Volume 5, Issue 4, April 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

An Analytical Study on Different Selection Functions for Genetic Algorithm

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Abstract*— *Genetic is one of the evolutionary models used to optimize the solution process and provide the effective value derivations. This model is defined with different integrated stages where each stage itself can affect the optimization process. In this work, a study on selection layer of genetic model is defined. To perform the experimentation the dejong function II is taken as the input vector and fitness rule. The analytical study is here performed on rank selection method, roulette wheel selection and elitism selection model. The obtained results shows that the roulette wheel is most adaptive selection process for given problem.

Keywords – Genetic, roulette, Encoding, Crossover, Mutation

I. INTRODUCTION

Today one of the major challenges in each application area is to optimize the performance of associated process. Performance optimization not only provides the results in effective time but also reduces the energy consumption and provides the optimized use of available resources. One of the major phenomenons associated with performance optimization is the use of evolutionary algorithm. These kind of systems are specially designed to perform parallel execution of process so that the computation time will be distributed and the overall system performance will be improved. These kind of system provides the distribution of available resources under fitness rule specification so that the overall system process will be improved. The distribution of the problem and its split ion depends on the required resources. Algorithm process and application program itself. There is lot of work done in last few years to perform the effective and optimized mapping. The main objective of these mapping approaches is to provide the equalize distribution so that the problem will be resolved in polynomial time.

The optimizations systems are having their significance in almost all application areas that are having large size problems. One of such application area is network application or graph processing. The optimization in these kinds of systems is required to reduce the energy consumption and to improve the processing power. The multi processor systems are able to provide the load distributed in balanced way by assigning the multiple cores along with shared resources. As the overall workload is dependent on the application itself so that the first estimation is performed on application to identify the actual processing framework. Overall working of multi-core processor system is divided in three main stages given here under

A) Task Partitioning

As some task is assigned the multi-processor system, it is required to divide the process in sub-tasks. This division is based on the process level parallelism analysis as well as available number of processors. The division must be made in such way each subtask will be defined with specific memory and resources.

B) Task Mapping

Once the separate tasks are identified along with resource specification, the next work is to map the sub-tasks with relative processing system. The identification of appropriate processing system is required that can provide the required resources and processing along with process criticality. This mapping includes the analysis on computing resources that will be utilized by the subtask as well as analyze the contention among the available shared resources.

C) Dynamic Adaptation

After assigning the tasks to processing system, the analysis on the dynamic behavior of process and processor is required. This analysis is performed after adaptive interval so that the effectiveness of process execution can be identified. This analysis also includes the identification of critical situation if some collision or the invalid mapping is done during the resource assignment. This kind of mapping also required tracking the processing system along with process level adjustment. The adjustment is here defined to switch the task from one processing system to other if required

II. EXISITNG WORK

In this section the work defined by earlier researchers is presented. Lot of researchers defined work on various algorithmic approaches to optimize the relative mathematical and application specific processes. In this section, contribution of some of researchers is discussed. Author [1] has defined a comparative study on different optimization function. Author defined the work on both swarm based approaches and evolutionary approaches. The designed model is applied for circular array optimization under amplitude and phase variation parameters. The excitation value analysis is defined for antenna elements os that the optimal performance for the work will be obtained. The optimized value shows that the evolutionary algorithms are more effective then swarm based approaches. Author [2] defined a work on comparative analysis on some conventional algorithms. Author defined the work under the specification of problems for online applications. The comparative analytical study is presented by the author. Andrea Malossini [3] defined a work on quantum integration to the genetic approach. Author improved the selection process so that the overall complexity of this selection process will be improved. Author defined the class generation and derivation under fitness rule specification. Author defined the improved quantum model to analyze the computation with speed up process defined for genetic approach. Author defined a classical quantum and genetic approach so that the effective results will be confirmed from the work.

III. EXPERIMENTATION

In this present work, estimation on the significance of genetic algorithm is analyzed respective to data selection function. In this work, a comparative analysis is defined for three selection algorithms called rank selection algorithm, roulette wheel algorithm and elitism selection algorithm. To apply this algorithm, DeJong Function 2 is optimized under minimization approach. The description of this function is already given in section III. The work is here defined in two main stages. In first stage, the implementation of genetic algorithm is done to optimize the dejong function2 and later on the alteration to the selection phase is done under defined selection algorithms. In this section, these three selection algorithms are explained in detail. Here figure 1 is sowing the basic genetic model. This model is defined to optimize the Dejong function as well as to present the analytical results obtained from various selection methods. All the stages associated with this model are explained in this section

