

Optimization of Software Testing Technique using Novel Genetic Algorithm

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Abstract

Software Testing is a process performed to maintain software quality. Thus, the goal of testing is systematically and stepwise detection of different classes of errors within a minimum amount of time and also with a much less amount of effort. Software testing is also an important component of software quality assurance (SQA), and a number of software organizations are spending up to 40% of their resources on testing.

Software testing is a very broad area, which involves many other technical and non-technical areas, such as specification, design and implementation, maintenance, process and management issues in software engineering. The study focuses on the state of the art in testing techniques, as well as the latest techniques which represents the future direction in this domain.

Numerous genetic algorithms have been developed and implemented for optimizing the testing techniques.

In this research work, a novel genetic algorithm (GA) which combines Cuckoo search and Particle Swarm Optimization (PSO) is designed and implemented to optimize the testing technique.

For implementing this novel genetic algorithm (GA), the Booth's and Hump Camel functions are used to calculate global best evaluation. The global or final best evaluation is calculated based on the number of particles and epochs.

Key Words: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Cuckoo Search Algorithm, White Box Testing.

I. INTRODUCTION

Testing [1] is the process of evaluating a system or its component(s) with the intent to find whether it satisfies the specified requirements or not. Testing [2] is executing a system in order to identify any gaps, errors, or missing requirements in contrary to the actual requirements.

1.1. Objectives of Software Testing

- A good test case is one that has a probability of finding an as yet undiscovered error.
- A good test is not redundant.
- A successful test is one that uncovers a yet undiscovered error [3].
- A good test should be "best of breed".
- A good test should neither be too simple nor too complex.
- To check if the system does what it is expected to do.
- To check if the system is "Fit for purpose".
- To check if the system meets the requirements and be executed successfully in the Intended environment.
- Executing a program with the intent of finding an *error*.

Different phases of software testing life cycle are represented in the

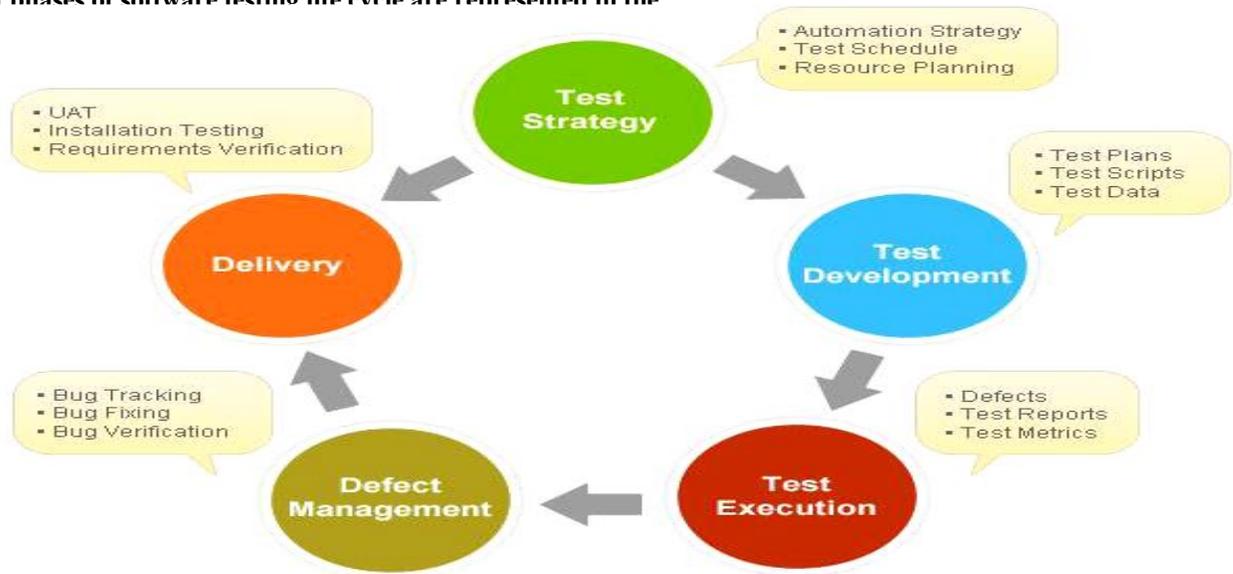


figure1.

Fig.1.: Testing activities

II. OBJECTIVES AND AIM

2.1. Objectives and aims of the research

The overall aim of this research project is to design a new Genetic Algorithm (GA) [6] that is cuckoo bird search algorithm, implement and investigate the effectiveness of Genetic Algorithm (GA) with regard to random testing and to automatically generate test data to traverse all branches of software. The objectives of the research activity can be defined as follows:

- The furtherance of basic knowledge required to develop new techniques[7] for automatic testing.
- To assess the feasibility of using GA to automatically generate test data for a variety of data type variables and complex data structures for software testing.
- To analyze the performance of GAs under various circumstances e.g. large systems.
- Comparison of the effectiveness of GAs with pure random testing for software developed in Java
- The automatic testing of complex software procedures.
- Analysis of the test data adequacy using mutation testing.

The performance of GAs in automatically generating test data for small procedures is assessed and analyzed. A library of GA is developed and then applied to larger systems.

The efficiency of GAs in generating test data is compared to random testing with regard to the number of test data sets generated and the CPU time required.

This research project presents a system for the generation of test data for software written in Java. The problem of test data generation is formed and solved completely as a numerical optimization problem using Genetic Algorithm and structural testing techniques.

Software testing is about searching and generating certain test data in a domain to satisfy the test criteria. Since GAs are an established search and optimization process. The basic aim of this research is to generate test sets which will traverse all branches in a given procedure under test.

