EPJ Web of Conferences **336**, 03004 (2025) https://doi.org/10.1051/epjconf/202533603004
INSDAM'25

A new hybrid algorithm for solving N jobs and M machines scheduling problems with improved local search techniques

M Venkatesan[1*], *A karthikeyan*[2], *J Vinoth Kumar*[3], *S Muthuvel*[4], *D Vasudevan*[5], *A Sankar*[6]

[1]Associate Professor, Department of Mechanical Engineering, Excel Engineering College, Komarapalayam - 637303, Tamil Nadu, India
[2]Associate Professor, Department of Aeronautical Engineering, Excel Engineering College, Komarapalayam - 637303, Tamil Nadu, India
[3]Assistant Professor, Department of Mechanical Engineering, Bannari Amman Institute of Technology, Sathyamangalam - 638 401, Tamil Nadu, India
[4]Professor, Department of Mechanical Engineering, Kalasalingam Academy of Research and Education, Krishnankoil - 626126, Tamil Nadu, India
[5]Associate Professor, Department of Mechanical Engineering, K.S.Rangasamy College of Technology, Tiruchengode - 637215, Tamil Nadu, India
[6]Assistant Professor, Department of Agricultural Engineering, Dhirajlal Gandhi College of Technology, Salem – 636309, Tamil Nadu, India

Abstract. Scheduling is one of the most critical tasks in manufacturing, assembling, service industries, etc. Current research attempts to maximize the makespan of any complex scheduling procedure that involves N jobs and M machines. Conventional algorithms fail to perform global optimum solutions when the number of machines & jobs is high due to the NP-hard nature of the problem. Proposed approach employs a hybrid genetic-simulated annealing algorithm with an improved local searching technique, which converges to the global optimum solutions more quickly. Numerous benchmark problems and case studies from the standard literature have been employed to test the suggested algorithm's performance. Comprehensive computational test results demonstrated that the recommended algorithm outperforms alternative heuristic and traditional approaches.

*Corresponding author: venkatesanm1972@gmail.com

1. Introduction

During the early 1950s, the operations research community concentrated on simple job-shop scheduling problems. Among the most significant advances in early scheduling, which is employed for simple problems, is Johnson's solution of two machines, N jobs, that minimizes total idle time and production time. Latin multiplication method was used and the cost was reduced by introducing alternate plans [1]. During the planning process, the computer is used to sequence the machining operation to reduce cost. The STEP-NC data was used for roughing and finishing operations [2]. Using CAPP, an alternate optimum solution for sequencing operations was made with a tree-structured approach [3]. A comprehensive survey was made to identify where computer application is possible and where human operators have marked average [4]. The selection of machining operation decides the type of manufacturing process needed for making a product. After the selection of the partial process, operation sequencing is an important task that decides the order of machining operations that will minimize cutting tool travel distance (Routing), number of tool changes, number of setup changes, number of machine changes, minimize the indexing time, number of cutting parameter changes and direction of tool approach or tool approach direction. A discrete swarm optimization (DPSO) method is used to minimize setup time on the multi-head surface mounting machine (SMM) [5]. The MATLAB program was used for optimizing the sequencing problem, compared with other optimization techniques and algorithms, and proved faster and better results [6]. In a CAPP study, the ant colony algorithm technique was used to find operation sequence optimization in a couple of case studies. The alternate sequences that were found were same time and with low cost [7]. A MDTS (multi-dimensional tabu search) algorithm was used for optimizing sequencing and machining problems. The results were compared with SA (simulated annealing), GA (genetic algorithm), and TS (tabu search) and showed quality and efficiency [8]. Using a modified clustering algorithm, three case studies were made for optimizing sequence problems. The optimized result showed that the operation time was significantly reduced and more optimum solutions were obtained [9]. The genetic algorithm (GA) is frequently employed, and it was found that computation time for optimizing sequencing was low and alternate optimum solutions can made fast and effective [10]. The GA is used for the rapid and optimum feasible solution in the CAPP applications. In addition, artificial intelligence (AI) was introduced and showed increasing performance [11]. The TSPPC (traveling salesman problem with precedence constraints) is much more difficult to attain and also many possible and optimum solutions. The GA was applied on TSPPC and it was found a superior performance than the traditional one [12]. An experimental study was conducted in a job shop and the GA was applied for sequencing operations of 23 operations. On a challenging problem, it was discovered that the GA algorithm operated effectively and consistently [13]. The activity-based scheduling optimization problems are reviewed and found that GAs were used frequently for effective solutions [14].

