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Implementation GASAO Algorithm for Circuit Minimization and Optimization

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Abstract :- **With VLSI, circuits are shrinking in physical size while growing both in speed and capability. If partitioning is not done in effective manner, ignoring the parameters like compactness, time delay and robustness it may degrade the overall performance of a design. Optimization is used to make a design particularly effective in mathematically, finding the maximum of a function. In this paper an effort has been done to combine two meta-heuristic approaches i.e genetic algorithm and simulated annealing owing to get the best of both. The hybrid GASAO algorithm is tested on various benchmark circuits to get better results.**

Keywords: **Partioning, Optimization, Genetic Algorithm, Stimulated Annealing Hybrid Algorithm.**

1 Introduction

The process of creating integrated circuits by combining thousands of transistors into a single chip began in the 1970s and is called as very- large-scale integration. VLSI technology is moving towards miniaturization [1]. In circuit petitioning, the circuit is divided into bi-partitioning and multi-way partitioning. Partitioning is applied recursively in large circuits until the complexity in each part is reduced to the extend that it can be handled efficiently by existing tools[8]. Optimization is a procedure to find an alternative with the most cost effective or highest achievable performance by maximizing the desired factors and minimizing the undesired ones. Important considerations include minimum area of each partion, minimum number of interconnection i.e minicut, logic functionality, delay due to patitioning and fitness function which is the measure of improvement in circuit parameters to obtain better performance[7]. Next comes the available algorithm technology which determines how effectively we can address a given partitioning formulation and optimize a given objective.

Since exact algorithm are often slow when applied to practical problem, heuristic and meta heuristic approaches are usually preferred solution methods[9]. Various researchers have achieved varying levels of success using various optimization techniques. Hybridization of evolutionary algorithms with local search has been investigated in many studies[13]

II Description of Algorithms

2.1 Genetic algorithm(GA)

Genetic algorithm being an evolutionary computational model is based on charles Darwin's theory of natural evolution. The theory is based on the concept of survival of the fittest. With each new generation, the less-fit individuals tend to die off and this survival of fittest leads to improvements in species. GA are based on two basic processes from evolution i.e Inheritance which is passing of features from one generation to the next and the other one is competition which is the survival of the fittest leaving out the bad features from individuals in the population.

GAs are heuristic procedures so they are not guaranteed to find the optimum solution but are able to find very good solutions. Each individual in the population is called a string or chromosome. The population size determines the amount of information stored in the GA. GA works based on evolution from generation to generation so that changes of individual;s in a single generation are not considered. A typical genetic algorithm requires:

- A genetic representation of the solution domain,
- A fitness function to evaluate the solution domain

The circuit to be partitioned is accepted in the form of circuit net list. Then the information of interconnection between the components in the ne tlist is converted in the form of matrix. Using the initial solution, the random population is generated and the population size is specified by the user. Each individual is evaluated for its fitness function. Based on fitness value individuals are randomly selected. Each individual is considered for selection as parent for crossover depending on its fitness value.

Offspring's having higher fitness value replace the lower fit individuals otherwise no replacement is made in the original population. This is repeated generation by generation until some condition is satisfied or the improvement of the best solution found so far is good enough and there is no more improvements possible. After population replacement mutation is performed where part of the chromosome is changed. If mutation is 100% the whole chromosome is changed.

2.2 Stimulated Annealing (SA)

The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. The slowly falling temperature allows the atoms in the molten state to line them up and form a regular crystalline structure that has high density and lower energy. This notion of slow cooling is implemented in the Simulated Annealing algorithm as a slow decrease in the probability of accepting worse solutions as it explores the solution space. S the best solution found by such algorithms is called a local optimum in contrast with the actual best solution which is called a global optimum

The probability of making the transition from the current state s to a candidate new state s' is specified by an acceptance probability function $P(e, e', T)$, that depends on the energies $e = E(s)$ and $e' = E(s')$ of the two states, and on a global time-varying parameter T called the temperature. States with a smaller energy are better than those with a greater energy. The probability function P must be positive even when e' is greater than e. This feature prevents the method from becoming stuck at a local minimum that is worse than the global one.

