery (*e.g*. electron or ion beam apparatus, X-Ray, scanning probe microscopy, catheters, micro-surgery knives, tele-surgery) and in high magnetic field area (*e.g*. in MRI or magnetic resonance imaging) [1-7].

Although USM has several advantages and excellent features, they have some problems. Due to no-accurate mathematical model and characteristic changes during operation, it is difficult to control USM in order to get a best performance. Deriving the mathematical model of USM using physical analysis is too hard because of its nonlinearity, uncertainty, complexity in working principle. Moreover, due to temperature, loading, input frequency and other disturbances, the characteristic of USM is easily changing during operation. Although, some mathematical models of USM are available and have been proposed, they are unsatisfactory because the given models used the simplified model with some assumptions as limiting variables, so they have limitations and significant modeling error. They cannot cover all properties of USM [8-13]. How to control USM or what is the proper controller for USM is an important problem. The research to develop the proper controller for USM is being conducted intensively [14].

There are no perfect control schemes for USM, especially in the precise speed and position servo system. In general, there are two control schemes for USM, *i.e*., model-based controller and model-free controller. Designing of model-based controller absolutely requires a mathematical model of USM and needs a complex mathematical calculation or a high expertise in control theory. Using the simplified model of the USM in this scheme will cause difficulties in achieving a best performance. Thus, it is not easy to apply model-based controller for USM. This scheme is rarely used for USM. For examples of model-based controller are robust controllers [15-16] and generalized predictive control [12]. Designing of model-free controller for USM is easier because they can be designed without using a mathematical model of plant. The popular of model-free controller are fuzzy logic controller (FLC), neural network (NN) controller and PID controller. FLC is a new type controller based on the linguistic control rules.

FLC has been successfully applied for USM in recent years [17-19]. But, FLC has disadvantages. The performance of system controlled by FLC absolutely depends on the designer's experiences and intuitions. FLC has a lot of parameters. So, it is difficult to represent the designer's experiences and intuitions perfectly into linguistic control rules. It is difficult to make a proper control rules. If the characteristic of plant is changed during operation, the control rules must be changed or updated. It is ineffective and time-consuming. Neural network (NN) controller is a new type controller based on the structure and functions of biological brain called neural network. The NN controller and FLC are suitable in controlling a nonlinear system with unknown mathematical model, such as USM [33-34]. The NN can be used to find the parameters of a fuzzy system (*i.e.*, fuzzy set and fuzzy rule). The combination between fuzzy system and NN creates a new type controller called fuzzy neural network (FNN) or neuro-fuzzy controller and has been applied to USM [31-32]. The performance of system controlled by NN controller absolutely depends on the configurations or model of the used NN and learning process. It is not easy to create or determine a proper model of NN because too many configurations are available. Each configuration for solving one problem may not be able or suitable to solve other problems. Sophisticated or complicated configuration may give a better performance. But, the sophisticated model of NN requires a long time in learning process. NN controller should be trained using learning process. There are several learning methods and they are not easy. Unsuccessfully learning process may lead to a poor performance. Learning process cannot guarantee to get a best performance. According to those reasons, PID controller is widely used for USM. PID controller has superior features, such as simple, easy implementation, efficient, effective and quite robust [20-22]. PID controller has three parameters to be tuned, *i.e.*, K_p, K_i and K_d. The performance of system absolutely depends on these parameters. The process to determine the parameters of PID controller is called tuning. Sometimes, we called it as optimal tuning because the goal of this process is to get the best possible performance. Many tuning methods are available, *e.g.*, Ziegler-Nichols, Cohen-Coon, Astrom-Hagglund and Paulin-Pemerleau. Self-tuning scheme is developed to compensate the characteristic changes of USM during operation. Due to this scheme, the parameters of PID controller can be adjusted automatically and easily according the USM's behavior. Recently, self-tuning scheme using intelligent soft computations called intelligent self-tuning is developed to avoid the difficulties or complexity of the conventional self-tuning scheme. Intelligent self-tuning PID controller has been applied successfully for USM in recent years, *e.g.*, BPNN-PID [23], NN-PID [24], GA-PID [25], Fuzzy-PID [26, 30], PSO-PID [27- 28] and IMC-PID-NN [29].

1.2 Related Works

As stated in previous section, because of no accurate mathematical model of USM and characteristic changes of USM during operation, it is difficult to control USM in order to get a best performance. Developing of proper control scheme for USM is being conducted intensively because the using USM offers great advantages than the common EM motor. Some control schemes have been proposed for USM in recent years.

Due to complexities and difficulties in designing fuzzy logic controller and neural network controller, PID controller is widely used for USM. Designing PID controller is easier because this controller has only three parameters to be tuned. PID controller has a long history since 1900 and has been applied in many applications in industry. Many systems in industry, including nonlinear systems and complicated or sophisticated systems, controlled by PID controller show a satisfactory performance.

K. Tanaka *et al.* designed variable gain-type PID controller using PSO for USM [28]. In the scheme, PSO algorithm is used to determine or optimize the gains of PID controller automatically. PSO is used as self-tuning scheme instead of the other intelligent soft computations, *e.g.*, fuzzy, BPNN, NN, GA, FNN, ACO, and BFO, because of its superior features, such as simple algorithm, easy implantation, faster convergence and efficient in time-calculation. The effectiveness of PSO as intelligent self-tuning PID controller has been proved and demonstrated by other researchers in various plants, *e.g.*, linear brushless DC motor [35], the ball and hoop system [36], the drilling machine [37], rotary inverted pendulum [38], automatic voltage regulator (AVR) [39], and nonlinear systems [40]. PID controller tuned by PSO algorithm has superiority in term of simplicity, easy implementation, effectiveness, efficient, robustness and good or suitable controller for USM. However, this method has disadvantages. The used PSO is still a standard type of PSO that has shortcoming, *i.e.*, premature convergence and easy to get stuck or fall into local optima Due to the shortcoming, the performance of system is not optimal. The shortcoming may lead to a poor performance, especially in loaded condition.

In computer science, PSO is very popular as a powerfully optimization technique instead of genetic algorithm (GA). Since the shortcoming of PSO is known, research to overcome the shortcoming was conducted intensively. It was reported that the causes of the shortcoming has to be indicated as follows: unbalance between exploration-exploitation ability, lost diversity and lack-information due to fast rate flow in sharing information and particle's movement mechanism. These causes are very closely related to parameters setting of PSO. However, how to adjust these parameters is still unclear and more need investigation. A. Chatterjee *et al.* proposed a strategy for adjusting inertia weight called nonlinearly decreased inertia weight (PSO-NDW) instead of linearly decreased inertia weight that is used in the standard type of PSO or PSO-LDW [64]. PSO-NDW has been tested successfully for several benchmark functions. Dawei Zhou *et al.* proposed a strategy for adjusting inertia weight called random inertia weigh (PSO-RIW) to increase global ability [65]. Chen Dong *et al.* proposed a strategy for adjusting inertia weight called adaptive inertia weight (PSO-AIW), where inertia weight is adjusted based on number of population, dimensions and fitness of particles [66]. Research of Enhanced PSO is still conducted intensively [41-45, 67-68].

According to the related works introduced above, it is clear that the self-tuning PID controller for USM based on an Enhanced PSO can be considered as an attractive, effective and efficient controller, which is able to compensate the characteristic changes of USM in real applications. However, there are still some weakness may reduce the performance of USM. For developing of the method, the motivation of this research is introduced in the following section.

1.3 Motivation

The research is motivated by several reasons as follows:

1. We chose USM as an object or a plant of the research because USM is a new type motor that has many advantages than the common electromagnetic motor. The USM is better and more suitable than the common EM motor for several applications. For special cases, it is too difficult or impossible to apply the common EM motor. For examples, in area with strong magnetic field and as micro-actuator with high-torque on micro-robot.
2. How to control USM is not easy because of no-accurate mathematical model of USM and characteristic changes during operation. Many control strategies have been proposed for USM. However, the research to develop the proper controller for USM is still being conducted intensively.
3. The previous research or method, called Self-Tuning PID Controller using PSO Algorithm, has disadvantage or weakness. The used PSO is the standard type of PSO algorithm that is commonly used in many applications as optimization technique. The standard type of PSO has shortcoming, namely premature convergence and easy to get stuck or fall into local optima. The shortcoming may lead to a poor performance.
4. Recently, PSO has become popular and many researchers are trying to develop PSO for solving the shortcoming of PSO because PSO is a new optimization technique that has superior features than other techniques, such as simple algorithm, easy implementation, faster convergence and efficient in time-calculation. Compare with other tecgniques, PSO has a few of parameters. However, the selection of these parameters is still unclear and need more investigation. This is a new challange.

1.4 Problem Statement and Target

According to previous sections, there are two problems to be solved in the research. The first problem is the difficulties in controlling USM and how to develop a new proper controller for USM in order to get a best performance in term of position accuracy and ability to compensate its characteristic changes during operation. The second problem is the difficulties in parameters setting of PSO and how to improve PSO in order to overcome its shortcoming. Investigation to develop the new or proper strategy is focused on how to reduce the risk of premature convergence and possibility of particles trapped into local optima.

The target of the research is to make or design a new proper controller for USM with hold on the properties of simplicity, reliability, effectiveness, efficient, and robust. Also, increasing accuracy in USM servo system is an important target.

1.5 Outline

In this dissertation, the contents of the research about "Enhanced PSO and Its Applications for Intelligent Self-Tuning PID Controller on Ultrasonic Motor" in my doctoral course are organized into five chapters summarized as follows.

This Chapter 1 is the introduction of this research. In this chapter, the background of the research, related works, the motivation, the problem statement and target are introduced.

In Chapter 2, Ultrasonic Motor and PID-PSO Controller for Ultrasonic Motor are provided. The basic principle and applications of ultrasonic motor, the basic principle of PID controller, the theory of PSO algorithm and several strategies for addressing the shortcoming of PSO are explained to give understanding of the research.

In Chapter 3, New Inertia Weight Approach PSO based Intelligent PID Controller for USM are explained. In here, two inertia weight approaches, i.e., Nonlinearly Inertia Weight (NDW) and Random Inertia Weight (RIW), for improving PSO are delivered. Each New Inertia Weight Approach PSO is investigated on USM servo system to know its properties and its characteristics. Then, the comparison of performances, *i.e.*, accuracy in histogram, convergence speed, Success Rate (SR) and number of parameters, are described in detail.

In Chapter 4, Adaptive Inertia Weight Approach PSO based Intelligent Self-Tuning PID Controller for USM is delivered. There are three types of these Adaptive PSO used as intelligent self-tuning PID controller, *i.e.*, APSO (Adaptive Particle Swarm Optimization), APSO-RIW (Adaptive Particle Swarm Optimization with Random Inertia Weight) and HAIPSO (Hybrid Adaptive Improved Particle Swarm Optimization). Each Adaptive PSO is investigated on USM servo system to know its properties and its characteristics. Then, the comparison of performances, *i.e.*, accuracy in histogram, convergence speed, Success Rate (SR) and number of parameters, are described in detail.

Finally, in Chapter 5, the discussion about general performances of all proposed methods and using policy of PSO algorithm, the general conclusion, the originality and the contribution are provided. Based on the results, the future works are studied for research in next phase.

Chapter 2

Ultrasonic Motor and PID-PSO Controller for Ultrasonic Motor

2.1 Ultrasonic Motor Review

Ultrasonic motor (USM) is a new type of motor driven by ultrasonic vibration generated by piezoelectric materials [1-2, 4]. USM can be considered as a new actuator since they are commercialized in 1980. Even in the future, USM will be an important actuator for special applications where the size, torque and other requirements could not be satisfied by the common electromagnetic (EM) motor. Actually, the development of the actuator that applies piezoelectric materials has been started since 1948 by William and Brown [46]. Their inventions have become the beginning of the development of the USM in the future. Nevertheless, USM was not developed quickly because of the limitation of resources and processing technologies at that time [47]. In 1973, H.V. Bart and V.V. Lavrinenco have introduced a new concept of USM. After a long research, in 1982, a standing wave ultrasonic motor (SWUSM) was successfully made by Sashida and after that the USM began to be produced commercially for some applications at the first time. Later, in 1983, Sashida designed a new type of USM, called travelling wave ultrasonic motor (TWUSM) and in 1984 was granted a patent in USA [48]. Owing to USM's excellent features, *e.g.*, compactness, lightweight, high retention torque, high position accuracy, Electromagnetic Compatibility (EMC) compliance (no emitted electromagnetic noise or noaffected by external electromagnetic fields), no running sound, self-brake without power and quick response, over the common EM motor, they were widely applied in various kinds of applications, especially, applications that require high accuracy, for micro or nano-actuator and for medical equipment with EMC compliance.

A common application of USM we can see in our real life is the autofocus of camera (including camera on cellular phone). Figure 2.1 shows the illustration of USM applied in autofocus of camera. Conventional autofocus camera lens used to be driven by motors with gears. These are characterized by a somewhat loud whirring/gears grinding sound while it focuses. It would be very disturbing for camera-equipped sensitive microphone like a handy-cam. By using USM on camera, the problem can be solved. Moreover, the accuracy of the focusing lens to be getting better and finally the image processing can be increased significantly.

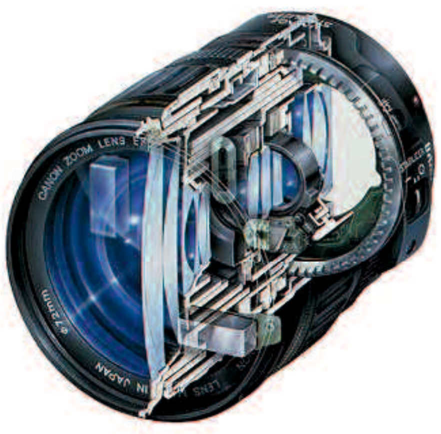

Fig. 2.1: Canon zoom auto-focus lens using USM

A novel orthogonal nut-type USM [49], BolyMotion, is produced which is used an actuator in the mobile-phone auto-focus (AF) module. The exploded view of the assembly structure of BolyMotion is shown in Fig. 2.2. The threaded metal nut by which the piezoelectric ceramic plates are attached to it as the stator and the lens is the rotor. An in-plane traveling wave is stimulated on the stator when a harmonic signal is applied to the piezoelectric plates. The traveling wave drives the lens to rotate, and the threads transform the rotation into a linear motion. Thereby, an AF function can be achieved.

Meanwhile, according to USM's excellent features in EMC (electromagnetic compatibility) compliance, USM can be applied in medical equipment, such as in MRI (magnetic resonance imaging). MRI is medical equipment that uses a strong magnetic resonance to visualize the internal body, as shown in Fig. 2.3. It is difficult to apply a conventional electromagnetic motor because it requires special treatment to overcome the magnetic interference.

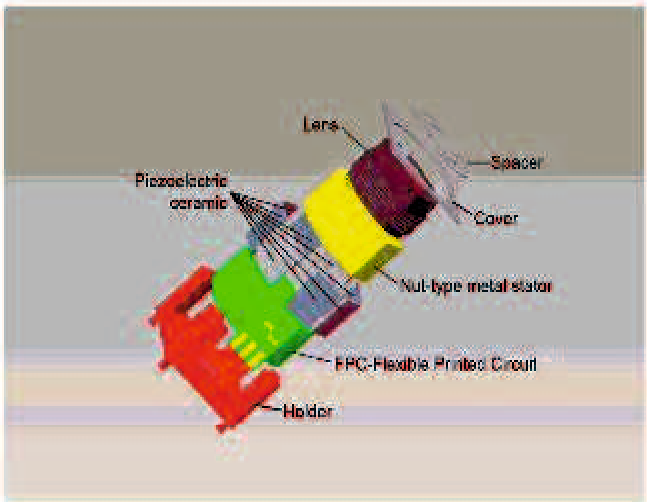

Fig. 2.2: USM structure for the mobile-phone auto-focus (AF)

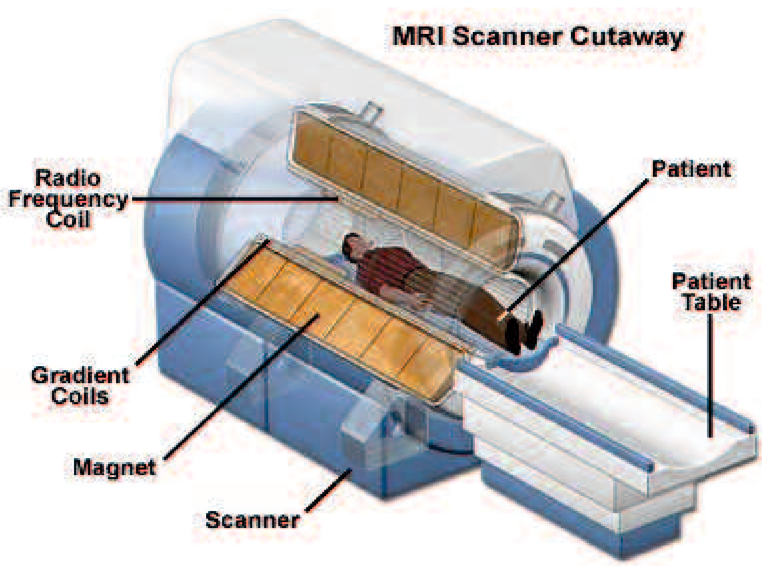

Fig. 2.3: Magnetic Resonance Imaging (MRI)

The typical model of USM that we have used in the research is the basic structure of TWUSM manufactured by Shinsei Corporation as shown in Fig. 2.4. In the figure, the main components of USM covered by the case, including bearings, axis, rotor and stator, are shown clearly. The shape variation is constructed in the elastic body and oscillated by the piezoelectric ceramic in the stator. The driven source of USM is the friction generated on the surface between the stator and rotor. The TWUSM realized the rotor rotation through the travelling wave instead of the standing wave [11, 14].

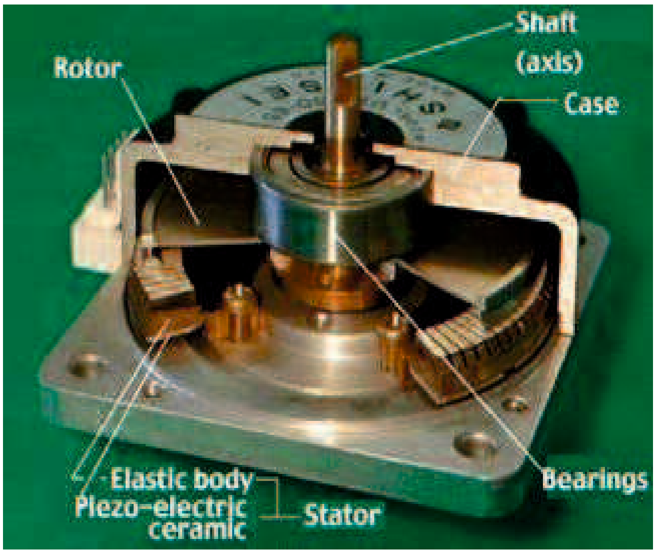

Fig. 2.4: Cutaway view of typical USM

2.1.1 Working Principle of USM

Figure 2.5 shows the driving principle of TWUSM. In the figure, the bar shape part above is the rotor, and the wave-shape part below is the stator of the USM. These two parts contact with each other at the surface between them. The electrode and the piezoelectric ceramic are set under the stator. When two input signals with frequency around piezoelectric ceramic's resonant frequency and orthogonal mode, such as *sin wt* and *cos wt*, are introduced to the piezoelectric ceramic, a standing wave will be generated. Then, the points in the stator are driven into elliptical motion as the figure shows. The motion of points causes a traveling wave propagating in the stator. Meanwhile, because of the pressure added at the surface between the stator and the rotor, there is friction generated at the contact surface. The friction drives the rotor running in the opposite direction.

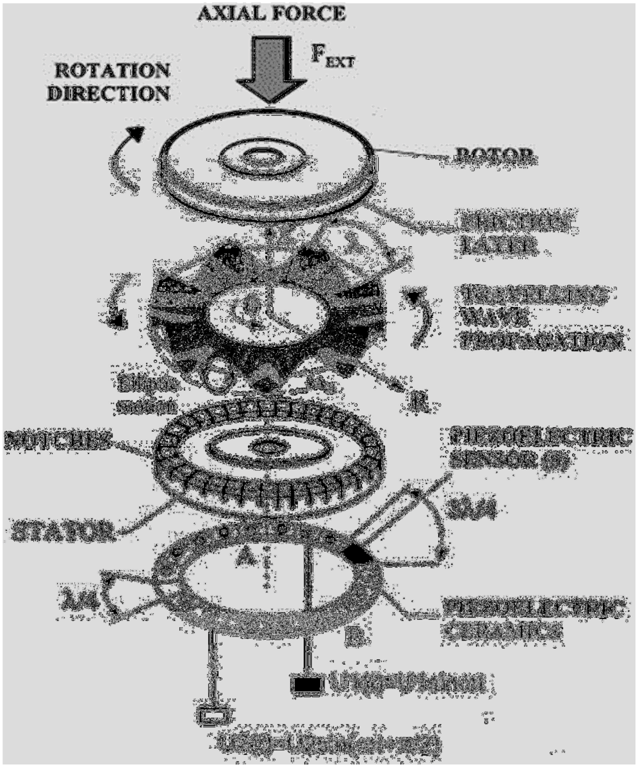

Fig. 2.5: The driving principle of USM

2.1.2 Features of USM

In the future, the USM will be an important actuator in specific applications because they have excellent features as follows:

1. *Compactness and lightweight*: because of no coil and magnet, a micro motor with 1.5 mm in diameter can be realized by USM.
2. *High torque*: because of the friction driven principle, USM have high torque without gear mechanism. USM have high holding torque, which acts as a brake function, even in the power off condition. Comparing to the conventional electromagnetic motor in same size (1 cm in diameter), the torque of USM is around 100 times greater.

3. *High precision accuracy*: because of no gear mechanism, there is no backlash in position control of USM. The accuracy of USM can achieve 0.69 [nm].
4. *EMC compliance*: USM is driven by ultrasonic vibration instead of electromagnetic principle. Therefore, there is no-radiated electromagnetic emission from USM. Also, USM operation cannot be influenced by external electric or magnetic field.
5. *Quick response*: very quick response of less than 1 [msec] rotation is obtained with the development of a small-sized 17 [mm] diameter ultrasonic motor.
6. *No running sound*: The ultrasonic level vibration in USM is not in the ranges audible of human being. There is no sound from gear mechanism.

Although USM have excellent features, they have several problems as follows:

1. *No accurate mathematical model*: It is hard to derive the mathematical model of USM based on physical analysis because of its nonlinearity (*e.g.*, dead-zone and hysteresis), uncertainty and complexity of driving principle.
2. *Characteristic change according to condition*: Due to temperature, loading, input frequency and other disturbances; the characteristic of USM is easily changed during operation. It is a main difficulty in USM controlling.
3. *Low speed*: USM is a low speed motors. Their control performance at high speed range is not as good as at low speed range.
4. *Short lifetime:* Because of the friction of driving principle, the abrasion makes lifetime of USM is shorter.

2.2 PID-PSO Controller Review

2.2.1 PID Controller

A proportional-integral-derivative controller (PID controller) is a generic control loop feedback mechanism (controller) widely used in industrial control systems. PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control inputs [20-22]. It is considered as the most significant control algorithm in process control. Now more than 90% control system is still PID controller. PID controller has simple structure, efficient, effective, easy implantation and quite robust. It was reported that many control system that use PID controller have shown a satisfactory performance. The PID controller calculation (algorithm) involves three separate constant parameters, and is accordingly sometimes called **three-term control**: the proportional, the integral and derivative values, denoted *P, I,* and *D*. Heuristically, these values can be interpreted in terms of time: *P* depends on the present error, *I* on the accumulation of *past* errors, and *D* is a prediction of future errors, based on current rate of change. That is why it is simple and easy to be employed. Meanwhile, it is attractive also because that it works quite well even without mathematical model of plant. We can apply PID controller on plant without model, deciding the gains for three manipulations by trial and error, manually tuning or hand-tuning. Therefore, PID controller is adopted in USM control as an important controlling tool without requiring model of USM.