Testing criteria

The criterion of testing [12] in this thesis is branch testing, the aim is to develop a test system to exercise every branch of the software under test. In order to generate the required test data for branch testing Genetic Algorithm, PSO and Cuckoo search are used. Flow chart for genetic Algorithm process is represented in figure 2.

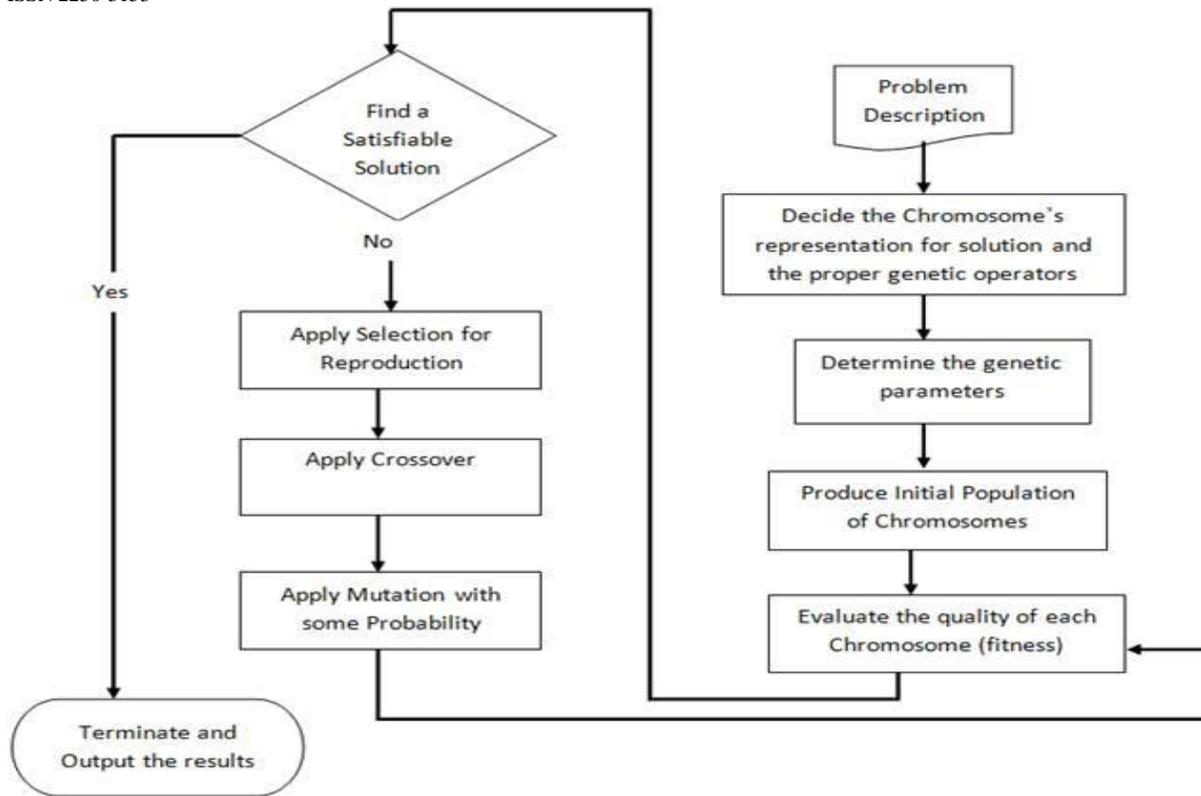


Fig. 2. Flow chart for genetic Algorithm Process

III. Methodology in this research work

In this work, The Particle Swarm Optimization (PSO), Cuckoo search and Genetic Algorithm (GA) are used for designing and Implementing a Novel Genetic algorithm for Optimization of Testing Technique.

Structural testing can be done by the method of data flow testing or path testing [8]. Path testing comprises generating a set of paths that will cover every branch in the program and discover the set of test cases that will execute every path in this set of program path. In data flow testing, the emphasis is on the points at which variables obtain values and the points at which these values are used up.

In the area of structural or white-box testing [9], evolutionary algorithms can assist in finding test cases which cover the code base under test to maximum extent. The aim is to execute the code under test with as many different input parameters as possible, in order to maximize the chance of detecting errors in the code.

The actual aim of this work is to offer better optimization approach, which is introduced in the test case by using Genetic Algorithm [10]. Optimization approach adapted with different layer tasks to inspect. This research also provides a survey to determine better quality testing process within the time. In this study we analyze how test cases can be optimized and gives best solution. Evolutionary tests generally are a very good growing methodology associated with routinely bringing in high quality analyzes information. The actual evolutionary algorithms are now put on inside many correct living problems.

In this work, we proposed a new approach to optimize the software testing techniques [11] by test case suite reduction. The proposed technique is based on concepts of PSO, Cuckoo search and GA. The technique selects the set of test case from the available test suite that will cover all the faults detected earlier in minimum execution time. Here particles are used as agents who explore the minimum set of test cases. Half of the particles will initially start foraging with randomly selected test cases. Now particles will add new test cases on the explored path if adding of a test case increases its fault detection capacity.

Population based search protocol can turn out to be Particle swarm Optimization (PSO). PSO was designed on the basis of the social presentation of birds in a flock. Each particle flies in the search space with a velocity varied by its own flying memory and its companion's flying experience in PSO. Each particle has its major function value which is settled on by a fitness function.