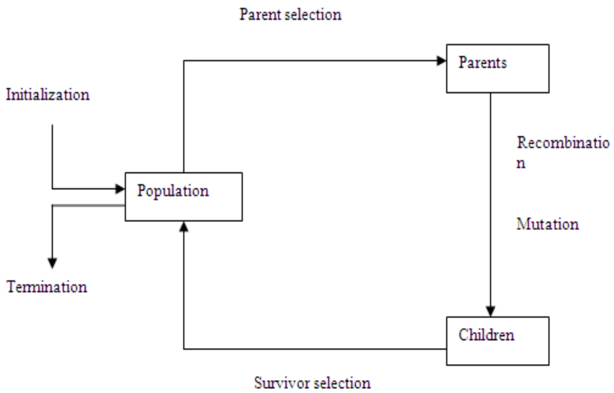

Figure 1: Genetic Model

A) Population

To apply the genetic algorithm, the first work is to formulate the problem. As the work is defined for DeJong function optimization so the problem population set is also defined respective to dejong Function 2. This function is defined as the classic optimization problem to represent the curvature in graph architecture. This function is also known as Rosenbrock's valley. This valley is identified as the banana function that itself represent a long, and parabolic shaped float valley. The function is required to optimize to converge this valley to optimum value. As the valley is trivial so that to identify the optimum solution for this problem is challenging task. The equational representation of this function is given here

$f_2(x) =$

Where

$-2.048 <= x_i <= 2.048$

As shown in the formula, the value of x will lie within the range the respectively the value of f2x will be identified. For these values the population set is defined for genetic process.

B) Fitness Function

Fitness function is here defined as the rule to perform the element selection from the population set as well as to identify the effective solution. The fitness function defines the data validity so that the acceptance of an element to the genetic process is identified. This function also adjust donw the values so that the performer and promoting values are identified effectively. The fitness function is also known as objective function based on which final optimized values will be identified. In this presented optimization function, the minimization method is used as the fitness vector. The Dejong function2 generates a banana valley, and the fitness function is about to reach to the optimal deep valley point in effective time.

C) Selection

As the population elements are defined, it is required to select two parents from the population set with each iteration and apply the fitness function. The selection is adaptive to the fitness function as well as respective to some algorithmic approach. This approach is defined in such way; the objective solution will be identified more easy and early. This paper is basically focused on selection process. In this paper, three selection functions are defined for the analysis. In this section, all these algorithms are defined in detail.

a) Rank Selection

The rank selection process is defined based on the fitness rule applied on the whole dataset collectively and based on the weightage assigned to these data values or individuals the data selection will be performed. The selection probability is here defined to perform the population data value selection. The selection is here based on the estimation on best and worst value based analysis. The probability adaptive value is here defined as under

$$pi = 1/N * \{pworst + (pbest – pworst) * [(I-1)/(N-1)]\}$$

The probabilistic estimation is here been defined under best case, worst case and the number of associated terms so that the effective data selection will be performed. The algorithmic specification of genetic optimization for this selection is given in
table 1.

Table 1:Rank Selection Adaptive Algorithm

```
RankSelectionAdaptiveGenetics(Population)

        /*Population is the data set obtained from Dejong function 2 equational specifcation*/
{
1.      Fitness(Min)
        [Define the Minimization based fitness function as objective function]
2.      AssignWeights(Population)
        [Assign the weights to population set based on the fitness adaptive values]
3.      selectedvalue=RankedSelection(Population)
        [Peform the rank adaptive selection based on the higher probability in the weighted values]
4.      Measure(selectedvalue)
        [Peform the fitness rule adpative analysis on  selected value for specific training period so best
        rule is identified]
5.      child=ApplyCrossover(selectedvalues)
        [Use the selected values as parent vector and   generate new child using crossover operation]
6.      Mutation(child)
        [Apply Mutation to modify the selected value]
7.      Update(child)
        [Update the child in the population set itself]
8.      Repeat steps from 2 till opjective not identified
}
```

b) Roulette Wheel Selection

Another adaptive selection process defined to select the data from population set is using Roulette Wheel Selection method. This method is defined specific for the application and based on the chance based proportional derivation. The selected elements are always the part of population itself, it means all data values are having the chance to select again. The measure of this method in terms of algorithmic approach is given in table 2.