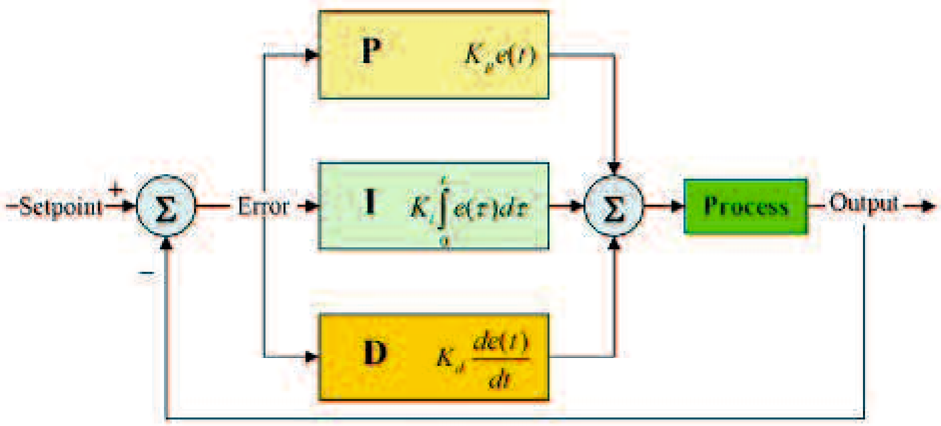

Fig. 2.6: The basic structure of PID controller

Figure 2.6 shows the basic structure of PID controller with feedback mechanism. Error is the difference between set-point signal and the output as shown in the following equation:

$$e(t) = r(t) - y(t) \tag{2.1}$$

The control input can be expected as:

$$u(t) = K_P\left[e(t) + \frac{1}{T_I}\int e(t)dt + T_D\frac{de(t)}{dt}\right] \tag{2.2}$$

In the equation, K_P is the proportional gain, T_I is the integral time, and T_D is the derivative time, respectively. Equation 2.2 can be expressed in discrete time form with time sampling of T. The proportional term can be rewritten as $K_P.e(t)$. In continuous form, the integration can be defined as:

$$\int e(t)dt = \lim_{\Delta t\to 0}\left(\sum_{j=0}^{k} e(j)\Delta t\right) \tag{2.3}$$

In continuous form the limit $\Delta t\to 0$ is possible. But in discrete time form, Δt can be set as minimum as the sampling time T. It is impossible for Δt to approach to 0. Then the integral term can be estimated as $\frac{T}{T_I}\sum_{j=0}^{k} e(j)$. Considering the derivative term by the same way, the derivative in continuous time can be expressed as:

$$\frac{de(t)}{dt} = \lim_{\Delta t\to 0}\frac{\Delta e(t)}{\Delta t} \tag{2.4}$$

Then consider $\Delta e(t) = e(k) - e(k-1)$, and $\Delta t \to T$, the derivative term can be expressed as $\frac{T_D}{T}[e(k) - e(k-1)]$. The PID controller expressed by discrete time form can be synthesized as:

$$u(k) = K_P\left[e(k) + \frac{T}{T_I}\sum_{j=0}^{k} e(j) + \frac{T_D}{T}(e(k) - e(k-1))\right] \tag{2.5}$$

To get the expression of the incremental type PID control, the expression in previous step can be estimated as:

$$u(k-1) = K_P\left[e(k-1) + \frac{T}{T_I}\sum_{j=0}^{k-1} e(j) + \frac{T_D}{T}(e(k-1) - e(k-2))\right] \tag{2.6}$$

Then, the difference between the two steps expressed in Eq. 2.5 and Eq. 2.6 can be calculated as the following equation.

$$u(k) - u(k-1) = K_P \left\{ [e(k) - e(k-1)] + \frac{T}{T_I} e(k) \right.$$

$$\left. + \frac{T_D}{T} [e(k) - 2e(k-1) + e(k-2)] \right\} \tag{2.7}$$

According to Eq. 2.7, the other two gains, the integral gain K_I and the derivative gain K_D can be estimated as $K_I = K_P.\frac{T}{T_I}$ and $K_D = K_P.\frac{T_D}{T}$, respectively. The control input of incremental PID controller can be synthesized as:

$$u(k) = u(k-1) + K_P[e(k) - e(k-1)] + K_I e(k)$$

$$K_D[e(k) - 2e(k-1) + e(k-2)] \tag{2.8}$$

As we see in Fig. 2.7, it is the PID control scheme for USM. In the block diagram, $G_{PID}(z^{-1})$ represents the PID controller for the USM plant. In the scheme, $r(k)$, $u(k)$, and $y(k)$ are the objective input, the control input and the output in discrete time, respectively. The $e(k)$ is the error between the objective input and the output as shown in the following equation.

$$e(k) = r(k) - y(k) \tag{2.9}$$

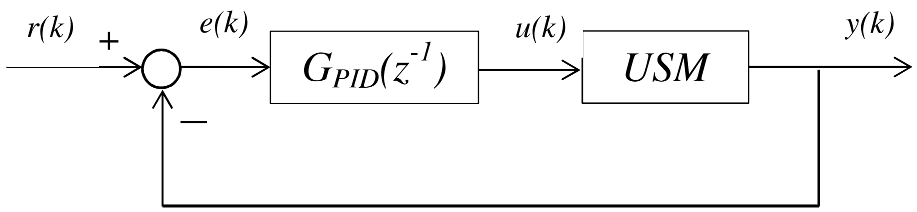

Fig. 2.7: Block diagram of PID control for USM

The control input of the system in discrete time can be synthesized as:

$$u(k) = u(k-1) + (K_P + K_I + K_D)e(k)$$

$$-(K_P + 2K_D)e(k-1) + K_D e(k-2) \tag{2.10}$$

In this feedback system, the PID controller can be denoted as following:

$$G_{PID}(z^{-1}) = \frac{K_P(1-z^{-1}) + K_I + K_D(1-z^{-1})^2}{1-z^{-1}} \tag{2.11}$$

According to general PID theory, the proportional response can be adjusted by multiplying the error by the proportional gain K_P. The magnitude of the contribution of the integral gain to the overall control action is determined by the integral gain K_I. And, the derivative gain K_D slows the rate of change of the controller output and this effect is most noticeable close to controller objective input.

The most critical step in application of PID controller is tuning process. Tuning process is the process to determine the parameters of PID controller. Sometimes, this process is called as optimal tuning because the goal of this process is to get a best possible performance. The performance of system absolutely depends on the tuning process. The simple method for tuning PID controller that is still widely used in industry is trial and error or manually tuning or hand-tuning. One of the hand-tuning is introduced by Ellis [50] and called the zone-based tuning. It means that the low and high frequency part of the controller can be tuned separately, starting with the high frequency part. For PID controller, this means that first the *P* and *D* action are tuned and then *I* action. The procedure with steps to follow to tune PID controller is given as follows:

1. Set K_P low, while $K_I = 0$ and $K_D = 0$.
2. Apply reference signal 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.

Several conventional tuning methods, such as Ziegler-Nichols, Astrom-Haglun, and Poulin-Pemerlau, are also still used in industry. However, these methods have some difficulties, such as time-consuming and cannot guarantee to find the optimal gains. Also, the conventional fixed-gain PID controller cannot compensate the characteristic changes of plant.

To overcome these problems, self-tuning schemes have been developed. In the self-tuning schemes, the gains of controller can be adjusted automatically according to the plant's behavior during operation or online. By using the self-tuning schemes, the gain of PID controller will always adapt to the changes of plant's behavior, so that the general performance of system can be optimized. Figure 2.8 shows the structure of the self-tuning PID controller for USM. There are two groups of self-tuning schemes. The first group is the traditional methods that contain complex mathematical calculations, such as steepest descent, Newton's methods, Hill climbing, and gradient method. The second group is the intelligence methods that use algorithm based on the nature-inspired behavior, such as genetic algorithm (GA), neural network (NN), fuzzy, ant colony optimization (ACO) [77-78], bacterial foraging optimization (BFO) [79], and particle swarm optimization (PSO).

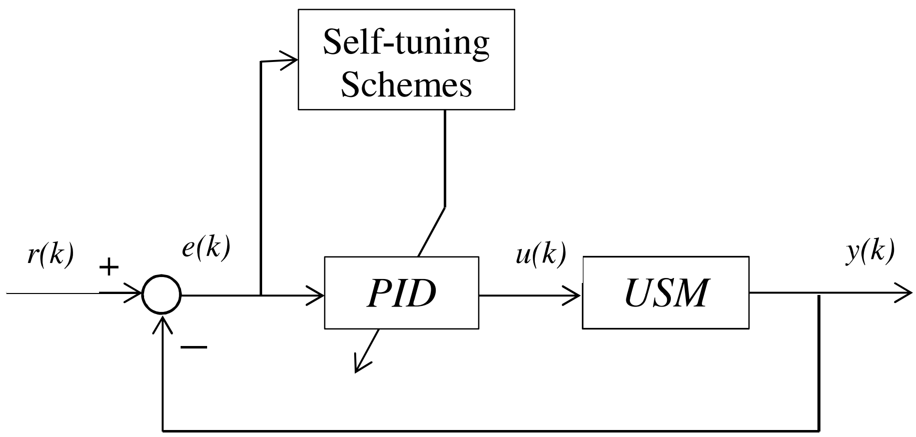

Fig. 2.8: Self-tuning PID controller for USM

2.2.2 Particle Swarm Optimization Review

Particle swarm optimization (PSO) is a new population-based optimization technique inspired by social behavior of bird flocking or fish schooling in search of food. PSO was introduced at the first time by Dr. Eberhart and Dr. Kennedy in 1995 [51]. After that, PSO became very popular as powerfully optimization technique that can be widely used in various fields instead of Genetic Algorithm (GA), *e.g.*, any east routing communication [52], document clustering [53], robot-path planning [54], economic dispatch [55] and image processing [56]. The basic idea of PSO is cooperation and sharing information in birds flocking or fish schooling for finding a food, as shown in Fig. 2.9. If one of bird or fish found a potentially region with the food, he will send information of its position to other birds or fishes thus the swarm will move towards the targeted region and capture the food.

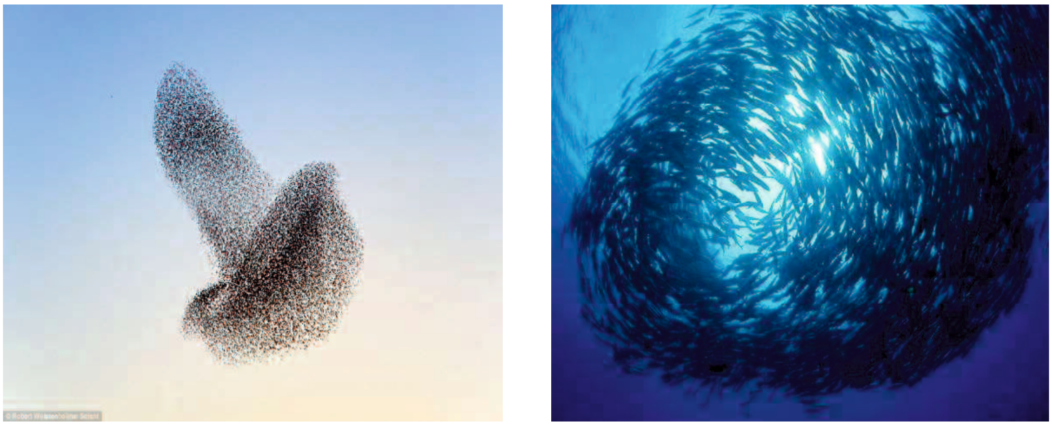

Fig. 2.9: Birds flocking and fish schooling

Compare with other optimization techniques, *e.g.*, the first popular optimization method called Genetic Algorithm (GA), PSO has superior features, such as simple algorithm, easy implementation, faster convergence and efficient in time-calculation [53, 58, 69-70]. Basically, there are some similarities between GA and PSO. Both of them are optimization technique based on population and stochastic or random process for solving the optimization problems. Each member of population is a candidate of the solution. The main difference between GA and PSO is working principle in searching process to improve a candidate solution. The working principle of GA uses competition and selection, but PSO uses cooperation and sharing information. Each member of population in GA will be selected based on the fitness value. Due to this competition, there are members of the population who are dead and live to continue to the next process. In PSO, each member of the population will cooperate in the form of sharing information. One of the members of population with a best fitness value called *gbest* will send information of its position to other members and this information will be updated until the end of process. There is no-death population in PSO. In GA, during process to improve a candidate solution, evolution operator, *i.e.*, crossover and mutation, and coding-decoding are used. It means that each candidate solution should be converted into binary number during searching process, *i.e.*, it is a coding mechanism. If the process is completed, a binary number should be converted again into a real number, it is a decoding mechanism. But, PSO doesn't use evolution operator and coding-decoding mechanism. A candidate solution handled by each particle in PSO is a real number. Thus, PSO is a new optimization technique with simplicity in process, so the convergence speed is faster and time-calculation is shorter than GA.

In computer science, particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality (here called value of fitness function).

PSO optimizes a problem by having/using a population of candidate solutions, here called particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity as shown in the following equations.

$$v_{i,d}^{m+1} = w.v_{i,d}^{m} + c_1.r_1.\left(Pb_{i,d} - x_{i,d}^{m}\right) + c_2.r_2.\left(gb_d - x_{i,d}^{m}\right) \tag{2.12}$$

$$x_{i,d}^{m+1} = x_{i,d}^{m} + v_{i,d}^{m+1} \tag{2.13}$$

where $d = 1,2,\ldots n$ represents the dimension; $i = 1,2,\ldots S$ represents the particle index; m represents the searching number or iteration; w represents the inertia weight; c_1 and c_2 are constants, called cognitive and social scaling parameters respectively (usually, $c_1 = c_2$); r_1 and r_2 are random numbers drawn from a uniform distribution; *Pb* (personal best) represents the local best known position; *gb* (global best) represents the best known position among all particles.

Each particle's movement is influenced by its local best known position (called *Pb*) and is also guided toward the best known positions among all particles in the search-space (called *gb*), which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions and get convergence. It means that there is a learning process in PSO algorithm. Each particle will learn from own experience and the experience of other particles in the group. The particle's movement in PSO algorithm can be illustrated in Fig. 2.10. The movement of particles is governed by three parts: (1) the inertial part, $w.v_i^m$;

(2) the cognitive part, $(Pb_i - x_i^m)$; (3) the social part, $(gb - x_i^m)$. The velocity vector of v_i^{m+1} is formed based on three vectors as shown in Eq. (2.12). The first one is inertia vector, which is the vector from weighting factor w and the velocity vector v_i^m. The remaining two are vectors for each $(Pb_i - x_i^m)$ and $(gb - x_i^m)$, which formed from learning factor c_1 as well as c_2, and also [0, 1] of uniform random numbers R. From those interactions, velocity vector v_i^{m+1} act so that the particle moves to new position, x_i^{m+1}.

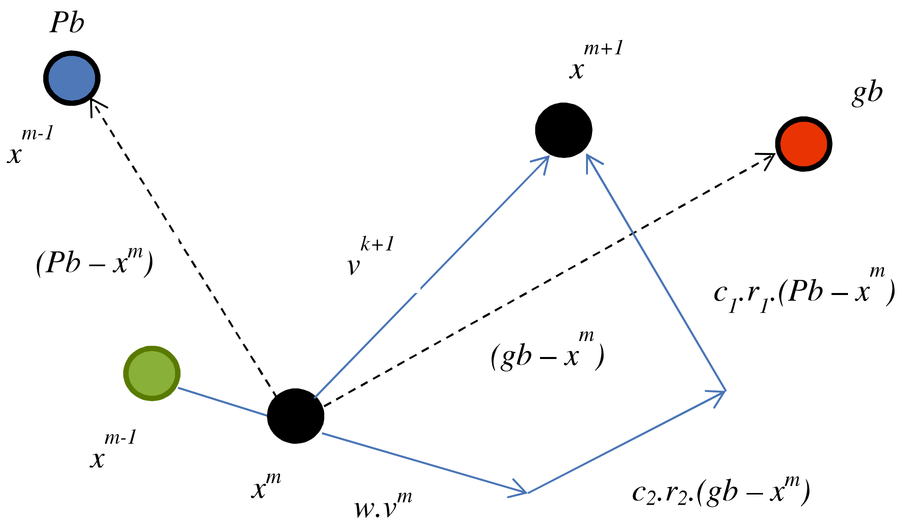

Fig. 2.10: Particle's moving mechanism

The working mechanism of PSO algorithm can be described in four steps as follows:

1. Deploy a population of candidate solution (or particles) in the searching-area randomly. Each particle can handle a candidate solution with *D*-dimension.
2. Evaluate the fitness value of each particle and set as *pbest* and *gbest.*
3. Update the position and velocity of each particle using Eq. 2.12 and Eq. 2.13.
4. Check the termination condition. If the condition is not met, return to No. 2. If the condition is met, the process is complete and the optimal solution is the particle with *gbest*.

The working mechanism of PSO algorithm also can be expressed into flowchart as shown in Fig. 2.11.

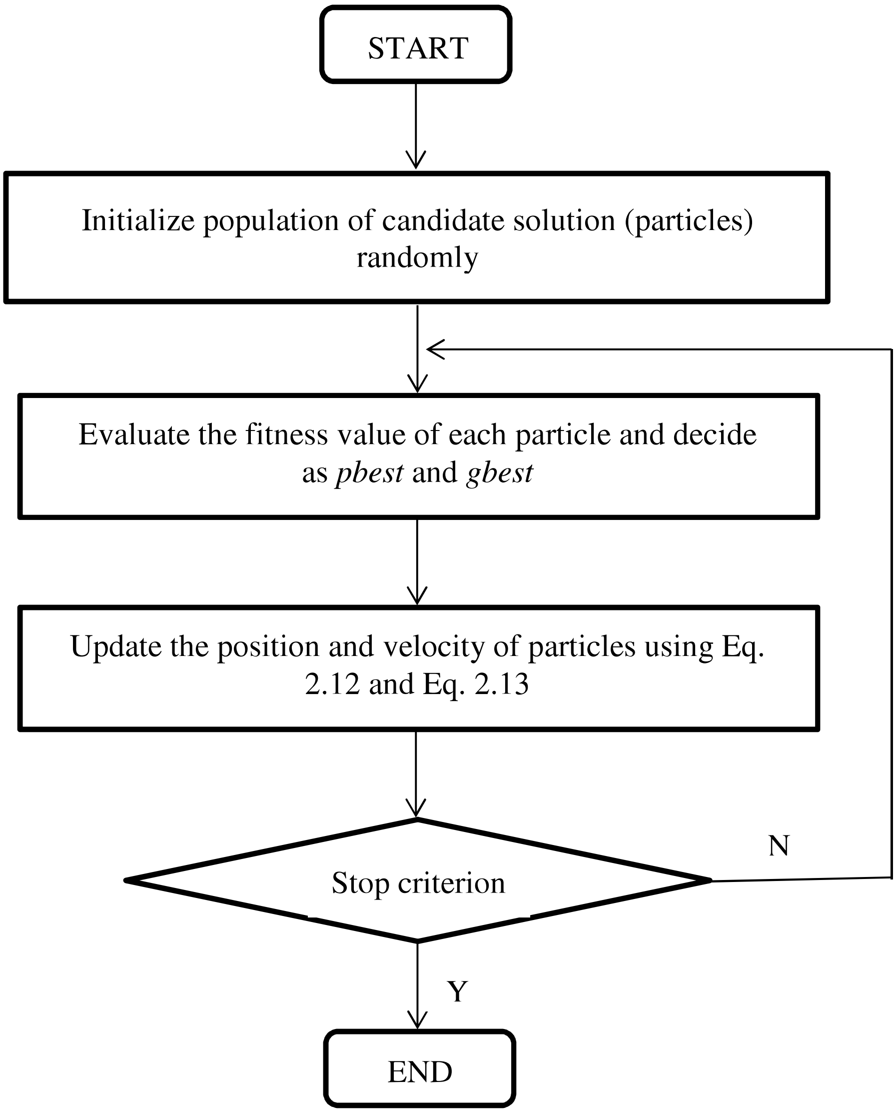

Fig. 2.11: Flowchart of PSO algorithm

2.2.3 PID-PSO Controller Performance

In the previous research, PID controller was chose as controller for USM because of the difficulty in getting the mathematical model of USM. PID controller is one of the model-free controller that can be designed without using the mathematical model of plant. Also, PID controller has superior features, such as simple, easy implementation, efficient and effective. The fact shows that many control system in industry that use PID controller have shown a satisfactory performance. However, adjusting three gains of PID controller for obtaining an optimal performance is not easy because the characteristic USM is easy changed during operation due to temperature, input frequency, loading and other disturbances. To compensate this characteristic changes, self-tuning scheme is used for PID controller. Due to self-tuning scheme, the gains of PID controller can be adjusted automatically according to the behavior of USM.

Design of self-tuning PID controller for USM using PSO is shown in Fig. 2.12. The references input position are +45 [deg] or clock wise (CW) direction and -45 [deg] or counter clock wise (CCW) direction. The output of PSO is position of particle that handles three PID parameters. Based on this reason, PSO is set in three dimesions. Because of computer-based controller, we decided to use 1 [ms] of sampling time. It means that the error signal or other data is taken every 1 [ms]. To evaluate the fitness value of each particle, we use fitness function as shown in Eq. (2.14) and Eq. (2.15). Equation (2.14) is in continous time and Equation (2.15) is in discrete time. Fitness value is calculated based on the performace index called Integral Squared Error (ISE).

$$fitness(t) = \frac{1}{1+\int_0^T \{e(t)\}^2 dt} \tag{2.14}$$

$$fitness(k) = \frac{1}{1+\sum_0^T \{e(k)\}^2} \tag{2.15}$$

In here, T is the expected calculation-time. In experiment, we used $T = 10$ [ms], so the fitness value is updated every 10 [ms] or is calculated from the sum of the 10 pieces of data. Also, position, velocity and PID parameters are updated every 10 [ms]. The number of particles used in the research is 5 particles to keep efficiency in time-calculation.

The USM servo system constructed in this study is shown in Fig. 2.13. USM, the electromagnetic brake and the encoder are connected on a same axis. The typical USM for our reseach is USR 60 manufactured by Shinsei Corporation. Driver circuit is to drive USM in both directions. Electromagnetic brake is to give loading effect for USM. Encoder is to measure the position of USM. The resolution of encoder is 0.0011 [deg]. It means that the encoder can not measure the position of USM if its position is smaller than 0.0011 [deg]. Measurement result is sent to Personal Computer (PC) through counter board. In PC, an error signal is calculated based on the difference between reference input position and actual position of USM measured by encoder. Then, a control signal is calculated based on this error signal and sent to driver circuit through IO board.

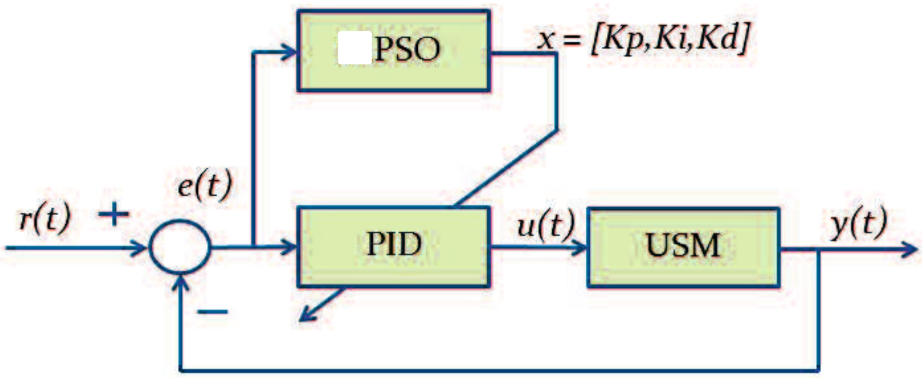

Fig. 2.12 PSO-based PID Controller

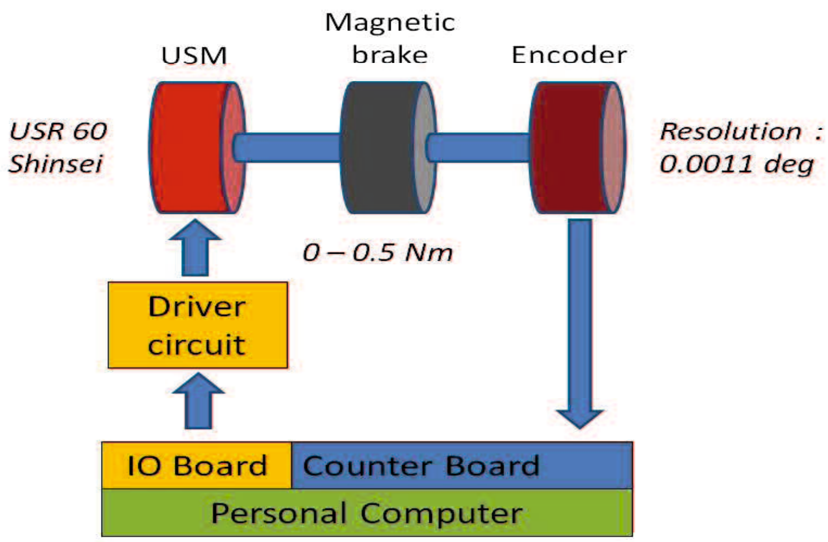

Fig. 2.13 USM Servo System

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 given, the force of 0.25 [Nm] could be loaded to the shaft of the USM. The specifications of USM servo system is shown in Table 2.1.

Table 2.1 Specifications of USM, Encoder, and Magnetic Brake

USM	Rate rotational speed: 100 [rpm]
	Rated torque: 0.5 [N.m]
	Maximum torque: 1.0 [N.m]
	Holding torque: 1.0 [N.m]
Encoder	Resolution: 0.0011 [deg]
Load	0 to 0.5 [N.m]

Figure 2.14 shows the flowchart of PSO algorithm for self-tuning PID controller on USM servo system. Firstly, we set parameters of PSO algorithm, *e.g.*, in here, number of particles, n = 5; maximum value of inertia weight, w_{max} = 0.8; minimum value of inertia weight, w_{min} = 0.3; cognitive constant, c_1 = 1; social constant, c_3 = 1; dimension, D = 3; and iteration maximum, m_{max} = 80. Secondly, PSO will generate an initial velocity and position of particles randomly. Thirdly, in the first step-discrete time, k = 1 [ms] and set time-calculation, VTM = 10 [ms]. Then, the algorithm calculates the parameters of PID controller as follows:

$$K_p = K_{po} \cdot (1 - x_{i,1}) \tag{2.15}$$

$$K_i = K_{io} \cdot (1 - x_{i,2}) \tag{2.16}$$

$$K_d = K_{do} \cdot (1 - x_{i,3}) \tag{2.17}$$

Where K_{po}, K_{io}, K_{do} are initial value of PID parameters; $x_{i,1}$, $x_{i,2}$, $x_{i,3}$ are position of each particle in first, second and third dimension, respectively. Then, the parameters are sent to driver circuit for driving USM. The error signal is taken every 1 [ms] for fitness calculation. Fitness of each particle is calculated and accumulated until 10 [ms]. Fourthly, after 10 [ms] the fitness of particles is evaluated to determine a new *Pb* and *gb*. If the current fitness of particles is better than its previous value, then *pbest* = current position of particle. If not, *pbest* = its previous position of particle. If the current fitness of particles is better than *gbest*, then *gbest* = current position of particle. If not, *gbest* = its previous *gbest*. Fifthly, PSO updates velocity and position of particles using PSO equations. The processes in PSO will be repeated until m_{max} is met. These processes in PSO-PID controller will be repeated until stop criteria called k_{max} is met.

2.2.4 Shortcoming of PSO

Kanya Tanaka *et al.* proposed a self-tuning PID controller using PSO algorithm for USM [28]. In general, the method is a proper controller for USM. However, the method has disadvantages because of the shortcoming of the standard type of PSO. The shortcoming of the standard type of PSO are premature convergence and easy to get stuck or fall into local optima [57, 60]. Premature convergence is the condition where particles converge too early before finding the global best solution. As shown in Fig.2.15, the black line represents a normal convergence and the dash line represents a premature convergence. Some problems may have multiple peak optimum, such as one of global optima and one or more local optima. Figure 2.16 shows a problem with one of global optima and one of local optima. For like this problem, the particles easily get stuck or fall into local optima. Once *gbest* trapped into local optima, other particles will follow it and trapped into local optima and cannot jump-out from it. Due to this shortcoming, the accuracy of USM servo system is not optimal, especially in loaded condition. The shortcoming may lead to a poor performance.

