A Mating Strategy for Multi-parent Genetic Algorithms by Integrating Tabu Search

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Abstract- Multi-parent crossovers have been validated their outperformance on several optimization problems. However, there are two issues to be considered – the number of parents and the disruptiveness caused by multiple parents. This paper presents a tabu multi-parent genetic algorithm (TMPGA) to address these two issues by integrating tabu search into the mating of multi-parent genetic algorithms. TMPGA utilizes the tabu restriction and the aspiration criterion to sift selected parents in consideration of population diversity and selection pressure. Furthermore, the resulting mating validity further adjusts the number of parents participating in a mating. Experiments are conducted with four common test functions. The results indicate that TMPGA can achieve better performance than both two-parent GA and multi-parent GA with the diagonal crossover.

1. Introduction

Genetic algorithms (GAs) have been validated their outstanding performance on a variety of optimization problems. The basic idea of GA is to simulate the mechanisms in biological evolution such as selection, crossover, and mutation [15]. Crossover is one of the most salient features in GA. It reproduces offspring by exchanging and recombining genetic information from two selected parents. This operation is believed capable of exploring the problem space effectively.

The number of parents selected to crossover is traditionally set to two. This is reasonable because all sexual organisms on earth adopt two parents to reproduce their offspring. However, it is possible for GAs to break through such a limitation. Beyond two parents, Eiben et al. proposed two multi-parent crossovers: scanning crossover [7] and diagonal crossover [8, 9]. These two methods generalize uniform crossover and 1-point crossover respectively. With several common test functions, the experimental results indicate both scanning crossover and diagonal crossover can achieve better performance than their two-parent versions, namely uniform and 1-point crossover. The results also reveal that diagonal crossover holds a positive correlation between the accuracy and the number of parents from 11 to 15 parents. Such a correlation, however, does not hold on the scanning crossover. Moreover, Schippers [21] gave an advanced analysis on the influence of scanning crossover upon genetic drift. Besides, Mühlenbein and Voigt [19, 30] introduced the gene pool, which consists of several pre-selected parents. Gene pool recombination (GPR) samples the genes used for recombination from the whole gene pool instead of two parents. The studies show that GPR and its variants are easier to analyze and can converge faster than two-parent recombination. Tsutsui and Jain [26] proposed multi-cut crossover (MX) and seed crossover (SX). Multi-cut crossover generalizes 2-point crossover and performs better than diagonal crossover on De Jong's test functions.

In addition to binary-coded GAs, Tsutsui and Ghosh [26, 27] presented several multi-parent crossovers for real-coded GAs: the center of mass crossover (CMX), multi-parent feature-wise crossover (MFX), and seed crossover (SX). Their experimental results reveal that multi-parent crossovers can lead to better performance in spite of its dependence upon problem types. Simplex crossover (SPX) [29] was proposed to reproduce by sampling a simplex formed from multiple parents. The results show its well performance with three or four parents for multimodal or epistatic problems. Kita et al. [16] introduced multiple parents into the unimodal normal distribution crossover (UNDX) to enhance the diversity of offspring. This multi-parent extension of UNDX demonstrates its improvement in search ability on highly epistatic problems.

For multi-objective optimization problems, Lis and Eiben [17] introduced the concept of sex into multi-parent crossover. The sex or gender, which is appended in each chromosome, indicates a specific criterion to optimize; that is, the fitness is evaluated by the corresponding objective function of sex. Esquivel et al. [11, 12] extended this method to MSPC-GA by allowing multiple parents per sex and multiple crossovers per mating. This approach obtains a satisfactory result in the number of non-dominated solutions on the Pareto front. The study [18] further enhances this method by incorporating local search and achieves better results.