The initial solution from which the SA will progress is created by generating a number of random solutions, in a manner similar to the creation of an intial genetic population and the best solution among them, in terms of the objective function value is selected. Stimulated annealing was introduced by metropolis. SA was mostly known for its effectiveness in finding near optimal solutions for large scale combinatorial optimization problems but recent approaches of SA Demonstrated that this class of optimization could be considered competitive with other approaches[10].

2.3 GASAO Simulator using VB.Net

To calculate the minimum number of interconnections, select the number of particles along with the number of iterations, then load the netlist data in the simulator. Partition value is half of the number of gates. By calculating the number of interconnections once again select the another file from the netlist and calculate the minimum number of interconnections.

The Algorithm is capable of using multiple net lists simultaneously against single netlist at a time approach on the basis of fitness function, time and number of interconnections.

III Results

The results calculated for various number of gates ranges from 5 to 65 according to the given net list. Average cut is calculated on the total number of files in the given net list.

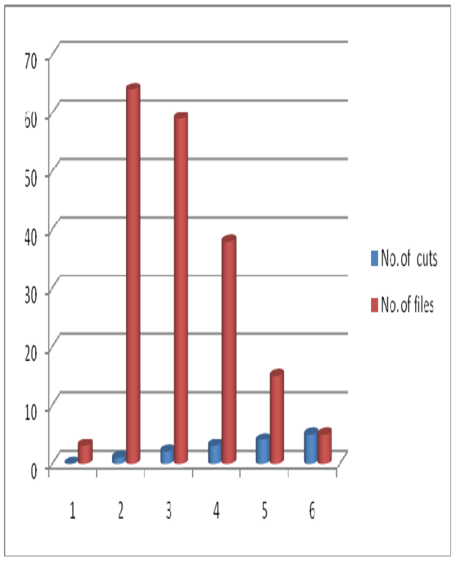
3.1 Performance evaluation of netlist 10 at iteration value 10 and particle value 5

Total Number of Files – 483
Total Number of Gates – 10

Table 1: No. of cuts vs. No. of Files using Netlist 10

S. No	No. of cuts	No. of files
1	0	12
2	1	252
3	2	170
4	3	44
5	4	5

No. of Files



No. of Files

No. of cuts

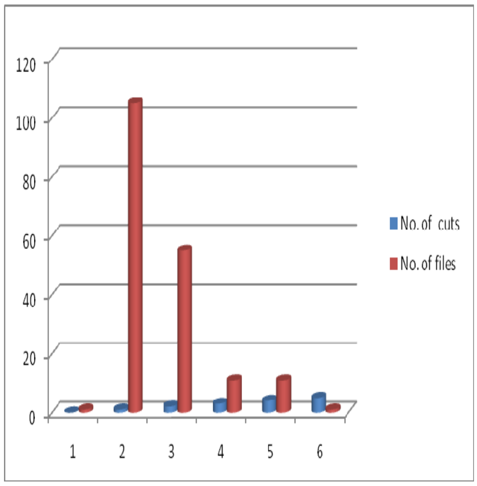
fig1:No. of cuts vs. No. of Files using Netlist 10
Average cut obtained is 1.54

