

Auto-Tuning Fuzzy Granulation for Evolutionary Optimization

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Abstract—Much of the computational complexity in employing evolutionary algorithms as optimization tool is due to the fitness function evaluation that may either not exist or be computationally very expensive. With the proposed approach, the expensive fitness evaluation step is replaced by an approximate model. An intelligent guided technique via an adaptive fuzzy similarity analysis for fitness granulation is used to decide on use of expensive function evaluation and dynamically adapt the predicted model. In order to avoid tuning parameters in this approach, a fuzzy supervisor as auto-tuning algorithm is employed with three inputs. The proposed method is then applied to three traditional optimization benchmarks with four different choices for the dimensionality of the search space. Effect of number of granules on rate of convergence is also studied. In comparison with standard application of evolutionary algorithms, statistical analysis confirms that the proposed approach demonstrates an ability to reduce the computational complexity of the design problem without sacrificing performance. Furthermore, the auto-tuning of the fuzzy supervisory removes the need for exact parameter determination.

I. INTRODUCTION

Evolution-based algorithms have long been accepted as promising global optimizers and shown to be very powerful in solving many real-world and complex optimization tasks such as design optimization, see e.g., [1]. Unfortunately, repeated fitness function evaluation (FFE) for such complex problems is often the most prohibitive and limiting segment of artificial evolutionary algorithms. Finding optimal solution for complex high dimensional, multimodal problems often requires very expensive FFEs. In real world problems such as structural optimization problems, one single function evaluation may require several hours to several days of complete simulation. Typical optimization method can not deal with such a type of problem. In this case, it may be necessary to forgo an exact evaluation and use an approximated fitness that is

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computationally efficient. It is apparent that amalgamation of approximate models may be one of the most promising approaches to convincingly use EA to solve complex real life problems, especially where: (i). Fitness computation time of a single solution is extremely high, (ii). Precise model for fitness computation is missing, (iii). The fitness function (FF) is uncertain or noisy as a result of simulation/measurement errors or changes in the design variables and/or the environmental parameters etc. To alleviate this problem, a variety of techniques for constructions of approximation models—often also referred to as metamodels or surrogates - for computationally expensive optimization problems are investigated [2, 3].

A popular subclass of FF approximation methods is fitness inheritance where fitness is simply inherited [4]. A similar approach named “Fast Evolution Strategy” (FES) has also been suggested in [9] for fitness approximation where the fitness of a child individual is the weighted sum of its parents. In [10] it has been shown that this simple strategy can fail in sufficiently complex and multi objective problems.

Other common approaches based on learning and interpolation from known fitness values of a small population, (e.g. low-order polynomials and the least square estimations [5], artificial neural networks (ANN), including multi-layer perceptrons [6] and radial basis function networks [7], support vector machine (SVM) [8, 15] regression model [11], etc.) are also been employed.

Because of the limited number of training samples and high dimensionality encountered in engineering design optimization, constructing a globally valid approximate model remains to be difficult. Evolutionary algorithms using such approximate FFs may converge to local optimums. Therefore, it can be beneficial to selectively use the original FF together with the approximate model [13]. For example, Khorsand and Akbarzadeh [14] recently investigated structural optimization by a hybrid of neural network and finite element analysis, where expensive function evaluation is partially replaces by its approximate model. Also Jin and Sendhoff [17] applied k-nearest-neighbour method to group the individuals of a population into a number of clusters. For each cluster, only the individual that is closest to the cluster center will be evaluated using the expensive original FF.

Fuzzy granulation of information is a vehicle for handling information, as well as a lack of it (uncertainty), at the level of coarseness that can still solve problems appropriately and efficiently. Zadeh proposed fuzzy information granulation in 1977 as a technique by which a class of points (objects) are partitioned into granules, with a granule being a clump of

objects drawn together by indistinguishability, similarity, or functionality. The fuzziness of granules and their attributes is characteristic of the ways by which human concept and reasoning is formed, organized and manipulated. The concept of a granule is more general than that of a cluster, potentially giving rise to various conceptual structures in various fields of science as well as mathematics.