Two excellent overviews of multi-parent crossovers can be found in Eiben's studies [4, 5]. These researches have demonstrated the effectiveness of multi-parent crossovers in binary-coded or real-coded GAs on functional optimization problems as well as multi-objective problems. However, there are two advanced issues for multi-parent

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crossovers. The first issue is the increasing disruptiveness caused by multiple parents. This disruptiveness on the one hand leads to a more diverse exploration which can prevent premature convergence, but on the other hand, it slows convergence speed at the same time. Second, the number of parents adopted is more than two but nevertheless, is traditionally set fixed in multi-parent crossovers. Adaptive methods for two-parent crossover or mutation have obtained many successful results in GAs [6, 14, 23]. Accordingly, the idea of adaptively tuning the number of parents emerges. In this paper, we integrate the strategy of tabu search (TS) into multi-parent crossover to address these two issues. The proposed method, called tabu multi-parents genetic algorithm (TMPGA), uses the tabu restriction and the aspiration criterion to sift the mating of multiple parents. The advantage of such a strategy has been verified for two-parent crossover to harmonize selection pressure and diversity maintenance [24, 25]. Furthermore, the tabu strategy adjusts the number of parents according to the condition of mating pool. Consequently, the disruptiveness caused by multi-parent crossover is controlled in consideration of exploitation and exploration. The effectiveness of TMPGA is examined by several experiments and comparisons with traditional two-parent crossover and multi-parent diagonal crossover on four common test functions.

The rest of this paper is organized as follows. In the next section, we give a detailed description of the proposed TMPGA. Section 3 presents performance comparisons and result analysis of TMPGA. Finally, conclusions are drawn in Section 4.

2. Tabu Multi-Parent GA (TMPGA)

TMPGA integrates the strategy of tabu search into the mating strategy of multi-parent genetic algorithms. First, the tabu list restricts the mating in an incest-prevention manner to maintain diversity. Second, the aspiration criterion releases the restriction on mating to supply selection pressure. Such a synergy of tabu list and aspiration criterion is expected to achieve a harmony in diversity maintenance and selection pressure. Moreover, the outcome of mating affects the number of parents participating in multi-parent crossover. Therefore, by the integration of TS, a harmony in mating and a further control on the disruptiveness for multi-parent GA are obtained. However, some corresponding modifications are necessary for GAs to incorporate the strategy of TS. The following subsections provide more detailed descriptions about the components for multi-parent GA to combine the strategy of TS. The proposed algorithm TMPGA is presented afterward.

2.1. Representation

Tabu Search (TS) uses a memory structure, called tabu list, to guide the search in consideration of diversification and intensification [13]. To accommodate such a memory structure to GA, two components are necessarily appended to the representation of chromosomes. First, a clan number is introduced to identify chromosomes. This number is assigned uniquely at the initialization stage. During reproduction offspring inherit the clan number from one of their parents. The second component is the tabu list, which records a set of forbidden clans to mate. Figure 2.1 illustrates a representation in binary-coded GAs. The genes are encoded in bit strings concerning the solutions of the optimizing problem. Additionally the clan (8) with the tabu list (2, 6) carries the information for tabu mating strategy.

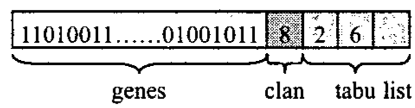

Figure 2.1 Representation of chromosomes

2.2. Mating Strategy

In TMPGA, the mating of multiple parents is not unbridled but is restricted by the strategy of tabu search. This restriction further affects the number of parents participating in a reproduction.

The mating strategy of TMPGA is made up of two forces in TS, specifically, the tabu restriction and the aspiration criterion. First, the clans indicated in the tabu list mean that these clans are forbidden for one to mate. A check is performed on the selected parents to see whether the mating of these parents is forbidden or not. Such a restrictive mechanism is helpful to maintain population diversity through an incest-prevention manner [2, 10, 22]. However, for a moderate restriction and a reduction of computation, TMPGA adopts the concept of polygamy; the tabu-checking procedure is only performed upon the first selected parent with other selected parents. As Figure 2.2 shows, the tabu restriction occurs when the first parent detect its clan appears in another parent's tabu list, and vice versa. Due to the tabu restriction, this mating is judged invalid unless the following aspiration criterion is satisfied.

