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Automatic PSO Based Path Generation Technique for Data Flow Coverage

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Abstract: Path-based testing involves two main steps: 1) finding all paths throughout the code under test; 2) creating a test suite to cover these paths. Unfortunately, covering all paths in the code under test is impossible. Path-based testing could be achieved by targeting a subset of all feasible paths that satisfy a given testing criterion. Then, a test suite is created to execute this paths subset. Generating those paths is a key problem in path testing. In this paper, a new path testing technique is presented. This technique employs Particle Swarm Optimization (PSO) for generating a set of paths to satisfy the all-uses criterion. To construct such paths for programs with loops, the proposed technique applies the ZOT-criterion. This criterion selects paths that traverse loops 0, 1, and 2 times. The proposed technique utilizes the decision-decision graph of the program under test to represent the position vector of the particle. To evaluate the efficiency of the presented technique, an empirical study has been conducted, which included 15 C# programs. In this study, the proposed technique has been compared with a genetic algorithm (GA)-based one. The results showed that the PSO required 199 generations, while the GA required 349 generations, to satisfy all def-use paths of all programs. In addition, the proposed technique required a smaller number of paths than the GA-based one.

Keywords: Data flow testing; genetic algorithm; path testing; particle swarm optimization

1 Introduction

Path testing requires executing each path in the code under test at least once. However, executing all paths is impossible as a program with loops may include an infinite number of paths. This issue may be addressed by using a subset of all executable paths that satisfy a given path selection criterion. Finding this subset of paths is a significant challenge in path testing.

Scholars presented many path-generation approaches. Bertolino and Marre [1] presented a technique constructing a set of paths that satisfy all arcs of the tested program control-flow graph. Other studies have concentrated on generating the set of basis paths (i.e., the class of all linearly independent paths)

[2–8]. The number of the basis paths can be estimated by the Cyclomatic Complexity [2] of the code under test.

Particle Swarm Optimization (PSO) is an evolutionary search-based technique proposed in 1995 by Kennedy and Eberhart [9]. PSO simulates the behavior of animal species that live in large colonies such as bird flocks and fish schools [9,10]. PSO was used for the first time to solve the traveling salesman problem [11]. PSO [12–17], Adaptive Random [18], and Genetic Algorithms (GAs) [19–21] have been applied in many software testing activities such as test data generation. GAs [8,22–25], Tabu Search Algorithm [23,26–31], State-based meta-heuristic Algorithm [32], and Clustering and Code Change Algorithm [33–35], have been used to find test paths. According to the best of our knowledge, there is not any scientific work that applies PSO in test paths generation.

This paper introduces a path testing approach that utilizes PSO for finding the paths required to cover the all-uses criterion proposed by Rapps and Weyuker [36]. The presented technique accomplishes this process by creating new paths using the formerly promising ones. The approach uses a criterion called ZOT-criterion to construct paths for programs with loops [37]. This criterion targets paths that traverse loops 0, 1, and 2 times. The approach also uses the edges of the decision-decision graph (dd-graph) of the code under test for encoding the position vector. The approach encodes the position vector of any particle as an integer array. The paper presented an experimental comparison between the proposed approach and a GA-based one. This comparison considered two main factors: 1) the number of generations required to find a path-cover for all def-use criterion, and 2) the size of this path-cover.

The rest of this paper is organized as follows. Section 2 presents a description of data-flow concepts. Section 3 discusses the basic PSO algorithm. Section 4 presents the proposed POS algorithm. Section 5 introduces the proposed PSO-based approach. Section 6 discusses the findings of the experimental study carried out to evaluate the proposed technique. Finally, Section 7 summarizes this work and gives some points for future work.

2 Data-Flow Concepts

Data-flow concepts consider the relations between the definitions (def) and references (use) of the variables in the program under test. Data-flow methods employ the control-flow graph of the program to find the relations between defs and uses.

The control flow of a program may be represented by a directed graph, named the control-flow graph (CFG). A CFG consists of a group of vertices and a group of arcs (edges). Each vertex represents one statement or a group of consecutive statements. Each arc represents a potential transfer of control flow between vertices. A path in a CFG is a finite sequence of vertices linked by arcs. A complete path is a path that starts at the entry vertex and ends at the exit vertex of the CFG. A path is called a def-clear path for a variable if it does not include a new definition for that variable.

The proposed approach uses a reduced form of the CFG, named a decision-decision graph (dd-graph). In a dd-graph, every arc is a decision-to-decision path (dd-path). Fig. 3 shows the dd-graph that corresponds to the CFG (shown in Fig. 2) of the C# code given in Fig. 1. Tab. 1 presents the dd-paths, which match the arcs of the dd-graph shown in Fig. 3.

Rapps and Weyuker [32] presented a set of dataflow testing criteria, such as the all-uses criterion. All-uses criterion requires the execution of a def-clear path from each def of a variable to each use of that variable. The required def-clear paths to fulfil the all-uses criterion are named def-use paths. Def-use paths are built using the def-use associations of program variables by the method presented by Girgis [38]. Tab. 2 presents all def-use associations of the C# code given in Fig. 1 and their killing nodes.

```
using System;
using System.IO;
public class prog5
{
   static void Main()
   {
     int a, b, c, n;
     a = Int32.Parse(Console.ReadLine());
     b = Int32.Parse(Console.ReadLine());
           if (a < 5)
           {
              c = a;
           }
           else
           {
             c = b;
           }
           n = c;
           while (n <= 8)
           {
             if (b > c)
             {
                c = 3;
             }
             else
             {
                n = n + c;
             }
             n = n + 1;
           }
           Console.WriteLine(" {0} {1} {2}", a, b, n);
        }//end main
      }//end class
```

Figure 1: C# example code

Killing nodes are those nodes that must not be included in a def-use path of a variable (i.e., nodes that contain other definitions for that variable).

3 Particle Swarm Optimization

PSO is a search-based optimization algorithm that is inspired by the motion and intelligence of flocks of animals. PSO employs the concept of social interaction to solve the given problem. A comprehensive survey of PSO applications was presented by Sengupta et al. [39]. PSO concepts are based on the motion of a set of particles in the search domain to find the best solution. Every particle is handled as a single node in an N-dimensional domain. Every particle regulates its "flying" based on its personal "flying experience" and the "flying experience" of the others.

Each particle has a fitness value estimated using a fitness function and velocities. PSO has two changeable variables:

1. pbest (personal best): saves the coordinates of the best position of the current particle in the solution domain. This position corresponds to the greatest solution achieved up to now by the particle.
2. gbest (global best): is the greatest value achieved up to now by any particle inside the neighborhood of the current particle.

Every particle attempts to adjust its position based on four factors: 1) the present place; 2) the present velocity; 3) the distance from the present place to pbest; and 4) the distance between the present place and gbest. The PSO steps are demonstrated below.