The optimization problems that are bound-constrained and unconstrained can be resolved using the SA approach. In hydrogen production, a permeability model is optimized using the SA algorithm [15]. SA was utilized in a case study to optimize routing and sequencing, and the outcomes were contrasted with those of a GA. It was found that the SA is effective compared to the other approaches. Two prismatic parts were studied for optimum sequence solution with SA algorithm, GA, and tabu search algorithm. The ACO (ant colony optimization) algorithm was found to be more effective than the other three algorithms. Similarly, for controlling the reactive power system, three prismatic parts were studied for optimum sequencing using the PSO (particle swarm optimization) algorithm. The altered PSO algorithm generated an efficient optimal solution for less time compared to the GA as well as the simulated algorithm [19]. A simple SA algorithm was applied to three case studies and found that the SA produced an efficient and optimum solution in less time. Recently an adaptive SA algorithm was proposed on an experimental job shop sequence and found that the developed algorithm is more effective. An approach that blends two or more different algorithms to solve a single problem is called a hybrid algorithm. The most well-known solution to the mTSP (Multiple Traveling Salesman Problem), which is to reduce the longest tour's length, has recently been improved by a hybrid GA. The branch and fathering (B&F) algorithm demonstrated a significantly better solution in a shorter amount of time. For the best process plan and minimum makespan, a hybrid dynamic DNA (HD-DNA) algorithm technique has been created, which has improved the manufacturing system's efficiency. A hybrid CSG (cuckoo search-genetic) algorithm was used for sequencing operations of hole-making. The solved computational test results showed an improvement than other algorithms. A sequence optimization problem was proposed with a PSO algorithm. The numerical experiments and comparison results showed good quality and efficiency. The machining processes in a case study have been sequenced utilizing a GA and SA algorithm. The results showed satisfactory results of the hybrid approach. Many heuristic methods are proposed in the literature, still, there is a scope for finding optimal makespan for complicated problems with a larger number of jobs and machines. By combining the merits of the two algorithms, the improved optimal solutions were achieved very early. In this research, the well-known Genetic and simulated annealing algorithms are integrated due to their strong searching ability, the randomness of the solutions, fast convergence, stable solutions, and simplicity.

2. Hybrid Genetic and Simulated Annealing (HGSA) algorithm

2.1 Genetic Algorithm

Genetic algorithm is recognized as a global searching heuristic technique for solving many optimization problems more efficiently. It is inspired by genetic & evolutionary mechanisms, which are observed from natural systems and populations. It is coded with a chromosome-like data structure. Genes, chromosomes, and populations are the fundamental building blocks of genetic algorithms. GA determines optimal solutions by navigating broader, potentially enormous search areas. Generally, the genetic algorithm comprises three different phases of search: phase 1. Creating an initial population, phase 2. Evaluating a fitness function and phase. 3. Producing a new population.

2.2 Simulated annealing

The main objective of the annealing process of materials is cooling the material from a higher energy to a lower energy which depends upon the initial temperature and cooling rate. The same concept is used to solve the optimization problem for the minimization or maximization of the objective function. The cooling schedule is very important in simulated annealing for deciding how the temperature decreases from a higher level to a lower level. Though it selects a random move rather than the optimum move, this algorithm is comparable to the hill-climbing algorithm. If moves give improved solutions, then it is accepted, otherwise, the moves are selected in other directions randomly with some probability of acceptance less than 1.

2.3 Hybridization

A genetic algorithm is an algorithm that searches the solutions in a larger space but does not ensure optimal solutions. It may get stuck in local minima, and it takes more time. Simulated annealing proved an efficient searching tool to determine optimal or near-optimal solutions for searching in local space. For achieving a global optimal solution at a shorter computational time, it is necessary to merge the genetic and simulated annealing algorithms.