Table 2 : Roulette Wheel Algorithm

```
RouletteWheel(Population)

        /*Population is the data set obtained from Dejong function 2 equational specifcation*/
{
1.      fitnessvalue=Fitness(Min)
        [Define the Minimization based fitness function as objective function]
2.      svalue=Sum(fitnessvalue)
        [Obtain the sum of fitness values of all population    elements]
3.      r=Random(svalue)
        [Generate a random decision vector between 0        and svalue]
4.      selecedvalue=Select(Population(r))
        [Selected this random adaptive value as the  population element]
5.      child=ApplyCrossover(selectedvalues)
        [Use the selected values as parent vector and   generate new child using crossover operation]
6.      Mutation(child)
        [Apply Mutation to modify the selected value]
7.      Update(child)
```

[Update the child in the population set itself]
8. Repeat steps from 2 till opjective not identified
}

c) Elitism Selection Approach

This is another selection process defined to preserve the fitness rule for the individual. This method is defined as the preemptive seeding approach applied on the population set. This method identifies the best population element then all previous runs. This method is also called jump-start method as the evolution of new best value. When the population set is updated regularly the election of effective element can be done using this method. This method is defined under specification of multiple vectors based on which the data element selection from population set can be done. The algorithmic approach adaptive to this approach is shown in table 3.

Table 3 : Elitism Selection Algorithm

ElitismSelection (Population)
/*Population is the data set obtained from Dejong function 2 equational specifcation*/
{
1. Fitness(Min)
[Define the Minimization based fitness function as objective function]
2. CheckWeights(Population)
[Get the weights to population set based on the fitness adaptive values]
3. analysis=Measure(Weight, PrevPopulation)
[Perform the analysis based on the previous weights defined on the early population vector]
4. selectedvalue=Select(best)
[Selected the best parent value based on the updated data vector]
5. child=ApplyCrossover(selectedvalues)
[Use the selected values as parent vector and generate new child using crossover operation]
6. Mutation(child)
[Apply Mutation to modify the selected value]
7. Update(child)
[Update the child in the population set itself]
8. Repeat steps from 2 till objective not identified
}

D) Crossover

The crossover operator is applied on selected data values to generate a new child. The genetic process meaning actually comes from crossover operator that produces the new value that again becomes the population part. The crossover can be of different types including one point crossover, two point crossovers etc. In this work, two point crossovers is taken. According to this proposed work, the selected population element will be split in two sub parts by specifying the crossover point. These two half are then mapped under the sequence analysis. The first half elements are mapped with second and finally a new child is obtained. This child is considered as the produced population element.

E) Mutation

The mutation process is defined as the optimal process to modify the generated value so that the true and significant data values will be obtained. The changes to the data values are made adaptive to the application or the process. In the simplest form, swapping is performed among the data part.

IV. RESULTS

As the work is here defined to optimize the Dejong function using genetic function. To present the analytical results under three defined selection algorithm, the work is experimented with all three methods. The parameters considered for the genetic process are shown in table 4.

Table 4: Experimental Parameters

Parameter	**Value**
Encoding	Real Encoding
Fitness Function	De Jong Function 2
Selection	Rank Selection, RouletteWheel,

	Elitism
Number of Iterations	100
Mutation Rate	1%
Population Size	20
Mutation	Interchanging

The result is here been defined in terms of optimization vectors obtained from the work. The comparative analysis is here shown in the form of graph.

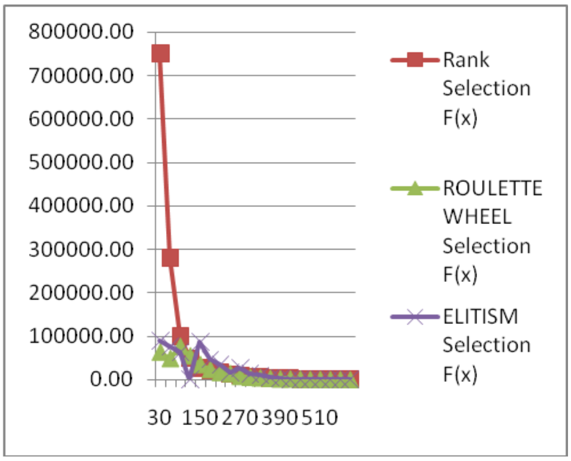

Figure 2 : Analysis Graph

Here figure 2 is showing the analytical graph obtained from the work. The figure shows that the routelette wheel has given most effective results. The optimized value after 600 iterations is 23.59 whereas in other approaches it is higher.

IV. CONCLUSION

In this paper, an analytical study to the genetic process is defined for selection stage. Here three selection algorithms called roulette wheel, elitism and rank selection are analyzed. To perform the experimentation, the dejong function II for parabola valley is defined and optimized. The result shows that the roulette wheel selection process is more adaptive then other approaches.

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