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NORMALIZED RANK SELECTION METHOD AND ITS APPLICATION IN DESIGN OF FAULT-TOLERANT PLD-BASED SYSTEMS USING GENETIC ALGORITHMS

The paper deals with several selection schemes which evolve fault-tolerant PLD-based systems using genetic algorithms. It has been suggested to use the new normalized rank selection method instead of common rank selection while designing PLD-based systems. The considered selection schemes have been investigated by the example of heating controller for AN-70 plane.

PLD-systems, diversification, genetic algorithms, selection methods

Introduction

Genetic algorithms (GA) represent a relatively new direction in computer science. Based on natural evolution principle, they are an effective tool for solving functional optimization tasks [1, 2]. Digital system design is one of many fields where GA can be applied. Nowadays, there is a lot of research that investigates GA application in designing digital systems, which are implemented on programmable logic devices (PLD) [3, 4]. In fact, such a design technique is beyond the classical paradigm of system creation and allows obtaining non-trivial and non-conventional solutions [5]. This feature of GA-guided design is useful within the multi-version approach to design of fault-tolerant PLD-based systems [6 – 8], as it helps to obtain the least correlated versions of a system.

The analysis of the related works shows that the multi-version approach gives the best results if several techniques are used in system design: classical CAD-guided and new GA-guided designs [6, 8]. Nowadays, we have well-known methods to diversify the projects of PLD-based systems at several stages of their lifecycle, when CAD tools are applied for system design [9]. Regarding the GA-guided design, the ways of diversifying digital systems have not been properly investigated yet.

Another important issue that arises when using GA is that the inefficient utilization of some genetic operators causes deterioration of evolutionary process effectiveness [10, 11]. There is an evident interdependency between GA effectiveness and type, scheme and probability of using genetic operators [12, 13].

The main purpose of this research is to investigate the selection operator as one of the ways to diversify PLD-based systems by means of GA and to challenge different selection schemes as well as to suggest the new selection method to avoid some difficulties that arise while ranking individuals with equal fitness.

Selection Methods in Genetic Algorithms

The projects of PLD-based systems can be diversified at the stages of GA presetting, selection, crossing, mutation and inversion of individuals (the versions of PLD-based system) [14]. One of the important stages of GA-guided system diversification is to choose the selection methods, as the logic of these methods impacts the effectiveness of selecting the best individuals from a population.

At the stage of selecting the fitting individuals the developer may choose the appropriate selection method: roulette wheel, rank, tournament, steady-state or elite selection, etc.

Roulette wheel selection (fig. 1) means that parents are selected according to their fitness. The better the individuals are, the more chances to be selected they have. The size of sections in the roulette wheel is proportional to the values of the fitness function of every individual - the bigger is the value, the larger is the section. The individuals with bigger fitness value will be selected more often.

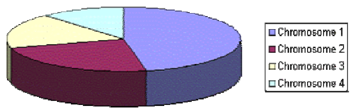

Fig. 1. Roulette wheel selection.

The effectiveness of this selection method equals o(n), where n is the population size.

In spite of simplicity and obviousness of such a scheme, GA tends to premature rapid convergence if there are big differences between the fitness values of individuals in a population. To avoid this issue, some other selection methods should be applied – for example, rank selection.

Rank selection (fig. 2) ranks a population first and then every individual receives fitness value determined by this ranking. The worst one will have fitness 1, the second worst – fitness, etc. The best individual will have fitness n (the amount of individuals in a population)

Fig. 2. Rank selection.

The total number of roulette sectors M according to the given method is

$$M = \sum_{i=1}^{n} i\,, \tag{1}$$

n – the population size.

The effectiveness of this selection method, while designing PLD-based systems, equals $o(2^k \times n)$, where k is a bit capacity of the system input data.

This scheme can lead to slower GA convergence, because a minor difference between probabilities to be selected for the best and the worst individuals is the reason why the best individuals do not differ very much from other ones.