3.2 Performance evaluation of netlist 15 at iteration value 20 and particle value 5

Total Number of Files – 184
Total Number of Gates – 15

Table 2: No. of cuts vs. No. of Files using Netlist 15

S. N0	No. of cuts	No. of files
1	0	1
2	1	105
3	2	55
4	3	11
5	4	11
6	5	1



No. of cuts

fig2:No. of cuts vs. No. of Files using Netlist 15
Average cut obtained is 1.61

3.3 Performance evaluation of netlist 20 at iteration value 30 and particle value 5

Total Number of Files – 121
Total Number of Gates – 20

Table 3: No. of cuts vs. No. of Files using Netlist 25

S.no	Number of cuts	Number of files
1	1	16
2	2	29
3	3	36
4	4	19
5	5	19
6	6	2

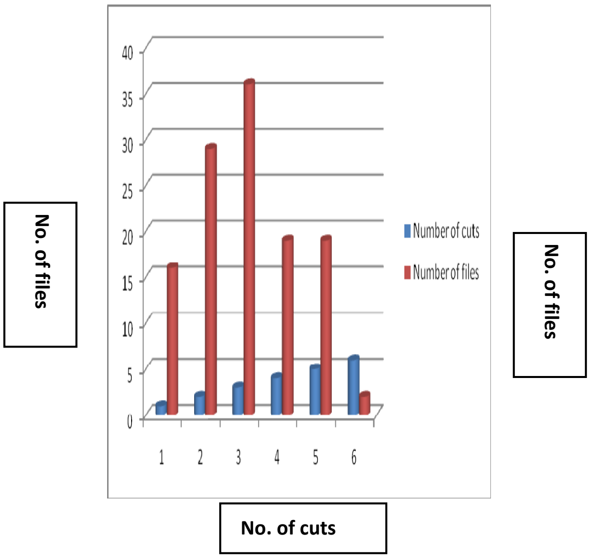


fig3:No. of cuts vs. No. of Files using Netlist 25
Average cut obtained is 3.00

3.4 Performance evaluation of netlist 35 at iteration value 10 and particle value 5

Total Number of Files – 31
Total Number of Gates – 35

Table 4: No. of cuts vs. No. of Files using Netlist 35

S.no	Number of cuts	Number of files
1	1	1
2	2	4
3	3	3
4	4	1
5	6	5
6	7	2
7	8	4
8	9	2
9	10	4
10	11	3
11	12	2

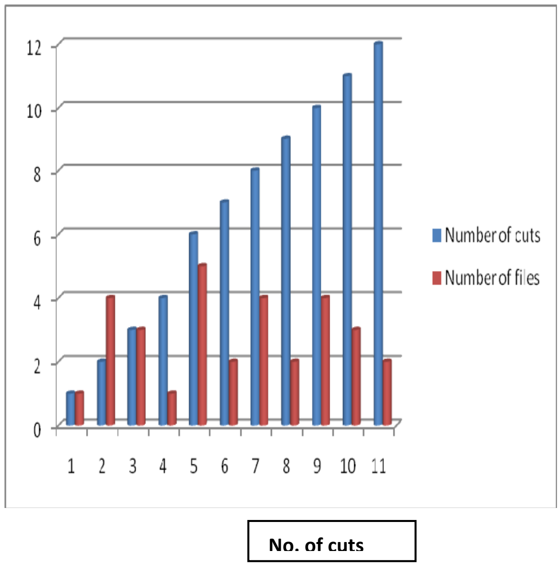


fig4:No. of cuts vs. No. of Files using Netlist 25
Average cut obtained is 6.87

3.5 Performance evaluation of netlist 50 at iteration value 10 and particle value 5

Total Number of Files – 24
Total Number of Gates – 50

Table 5: No. of cuts vs. No. of Files using Netlist 50

S.no	Number of cuts	Number of files
1	4	1
2	5	3
3	6	1
4	8	2
5	11	3
6	12	2
7	13	4
8	14	4
9	15	1
10	16	3

Average cut obtained is 11.2

3.6 Performance evaluation of netlist 65 at iteration value 10 and particle value 5

Total Number of Files – 7
Total Number of Gates – 65

Table 6: No. of cuts vs. No. of Files using Netlist 65

S.no	Number of cuts	Number of files
1	**6**	2
2	**7**	1
3	**10**	1
4	**12**	1
5	**15**	1
6	**16**	1

Average cut-obtained is 10.28

Table 7: Comparison of results obtained using hybrid GA&SA and hybrid PSO&GA

Circuit series of different netlists	No. of Nodes	No. of Files	Average no. of Cuts (GASAO)	Average no. of Cuts (PSOGA)
SPP N-10 Series	10	483	1.54	1.55
SPP N-15 Series	15	184	2.07	2.135
SPP N-20 Series	20	121	3.00	3.365
SPP N-25 Series	25	107	4.00	3.99
SPP N-30 Series	30	52	5.25	4.90
SPP N-35 Series	35	31	6.87	6.93
SPP N-40 Series	40	41	8.80	8.90
SPP N-50 Series	50	24	11.20	11.50
SPP N-60 Series	60	9	12.66	12.66
SPP N-65 Series	65	7	10.28	11.28

IV CONCLUSION

It has been concluded that by the use of this hybrid GASAO Algorithm, the sum of average number of cuts achieved is 65.67 in contrast with the sum of average number of cuts achieved in hybrid PSO and GA which is 67.22. The Average cut can be further reduced by using other evolutionary algorithms or their combination.

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