3.1. Particle Swarm Optimization

PSO is an optimization seeks technique based on population. It is an innovative branch of evolutionary computation and the particle swarm can be seen as a simple social system. In PSO, each individual is called a particle and each particle denotes a potential solution, which forms the population set. The particles in searching space influence each other, exchanging information, to adjust the location and speed of itself and approach to the optimal solution. PSO initialize a group of particles, finding the optimal solution by iteration. During each iteration, the particle updates its speed and location by tracing individual extremism and global extremism

$v_i = \{v_{i1}, v_{i2}, \dots, v_{id}\}$ denotes the speed of the i^{th} particle;

$X_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}$,

$i = 1, 2, \dots, N$ denotes a vector point of i^{th} particle in d -dimension solution space, t is the iteration number;

$[Math Processing Error]$ denote the location after t^{th} iteration and d^{th} dimensional component of speed vector of i^{th} particle,

r_1 and r_2 are random numbers obeying the distribution of $U(0, 1)$;

c_1 and c_2 are accelerate factors and usually $c_1 = c_2 = 2$.

We use $P_i = \{p_{i1}, p_{i2}, \dots, p_{id}\}$ to record the optimal point that is searched by the i^{th} particle, as p_{best} .

Thus there must exist an optimal point in the population, whose number is g .

Then $P_g = \{p_{g1}, p_{g2}, \dots, p_{gd}\}$ is the optimal value of the population search.

During the process of particle optimization, it is crucial to balance the local developing ability and the global detecting ability. For different problems the balance of these two abilities are not the same.

PSO algorithm has deficiency in premature convergence, and the local search accuracy is low. It also brings factors of program structure in testing case generation. Therefore the PSO-based testing case generation technology is discussed intensively in this article. To balance the ability of exploring and self-improvement of algorithms, and to achieve better convergence speed in global search, we provide adaptive particle inertia weight factor adjusting approach, integrated with fitness and particle aggregation degree. During evolution, a local searching strategy is performed on the optimal individual of each generation to further improve the efficiency of testing case generation.

The simulations indicate that Solving Particle Swarm Optimization with Local Search (SPSOLS) algorithm proposed in this article shows better testing case generation performance and it achieves coverage rate optimization of the tested cases. It also has certain advantages in testing case generation [14] compared to homogeneous algorithm under approximate environment. Executing the function under test using the input variables from a particular test case causes a particular control path through the function to be taken. In the case of the branch coverage metric and assuming the function under test contains branch statements, the function will typically need to be executed using several test cases in order to exercise (cover) each branch. For small functions containing few branch statements, the task of finding test cases, which use all branches, is relatively simple. For more complex functions with many branch statements and input variables it makes sense to automate the task, and one approach is to use evolutionary algorithms. Evolutionary algorithms use the principles of evolution to achieve optimization based on the result of a fitness function. The fitness of a first generation of random individuals is tested, and the characteristics, known as genes, of the fittest individuals are propagated to the next generation. This process is governed by rules regarding which percentage of individuals whether their genes have propagated to the next generation, how their genes are combined to form the next generation's individuals and how the genes are randomly mutated. Figure 3 shows the flow chart for particle swarm optimization process.

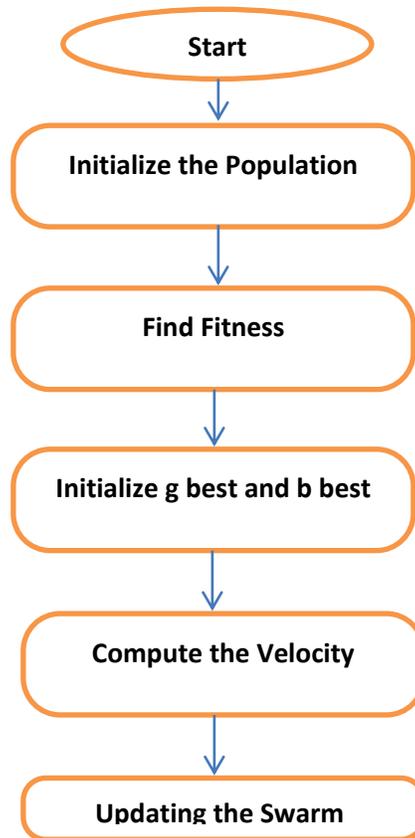


Figure. 3: Flow chart for Particle Swarm Optimization

“Individual best”: It is the individual best choice algorithm by assessing each individual position of the particle to its own best position *pbest*, only. The data about the other particles is not used in this *pbest*.

“Global best”: It is the universal best selection algorithm, which obtains the global information by making the movement of the particles encloses the position of the best particle from the complete swarm. Additionally, every particle uses its experience with earlier incidents in terms of its own best solution.

- **Swarm initialization**: For a population size u , arbitrarily generate a solution.
- **Define the fitness function**: According to the current solution, the fitness function chosen should be used for the constraints.
- ***gb* and *pb* Initialization**: In the start the fitness value estimated for every particle is placed as the *Pbest* value of each particle. Among the *Pbest* values, the optimal one is chooses as the *gb* value.
- **Velocity Computation**: The new velocity is calculated using the beneath equation

$$v[i] = v[i] + c1 * rand() * (pbest[i] - present[i]) + c2 * rand() * (gbest[i] - present[i]) \dots (a)$$

$$present[i] = present[i] + v[i] \dots (b)$$

$v[i]$ is the particle velocity, $present[i]$ is the current particle (solution).

$pbest[i]$ and $gbest[i]$ are defined as stated before.

$rand()$ is a random number between (0,1). $c1, c2$ are learning factors. usually $c1 = c2 = 2$.