Another disadvantage of rank selection is that this method can not provide reasonable ranking if large quantity of individuals has equal fitness. This can often happen in case of GA-guided PLD-based system design, while forming the early populations. So, individuals with the same fitness value have different ranks which are set randomly. As a result, these individuals have different probability to take part in forming a new population. Hence, the more individuals with the same fitness value, the more differences between their probabilities to be selected.

Assumption 1: application of rank selection is more effective in the early generations, when even individuals with the small fitness value should not be ignored while forming a new population, whereas roulette wheel scheme is preferred latter on.

To avoid incorrect ranking of individuals with equal fitness, it has been suggested to improve rank selection by normalizing individuals' fitness.

Application of **normalized rank selection** includes several steps (fig. 3):

– individuals with the equal fitness are joined in groups;

– roulette wheel is divided into $g(g + 1)/2$ sectors, where g is the amount of formed groups;

– group with the least fitness value receives one share, next group – two shares, etc. The group with the best fitness receives g shares;

– roulette space of every group is shared between all individuals from this group by equal sectors.

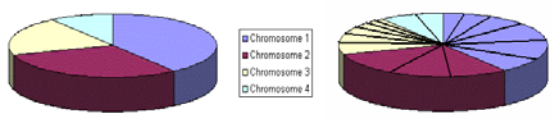

Fig. 3. Normalized rank selection

The total number of roulette sectors M according to the given method is

$$M = \sum_{i=1}^{g} h_i \times i , \qquad (2)$$

g – the amount of groups of individuals with the same fitness; h_i – the total number of individuals in group i.

The effectiveness of this selection method, if it is used for designing PLD-based systems, is $o(2^k \times n \times g)$.

This normalized rank selection provides reasonable probability to be selected for each individual but in contrast to the simple rank selection, the individuals with the same fitness have equal probabilities to be selected for reproduction.

Assumption 2: normalized rank selection should be applied during the early GA iterations as in this case the probability to evolve individuals with the same fitness value is the highest.

Experience

Effectiveness of the considered selection methods and their combinations have been challenged by series of experiments, which were intended to evolve a model of heating controller for AN-70 plane. Five experiments have been carried out. In each experiment there has been implemented one of the following selection schemes:

– roulette wheel selection combined with elitism;

– rank selection combined with elitism;

– combination of rank, roulette wheel and elite selections;

– normalized rank selection combined with elitism;

– combination of normalized rank, roulette wheel and elite selections.

Every experiment has included six GA runs to avoid statistic distortions. The table1 shows the initial data accepted for the experiments.

Table 1

Initial Data

The initial data	**Value**				
The area for modeling (logic cells)	8×8				
Project requirements, the truth table	The input 7-bit data: 1-st bit determines a sign; 2–7 bits determine value of temperature (°C). The output 2-bit data: '01' – the temperature is lower than 15°C; '10' – the temperature from 15°C up to 35 °C; '11' – the temperature is higher than 35°C.				
GA options	1	2	3	4	5
– population size	70	50	50	50	50
– type of selection	roulette, elitism	ranking, elitism	roulette, ranking, elitism	normalized ranking, elitism	normalized ranking, roulette, elitism
– crossover probability	0,70	0,80	0,80	0,80	0,80
– mutation probability	0,20	0,10	0,10	0,10	0,10
– probability of gene mutation	0,05	0,05	0,05	0,05	0,05
– inversion probability	0,10	0,10	0,10	0,10	0,10
– probability of gene inversion	0,01	0,01	0,01	0,01	0,01
– type of crossover	uniform	uniform	uniform	uniform	uniform
– GA iterations	1000	800	1600	1000	1000
– distribution law	normal	normal	normal	normal	normal

Experiment 1: combination of roulette wheel selection and elitism. The analysis of the first experiment shows that GA tends to premature rapid convergence if there are big differences between the fitness values of

individuals in a population. Using this selection scheme, the best individual has been evolved in 651-704 generations (fig. 4).