At first, the initial position and the initial velocity of each particle are randomly assigned. Then, the fitness function of each particle is calculated and compared to the fitness value of the pbest location. If the present location has a fitness value greater than the pbest, then the present location becomes the new

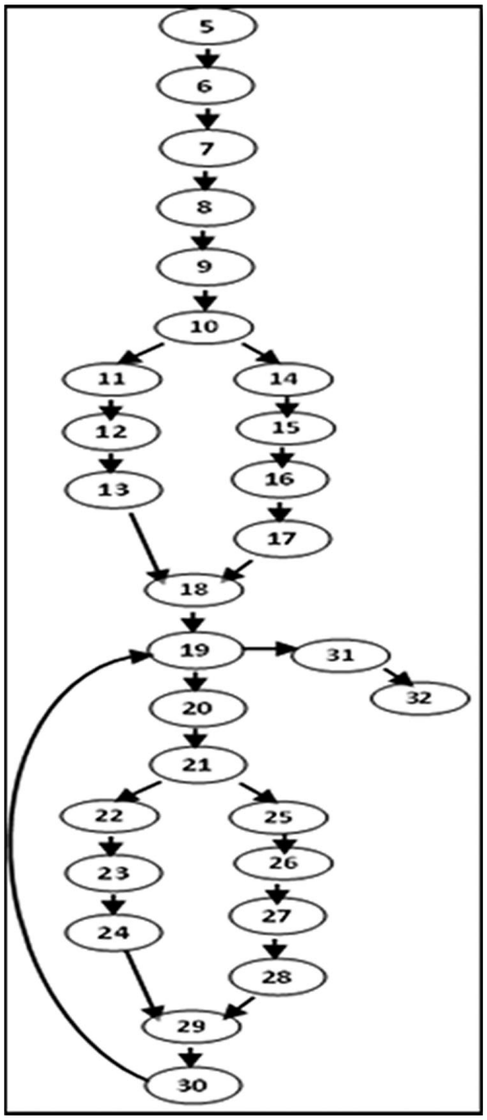


Figure 2: CFG of the main class of the C# example code

pbest. The greatest value of all pbests becomes the gbest. The position and velocity of each particle in the swarm are modified based on this gbest. The overall procedure is repeated until a specific number of generations (mGens) is reached.

The outcome of this algorithm is the global best value. The fitness function of the algorithm depends on the type of the application of the PSO. The updates of the position and velocity of each particle are calculated by the following equations [40]:

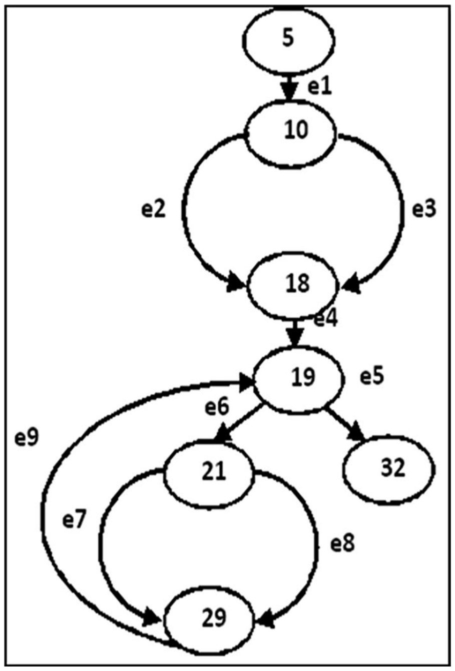


Figure 3: dd-graph for the main class of the example code

Table 1: The edges of the dd-graph shown in Fig. 2 and the corresponding dd-paths

Edge	*dd − Path*
e_1	5 6 7 8 9 10
e_2	10 14 15 16 17 18
e_3	10 11 12 13 18
e_4	18 19
e_5	19 31 32
e_6	19 20 21
e_7	21 25 26 27 28 29
e_8	21 22 23 24 29
e_9	29 30 19

Table 2: List of def-use pairs and killing nodes of the example program, (−1 means no killing nodes)

DU Pair #	*Variable*	*Def*	*Use*	*Killing Node*
1	*a*	8	10	−1
2	*a*	8	12	−1
3	*b*	9	16	−1
4	*c*	12	18	16
5	*c*	16	18	12

(Continued)

Table 2 (continued).

DU Pair #	*Variable*	*Def*	*Use*	*Killing Node*
6	*n*	18	19	−1
7	*n*	29	19	18
8	*b*	9	21	−1
9	*c*	12	21	16
10	*c*	16	21	12
11	*c*	23	21	12, 16
12	*c*	12	27	16, 23
13	*c*	16	27	12, 23
14	*n*	18	27	−1
15	*c*	23	27	12, 16
16	*n*	29	27	18
17	*n*	18	29	27
18	*n*	27	29	18
19	*n*	29	29	18
20	*a*	8	31	−1
21	*b*	9	31	−1
22	*n*	18	31	27, 29
23	*n*	29	31	18, 27

$$v_i^{k+1} = K \times \left(v_i^k + c_1 \times r_1 \times \left(pbest_i - p_i^k\right) + c_2 \times r_2 \times \left(gbest - p_i^k\right)\right) \tag{1}$$

$$p_i^{k+1} = p_i^k + v_i^{k+1} \tag{2}$$

$$\mathrm{K} = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \text{where } \varphi = c_1 + c_2, \varphi > 4, \tag{3}$$

where:

1. v_i^k: velocity of particle *i* at iteration *k*.
2. K: constriction factor that is required to guarantee the convergence of the PSO [41].
3. c_1, c_2 : learning factors.
4. r_1, r_2 : uniformly distributed random number between 0 and 1.
5. p_i^k: current position of particle *i* at iteration *k*.
6. $pbest_i$: *pbest* of particle *i* .
7. *gbest*: *gbest* of the group.

Eq. (1) is applied to update the velocity of the particles. In addition, Eq. (2) is applied to update the position of the particles.

The PSO specifications can be:

1. The learning factors c_1 and c_2 are values in the interval from 0 to 4. Where the best values of c_1 and c_2 are determined empirically. The proposed algorithm was executed 20 times on each subject program and the best values of c_1 and c_2 were determined.
2. The number of particles is based on the PSO application. Commonly, the number of particles is in the range from 20 to 40;
3. The fitness function of the PSO is very related to the representation of the given problem.

4 The Proposed PSO Algorithm

The proposed PSO-based approach targets the automatic generation of test paths. The technique looks for the paths that fulfill the all-uses criterion. If the program under test contains loops, the proposed technique creates a subset of those paths that satisfies the ZOT-criterion.

4.1 Representation

In the proposed PSO algorithm, the position vector of a particle symbolizes the edges of a path through the program dd-graph. The length, L, of any position vector can be calculated using the formula $L = n + 2 + p$, where $n + 2$ is the number of edges in the dd-graph plus two more edges representing the entry and exit ones. In addition, p is the number of edges enclosed in the loops, which are included twice. This representation guarantees that the paths created for any program with loops satisfy the ZOT-criterion. For instance, the basic edges of the dd-graph of the C# code given in Fig. 3 are e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, e_9. Therefore, n = 9, plus 2 (entry edge, e_0, and exit edge, e_{14}). In addition, p = 4, which are the edges enclosed in "while" loop, which are e_6, e_7, e_8, e_9. Moreover, the duplicate of the edges of the loop is placed after the final edge, e_9, with labels beginning by 10, i.e., e_{10}, e_{11}, e_{12}, e_{13}. Consequently, the length of this position vector is L = 15. The position vector of the particle has the following form:

e_0	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9	e_{10}	e_{11}	e_{12}	e_{13}	e_{14}

where edges $e_{10}, e_{11}, e_{12}, e_{13}$ are the duplicate of the edges of the loop, e_6, e_7, e_8, e_9 .