- **Swarm Updating**: Find out the fitness function once more and improve the *pb* and *gb* values. If the new value is better than the earlier one, replace the old by the current one. And as well select the optimal *pb* as the *gb*.
- **Criterion to stop**: Extend till the solution is really appropriate or maximum iteration is attained is

The pseudo code of the procedure is as follows

```
For each particle
  Initialize particle
END
Do
  For each particle
    Calculate fitness value
    If the fitness value is better than the best fitness value (pBest) in history
      set current value as the new pBest
  End
  Choose the particle with the best fitness value of all the particles as the gBest
  For each particle
    Calculate particle velocity according equation (a)
    Update particle position according equation (b)
  End
While maximum iterations or minimum error criteria is not attained
```

Particles' velocities on each dimension are clamped to a maximum velocity V_{max} . If the sum of accelerations would cause the velocity on that dimension to exceed V_{max} , which is a parameter specified by the user. Then the velocity on that dimension limited to V_{max} .

Then we apply the cuckoo search algorithm

3.2.Cuckoo search algorithm

Cuckoo search algorithm is a metaheuristic algorithm which was inspired by the breeding behavior of the cuckoos and alleviates to implement. There are a number of nests in cuckoo search. Each egg points out a solution and an egg of cuckoo indicates a new solution. The new and better solution is replacing the most awful solution in the nest. The subsequent representation scheme is selected by Cuckoo Search algorithm: Each egg in a nest symbolizes a solution, and a Cuckoo egg symbolizes a novel solution. The plan is to employ the novel and probably better egg to substitute a not- so-good egg of Cuckoo in the nests. On the other hand this is the fundamental case i.e., one cuckoo per nest, but the extent of the approach can be raised by incorporating the property that each nest can have more than one egg which symbolizes a set of solutions. The process of clustering is given beneath,

- At a time only one egg is laid by cuckoo. Cuckoo dumps its egg in a arbitrarily selected nest.
- The number of accessible host nests is fixed, and nests with high quality of eggs will transmit over to the next generations.
- In case of a host bird found out the cuckoo egg, it can throw the egg away or discard the nest, and build a totally novel nest.

Step 1: Initialization Phase

The population (m_i , where $i=1, 2, \dots, n$) of host nest is started arbitrarily.

Step 2: Generating New Cuckoo Phase

Using levy flights a cuckoo is selected at random and it produces new solutions. After that the produced cuckoo is evaluated using the objective function for finding out the quality of the solutions.

Step 3: Fitness Evaluation Phase

Evaluate the fitness function based on the equation and next select the best one.

Step 4: Updating Phase

The superiority of the new solution is evaluated and a nest is selected among arbitrarily. If the excellence of new solution in the selected nest is better than the old solutions, it will be replaced by the new solution (Cuckoo). Otherwise, the previous solution is placed aside as the best solution.

Step 5: Reject Worst Nest Phase

The worst nests are thrown away in this part, based on their chance values and new ones are built. Presently, function the best solutions are ranked based on their fitness. After that the best solutions are identified and spotted as optimal solutions.

Step 6: Stopping Criterion Phase

Till the maximum iteration achieves this process is repeated. The optimized effect will be inspected for the measure of software quality. The précised process is clearly shown in flowchart in figure 4.