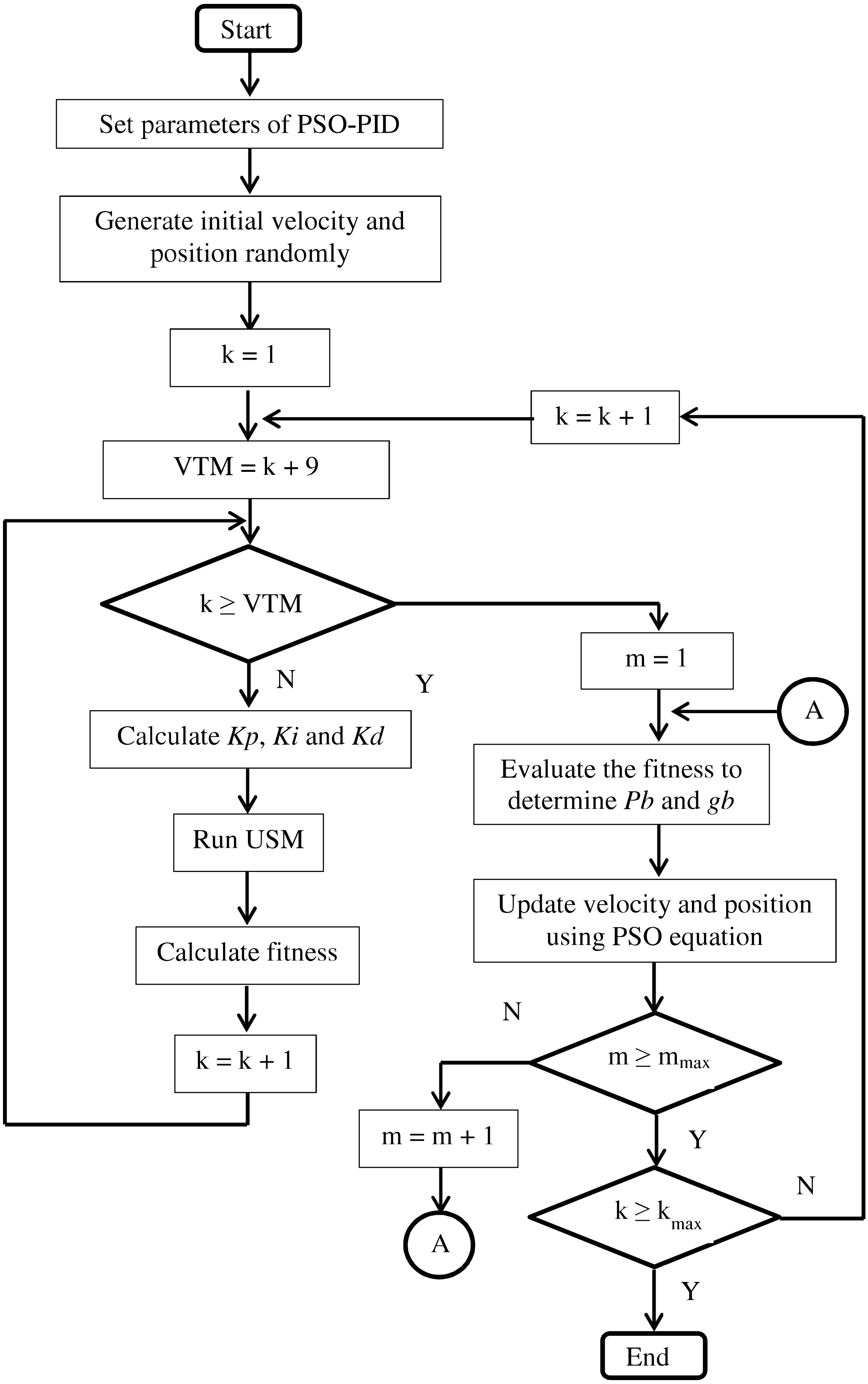

Fig. 2.14 Flowchart of PSO-PID controller

2.2.5 The Causes of Shortcoming

Some studies on PSO indicate that the causes of shortcoming in PSO algorithm is derived from the internal mechanism of particles movement, as follows [58-59]:

1. Unbalance between exploration and exploitation ability. PSO has two abilities in order to search the best solution,i.e., exploration ability and explotation ability. Exploration ability or global search ability is the ability of particles to identify a region with potentially high qualified solution. Particles with this ability have high speed velocity to search in a wider area. Exploitation ability or local search ability is the ability of particles to find a best solution in the limited area. Particles with this ability have low speed velocity to refined-search in order to get a solution as accurate as possible. However, it is difficult to find a proper balance because it influenced by several factors, e.g., model or type and dynamic characteritic of problem optimization. The proper balance is specific to each problem. It have s strong relationship with parameters adjustment of PSO. How to adjust the parameters for proper balance is still unclear and need more investigation.
2. Lost diversity and lack information due to fast rate of information flow between particles. In the PSO, particles are attracted by their corresponding previous best particles, Pb, and the global best particle, gb. With the movement of particles, particles are close to pb and gb, and then $(pb - x)$ and $(gb - x)$ becomes small. According to the updating equation of velocity, the velocity of each particle becomes small. Once the gb fall into local optima, all particles will quickly converge to the position of them. The cognitive part and social part of each particle will be near to to because of $x = pb = gb$. As a result, the velocity of each particle tends to zero, and the updating equation of position is invalid. In this condition, there is no-information for particles anymore, thus the particles loses diversity and in 'lack information'. The particles cannot move anywhere

or stagnant. Finally, all particles will be stagnate and hardly escape from local optima.

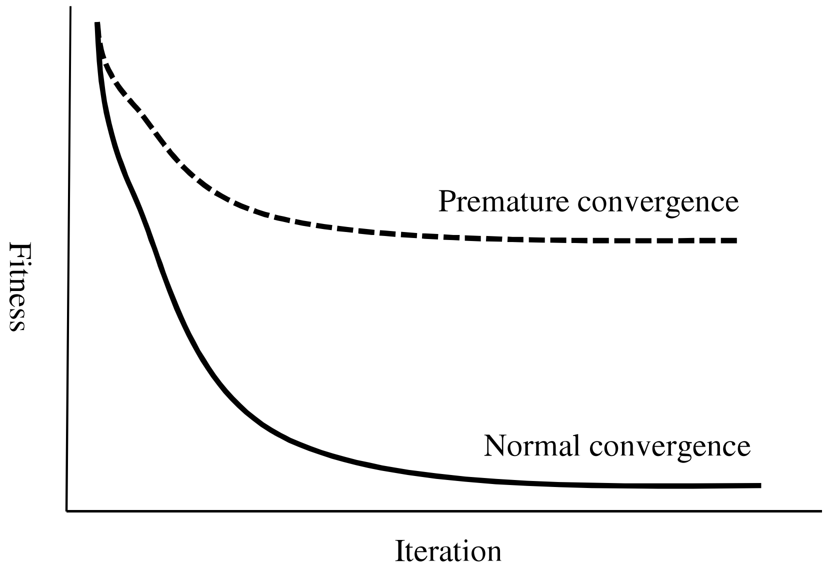

Fig. 2.15 Premature convergence

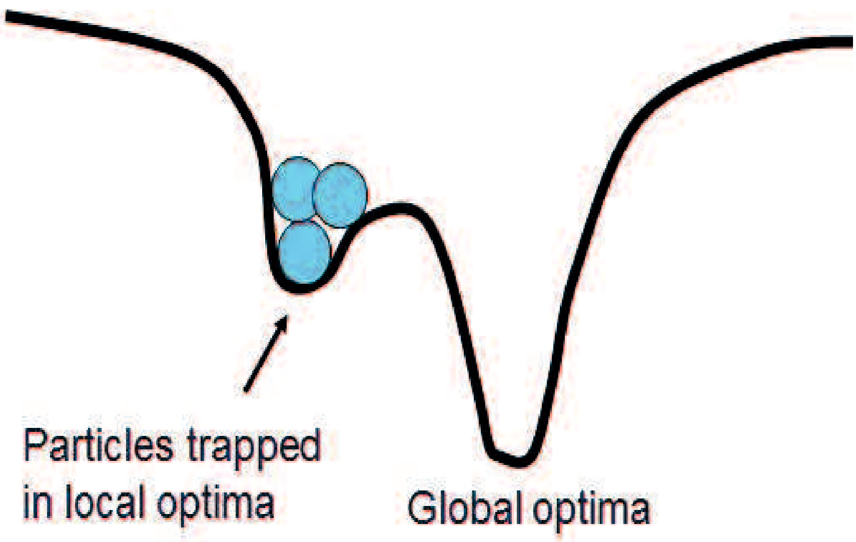

Fig. 2.16 Trapped particle in local optima

2.2.6 Difficulty in Determining Parameters Setting

Compare with other optimization techniques, PSO has a few of parameters to be adjusted. There are three parameters in PSO, namely inertia weight, cognitive constant and social constant. It was reported that inertia weight is most important parameter because it can control the balance between exploration-exploitation ability. The performance of PSO absolutely depends on the balance. Adjusting inertia weight is key role for improving PSO. So, many researchers focus on how to adjust inertia weight in order to get a best possible performance. Generally, cognitive constant and social constant is set with a constant number, *i.e.*, 1.0, 1.5 and 2.0.

The impact of inertia weight is illustrated in Fig. 2.17. Higher inertia weight will lead to stronger exploration ability. Smaller inertia weight will lead to stronger exploitation ability. Particles that hold exploration ability have high speed velocity to search in wider area. Particles that hold exploitation ability have low speed velocity to capture a best possible solution. Higher inertia weight during iteration will cause the particles cannot find and capture a best solution. Particles oscillate around a best solution due to its high speed. PSO with higher inertia weight has too longer settling time. Smaller inertia weight during iteration will cause the particles cannot search at wider area and stagnate. The particles stop before they find a best solution.

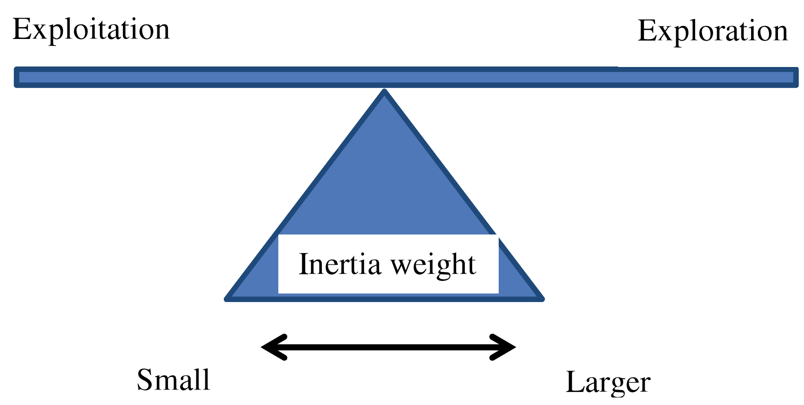

Fig. 2.17 The impact of inertia weight

Figure 2.18, 2.19 and 2.20 show the performance of PSO set with higher inertia weight (*i.e.*, w = 0.9), smaller inertia weight (*i.e.*, w = 0.1) and proper inertia weight (*i.e.*, w = 0.7), respectively. In this case, PSO is used to optimize the optimization problem called Sphere function: $\mathrm{f(x, y)} = (x - 15)^2 +$

$(y-20)^2$, the solution of this function is f_{min} = 0 at (15, 20). The parameters setting of PSO are: c_1 = 1.0, c_2 = 1.0, particles number, n = 5, iteration maximum, $iter_{max}$ = 20. The proper inertia weight for this problem is 0.7 and due to proper inertia weight, the average error becomes minimal and the value of x and y can approach to the best solution at [15, 20]. The effect of particles number to proper balance is shown in Fig. 2.21. The average error is calculated from 100 runs to compensate the stochastic process. The proper inertia weight for n = 5 and n = 15 are 0.7 and 0.3, respectively. It clears that the proper balance depends on particles number. Proper inertia weight is specific to each problem. It means that proper inertia weight for one problem may not suitable for other problems. Figure 2.22 shows two optimization problems, Sphere function: $f_1(x,y)=(x-15)^2+(y-20)^2$ and Rosenbrock function: $f_2(x,y)=100(y-x^2)^2+(x-1)^2$, solved by PSO and gives difference proper inertia, w_1 = 0.7 and w_2 = 0.4. The solution of the Rosenbrock function is f_{min} = 0 at (1, 1). It clears that proper inertia weight depends on the kind of problem. Fitness of the best particle for Sphere function in the difference inertia weight is shown in Fig. 2.23. Proper inertia weight causes minimum of fitness.

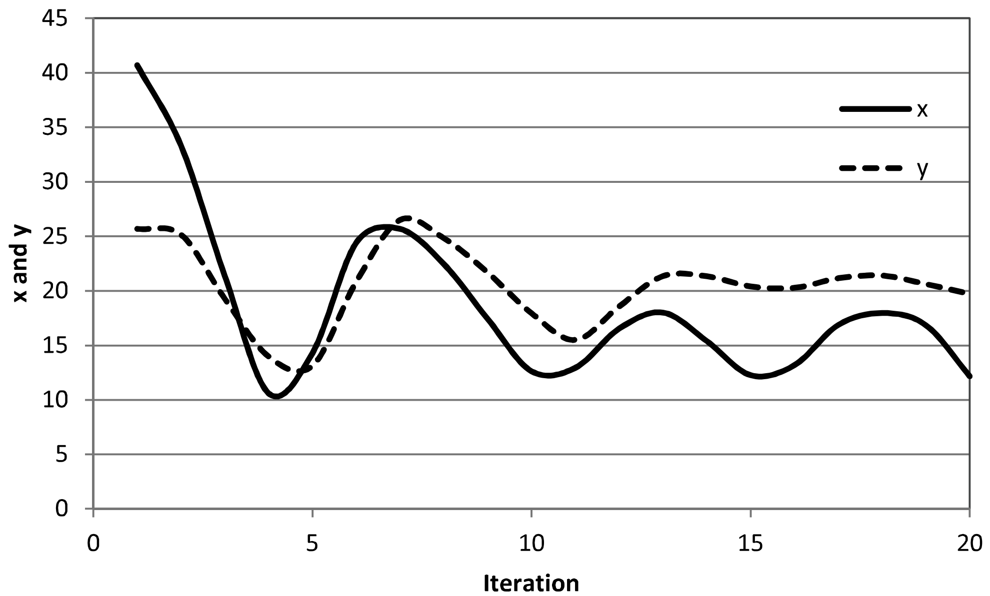

Fig. 2.18 The impact of higher inertia weight

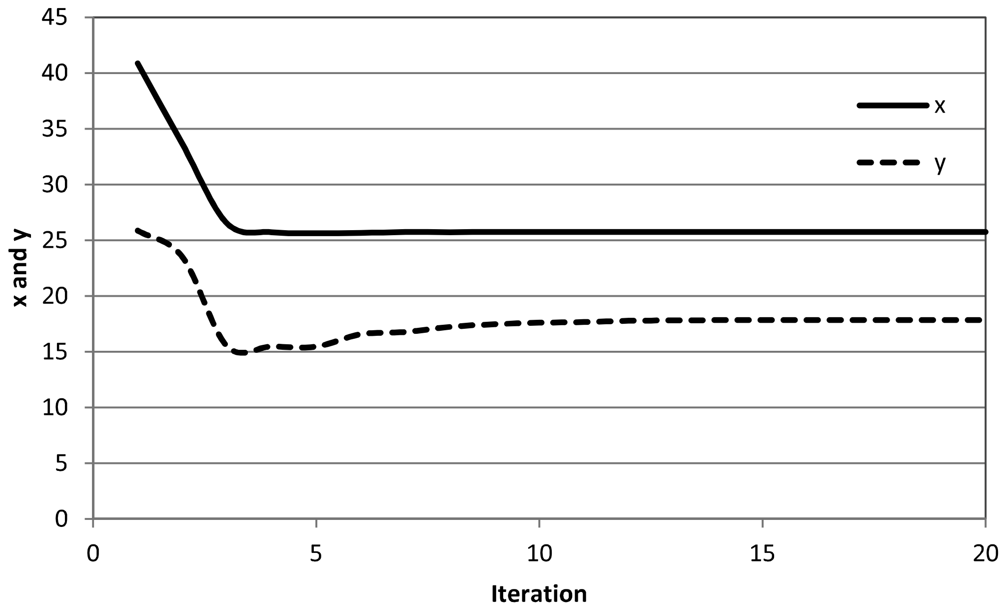

Fig. 2.19 The impact of smaller inertia weight

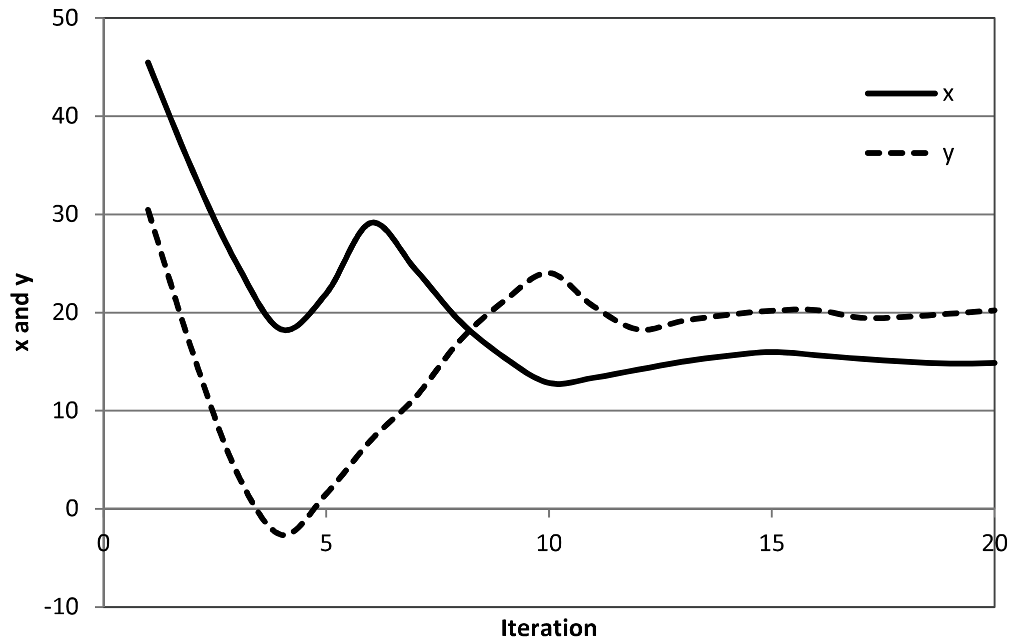

Fig. 2.20 The impact of proper inertia weight

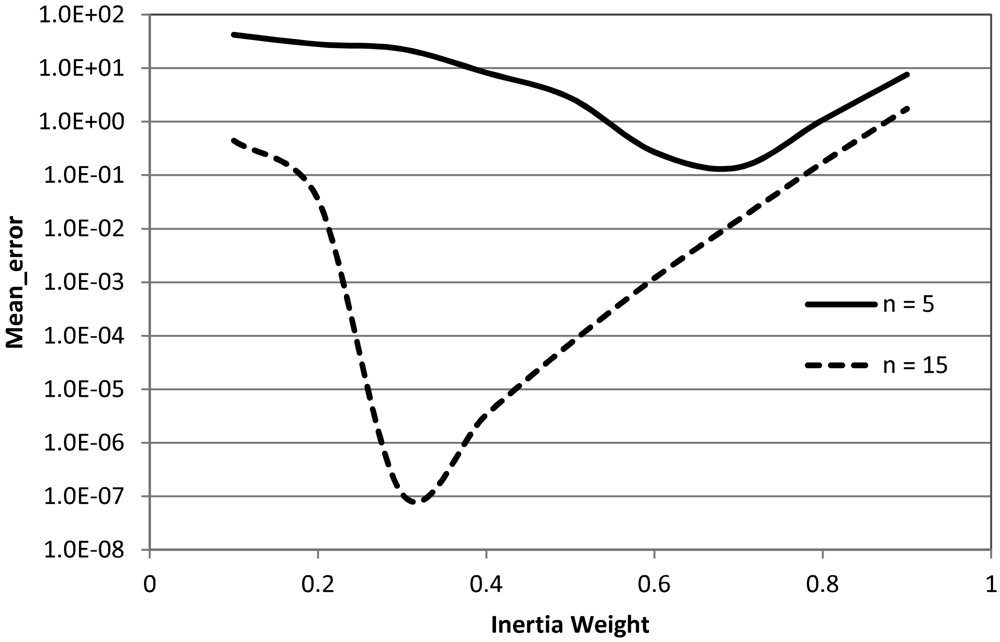

Fig. 2.21 The effect of particles number on the proper balance

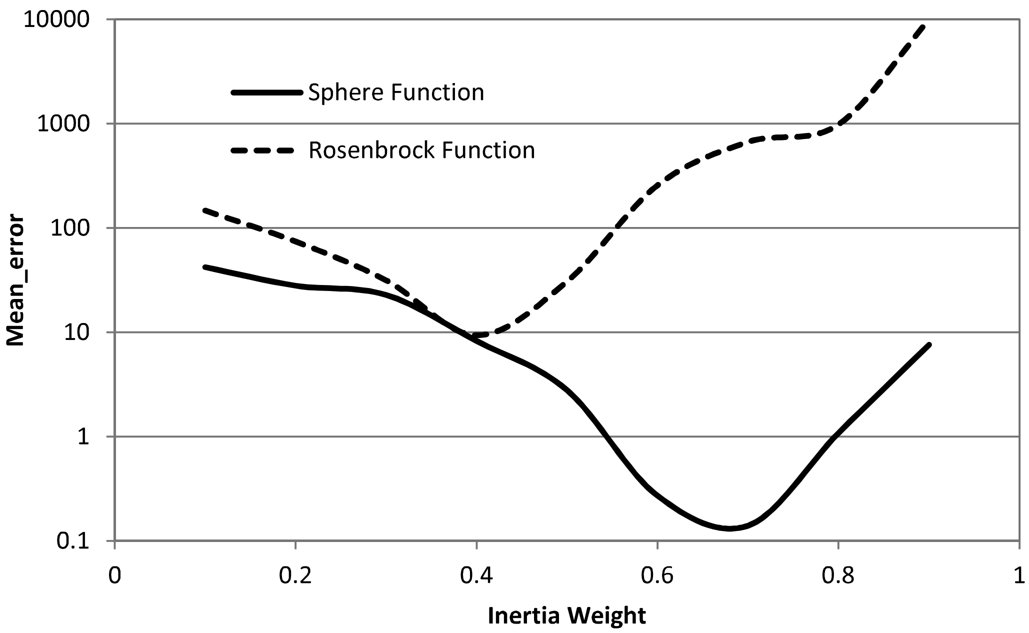

Fig. 2.22 The proper balance of difference problems

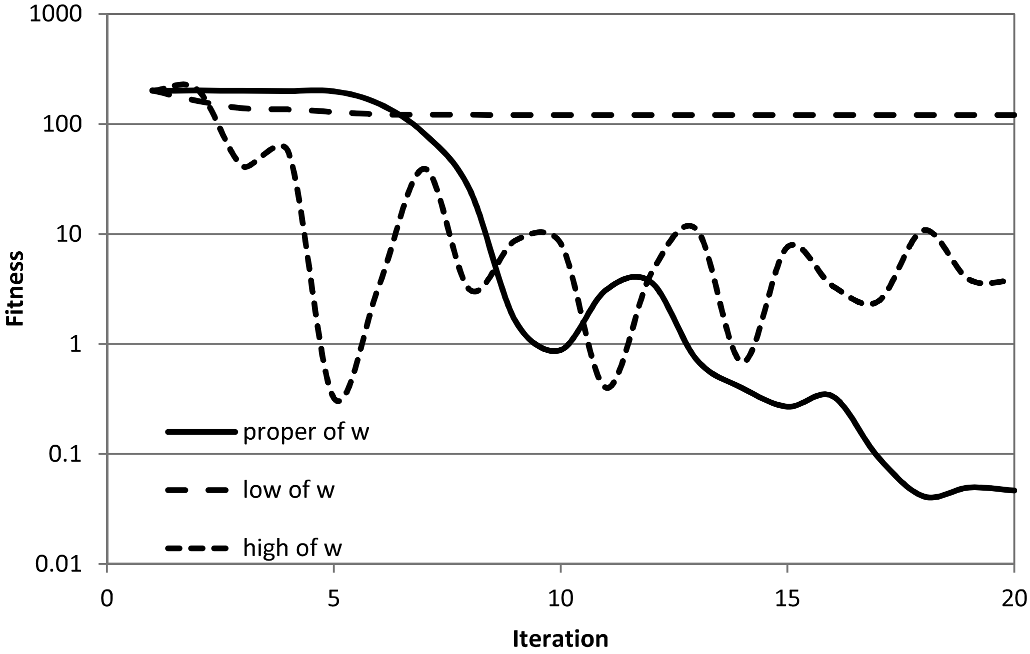

Fig. 2.23 The fitness of difference inertia weight

Particles condition also should be considered in determining inertia weight. Due to stochastic process, sometimes the particles are too far from the best solution and applying stronger exploration ability is better. Sometimes, the particles are close to the best solution and applying stronger exploitation ability is better. Figure 2.24 and 2.25 show the condition where the particles (marked with black circle) are too far from the best solution (marked with a black star). In this condition, higher inertia weight is better. Figure 2.26 shows the condition where the particles are close to the best solution. In this condition, smaller inertia weight is better. Figure 2.27 shows the condition where many particles are deployed in searching area. In this condition, smaller inertia weight is better because particles evenly dispersed.