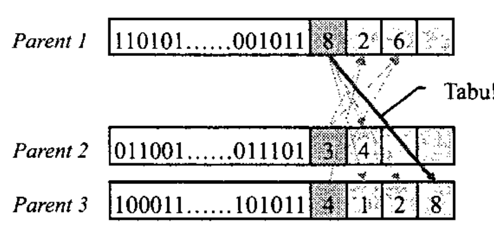

Figure 2.2 Tabu checking procedures

The aspiration criterion is another measure used to judge mating. This criterion defines that the tabu restriction for a mating is overridden if any of offspring reproduced by this mating is superior to the best chromosome so far. In other words, a mating is allowed by the aspiration criteria even though the mating is forbidden by the tabu restriction. This release from restriction provides moderate reinforcement in selection pressure. The interaction of the tabu restriction and the aspiration criterion consequently achieves a harmony in diversity maintenance and selection pressure.

A mating is classified invalid and is not allowed if this mating incurs a tabu restriction but is unable to meet the aspiration criterion. Only offspring from a valid mating can be put into subpopulation. Besides, after a valid mating, parents have to update their tabu lists: the first parent adds all mates' clans to its tabu list while the rest of the parents just add the first parent's clan to their tabu lists. Afterward, offspring inherit the updated tabu list from one of their parents. The operation of updating the tabu list works in a FIFO manner. The oldest clans will be released from the tabu list while some new forbidden clans are added. These released clans regain the permission for one to mate. Figure 2.3 illustrates the procedures of updating the tabu list. The first parent adds the clans (3, 4) of the mates to its tabu list; other parents only add the clan (8) of the first parent to their respective tabu list. The released clan (6) means that the first parent regains the permission to mate the chromosomes with clan (6).

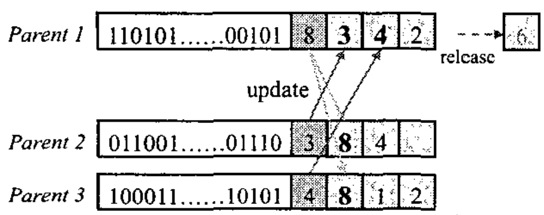

Figure 2.3 Update of tabu list

TMPGA further uses the resulting validity of mating to control the number of parents. If a mating is valid, its offspring will be put into subpopulation normally. Otherwise, in case of an invalid mating, TMPGA will remove all the tabu parents to enable this mating valid, and then re-apply multi-parent crossover with the remaining parents to reproduce offspring. Provided all mates of the first parent are removed, the selection operator will re-choose another mate from population to keep the mating has at least two parents. Accordingly, the number of parents varies with the situation of population. In the beginning of evolution, the parent number is large because the mating is less likely to incur a tabu restriction and has a higher possibility to meet the aspiration criterion. This large number of parents leads to a more diverse search around the problem space [8]. Such an enhanced exploration can contribute to a better solution quality. Next, the number of parents is on the decrease with convergence. During evolution the population becomes more and more similar and then results in a higher probability to get invalid mating. Correspondingly, the number of parents will decrease with the growing number of tabu parents in an invalid mating. Finally, the number of parents will decline to two; at that time, multi-parent crossover will degenerate to traditional two-parent crossover. This declining procedure keeps the search from violent perturbation and allows it more exploitation when the search approaches the promising region of problem space. On the whole, this adaptive strategy of varying parent number will take exploration and exploitation into account in different phases of evolution.

