1. Introduction

Optimization is a goal to explore the excellent solutions in a given discrete space. The challenging optimize problem are NP (Nondeterministic Polynomial time) - hard problem. These challenging optimization problems are solved by trial and error using various optimization techniques. To solve the optimization problem Nature is key source of inspiration for many researchers. Nature inspiration computation comes to the group of meta-heuristics search. The nature inspired optimization meta-heuristic algorithms focused in this paper are Evolutionary Computations techniques: Differential Evolution (DE), Genetic Algorithm (GA), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO). The problem area chosen is Hardware Abstraction Layer (HAL) benchmark scheduling problem using Integer Linear Programming method.

The motivation for this paper is to formally have an Integer Linear Programming (ILP) approach which guarantees solution quality and guarantee of quickly finding for optimal resource solution problem using Evolutionary Computations.

The different resource scheduling algorithm and its draw back has been reported and shown before paper. The Evolutionary Algorithm inspired by natural evolution, to solve complex function and combinatorial optimization with precision results. Genetic Algorithm and Evolutionary Programming effectively solves nonlinear optimization problem, it main drawback is slow convergence and may struck to local minima. PSO has few operators and better convergence, Differential Evolution has better convergence and few control parameters.
2. Overview of Nature Inspired Algorithm (DE, GA, EP, PSO)

2.1 Differential Evolution (DE)
Differential Evolution (DE)\(^9\text{-}^{10}\) is an evolution search initiated by Storn and Price (1997). The method is based on Evolutionary operator crossover, mutation and selection, with unique feature of DE is its differential weight technique in mutation operation. The DE is simple algorithm, robust with fast convergence to optimal solution.

2.2 Genetic Algorithm (GA)
 Genetic Algorithm\(^11\text{-}^{12}\) is exploration approach of natural evolutionary theory for combinatorial optimization problem. The general procedure of GA is to evaluate objective function value for random initial population, followed by the diversity operators: Crossover, mutation, selection function. The diversity operator avoids local optima; this process is carried until best solution is achieved. GA\(^13\) is very effective for multi-dimensional optimization.

2.3 Evolutionary Programming (EP)
Evolutionary Programming\(^14\) was coined by Fogel, the flow of the algorithm is to initialize population and calculate fitness values for initial population, secondly mutate the parents and generate new population. Calculate fitness values of new generation and continue from the second step. Mutation is the key point which leads to exploration in the algorithm. EP convergence speed is very slow.

Table 1. A brief comparison of four nature inspired algorithm

| GA (Genetic Algorithm) | EP (Evolutionary Programming) | PSO (Particle swarm optimization) | DE (Differential Evolution) |
|-------------------------|-------------------------------|-----------------------------------|----------------------------|
| GA an optimization method of biological evolution. | EP an optimization mode of biological evolution. | PSO an optimization technique inspired by social behavior of bird flocking or fish schooling | DE an optimization method of biological evolution. |
| John Henry Holland introduced the concept of GA | Lawrence J. Fogel introduced EP | PSO initiated by Eberhart and Kennedy | DE introduced by Storn and Price |
| Original Binary valued representation | Real valued representation | Real valued representation | Real valued representation |
| Random population is initialized and searches updating generation | Random population is initialized and searches updating generation | potential solutions are called particles, fly through the problem space by following the current optimum particles | Random population is initialized and searches updating generation |
| Diversity operator: selection, crossover, and mutation. | EP typically requires only mutation and selection operator | In the PSO, there is one simple operator: velocity calculation. | Diversity operator: selection, crossover, and mutation. |
| GA crossover has more effect at the beginning of the run | EP does not have crossover operation | PSO does not have crossover operation | DE crossover has more effect at the end of the run |
| GA mutation has more effect at the end of the run | Mutation is the only main reproduction operator | PSO does not mutation operator | DE mutation has more effect at the beginning of the run |
| More operators for computation | Less operators for computation than GA | PSO is easy to perform, few parameters to adjust. | DE is simple to implement. |
| Convergence rate is less than PSO | Convergence rate is slow compared to GA and PSO | Convergences rate is faster | Convergences rate is faster |
| Number of Computation is more than PSO | Number of Computation is more than GA | Number of computation is minimum | Number of computation is minimum |
| Maximum probability to achieve global solution | Delivers the global solution better compared to PSO and equivalent to GA | Probability to struck to local minima. | Maximum probability to achieve global solution |
2.4 Particle Swarm Optimization (PSO)