The proposed algorithm employs two different forms for the position vector. The first form is a binary form called bit position vector. The second form is an integer form called actual position vector. Through any bit position vector, the digit 1 means that an edge is existing and the digit 0 means an edge is missing. In the actual position vector, each "1" digit in the bit vector is replaced by the index of the matching edge. Then, the bit vector is filled out with "−1" instead of the digits "0". The digit −1 is used to replace the missing edges to differentiate these edges from the indices of the existing edges, which are positive integers. The velocity vector of a particle consists of L digits in the interval [0, L] (for the example code the interval is [0,15].

Suppose a particle has the following bit position vector: 11011110111011. This bit vector symbolizes the edges: e_0 , e_1 , e_3 , e_4 , e_5 , e_6 , e_8 , e_9 , e_{10} , e_{12} , e_{13} , e_{14}. The equivalent actual position vector is: 0 , 1 , 3 , 4 , 5 , 6 , 8 , 9, 10, 12, 13, 14, − 1, − 1, − 1. Those edges form the connected path: e_0 , e_1 , e_3 , e_4 , e_5 , e_6 , e_8 , e_9 , e_{10} , e_{12} , e_{13} , e_{14}. By substituting every edge with the corresponding dd-path, the path is rewritten in terms of the program statements:
5, 6, 7, 8, 9, 10, 11, 12, 13, 18, 19, 20, 21, 22, 23, 24, 29, 30, 19, 20, 21, 22, 23, 24, 29, 30, 19, 31, 32.

4.2 Initial Population

The position vectors of the particles represent a group of paths. These vectors are symbolized by two forms of length L: bit position vector and actual position vector. To form the initial population, the proposed technique randomly creates PS bit arrays of length L, where PS is the population size. In each vector, the first, second, and last cells are filled with 1's to represent the entry, first, and exit edges that have to be exist in all paths. The proper value of the size of the population is empirically determined. The algorithm creates for every produced binary position vector the corresponding actual position vector. All paths in the produced population must satisfy the connectivity rule (i.e., composed of a series of connected edges). The algorithm discards any disconnected path and generates another one to replace it. Also, the algorithm randomly creates PS velocity vectors for the initial position population. The values of every velocity vector are integers randomly selected from the interval [0, L-1]. The values of the first, second, and last cells are 0, 0, and L, respectively. This configuration guarantees that the update process of the actual position vector produces a path that contains the entry, first, and exit edges.

4.3 Position and Velocity Vectors Updating

PSO algorithms update the position and velocity of a particle using Eqs. (1) and (2). These equations can only be applied in continuous optimization problems. In the proposed approach, updating the velocity and position are accomplished using the actual position and velocity vectors, which are encoded as integer sequences, rather than real-number vectors. So, the current forms of addition and subtraction in Eqs. (1) and (2) are not applicable to the problem of path generation. Therefore, in the proposed algorithm, addition and subtraction operations in the basic velocity and position updating equations are modified to work with the path generation problem.

The presented technique utilizes two operators: the first is subtracting-two-positions operator and the second is adding-position-to-velocity operator. The two operators are applied to the members of the current population to form a new population.

Subtracting-two-positions operator: The equation of updating the velocity vector (Eq. (1)) contains two terms for subtracting positions. We suggested the following definition (Eq. (4)) for this operator.

$$p_i^{'} - p_i = \begin{cases} p_i^{'} - p_i & \mathit{if}\ p_i^{'} - p_i > 0 \\ (p_i^{'} - p_i) + (L-3) & \mathit{if}\ p_i^{'} - p_i \le 0 \end{cases} \tag{4}$$

where $\{p_i\}_{i=0}^{L-1}$ and $\{p_i^{'}\}_{i=0}^{L-1}$ are two position vectors.

Adding-position-to-velocity operator: The equation of updating the position vector (Eq. (2)) adds the new velocity to the old position. We suggested the following definition (Eq. (5)) for this operator.

$$p_i + v_i = \begin{cases} p_i + v_i & \mathit{if}\ p_i + v_i < L \\ ((p_i + v_i)\%(L-1)) + 2 & \mathit{if}\ p_i + v_i \ge L \end{cases} \tag{5}$$

where $\{p_i\}_{i=0}^{L-1}$ and $\{v_i\}_{i=0}^{L-1}$ are position and velocity vectors, respectively.

If the updated position vector is disconnected (i.e., it contains two consecutive edges that are not adjacent edges in the dd-graph), the algorithm tries to make it connected, by adding and/or removing one or more edges to/from it. The number of edges to be added or removed to connect the disconnected part depends on the length of the sub-path between the two disconnected edges and according to their positions in the dd-graph. If no sub-path can be added to fill the gap in the disconnected path, the algorithm tries to remove some edges to connect that path. Otherwise, the algorithm discards the disconnected vector and replaces it with the original position vector. Finding a sub-path to be added or removed to fill the gap in a disconnected path is a trial-and-error process. We used the algorithm given below (Algorithm Connect) to fill the gap between any two edges in the vector.

Algorithm Connect(v: is a position vector; e1, e2: are two edges, D: is a dd-graph)

```
 If v is disconnected at e1, and e2 then
  Call ConnectByAdd (v, e1, e2, D)
  If v is connected then
     Return v;
  Else If v is disconnected at e1, and e2 then
     Call ConnectByRemove(v, e1, e2,)
  If v is connected then
     Return v;
  Else
     Return v cannot be connected
  End if
 End if
 Return v;
End Connect
ConnectByAdd (v, e1, e2, D)
       If (e1 = e2 )
     Update v by replacing e1, e2 by e1;
     Return v;
  Else
  Find the successors edges of e1 ;
  For each e in the set of successors edges of e1
     If e is a predecessors of e2 then
         Replace e1, e2 by e1, e , e2
         Return v
       End if
     Call ConnectByAdd (v, e , e2, D)
    End for
End ConnectByAdd
ConnectByRemove(v, e1 , e2)
If v is empty return v cannot be connected
   Else if the predecessor of e1 in v is a predecessor of e2
     remove e1 and return v
  Else if the successors of e2 in v is a successors of e1 remove e2 and return v
  Else remove e1 and e2
  ConnectByRemove (v, predecessor of e1, successors of e2)
End ConnectByRemove
```

It should be noted that the resultant position vector p' may include a set of repeated values. If the repeated values are not indices of edges of a loop, these values are replaced by −1. The cells of the vector that represent indices for edges of a loop are allowed to be repeated only once. Therefore, an index for an edge in a loop can exist twice in the resulting position vector: the first existence is the original index and the second is the copy. To illustrate this rule, assume that p' is 0, 1, 5, 6, 6, 12, 4, 12, 13, 3, 3, 12, 13, 8, 14. Now, the rule is applied to the resultant position p' as follows:

1. The value 6 is an index of an edge in a loop. This edge is repeated twice. So, the first existence is not changed, while the second existence is replaced by the index of its copy, 10.
2. The value 12 is the index of the copy of the edge 8 in a loop. This edge is repeated three times, and the value 8 already exists as well. This means that this edge has 4 occurrences. The last two occurrences are replaced by the value −1. The other two occurrences are kept with changing the value of the first occurrence to the index of the original loop edge, 8.
3. The value 13 is the index of the copy of the edge 9 in a loop. This edge is repeated twice. These two edges are kept with changing the value of the first occurrence to the index of the original loop edge, 9.
4. The value 3 is not the index of a loop edge. This edge is repeated twice. The second occurrence is replaced by the value −1.
5. The values 0, 1, 4, and 14 are kept without change.