3. Implementation of Hybrid Algorithm

Due to more complex nature of process planning and production sequencing problems with N! alternate sequences were possible out of which finding globally optimum solutions are hectic task by conventional methods or individual algorithms. Hence the integration of two algorithms takes the benefits of two algorithms and overcomes the drawbacks of individual algorithms, The Proposed HGSA algorithm is categorized into Phase I (GA) and Phase II (SAA). GA used three important reproduction, crossover, and mutation operators which improve the results stage by stage, and the best results obtained at the end of a fixed number of iterations (generations) were taken as input to the Phase II algorithm which improves the solutions further by doing nearby search and escape from the local minima solutions and avoid worst solutions due to this nature of SA algorithm finally the globally optimal results can be achieved.

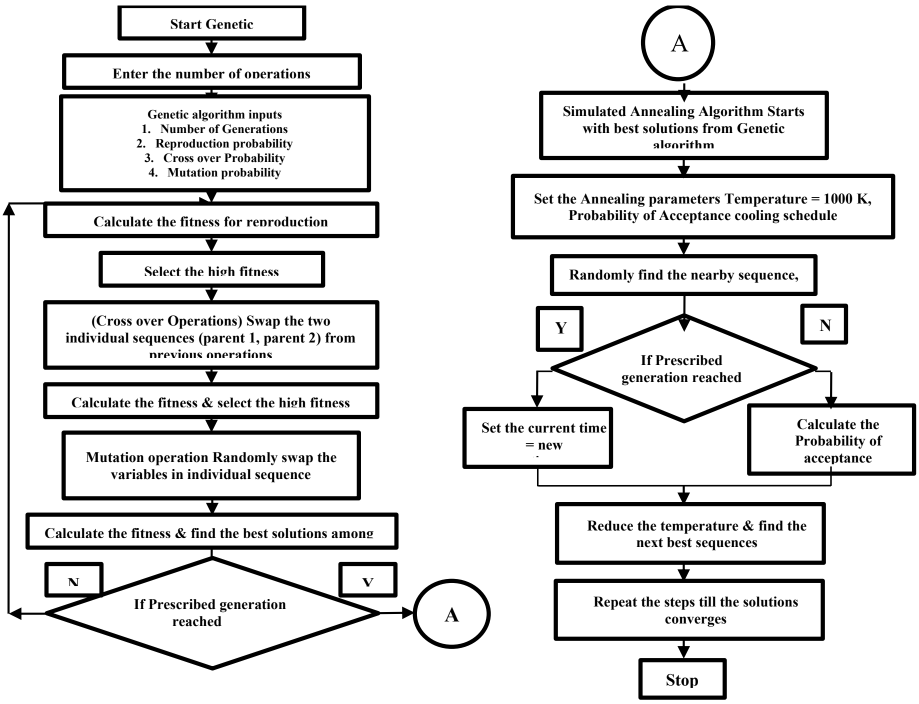

Figure 1. Flow chart of proposed HGSA algorithm

The assumptions for sequencing problems are:
One operation per machine: Only one operation can be performed on a machine at a time.
Processing times: Processing times are known and don't change.
Order independence: Processing times are independent of the order in which jobs are processed.
Job completion: An operation must be completed before starting another.
Job priority: Jobs are processed as soon as possible
800 lines of Turbo C++ code have been employed for developing the recommended IGSA algorithm, which was then executed on a 1.7GHz Core 2 Duo CPU with 4 GB of RAM. The suggested technique has been computationally verified on eight case studies and three benchmark problems to confirm its performance and practicality. Together with the optimal genetic and SA algorithm parameters derived from earlier computational investigations, the component PCM is sent as input to the algorithm.

4. Performance of HIGSA algorithm

4.1 Case study 1: N jobs Scheduling on a Single Machine

This is a vital task in most industries and organizations, where managers plan the tasks or jobs according to the total processing time of each job, and based on the job's arrival and completion time, the due dates of each job are fixed. A typical example of six jobs, their processing time, and their due dates, is shown in Table 1.

Table 1. Jobs and processing time of single machine scheduling with N jobs

job (j) / time (t)	1	2	3	4	5	6
Processing time (min)	10	3	4	8	10	6
Due time (min)	15	6	9	23	20	30

Table 2 compares recommended HGSA algorithm with best sequences identified through conventional first come, first served, lowest processing time, early due date, greatest processing time, and other methods.