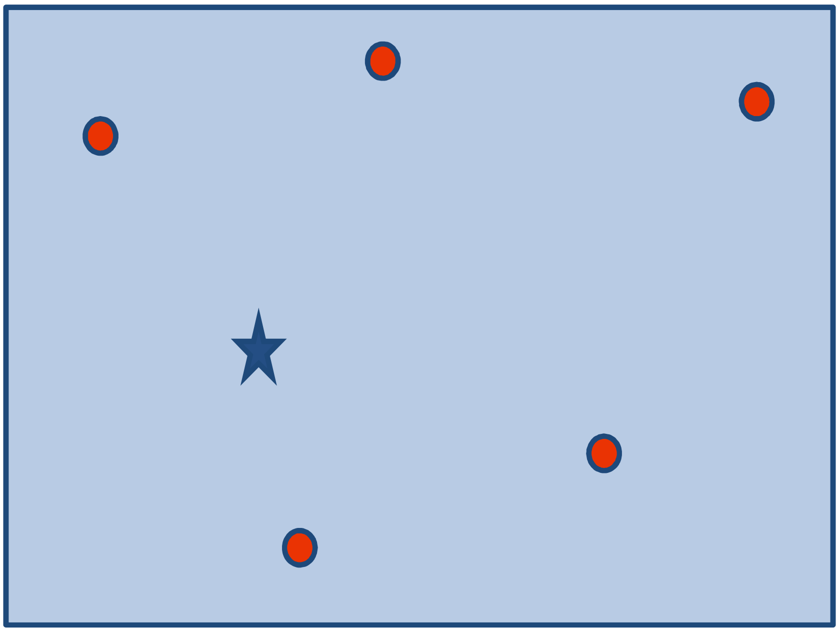

Fig. 2.24 Perticles are too far from the best solution (1)

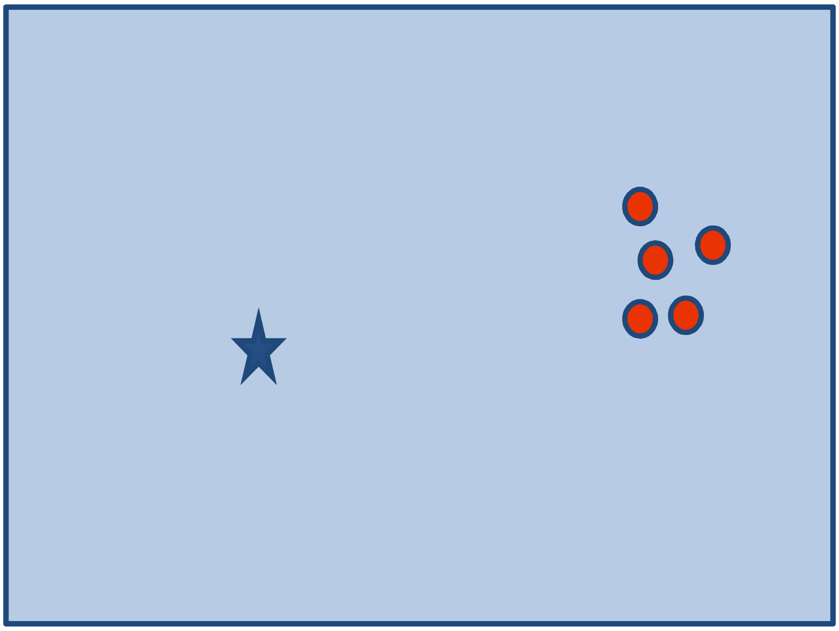

Fig. 2.25 Perticles are too far from the best solution (2)

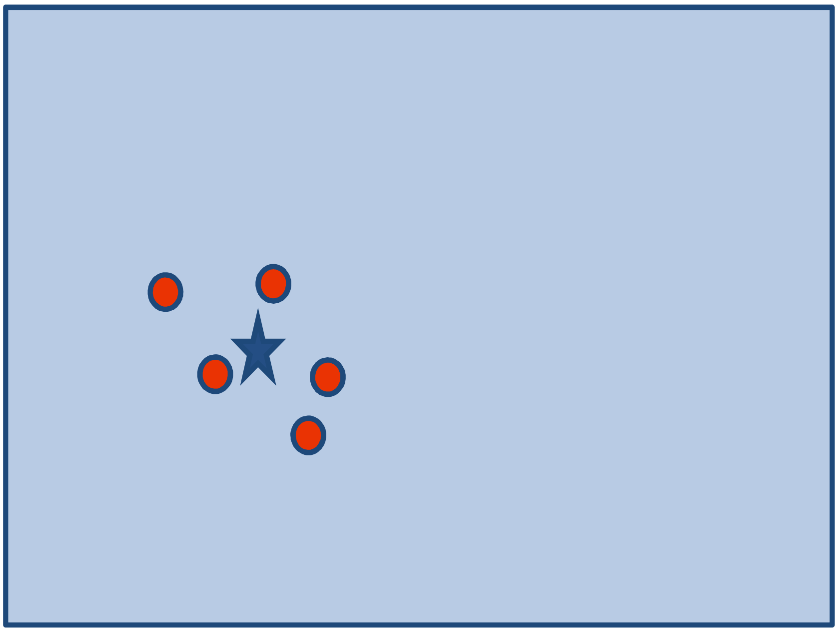

Fig. 2.26 Perticles are close to the best solution

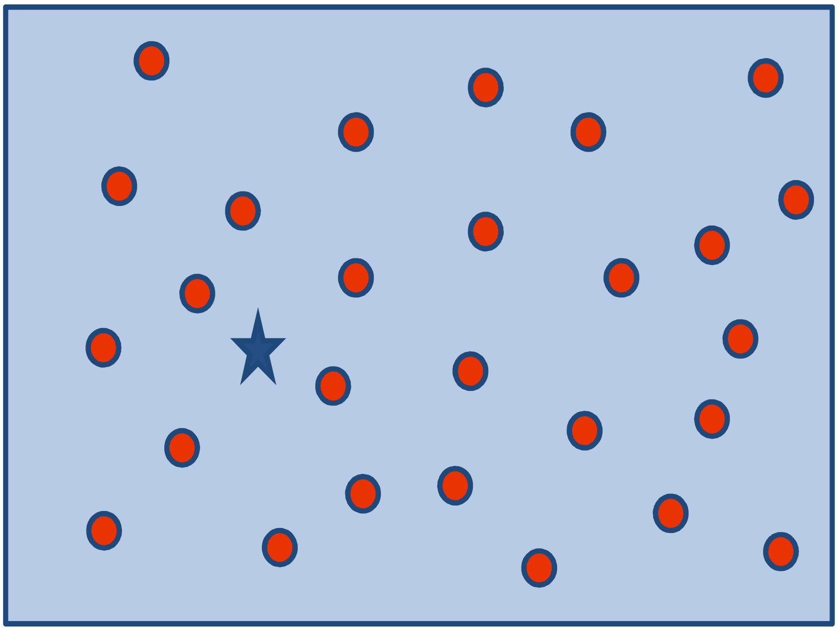

Fig. 2.27 Perticles are evenly dispersed

Due to these reasons, the constant inertia weight is not good. Inertia weight must be adjusted during iteration. Proper inertia weight means that when inertia weight is set high, medium or small in order to apply exploration or exploitation ability according to the particles condition. Proper inertia weight depends on some factors, such as the type of problems, number of particles, swarm condition, initial deployment and other unknown factors. Proper inertia weight for one problem may not suitable for other problems. Moreover, due to complexity of problems, uncertainty problems, dynamics in problems, it is hard to derive a mathematical model of problem. According to those difficulties, research to develop a proper adjusting inertia weight method is being conducted intensively. It is a new challenge to build a new variant of PSO.

2.2.7 Strategy for Improving PSO

Improving PSO became a new topic in computer science since PSO was introduced at the first time by Dr. Eberhart and Dr. Kennedy in 1995. Many researchers focused on how to adjust inertia weight in order to get a proper balance between exploration-exploitation ability. According to the causes of the shortcoming of PSO, there are three ways to improve PSO.

The first way is parameters adjustment, especially inertia weight. During searching process, inertia weight should be adjusted any time. The target of inertia weight adjustment is to find a proper balance quickly. So, inertia weight is created as a function of searching process or iteration called time-varying inertia weight function. Inertia weight can be adjusted as linear increased function, linear decreased function, nonlinear increased function, nonlinear decreased function, sigmoid increased function, sigmoid decreased function, random function, adaptive function, etc. Each function will give a different impact to performance of PSO. The investigation of inertia weight adjustment is being needed because the relationship between parameters adjustment and performance of PSO is still unclear.

The second way is to create a new mechanism in particle's movement in order to compensate the lack-information due to fast rate flow in sharing information. In PSO algorithm, there are three information determined the next position of particle, *i.e.*, momentum part, cognitive part and social part. Unlike GA algorithm, there is no coding-decoding process, mutation, crossover and other evolution operators in PSO, thus time-process in PSO is too fast. Due to stochastic process, sometimes cognitive and social part is too early approaching zero and no information anymore for particle. Consequently, the particles become stagnant and lost-diversity. New information is needed to overcome those problems.

The third way is hybrid or combination with others techniques. PSO uses stochastic approaches to solve the optimization problems. The stochastic approaches have problem-dependent performance. This dependency usually results from the parameter settings in each algorithm. The different parameter settings for a stochastic search algorithm result in high performance variances. In general, no single parameter setting can be applied to all problems. It may differ from one problem to another. Therefore, from the above, it can be concluded that the PSO performance is problem-dependent. The problem-dependent performance can be addressed through hybrid mechanism. It combines different approaches or methods to be benefited from the advantages of each approach.

Chapter 3

New Inertia Weight Approach PSO based Intelligent Self-tuning PID Controller for USM

Developing a proper controller for USM is a focus of our research. Based on the previous research, we have investigated several strategies for improving PSO to reduce the risk of premature convergence and possibility of being trapped in local optima. In this section, the used strategy for improving PSO is based on inertia weight adjustment strategy or new inertia approach, called Nonlinearly Decreased Inertia Weight (NDW) and Random Inertia Weight (RIW).

3.1 PSO-NDW based Intelligent Self-Tuning PID

3.1.1 Concept of Nonlinearly Decreased Inertia Weight

It was reported that an inertia weight is most important parameter to control balance between exploration-exploitation ability in PSO. The balance is key role to improve PSO that can reduce the risk of premature convergence and easy to get stuck into local optima. However, how to adjust an inertia weight in getting a proper balance is not easy.

In the previous research, the commonly PSO have been used for self-tuning PID controller on USM servo system. In here, inertia weight was decreased linearly from high value (w_{max}) to small value (w_{min}) during iteration or seraching process. The equations of the commonly PSO are shown as follows:

$$v_{i,d}^{m+1} = w.v_{i,d}^{m} + c_1.r_1.\left(Pb_{i,d} - x_{i,d}^{m}\right) + c_2.r_2.\left(gb_d - x_{i,d}^{m}\right) \tag{3.1}$$

$$x_{i,d}^{m+1} = x_{i,d}^{m} + v_{i,d}^{m+1} \tag{3.2}$$

$$w = w_{max} - (w_{max} - w_{min}).\frac{m}{m_{max}} \tag{3.3}$$

It means that the particles is set in stronger exploration ability at the beginning of iteration and then stronger exploitation ability at the end of iteration. This method is also called PSO with linearly decreased inertia weight or PSO-LDW. PSO-LDW is commonly used in many applications as optimization technique.

Due to LDW strategy, how long of exploration ability and exploitation ability is devided in same period during iteration. The proposed NDW (nonlinearly decresed inertia weight) is to control the period of exploration-exploitation ability. We proposed NDW strategy to investigate the effect of the period of these abilities. In the proposed strategy, an inertia weight is nonlinearly decreased from w_{max} to w_{min}, as follows:

$$w(m) = w_{min} + (w_{max} - w_{min}) \cdot \left\{\frac{m_{max}-m}{m_{max}-1}\right\}^{x} \tag{3.4}$$

where x is a new parameter called nonlinear index number. The value of nonlinear index number will determine the degree of nonlinear path of decreasing inertia weight. The high of this new parameter will shorten the length-time of exploration ability and extend the length-time of exploitation ability. The influence of nonlinear index number is shown in Fig. 3.1.

3.1.2 Experimental Results

Some experimental results are provided in this Section to verify the effectiveness of the proposed PSO-NDW-based PID controller for USM. We also have compared our method with previous methods, *i.e.*, conventional fixed-gain PID and PSO-LDW based PID (the standard type of PSO) with the same system condition.

The reference input *r(t)* 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]. Two test conditions are provided in the experimentation, which are the unloaded condition and the loaded condition.

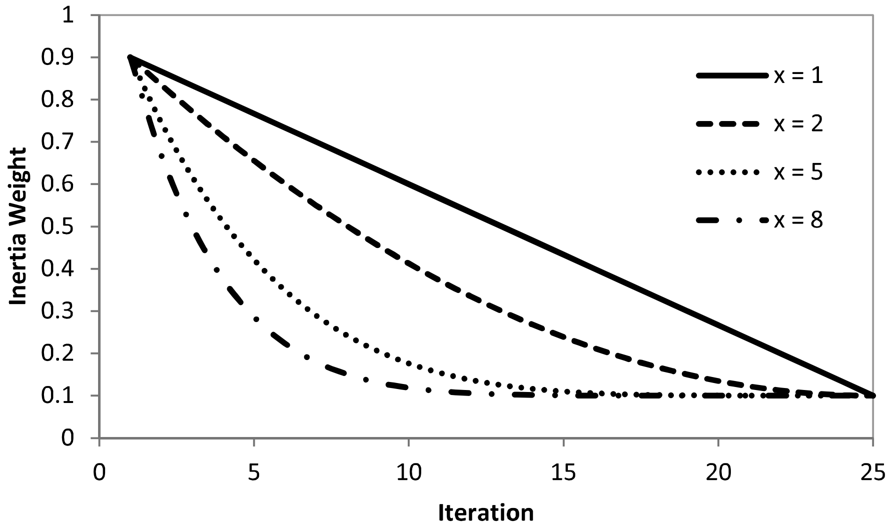

Fig. 3.1 The impact of nonlinear index number

The loaded condition is the addition of load from electromagnetic brake with 0.25 [Nm] of force. Each method has been performed for 10 trials of CW direction and 10 trials of CCW direction. The parameters of the standard type of PSO and Enhanced PSO-NDW are set as follows:

1. Particle number, $n = 5$
2. Cognitive constant, $c_1 = 1.0$
3. Social constant, $c_2 = 1.0$
4. Maximum value of inertia weight, $w_{max} = 0.9$
5. Minimum value of inertia weight, $w_{min} = 0.4$

Firstly, we used the conventional tuning or hand-tuned to determine the parameters of PID controller. This method is introduced by Ellis [63] and called the zone-based tuning. 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 trials of CW direction (*i.e.*, +45 deg) and 10 trials of

CCW direction (*i.e.*, -45 deg) for unloaded condition. After that, we repeat again for with loaded condition, *i.e.*, 0.25 [Nm].

Figure 3.2 and 3.3 present the position accuracy of USM in histogram for unloaded and loaded condition. Each bucket of the histogram is set to a width of 0.0011 [deg]. It is a resolution of the encoder. We can say that the position accuracy of USM using a hand-tuned PID is good and reliable in unloaded condition, but becomes poor and inaccurate in loaded condition. The gains have been determined previously only applicable to unloaded 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. The conventional fixed-gain PID cannot compensate the characteristics changes of USM during operation.

Secondly, we tested a standard type of PSO (or PSO-LDW) for self-tuning PID controller on USM servo system. Figure 3.4 and 3.5 show the position accuracy of USM in unloaded and loaded condition. We can see that the accuracy of USM using PSO-LDW based PID is better than using fixed-gain PID controller.

Thirdly, we tested the proposed PSO-NDW for self-tuning PID controller on USM servo system. Figure 3.6 and 3.7 show the position accuracy of USM in unloaded and loaded condition. We can see that the accuracy of USM using PSO-NDW based PID is better than using both fixed-gain PID controller and PSO-LDW based PID.

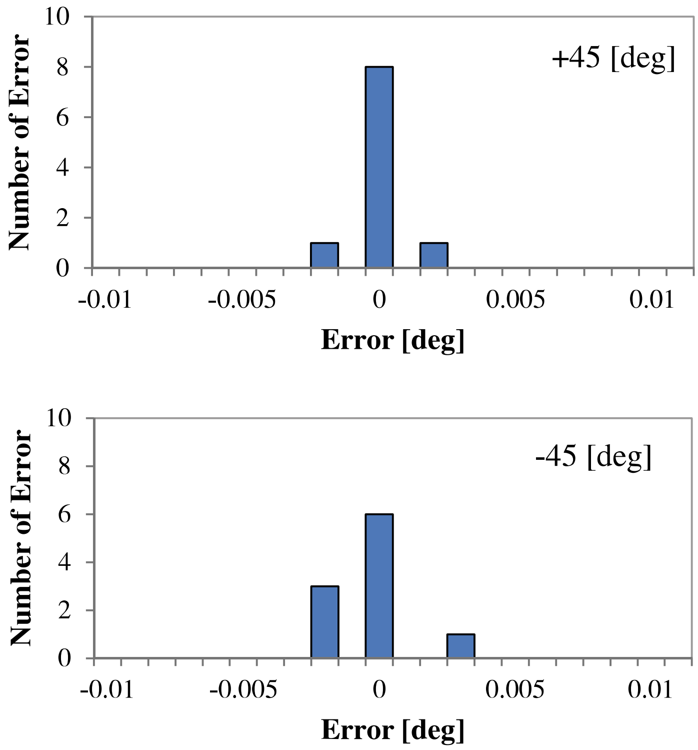

Fig. 3.2 Position accuracy of USM using PID (unloaded)

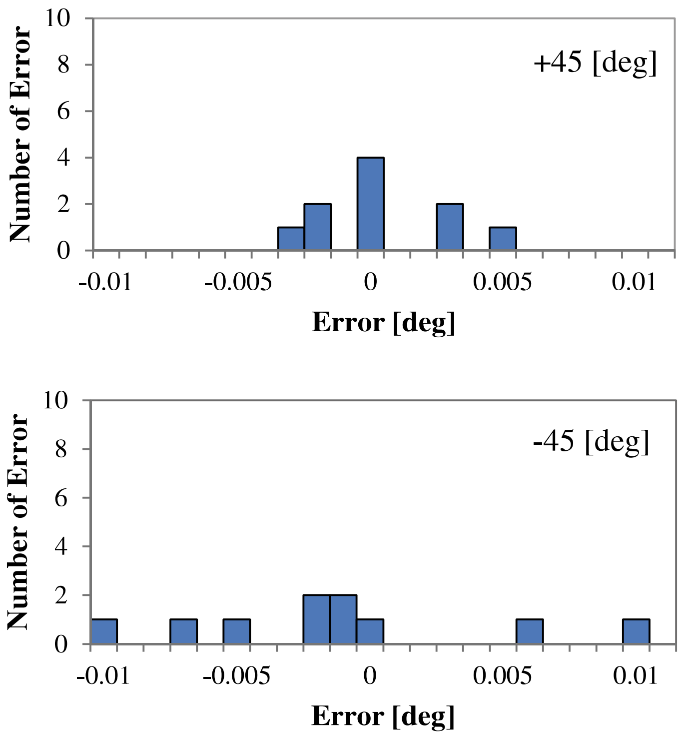

Fig. 3.3 Position accuracy of USM using PID (loaded)

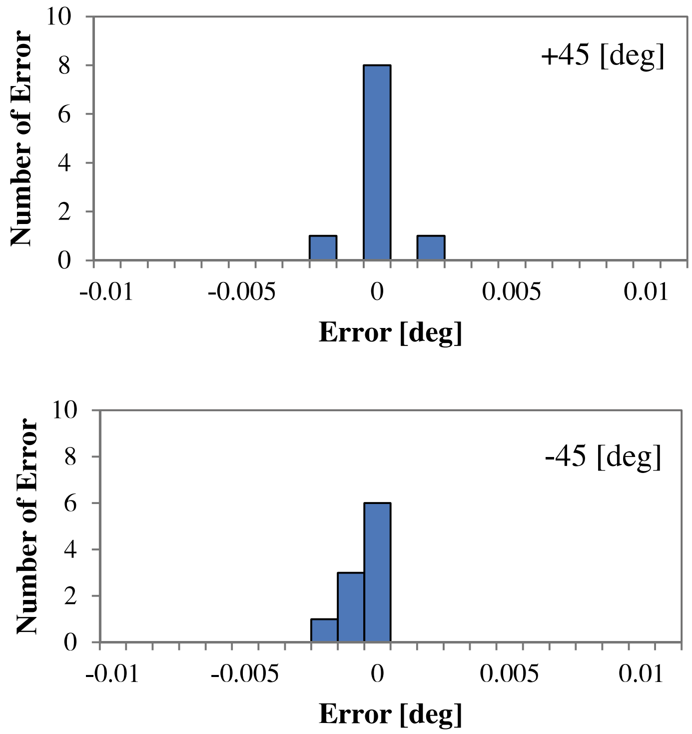

Fig. 3.4 Position accuracy of USM using PSO-PID (unloaded)

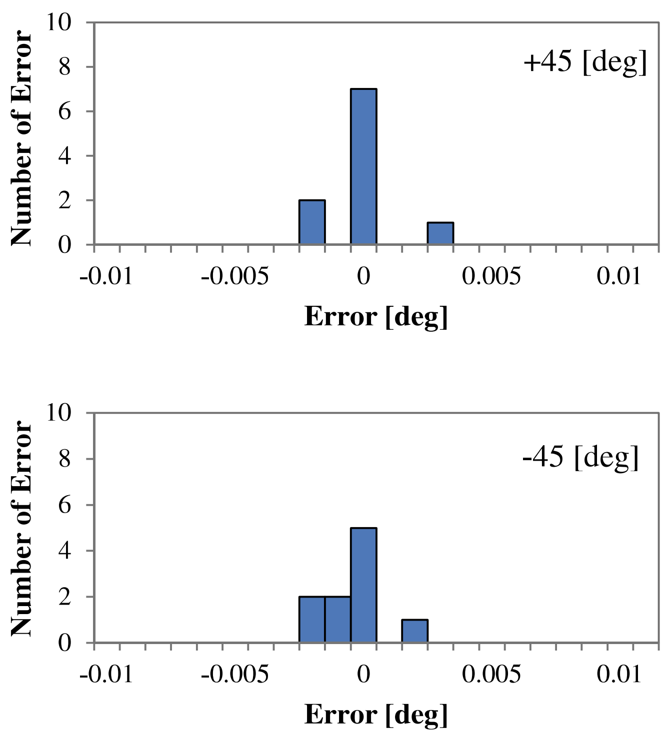

Fig. 3.5 Position accuracy of USM using PSO-PID (loaded)

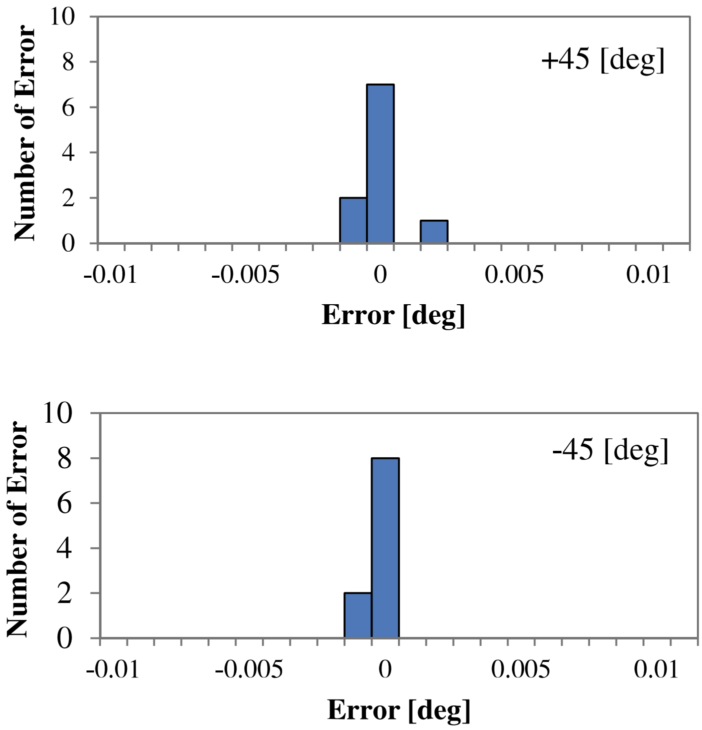

Fig. 3.6 Position accuracy of USM using PSO-NDW PID (unloaded)

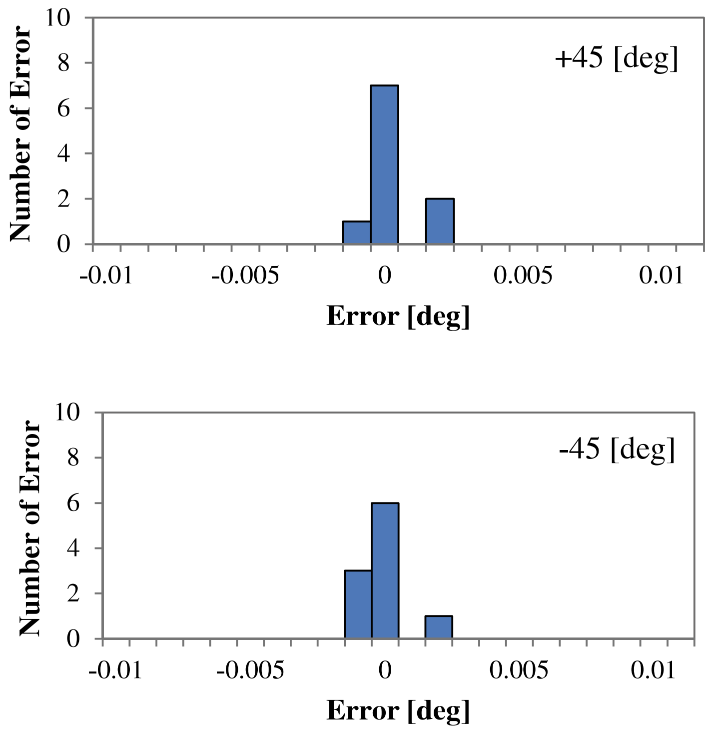

Fig. 3.7 Position accuracy of USM using PSO-NDW PID (loaded)

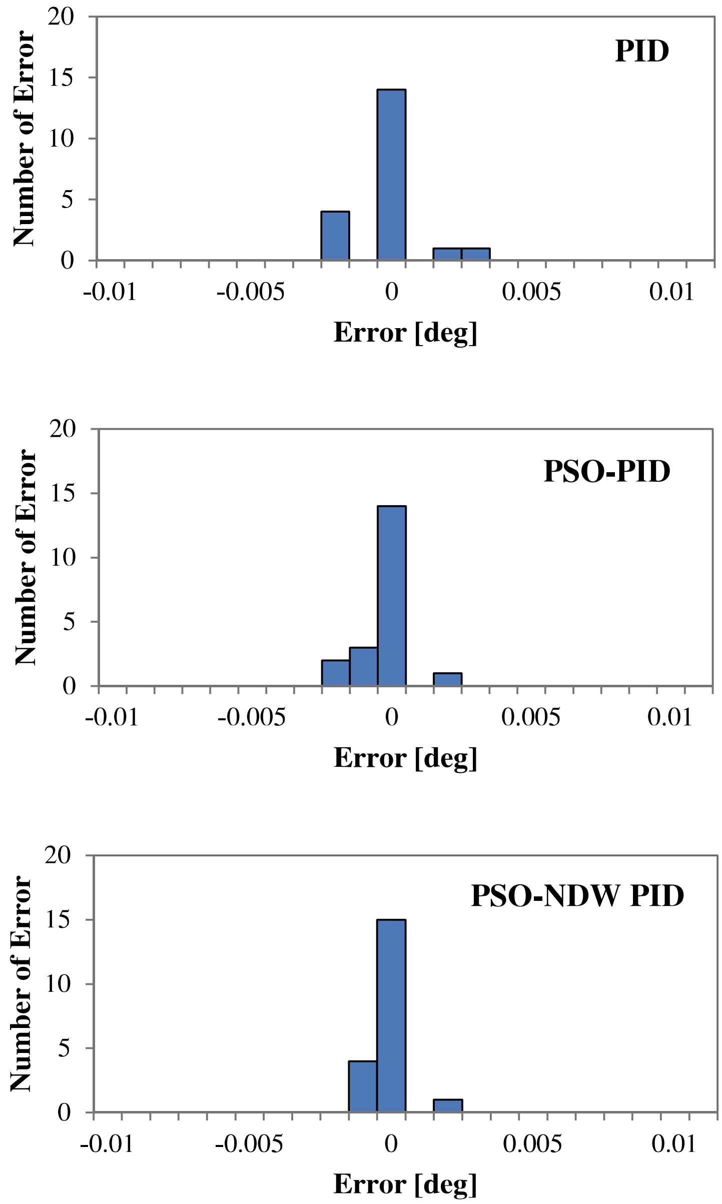

Fig. 3.8 Position accuracy of USM in both directions (unloaded)

Figure 3.8 and 3.9 show the position accuracy of USM in both directions with unloaded and loaded condition using three methods, *i.e.*, fixed-gain PID, PSO-PID and PSO-NDW PID controller. It can be seen that the proposed PSO-NDW PID can improve the performance of USM servo system. The characteristic changes of USM during operation due to loading effect can be compensate by the proposed PSO-NDW PID controller.

