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Optimization Of Travelling Salesman Problem Using Genetic And Simulated Annealing Hybrid Algorithm

A. KARTHIKEYAN[1], M. VENKATESAN[2*], P. DINESHKUMAR[3], N. PRITHIVIRAJ[2]

[1] *Associate Professor, Department of Aeronautical Engineering, Excel Engineering College, Komarapalayam-637303, Tamil Nadu, India.*

[2] *Assistant Professor, Department of Mechanical Engineering, Excel Engineering College, Komarapalayam-637303, Tamil Nadu, India.*

[3] *Assistant professor, Department of Agricultural Engineering, Kongunadu College of Engineering and Technology, Tiruchirapalli-621215, Tamil Nadu, India.*

** Corresponding author, e-mail: venkatesanm1972@gmail.com*

Abstract

Optimization of the machining operation sequence is one of the most critical and challenging tasks in any Computer Aided Process Planning (CAPP). The main purpose of optimizing machine operation sequence is to minimize the number of tool changes and machine setup iterations. In this research, a genetic and simulated annealing hybrid algorithm is proposed to solve the CAPP problem to find the least production time. The best sequence with the least manufacturing time which is obtained in the first algorithm (genetic algorithm) has been considered as an opening sequence of the second algorithm (simulated annealing algorithm) which searches nearby optimal sequences. The best sequences obtained by this integration technique are the least possible solutions for a particular problem. The proposed hybrid algorithm was tested with four benchmark traveling salesman problems and optimum results were compared with the literature. They were computationally executed in 10 to 20 trials and found improvement in the computational time which is a maximum of 69% faster. This proposed genetic integrated simulated annealing hybrid algorithm significantly performs better than other algorithms. This combination converges very fast and is also able to find many possible alternative feasible solutions in the global searching space. It is a very simple and more efficient algorithm for solving globally optimum results by easily applying any kind of precedence constraints. This algorithm completely checks the precedence constraints from the beginning itself, it won't generate any infeasible sequences at any time during the iteration. The acceptance probability will help this algorithm to reach the stopping criteria of the solution.

Keywords: *Process planning, Operations sequencing, Genetic algorithm, Simulated annealing algorithm, Hybrid algorithm*

1. INTRODUCTION

In earlier days, conventional optimization methods like dynamic programming, branch-bound techniques, etc. were used to solve the optimization of process planning problems. Computer-aided process planning (CAPP) is the computer-based technology used

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to support manufacturing process planning activities in any industry. The major type of CAPP is approximated as a generative and variant type. In the generative type, every time new process planning is generated the variant type uses existing process planning charts by using group technology classification and coding system. The proposed approach using generative type CAPP will generate a new and alternate sequence every time based on inputs.

In the last two decades, many research methods have been used to solve optimization problems. The genetic algorithm is one of the earliest approaches used in the process planning area and has done extensive research on operations sequencing and tool indexing for prismatic parts [1][2][3]. Nallakumarasamy *et al.* (2011) developed a simulated annealing algorithm to solve optimum sequencing problems for prismatic components [4]. Similarly, the simulated annealing concept solves operations sequencing problems [5]. In another computational experiment, the tabu search algorithm was used in process planning [6]. A multi-dimensional tabu search algorithm to solve the process planning problem [7].

The rule-based method was used for solving process planning problems with hard and soft precedence constraints [8]. Manupati *et al.* handled optimal process plan problems using networked-based manufacturing using a game-theoretic approach and evolutionary algorithm [9]. In another study, a honey bee mating algorithm was used to optimize the process planning problem [10]. A graph model was used to solve the process planning problem and compared it with an ant colony optimization algorithm [11]. Sneha Singh and Sankha Deb used an improved ant colony-based algorithm for process planning with precedence constraints. It gives a better solution but has time limitations [12]. The neighbor search algorithm was used to solve the process planning problem [13]. Phung *et al.* used a modified cluster approach for optimizing the prismatic components with precedence constraints and compared them with other algorithms [14].