In this paper, the concept of fitness granulation is applied to exploit the natural tolerance of evolutionary algorithms in FF computations. Nature's "survival of the fittest" is not about exact measures of fitness; rather it is about rankings among competing peers. By exploiting this natural tolerance for imprecision, optimization performance can be preserved by computing fitness only selectively and only to preserve this ranking among individuals in a given population. Also, fitness is not interpolated or estimated; rather the similarity and indistinguishability among real solutions is exploited. The basic ideas behind the proposed framework are to:

- Avoid initial training.
- Use guided approximation to speed up search process.
- Exploit design variable space by means of Fuzzy Similarity Analysis (FSA) as a type of fuzzy approximation model to avoid premature convergence.
- Gradually set up an independent model of initial training data to compensate the Lack of sufficient training data and to reach a model with sufficient approximation accuracy.
- Dynamic updating the approximate model with no or negligible overhead cost.
- Avoiding the use of model in unrepresented design variable regions in the training set.

In the proposed algorithm as explained in detail by authors in [12, 16], an adaptive pool of solutions (fuzzy granules) with an exactly computed FF is maintained. If a new individual is sufficiently similar to a known fuzzy granule, then that granule's fitness is used instead as a crude estimate. Otherwise, that individual is added to the pool as a new fuzzy granule. In this fashion, regardless of the competition's outcome, fitness of the new individual is always a physically realizable one, even if it is a "crude" estimate and not an exact measurement. The pool size as well as each granule's radius of influence is adaptive and will grow/shrink depending on the utility of each granule and the overall population fitness. To encourage fewer function evaluations, each granule's radius of influence is initially large and is gradually shrunk in latter stages of evolution. This encourages more exact fitness evaluations when competition is fierce among more similar and converging solutions. Furthermore, to prevent the pool from growing too large, granules that are not used are gradually eliminated. This fuzzy granulation scheme is applied here as a type of fuzzy approximation model to solve applied to solve 3 traditional optimization benchmarks with 4 different dimensions in each.

The paper is organised as follows: Section 2 presents a brief overview of the proposed method. For future details,

readers are referred to [16] were proposed method is described in more details and also provides an example. In Section 3, an auto-tuning strategy for determining the width of membership functions (MFs) is presented; which removes the need for exact parameter determination, without obvious influence on convergence speed. Some supporting simulation results and discussion thereof are presented in section 4. Finally conclusion is drawn in Section 5.

II. THE AFFG FRAMEWORK [12]

The AFFG framework [Figure 1] includes a global model of genetic algorithm (GA), hybridised with fuzzy granulation (FG) tool. Expensive FFE of individuals as required in traditional evolutionary algorithm is partially replaced by approximation model. Explicit control strategies are used for evolution control, leading to considerable speedup without compromising heavily on solution accuracy.

While approximation is not a new idea in accelerating iterative optimization process, AFFG focuses on controlled speedup to avoid detrimental effects of approximation. The following section presents the main algorithm structure of AFFG.

A. The Main Idea

The proposed adaptive fuzzy fitness granulation aims to minimize the number of exact FFEs by creating a pool of solutions (fuzzy granules) by which an approximate solution may be sufficiently applied to proceed with the evolution. The algorithm uses Fuzzy Similarity Analysis (FSA) to produce and update an adaptive competitive pool of dissimilar solutions/granules. When a new solution is introduced to this pool, granules compete by a measure of similarity to win the new solution and thereby to prolong their lives in the pool. In turn, the new individual simply assumes fitness of the winning (most similar) individual in this pool. If none of the granules are sufficiently similar to the new individual, i.e. their similarity is below a certain threshold, the new individual is instead added to the pool after its fitness is evaluated exactly by the known FF. Finally, granules that cannot win new individuals are gradually eliminated in order to avoid a continuously enlarging pool [12, 16]. The proposed algorithm is shown in Figure 1.

B. Basic Algorithm Structure

Step One: Create a random parent population $P_0 = \{X_1^1, X_2^1, \dots, X_j^1, \dots, X_t^1\}$, where $X_j^i = \{x_{j,1}^i, x_{j,2}^i, \dots, x_{j,r}^i, \dots, x_{j,m}^i\}$ is j-th individual in i-th generation, $x_{j,r}^i$ is the r-th parameter of X_j^i , m is the number of design variables and t is population size.