2.3. TMPGA Algorithm

The proposed algorithm TMPGA is described in Figure 2.4. Most procedures of TMPGA follow the original architecture of GA except the screening process, i.e. steps 12~13, conducted by the tabu strategy. Additionally, a special rule is designed for the variation of parent number n in order to reduce the computation cost of the tabu checking. This rule initially sets the trial number of parents to a maximal value and then changes the number to the largest parent number of valid mating in each generation. As the trial number is reduced to two, the checks of tabu restriction and aspiration criterion are omitted because at this time multi-parent crossover degenerates to a two-parent version. The reason for this rule is that the population will gradually lose its diversity and yield a higher and higher probability of invalid mating; that is to say, it takes increasing computation on the removal of tabu parents. By the rule, the number of parents is defined according to the situation of population in the preceding generation. Generally the rule causes fewer and fewer parents participating in a mating. Hence, the number of trivial tabu checking can be significantly reduced, especially when the population loses most of its diversity and the probable number of parents is two.

TMPGA( )

1 $t \leftarrow 0$ *// t :generation*
2 initialize $P(t)$ *// P(t) :population*
3 evaluate $P(t)$
4 $n \leftarrow$ MAX_PARENTS *// n :parent number*
5 **while** (not terminated) **do**
6 $t \leftarrow t+1$
7 **while** ($P(t)$ is not filled) **do**
8 $p_{1...n} \leftarrow$ select($P(t-1)$) *// p :parents*
9 $c_{1...m} \leftarrow$ reproduce($p_{1...n}$) *// c :offspring*
10 evaluate $c_{1...m}$
11 **if** ($n > 2$) **then**
12 **if** (Tabu($p_{1...n}$)) and (not Aspiration($c_{1...m}$)) **then** *//[Tabu] //[Aspire]*
13 $p_{1...n'} \leftarrow$ removeTabu($p_{1...n}$)
14 $c_{1...m} \leftarrow$ reproduce($p_{1...n'}$)
15 $P(t) \leftarrow P(t) \cup c_{1...m}$
16 $P(t) \leftarrow$ survival($P(t-1), P(t)$)
17 $n \leftarrow$ the largest n of valid mating

Figure 2.4 The algorithm TMPGA

3. Performance Evaluation

In this paper, several experiments are conducted to evaluate the performance of TMPGA. A test suite consisting of four common test functions [1, 3, 19] is implemented for each experiment: De Jong's second test function (F2), the Rastrigin (RAS), the Schwefel (SCH), and the Griewangk (GRI). Table 3.1 presents these test functions and the related parameters used in our experiments. Besides, classic two-parent GA and multi-parent GA (MPGA) are implemented to verify the superiority of TMPGA.

The schemes of GA employed in our experiments are generational GA, bit-string representation, roulette wheel selection, flip mutation, and elitism. A population size of 200 chromosomes is used for all problems. Each experimental setting includes 50 trials; each trial runs 100 generations. Population is initialized randomly at each run. For all algorithms the crossover rate P_c is fixed to 1.0 and the mutation rate P_m is set to (1/chromosome_length). Besides, traditional 1-point crossover is adopted for GA, and diagonal crossover is used for MPGA. The algorithm TMPGA does not prescribe the option of multi-parent crossover; however, in order to give a fair comparison, the crossover that TMPGA adopts here follows the same multi-parent crossover, namely diagonal crossover, as MPGA in all experiments. The diagonal crossover of MPGA adopts 15 parents because of its best performance among our several experiments on the extent of 11 to 15 parents. For TMPGA, the trial parent number is also set to 15 initially, and then it is adjusted adaptively by the strategy of tabu search as mentioned in Chapter 2. The size of tabu list in TMPGA is empirically set to 10 for a reasonable restriction.

3.1. Performance Comparison

Figure 3.1 compares the convergence of TMPGA with that of GA and diagonal-crossover (MPGA) on four test functions. The results show that TMPGA converges faster than both GA and MPGA on all functions except the first half of convergence on function F2. Besides, MPGA converges faster than GA on functions SCH and GRI but slower than GA on F2 and RAS. In terms of solution quality, TMPGA yields better solutions than GA does on all functions and MPGA does on function RAS. Nevertheless, the differences of the best solutions obtained from MPGA and TMPGA are not significant on functions F2, SCH, and GRI.