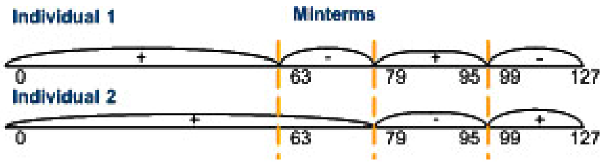

Fig. 4. The scheme of minterm overlapping in the heating controller model submitted by experiment 1

Experiment 2: combination of rank selection and elitism. The scheme of rank selection combined with elitism leads to slower GA convergence, as shares for the best and the worst individuals do not differ significantly from one another. Using this selection scheme, the best individual has been evolved in 638-812 generations (fig. 5).

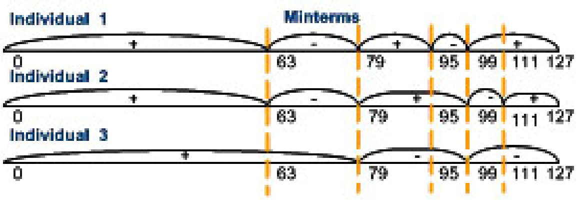

Fig. 5. The scheme of minterm overlapping in the heating controller model submitted by experiment 2

Experiment 3: combination of rank, roulette wheel and elite selections. The results of the third experiment have confirmed assumption 1. They show that if an average fitness of individuals in a population is less than 5%, the rank selection scheme works better than the roulette wheel one. In case the average fitness is more than 5%, the roulette wheel selection provides better results. In this experiment the best individual has been obtained in 316-711 generations.

Experiment 4: normalized rank selection combined with elitism. The results of the fourth experiment have confirmed that normalized rank selection should be applied in the early GA iterations, as the probability to evolve individuals with the same fitness is the highest. By this selection scheme the best individual has been got in 586-764 generations.

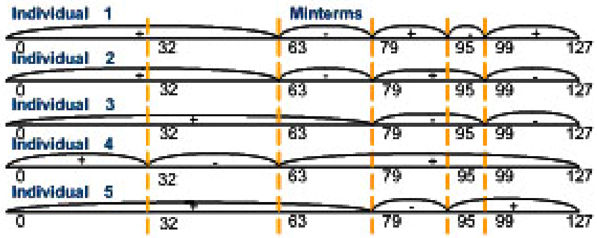

Fig. 6. The scheme of minterm overlapping in the heating controller model submitted by experiment 3

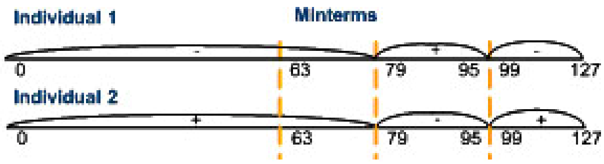

Fig. 7. The scheme of minterm overlapping in the heating controller model submitted by experiment 4

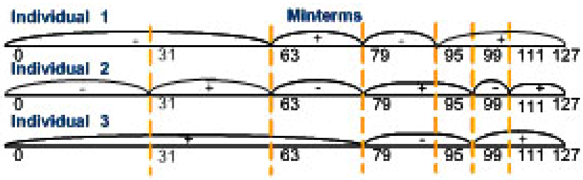

Fig. 8. The scheme of minterm overlapping in the heating controller model submitted by experiment 5

Experiment 5: combination of normalized rank, roulette wheel and elite selection. The conclusions obtained from the third and forth experiments have been united in the fifth experiment, where we used a combination of normalized rank (if an average fitness of individuals is less than 5%), roulette wheel (if an average fitness of individuals is more than 5%) and elite selections. Assumption 2 has also been confirmed: application of this scheme provided the best results and the individual with the highest fitness has been evolved as early as in 194-458 generations.

Conclusions

The analysis of the selection schemes that can be applied while designing PLD-based systems shows that combining several selection methods during the

GA flow is more effective than utilizing only one method.

The use of the normalized rank selection in the early populations and roulette wheel selection latter on allows avoiding disadvantages of each method and achieves the best results in GA-guided designing PLD-based systems.

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