NEW EVOLUTIONARY ALGORITHM BASED ON PARTICLE SWARM OPTIMIZATION AND ADAPTIVE PLAN SYSTEM WITH GENETIC ALGORITHM

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ABSTRACT

To reduce a large amount of calculation cost and to improve the convergence to the optimal solution for multi-peak optimization problems with multi-dimensions, we purpose a new method of Adaptive plan system with Genetic Algorithm (APGA). This is an approach for improving Particle Swarm Optimization (PSO) using APGA. The new strategy based on PSO operator and APGA (PSO-APGA) to improve the convergence towards the optimal solution. The PSO-APGA is applied to some benchmark functions with 20 dimensions to evaluate its performance.

Keywords: Particle Swarm Optimization, Genetic Algorithm, Adaptive System, Multi-peak problems.

1. INTRODUCTION

The product design is becoming more and more complex for various requirements from customers and claims. As a consequence, its design problem seems to be multi-peak problem with multi-dimensions. The Genetic Algorithm (GA) (Goldberg 1989) is the most emergent computing method has been applied to various multi-peak optimization problems. The validity of this method has been reported by many researchers (Digalakis and Margaritis 2000, Sakuma and Kobayashi 2001, Li and Kirley 2002). However, it requires a huge computational cost to obtain stability in the convergence to an optimal solution. To reduce the cost and to improve stability, a strategy that combines global and local search methods becomes necessary. As for this strategy, current research has proposed various methods (Mahfoud and Goldberg 1992; Goldberg and Voessner 1999; Hiroyasu, Miki and Ogura 2000; Miki, Hiroyasu and Fushimi 2003). For instance, Memetic Algorithms (MAs) are a class of stochastic global search heuristics in which Evolutionary Algorithms-based approaches (EAs) are combined with local search techniques to improve the quality of the solutions created by evolution. MAs have proven very successful across the search ability for multi-peak functions with multiple dimensions (Smith, Hart and Krasnogor 2005). These methodologies need to choose suitably a best local search method from various local search methods for combining with a global search method within the optimization process. Furthermore, since genetic operators are employed for a global search method within these algorithms, design variable vectors (DVs) which are renewed via a local search are encoded into its genes many times at its GA process. These certainly have the potential to break its improved chromosomes via gene manipulation by GA operators, even if these approaches choose a proper survival strategy.

To solve these problems and maintain the stability of the convergence to an optimal solution for multi-peak optimization problems with multiple dimensions, Hasegawa et al. proposed a new evolutionary algorithm (EA) called an Adaptive Plan system with Genetic Algorithm (APGA) (Hasegawa 2007).

Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart (2001) is one of the modern meta-heuristics algorithms. It has been developed through simulation of a simplified social system, and has been found to be robust in solving optimization problems. Nevertheless, the performance of the PSO greatly depends on its parameters and it often suffers from the problem of being trapped in the local optimum. To resolve this problem, various improvement algorithms are proposed. It is proven to be a successful in solving a variety of optimal problems.

In this paper, we purposed a new strategy for optimization using PSO and APGA (PSO-APGA) to converge to the optimal solution.

This paper is organized in the following manner. The concept of PSO is described in Section 2, concept of APGA is in Section 3. Section 4 explains the algorithm of proposed strategy (PSO-APGA), and Section 5 discussed about the convergence to the optimal solution of multi-peak benchmark functions. Finally, Section 6 includes some brief conclusions.

2. PARTICLE SWARM OPTIMIZATION

PSO is a robust stochastic optimization algorithm which is defined by the behavior of a swarm of particles in a multidimensional search space looking for the best solution (Kennedy and Eberhart 2001, Clerc 2005).