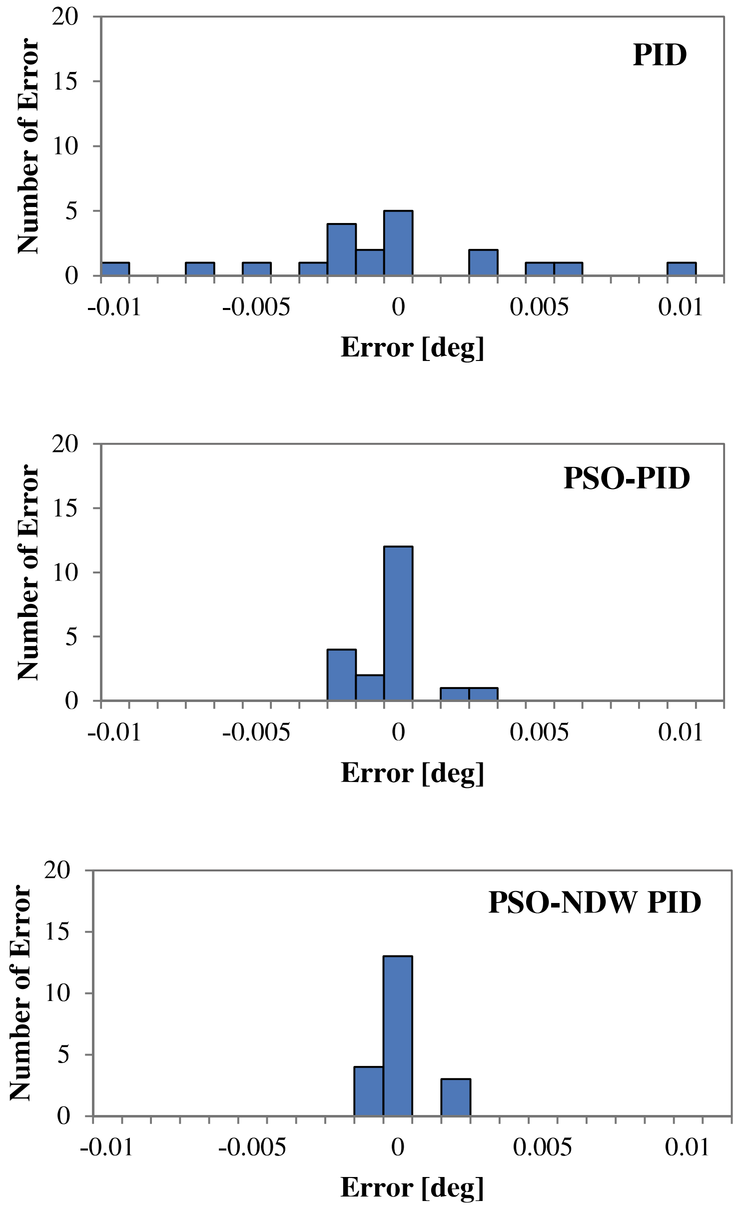

Fig. 3.9 Position accuracy of USM in both directions (loaded)

The impact of nonlinear index number on the proposed PSO-NDW is shown in Fig. 3.10. We can say that nonlinear index number of 1.5 gives a best performance, *i.e.*, smallest error. Due to this value, the exploration period is a bit shorter and the exploitation period is a bit longer. The nonlinear index number is a new parameters in PSO-NDW that can improve the performance of PSO. The proper value of this parameter is needed. According to this result, the proper value of this parameter is 1.5.

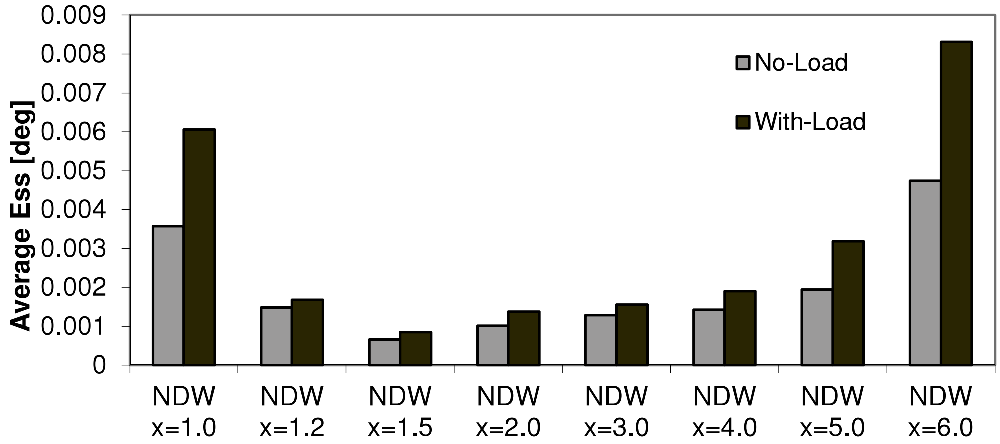

Fig. 3.10 The impact of nonlinear index number

Table 3.1 Comparison of average error and Success Rate

Methods	**Average of Ess [deg]**		**Frequency of Zero-Ess (Ess < 0.0011 deg) or Success Rate (SR) in 20 trials**	
	Unloaded	**Loaded**	**Unloaded**	**Loaded**
PID	5.78E-4	3.31E-3	14 (70%)	5 (25%)
PSO-LDW PID	5.11E-4	8.94E-4	14 (70%)	12 (60%)
PSO-NDW PID	4.17E-4	4.44E-4	15 (75%)	13(65%)

The comparisson results of average error and frequency of zero-error between the proposed PSO-NDW and the previous methods is shown in Table 3.1. Zero-error means that the error is smaller than 0.001 [deg], *i.e.*, the resolution of encoder. Success Rate (*SR*) shows the success of method in achieving the zero-error within all trials. It clears that the proposed PSO-NDW PID can outperform a fixed-gain PID and PSO-LDW PID. The average of error of PSO-NDW PID is smallest or 18.4% (unloaded) and 50.35% (loaded) lower than the PSO-LDW PID. Moreover, the frequency of zero-error of PSO-NDW PID is more often than the previous methods or *SR* of PSO-NDW PID is higher than the previous methods.

Higher of SR shows that the particles have better ability to avoid premature convergence and escape from the local optima.

Figure 3.11 shows the convergence speed of PSO-NDW and PSO-LDW. It seen clearly that the particles in PSO-NDW achieve faster convergence than the standard type of PSO. The PSO-NDW and PSO-LDW achieve convergence in 0.23 [sec] and 0.26 [sec], respectively.

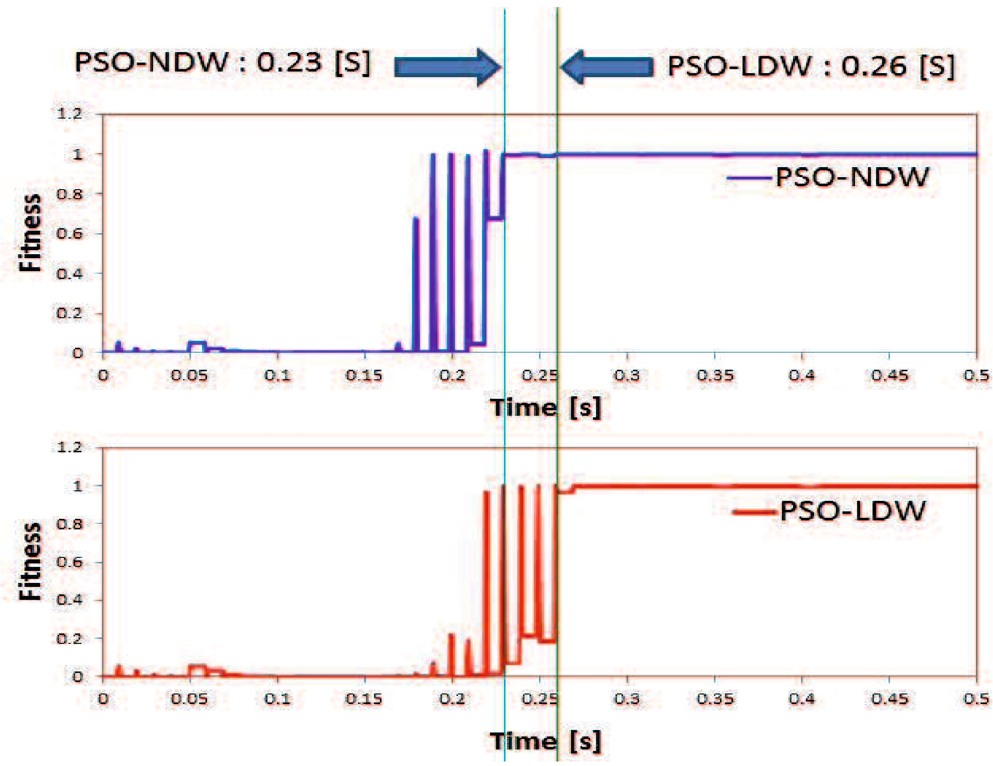

Fig. 3.11 Convergence speed of PSO-NDW PID

3.1.3 Summary

The first proposed Enhanced PSO, called PSO-NDW, uses time-varying of inertia weight, where the inertia weight is linearly decreased from maximum value to minimum value based on iteration during searching process [71-73].

We could conclude that:

1. According to the higher of *SR*, the NDW strategy could reduce the risk of premature convergence and possibility of being trapped in local

optima because controlling a period of both abilities gives a better balance than the previous method, *i.e.*, The LDW strategy.

2. Nonlinear index number is a new parameter of NDW to control the length- time (period) of exploration and exploitation ability or the degree of nonlinear path of decreasing inertia weight. The parameter should be set and based on the results the best value for this parameter is 1.5. It means that a bit shorter of period of exploration ability and a bit longer of period of exploitation ability is an optimal in controlling PSO-NDW.
3. PSO-NDW for self-tuning PID on USM gives a better performace than the previous methods in term of convergence speed and position accuracy of USM.

3.2 PSO-RIW based Intelligent Self-tuning PID

3.2.1 Concept of Random Inertia Weight

The previous methods, *i.e.*, PSO-LDW and PSO-NDW, use stronger exploration ability at the beginning and stronger exploitation ability at the end of iteration. Due to this strategy, there are lack exploitation ability at the beginning and lack exploration ability at the end of iteration. This is one of disadvantages of the previous methods. Due to random mechanism in particle's movement, sometimes the particles are approaching the best solution at the beginning of iteration. So, in this situation the exploitation ability is more needed to refined-search. Also, sometimes the particles have not found the best solution at the end of iteration. So, in this situation the exploration ability is more needed to search again in other area. Another disadvantage of the previous methods is that it needs a proper value for w_{max}, w_{min} and x. Improper values for these parameters may decrease the performance of PSO. Moreover, for optimization problem with dynamic environment, the previous methods become less effective because once the particles accumulate at point in searching area, but the global best solution is still uncertain, the particles have difficulty in escaping from the accumulating point.

To overcome those problems, the inertia weight employing a uniform random number is introduced to improve the performance of PSO. We called the second proposed strategy as PSO with random inertia weight or PSO-RIW. In this method, exploration and exploitation ability can be processed in the 'same time'. It means that the both abilities are always balanced during iteration. Inertia weight is adjusted randomly according to the following equation:

$$w = w_{min} + (w_{max} - w_{min}) \cdot r \tag{3.5}$$

where r is uniform random number. Figure 3.12 shows the inertia weight adjustment of PSO-LDW, PSO-NDW and PSO-RIW.

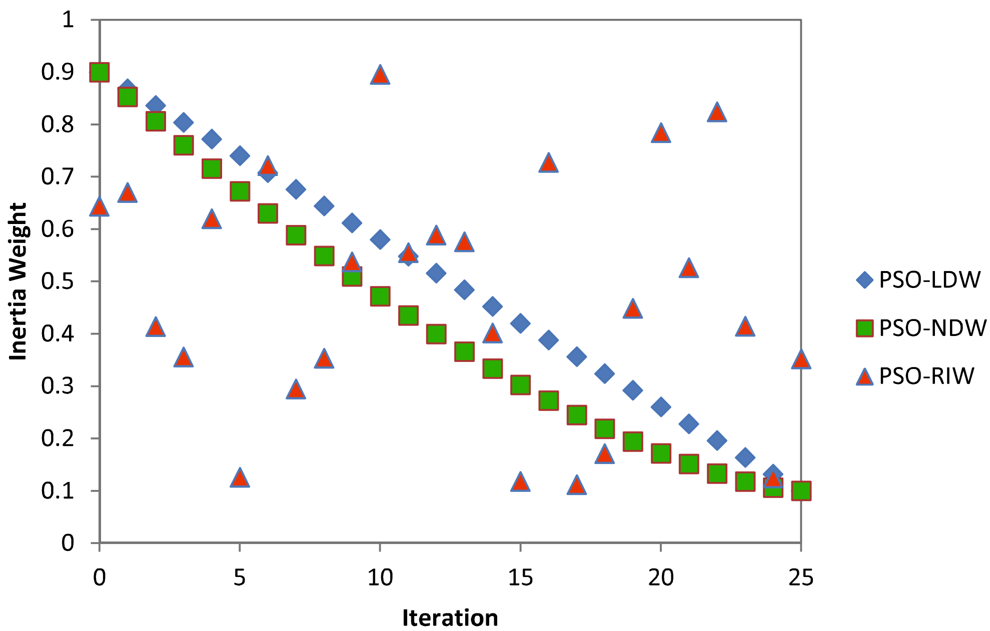

Fig. 3.12 Randomly inertia weight adjustment

3.2.2 Experimental Results

To evaluate the effectiveness of the proposed PSO-RIW for self-tuning PID controller on USM, we tested it and compared with the previous methods, *i.e.*, fixed-gain PID, PSO-LDW PID, and PSO-NDW PID. The setting parameters of each method are shown in Table 3.2. The conditions of experiment is set similar to the previous conditions, *i.e.*, the reference input is rectangular wave with +45 [deg] or CW direction and -45 [deg] or CCW direction, the period is 4 [s], unloaded and loaded with 0.25 [Nm] from electromagnetic brake.

Figure 3.13 and 3.14 show the position accuracy of USM controlled by proposed PSO-RIW PID controller. Compared with the previous methods, *i.e.*, Fig. 3.2 - 3.7, it can be seen that the proposed PSO-RIW PID has better accuracy, where its density around zero is higher than previous methods. In both direction and conditions, as shown in Fig. 3.15 and 3.16, PSO-RIW PID controller indicated its effectiveness and its accuracy in order to compensate the characteristic changes of USM due to loading effect. RIW strategy can improve the performance of the standard type of PSO by reducing the risk of premature convergence and fall into local optima.

The comparisson of average error and frequency of zero-error between the proposed PSO-RIW and the previous methods is shown in Table 3.3. It clears that the proposed PSO-RIW PID can outperform a fixed-gain PID, PSO-LDW PID, and PSO-NDW PID.

Table 3.2 Setting parameters of the methods

Fixed-gain PID	**PSO-LDW PID**	**PSO-NDW PID**	**PSO-RIW PID**
$K_p = 0.3692$ $K_i = 12.175$ $K_d = 0.000085$ (hand-tuned)	$n = 5$ particles $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ particles $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ particles $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.6$ $w_{min} = 0.3$

The average of error of PSO-RIW PID is smallest or 63.21% (unloaded) and 62.98% (loaded) lower than the PSO-LDW PID. Moreover, the frequency of zero-error of PSO-RIW PID is more often than the previous methods or *SR* of PSO-RIW PID is higher than the previous methods. It means that RIW can increase the ability to avoid premature convergence and escape from the local optima.

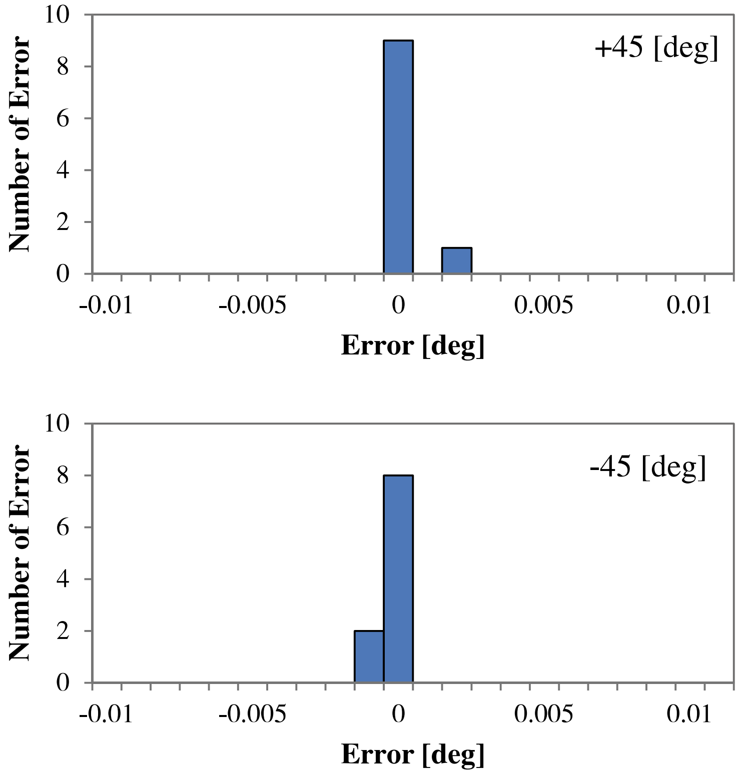

Fig. 3.13 Position accuracy of USM using PSO-RIW PID (unloaded)

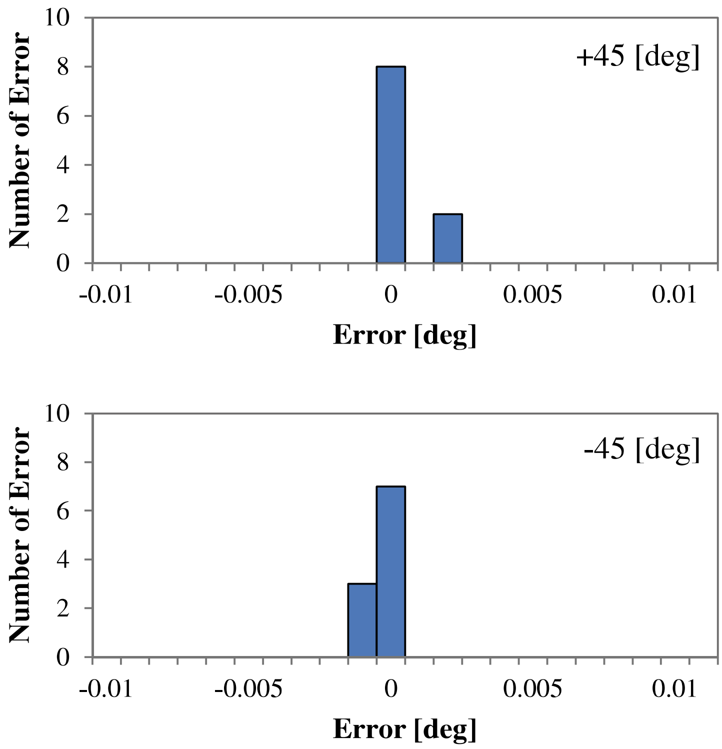

Fig. 3.14 Position accuracy of USM using PSO-RIW PID (loaded)

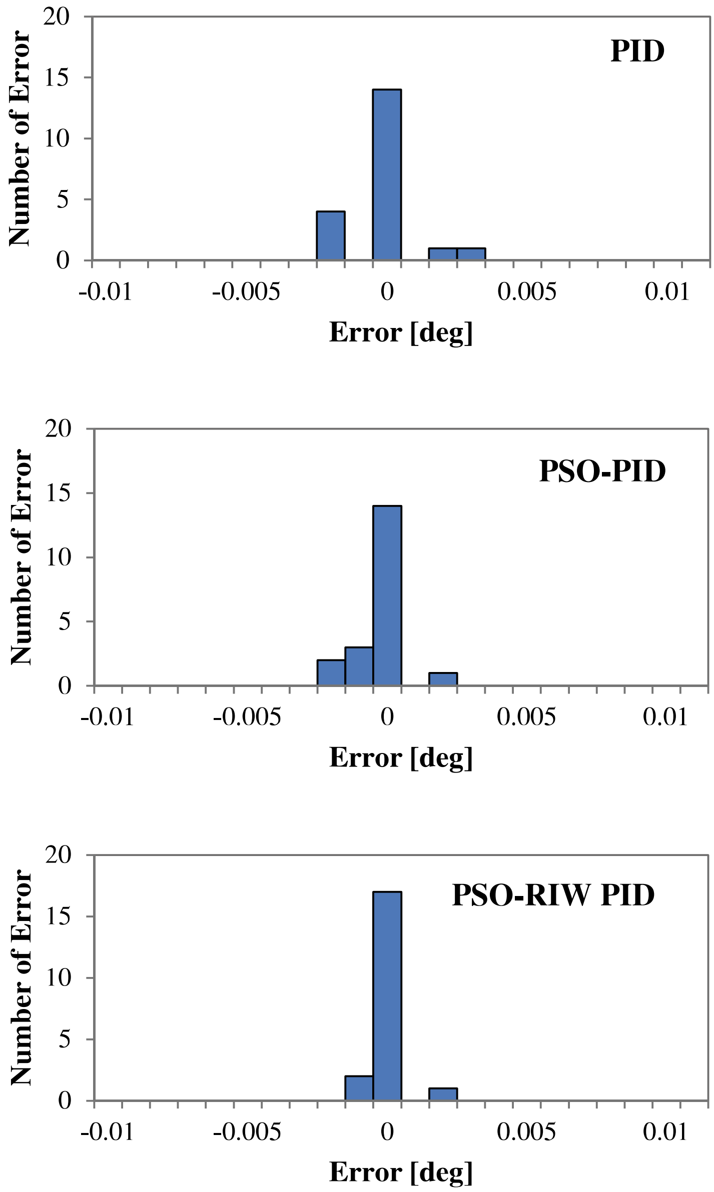

Fig. 3.15 Position accuracy of USM in both directions (unloaded)

Figure 3.17 shows the convergence speed of PSO-RIW and PSO-LDW. It seen clearly that the particles in PSO-RIW achieve faster convergence than the standard type of PSO. The PSO-NDW and PSO-LDW achieve convergence in 0.16 [sec] and 0.26 [sec], respectively.