The resultant actual position becomes:

$0,\ 1,\ 5,\ 6,\ 10,\ 8,\ 4,\ 12,\ 9,\ 3,\ -1,\ -1,\ 13,\ -1,\ 14.$

The final form of the updated actual position vector is obtained by sorting the positive values and keeping −1's at the end, as follows: $0,\ 1,\ 3,\ 4,\ 5,\ 6,\ 8,\ 9,\ 10,\ 12,\ 13,\ 14,\ -1,\ -1,\ -1.$ This position vector corresponds to the edges: $e_0,\ e_1,\ e_3,\ e_4,\ e_5,\ e_6,\ e_8,\ e_9,\ e_{10},\ e_{12},\ e_{13},\ e_{14}$. These edges form the connected path: $e_0,\ e_1,\ e_3,\ e_4,\ e_6,\ e_8,\ e_9,\ e_{10},\ e_{12},\ e_{13},\ e_5,\ e_{14}$. The corresponding updated binary position vector will be: 110111101110111.

4.4 Fitness Function

The algorithm assesses every path (p) using the ratio of the number of the def-use paths, which it covers, to the total number of def-use paths in the program. A def-use (du) is covered if there is a path contains a sub-path that begins with the def-node (d) and finishes with the use-node (u) and that path doesn't contain any killing node for that def-use. The fitness value fitness(P_i) of a particle P_i (i = 1, …, PS) is computed using the following formula [42,43]:

$$fitness(P_i) = \frac{no.\ of\ def - use\ paths\ covered\ by\ P_i}{total\ no.\ of\ def - use\ paths} \tag{6}$$

5 The Proposed Technique

The main modules of the system that implements the presented path generation technique are described below.

The system is written using C# programing language. It contains the following modules:

1. Analysis module.
2. Path generation module.

These modules are discussed in more detail in the following subsections. Fig. 4 presents the pseudo-code of the proposed system. This system applies the proposed PSO algorithm given in Section 4.

5.1 Analysis Module

This module accepts as input the source code P to be tested, analyses it, and produces the following outputs:

1. A report that involves the details of the components of P.
2. The CFG of P.

3. The set of all def-use pairs for each variable in P.
4. The dd-graph of the CFG of P.

For instance, the analysis module generates for the C# code given in Fig. 1: 1) the CFG given in Fig. 2, 2) the dd-graph given in Fig. 3, 3) dd-edges and its corresponding nodes given in Tab. 1, and 4) all def-use pairs given in Tab. 2.

```
/* A PSO algorithm to automatically generate test paths that cover the all-uses criterion for a given program */
  Input:
      The program to be tested P;
      Population size;
      Maximum no. of generations (mGens);
      c1, c2: learning factors
  Output:
      Set of test paths, and the set of def-use paths covered by each test path;
      List of uncovered def-use paths, if any;
  Begin
      //The Analysis Phase
        Extract the components of the program P: classes,objects,statements,variables,functions.
        Form the control flow graph of P.
        Determine the variables def-use pairs of P.
        Form the DD-graph of P by reducing its control flow graph
      //Test path-Generation Phase
      Step 1: Initialization
        Initialize the def-use coverage vector to zeros;
        Randomly create Initial_Population of particles with random positions (test paths) and velocities for each particle such that each
        generated test path must be connected;
        Current_population = Initial_Population;
        def-use coverage percent = 0
        accumulated def-use-coverage percent = 0
        No_Of_Generations=0;
        nPaths=0;
      Step 2: Generate test paths
        For each particle p with position $x_p$ in Current_population do
        Begin
          Convert $x_p$ to the corresponding path;
          Evaluate the current test path (calculate its fitness value);
          If (fitness($x_p$) is better than fitness($pbest_p$)) then
              $pbest_p = x_p$.
          If (some def-use paths are covered) then
              nPaths = nPaths + 1;
              Add effective test path to set of test paths for P;
              Update the def-use coverage vector;
              Update accumulated def-use-coverage percent;
          End If
        End For;
        Identify the particle in the swarm with the best pbest,
        gbest = best pbest.
        While (Coverage_Percent  != 100 and No_Of_Generations <=  mGens) do
        Begin
          For each particle p in Current_population do
          Begin
            Update velocity $v_p$;
            Update position $x_p$;
            // Check connectivity
            Convert updated $x_p$ to the corresponding path pth;
            If (pth is connected) then
              Add new particle to new population
            Else
              Try to repair pth
              If(repaired) then
                  Add repaired new particle to new population
              Else
                  Add the original particle to the new population
              End If
            End If;
          End for
          For each particle p with position $x_p$ in new population do
          Begin
            Convert $x_p$ to the corresponding path;
            Evaluate the current test path (calculate fitness value);
            If (fitness($x_p$) is better than fitness($pbest_p$)) then
              $pbest_p = x_p$.
            If (some def-use paths are covered) then
              nPaths = nPaths + 1;
              Add effective test path to set of test paths for P;
              Update the def-use coverage vector;
              Update accumulated def-use-coverage percent;
            End If
          End For;
          Identify the particle in the swarm with the best pbest,
          If (best pbest is better than gbest) then
              gbest = best pbest;
              Current_population =  new population;
              Increment No_Of_Generations;
        End While
        Step 3: Produce output
          Return set of test paths for P, and set of def-use paths covered by each test path; Report on uncovered def-use paths, if any;
      End.
```

Figure 4: The whole pseudo-code of the proposed system

5.2 Path Generation Module

This module applies the PSO algorithm given in Section 4 to create paths to cover all def-use pairs of the code under test. The inputs of that module are:

1. Set of def-use paths (to be covered).
2. The dd-graph size (number of edges).
3. The population size (PS).
4. Maximum number of generations (mGens).
5. Learning factors (c_1 and c_2).

The outputs of this module are:

1. List of paths, which satisfy the def-use criterion of the given code. It should be noted that the algorithm may fail to find paths to cover some def-use paths when these paths are infeasible, i.e., no executable path can be found to cover these paths.
2. A report presents the constructed path(s) and the satisfied def-use pairs and the set of unsatisfied def-use pairs, if any.