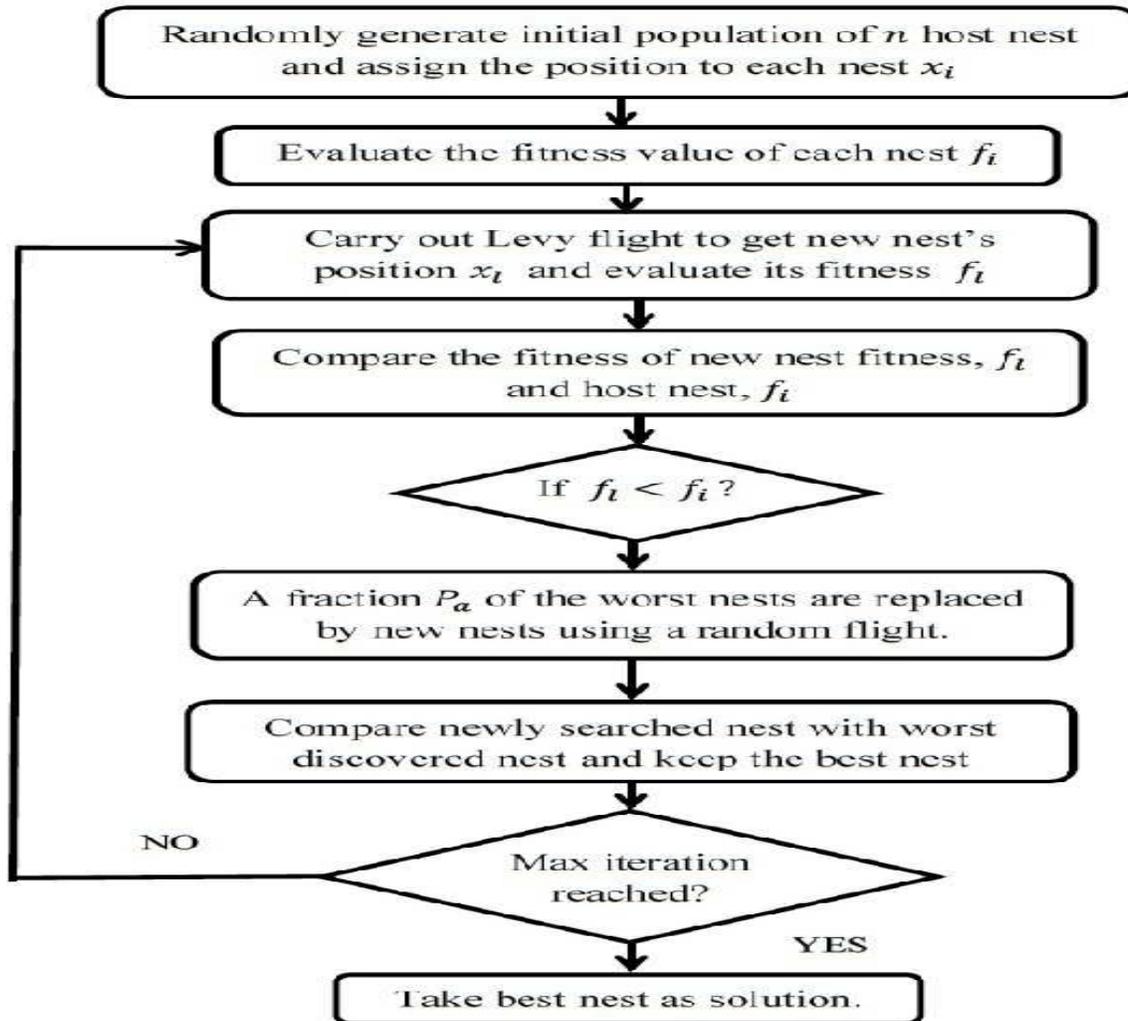


Figure. 4: Flow chart for Cuckoo search algorithm

IV. Implementation

The implementation of the algorithm is demonstrated in the following screens with the help of Booth’s function and Three Hump Camel function.

The functions used in this work for optimization are as follows :

$$f(x) = -a \exp\left(-b \sqrt{\sum_{i=1}^d x_i^2}\right) - \exp\left(\frac{1}{d} \sum_{i=1}^d \cos(cx_i)\right) + a + \exp(1)$$

In the above equation, the values a, b and c are constants and are usually chosen as a=20, b=0.2 and c=2π.

On a 2-dimensional domain it is defined by:

$$f(x, y) = -20 \exp\left[-0.2 \sqrt{0.5(x^2 + y^2)}\right] - \exp[0.5(\cos 2\pi x + \cos 2\pi y)] + e + 20$$

4.1.Booth's Function

The Booth function is a unimodal, 2-dimensional convex mathematical function widely used for testing optimization algorithms.

Booth Function

Number of variables: $n = 2$.

Search domain: $-10 \leq x_i \leq 10, i = 1, 2$.

Number of local minima: several local minima.

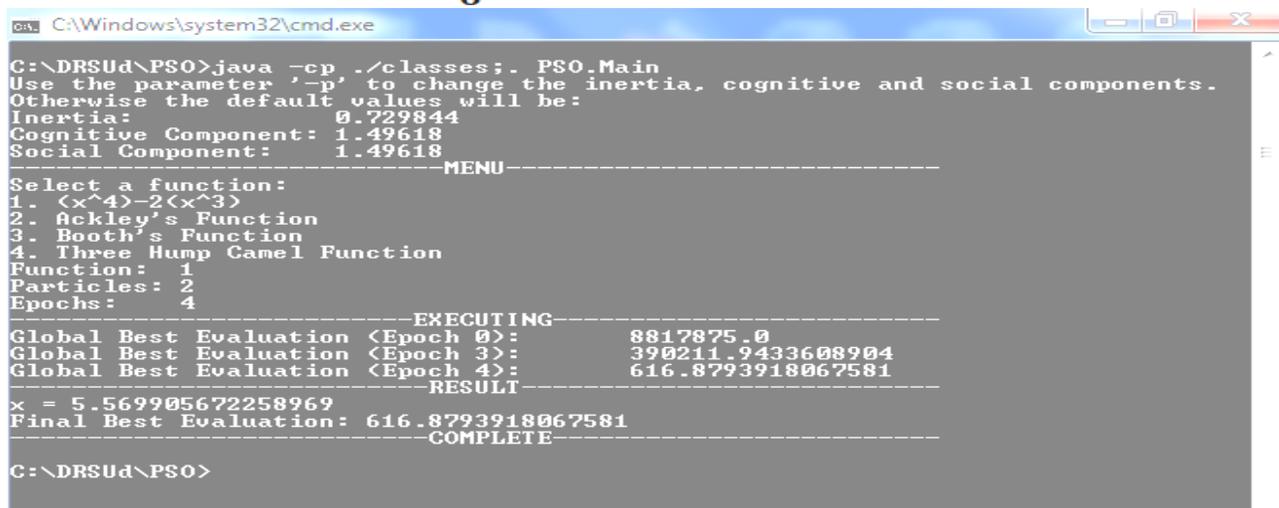
Booth's Function

$$f(x,y) = (x + 2y - 7)^2 + (2x + y - 5)^2$$

4.2.Three Hump Camel Function

This function is used as a test function in order to evaluate the performance of optimization algorithms

$$f(x,y) = 2x_1^2 - 1.05 x_1^4 + \frac{x_1^6}{6} + x_1 x_2 + x_2^2$$



```
C:\Windows\system32\cmd.exe
C:\DRSUd\PSO>java -cp ./classes;. PSO.Main
Use the parameter '-p' to change the inertia, cognitive and social components.
Otherwise the default values will be:
Inertia: 0.729844
Cognitive Component: 1.49618
Social Component: 1.49618
-----MENU-----
Select a function:
1. (x^4)-2(x^3)
2. Ackley's Function
3. Booth's Function
4. Three Hump Camel Function
Function: 1
Particles: 2
Epochs: 4
-----EXECUTING-----
Global Best Evaluation <Epoch 0>: 8817875.0
Global Best Evaluation <Epoch 3>: 390211.9433608904
Global Best Evaluation <Epoch 4>: 616.8793918067581
-----RESULT-----
x = 5.569905672258969
Final Best Evaluation: 616.8793918067581
-----COMPLETE-----
C:\DRSUd\PSO>
```

Fig 5. Find the Global Best Evaluation

The above figure displays a menu to calculate the global best.