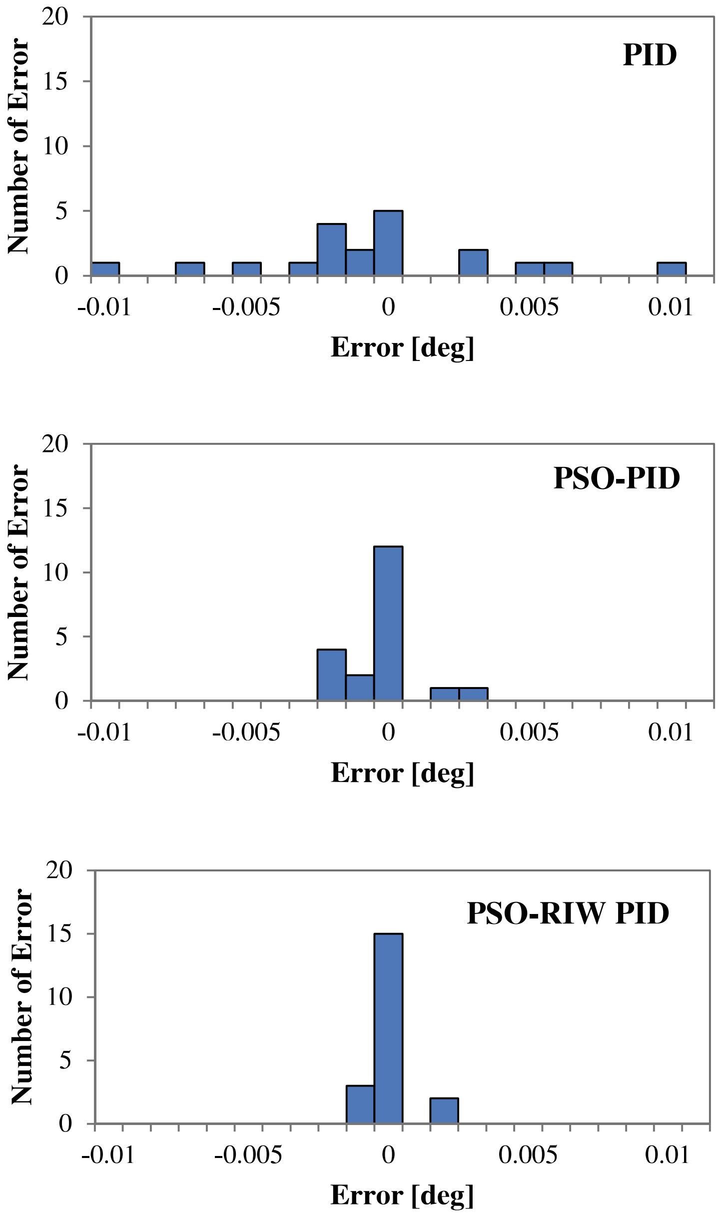

Fig. 3.16 Position accuracy of USM in both directions (loaded)

Table 3.3 Comparison of average error and Success Rate

Methods	**Average of Ess [deg]**		**Frequency of Zero-Ess (Ess < 0.0011 deg) or Success Rate (SR) in 20 trials**	
	Unloaded	**Loaded**	**Unloaded**	**Loaded**
PID	5.78E-4	3.31E-3	14 (70%)	5 (25%)
PSO-LDW PID	5.11E-4	8.94E-4	14 (70%)	12 (60%)
PSO-NDW PID	4.17E-4	4.44E-4	15 (75%)	13(65%)
PSO-RIW PID	1.883E-4	3.31E-4	17 (85%)	15 (75%)

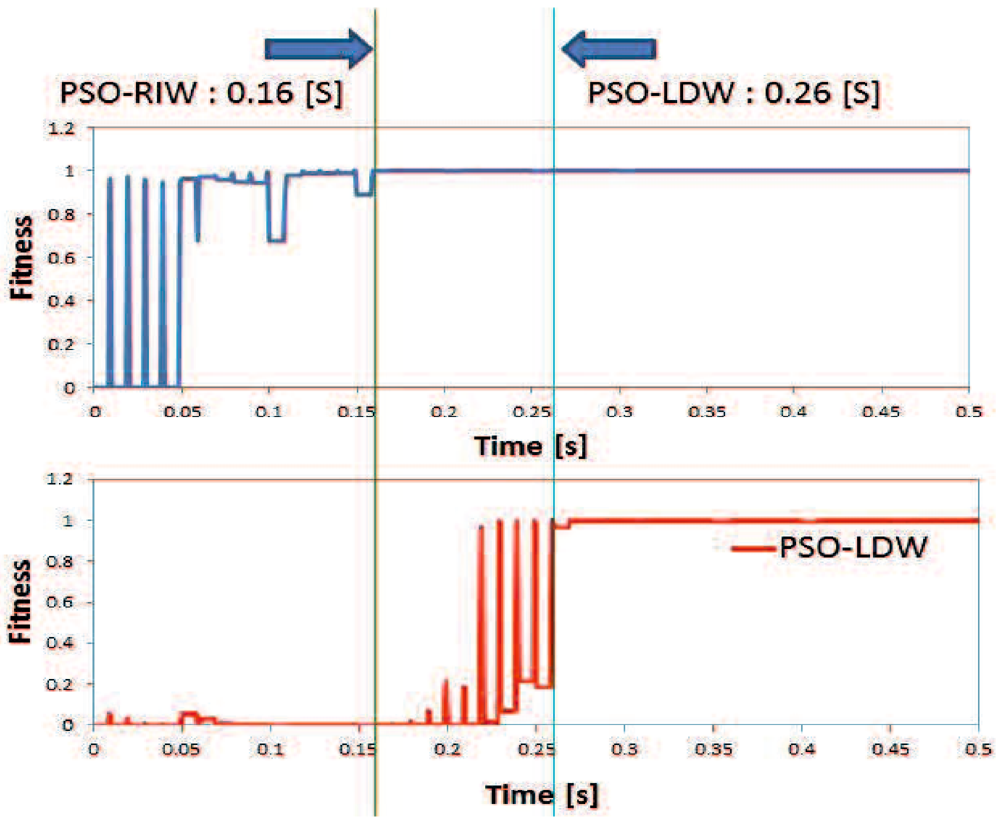

Fig. 3.17 Convergence speed of PSO-RIW PID

3.2.3 Summary

The second proposed Enhanced PSO, called PSO-RIW, uses randomly adjusting of inertia weight, where the inertia weight is a random number in interval [w_{min}, w_{max}] during searching process [74].

We could conclude that:

1. Random inertia weight strategy can effectively overcome the lack ability during iteration due to LDW or NDW strategy and help trapped particles for escaping from local optima. Thus, the ability of particles to avoid premature convergence and escape from local optima is increasing.
2. Random inertia weight strategy can increase the aggressiveness of particles. Particles actively search the best solution, and finally they can capture the best solution.
3. PSO-RIW for self-tuning PID on USM gives a better performace than the previous methods in term of position accuracy of USM and convergence speed.

Chapter 4

Adaptive PSO based Intelligent Self-tuning PID Controller for USM

4.1 APSO based Intelligent Self-tuning PID

4.1.1 Concept of Adaptive Inertia Weight

Particles in swarm are always moving during searching process. Thus, the previous best particle (*Pb*) and the global best particle (*gb*) is always changing. It means that the swarm condition is always changing during searching process. In the previous methods, *i.e.*, PSO-LDW, PSO-NDW, and PSO-RIW, inertia weight is adjusted without regard to the condition of swarm. The inertia weight is still based on iteration or as function of iteration, *i.e.*, linear, nonlinear, and random. There is no information about the condition of swarm. So, there is a possibility that the value of the inertia weight is not suitable with the condition of swarm. This is a weakness of the previous methods.

To overcome those problems, we proposed third strategy, which inertia weight is adjusted adaptively based on the swarm condition. We called the proposed method as PSO with adaptive inertia weight (PSO-AIW) or Adaptive PSO (APSO). The basic idea of APSO is that the *gb* and *Pb* of particles always change during iteration and tend to the similar fitness value if the swarm has approached the best solution. The values of *Pb* and *gb* can be taken from the swarm by using feedback mechanism and then can be used to calculate the inertia weight. We need an initial inertia weight whose value is greater than one, *e.g.*, 1.4.

If the particles are too far from the best solution, the fitness value of *Pb* is greater than *gb*, so the comparison between *gb* and *Pb* is smaller than one ($gb/pb < 1$). In this condition, inertia weight should be set to larger value. If the particles are too close to the best solution, the fitness value of *Pb* is similar to *gb*, so the comparison between *gb* and *Pb* is close to one ($gb/pb \approx 1$). In this condition, inertia weight should be set to smaller value. Due to this strategy, the balancing between exploration-exploitation ability can be controlled according to the swarm condition. The proposed adaptive inertia weight can be shown in following equation:

$$w = w_o - \left(\frac{gb}{Pb_i}\right) \tag{4.1}$$

where w_o is an initial value of inertia weight. The feedback mechanism in APSO is shown in Fig. 4.1. The proposed APSO can eliminate the difficulty in selecting of w_{max}, w_{min} and x.

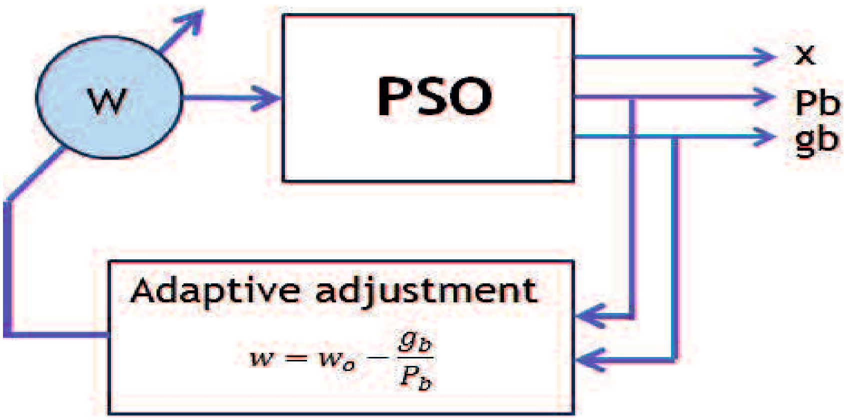

Fig. 4.1 Feedback mechanism in APSO

4.1.2 Experimental Results

To evaluate the effectiveness of the proposed APSO for self-tuning PID controller on USM, we tested it and compared with the previous methods, *i.e.*, fixed-gain PID, PSO-LDW PID, PSO-NDW PID, and PSO-RIW PID. The setting parameters of each method are shown in Table 4.4. The conditions of experiment is set similar to the previous conditions, *i.e.*, the reference input is rectangular wave with +45 [deg] or CW direction and -45 [deg] or CCW direction, the period is 4 [s], unloaded and loaded with 0.25 [Nm] from electromagnetic brake.

The position accuracy of USM controlled by APSO-PID is shown in Fig. 4.2 and 4.3. Compared with the previous methods, *i.e.*, Fig. 3.2 - 3.7, it can be seen that the proposed APSO-PID has better accuracy, where its density around zero is higher than previous methods. In both direction and conditions, as shown in Fig. 4.4 and 4.5, APSO-PID controller indicated its effectiveness and its accuracy in order to compensate the characteristic changes of USM due to loading effect. The AIW strategy can improve the performance of standard type of PSO by reducing the risk of premature convergence and fall into local optima.

The comparisson results of average error and frequency of zero-error between the proposed APSO and the previous methods is shown in Table 4.2. It clears that the proposed APSO PID can outperform a fixed-gain PID, PSO-LDW PID, PSO-NDW PID, and PSO-RIW PID.

Table 4.1 Setting parameters of the methods

Fixed-gain PID	**PSO-LDW PID**	**PSO-NDW PID**	**PSO-RIW PID**	**APSO PID**
$K_p = 0.3692$ $K_i = 12.175$ $K_d = 0.000085$ (hand-tuned)	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.6$ $w_{min} = 0.3$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$

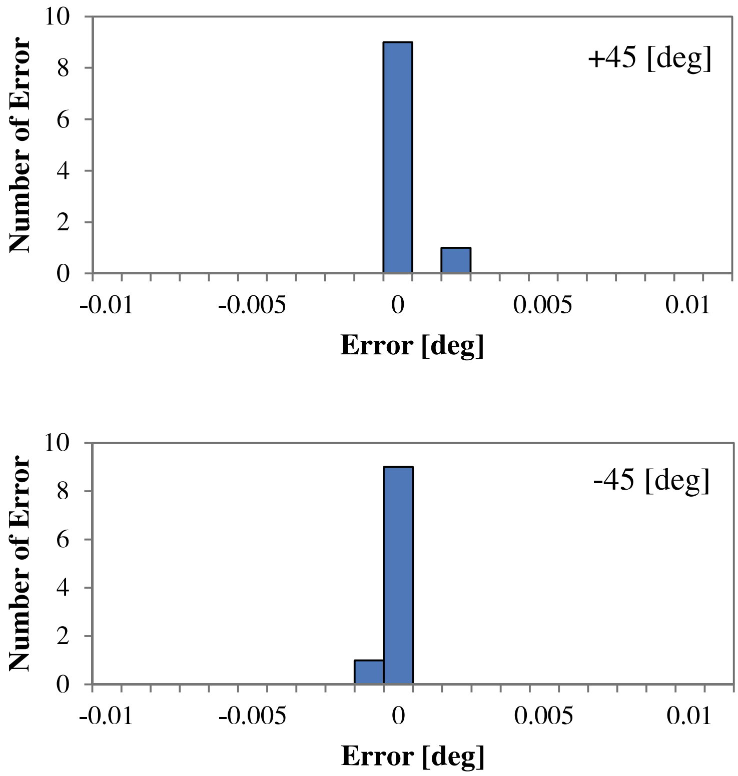

Fig.4.2 Position accuracy of USM using APSO-PID (unloaded)

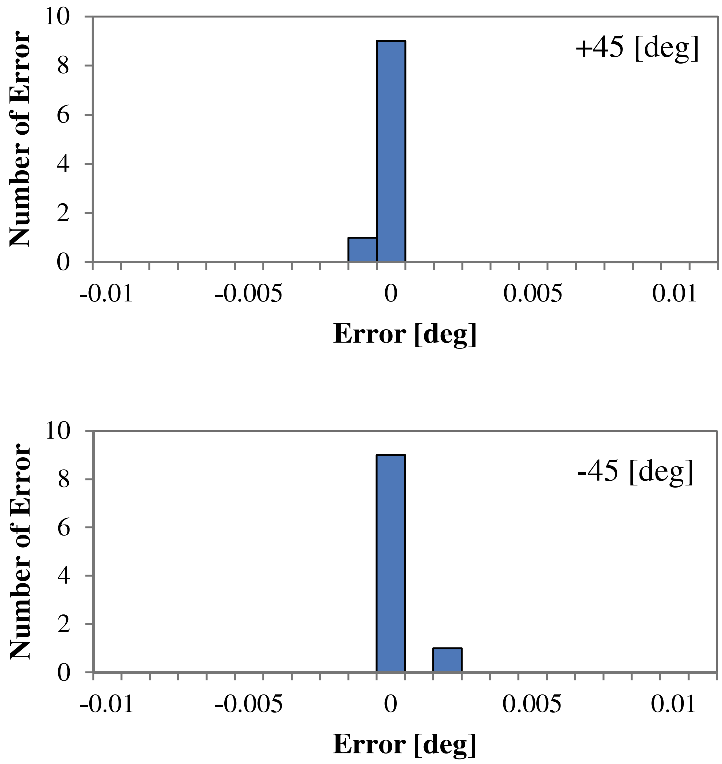

Fig.4.3 Position accuracy of USM using APSO-PID (loaded)

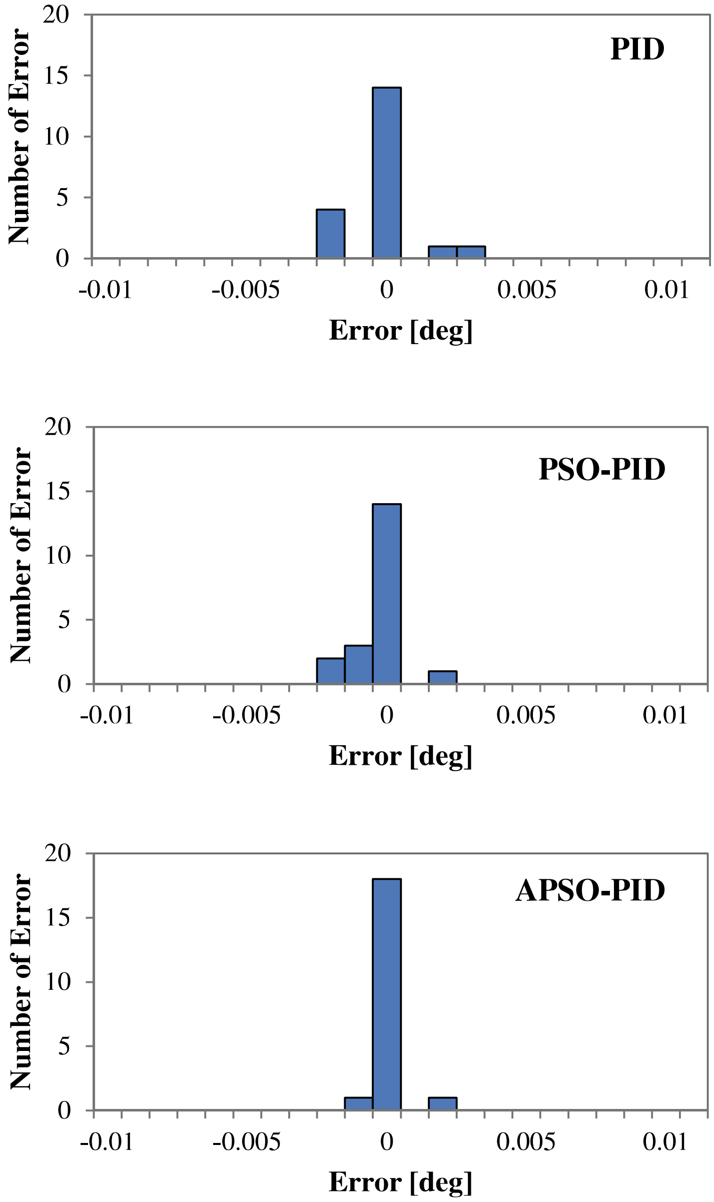

Fig. 4.4 Position accuracy of USM in both directions (unloaded)

The average of error of APSO PID is smallest or 67.32% (unloaded) and 72.71% (loaded) lower than the PSO-LDW PID. Moreover, the frequency of zero-error of APSO PID is more often than the previous methods or success rate *(SR)* of APSO PID is higher than the previous methods. Higher of success rate (*SR)* shows that the particles have better ability to avoid premature convergence and escape from the local optima.

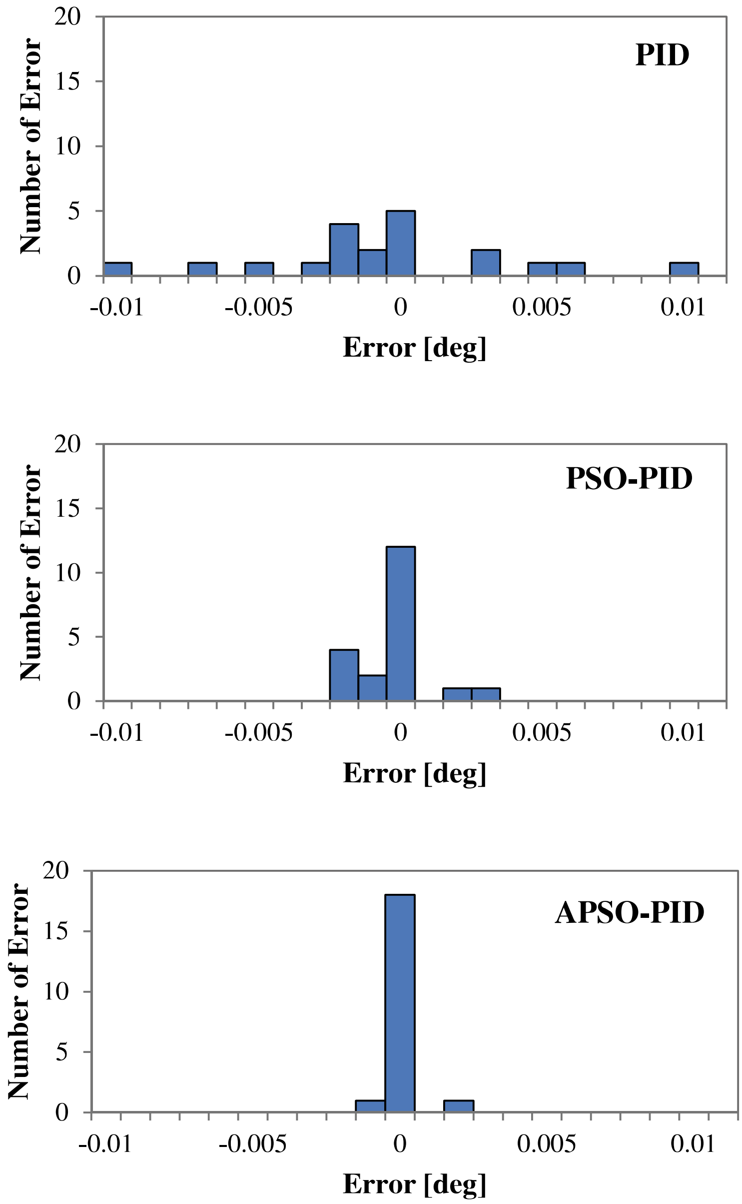

Fig. 4.5 Position accuracy of USM in both directions (loaded)

Figure 4.6 shows the convergence speed of APSO and PSO-LDW. It seen clearly that the particles in APSO-RIW are very aggressive and faster to achieve convergence than the standard type of PSO. The APSO and PSO-LDW achieve convergence in 0.11 [sec] and 0.26 [sec], respectively. So, the convergence speed of APSO is more two time faster than PSO-LDW.

Table 4.2 Comparison of average error and Success Rate

Methods	Average of Ess [deg]		Frequency of Zero-Ess (Ess < 0.0011 deg) or Success Rate (SR) in 20 trials	
	Unloaded	**Loaded**	**Unloaded**	**Loaded**
PID	5.78E-4	3.31E-3	14 (70%)	5 (25%)
PSO-LDW PID	5.11E-4	8.94E-4	14 (70%)	12 (60%)
PSO-NDW PID	4.17E-4	4.44E-4	15 (75%)	13(65%)
PSO-RIW PID	1.883E-4	3.31E-4	17 (85%)	15 (75%)
APSO-PID	1.67E-4	2.44E-4	18 (90%)	18 (90%)

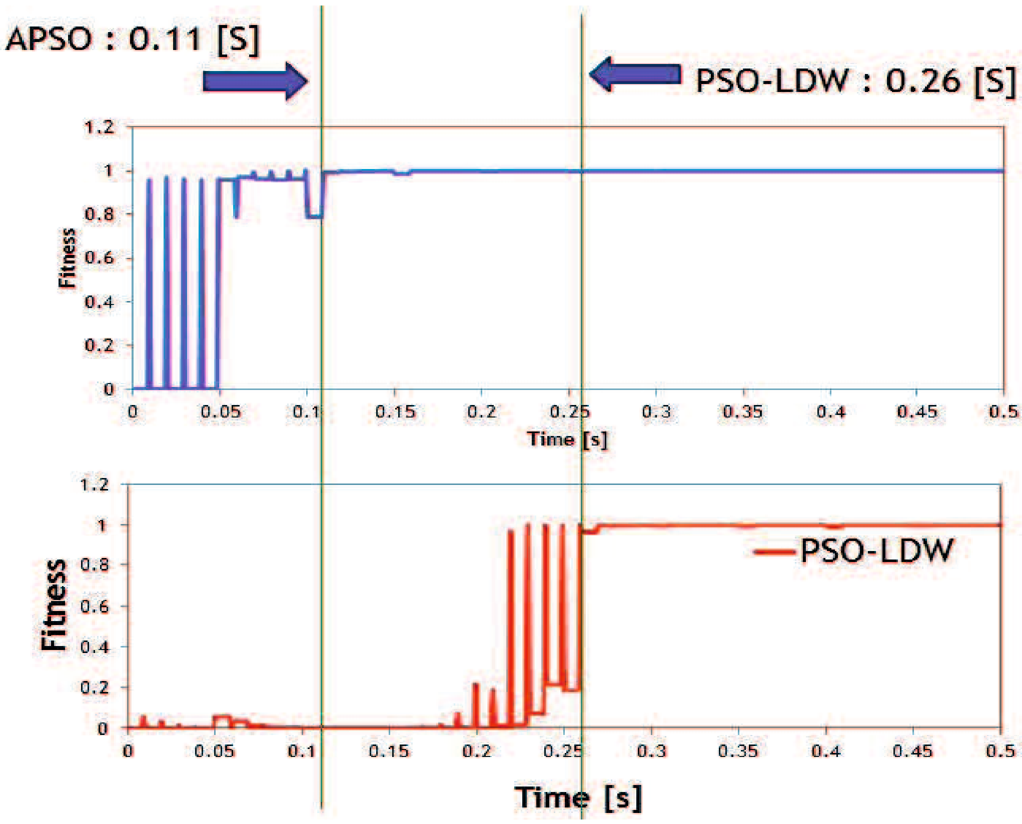

Fig. 4.6 Convergence speed of APSO-PID

4.1.3 Summary

The third proposed Enhanced PSO, called APSO, uses adaptively adjusting of inertia weight based on the swarm condition [75].

We could conclude that:

1. Adaptive inertia weight strategy uses the swarm condition at any time to calculate inertia weight. Due to this strategy, a proper inertia weight can be achieved appropriately and quickly.
2. Adaptive inertia weight strategy shows more simplicity and effective to improve PSO and eliminate the difficulty in selecting w_{max}, w_{min}, and x as in PSO-LDW,PSO-NDW, and PSO-RIW.
3. A new parameter in APSO is initial inertia weight to give a final value when the solution is found.
4. APSO for self-tuning PID on USM gives a better performace than the previous methods in term of position accuracy of USM and convergence speed.

4.2 APSO-RIW based Intelligent Self-tuning PID

4.2.1 Concept of Hybrid APSO-RIW

Improving PSO to reduce the risk of premature convergence and fall into local optima is being investigated intensively. Several strategies have been proposed for improving PSO. However, the research to improve PSO is still being conducted.