Sometimes the standard algorithms have been modified for the particular application and to improve its performance. The particle swarm algorithm utilized the penalty approach to eliminate unfeasible operation sequences [15]. The modified particle swarm algorithm is used to optimize the operation sequencing problem to improve the computational time [16]. In another study, the same modified particle swarm algorithm was used for solving process planning and found cost and time saving [17].

A combination of algorithms, a hybrid algorithm is used to ensure better performance of both two algorithms. A hybrid cuckoo search-genetic algorithm for drilling hole optimization sequences [18]. In addition, some hybrid meta-heuristics [19], [20] have been utilized to solve the Process Planning problem.

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Much research is carried out in the area of optimization of operations sequence. By using various nontraditional Meta heuristic techniques, still there is a gap for improvement in this proposed algorithm. These improvements can be done by the combination of genetic and simulated annealing algorithms for reducing computational time, minimizing machine cost, easy implementation of constraints, and finding alternate sequences.

2. IMPLEMENTATION PROCEDURE

The genetic algorithm applies to many practical problems, this theory is derived from Darwin's "survival of the fittest". It is one of the metaheuristic techniques for searching the solutions in a global random space but it may trap in local minima and also consume more computational time. The solutions which are having high fitness can able to survive in the global space. To overcome this drawback, a simulated annealing algorithm is integrated with a genetic algorithm. The best sequences obtained from the genetic algorithm are taken to the simulated annealing algorithm as the beginning sequence which can search the nearby optimal sequence by randomly reversing the two sets of variables. This search technique helps the solutions escape from local minima. This integration will reduce the overall computation time of the algorithm.

The steps followed in GISA are given below

Step 1: First read the input data about the component: (Number of operations, Precedence cost matrix)

Step 2: Get the inputs for the algorithm: (No of generations, Reproduction probability, Crossover probability, Mutation probability, Initial Temperature, Cooling rate, Acceptance probability, and Convergence criteria)

Step 3: Genetic algorithm starts,

- Get the Number of generations : 1 to 10000
- Enter the size of initial populations : 1 to 100
- Enter the reproduction probability : 0 to 1
- Enter the crossover probability : 0 to 1
- Enter the mutation probability : 0 to 1
- Do you want to display the results on screen (Y/N) : Y

It searches for the solution in the global space by using three operators (initialization, crossover, Mutation)

Finally, the best sequence obtained is stored

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```
Sequence    ::>6 7 15 5 2 10 11 13 8 4 16 14 3 1 12 9

Cost        ::>9002 units

Generation  ::>1 th Generation

Posibility  ::>2.092279e+13 sequences

Available   ::>10 sequences

Solution    ::>11 th sequence
```

Figure 1. Sequence result using genetic algorithm

Step 4: Next, the simulated annealing algorithm continuous: The best sequence obtained from the genetic algorithm is considered as the beginning solution for the simulated annealing algorithm. It will do the local search for the best solution till the next optimal is reached.

- Do you want to integrate simulated annealing : Y
- Enter the starting temperature : 10 to 100000
- Enter the acceptance probability : 0 to 1
- Enter the cooling rate : 0 to 1
- Do you want to display the results (Y/N) : Y