Table 2. Comparison of results with other methods

Algorithm	Sequence	Total makespan
First Come First Serve (FSFS)	1 2 3 4 5 6	36
Shortest Processing Time (SPT)	2 3 6 4 5 1	37
	2 3 6 4 1 5	39
Earlier Due Date (EDD)	2 3 1 5 4 6	32
Largest Processing Time (LPT)	1 5 4 6 3 2	73
	5 1 4 6 3 2	78
Minimum Slack Time (MST)	2 3 1 5 4 6	34
	2 1 3 5 4 6	38
Proposed algorithm (HGSA)	2 3 1 4 6 5	26

4.2 Case study 2: Job shop scheduling with N jobs and M machines

The proposed algorithm can solve N jobs on M machines problems. Consider typical practical applications referred from Abbas et al (2016), [1] it consists of 13 jobs which are processed by six machines as shown in Table 3.

Table 3. Processing Time of 13 jobs on six machines

Job No.	Job Name	Machine to be processed						Priority
		Shaper	Lathe	Milling	Boring	Welding	Grinding	
1	Nut	0	17	0	0	0	0	2
2	Bolt	0	19.5	0	0	0	0	2

3	Gear	60	18.5	30	15	0	4	1
4	Hexagonal gear	65	17.5	45	4	0	6	1
5	Flange pipe	0	50	35	35	27	25	2
6	Screw	62	58	15	0	0	0	1
7	Lead screw	60	34.5	20	0	0	0	2
8	Universal coupling	60	17.5	20	10	0	6	3
9	Lathe center	63	29.5	0	0	0	5	3
10	Piston connecting rod	0	0	17	11	0	7	3
11	Sprocket	0	0	15	55	0	5	2
12	Tie rod end	0	26	27.5	27	0	6.5	3
13	Gear pump flange	0	27	15	31	17	5	3

The processing time is rearranged according to priority and is shown in Table 4.

Table 4. Processing Time of 13 jobs on six machines (Revised)

Job No.	Job Name	Machine to be processed						Lead time
		Shaper	Lathe	Milling	Boring	Welding	Grinding	
6	Screw	62	58	15	0	0	0	1
3	Gear	60	18.5	30	15	0	4	1
4	Hexagonal gear	65	17.5	45	4	0	6	1
5	Flange pipe	0	50	35	35	27	25	2
1	Nut	0	17	0	0	0	0	2
7	Lead screw	60	34.5	20	0	0	0	2
11	Sprocket	0	0	15	55	0	5	2
2	Bolt	0	19.5	0	0	0	0	2
10	Piston connecting rod	0	0	17	11	0	7	3
12	Tie rod end	0	26	27.5	27	0	6.5	3
13	Gear pump flange	0	27	15	31	17	5	3
8	Universal coupling	60	17.5	20	10	0	6	3
9	Lathe center	63	29.5	0	0	0	5	3

The optimum result obtained by proposed HGSA algorithm is compared with other algorithms which are proposed in the literature. Many optimum sequences were obtained for the same value of makespan 404.5 which is shown in Table 5.

Table 5. Comparison of results with other methods

Algorithm	job sequence													Makespan (Minutes)
Largest Processing Time (LPT)	5	4	6	3	7	8	9	13	12	11	10	2	1	580
Shortest Processing Time (SPT)	1	2	10	11	12	13	9	8	7	3	6	4	5	559.5
Palmer	11	5	10	13	12	1	2	8	3	9	4	7	6	443
Campbell Dudek Smith (CDS)	1	2	11	13	12	10	8	4	5	9	3	6	7	424.5
Johnsons	1	2	10	11	12	13	5	6	4	3	7	8	9	404.5
Guptha	1	2	10	11	13	12	5	6	4	3	7	8	9	404.5
WI	10	5	12	11	13	1	2	6	3	4	7	8	9	404.5
HGSA	3	5	2	11	10	6	8	13	1	4	12	7	9	404.5
	12	5	6	11	10	2	7	1	3	13	8	4	9	

4.3 Case Study 3: Partial flexible job shop scheduling

Six jobs with 27 operations executed by eight machines constitute another significant problem taken into consideration in this case investigation. Table 6 displays processing time in corresponding machine for each operation.