We are concerned here with gbest-model which is known to be conventional PSO. In this model, each particle which make up a swarm has information of its position x_i and velocity v_i (i is the index of the particle) at the present in the search space. Each particle aims at the global optimal solution by updating next velocity making use of the position at the present, based on its best solution has been achieved so far p_{id} and the best solution of all particles p_{gd} (d is the dimension of the solution vector), as following equation:

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 \left(p_{id}^{t} - x_{id}^{t}\right) + c_2 r_2 \left(p_{gd}^{t} - x_{id}^{t}\right) \tag{1}$$

where w is inertia weight; c_1 and c_2 are cognitive acceleration and social acceleration, respectively; r_1 and r_2 are random numbers uniformly distributed in the range [0.0, 1.0].

In our strategy, the discrete version of PSO designed for binary optimization has been adapted, which developed by Kennedy and Eberhart (1997). Discrete PSO is composed of the binary variable, so the velocity must be transformed into the change of probability. In this version of PSO, the velocity update is same as continuous PSO, but for adjusting the new position the probability function of particle velocity was used as follows:

$$S\left(v_{id}^{t}\right) = \frac{1}{1 + e^{-v_{id}^{t}}} \tag{2}$$

$$x_{id}^{t+1} = \begin{cases} 1, & \rho \le S\left(v_{id}^{t}\right) \\ 0 \end{cases} \tag{3}$$

where $S\left(v_{id}^{t}\right)$ and ρ are sigmoid limiting transformation and random number selected from a uniform distribution in [0.0, 1.0] respectively.

3. ADAPTIVE PLAN SYSTEM WITH GENETIC ALGORITHM

3.1. Formulation of the optimization problem

The optimization problem is formulated in this section. Design variable, objective function and constrain condition are defined as follows:

$$X = \left[x_1, \ldots, x_n\right] \tag{4}$$

$$-f\left(X\right) \rightarrow Max \tag{5}$$

$$X^{LB} \le X \le X^{UB} \tag{6}$$

where $X^{LB} = [x_1^{LB}, \ldots, x_n^{LB}]$, $X^{UB} = [x_1^{UB}, \ldots, x_n^{UB}]$ and n denote the lower boundary condition vectors, the upper boundary condition vectors and the number of design variable vectors (DVs) respectively. A number of DV's significant figure is defined, and DV is rounded off its places within optimization process.

3.2. APGA

The APGA concept was introduced as a new EA strategy for multi-peak optimization problems. Its concept differs in handling DVs from general EAs based on GAs. EAs generally encode DVs into the genes of a chromosome, and handle them through GA operators. However, APGA completely separates DVs of global search and local search methods. It encodes control variable vectors (CVs) of AP into its genes on Adaptive system (AS). Moreover, this separation strategy for DVs and chromosomes can solve Memetic Algorithm (MA) problem of breaking chromosomes (Smith, Hart and Krasnogor 2005).

The conceptual process of APGA is shown in Figure 1. The control variable vectors (CVs) steer the behavior of adaptive plan (AP) for a global search, and are renewed via genetic operations by estimating fitness value. For a local search, AP generates next values of DVs by using CVs, response value vectors (RVs) and current values of DVs according to the formula:

$$X_{t+1} = X_t + NR_t \cdot AP(C_t, R_t) \tag{7}$$

where NR, $AP()$, X, C, R, t denote neighborhood ratio, a function of AP, DVs, CVs, RVs and generation, respectively. In addition, for a verification of APGA search process, refer to ref. (Hasegawa 2007).

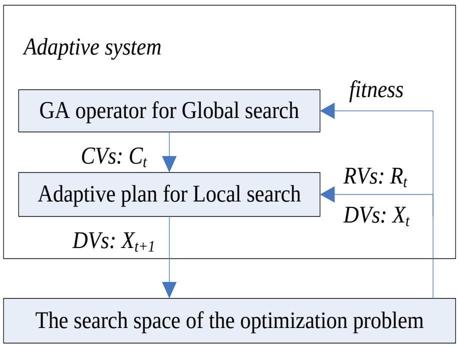

Figure 1: Conceptual Process Of APGA

3.3. Adaptive Plan (AP)

It is necessary that the AP realizes a local search process by applying various heuristics rules. In this paper, the plan introduces a DV generation formula using a sensitivity analysis that is effective in the convex function problem as a heuristic rule, because a multi-peak problem is combined of convex functions. This plan uses the following equation:

$$AP(C_t, R_t) = -Scale \cdot SP \cdot sign(\nabla R_t) \tag{8}$$

$$SP = 2C_t - 1 \tag{9}$$

where $Scale$, ∇R denote the scale factor and sensitivity of RVs, respectively.