```
    Total execution time is 0.010000 seconds

    Simulated Annealing::>1

1 2 11 8 4 5 10 12 15 13 3 16 9 6 7 14     7007    10000
1 2 3 8 10 4 11 14 5 12 9 16 15 13 6 7     6018    9000
1 2 8 16 3 10 4 11 5 6 7 12 13 14 15 9     6010    8100
1 8 10 2 11 3 4 5 6 7 12 14 15 13 9 16     5014    7290
1 2 3 4 5 6 7 8 12 9 10 15 16 11 14 13     4024    6561
1 2 3 11 12 4 10 8 9 5 6 7 16 14 13 15     4024    5904.899902
1 2 11 10 8 3 13 4 5 6 7 12 14 15 16 9     4016    5314.410156
1 2 12 3 4 8 9 16 10 11 5 6 7 13 14 15     4016    4782.969238
1 2 10 12 13 11 14 8 9 15 16 3 4 5 6 7     3019    4304.672363
1 2 3 4 5 6 7 8 11 9 10 12 13 15 16 14     2030    3874.205078
1 2 3 4 5 6 7 12 8 9 16 10 11 13 14 15     1033    3486.784668
1 2 3 4 16 8 9 10 11 14 12 13 15 5 6 7     1033    3138.106201
1 2 3 4 5 6 7 8 9 12 10 11 13 15 16 14     1033    2824.295654
1 2 3 4 5 6 7 8 9 12 10 11 13 14 16 15     1033    2541.866211
1 2 3 16 10 11 12 14 15 13 4 5 6 7 8 9     1033    2287.679688
1 2 3 4 5 6 7 8 9 10 11 12 16 15 13 14     1033    2058.911621
1 2 3 4 8 5 6 7 16 9 10 11 12 14 13 15     1033    1853.020508
1 2 3 4 8 10 11 5 6 7 12 13 14 15 16 9     1033    1667.718506
1 2 3 8 9 10 16 4 5 6 7 12 11 13 14 15     1033    1500.946655
1 2 3 8 4 5 6 7 16 9 10 11 12 13 14 15     36    1350.852051
```

Figure 2. Sequence result using simulated annealing algorithm

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At the end of the algorithm, the optimal solution is obtained which is the least among all. The algorithm stops when the prescribed convergence criteria are reached. This algorithm converges when the temperature reaches the zero value. Figure 1 and Figure 2 show the obtained sequence result of a 15-sequence problem using the genetic and simulated annealing hybrid algorithm.

Step 5: The obtained optimal result is stored separately. Again step 3 and step 4 are continuous for 10 to 20 times till the solutions reach the minimum value. The solution convergence of the algorithm depends upon the various algorithm parameters which are given below. The optimal value is obtained by conducting an enormous computation study.

Genetic Algorithm parameters

- Number of Generations : 1 to 10000
- Reproduction probability : 0 to 1
- Crossover probability : 0 to 1

Simulated Annealing parameters

- Starting Temperature : 10 to 10000' K
- Cooling rate, acceptance probability : 0 to 1

These parameters were used for solving all benchmark case studies and application problems. From the computational experiments, the genetic algorithm searches the solution randomly in the search space but is sometimes struck in the local minima solutions and it takes more computational time and may not be individually suitable for optimization problems with a greater number of operations (more than 10). Hybrid with a simulated annealing algorithm, it will help to find the optimal or near-optimal solutions by escaping from local minimum solutions. The integration of genetic and simulated annealing algorithms is necessary for achieving globally optimum results. The flow chart of the proposed genetic and simulated annealing hybrid algorithm is shown in Figure 3.