Table 6. Six jobs in eight machines

Job	Operation	Sequence	M1	M2	M3	M4	M5	M6	M7	M8
J_1	O11	1	-	12	-	9	14	-	20	-
	O12	2	18	-	-	19	-	15	11	-
	O13	3	-	12	14	9	-	17	-	-
	O14	4	-	11	-	-	9	-	-	12
	O15	5	15	-	-	8	-	-	-	18
	O16	6	12	-	9	-	-	11	-	-
J_2	O21	7	-	-	12	19	14	-	-	-
	O22	8	8	-	-	9	11	-	15	-
	O23	9	16	7	-	-	-	9	-	-
J_3	O31	10	-	-	-	11	10	-	-	13
	O32	11	-	-	12	18	-	-	14	-
	O33	12	9	-	-	15	7	-	12	-
	O34	13	-	12	-	15	-	7	-	9
	O35	14	3	-	-	4	-	8	-	-
J_4	O41	15	-	19	-	-	7	-	13	-
	O42	16	-	-	8	-	11	-	-	16
	O43	17	9	11	-	8	-	-	18	-
J_5	O51	18	6	-	-	12	-	-	14	9
	O52	19	-	-	-	22	-	12	17	-
	O53	20	-	18	-	-	11	-	-	9
	O54	21	9	-	12	-	-	-	-	7
	O55	22	-	11	-	-	-	9	14	-
	O56	23	8	-	-	12	6	-	-	9
J_6	O61	24	-	-	11	-	17	-	-	18
	O62	25	5	-	12	-	-	-	7	9
	O63	26	-	11	-	-	-	8	13	7
	O64	27	19	-	13	7	-	15	-	-

The “- “indicates the machine not used for the particular operations. The partial selection of machines is a complicated process that involves more searching space which shows the proposed algorithm performance. Algorithm performance is compared with Genetic algorithm (GA), Discrete Particle Swarm Optimization (DPSO) Algorithm, and Improved Bat Algorithm (IBA) which are shown in Table 7.
Table 7. Comparison of the performance of the algorithm

Method	**Optimal makespan**
Genetic algorithm (GA),	65
Discrete Particle Swarm Optimization (DPSO) Algorithm	62
Improved Bat Algorithm (IBA)	55
HGSA	55

The optimal sequence obtained for 27 operations (6 jobs) and 8 machines is 18-8-25-23-17-9-22-7-24-16-6-1-3-14-5-27-15-4-12-19-26-13-2-11-10-20-21 which is similar to the improved bat algorithm. The above case studies and benchmark problems show the proposed algorithm which has superior quality results. Further, this method extended to more complicated problems in the size of 500×50, 1000×100 problems, and also more priority-based constraints.

5. Conclusions and Future Scope

This study shows the importance of a meta-heuristic method in the milling and turning center's machining operations optimization. Numerous case studies from the standard literature demonstrate suggested CAPP methodology efficacy. Comparison demonstrates that the best results are frequently found in the literature with a more practical sequence and less computing time. One of the key efforts in this field is parameter optimization, which may determine the ideal range of parameters for resolving any type of issue. Integrating precedence constraints (fixed and dynamic) into process design is another crucial topic. This allows for the generation of workable solutions at every level without going against the precedence constraints. With a chance of acceptance through the selection of high-fitness solutions in both algorithms, the hybrid genetic and SA algorithm's unique features may shorten computing time. Because GA suffers, hybridization is essential to achieving globally optimal results. Recommended strategy efficacy is demonstrated by experiments, that demonstrate that when number of tasks is less than or equal to number of machines, recommended algorithm generates lower makespan in shorter computational time of few seconds. Computational time also increases with problem size, spanning a few minutes. Another important advantage is algorithm generates many alternate feasible sequences for the same optimal solution are highly useful when any machine breakdown or setup failures happen in practical situations. Future research is extended to solve multi-objective scheduling applications such as tardiness, lateness, flow time, priority, etc. Further, this algorithm extends to Assembly line balancing, assembly sequence planning, and drilling hole routing Finally the hybridization of these two Meta heuristic algorithms gives globally improved solutions.