Step Two: G serves as a multi-set of fuzzy granules, whereas a fuzzy granules is defines as: $G = \{(C_k, \sigma_k, L_k) | C_k \in \mathfrak{R}^m, \sigma_k \in \mathfrak{R}, L_k \in \mathfrak{R}, k = 1, \dots, l\}$ that is initially empty, i.e. $l = 0$. C_k is an m-dimensional vector of centers, σ_k is the Width of Membership Functions (WMFs) of the k-th fuzzy granule, and L_k is the granule's life index.

Step Three: The phenotype of first chromosome i.e. $X_1^1 = \{x_{1,1}^1, x_{1,2}^1, \dots, x_{1,r}^1, \dots, x_{1,m}^1\}$ is chosen as the center $C_1 = \{c_{1,1}, c_{1,2}, \dots, c_{1,r}, \dots, c_{1,m}\} = X_1^1$ of first granule.

Step Four: The membership function $\mu_{r,k}$ describes a Gaussian similarity neighborhood for each parameter k as follows,

$$\mu_{k,r}(x_{j,r}^i) = \exp\left(-\frac{(x_{j,r}^i - C_{k,r})^2}{(\sigma_{k,r})^2}\right) \quad (1)$$

for $k = 1, 2, \dots, l$ where 1 is the number of fuzzy granules.

Remark: σ_k is distance measurement parameter that controls the degree of similarity between two individuals. In [12], σ_k is defined based on equation (2). Based on this definition, the granules shrink or enlarge in reverse proportion to their fitness as below.

$$\sigma_k = \frac{\gamma}{\left(e^{f(C_k)}\right)^\beta} \quad (2)$$

Where $\beta > 0$ is an emphasis operator and γ is constant of proportion. The problem arising here is how to determine β and γ as design parameters. The fact is that these two parameters are problem dependent and it seems to need some trials to adjust these parameters. This trial is base on the simple rule; how much do you want to accelerate the optimization procedure? High speed needs to have enlargement in granule spread and in consequence, less accuracy in fitness approximation is resulted and vice versa. To overcome this drawback, a fuzzy controller with three inputs is introduced in section III.

Step Five: Compute the average similarity of a new solution $X_j^i = \{x_{j,1}^i, x_{j,2}^i, \dots, x_{j,r}^i, \dots, x_{j,m}^i\}$ to each granule G_k Using $\bar{\mu}_{j,k} = \frac{\sum_{r=1}^m \mu_{k,r}(x_{j,r}^i)}{m}$.

Step Six: Fitness of X_j^i is either calculated by exact FF computing or estimated by associating it to one of the granules in the pool if there is a granule in the pool with higher similarity to X_j^i than a predefined threshold, as follows.

$$f(X_j^i) = \begin{cases} f(C_K) & \text{if } \max_{k \in \{1, 2, \dots, l\}} \{\bar{\mu}_{j,k}\} > \theta^i \\ f(X_j^i) & \text{otherwise} \end{cases}$$

where $f(C_K)$ is the FF of the fuzzy granule, $f(X_j^i)$ is the real fitness calculation of the individual,

$$\theta^i = \alpha \cdot \frac{\text{Max}\{f(X_1^{i-1}), f(X_2^{i-1}), \dots, f(X_t^{i-1})\}}{\bar{f}^{i-1}},$$

$$K = \arg \text{Max}_{k \in \{1, 2, \dots, l\}} \{\bar{\mu}_{j,k}\}, \quad \bar{f}^i = \sum_{j=1}^t \frac{f(X_j^i)}{t}, \quad \text{and } \alpha > 0$$

is a constant of proportionality. Threshold θ^i increases as the best individual's fitness in generation i increases. Hence as the population matures and reaches higher fitness valuations while also converging more, the algorithm becomes more selective and uses exact fitness calculations more often. Therefore, with this technique we can utilize the previous computational efforts during previous generations.

Alternatively, if $\text{Max}_{k \in \{1, 2, \dots, l\}} \{\bar{\mu}_{j,k}\} < \theta^i$, X_j^i is chosen as a newly created granule.

Step Seven: If the population size is not completed, repeat Step Five to Step Seven.

Step Eight: Select parents using suitable selection operator and apply genetic operators namely recombination and mutation to create new generation.

Step Nine: When termination/evolution control criteria are not met, then update σ_k using "Equation 2" and repeat Step Five to Step Nine.