In the basic PSO algorithm, the population is evolved until one of its members represents the solution of the given problem. In the test path generation problem, this would correspond to one path achieving the coverage of all def-use paths of the program. Whilst this feasible for some programs, the majority of programs cannot be covered by just one test path – it might take many test paths to cover all def-use paths. Therefore, in the proposed PSO algorithm, the population evolves until a combined subset of the population satisfies the def-use criterion. This is done by recording which def-use paths of the program each member has covered and halting the evolution when a set of members has traversed the entire def-use paths of program, if possible. The solution is this set.

Figs. 5a and 5b present a part of the report generated by the path generation module after applying it to the C# program given in Fig. 1. The report illustrates that the technique created 8 paths to cover 100% of all def-use pairs given in Tab. 2. Fig. 6 presents the report generated by the technique for these 8 paths that needed 9 iterations to be covered. The list of paths that were created by the presented technique may be input to a data generation system for creating a number of inputs, which satisfy the data-flow paths testing.

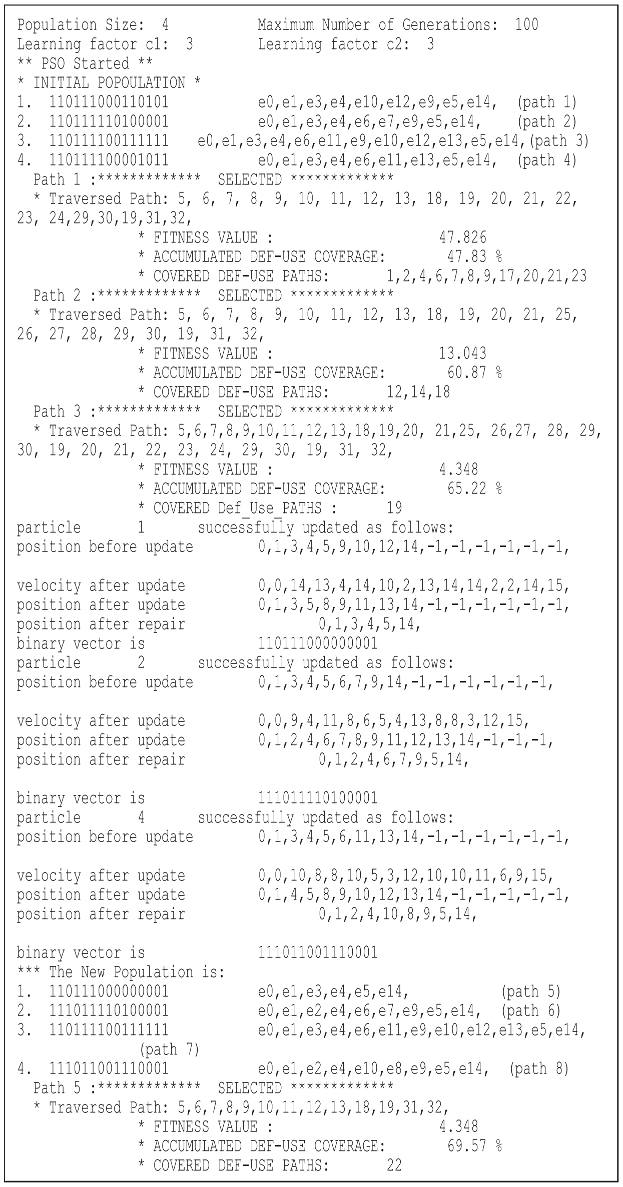
6 Experimental Study

This section describes the experimental study that was carried out to assess the efficiency of the proposed technique. In this study, we compared the proposed technique with the GA-based path generation system presented by Girgis et al. [22]. For fair comparison, the GA-based system was modified to repair any chromosome, which represents a disconnected path to be connected, if possible.

The experiment includes 15 C# programs. The specifications of the PSO algorithm were set to: $\text{mGens} = 100,\ c_1 = 3,\ c_2 = 3,\ \text{and PS} = 4,\ 50,\ \text{and } 100$. The GA-based algorithm and the proposed algorithm were executed 20 times on each subject program and the average is computed.

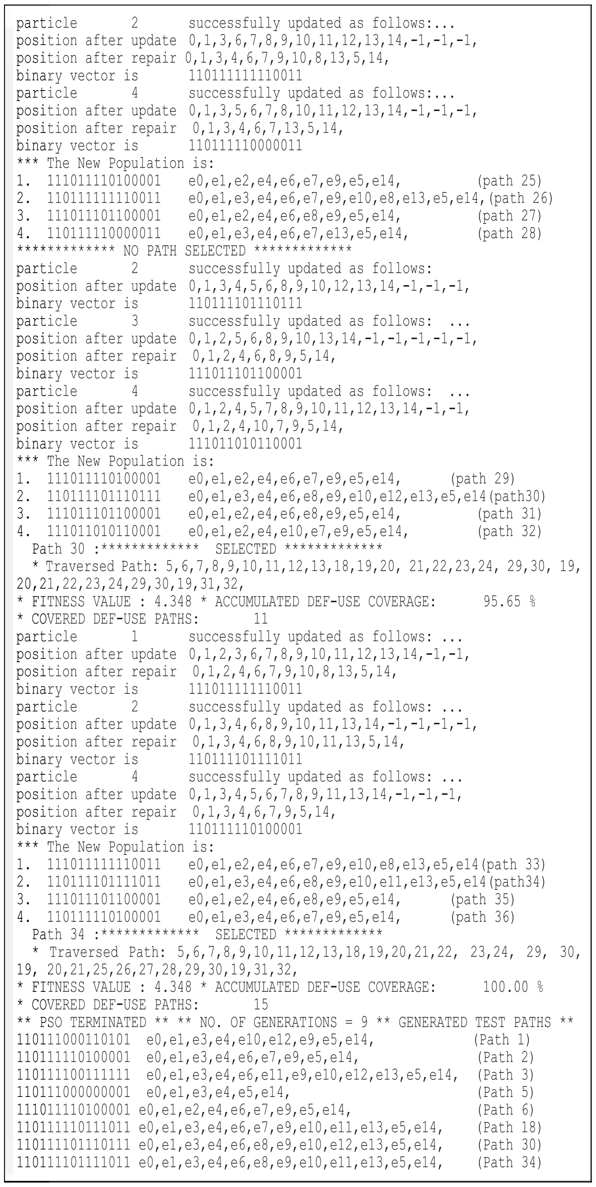
Tab. 3 presents the findings of applying the PSO-based and the GA-based systems to the 15 programs. From the results given in Tab. 3, the PSO-based system overcame the GA-based system in 14 out of the 15 programs in the number of generations needed for satisfying the def-use criterion.