References

1. S. A. Irani, H. Y. Koo, and S. Raman, "Feature-based operation sequence generation in CAPP," Int. J. Prod. Res., vol. 33, no. 1, pp. 17–39, 1995, doi: 10.1080/00207549508930135.
2. A. Mokhtar and X. Xu, "Machining precedence of 21/2D interacting features in a feature-based data model," J. Intell. Manuf., vol. 22, no. 2, pp. 145–161, 2011, doi: 10.1007/s10845-009-0268-8.
3. P. Prabhu, S. Elhence, H. Wang, and R. Wysk, "An operations network generator for computer aided process planning," J. Manuf. Syst., vol. 9, no. 4, pp. 283–291, 1990, doi: 10.1016/0278-6125(90)90036-H.
4. R. Weill, G. Spur, and W. Eversheim, "Survey of Computer-Aided Process Planning Systems," CIRP Ann. - Manuf. Technol., vol. 31, no. 2, pp. 539–551, 1982, doi: 10.1016/S0007-8506(07)60176-0.
5. Y. M. Chen and C.-T. Lin, "Optimizing the Operation Sequence of a Multihead Surface Mounting Machine Using a Discrete Particle Swarm Optimization Algorithm," J. Artif. Evol. Appl., vol. 2008, p. 315950, 2008, doi: 10.1155/2008/315950.
6. S. Singh and S. Deb, "An intelligent methodology for optimising machining operation sequence by ant system algorithm," Int. J. Ind. Syst. Eng., vol. 16, no. 4, pp. 451–471, 2014, doi: 10.1504/IJISE.2014.060654.
7. A. G. Krishna and K. Mallikarjuna Rao, "Optimisation of operations sequence in CAPP using an ant colony algorithm," Int. J. Adv. Manuf. Technol., vol. 29, no. 1–2, pp. 159–164, 2006, doi: 10.1007/s00170-004-2491-y.
8. K. Lian, C. Zhang, X. Shao, and Y. Zeng, "A multi-dimensional tabu search algorithm for the optimization of process planning," Sci. China Technol. Sci., vol. 54, no. 12, pp. 3211–3219, 2011, doi: 10.1007/s11431-011-4594-7.
9. L. X. Phung, D. Van Tran, S. V. Hoang, and S. H. Truong, "Effective method of operation sequence optimization in CAPP based on modified clustering algorithm," J. Adv. Mech. Des. Syst. Manuf., vol. 11, no. 1, pp. 1–12, 2017, doi: 10.1299/jamdsm.2017jamdsm0001.
10. S. V. B. Reddy, M. S. Shunmugam, and T. T. Narendran, "Operation sequencing in CAPP using genetic algorithms," Int. J. Prod. Res., vol. 37, no. 5, pp. 1063–1074, 1999, doi: 10.1080/002075499191409.
11. T. Dereli and I. H. Filiz, "Optimisation of process planning functions by genetic algorithms," Comput. Ind. Eng., vol. 36, no. 2, pp. 281–308, 1999, doi: 10.1016/S0360-8352(99)00133-3.
12. C. Moon, J. Kim, G. Choi, and Y. Seo, "An efficient genetic algorithm for the traveling salesman problem with precedence constraints," Eur. J. Oper. Res., vol. 140, no. 3, pp. 606–617, 2002, doi: 10.1016/S0377-2217(01)00227-2.
13. F. Zhang, Y. F. Zhang, and A. Y. C. Nee, "Using genetic algorithms in process planning for job shop machining," IEEE Trans. Evol. Comput., vol. 1, no. 4, pp. 278–289, 1997, doi: 10.1109/4235.687888.
14. B. Toaza and D. Esztergár-Kiss, "A review of metaheuristic algorithms for

solving TSP-based scheduling optimization problems [Formula presented],” Appl. Soft Comput., vol. 148, no. October, 2023, doi: 10.1016/j.asoc.2023.110908.
15. F. Deng, P. Zeng, G. Li, Y. Wang, and B. Huang, “Study on three-dimensional permeability model of gravel sand control layer based on simulated annealing algorithm,” Int. J. Hydrogen Energy, vol. 91, pp. 106–117, 2024, doi: https://doi.org/10.1016/j.ijhydene.2024.10.112.