A step size *SP* is defined by CVs for controlling a global behavior to *prevent* it falling into the local optimum. $C = [c_{i,j}, \ldots, c_{i,p}]$; $0.0 \le c_{i,j} \le 1.0$ is used by (9) so that it can change the direction to improve or worsen the objective function, and *C* is encoded into a chromosome by 10 bit strings with two values (0 and 1). In addition, *i*, *j* and *p* are the individual number, design variable number and its size, respectively.

3.4. GA Operators

Selection is performed using a tournament strategy to maintain the diverseness of individuals with a goal of keeping off an early convergence. A tournament size of 2 is used.

Elite strategy, where the best individual survives in the next generation, is adopted during each generation process. It is necessary to assume that the best individual, i.e., as for the elite individual, generates two behaviors of AP by updating DVs with AP, not GA operators. Therefore, its strategy replicates the best individual to two elite individuals, and keeps them to next generation. As shown in Figure 2, DVs of one of them (▲ symbol) is renewed by AP, and its CVs which are coded into chromosome aren't changed by GA operators. Another one (● symbol) is that both DVs and CVs are not renewed, and are kept to next generation as an elite individual at the same search point.

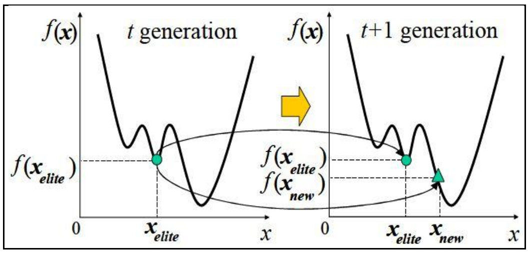

Figure 2: Elite Strategy

In order to pick up the best values of each CV, a single point crossover is used for the string of each CV. This can be considered to be a uniform crossover for the string of the chromosome. Mutation are performed for each string at mutation ratio on each generation, and set to maintain the strings diverse.

At following conditions, the genetic information on chromosome of individual is recombined by uniform random function.

- One fitness value occupies 80% of the fitness of all individuals.
- One chromosome occupies 80% of the population.

If this manipulation is applied to general GAs, an improved chromosome into which DVs have been encoded is broken down. However, in the APGA, the genetic information is only CVs used to make a decision for the AP behavior. Therefore, to prevent from falling into a local optimum, and to get out from the condition of being converged with a local optimum, a new AP behavior is provided by recombining the genes of the CVs into a chromosome. And the optimal search process starts to re-explore by a new one. This strategy is believed to make behavior like the re-annealing of the Simulated Annealing (SA).

4. NEW EVOLUTIONARY ALGORITHM

Many of optimization techniques called meta-heuristics including PSO are designed based on the concept. In case of PSO, when a particle discovers a good solution, other particles also gather around the solution. Therefore, they cannot escape from a local optimal solution. Consequently, PSO cannot achieve the global search. However, APGA that combines the global search ability of a GA and an Adaptive Plan with excellent local search ability is superior to other EAs (MAs) (Hasegawa 2007, Tooyama and Hasegawa 2009, Pham and Hasegawa 2010). With a view to global search, we propose the new evolutionary algorithm based on PSO and APGA named PSO-APGA, as shown in Figure 4.