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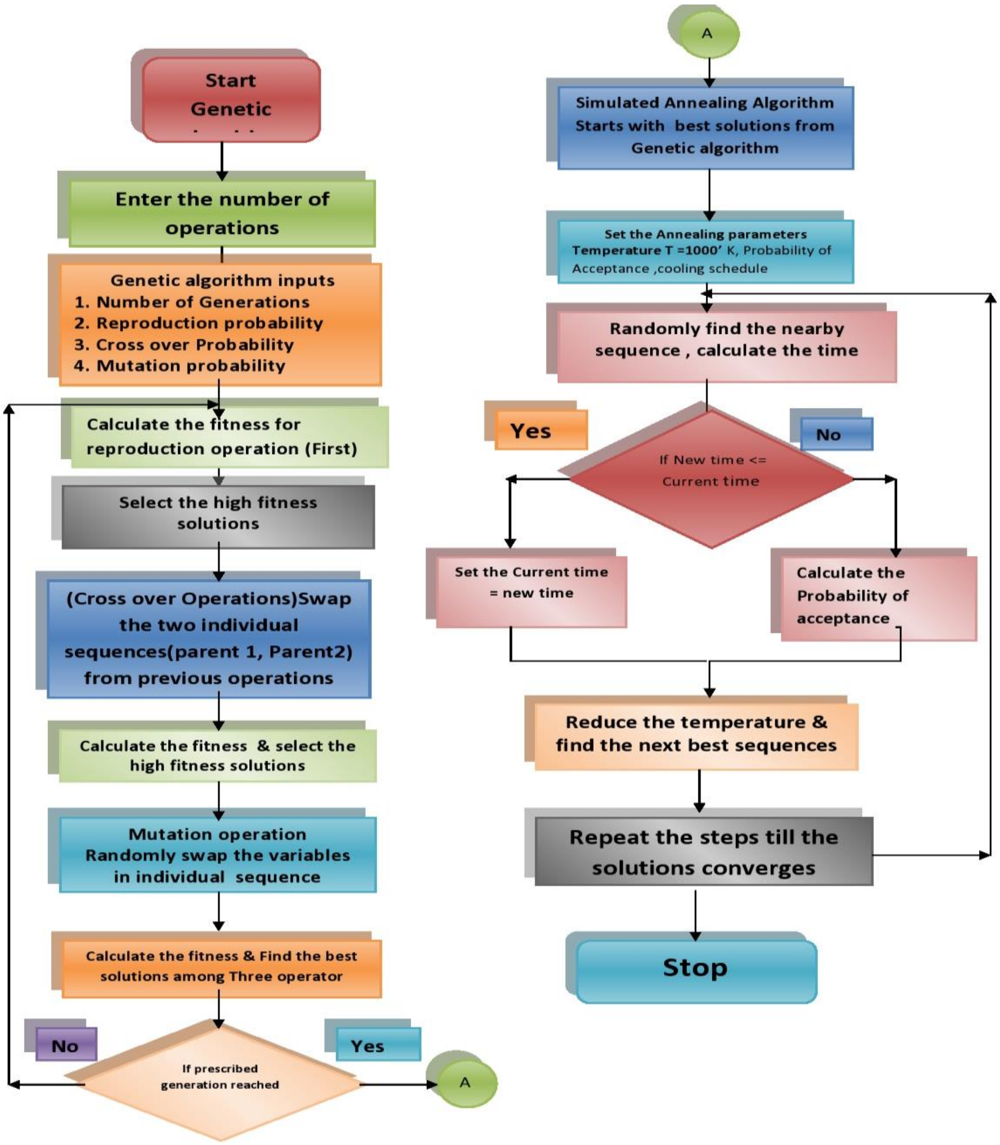

Figure 3. Flow chart of the proposed genetic and simulated annealing hybrid algorithm.

The proposed genetic and simulated annealing algorithm is coded in Turbo C++ and implemented on a computer 1.7 GHz Core 2 Duo processor CPU with 4 GB RAM, the program was written in 800 lines. To verify the feasibility and performance of the proposed algorithm it has been computationally validated. The component precedence cost matrix is given as input to the algorithm along optimum genetic and simulated annealing algorithm parameters which were obtained from previous computational studies.

3. CASE STUDIES

Four benchmark problems have been taken from the literature to prove the effectiveness of the hybrid algorithm. A simple traveling salesman problem with coordinates has been considered as the first benchmark problem. The second, third, and fourth benchmark problems are 6 tasks, 7 tasks, and 20 tasks, with 6, 9, and 31 precedence constraints

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respectively. The benchmark problems are taken from the literature, Moon *et al.* [20]. The results from the proposed genetic and simulated hybrid algorithm will be compared with the literature, in which the genetic algorithm was used.

3.1 Benchmark Problem 1: Without Constraints

The first benchmark problem is considered a traveling salesman problem visiting 5 cities without any constraints. The main objective is to calculate the shortest distance for visiting all cities.

Table 1. Distance matrix of benchmark problem 1

	1	**2**	**3**	**4**	**5**
1	-	4	5	7.6	5.8
2	4	-	3	4.2	3.1
3	5	3	-	3	6
4	7.6	4.2	3	-	6.3
5	5.8	3.1	6	6.3	-

The distance matrix between the five cities is shown in Table 1. By applying the proposed method, the solutions were obtained in the first algorithm (genetic algorithm) itself due to the simple nature of the problem without any constraints. The best tour obtained by the proposed algorithm is 1-3-4-2-5-1 with a total distance of 21.23 units which is the same as the literature, Moon *et al.* [20]. However, the computation time (0.2 seconds) is lesser than the genetic algorithm was used. Further simulated annealing algorithm gives the same solutions from beginning to end with many alternate routes.

3.2 Benchmark Problem 2: 6 Tasks with 6 Pre-Constraints

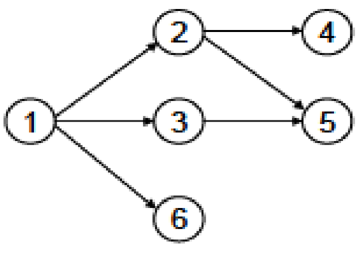

Figure 4. Benchmark problem 2 - 6 task with 6 constraints