The results shown in Figure 3.1 are compared with respect to generations. TMPGA, however, spends additional computation on tabu checking and invalid mating in each generation. Thus, the comparison by generations may not be so fair. Considering this, we further compare convergence in terms of running time. Figure 3.2 depicts the convergence comparisons regarding the time taken in each generation. The comparing algorithms are coded in C language and run on an Intel Pentium III – 1.7GHz machine. From Figure 3.2 we conclude that the additional computation somewhat decreases TMPGA's outperformance upon convergence speed if compared with the results in Figure 3.1. Nevertheless, TMPGA still achieve a faster convergence than GA does on functions RAS, SCH, and GRI. TMPGA also converges faster than MPGA on all test functions even though the convergence of TMPGA and MPGA are close on functions SCH and GRI. This superiority supports that the extra computation cost of TMPGA is worthwhile in terms of convergence speed.

Table 3.2 quantifies the improvements of MPGA and TMPGA in the convergence speed of GA. The values t_{MPGA} and t_{TMPGA} respectively indicate the generations (time) taken for MPGA and TMPGA to achieve GA's best fitness in our experiments. The results in Table 3.2 show that TMPGA converges faster than GA by 24 to 66 generations or by 0.881 to 3.352 seconds; in other words, TMPGA saves 22% to 69% of GA's convergence time. MPGA also converges faster than GA except the convergence on RAS, in which MPGA performs similar to GA. Altogether, these comparisons further demonstrate that TMPGA is capable of a more efficient convergence and a more constant outperformance than that of MPGA.

Table 3.1 Test functions

	Functions	Range of x_i	N	Bits of x_i	Chrom. length
F2	$f=100\left(x_1^2-x_2^2\right)^2+\left(1-x_1\right)^2$	[-2.048, 2.047]	2	12	24
RAS	$f=10N+\sum_{i=1}^{N}\left(x_i^2-10\cos(2\pi x_i)\right)$	[-5.12, 5.11]	20	10	200
SCH	$f=\sum_{i=1}^{N}-x\sin\left(\sqrt{\lvert x_i\rvert}\right)$	[-512, 511]	10	10	100
GRI	$f=1+\sum_{i=1}^{N}\frac{x_i^2}{4000}-\prod_{i=1}^{N}\left(\cos(\frac{x_i}{\sqrt{i}})\right)$	[-512, 511]	10	10	100