To improve the multi-point search capability of APGA, applying neighborhood range control is used. The distance for a search point can be changed by controlling *NR* for determining the neighborhood range. *NR* is adjusted by following sigmoid function:

$$NR = \frac{1}{1 + \exp\left(\beta \cdot \dfrac{inv - (invidual/2)}{invidual}\right)} \tag{10}$$

$$0.0 \le NR \le 1.0 \tag{11}$$

where β, inv denote the gain of the sigmoid function and the individual number, respectively.

PSO-APGA aims at getting direction from particle swarm to adjust into adaptive system. This strategy introduces a handling sign of the gain β for assignation of neighborhood range control. The velocity update is same as discrete PSO operator, in which a moving in a state space restricted to local search and global search on each dimension, in terms of the changes in probabilities that a bit will be in one state or the other. Such a situation, in which the individual searches its own neighborhood area without performing a global search, can generally occur at any time in search process. Therefore, it cannot escape from the local optimum solution. To solve this problem, this method employs sign of the gain β using the probability function of particle velocity as follows:

$$\begin{cases} \beta > 0, & \rho \le S\left(v_{id}^{t}\right) \\ \beta < 0 \end{cases} \tag{12}$$

As the assignation step shown in Figure 2, the individuals are allocated small *NR* values to perform a local search efficiently, and the individuals are allocated large *NR* values to search the global area in the design space of DVs by $\beta < 0$. On the other hand, just before converging to the global optimum solution, individuals can gather in the neighborhood area of the elite individual by $\beta > 0$.

In this approach, PSO and APGA run individually. The iteration is run by PSO operator and the velocity update is given as initial parameter for APGA process.

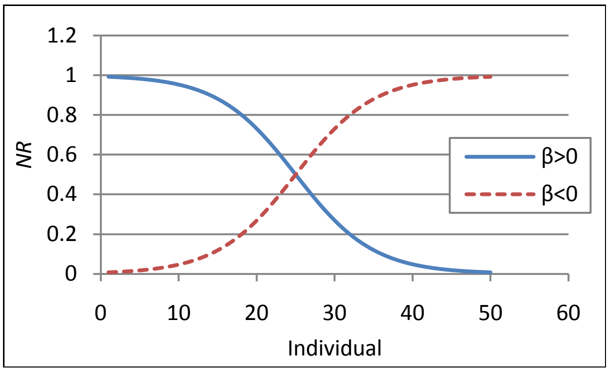

Figure 3: Neighborhood Range Control

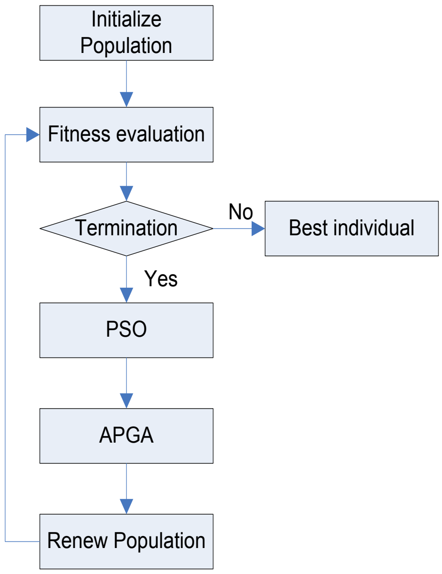

Figure 4: Flow-chart Of PSO-APGA

5. NUMERICAL EXPERIMENTS

To show the effects of PSO-APGA whether particles can escape from a local optimal solution and find the global optimal solution, we compare with other methodologies for the robustness of the optimization process. These experiments are performed 20 trials for every function. The initial seed number is randomly varied during every trial. In each experiment, the inertia weight w is set 0.9, and the acceleration coefficients c_1 and c_2 are set by fixed value of 2.0. The GA parameters used in solving benchmark functions are set as follows: selection ratio, crossover ratio and mutation ratio are 1.0, 0.8 and 0.01 respectively. The population size is 50 individuals and the terminal generation is 5000^{th} generation. The sensitivity plan parameters in (8) for normalizing functions are listed in Table 3.