Here the result of global best evaluation is obtained using the quadratic formula

$X^4-2(x^3)$

Using Particle Swarm optimization no of particles taken here is 2 and number of epochs is chosen as 4.

Final Best Evaluation calculated is 616.87939

```
C:\Windows\system32\cmd.exe
Global Best Evaluation <Epoch 116>: 1.720121592896362E-5
Global Best Evaluation <Epoch 117>: 1.5408768671676398E-5
Global Best Evaluation <Epoch 118>: 1.4216946070177983E-5
Global Best Evaluation <Epoch 119>: 1.346002078150832E-5
Global Best Evaluation <Epoch 120>: 1.3282954039794959E-5
Global Best Evaluation <Epoch 121>: 1.1503391188938394E-5
Global Best Evaluation <Epoch 122>: 9.83839495560801E-6
Global Best Evaluation <Epoch 123>: 8.624002649781914E-6
Global Best Evaluation <Epoch 124>: 7.738312351790455E-6
Global Best Evaluation <Epoch 125>: 7.092358337956739E-6
Global Best Evaluation <Epoch 126>: 6.621232493841944E-6
Global Best Evaluation <Epoch 127>: 6.277593886494515E-6
Global Best Evaluation <Epoch 128>: 4.086593452967691E-6
Global Best Evaluation <Epoch 129>: 1.6047339670421934E-6
Global Best Evaluation <Epoch 130>: 1.564313350854718E-6
Global Best Evaluation <Epoch 137>: 7.833048094596506E-7
Global Best Evaluation <Epoch 138>: 2.8808031515836774E-8
Global Best Evaluation <Epoch 159>: 2.7850891370917452E-8
Global Best Evaluation <Epoch 166>: 2.7841647209925213E-8
Global Best Evaluation <Epoch 168>: 2.3917714031540527E-8
Global Best Evaluation <Epoch 169>: 1.247825309746986E-8
Global Best Evaluation <Epoch 170>: 6.376549066544612E-9
Global Best Evaluation <Epoch 181>: 5.492175603194482E-10
Global Best Evaluation <Epoch 191>: 4.645919204904203E-10
Global Best Evaluation <Epoch 197>: 4.2956571633112617E-10
Global Best Evaluation <Epoch 205>: 3.232578649203788E-10
Global Best Evaluation <Epoch 207>: 3.2092017931972805E-10
Global Best Evaluation <Epoch 209>: 3.192255348949402E-10
Global Best Evaluation <Epoch 211>: 3.190905317751458E-10
Global Best Evaluation <Epoch 213>: 1.3677237120646168E-10
Global Best Evaluation <Epoch 217>: 1.2354917089396622E-10
Global Best Evaluation <Epoch 219>: 1.1929657262044202E-10
Global Best Evaluation <Epoch 222>: 1.0269474159940728E-10
Global Best Evaluation <Epoch 230>: 5.1798565436911304E-11
Global Best Evaluation <Epoch 231>: 4.980549306310422E-11
Global Best Evaluation <Epoch 234>: 4.446221169018827E-11
Global Best Evaluation <Epoch 235>: 3.020872441084066E-11
Global Best Evaluation <Epoch 237>: 1.440270125385723E-11
Global Best Evaluation <Epoch 238>: 1.1468159755168017E-11
Global Best Evaluation <Epoch 241>: 6.323830348264892E-12
Global Best Evaluation <Epoch 245>: 2.9629632081196178E-12
Global Best Evaluation <Epoch 247>: 1.943334382303874E-12
Global Best Evaluation <Epoch 248>: 1.0800249583553523E-12
Global Best Evaluation <Epoch 262>: 9.876544027065393E-13
Global Best Evaluation <Epoch 263>: 9.521272659185342E-13
Global Best Evaluation <Epoch 264>: 8.988365607365267E-13
Global Best Evaluation <Epoch 266>: 8.562039965909207E-13
Global Best Evaluation <Epoch 269>: 6.430411758628907E-13
Global Best Evaluation <Epoch 273>: 9.237055564881302E-14
Global Best Evaluation <Epoch 276>: 7.815970093361102E-14
-----
RESULT
x = 5.9029740804458135E-15
y = -7.242330460787715E-15
Final Best Evaluation: 2.8421709430404007E-14
-----
COMPLETE
C:\DRSud\PSO>
```