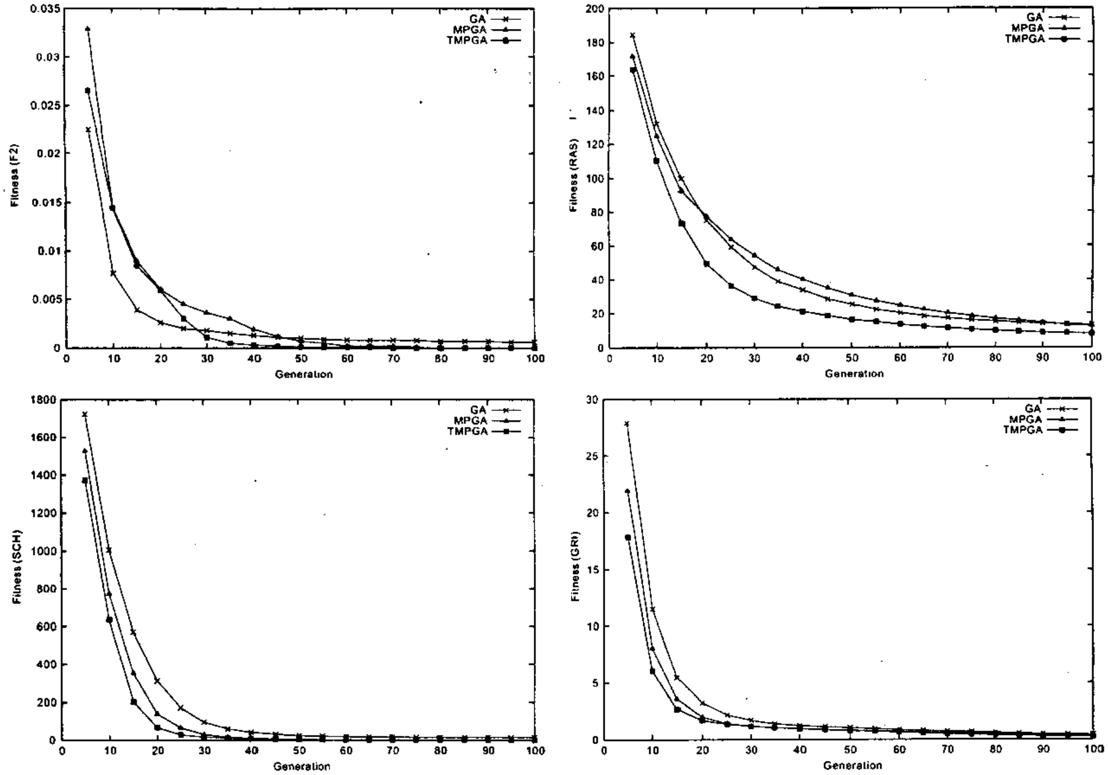

Figure 3.1 Comparison of GA, MPGA, and TMPGA in terms of generations

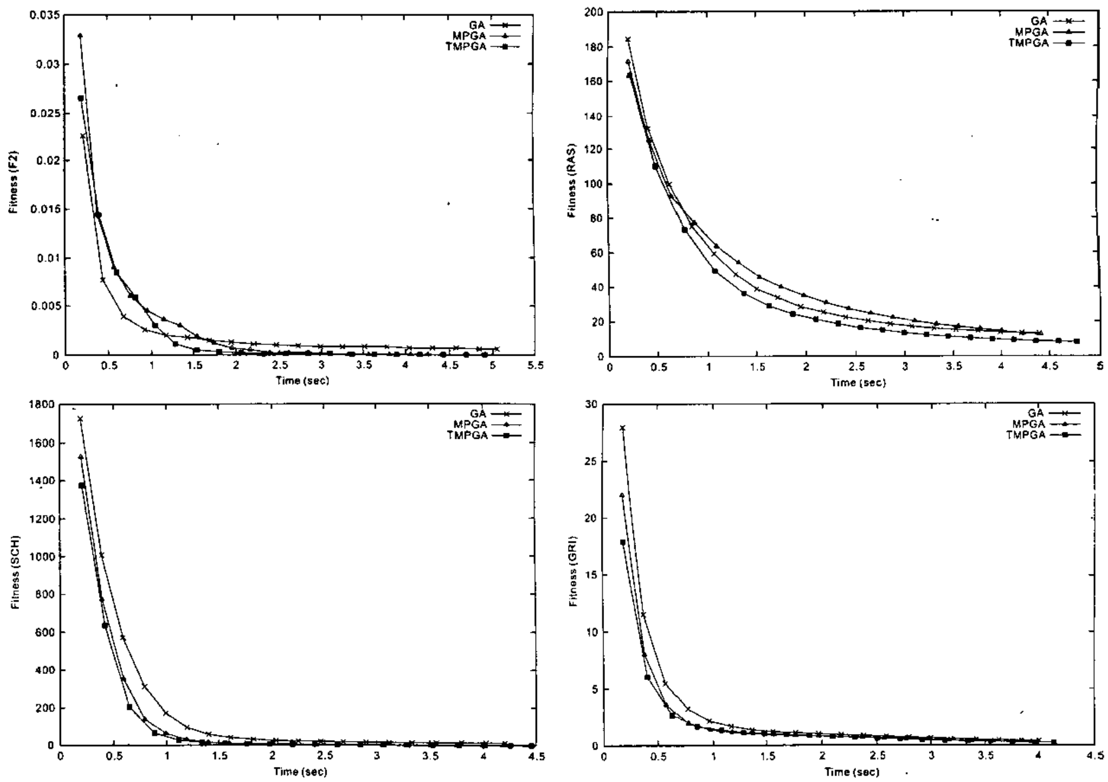

Figure 3.2 Comparison of GA, MPGA, and TMPGA in terms of running time

Table 3.2 Generations (time) for MPGA and TMPGA to achieve the best fitness of GA