The results showed that the PSO technique is more effective than GA technique in reducing the number of generations. The PSO technique required 199 generations to cover 99.3% of all def-use paths, while the GA technique needed 349 generations to cover 98.6% of all def-use paths.



```
Population Size:  4           Maximum Number of Generations:  100
Learning factor c1:  3        Learning factor c2:  3
** PSO Started **
* INITIAL POPOULATION *
1.  110111000110101           e0,e1,e3,e4,e10,e12,e9,e5,e14,  (path 1)
2.  110111110100001           e0,e1,e3,e4,e6,e7,e9,e5,e14,    (path 2)
3.  110111100111111   e0,e1,e3,e4,e6,e11,e9,e10,e12,e13,e5,e14,(path 3)
4.  110111100001011           e0,e1,e3,e4,e6,e11,e13,e5,e14,  (path 4)
  Path 1 :*************  SELECTED *************
  * Traversed Path: 5, 6, 7, 8, 9, 10, 11, 12, 13, 18, 19, 20, 21, 22,
23, 24,29,30,19,31,32,
               * FITNESS VALUE :                    47.826
               * ACCUMULATED DEF-USE COVERAGE:       47.83 %
               * COVERED DEF-USE PATHS:      1,2,4,6,7,8,9,17,20,21,23
  Path 2 :*************  SELECTED *************
  * Traversed Path: 5, 6, 7, 8, 9, 10, 11, 12, 13, 18, 19, 20, 21, 25,
26, 27, 28, 29, 30, 19, 31, 32,
               * FITNESS VALUE :                    13.043
               * ACCUMULATED DEF-USE COVERAGE:       60.87 %
               * COVERED DEF-USE PATHS:      12,14,18
  Path 3 :*************  SELECTED *************
  * Traversed Path: 5,6,7,8,9,10,11,12,13,18,19,20, 21,25, 26,27, 28, 29,
30, 19, 20, 21, 22, 23, 24, 29, 30, 19, 31, 32,
               * FITNESS VALUE :                    4.348
               * ACCUMULATED DEF-USE COVERAGE:       65.22 %
               * COVERED Def_Use_PATHS :     19
particle      1      successfully updated as follows:
position before update        0,1,3,4,5,9,10,12,14,-1,-1,-1,-1,-1,-1,

velocity after update         0,0,14,13,4,14,10,2,13,14,14,2,2,14,15,
position after update         0,1,3,5,8,9,11,13,14,-1,-1,-1,-1,-1,-1,
position after repair                0,1,3,4,5,14,
binary vector is              110111000000001
particle      2      successfully updated as follows:
position before update        0,1,3,4,5,6,7,9,14,-1,-1,-1,-1,-1,-1,

velocity after update         0,0,9,4,11,8,6,5,4,13,8,8,3,12,15,
position after update         0,1,2,4,6,7,8,9,11,12,13,14,-1,-1,-1,
position after repair                0,1,2,4,6,7,9,5,14,

binary vector is              111011110100001
particle      4      successfully updated as follows:
position before update        0,1,3,4,5,6,11,13,14,-1,-1,-1,-1,-1,-1,

velocity after update         0,0,10,8,8,10,5,3,12,10,10,11,6,9,15,
position after update         0,1,4,5,8,9,10,12,13,14,-1,-1,-1,-1,-1,
position after repair                0,1,2,4,10,8,9,5,14,

binary vector is              111011001110001
*** The New Population is:
1.  110111000000001           e0,e1,e3,e4,e5,e14,           (path 5)
2.  111011110100001           e0,e1,e2,e4,e6,e7,e9,e5,e14,  (path 6)
3.  110111100111111           e0,e1,e3,e4,e6,e11,e9,e10,e12,e13,e5,e14,
               (path 7)
4.  111011001110001           e0,e1,e2,e4,e10,e8,e9,e5,e14,  (path 8)
  Path 5 :*************  SELECTED *************
  * Traversed Path: 5,6,7,8,9,10,11,12,13,18,19,31,32,
               * FITNESS VALUE :                    4.348
               * ACCUMULATED DEF-USE COVERAGE:       69.57 %
               * COVERED DEF-USE PATHS:      22
```

(a)