Another benchmark problem referred to from the literature is shown in Figure 4. The traveling sales man problem has a total of 6 tasks with 6 precedence constraints. The constraints are as follows (2 after 1), (3 after 1), (6 after 1), (4 after 2), (5 after 2), (5 after 3)

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which is given as input to the problem as fixed and dynamic constraints. Task 1 is considered a fixed constraint; the other 6 tasks are considered dynamic constraints. The traveling distance between each node is shown in Table 2.

The proposed algorithm was tested and optimum results were compared with literature results satisfying all the precedence constraints which are given below in table 5. The optimal sequence obtained is 1-3-6-2-4-5 with an optimum 39 units. The convergence time taken for the genetic algorithm is 0.22 sec, but the proposed hybrid algorithm will give the optimum solution within 0.1 sec which is better than 54%.

Table 2. Distance matrix of benchmark problem 2

	1	**2**	**3**	**4**	**5**	**6**
1	-	7	5	6	10	9
2	7	-	14	6	10	8
3	5	14	-	16	16	10
4	6	6	16	-	10	6
5	10	10	16	10	-	12
6	9	8	10	6	12	-

3.3 Benchmark Problem 3: 8 tasks with 9 pre-constraints

Another example uses asymmetric data from the literature, Moon *et al.* [20] to get the minimum cost in the flexible manufacturing scheduling. Consider 8 tasks with 9 precedence constraints as shown in Figure 5. The constraints are (2 after 0) (3 after 0), (1 after 0), (4 after 1), (6 after 1), (7 after 1), (5 after 4), (5 after 7), and (5 after 6).

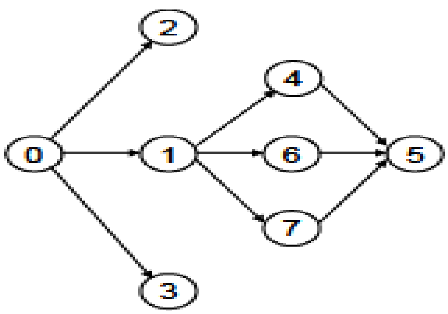

Figure 5. Benchmark problem 3 - 8 task with 9 constraints

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For the benchmark problem same algorithm parameters were used which are obtained from the previous studies and give optimal solutions in a shorter duration. The traveling distance between nodes is given in Table 3.

Table 3. Distance matrix of benchmark problem 3

	1	2	3	4	5	6	7	8
1	-	0	0	0	-	-	-	-
2	-	-	1	2	0.75	0	3	1
3	0	4	-	5	3.25	4	6	0
4	0	7	8	-	5.5	7	-	8
5	-	2.75	2.5	2.25	-	2.75	5.25	2.5
6	0	0	1	2	0.75	-	3	1
7	-	10	11	12	10.75	10	-	11
8	-	4	0	5	3.25	4	6	-

3.4 Benchmark Problem 4: 20 Tasks with 31 Pre-Constraints

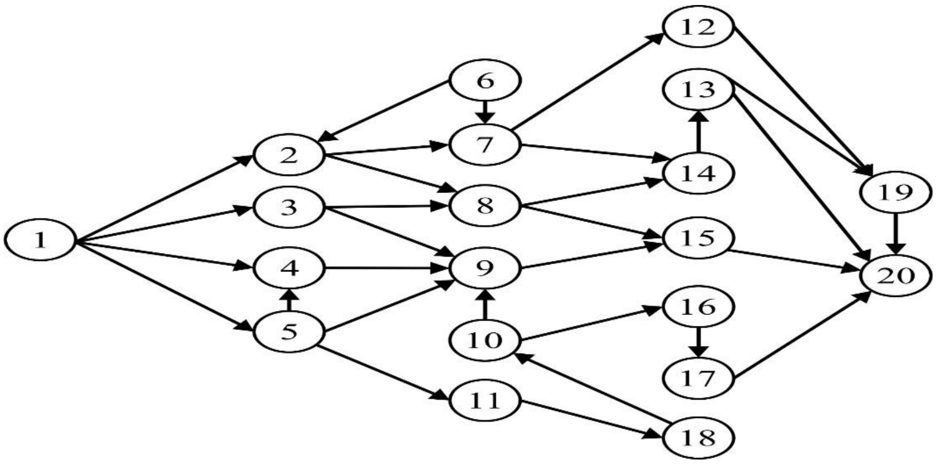

Figure 6. Benchmark problem 4 - 20 task with 31 constraints

For the benchmark problem 4 is an experiment on a more complex problem with 20 vertices and 31 precedence constraints. The precedence relation network is shown in Figure 6 and Table 4 shows the distance matrix of the problem.

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Table 4. Distance matrix of benchmark problem 4

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	-	2	10	4	10	2	11	9	1	3	7	12	5	8	8	8	13	7	2	12
2		-	12	12	4	6	2	8	6	7	14	10	11	9	2	6	13	14	1	3
3			-	5	8	2	5	9	7	8	13	6	9	2	6	6	14	2	4	5
4				-	6	6	11	12	5	11	4	5	11	1	3	10	17	10	14	14