The previous proposed strategy called PSO-RIW has a main benefit, *e.g.*, high ability to avoid premature convergence and escape from local optima. And other previous strategy called APSO has a main benefit, *e.g.*, faster convergence or quick to achieve a proper balance between exploration-eplotation ability. The fourth proposed Enhanced PSO is motivated by benefit of the PSO-RIW and APSO. We called it as hybrid APSO-RIW (Adaptive Particle Swarm Optimization with Random Inertia Weight). The method is to combine the benefit of both PSO-RIW and APSO. During searching process, the fitness value of *Pb* and gb is taken from the ouput of PSO and is used to calculate inertia weight. The RIW strategy is inserted into APSO equation to give higher ability or aggressiveness for particles. Adjusting of inertia weight in the proposed hybrid APSO-RIW is shown as folllows:

$$w = \left\{w_o - \frac{gb}{Pb_i}\right\} \cdot \{w_{min} + (w_{max} - w_{min}) \cdot r\} \tag{4.2}$$

4.2.2 Experimental Results

To evaluate the effectiveness of the proposed Hybrid APSO-RIW for self-tuning PID controller on USM, we tested it and compared with the previous methods, *i.e.*, fixed-gain PID, PSO-LDW PID, PSO-NDW PID, PSO-RIW PID and APSO PID. The setting parameters of each method are shown in Table 4.6. The conditions of experiment is set similar to the previous conditions, *i.e.*, the reference input is rectangular wave with +45 [deg] or CW direction and -45 [deg] or CCW direction, the period is 4 [s], unloaded and loaded with 0.25 [Nm] from electromagnetic brake.

The position accuracy of USM controlled by APSO-RIW PID is shown in Fig. 4.7 and 4.8. Compared with the previous methods, *i.e.*, Fig. 3.2 - 3.7, it can be seen that the proposed APSO-RIW PID has better accuracy, where its density around zero is higher than previous methods. In both direction and conditions, as shown in Fig. 4.9 and 4.10, APSO-PID controller indicated its effectiveness and its accuracy in order to compensate the characteristic changes of USM due to loading effect. Hybrid APSO-RIW strategy can improve the performance of the standard type of PSO by reducing the risk of premature convergence and fall into local optima.

The comparisson of average error and frequency of zero-error between the proposed APSO and the previous methods is shown in Table 4.4. It clears that the proposed APSO-RIW PID can outperform a fixed-gain PID, PSO-LDW PID, PSO-NDW PID, PSO-RIW PID and APSO PID.

Table 4.3 Parameters setting

Fixed-gain PID	PSO-LDW PID	PSO-NDW PID	PSO-RIW PID	APSO PID	APSO-RIW PID
$K_p = 0.3692$ $K_i = 12.175$ $K_d =$ 0.000085 (hand-tuned)	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.6$ $w_{min} = 0.3$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$ $w_{max} = 0.6$ $w_{min} = 0.3$

The average of error of APSO-RIW PID is smallest or 100% (unloaded) and 93.18% (loaded) lower than the PSO-LDW PID. Moreover, the frequency of zero-error of APSO-RIW PID is more often than the previous methods or success rate (*SR)* of APSO-RIW PID is higher than the previous methods. Higher of success rate (*SR)* shows that the particles have better ability to avoid premature convergence and escape from the local optima.

Figure 4.28 shows the convergence speed of APSO-RIW and PSO-LDW. It seen clearly that the particles in APSO-RIW are aggressive and faster to achieve convergence than the standard type of PSO. The APSO-RIW and PSO-LDW achieve convergence in 0.15 [sec] and 0.26 [sec], respectively. So, the convergence speed of APSO is almost two times faster than PSO-LDW.

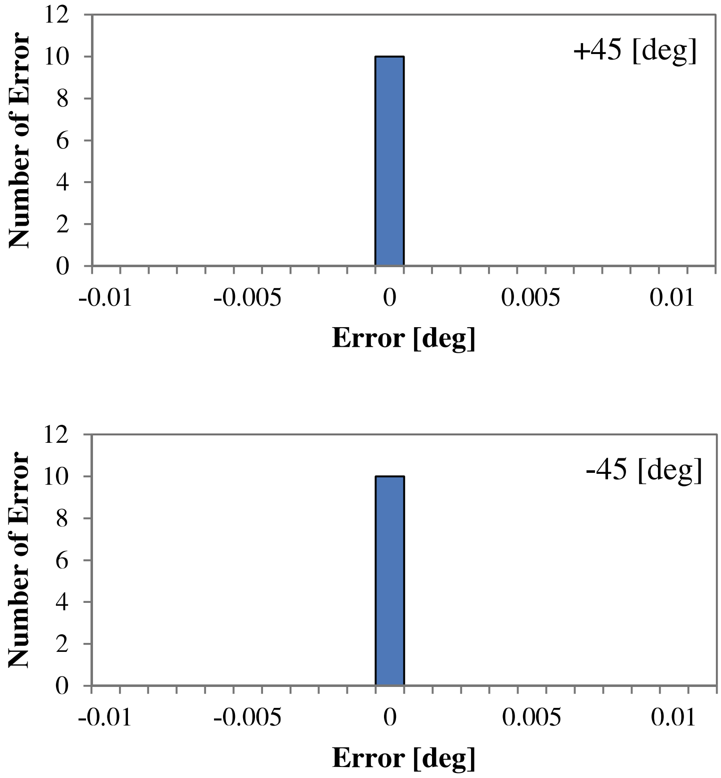

Fig. 4.7 Position accuracy of USM using APSO-RIW PID (unloaded)

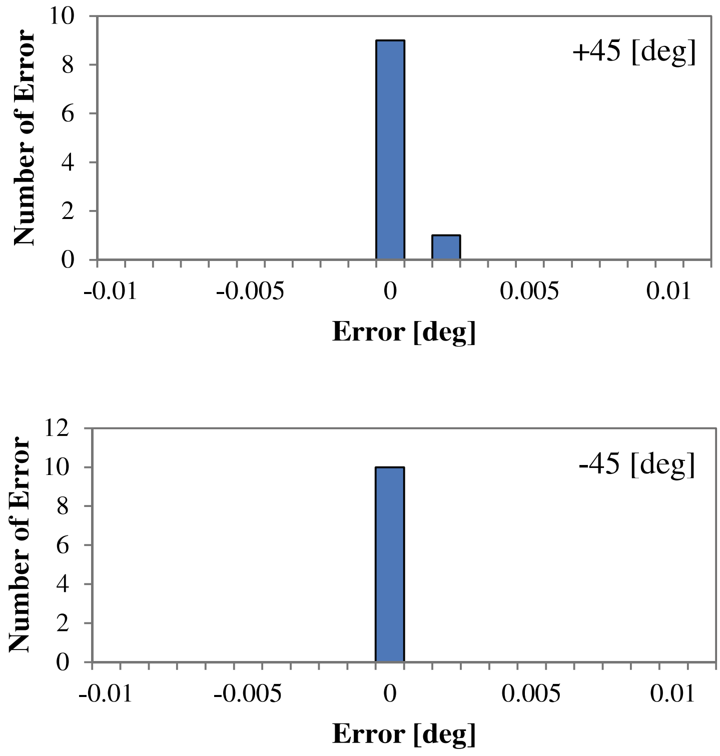

Fig. 4.8 Position accuracy of USM using APSO-RIW PID (loaded)

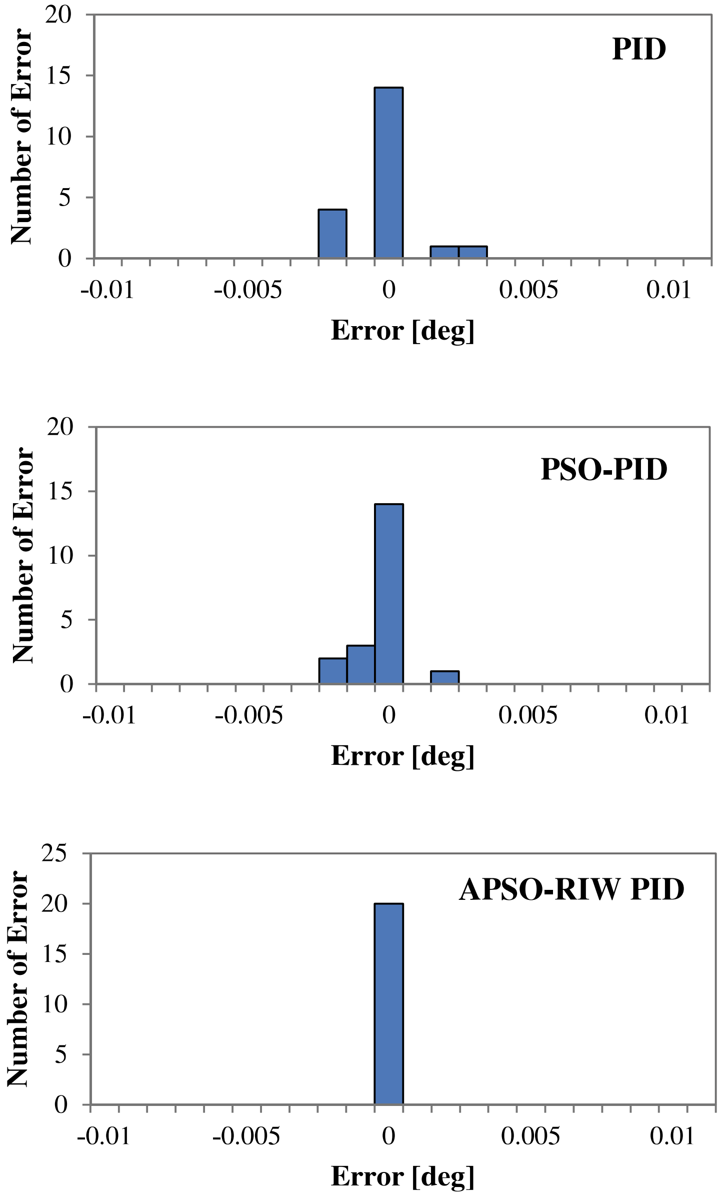

Fig. 4.9 Position accuracy of USM in both directions (unloaded)

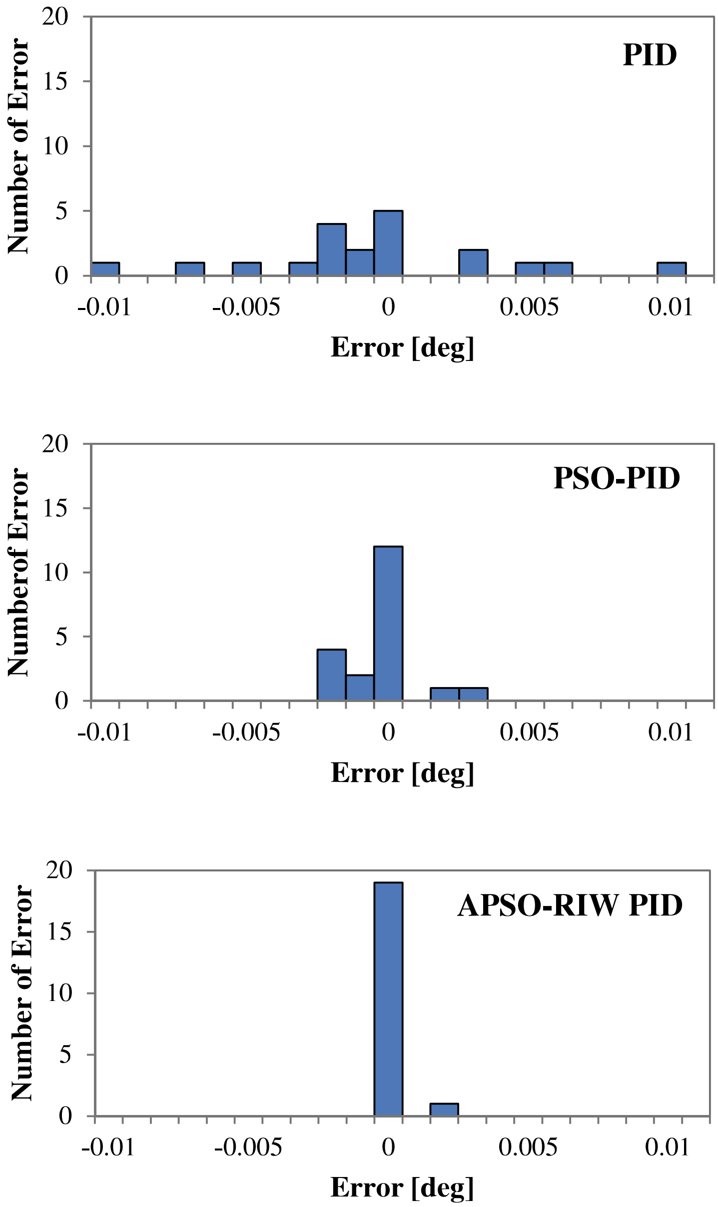

Fig. 4.10 Position accuracy of USM in both directions (loaded)

Table 4.4 Comparison of average error and Success Rate

Methods	**Average of Ess [deg]**		**Frequency of Zero-Ess (Ess < 0.0011 deg) or Success Rate (SR) in 20 trials**	
	Unloaded	**Loaded**	**Unloaded**	**Loaded**
PID	5.78E-4	3.31E-3	14 (70%)	5 (25%)
PSO-LDW PID	5.11E-4	8.94E-4	14 (70%)	12 (60%)
PSO-NDW PID	4.17E-4	4.44E-4	15 (75%)	13(65%)
PSO-RIW PID	1.883E-4	3.31E-4	17 (85%)	15 (75%)
APSO-PID	1.67E-4	2.44E-4	18 (90%)	18 (90%)
APSO-RIW PID	0	6.10E-5	20 (100%)	19 (95%)

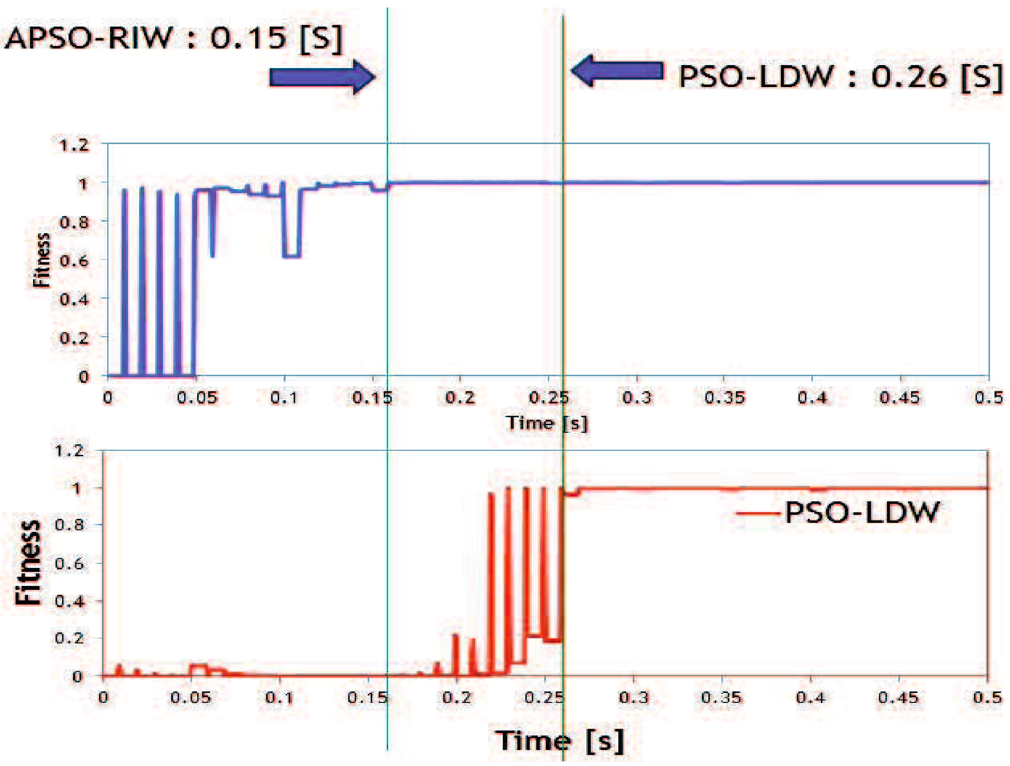

Fig. 4.11 Convergence speed of APSO-RIW PID

4.2.3 Summary

The fourth Enhanced PSO, called Hybrid APSO-RIW, uses combination between APSO and PSO-RIW atrategy [76].

We could conclude that:

1. The Hybrid APSO-RIW can combine both benefit of APSO and PSO-RIW. Inertia weight is adjusted adaptively according to swarm condition and also use random strategy at the same time. Due to this strategy, a proper inertia weight can be achieved appropriately and quickly.
2. Hybrid APSO-RIW strategy holds on simplicity and effective to improve PSO by increasing the ability of particles for avoiding premature convergence and escaping from local optima.
3. Hybrid APSO-RIW for self-tuning PID on USM gives a better performace than the previous methods in term of position accuracy of USM and convergence speed.

4.3 Hybrid Adaptive Improved PSO Based Intelligent Self-tuning PID

4.3.1 Concept of Hybrid Adaptive Improved PSO

To more reduce effectively the risk of premature convergence and fall into local optima requires combination between several strategies to overcome the causes of the shortcoming of PSO. In the fifth proposed method, we propose a new strategy to combine three strategies at the same time. The first strategy is adaptive inertia weight to find a proper inertia weight quickly. Due to proper inertia weight, the suitable balance between exploration-exploitation can reduce the shortcoming of PSO. The second strategy is using mutation operator to more ensure that the trapped particles can escape from local optima and to more increase the ability of particles to avoid premature convergence. The main idea of the proposed method is taken from the advantage of mutation operator in GA to give more diversity of particles for jumping-out from local optima. Mutation in

GA is flipping a bit of chromosome. Mutation rate are typically quite low (0.1-1.0 % is a common range), so that at the beginning the effect of mutation is relatively small and increasing toward the end. Mutation in PSO is operated on stagnated particles by giving small random variation. We use mutation operator on global best position of particle with small random variation below 10%. Therefore the diversity of populations can be maintained and prevent premature convergence or fall in the local optima. The third strategy is additional part called socio-cognitive part to create a new particle's moving mechanism and to compensate the lack information and fast rate flow in sharing information. The new factor connects between personal and global best position. The new factor together with the original factor, *i.e.*, cognitive and social factor, will influence the current particle to determine the next position of particles, so that the ability to find the best solution can be increased. We called the proposed method as Hybrid Adaptive Improved PSO combined with mutation or HAIPSO. Thus, the equations of the proposed method are changed as follows:

$$v_i^{m+1} = w.v_i^m + c_1.r_1.\{Pb_i - x_i^m\} + c_2.r_2.\{gb - x_i^m\} + c_3.r_3.\{gb - Pb_i\} \tag{4.3}$$

$$w = w_o - \left(\frac{gb^*}{Pb_i}\right) \tag{4.4}$$

$$gb^* = gb.\gamma \tag{4.5}$$

$$\gamma = 1 + 0.1 \cdot r \tag{4.6}$$

where gb^* is mutated gb, γ is mutation rate (in here, below 10%), r is random number, w_o is an initial value of inertia weight.

The new mechanism of information sharing in HIPSO can be illustrated in Fig. 4.12. Now, the next position of particle is the resultant of four vectors. Due to this new mechanism, fast rate flow of sharing information can be slightly reduced and additional information will give a better direction for particle to find a best solution.

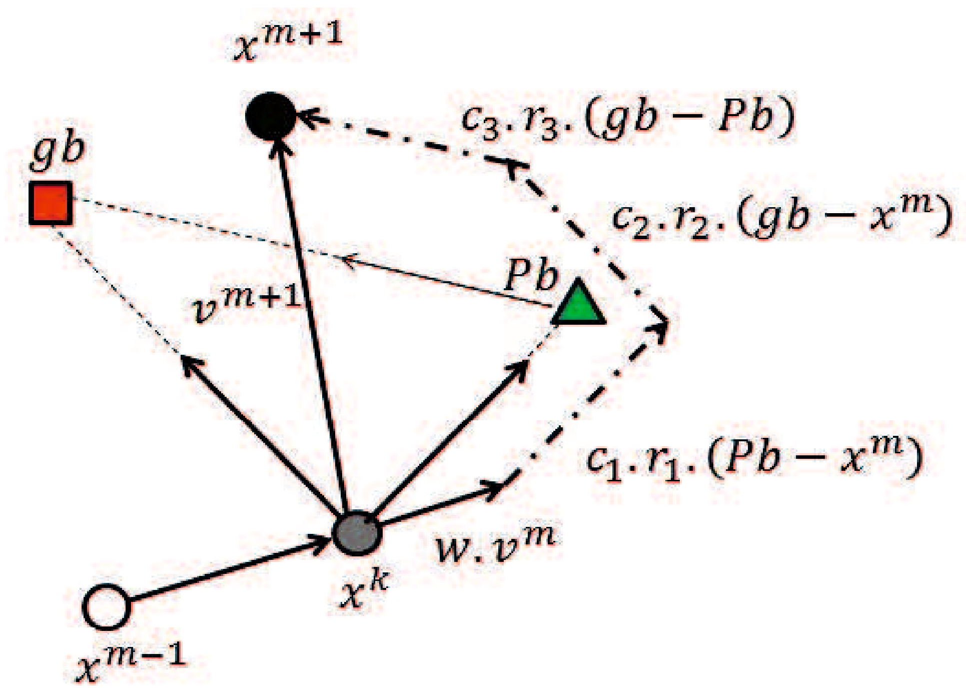

Fig. 4.12 New particle's movement in HAIPSO

4.3.2 Experimental Results

To evaluate the effectiveness of the proposed HAIPSO for self-tuning PID controller on USM, we tested it and compared with the previous methods, *i.e.*, fixed-gain PID, PSO-LDW PID, PSO-NDW PID, PSO-RIW PID , APSO PID, and APSO-RIW PID. The setting parameters of each method are shown in Table 4.8. The conditions of experiment is set similar to the previous conditions, *i.e.*, the reference input is rectangular wave with +45 [deg] or CW direction and -45 [deg] or CCW direction, the period is 4 [s], unloaded and loaded with 0.25 [Nm] from electromagnetic brake.

The position accuracy of USM controlled by HAIPSO-PID is shown in Fig. 4.13 and 4.14. Compared with the previous methods, *i.e.*, Fig. 3.2 – 3.7, it can be seen that the proposed HAIPSO-PID has better accuracy, where its density around zero is higher than previous methods. In both direction and conditions, as shown in Fig. 4.15 and 4.16, HAIPSO based PID controller indicated its effectiveness and its accuracy in order to compensate the characteristic changes of

USM due to loading effect. The HAIPSO strategy can improve the performance of the standard type of PSO by reducing the risk of premature convergence and fall into local optima.

The comparison of average error and frequency of zero-error between the proposed HAIPSO and the previous methods is shown in Table 4.6. It clears that the proposed HAIPSO-PID can outperform a fixed-gain PID, PSO-LDW PID, PSO-NDW PID, PSO-RIW PID, APSO PID, and APSO-RIW PID. The average of error of APSO-RIW PID is smallest or 0 in both conditions. Moreover, the frequency of zero-error of APSO-RIW PID is more often than the previous methods or success rate (*SR*) of APSO-RIW PID is higher than the previous methods. It means that the error is smaller than the resolution of the encoder, *i.e.*, 0.0011 [deg]. Or, we can say that the encoder cannot measure the position error because of its limitation. Higher of success rate (*SR*) shows that the particles have better ability to avoid premature convergence and escape from the local optima.

Figure 4.17 shows the convergence speed of HAIPSO and PSO-LDW. It seen clearly that the particles in HAIPSO are aggressive and faster to achieve convergence than the standard type of PSO. The HAIPSO and PSO-LDW achieve convergence in 0.16 [sec] and 0.26 [sec], respectively. So, the convergence speed of Hybrid AIPSO-Mut is one and half times faster than PSO-LDW.