C. How to Control the Length of Granule Pool?

As the evolutionary algorithm proceeds, it is inevitable that new granules are increasingly generated and added to the pool. Depending on complexity of the problem, the size

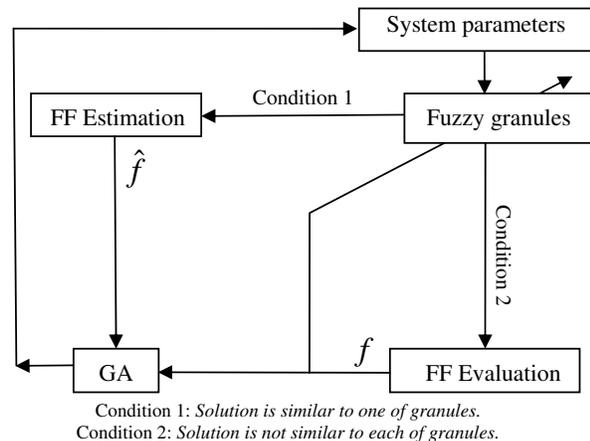


Fig 1. The architecture of the proposed algorithm

of this pool can become excessive and become a computational burden itself. To prevent such unnecessary computational effort, a “forgetting factor” is introduced in order to appropriately decrease the size of the pool. In other word, it is better to remove granules that do not win new individuals, thereby producing a bias against individuals that have low fitness and were likely produced by a failed mutation attempt. Hence, L_k is initially set at N and subsequently updated as below,

$$L_k = \begin{cases} L_k + M & \text{if } k = K \\ L_k & \text{Otherwise} \end{cases}$$

Where M is the life reward of the granule and K is the index of the winning granule for each individual in generation i. At each table update, only N_G granules with highest L_k index are kept, and others are discarded. In [12] an example is provided to illustrate the competitive granule pool update law.

III. HOW TO DETERMINE THE WIDTH OF MEMBERSHIP FUNCTIONS

As noted in [12], it is critically important to have accurate estimation of the FF of the individuals in the finishing generations and by the proposed method, it can be accomplished by controlling the width of produced MFs. In the early steps of evolution, by choosing the Width of Membership Functions (WMFs) relatively large, the algorithm accepts individuals with less degree of similarity as similar individual. Therefore, fitness is computed by more often by estimation/association to the granules. As the algorithm matures and reaches higher fitness valuations while also converging more, the width decreases and the similarity between individuals must be increase to be accepted as similar individuals. This prompts higher selectivity for granule associability and higher threshold for estimation. In other words, in the last generations, the degree of similarity between two individuals must be larger than the first generations to be accepted as similar individuals. This procedure ensures a fast convergence rate because of fast computation in the first steps and accurate estimation of FF in last generations.

In [12], the widths of produced MFs are determined using equation 2. Based on this equation, the combined effect of granule enlargement/shrinkage is accordance to the granule fitness and it needs to adjust 2 parameters, namely β and γ . These parameters are problem dependent and it seems critical to set up a procedure in order to avoid this difficulty.

To achieve this desideratum, a fuzzy supervisor with three inputs has been employed. During AFFG search, the fuzzy logic controller observes the Number of Design Variables (NDV), Maximum Range of Design Variables (MRDV) and percentage of completed trials and specifies the WMFs. The first input is NDV. Range of input variables (RIV) is the second input; large NDV and MRDV needs big width in

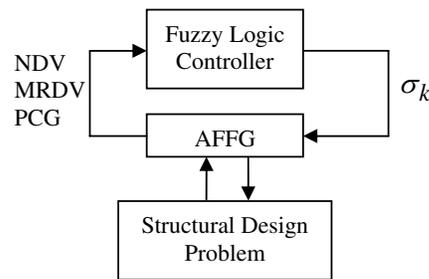


Fig. 2 Flowchart of the Purposed Fuzzy Controller

TABLE I
Fuzzy Rules of the First Controller

		NDV		
		Zero	Small	Big
MRDV	Zero	0	0.125	0.25
	Small	0.375	0.5	0.625
	Big	0.75	0.875	1

MFs and vice versa. Percent Completed Generations (PCG) is the 3rd input, and is a number in the range [0, 1], where 1 signifies exhaustion of all allowed trials, and consequently a maturity of the search given a fixed amount of resources. The combined effect of granule enlargement/shrinkage in accordance to the PCG is to have fast computation in the first steps and accurate estimation of FF in last generations.