5					-	7	2	13	3	10	6	7	14	8	7	7	5	1	8	13
6						-	2	6	14	6	9	3	7	13	13	3	13	10	13	3
7							-	11	14	6	4	10	7	6	12	9	10	8	5	4
8								-	14	14	3	11	1	1	3	10	6	5	14	14
9									-	3	12	12	2	12	4	2	14	13	11	7
10										-	8	4	8	5	4	4	3	6	12	11
11											-	5	9	4	9	9	6	12	14	11
12												-	7	6	10	13	7	1	6	8
13													-	1	1	4	1	12	4	6
14														-	4	9	12	4	9	13
15															-	1	1	1	1	5
16																-	8	5	2	14
17																	-	14	7	10
18																		-	5	6
19																			-	14
20																				-

4. RESULTS AND DISCUSSION

One of the most well-known algorithmic problems in CAPP and operations research (OR) is the traveling salesman problem. It is optimization-focused, and in this sense, a better solution is typically one that is less expensive, shorter, or faster. Normally, a genetic algorithm is used to find the shortest route and optimum solution. In this study, a genetic and simulated annealing hybrid algorithm is proposed and four benchmark problems were analyzed.

The proposed hybrid algorithm was tested and optimum results are compared and shown in Table 5. The first problem was selected as it is a simple sales man problem of 5 tasks without any constrains. For the second and third problem, they have 6 tasks with 6 constraints and 8 tasks with 9 constraints respectively. The fourth and last problem was selected a complex problem that has 20 tasks with 31 constraints. In all the benchmark problems, the performance of the proposed algorithms shows improvement in computational time with few alternate sequences.

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Table 5. Results comparison with benck mark problems

Description	Optimization algorithm	Optimum solution	Convergence time (sec)	improvement in time (%)	Best sequence
Benchmark problem 1	Moon *et al.*	21.23	5	-	1-3-4-2-5-1
	Proposed hybrid algorithm	21.23	<2	66%	1-3-4-2-5-1
Benchmark problem 2	Moon *et al.*	39	0.222	-	1-3-6-2-4-5
	Proposed hybrid algorithm	39	<0.1	54%	1-3-6-2-4-5
Benchmark problem 3	Moon *et al.*	21.25	0.333	-	0-1-4-2-7-6-5-3
	Proposed hybrid algorithm	21.25	<0.1	69%	0-1-4-7-2-6-5-3
					0-1-4-2-7-6-5-3
Benchmark problem 4	Moon *et al.*	61	5	-	6–1–2–7–5–11–4–3–18–12–10–9-16-17-8-14-13-19-15-20
	Proposed hybrid algorithm	61	<2	66%	6–1–2–7–5–11–4–3–18–12–10–9-16-17-8-14-13-19-15-20

All the benchmark problems were tested by the proposed algorithm by applying all precedence constraints with minimum cost. They were computationally executed in 10 to 20 trials. For the benchmark problems 1,2,3 and 4, the optimal sequences obtained are 1-3-4-2-5-1, 1-3-6-2-4-5, 0-1-4-2-7-6-5-3 and 6-1–2–7–5–11–4–3–18–12–10–9-16-17-8-14-13-19-15-20 by satisfying all precedence constraints. Almost all trials give similar solutions which are obtained in the literature, Moon et al. [20], but improve the computational time which is a maximum of 69 % faster.