Particle Swarm Optimization based on swarm intelligence introduced by Kennedy and Eberhart (1995). The computational operator are very less, the member of swarm have a cognitive behavior (personal best) and social behavior (global best) among them to explore the random search in design space.

The brief comparison of the four different nature inspired algorithm are summarized below in Table 1.

3. Problem Formulation

In Latency constrained Schedule, for the fixed the control steps, minimize the required resource. The Resource Schedule problem is np (nondeterministic polynomial time) - hard problem; The Integer Linear Programming (ILP) formulation for the resource schedule is given below:

- Firstly the mobility for each operation is calculated, where \( E_k = \text{ASAP (AS SOON AS POSSIBLE)} \) and \( L_k = \text{ALAP (AS LATE AS POSSIBLE)} \) values

\[
M = \{0 \leq j \leq L_k\} \quad (1)
\]

- Secondly the INTEGER LINEAR PROGRAMMING formulation is given as follows

\[
\text{Min} \sum_{k=1}^{n}[C_k \times R_k] \text{ while } \sum_{k,j} x_{i,j} = 1
\]

Where \( 1 \leq k \leq m \) indicate the number of resource operation available, \( R_k \) term is the computing unit of resource type \( k \), and \( C_k \) term is the cost of each resource computing type.

\[
[x_{i,j} = 1], \forall \text{ operation } = j
\]

- Thirdly the constraints on resource type,

\[
\sum_{k=1}^{n}[x_{i,j} \leq R_j] \quad (4)
\]

- Finally the constraint on data dependency, \((s \times x_{i,j}) -(t \times x_{j,s}) \leq -1, s \leq t, s \text{ and } t \text{ are control step for each operation.} \quad (5)\]

Latency constrained for the Hardware Abstraction Layer (HAL) benchmark problem is shown in Figure 1. Eleven vertices \(\{v1,v2,v3,v4,v5,v6,v7,v8,v9,v10,v11\}\) and eight edges \(\{e_{1,2}, e_{2,3}, e_{4,5}, e_{6,7}, e_{7,8}, e_{8,9}, e_{10,11}\}\). There are six multipliers, two adders, two substractors and one comparator, the goal is to minimize these resource units using Integer Linear Programming formulation is depicted in Figure 1.

The mobility M is four. \( C_m, C_a, C_s, C_c \): computing unit cost of the multiplier unit, adder unit, subtraction unit, comparator unit. \( R_m, R_a, R_s, R_c \): Number of computing resource of the multiplier unit, adder unit, subtraction unit, comparator unit. Let the assumption be \( C_m = 2, C_a = 1, C_s = 1, C_c = 1 \). The goal of the problem is to minimize the Resource unit for the scheduling problem, and satisfy the above mentioned constraints.

4. Experimental Setup

The comparison of nature inspired computational algorithm taken is DE, GA, EP, and PSO. Each algorithm is tested with uniform random number for population size = 200 population. Matlab simulation is considered for the optimization algorithms to solve for the optimal schedule. The fitness function considered is shown in (6).

\[
f = f_i + a \left( \sum_{i=1}^{n} (g_i(x_i))^2 + \sum_{n=1}^{m} (h(x_i))^2 \right) \quad (6)
\]

\( a = 1000, g_i \leq 0 \) and \( h = 0 \) are constraints violation terms.

The parameters setting for each optimization algorithm is described below:

- DE Setup: \( f_m \) scaling factor = 0.7, \( cr \): cross over rate = 0.8, the strategy = DE/rand to best/1 is considered, where rand: randomly chosen population, best: minimum value of objective function, \( 1 \): difference vector =1.