Fig 6. Find the Global Best

The above figure 6 displays a menu to calculate the global best evaluation and here it is computed as 2.8421709430404007E-14.

```
cmd: C:\Windows\system32\cmd.exe
Global Best Evaluation (Epoch 71): 3.1351458901454147E-7
Global Best Evaluation (Epoch 74): 1.1313168824888258E-7
Global Best Evaluation (Epoch 77): 5.3737285421101995E-8
Global Best Evaluation (Epoch 80): 4.044384886657726E-8
Global Best Evaluation (Epoch 81): 1.7626077490492093E-8
Global Best Evaluation (Epoch 82): 1.2024880450236953E-8
Global Best Evaluation (Epoch 84): 5.26676027843354E-9
Global Best Evaluation (Epoch 91): 4.8032459024866545E-9
Global Best Evaluation (Epoch 93): 2.5168173051430207E-9
Global Best Evaluation (Epoch 95): 8.51011358554175E-10
Global Best Evaluation (Epoch 99): 7.066416622489211E-10
Global Best Evaluation (Epoch 100): 2.526463015759532E-10
Global Best Evaluation (Epoch 109): 1.2230364863927627E-10
Global Best Evaluation (Epoch 110): 9.602530553777734E-12
Global Best Evaluation (Epoch 112): 1.7174389377777344E-12
Global Best Evaluation (Epoch 115): 4.4440517410897624E-13
Global Best Evaluation (Epoch 124): 8.731751965016752E-14
Global Best Evaluation (Epoch 129): 2.6270551269049566E-14
Global Best Evaluation (Epoch 138): 1.7558987782114585E-14
Global Best Evaluation (Epoch 142): 1.3297915398585387E-14
Global Best Evaluation (Epoch 143): 6.8462969567633745E-15
Global Best Evaluation (Epoch 146): 6.345705879390034E-15
Global Best Evaluation (Epoch 148): 3.1673364543036778E-15
Global Best Evaluation (Epoch 151): 3.05000005188250613E-16
Global Best Evaluation (Epoch 154): 3.3195927829919154E-17
Global Best Evaluation (Epoch 175): 2.8724817671173076E-17
Global Best Evaluation (Epoch 176): 1.3160689435193218E-17
Global Best Evaluation (Epoch 179): 1.013720049970425E-17
Global Best Evaluation (Epoch 182): 1.937974329602887E-18
Global Best Evaluation (Epoch 184): 4.3215752532943143E-19
Global Best Evaluation (Epoch 187): 5.1430913720438387E-20
Global Best Evaluation (Epoch 193): 2.4015987271665272E-21
Global Best Evaluation (Epoch 197): 7.508024717762488E-22
Global Best Evaluation (Epoch 201): 6.937057520752769E-22
Global Best Evaluation (Epoch 204): 2.1192544455990664E-22
Global Best Evaluation (Epoch 208): 1.7962563655868908E-22
Global Best Evaluation (Epoch 209): 1.2264118596402642E-22
Global Best Evaluation (Epoch 210): 1.069141173250729E-22
Global Best Evaluation (Epoch 212): 1.067617401637595E-22
Global Best Evaluation (Epoch 214): 1.0658193194218886E-22
Global Best Evaluation (Epoch 217): 1.0639090611854597E-22
Global Best Evaluation (Epoch 219): 1.0637179122995156E-22
Global Best Evaluation (Epoch 223): 5.563743273367433E-23
Global Best Evaluation (Epoch 231): 1.6560452853665212E-23
Global Best Evaluation (Epoch 232): 1.4276946657652811E-24
Global Best Evaluation (Epoch 238): 8.3109730694745E-25
Global Best Evaluation (Epoch 240): 7.847225409122224E-25
Global Best Evaluation (Epoch 242): 2.0904577330085247E-25
Global Best Evaluation (Epoch 243): 6.886755702579433E-26
Global Best Evaluation (Epoch 246): 4.81047380003773E-26
-----
RESULT
x = 0.99999999999999502
y = 3.00000000000001332
Final Best Evaluation: 4.81047380003773E-26
-----
COMPLETE
C:\DRSud\PSO>
```

Fig 7. Find the Global Best

The above figure 7 demonstrates a menu to calculate the global best evaluation and here it is computed as 4.81047380003773E-26.

```
C:\Windows\system32\cmd.exe
Cognitive Component: 1.49618
Social Component: 1.49618
-----MENU-----
select a function:
- (x^4)-2(x^3)
- Ackley's Function
- Booth's Function
- Three Hump Camel Function
function: 4
particles: 24
epochs: 179
-----EXECUTING-----
Global Best Evaluation (Epoch 0): 281659.11666666667
Global Best Evaluation (Epoch 3): 0.5524283239003591
Global Best Evaluation (Epoch 4): 0.2488942081277118
Global Best Evaluation (Epoch 13): 0.07365562760175412
Global Best Evaluation (Epoch 20): 0.012552510839737116
Global Best Evaluation (Epoch 25): 0.010238423422373563
Global Best Evaluation (Epoch 33): 0.007955632746970207
Global Best Evaluation (Epoch 34): 0.003940134873676934
Global Best Evaluation (Epoch 35): 4.7104527222551493E-4
Global Best Evaluation (Epoch 40): 2.2446358393861046E-4
Global Best Evaluation (Epoch 44): 2.8779134526911454E-5
Global Best Evaluation (Epoch 51): 2.227555795519142E-5
Global Best Evaluation (Epoch 53): 1.960214051379139E-5
Global Best Evaluation (Epoch 60): 5.894743881625259E-6
Global Best Evaluation (Epoch 61): 1.407606648537511E-6
Global Best Evaluation (Epoch 72): 8.016849068544081E-7
Global Best Evaluation (Epoch 75): 6.723320755764365E-7
Global Best Evaluation (Epoch 78): 3.068041783174973E-8
Global Best Evaluation (Epoch 82): 2.512400041303201E-8
Global Best Evaluation (Epoch 86): 1.9415169787736118E-8
Global Best Evaluation (Epoch 88): 1.8639441769072607E-9
Global Best Evaluation (Epoch 95): 4.0745406629031577E-10
Global Best Evaluation (Epoch 108): 2.382950262983028E-10
Global Best Evaluation (Epoch 111): 1.1224289433897071E-10
Global Best Evaluation (Epoch 112): 1.815566522649416E-11
Global Best Evaluation (Epoch 119): 1.5187861001614538E-11
Global Best Evaluation (Epoch 128): 1.1192958646258978E-11
Global Best Evaluation (Epoch 132): 4.7575774485095116E-12
Global Best Evaluation (Epoch 133): 1.0105246639823905E-12
Global Best Evaluation (Epoch 138): 2.443450599096396E-13
Global Best Evaluation (Epoch 140): 3.038917391118063E-14
Global Best Evaluation (Epoch 142): 1.8079425450837484E-14
Global Best Evaluation (Epoch 154): 8.709054141189466E-15
Global Best Evaluation (Epoch 159): 5.791281866436065E-16
Global Best Evaluation (Epoch 171): 2.985877778144496E-17
Global Best Evaluation (Epoch 176): 5.439405843516122E-18
Global Best Evaluation (Epoch 178): 1.2362988207368657E-18
-----RESULT-----
= 8.234965924001198E-10
= -6.343290787741626E-10
Final Best Evaluation: 1.2362988207368657E-18
-----COMPLETE-----
::\DRSud\PSO>
```