5.1. Benchmark Functions

For PSO-APGA, we estimate the stability of the convergence to the optimal solution by using three benchmark functions with 20 dimensions: Rastrigin (RA), Griewank (GR) and Rosenbrock (RO). These functions are given as follows:

$$RA = 10n + \sum_{i=1}^{n} \left\{ x_i^2 - 10\cos(2\pi x_i) \right\} \tag{13}$$

$$GR = 1 + \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) \tag{14}$$

$$RO = \sum_{i=1}^{n} 100\left(x_{i+1} + 1 - (x_i + 1)^2 \right)^2 + x_i^2 \tag{15}$$

Table 1 shows their characteristics, and the terms epistasis, multi-peak, steep denote the dependence relation of the DVs, presence of multi-peak and level of steepness, respectively. All functions are minimized to zero, when optimal DVs $X = 0$ are obtained. Moreover, it is difficult to search for their optimal solutions by applying one optimization strategy only, because each function has a different complicated characteristic. In Table 2, their design range, the digits of DVs are summarized. If the search point attains an optimal solution or a current generation process reaches the termination generation, the search process is terminated.

Table 1: Characteristics Of The Benchmark Functions

Function	Epitasis	Multi-peak	Steep
RA	No	Yes	Average
GR	Yes	Yes	Small
RO	Yes	No	Big

Table 2: Design Range. Digits Of DVs

Function	Design range	Digits
RA	$-5.12 \le X \le 5.12$	2
GR	$-51.2 \le X \le 51.2$	1
RO	$-2.048 \le X \le 2.048$	3

Table 3: Scale Factor For Normalizing The Benchmark Functions

Function	Scale Factor
RA	10.0
GR	100.0
RO	4.0

5.2. Experiment Results

The experiment results are shown in Table 4. The success ratio of all benchmark functions is 100% with small computation cost. The solutions of all benchmark functions reach their global optimum solutions.

Next, Figure 5, Figure 6 and Figure 7 show diagrams for the average fitness of individual until PSO-APGA reaches the global optimum solutions, in the numerical experiment again to confirm above mentioned result.

Table 4: Number Of Generations By PSO-APGA

Trial	Function		
	RA	GR	RO
1	198	360	1164
2	200	332	1118
3	225	394	1020
4	208	340	1018
5	228	412	913
6	178	323	1213
7	239	413	900
8	221	412	791
9	170	349	1400
10	238	399	1260
11	248	347	1253
12	212	331	843
13	229	399	996
14	207	373	1113
15	210	369	1251
16	155	371	1150
17	236	330	1269
18	204	317	1039
19	216	361	1155
20	198	359	1306
Average	211	364	1108

5.3. Comparison

PSO-APGA was compared with basic PSO and H-APGA (Pham and Hasegawa 2010). The results of these methods are shown in Table 5. In the table, when success rate of optimal solution is not 100%, "-" is described.

In particular, it was confirmed that the calculation cost with PSO-APGA could be reduced for benchmark functions. And it showed that the convergence to the optimal solution could be improved more significantly.

In summary, from the comparison among methods shown in Figure 8, we can confirm that the search ability of PSO-APGA with multi-dimensions optimization problems is very effective, compared with that of basic PSO. However, it did not gain a high probability by H-APGA.

Additionally, we calculated the standard deviation, used in combination with the average result to describe the normal distribution of PSO-APGA and H-APGA with RO function. As a result, PSO-APGA achieved at the optimal solution, however it still has the larger variation than H-APGA.

Overall, the PSO-APGA was capable of attaining robustness, high quality, low calculation cost and efficient performance on many benchmark problems.