The architecture for adaptive fuzzy control of the WMFs appears in Figure 2. Gaussian MFs are used for specification of the knowledge base of the fuzzy logic controller.

The knowledge base for control of the WMFs based on the above architecture has large number of rules and the extraction of these rules is very difficult. Consequently the new architecture based on Figure 3 is proposed in which the controller is separated in two controllers to diminish the complexity of rules. The first controller has two inputs (with three MFs in each, Zero(0, 0.3), Small(0.5, 0.3), Big(1.0,

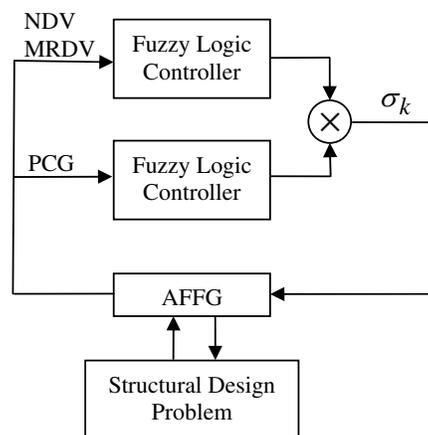


Fig. 3 Modified Flowchart of the Purposed Fuzzy Controller

0.3), the first number is the center and the second one is the spread) and the second controller has only one input which looks like a gain. The knowledge-base for the first controllers is shown in Table 1. The Gaussian MFs with equal width in each (0.3) are used for output. The second controller has just one Gaussian MF in which 0 and 1.25 are its center and spread respectively. The fuzzy controller which uses singleton fuzzifier, product inference engine and center average defuzzifier adjusts the σ_k after each generation.

IV. EMPIRICAL RESULTS

To illustrate the efficacy of the proposed granulation techniques, we have chosen a set of 3 traditional optimization benchmarks (Table 2) namely: Griewangk, Rastrigin and Akley. These benchmark functions in test suit are scaleable and are commonly used to assess the performance of optimization algorithms. For the first and the second one, the global minimum is $f(x) = 0$ at $\{x_i\}^n = 0$, and Akley has a global minimum of $f(x) = 0$ at $\{x_i\}^n = 1$, for competition purpose four sets of input dimensions are considered; namely $n = 5, 10, 20, 30$.

The empirical study consisted in comparing the GA performance, as a function optimizer, AFFG (the parameters are used as table III) and the proposed granulation techniques with fuzzy supervisory (AFFG-FS).

Since the GA was used as a function optimizer, we chose roulette wheel with elitism as the selection method, in order to keep track of the best solution found.

The GA was implemented with 1-point crossover. The population size was set to 20 with the elite size of 2. The

TABLE II
of Test benchmark Functions List

Function	Formula
Griewangk	$1 + \sum_{i=1}^n \frac{x_i^2}{4000} - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}), \quad i = 1:n;$ $-600 \leq x_i \leq 600;$
Rastrigin	$f(x) = 10 \cdot n + \sum_{i=1}^n (x_i^2 - 10 \cdot \cos(2 \cdot \pi \cdot x_i))$ $i = 1:n; \quad -5.12 \leq x_i \leq 5.12;$
Akley	$f(x) = 20 + e - 20e^{-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}} - e^{-\frac{1}{n} \sum_{i=1}^n \cos 2\pi x_i}$ $i = 1:n; \quad -32.768 \leq x_i \leq 32.768;$

TABLE III
Parameters used for AFFG

Function	β	γ
Griewangk	0.00012	190
Rastrigin	0.004	0.15
Akley	0.02	0.25

mutation and crossover rate used was 0.01 and 1.0, respectively. Ten runs of each experiment were executed.

A comparison made with "Fast Evolution Strategy" (FES) in which a fitness and associated reliability value are assigned to each new individual. The fitness truly evaluated if the reliability value is below a certain threshold. The reliability value varies between 0 and 1 and depends on two factors: first is the reliability of parents, and second is how close parents and children are in the solution space. Three different levels for T namely 0.5, 0.7, 0.9 are being used here as proposed in [9].

The report is given for the 5-D (dimension), 10-D, 20-D and 30-D scenarios. For AFFG, and AFFG-FS the number of individuals in granule pool is varied between 20, 20, 40 and 80 respectively. The report results were obtained by achieving same level of fitness evaluation for both canonical GA and the proposed methods namely 500 for 5-D, 1000 for 10-D, 2000 for 20-D and 3000 for 3-D.