Table 4.5 Parameters setting

Methods						
Fixed-gain PID	PSO-LDW PID	PSO-NDW PID	PSO-RIW PID	APSO PID	APSO-RIW PID	Hybrid APSO-Mut
$K_p = 0.3692$ $K_i = 12.175$ $K_d =$ 0.000085 (hand-tuned)	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.9$ $w_{min} = 0.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_{max} = 0.6$ $w_{min} = 0.3$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$ $w_{max} = 0.6$ $w_{min} = 0.3$	$n = 5$ $c_1 = 1.0$ $c_2 = 1.0$ $w_o = 1.4$ γ

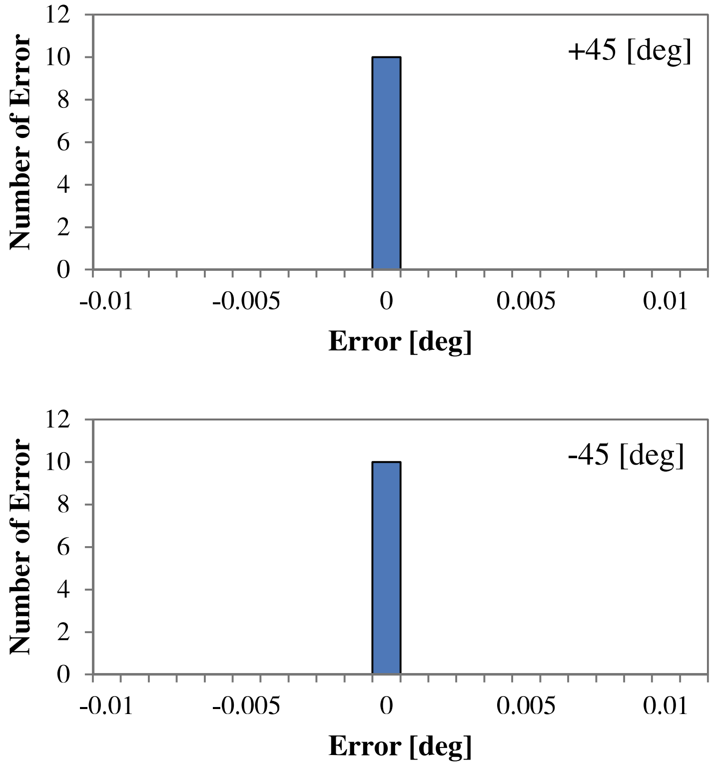

Fig.4.13 Position accuracy of USM using HAPSO-PID (unloaded)

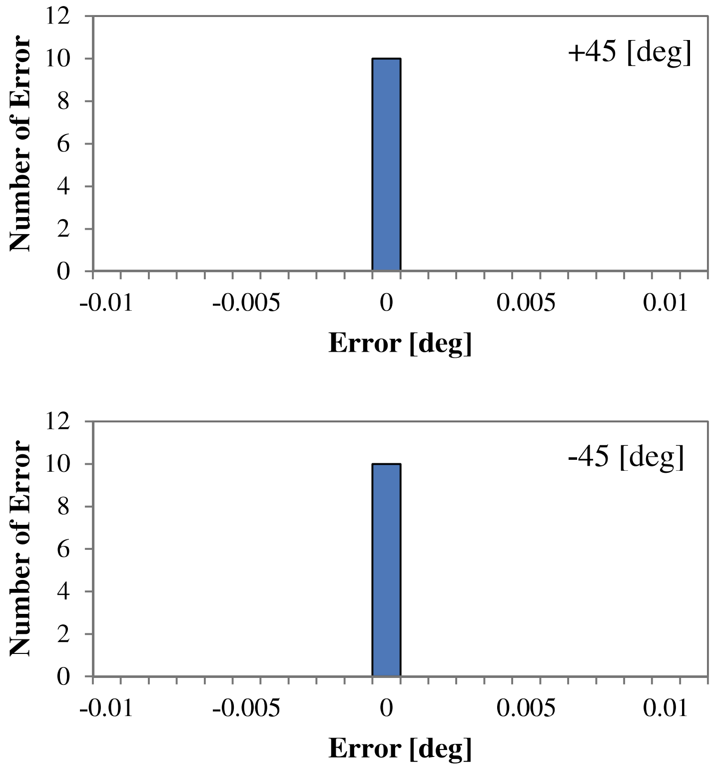

Fig.4.14 Position accuracy of USM using HAPSO-PID (loaded)

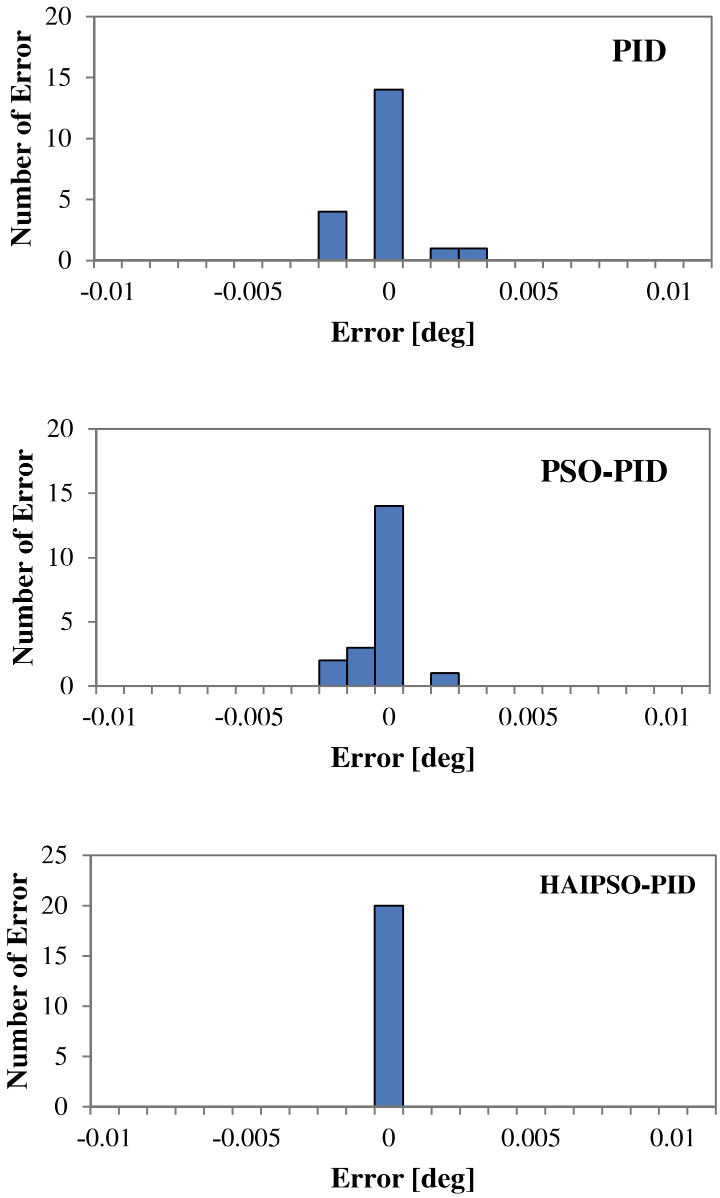

Fig. 4.15 Position accuracy of USM in both directions (unloaded)

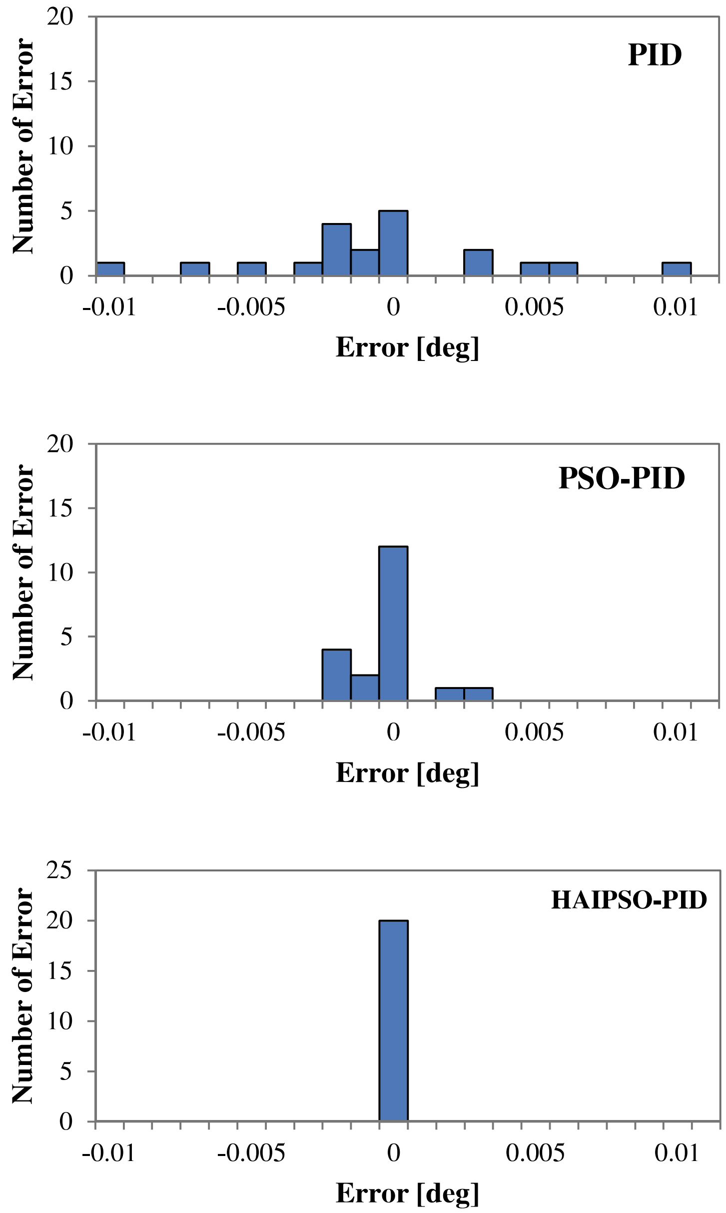

Fig. 4.16 Position accuracy of USM in both directions (loaded)

Table 4.6 Comparison of average error and Success Rate

Methods	**Average of Ess [deg]**		**Frequency of Zero-Ess (Ess < 0.0011 deg) or Success Rate (SR) in 20 trials**	
	Unloaded	**Loaded**	**Unloaded**	**Loaded**
PID	5.78E-4	3.31E-3	14 (70%)	5 (25%)
PSO-LDW PID	5.11E-4	8.94E-4	14 (70%)	12 (60%)
PSO-NDW PID	4.17E-4	4.44E-4	15 (75%)	13(65%)
PSO-RIW PID	1.883E-4	3.31E-4	17 (85%)	15 (75%)
APSO-PID	1.67E-4	2.44E-4	18 (90%)	18 (90%)
APSO-RIW PID	0	6.10E-5	20 (100%)	19 (95%)
HAIPSO- PID	0	0	20 (100%)	20 (100%)

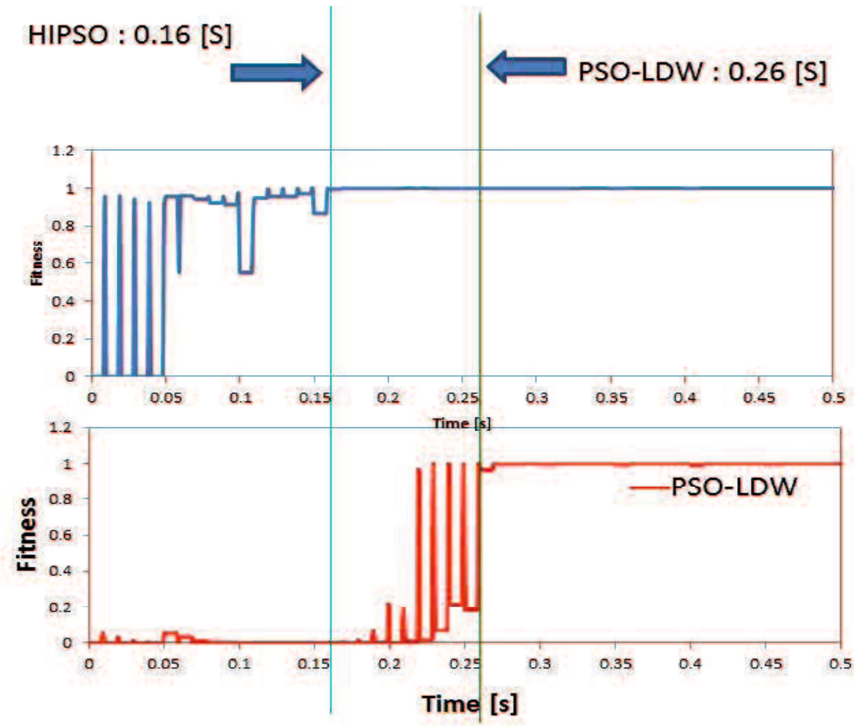

Fig. 4.17 Convergence speed of HAIPSO-PID

4.3.3 Summary

The fifth proposed Enhanced PSO, called Hybrid Adaptive Improved PSO (HAIPSO), uses combination of three strategies at the same time [80].

We could conclude that:

1. The HAIPSO combined three strategies at the same time shows best performance for self-tuning PID controller on USM. Adding a new factor, adaptive inertia weigh and using mutation operator in the proposed method has proven to be very effective in improving PSO and eliminating the risk of premature convergence and fall into local optima.
2. HAIPSO strategy holds on the properties of simple algorithm with a few of parameters to be tuned, faster convergence, efficient in time-calculation and at the same time enhances the capability of particles for accurately searching a best solution.
3. A new parameter in HAIPSO are initial inertia weight (w_o) and mutation rate. These parameters should be adjusted properly in order to get a best performance.
4. HAIPSO for self-tuning PID on USM gives a better performace than the previous methods in term of position accuracy, capability to avoid premature convergence and escape from local optima.

Chapter 5

Discussion and Conclusion

5.1 Discussion

Tuning process is a real complex optimization problem. The performance of PID controller absolutely depends on this process. Many conventional tuning methods are available, but they become more difficult for system with strong nonlinearity, uncertainty, complexity and disturbances. Intelligent self-tuning scheme is developed to overcome this problem, e.g., Genetic Algorithm (GA), Fuzzy, Neural-Netwotk (NN), Particle Swarm Optimization (PSO), etc. Each method has its advantages and disadvantages. For guaranteed optimal solution, even thought, it might take a lot of time or work, it is better not to use PSO. However, for an approximate solution or near optimal and it spend a less time or work, it better to use PSO. Due to PSO, we will get low computational cost, low memory requirement, robustness (good performance for a wide class of problems), and satisfactory accuracy. Also, it spend less time to obtain the results. So, PSO is more suitable for online or real-time system. Table 5.1 shows a comparison of optimization technique for self-tuning PID controller.

In the research, we have proposed five strategies to impove the standard type of PSO and apply them for intelligent self-tuning PID controller on USM servo system. In the first proposed strategy called PSO-NDW (PSO with nonlinearly decreased inertia weight), inertaia weight is decreased nonlinearly from maximum value to minimum value to give stronger exploration at the beginning and stronger exploitation at the end of iteration.

Table 5.1 Comparison of optimization technique

Parameters	Self-tuning scheme for PID control			
	GA	**Fuzzy**	**NN**	**PSO**
Guaranteed solution (Success Rate)	Best	Medium	Best	Medium
Convergence speed	Medium	Best	Worse	Best
Time calculation	Worse	Medium	Worse	Best
Premature convergence	Best	Medium	Medium	Worse
Simplicity	Worse	Medium	Worse	Best
Computational cost	Medium	Medium	Highest	Lowest
Memory requirement	Medium	Medium	Highest	Lowest

PSO-NDW requires a new parameter called nonlinear index number to control the period of exploration and exploitation ability. Inertia weight is a nonlinear function of iteration or generally called time-varying function or **iteration function**. In the second proposed strategy called PSO-RIW (PSO with random inertia weight), inertia weight is randomly number in interval $[w_{min}, w_{max}]$ to compensate the lack ability during searching process and to help trapped particles for escaping from local optima. Inertia weight is not a time-varying function or generally called **random-function**. Inertia weight doesn't depend on iteration. In the third proposed strategy called APSO (Adaptive PSO), inertia weight is adjusted adaptively according to the swarm condition to ensure for finding a proper balancing between exploration-exploitation ability. Inertia weight is a

condition-function. In the fourth proposed strategy called APSO-RIW (Adaptive PSO with random inertia weight), inertia weight is a **hybrid-function** of combination between APSO and PSO-RIW. In the fifth proposed strategy called HAIPSO (Hybrid Adaptive Improved PSO), inertia weight is a **hybrid-function** of combination between APSO and mutation function of GA. As shown in Table 5.2, each strategy requires several parameters to be tuned. The performance of each strategy depends on these parameters. For reasons of simplicity, the strategy with the fewer parameters is better. The APSO requires only three parameters to be tuned. Compare with other strategies, APSO is simplest as like the original PSO founded by Dr. Eberhart and Dr. Kennedy. But, the performance of APSO is much better.

Improving PSO to reduce the risk of premature convergence and fall into local optima requires knowledge why they could happen. There are several causes of shortcoming of PSO, *e.g.*, unbalance between exploration-exploitation ability, lost diversity and lack information due to fast rate flow and 'one direction' in sharing information. It was reported that inertia weight is most important parameter of PSO to control the balance. However, how to adjust inertia weight in order to get a proper balance is unclear and more need investigation. The first to fourth proposed strategy, *i.e.*, PSO-NDW, PSO-RIW, APSO, and APSO-RIW, used inertia weight adjustment strategy. The fifth proposed strategy, *i.e.*, HAIPSO,, used combination of three strategies, *i.e.*, adaptive inertia weight, mutation operator, and new sharing information. Figure 5.1 and 5.2 show the effectiveness of each strategy for compensating the characteristic changes of USM due to the loading effect. Position accuracy of USM and Success Rate (SR) is getting better on HAIPSO. It means that inertia weight strategy is effective for improving PSO and more effective when combine with other strategy. Adaptive inertia weight strategy is to get a proper balance quickly, mutation operator is to keep diversity of swarm, and new sharing information is to compensate the lack information during searching process. HAIPSO combined three strategies have proved effectively in reducing the risk of premature convergence and fall into local optima. Also, HAIPSO has the best effectiveness for addressing the characteristic changes of USM.

Convergence speed of each strategy is shown in Fig.5.3. Convergence speed of APSO is fastest. It means that due to adaptive inertia weight, the proper balance can be achieved very quickly, so particles can find the global best solution in very short time. The swarm condition will be monitored continuously during iteration to calculate a proper inertia weight. Convergence speed of HAIPSO is a little slower than APSO because there is a new factor or vector in particle's movement affecting the calculation-time.

Table 5.2 Number of parameters

Methods	**PSO-LDW**	**PSO-NDW**	**PSO-RIW**	**APSO**	**Hybrid APSO-RIW**	**HAIPSO**
Parameter	c_1 c_2 w_{max} w_{min}	c_1 c_2 w_{max} w_{min} x	c_1 c_2 w_{max} w_{min}	c_1 c_2 w_o	c_1 c_2 w_{max} w_{min} w_o	c_1 c_2 w_o γ
Number	4	5	4	3	5	4

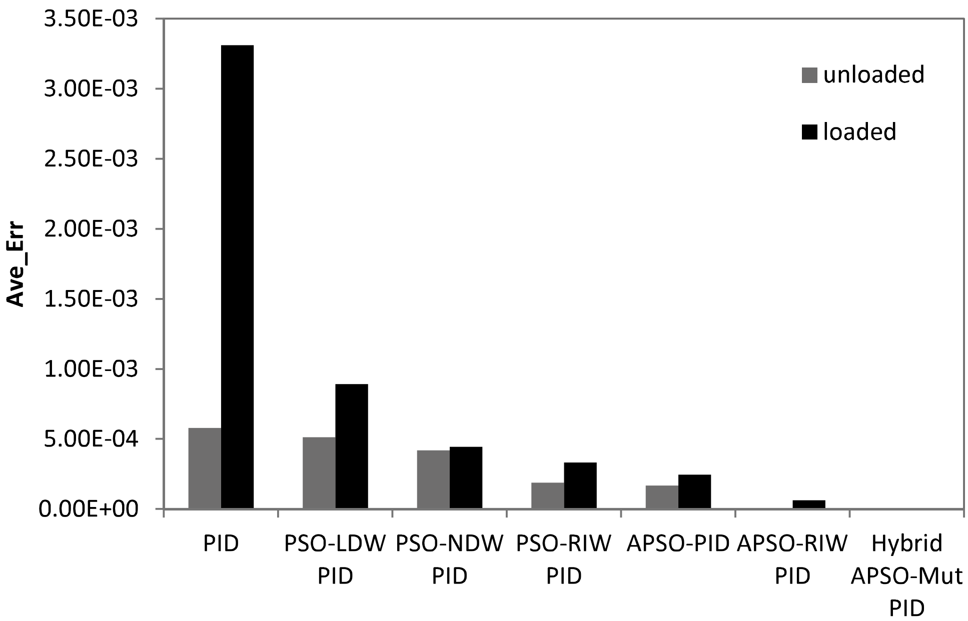

Fig. 5.1 Comparison of average error

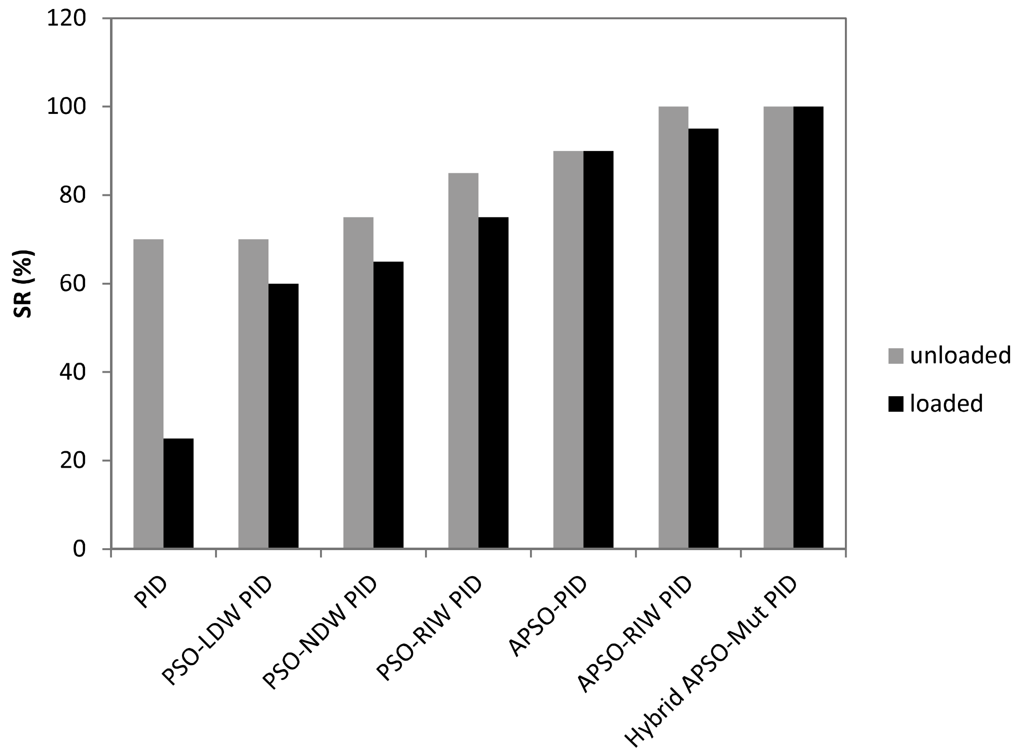

Fig. 5.2 Comparisons of success rate

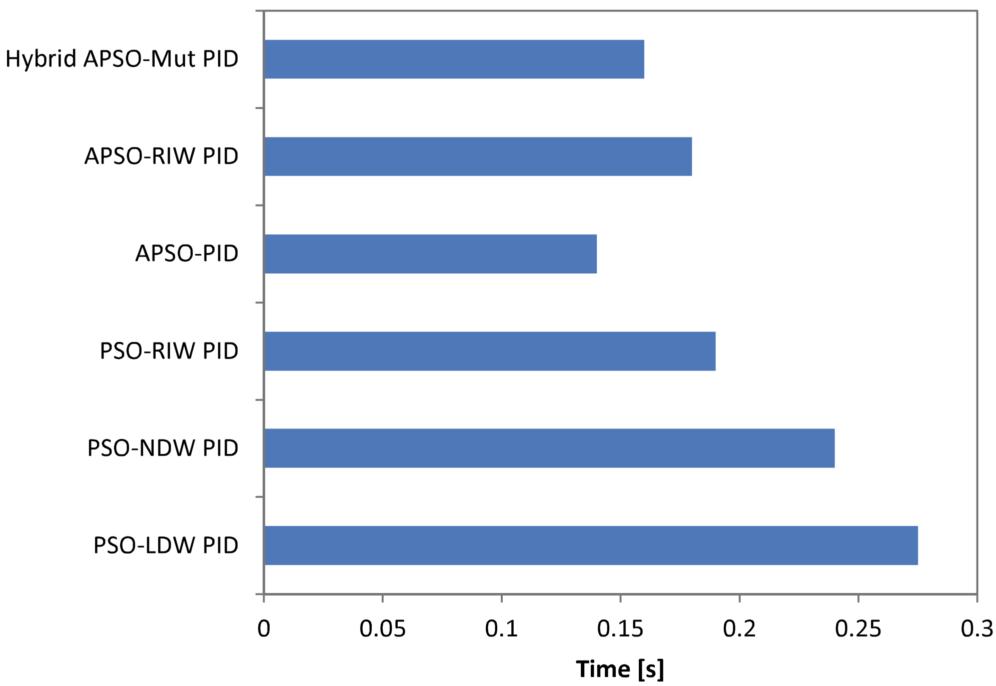

Fig. 5.3 Comparisons of convergence speed

5.2 Summary of Proposed Methods

In the research, we developed five variants of Enhanced PSO and applied it for intelligent self-tuning PID controller on USM servo system. In general, the proposed control method is better than the previous control methods in term of accuracy, convergence speed, success rate and capability to overcome the characteristic changes of USM. Also, the proposed APSO based PID controller is simpler than the previous PSO-LDW based PID controller. The previous PSO-LDW has four parameters to be adjusted, but the proposed APSO has only three parameters to be adjusted. In addition, the proposed control method still keeps low computational cost, low requirement memory and faster in obtaining a best solution. These are advantages of the proposed Enhanced PSO based PID controller.

As shown in Table 5.3, in order to get simplicity, convergence speed and time-calculation, it is better to use APSO based Intelligent PID controller. Due to this method, cheaper cost, shorter process time and high profit can be obtained. However, in order to get accuracy and success rate, it is better to use HAIPSO based Intelligent PID controller.

5.3 Originality and Contribution

The proposed control method has three originalities. Firstly, the proposed control method has originality in tools or technique. In the previous control method, the PID gain was adjusted by the standard type of PSO called PSO-LDW. In the research, we proposed five variants of Enhanced PSO to determine the PID gain. The proposed control method is different from the previous method and first applied for controlling USM. Secondly, the proposed control method has originality in idea. In HAIPSO, we used combination of three strategies to overcome several the causes of shortcoming of PSO simultaneously. These strategies are new additional parameter to create new sharing information; adaptive inertia weight to accelerate in obtaining a proper balance; and mutation operator to keep diversity of particles. This strategy is a new idea for improving PSO. Thirdly, the proposed control method has originality in analysis or interpretation. In PSO-NDW, we introduced and discussed about the impact of using period of exploration-exploitation abilities. In PSO-RIW, we introduced and discussed about how to overcome the lack-ability in PSO-LDW and PSO-NDW using random strategy. In APSO, we introduced and discussed about feedback mechanism to take information of swarm condition and used it to calculate an inertia weight. In APSO-RIW and HAIPSO, we introduced and discussed about hybrid strategy for improving PSO.

The main contribution of this study is a new control strategy for USM called intelligent self-tuning PID controller using Enhanced PSO with better performance than the previous control method. Also, the research offered new analysis and interpretation for improving PSO and the Enhanced PSO can be applied to other areas for solving optimization problem.

Table 5.3 General performance

Performance	**PSO-LDW**	**PSO-NDW**	**PSO-RIW**	**APSO**	**APSO-RIW**	**HAIPSO**
Simplicity		▲		■	▲	
Convergence speed	▲			■		
Time-calculation	▲			■		
Accuracy	▲					■
Capability to avoid premature convergence	▲					■
Capability to escape from local optima	▲					■

■ "BEST"

▲ "WORST"

5.4 Future Works

In the proposed Enhanced PSO, in order to get a best performance, the parameters should be adjusted properly and manually. Improperly parameters setting will decrease the performance of PSO. However, properly parameters setting are not an easy task because they are unique. It means that properly parameters setting are suitable for one problem or controlled plant, and it may not suitable for other problems. The properly parameters setting depend on several factors, e.g., problem to be solved, number of particles, condition of swarm and environmental changes. Therefore, this is the disadvantage of the proposed method. In the future, we want to investigate how to determine properly parameters setting effectively. Also, in the next research, we will develop an auto-tuning PSO or free-parameter tuning PSO, where the parameters can be adjusted automatically.

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