Table 5: Average Results With 20 Dimensions

Function	Basic PSO	H-APGA	PSO-APGA
RA	-	196	211
GR	2878	298	364
RO	2220	1088	1108

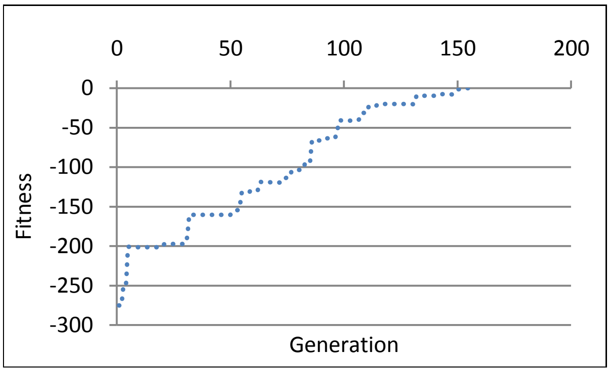

Figure 5: Elite Individual Fitness With RA

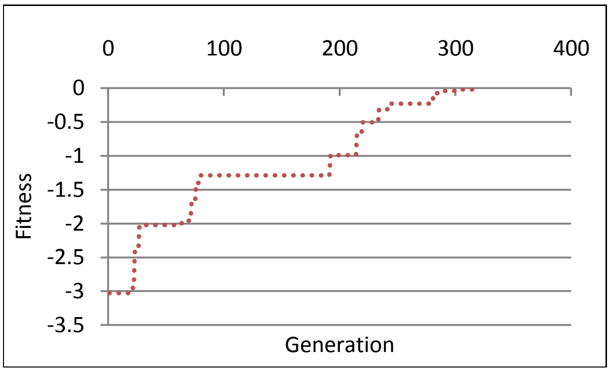

Figure 6: Elite Individual Fitness With GR

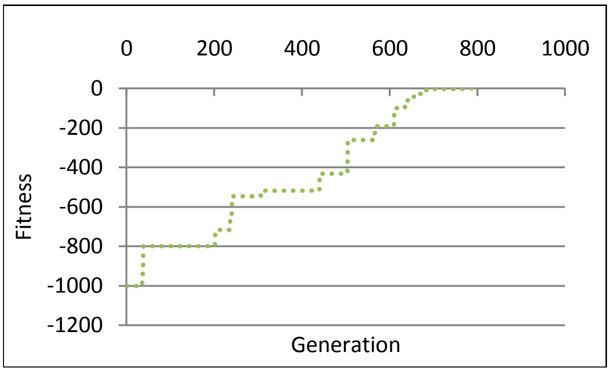

Figure 7: Elite Individual Fitness With RO

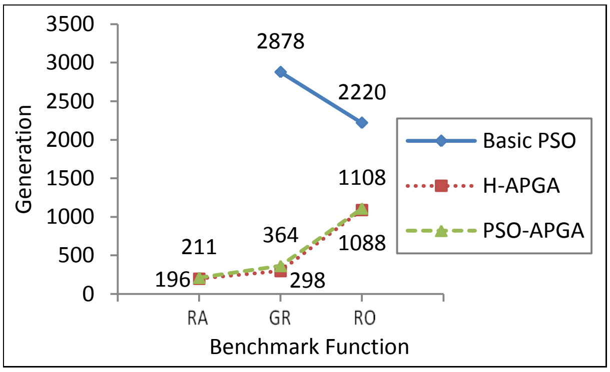

Figure 8: Comparison Among Methods

6. CONCLUSION

In this paper, to overcome the computational complexity, two efficient optimization evolutionary algorithms have been used. A new approach strategy based on PSO and APGA (PSO-APGA) has been proposed. Then, we verify the effectiveness of PSO-APGA by the numerical experiments performed three benchmark functions.

Moreover it was compared with basic PSO and H-APGA. As a result, we can confirm that the PSO-APGA reduces the calculation cost and improves the convergence to the optimal solution.

About the optimal solution such as minimum time and maximum reliability, it is a future work.

Finally, this study plans to do a comparison with the sensitivity plan of the AP by applying other optimization methods and optimizing the benchmark functions.

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