The average convergence trends of the standard GA, AFFG, AFFG-FG and FES are summarized in Figures 4-6. All results presented were averaged over 10 runs. As shown in Figures, the search performance of the AFFG and AFFG-FS are superior to the standard GA even with small number of individuals in granule pool. Figures shows that fitness inheritance has comparable performance when number of dimension is small, but its performance deteriorates as problem complexity increases.

We also studied the effect of varying number of granules N_G on the convergence behavior of AFFG and AFFG-FS. Comparison can be made by the results obtained in Figure 7. It can be shown that AFFG and AFFG-FS are not significantly sensitive to N_G . However, further increase of N_G , slows down the rate of convergence duo to the imposed computational complexity.

V. CONCLUDING REMARKS

An intelligent guided technique via an adaptive fuzzy similarity analysis for fitness granulation is used to decide on use of expensive function evaluation and dynamically adapt the predicted model. A fuzzy supervisor as auto-tuning algorithm is introduced in order to avoid tuning of parameters used in this approach.

A comparison is provided between FES and the proposed approach using three traditional optimization benchmarks with four different dimensions of the search space in each. Numerical results showed that the proposed technique is capable of optimizing functions of varied complexity efficiently. Furthermore in comparison with our previous work, it can be shown that AFFG and AFFG-FS are not significantly sensitive to N_G , and small N_G can still make good results. Moreover, the auto-tuning of fuzzy supervisor removes the need for exact parameter determination without obvious influence on convergence speed.