- GA Setup: Two point crossover probability =1, mutation probability = 0.01. Tournament Selection process is used

- EP Setup: Mutation probability = 0.00001. Tournament Selection process is used.
5. Results and Discussion

The following Table 2 compares the performance of DE, GA, EP, and PSO. The performances parameters are checked with optimization algorithm are optimal solution obtained for computing unit ($R_m$ multiplier unit, $R_a$ adder unit, $R_s$ subtraction unit, and $R_c$ comparator units). Numbers of generation taken for convergence, (convergence time taken in seconds) are presented. The convergence performance graph obtained to achieve the minimum optimal cost minimized factor is shown in Figure 2.

### 5.1 Discussion

A comparative study for the performance of latency constrained scheduling using DE, GA, EP and PSO is presented in Table 2 for 5 trails. Among all the trails, DE is the best in finding optimal solution, takes minimum convergence time and minimum number of generation taken to achieve minimum objective function. GA is also best in finding optimal solution similar to DE; but number of generation taken is more compared to DE, EP, PSO. EP delivers only 90% of optimal solution, but suffers badly in convergence time and number of generation taken for convergence compared to DE, PSO. PSO badly gets struck at local minima, fails to deliver optimal solution, but the convergence time and the number generation taken for convergence is much closed match.

### Table 1. Comparative results for the performance of DE, GA, EP, PSO

| Trail No. | Performance Parameters | DE | GA | EP | PSO |
|-----------|------------------------|----|----|----|----|
|           | Computing Units        | $R_m$ | $R_a$ | $R_s$ | $R_c$ | $R_m$ | $R_a$ | $R_s$ | $R_c$ | $R_m$ | $R_a$ | $R_s$ | $R_c$ | $R_m$ | $R_a$ | $R_s$ | $R_c$ |
| 01        | Optimal solution for required resource | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 3 | 1 | 1 | 1 |
|           | Convergence time (second) | 12.4060 | 40.6410 | 29.4370 | 12.8120 |
|           | No. of generation      | 51 | 101 | 291 | 52 |
| 02        | Optimal solution for required resource | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 4 | 1 | 1 | 1 |
|           | Convergence time (second) | 12.6560 | 40.7500 | 25.2970 | 12.3910 |
|           | No. of generation      | 51 | 101 | 271 | 51 |
| 03        | Optimal solution for required resource | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 3 | 1 | 1 | 1 | 2 | 1 | 1 | 1 |
|           | Convergence time (second) | 12.6400 | 41.0471 | 44.3910 | 14.6870 |
|           | No. of generation      | 51 | 101 | 463 | 52 |
| 04        | Optimal solution for required resource | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 3 | 2 | 1 | 1 | 3 | 2 | 1 | 1 |
|           | Convergence time (second) | 12.2650 | 41.8600 | 29.9840 | 12.656 |
|           | No. of generation      | 51 | 104 | 315 | 51 |
| 05        | Optimal solution for required resource | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 3 | 1 | 1 | 1 | 3 | 1 | 1 | 1 |
|           | Convergence time (second) | 12.1560 | 41.3590 | 54.8130 | 13.1720 |
|           | No. of generation      | 51 | 101 | 551 | 51 |
with DE. The minimum convergence to obtain minimum objective value for DE, GA, EP and PSO of the 5th trial is shown in Figure 2 (a), (b), (c), (d). In the optimal resources for scheduling in architectural level synthesis, the optimal value is for multiplier unit = 2, adder unit = 1, substractor unit = 1 and comparator = 1; hence the minimum objective function value obtained is 7 as shown in Figure 3.

6. Conclusion

Comparative study for the performance of Architectural Level Synthesis for Resource Schedule using Nature Inspired Algorithm using DE, GA, EP, PSO are presented. Experimental result indicates DE outperformed PSO, EP and GA in terms of optimal solution achieved, convergence speed, number of generation taken to achieve optimal solution. PSO struck at local minima and EP and GA suffer in having more convergence time. DE proves to be excellent nature inspired algorithm to solve scheduling problem in Architectural Level Synthesis.

7. References

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