Fig 8. Find the Global Best

The above figure 8 demonstrates a menu to calculate the global best evaluation and here it is computed as 4.81047380003773E-26. The function used is Three Hump camel Function, particles used are 24 and epochs are 179.

```

C:\Windows\system32\cmd.exe
Final Best Evaluation: 1.0126873541069057
-----COMPLETED-----
C:\DRSud\PSO>java -cp ./classes:. PSO.Main
Use the parameter '-p' to change the inertia, cognitive and social components.
Otherwise the default values will be:
Inertia: 0.729844
Cognitive Component: 1.49618
Social Component: 1.49618
-----MENU-----
Select a function:
1. (x^4)-2(x^3)
2. Ackley's Function
3. Booth's Function
4. Three Hump Camel Function
Function: 3
Particles: 20
Epochs: 16
-----EXECUTING-----
Global Best Evaluation (Epoch 0): 2601.0
Global Best Evaluation (Epoch 3): 72.42862375591895
Global Best Evaluation (Epoch 7): 6.142231146796034
Global Best Evaluation (Epoch 8): 3.7382403128708734
Global Best Evaluation (Epoch 11): 2.1666925175166085
-----RESULT-----
x = 0.5411627125209448
y = 2.7691174011010524
Final Best Evaluation: 2.1666925175166085
-----COMPLETED-----
C:\DRSud\PSO>java -cp ./classes:. PSO.Main
Use the parameter '-p' to change the inertia, cognitive and social components.
Otherwise the default values will be:
Inertia: 0.729844
Cognitive Component: 1.49618
Social Component: 1.49618
-----MENU-----
Select a function:
1. (x^4)-2(x^3)
2. Ackley's Function
3. Booth's Function
4. Three Hump Camel Function
Function: 3
Particles: 20
Epochs: 27
-----EXECUTING-----
Global Best Evaluation (Epoch 0): 452.0
Global Best Evaluation (Epoch 3): 27.677720162963375
Global Best Evaluation (Epoch 6): 0.09758845840619217
Global Best Evaluation (Epoch 24): 0.06849852497492503
-----RESULT-----
x = 1.19441581034717
y = 2.8348443395990146
Final Best Evaluation: 0.06849852497492503
-----COMPLETED-----
C:\DRSud\PSO>
    
```

Fig 9. Find the Global Best

The above figure 9 displays a menu to calculate the global best evaluation with Booth's function, particles 20 and with 16 and 27 epochs.

Final best evaluation is 2.1666925175166085, particles are 20 and epochs are 16.

Final best evaluation is 0.06849852497492503, particles are 20 and epochs are 27.

```

C:\Windows\system32\cmd.exe
C:\DRSud\PSO>
C:\DRSud\PSO>java -cp ./classes:. PSO.Main
Use the parameter '-p' to change the inertia, cognitive and social components.
Otherwise the default values will be:
Inertia: 0.729844
Cognitive Component: 1.49618
Social Component: 1.49618
-----MENU-----
Select a function:
1. (x^4)-2(x^3)
2. Ackley's Function
3. Booth's Function
4. Three Hump Camel Function
Function: 4
Particles: 12
Epochs: 24
-----EXECUTING-----
Global Best Evaluation (Epoch 0): 19065.116666666667
Global Best Evaluation (Epoch 3): 131.3864017916162
Global Best Evaluation (Epoch 4): 43.48624307990893
Global Best Evaluation (Epoch 8): 7.330981676779105
Global Best Evaluation (Epoch 10): 4.097153179656994
Global Best Evaluation (Epoch 12): 1.2478552302360455
Global Best Evaluation (Epoch 15): 0.31551322027008327
Global Best Evaluation (Epoch 16): 0.017757433051313328
-----RESULT-----
x = 0.09957880293456256
y = -0.027258951386635033
Final Best Evaluation: 0.017757433051313328
-----COMPLETED-----
C:\DRSud\PSO>
    
```

Fig 10. Find the Global Best

The above figure 10 displays a menu to calculate the global best evaluation with Hump Camel function, particles 12 and with 16 and 24 epochs.

Final best evaluation computed is 0.017757433051313328.

V. CONCLUSION

The main objective is to minimize the time, cost and effort required to test software where we need to implement certain evolutionary algorithms in software testing.

Genetic algorithm is one such evolutionary algorithm which can optimize the problem. The implementation study says that this novel genetic algorithm gives better results to increase quality of software by discovering errors. The overall aim was to develop a self-learning algorithm that has the ability to process and incorporate new information as the work environment changes (changing from one predicate to the next).

The GAs gives good results and their power lies in the good adaptation to the various and fast changing environments.

The primary objective of this research work was to propose a GA-based software test data generator and to demonstrate its feasibility. The main advantage of this novel Genetic Algorithm (GA) developed testing tool is the strength of GAs, in that the relationship between the predicate under investigation and the input variables may be complex and need not be known. Instrumentations capture the actual values of the predicates, so that the fitness can be based on these values.

In this research work a novel genetic algorithm (GA) is proposed, designed and implemented. The simulated results are shown in output screens. Global best evaluation is computed with the help of Booth's and Hump Camel functions.

All tests clearly show that the test data generated from Novel Genetic Algorithm are significantly better than randomly generated data.

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