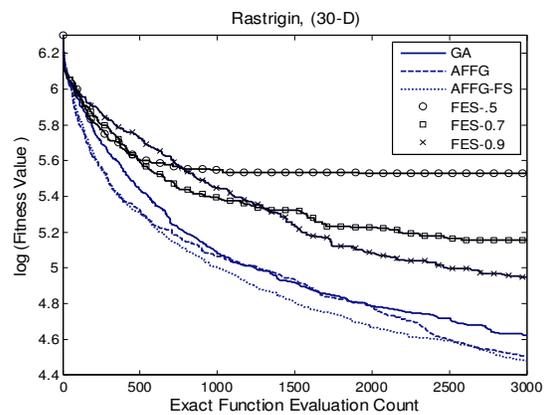
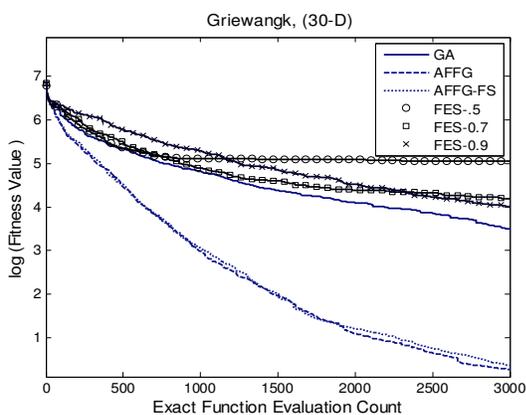
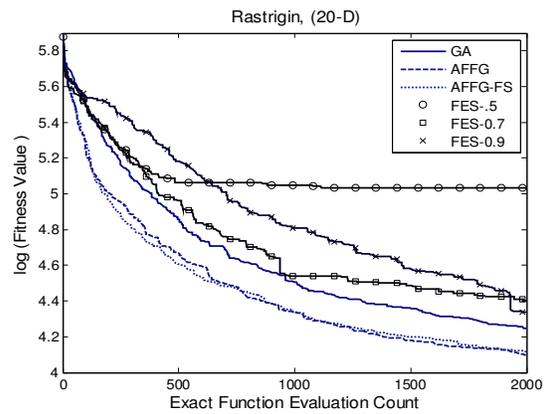
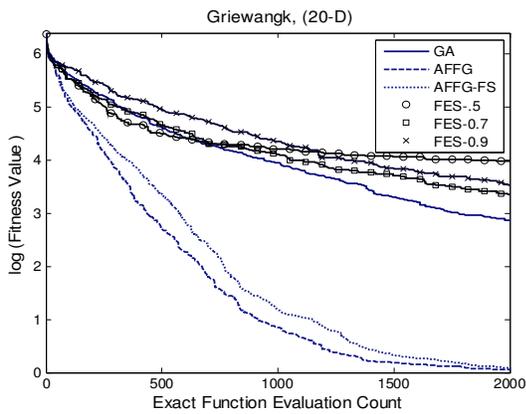
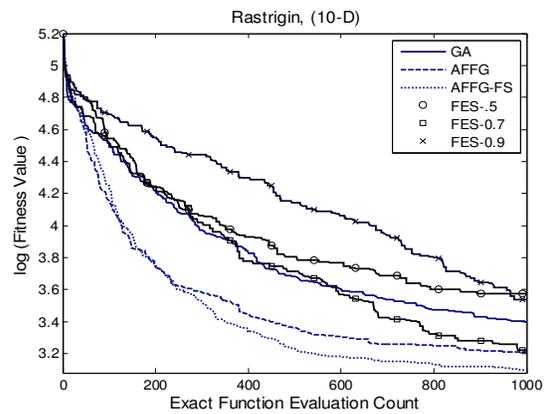
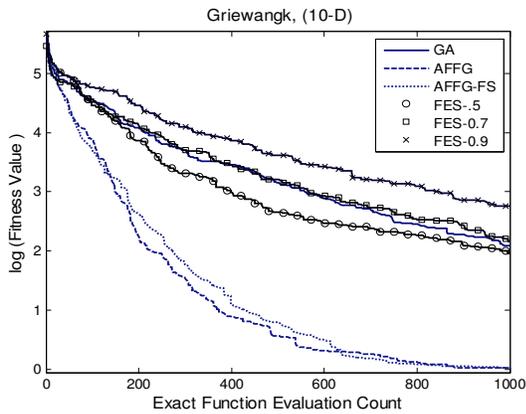
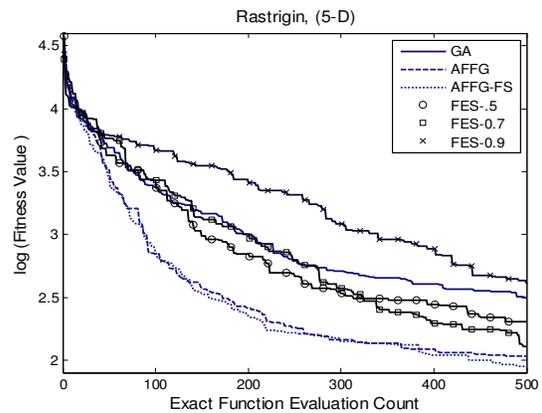
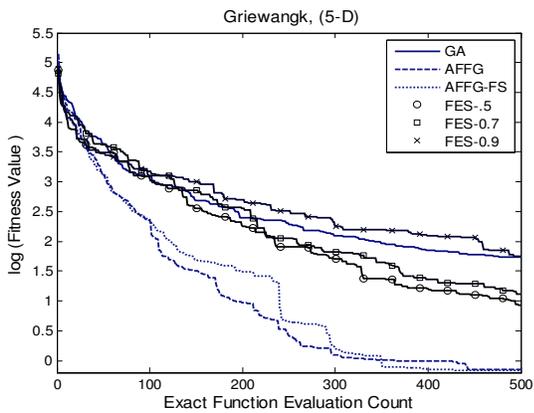


Fig 4. Convergence Trend of GA, AFG, AFG-FS, FES, $T \in \{0.5, 0.7, 0.9\}$ 2008 IEEE Congress on Evolutionary Computation (CEC 2008) 3577