	t_{GA}	t_{MPGA}	t_{TMPGA}	$\Delta t_{MPGA-GA}$ (%)	$\Delta t_{TMPGA-GA}$ (%)
F2	96 (4.840)	53 (2.036)	35 (1.488)	44.8 (57.9)	63.5 (69.3)
RAS	100 (4.398)	97 (4.277)	62 (3.041)	3.0 (2.8)	38.0 (30.9)
SCH	100 (4.207)	38 (1.478)	34 (1.470)	62.0 (64.9)	66.0 (65.1)
GRI	100 (4.009)	84 (3.289)	76 (3.128)	16.0 (18.0)	24.0 (22.0)

t_X : generations (time) for the algorithm X to achieve GA's best fitness

Δt_{X-GA} (%): relative deviation of generations (time) t_X and t_{GA}

3.2. Analysis of Results

Furthermore, we examine the impact of tabu restriction and aspiration criterion upon TMPGA's performance and number of parents. As Figure 3.3 shows, the numbers of tabu events peak around 40 generations on F2 and around 20 to 25 generations on RAS, SCH, and GRI. In comparison of this circumstance with the convergence of TMPGA on Figure 3.1, we find that the peak of tabu events corresponds to the point starting slow convergence. We attribute such a circumstance to the exhaustion of population diversity. During evolution the population gradually loses its diversity and becomes more and more similar. When the population is so similar that it fills a lot of chromosomes with the same clans, the probability of tabu events will raise correspondingly. On the other hand, it reflects that the population is too similar to explore the problem space effectively. The convergence of TMPGA, therefore, gets slow in correspondence with the peak of tabu events.

Figure 3.4 depicts the variation in the parent number of TMPGA on four test functions. Clearly, the number of parents decreases with evolution until two. This tendency results from the decreasing population diversity. As mentioned in Chapter 2, the validity of mating determines the number of parents in TMPGA. Initially the population is diverse and the best solution obtained is far from the global optimum; thus it is less likely to incur a tabu restriction but easier to meet the aspiration criterion. As shown in Figure 3.3, the beginning has only a few tabu events and relatively many aspiration events. In the course of evolution, the probability of valid mating gets lower and lower because of the growing tabu events and the declining aspiration probability. On the whole, the number of parents declines with the evolution as Figure 3.4 shows. Hence, the disruptiveness caused by multi-parent crossover is progressively restrained, especially when the search approaches to the promising region. However, the effect of tabu strategy upon the number of parents is not one-way but interactive. The tabu restriction reduces the number of parents while this reduced number of parents will further lower the probability to incur tabu restriction in the next generation. All in all, the synergy of tabu restriction and aspiration criterion achieves not only a harmonious mating but an adaptive restraint on disruptiveness; consequently, it leads to the outperformance of TMPGA.