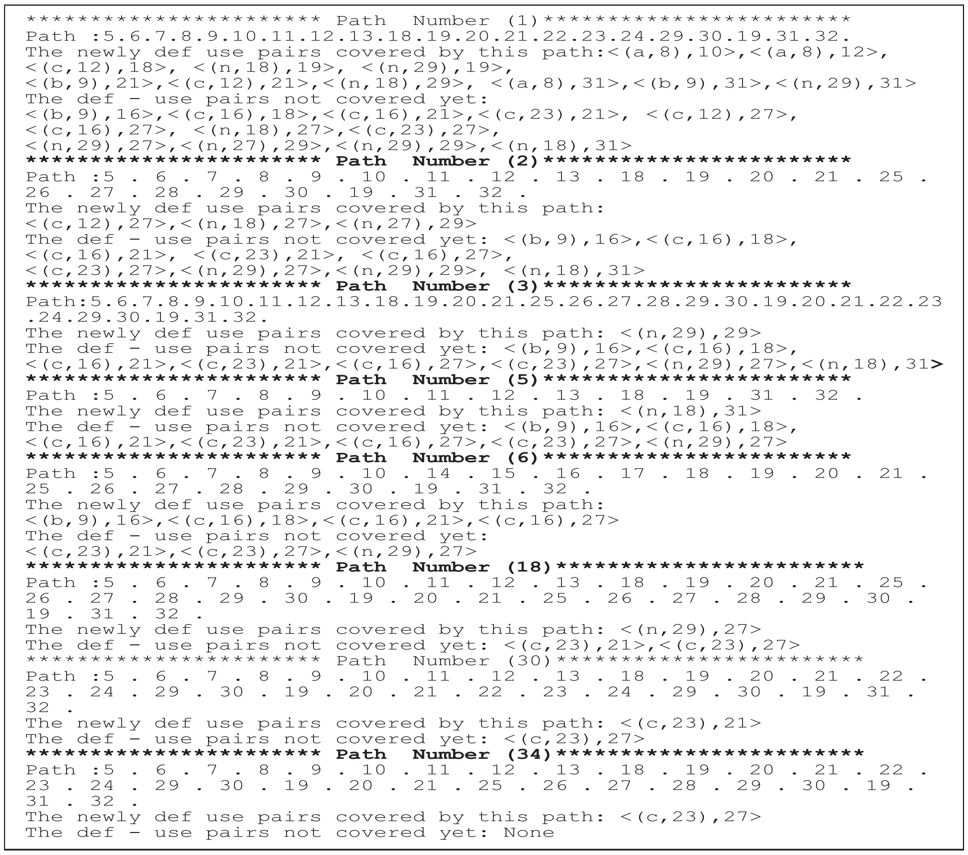


```
particle      2      successfully updated as follows:...
position after update  0,1,3,6,7,8,9,10,11,12,13,14,-1,-1,-1,
position after repair 0,1,3,4,6,7,9,10,8,13,5,14,
binary vector is      110111111110011
particle      4      successfully updated as follows:...
position after update  0,1,3,5,6,7,8,10,11,12,13,14,-1,-1,-1,
position after repair  0,1,3,4,6,7,13,5,14,
binary vector is      110111110000011
*** The New Population is:
1.  111011110100001   e0,e1,e2,e4,e6,e7,e9,e5,e14,         (path 25)
2.  110111111110011   e0,e1,e3,e4,e6,e7,e9,e10,e8,e13,e5,e14,(path 26)
3.  111011101100001   e0,e1,e2,e4,e6,e8,e9,e5,e14,         (path 27)
4.  110111110000011   e0,e1,e3,e4,e6,e7,e13,e5,e14,        (path 28)
************* NO PATH SELECTED *************
particle      2      successfully updated as follows:
position after update  0,1,3,4,5,6,8,9,10,12,13,14,-1,-1,-1,
binary vector is      110111101110111
particle      3      successfully updated as follows:  ...
position after update  0,1,2,5,6,8,9,10,13,14,-1,-1,-1,-1,-1,
position after repair  0,1,2,4,6,8,9,5,14,
binary vector is      111011101100001
particle      4      successfully updated as follows:  ...
position after update  0,1,2,4,5,7,8,9,10,11,12,13,14,-1,-1,
position after repair  0,1,2,4,10,7,9,5,14,
binary vector is      111011010110001
*** The New Population is:
1.  111011110100001   e0,e1,e2,e4,e6,e7,e9,e5,e14,      (path 29)
2.  110111101110111   e0,e1,e3,e4,e6,e8,e9,e10,e12,e13,e5,e14(path30)
3.  111011101100001   e0,e1,e2,e4,e6,e8,e9,e5,e14,         (path 31)
4.  111011010110001   e0,e1,e2,e4,e10,e7,e9,e5,e14,        (path 32)
  Path 30 :*************  SELECTED *************
  * Traversed Path: 5,6,7,8,9,10,11,12,13,18,19,20, 21,22,23,24, 29,30, 19,
20,21,22,23,24,29,30,19,31,32,
* FITNESS VALUE : 4.348 * ACCUMULATED DEF-USE COVERAGE:      95.65 %
* COVERED DEF-USE PATHS:       11
particle      1      successfully updated as follows: ...
position after update  0,1,2,3,6,7,8,9,10,11,12,13,14,-1,-1,
position after repair  0,1,2,4,6,7,9,10,8,13,5,14,
binary vector is      111011111110011
particle      2      successfully updated as follows: ...
position after update  0,1,3,4,6,8,9,10,11,13,14,-1,-1,-1,-1,
position after repair  0,1,3,4,6,8,9,10,11,13,5,14,
binary vector is      110111101111011
particle      4      successfully updated as follows: ...
position after update  0,1,3,4,5,6,7,8,9,11,13,14,-1,-1,-1,
position after repair  0,1,3,4,6,7,9,5,14,
binary vector is      110111110100001
*** The New Population is:
1.  111011111110011   e0,e1,e2,e4,e6,e7,e9,e10,e8,e13,e5,e14(path 33)
2.  110111101111011   e0,e1,e3,e4,e6,e8,e9,e10,e11,e13,e5,e14(path34)
3.  111011101100001   e0,e1,e2,e4,e6,e8,e9,e5,e14,      (path 35)
4.  110111110100001   e0,e1,e3,e4,e6,e7,e9,e5,e14,      (path 36)
  Path 34 :*************  SELECTED *************
  * Traversed Path: 5,6,7,8,9,10,11,12,13,18,19,20,21,22, 23,24, 29, 30,
19, 20,21,25,26,27,28,29,30,19,31,32,
* FITNESS VALUE : 4.348 * ACCUMULATED DEF-USE COVERAGE:      100.00 %
* COVERED DEF-USE PATHS:       15
** PSO TERMINATED ** ** NO. OF GENERATIONS = 9 ** GENERATED TEST PATHS **
110111000110101  e0,e1,e3,e4,e10,e12,e9,e5,e14,            (Path 1)
110111110100001  e0,e1,e3,e4,e6,e7,e9,e5,e14,              (Path 2)
110111100111111  e0,e1,e3,e4,e6,e11,e9,e10,e12,e13,e5,e14,  (Path 3)
110111000000001  e0,e1,e3,e4,e5,e14,                        (Path 5)
111011110100001 e0,e1,e2,e4,e6,e7,e9,e5,e14,                (Path 6)
110111110111011 e0,e1,e3,e4,e6,e7,e9,e10,e11,e13,e5,e14,    (Path 18)
110111101110111 e0,e1,e3,e4,e6,e8,e9,e10,e12,e13,e5,e14,    (Path 30)
110111101111011 e0,e1,e3,e4,e6,e8,e9,e10,e11,e13,e5,e14,    (Path 34)
```

(b)

Figure 5: Part of the report of the path generation module

For instance, for program P#8, the GA-based system needed 29 generations to cover 100% of all def-use paths. On the other hand, the PSO-based system needed 20 generations to cover 100% of all def-use paths. For the program P#4, both the PSO-based and GA-based systems reached the mGens of generations. The two techniques fulfilled only 88.89% coverage because this program contains a number of infeasible paths. For program P#13, the PSO-based system covered 100% in 12 generations, while the GA-based system reached the maximum number of generations (mGens = 100) and covered only 91.11% of all def-use paths.



```
*********************** Path  Number (1)************************
Path :5.6.7.8.9.10.11.12.13.18.19.20.21.22.23.24.29.30.19.31.32.
The newly def use pairs covered by this path:<(a,8),10>,<(a,8),12>,
<(c,12),18>, <(n,18),19>, <(n,29),19>,
<(b,9),21>,<(c,12),21>,<(n,18),29>, <(a,8),31>,<(b,9),31>,<(n,29),31>
The def - use pairs not covered yet:
<(b,9),16>,<(c,16),18>,<(c,16),21>,<(c,23),21>, <(c,12),27>,
<(c,16),27>, <(n,18),27>,<(c,23),27>,
<(n,29),27>,<(n,27),29>,<(n,29),29>,<(n,18),31>
*********************** Path  Number (2)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 11 . 12 . 13 . 18 . 19 . 20 . 21 . 25 .
26 . 27 . 28 . 29 . 30 . 19 . 31 . 32 .
The newly def use pairs covered by this path:
<(c,12),27>,<(n,18),27>,<(n,27),29>
The def - use pairs not covered yet: <(b,9),16>,<(c,16),18>,
<(c,16),21>, <(c,23),21>, <(c,16),27>,
<(c,23),27>,<(n,29),27>,<(n,29),29>, <(n,18),31>
*********************** Path  Number (3)************************
Path:5.6.7.8.9.10.11.12.13.18.19.20.21.25.26.27.28.29.30.19.20.21.22.23
.24.29.30.19.31.32.
The newly def use pairs covered by this path: <(n,29),29>
The def - use pairs not covered yet: <(b,9),16>,<(c,16),18>,
<(c,16),21>,<(c,23),21>,<(c,16),27>,<(c,23),27>,<(n,29),27>,<(n,18),31>
*********************** Path  Number (5)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 11 . 12 . 13 . 18 . 19 . 31 . 32 .
The newly def use pairs covered by this path: <(n,18),31>
The def - use pairs not covered yet: <(b,9),16>,<(c,16),18>,
<(c,16),21>,<(c,23),21>,<(c,16),27>,<(c,23),27>,<(n,29),27>
*********************** Path  Number (6)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 14 . 15 . 16 . 17 . 18 . 19 . 20 . 21 .
25 . 26 . 27 . 28 . 29 . 30 . 19 . 31 . 32 .
The newly def use pairs covered by this path:
<(b,9),16>,<(c,16),18>,<(c,16),21>,<(c,16),27>
The def - use pairs not covered yet:
<(c,23),21>,<(c,23),27>,<(n,29),27>
*********************** Path  Number (18)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 11 . 12 . 13 . 18 . 19 . 20 . 21 . 25 .
26 . 27 . 28 . 29 . 30 . 19 . 20 . 21 . 25 . 26 . 27 . 28 . 29 . 30 .
19 . 31 . 32 .
The newly def use pairs covered by this path: <(n,29),27>
The def - use pairs not covered yet: <(c,23),21>,<(c,23),27>
*********************** Path  Number (30)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 11 . 12 . 13 . 18 . 19 . 20 . 21 . 22 .
23 . 24 . 29 . 30 . 19 . 20 . 21 . 22 . 23 . 24 . 29 . 30 . 19 . 31 .
32 .
The newly def use pairs covered by this path: <(c,23),21>
The def - use pairs not covered yet: <(c,23),27>
*********************** Path  Number (34)************************
Path :5 . 6 . 7 . 8 . 9 . 10 . 11 . 12 . 13 . 18 . 19 . 20 . 21 . 22 .
23 . 24 . 29 . 30 . 19 . 20 . 21 . 25 . 26 . 27 . 28 . 29 . 30 . 19 .
31 . 32 .
The newly def use pairs covered by this path: <(c,23),27>
The def - use pairs not covered yet: None
```