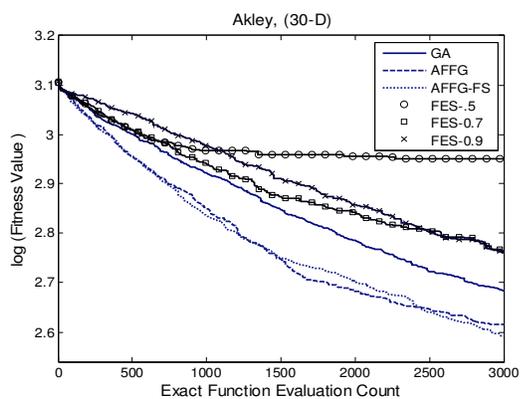
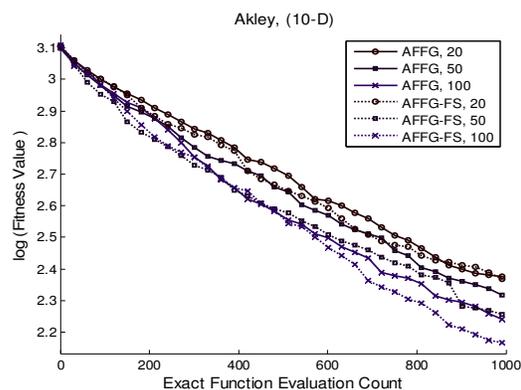
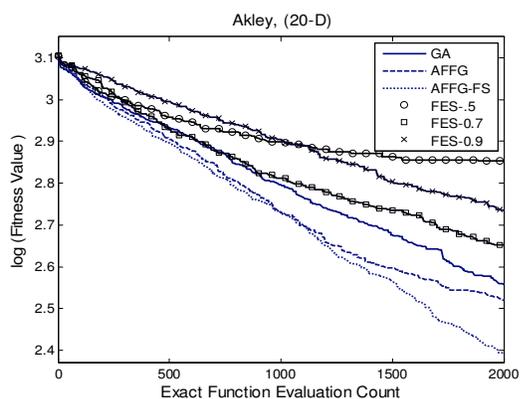
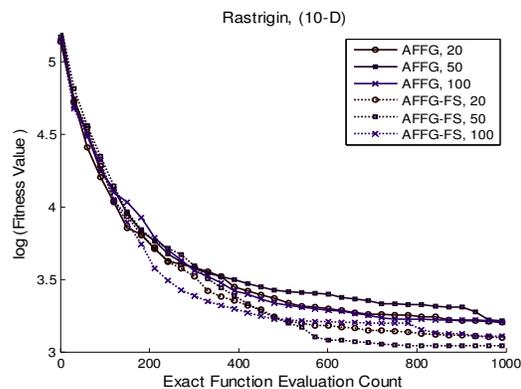
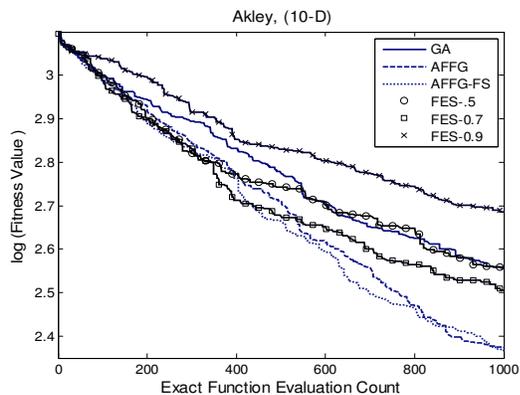
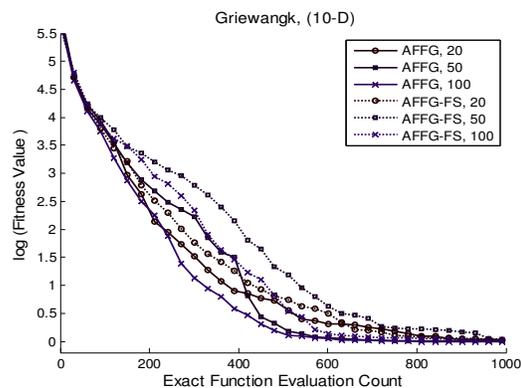
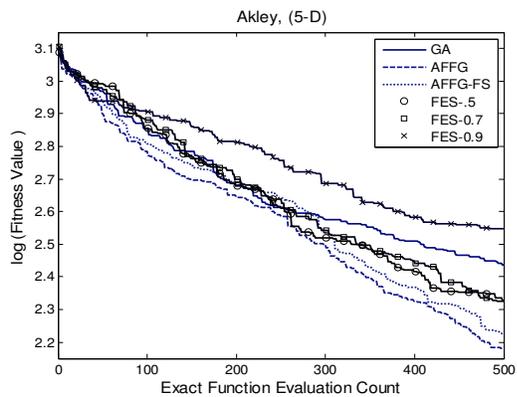


Fig 7. Effect of Varying Number of $N_G \in \{20, 50, 100\}$ on Convergence Trend

Fig 6. Convergence Trend of GA, AFG, AFG-FS, FES, $T \in \{0.5, 0.7, 0.9\}$

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