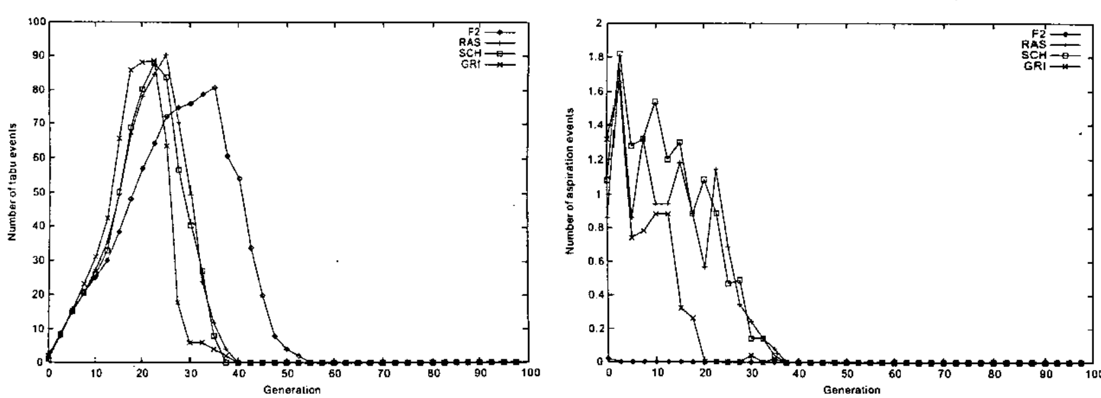

Figure 3.3 Variation in number of tabu events (left) and aspiration events (right) for TMPGA on four test functions

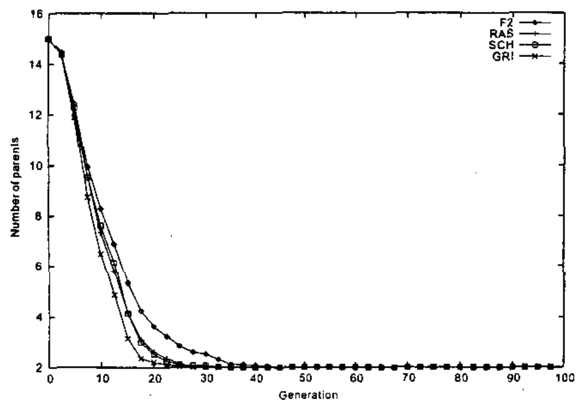

Figure 3.4 Variation in the number of parents for TMPGA on four test functions

4. Conclusions

This work presents a tabu multi-parent genetic algorithm (TMPGA), which integrates the strategy of tabu search into the mating of parents for the multi-parent crossover. First, an additional memory structure consisting of a clan number and a tabu list is appended to the representation of chromosomes. This memory structure records the trajectory of evolution and further acts as the basis of mating strategy. The tabu restriction contributes to maintain diversity in an incest-prevention manner by forbidding parents to mate with the chromosomes on the tabu list. The aspiration criterion, on the other hand, supplies moderate selection pressure by overriding the tabu restriction for those superior solutions. TMPGA utilizes the synergy of tabu restriction and aspiration criterion to control the mating of multiple parents for a good balance of diversity maintenance and selection pressure. The outcome of mating further adaptively adjusts the number of parent for the multi-parent crossover. Therefore, the disruptiveness caused by multiple parents is restrained progressively in the course of evolution.

The effectiveness of TMPGA is verified by the experiments on four common test functions. The results present the influence of tabu restriction and aspiration criterion upon the number of parents; nevertheless, the parent number affects tabu restriction as well. TMPGA's well performance reflects the advantages of such an interaction. The performance comparisons indicate that TMPGA achieves faster convergence and better solution quality than classic two-parent GA and multi-parent GA with diagonal crossover on the test functions. Altogether, these favorable results demonstrate the superiority of TMPGA due to the integration of tabu search into the mating strategy of multi-parent genetic algorithms.

However, more tests and analyses are needed to confirm the general outperformance of TMPGA. This paper only uses the diagonal crossover as the multi-parent crossover in TMPGA. More multi-parent crossovers such as scanning crossover or multi-cut crossover are needed to test for validating TMPGA's effectiveness on multi-parent GAs. On the performance evaluation, we compare the approaches in terms of running time to present the general influence of additional computation in tabu and aspiration checking upon the convergence. Nevertheless, other criterion, such as the number of function evaluations, should be further considered. Besides, in this paper, performance is only evaluated experimentally with functional optimization problems. Currently we are conducting a series of comprehensive experiments on the components of TMPGA. Theoretical analysis and further improvements in TMPGA are also underway.

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