Figure 6: The technique report for the 8 paths that covered all def-use pairs of the example program

Fig. 7 compares the PSO-based system and the GA-based system according to the number of generations needed to cover all def-uses paths for every subject program. According to this comparison, the PSO system is more effective than the GA-based system in reducing the number of generations needed to accomplish 100% def-use path coverage.

Fig. 8 compares the PSO-based and the GA-based systems according to the number of paths created to satisfy all def-uses paths. The PSO-based technique generated 60 paths for satisfying 99.3% of all def-use paths, while the GA-based technique generated 63 paths to cover 98.6% of all def-use paths.

According to this comparison, the PSO-based system is more effective than the GA-based system in reducing the number of paths for 5 out of the 15 programs. In the other 9 programs, the two systems created an equal number of paths. In P#13 the GA-based system created a number of paths smaller than the PSO-based system but it reached only 91.11% coverage, while the PSO-based system reached 100% coverage.

Table 3: A comparison between the PSO and GA techniques

Prog#	*No of generation*		*No of test path*		*DU coverage%*	
	GA	PSO	*GA*	*PSO*	GA	*PSO*
P#1	4	3	3	2	100	100
P#2	4	2	3	2	100	100
P#3	9	7	4	4	100	100
P#4	100	100	4	3	88.89	88.89
P#5	10	8	7	6	100	100
P#6	4	3	2	2	100	100
P#7	13	6	5	5	100	100
P#8	29	20	4	4	100	100
P#9	6	4	3	3	100	100
P#10	16	8	4	4	100	100
P#11	8	6	4	4	100	100
P#12	28	8	9	8	100	100
P#13	100	12	3	5	91.11	100
P#14	12	7	5	5	100	100
P#15	6	5	3	3	100	100
Total	349	199	63	60	98.6	99.3

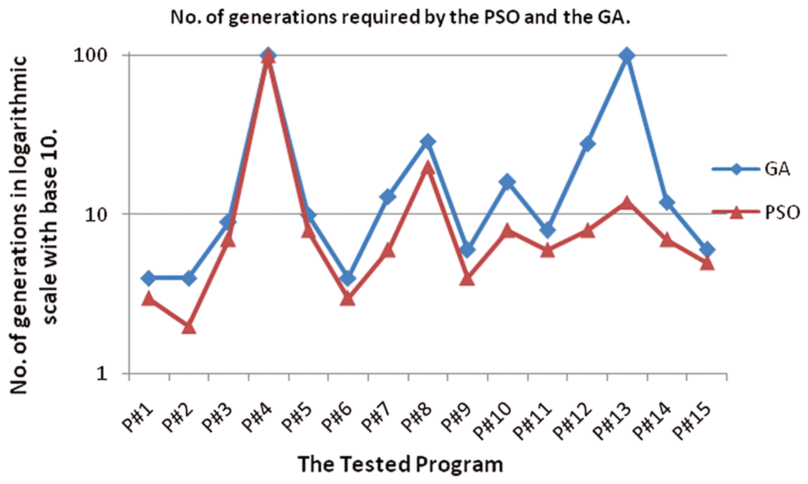


Figure 7: Number of generations of the GA-based and the PSO-based systems

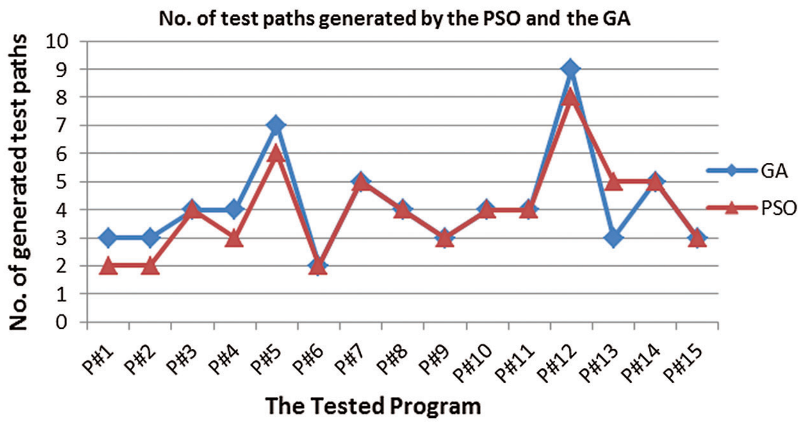


Figure 8: Number of paths created by the GA-based and the PSO-based systems

7 Conclusions and Future Work

This paper introduced a path-testing approach, which applies a PSO algorithm to construct test paths to satisfy the all-uses criterion. For programs that contain loops, the presented approach creates the paths according to the ZOT-criterion. An experiment that included 15 C# programs has been conducted to evaluate the efficiency of the presented technique compared to a GA-based path generation technique. The results showed that the PSO-based technique required 199 generations, while the GA-based technique needed 349 generations, to satisfy all def-uses of all programs. The PSO-based technique generated 60 paths and the GA-based technique generated 63 paths to satisfy all def-uses. In the future work, the experiments will be re-conducted to compare the time consumed by the two techniques using the same machine. Also, we will focus on conducting the experiments using another programing language such as Java with large data set. In addition, in the future work, we will focus on developing a system to find a set of test data to cover the generated paths.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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