The benchmark problem 4 is a complex problem with 20 vertices and 31 precedence constraints. In literature, initially, the same problem was solved by the genetic algorithm and found some infeasible solutions. The traditional genetic algorithm needs additional technics like penalty technique and, branch-and-bound technique for solving this type of more constrained problems. By using the proposed genetic and simulated annealing hybrid the same solution was found in literature. But there is no infeasible solution and time is reduced to 66%. The optimal path is 6–1–2–7–5–11–4–3–18–12–10–9–16–17–8–14–13–19–15–20 with the corresponding length 61.

This proposed genetic integrated simulated annealing hybrid algorithm significantly performs better than other algorithms. This combination converges very fast and is also able

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to find many possible alternative feasible solutions in the global searching space. It is a very simple and more efficient algorithm for solving globally optimum results by easily applying any kind of precedence constraints. This algorithm completely checks the precedence constraints from the beginning itself, it won't generate any infeasible sequences at any time during the iteration. The acceptance probability will help this algorithm to reach the stopping criteria of the solution.

CONCLUSION

This research article demonstrates how a meta-heuristic algorithm plays a vital role in optimizing salesman problems. The proposed genetic and simulated annealing hybrid algorithm performs well in benchmark problems from the standard literature. The comparison shows that in all the cases, the optimum results obtained as such in literature with more feasible sequences with shorter computation time. Parameter optimization is one of the important works in this which can able to identify the optimum range of parameters for solving any kind of problem. Another important issue is the integration of precedence constraints (fixed, dynamic) in process planning can able to generate feasible solutions in all stages without violating the precedence constraints. The special features of the genetic and simulated annealing hybrid algorithm with a probability of acceptance by selecting high-fitness solutions in both algorithms might reduce the computational time. The importance of hybridization is necessary due to genetic algorithm suffers to get globally optimum results. If the complexity increases with more pre-constraints the combination will perform more satisfactorily with significant improvement in results and computational time. In all the benchmark problems, the performance of the proposed algorithms shows improvement in computational time with few alternate sequences.

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