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Multi-Operator Genetic Algorithm for Dynamic Optimization Problems

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ABSTRACT

Maintaining population diversity is the most notable challenge in solving dynamic optimization problems (DOPs). Therefore, the objective of an efficient dynamic optimization algorithm is to track the optimum in these uncertain environments, and to locate the best solution. In this work, we propose a framework that is based on multi operators embedded in genetic algorithms (GA) and these operators are heuristic and arithmetic crossovers operators. The rationale behind this is to address the convergence problem and to maintain the diversity. The performance of the proposed framework is tested on the well-known dynamic optimization functions i.e., OneMax, Plateau, Royal Road and Deceptive. Empirical results show the superiority of the proposed algorithm when compared to state-of-the-art algorithms from the literature.

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1. INTRODUCTION

In the recent decades, dynamic optimisation problems (DOPs) have been one of the major interesting research subjects, due to the fact that DOPs represent real world optimisation scenarios [1]. The possibility of a problem changing over time influences on the functionally and behaver of an optimal solution. Therefore, there is a need to design an effective Evolutionary Algorithm (EA) to handle DOPs. Indeed, the nature of EA in generating different solutions in every single evolution helps EA to adapt with changes of DOPs. By employing an EA such as a genetic algorithm (GA), the DOPs will be solved [2, 3]. Existing studies show that adaptive algorithms that use diversity maintaining methods have been widely developed to address DOPs [4].

This paper aims to develop a crossover operator for GA in order to effectively address DOPs. Essentially, the dependency of GA on genetic operators generally and crossover operators practically effect its performance [4]. Yet, the chance of reproduction a new offspring will be lost in case of having identical chromosomes (parents) that have been selected for the crossover operator during the evolution stage. Hence, the diversifying the selecting cut-point rather than using fixed ones could overcome this identical case of failure. This paper introduces a hybrid adaptive crossover operator based on pre-evaluated chromosomes before passing individuals to the next stage. The idea of this work is to: reduce computation time, reduces the random chance of combine's gens of two chromosomes and enhance the results toward better solution.

To accomplish this aim and to respond to a recent call for research to address DOPs, we have to recall the well-known dynamic optimisation functions such as, One-man, Plateau, Royal Road and Deceptive, in order to examine the effectiveness of the proposed method. Experimental results show that the proposed algorithm is able to achieve competitive results when compared to other available methods. The rest of this paper is organized as follows. In section 2, the proposed method in this study is given. Next section deals with the experimental results and relevant discussion. Finally, section 4 concludes the results with some recommendations on the future work.

2. PROPOSED METHOD

In this paper, we propose a hybrid crossover operator for GA to effectively solve DOPs. The dependency of GA on genetic operators generally and crossover operators practically effect on its performance [1]. However, the chance of reproduction a new offspring will be lost in case of having identical chromosomes (parents) that have been selected for crossover operator during the evolution stage. Hence, the diversifying the cut-point selection instead of using fixed ones could overcome this identical case of failure as well as avoiding the random combination of the gens of the selected two chromosomes. This paper presents a hybrid adaptive crossover operator based on pre-evaluated chromosomes before passing individuals to the next stage. Basically, it uses two types of crossover as will be explained below:

2.1. Heuristic crossover operator (HCO)

HCO shifts marginally a child from worst fitness value to the best fitness value of parent [2]. This shifting is based on Ration value which is a random value between 0's and 1's. Indeed, the value of Ration could be setting in by default. If both P1 and P2 are parents and P1 has a better fitness value than P2, then 1.2 will be setting as a Ration value [1]. The new offspring will be generated based on the following equation:

$$\text{Offspring's} = \text{Best Parent} + \beta * (\text{Best Parent} - \text{Worst Parent}).$$

2.2. Arithmetic Crossover (ACO)

ACO returns an offspring that are hold mean fitness of two individuals [1]. Alpha is a tiny value between [0, 1] generated randomly. If Chromosome1 and Chromosome2 are parents, and Chromosome1 has the best fitness, the offspring with be generate as follows:

$$\textit{Offspring} = \alpha * \textit{Best Parent} + (1-\alpha) * \textit{Worst Parent}.$$

2.3. Hybrid Crossover Operator (HYCO)

Undoubtedly, the effectiveness of crossover is depends on the results of selected parent [1]. Due to the nature of evolution the necessity to produce better solution is represented in this stage. Our proposed operator investigates the advantages of HCO with ACO crossover. Both of them examine the fitness of chromosome before combining them. The random selection to cut-point invokes at first step. Our idea is to enhance the mating process. The complete procedure is presented in Figure 1.

```
Hybrid Crossover Operator: HYCO
Parameters (p1, p2: Parent, Ch1, Ch2: Offspring)
begin
if ( EliteP.fitness/4 > Worst P.fitness) then
begin
for i:=1 TO EliteP.size DO
begin
Offspring[i]=Best Parent + Ratio * (Best Parent – Worst)
endfor
end
else // if both of parent hold same feature
begin
for i:=1 to EliteP.size do
begin
Offspring[i] =alpha* Best Parent + (1-alpha)* Worst Parent
endfor
end
end;
```

Figure 1. Pseudo-Code for a Multi-Crossover-Based HC&AC

HYCO parametrize:

1. Ration is fixed value: =1.2.
2. Alpha random value between [0, 1].
3. CP is a crossover possibility.

As shown in Figure 1, the hybrid crossover based on combining the features of two chromosomes by:

1. If the parent X is more worth than parent Y then the offspring will be influenced by the better once by including its features inside their gens.
2. If both of chromosomes have similar quality, then the new one will has a combination of two chromosomes by employ arithmetic crossover which generates a hybrid solutions that effected by both parents.

3. RESULTS AND ANALYSIS

In this section, the performance of our proposed algorithm MCO is evaluated using four binary test functions, which are OneMax, Plateau, Royal Road and Deceptive [4]. These functions originally are stationary and have been widely used by many researchers to evaluate the performance of their algorithms. In this paper, we used a dynamic generator proposed by [5, 6] to generate dynamic environments. The parameter values of the proposed method are presented in Table 1.

Table 1. Parameters settings

Parameter	Value
Population Size	50
Solution size	100
Number of iterations	100
T	100
P	0.9

To assure fair comparison with the state-of-the-art approaches, the parameters T (which represents the periodically of changes) and P (which represents the amount of change) are set based on the work reported in [4].

The proposed method is compared against the following algorithms that have been proposed in the scientific literature:

Table 2. Results Comparison

Function name	MOC	Pop-HC	MIGA	MEGA	AHMA	MRIGA
OneMax	99.4	86.35	94.0	79.3	95.89	80.8
Pleateau	99.5	74.21	-	-	62.88	-
Royal Road	99.7	51.11	-	-	52.52	-
Deceptive	97.9	72.56	71.1	83.1	85.75	68.6

Note: values in bold font indicate the best results. “-“: no results reported.

Pop-HC: An Evolutionary Hill Climbing Algorithm for Dynamic Optimisation Problems [7].
MIGA: Genetic algorithm with memory based immigrants [6].
MEGA: memory-enhanced Genetic algorithm [8].
AHMA: Memetic algorithm with the AHC operator [1].
MRIGA: Genetic algorithm with memory and random immigrants schemes [6]

Table 2 contains the results of the proposed algorithm and state-of-the art algorithms.

A close scrutiny of Table 2 reveals that, out of all four instances, the proposed algorithm outperforms the other algorithms over three instances. Note that, the methods in comparison here did not attempt on all test functions. MOC is able to produce better results than all algorithms in 3 instances, and can be considered as competitive results across OneMax function. We believe this is due to the use of the MOC in order to preserve the diversity during the search process.

4. CONCLUSION

In this paper a multi-crossover operator which hybridises the heuristic crossover with the arithmetic crossover to effectively solve dynamic optimisation problems has been presented. The results of this study indicate that the diversity of populations need to a mechanism that can per-evaluate the gens before mating them. The performance of the proposed algorithm is assessed on the dynamic optimisation functions. The experimental results show that the proposed method obtained competitive results when compared to the methods in the literature. Further work needs to be done to establish whether employing another type of evolutionary algorithm or using a local search algorithm is effective in getting better solutions.

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