March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

Hybrid Artificial Immune System Algorithm for SDST Flow Shop Scheduling with Due Date

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Abstract:
Sequence dependent flow shop scheduling plays an important role in present situation. Setup time is used to set the tools, jigs, fixtures and cleaning work. System utilization is measured in terms of makespan whereas the system performance is measured in terms of tardiness for meeting the customer due dates. The objective of this paper is to minimize the makespan and number of tardy jobs. These two objectives are conflicting nature. It is a NP hard problem. Hybrid Artificial Immune System Algorithm is used to solve flowshop with the objective of makespan and number of tardy jobs. Computational result shows that the performance of the proposed methods for various size of problems.

Keywords: *Makespan, Tardiness, Setup time, Due Date and Artificial Immune System Algorithm.*

I. INTRODUCTION

Production system utilization is measured in terms of makespan whereas the system performance is measured in terms of tardiness for meeting the customer due dates. Many of the work is carried out by considering makespan as objective in flow shop only a few of them considered tardiness as objective. Parthasarathy & Rajendran (1997b) applied simulated annealing algorithm for solving SDST flow shop problem with the objective of minimizing the mean weighted tardiness in a drill bit manufacturing industry. They used random insertion perturbation scheme to generate the neighborhood sequence. Rajendran & Ziegler (2003) applied heuristic method to optimize the weighted flow time and weighted tardiness of jobs for SDST problem. They used the improvement scheme to enhance the solution quality. They compared the performance of the proposed heuristic with greedy local search method. Eren & Guner (2006) developed integer programming model for two machine flow shop with setup time problem. The objective is to minimize the total completion time and total tardiness. Ruiz & Stutzle (2008) proposed iterated greedy algorithm to minimize makespan and weighted tardiness in SDST flow shop problem. They conducted statistical analysis for evaluating the performance of the algorithm. Dhingra & Chandna (2009) solved SDST flow shop scheduling. They developed heuristic based genetic algorithm to optimize the combined objective of total tardiness, total earliness and makespan. Dhingra & Chandna (2010)

TEST Engineering & Management

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

developed modified heuristic genetic algorithm in SDST flow shop scheduling. The objective is to minimize the tardiness and makespan. They used modified heuristic algorithms along with other available heuristics and dispatching rules. They reported that modified heuristic genetic algorithm is an effective approach for large size problems. Kumar & Dhingra (2011) developed the variants of genetic algorithm (GA1, GA2, GA3, GA4 & GA5) to minimize the weighted sum of tardiness and makespan for SDST flow shop. They reported GA3 produced better results for most of the problems. Hooda & Dhingra (2012) applied simulated annealing algorithm based heuristic in SDST flow shop scheduling. The objective is to minimize makespan and number of tardy jobs. They reported that the SA (NEH) performed better than SA (NEH_EDD). Satyanarayana & Pramiladevi (2016) optimized the combined objective of weighted makespan, tardiness, earliness and number of tardy jobs in SDST flow shop scheduling problem. They evaluated the three special heuristic based genetic algorithms interms of Relative Percentage Difference (RPD). Xu et al. (2017) applied iterated local search algorithm for SDST permutation flow shop problem to minimize the makespan and total tardiness of the jobs. They compared the results of applied method with several multi-objective evolutionary algorithms reported in the literature. The proposed iterated local search method produced better results. From this literature, it is clear that Hybrid AIS algorithms are not used to minimize both makespan and number of tardy jobs in SDST permutation flow shop scheduling with due date problem.

II. PROBLEM DESCRIPTION

Problem Statement

In flow shop scheduling, n jobs are processed on m machines, where due date is considered for each job. The processing sequence of each job is the same on all machines. Based on the customer requirements, to complete each work within the stipulated period of time and to deliver the product at right time the due date has been consider. The problem is to find the optimum schedule that leads to minimize makespan and number of tardy jobs in SDST permutation flow shop scheduling with due date.

Assumptions

All jobs are not available at time zero for processing.

- Pre-emption is not allowed.
- Setup time and processing time are given separately.
- Due date is known and considered for each job.
- Jobs can wait for process on next machine.
- Machine cannot process the job more than one at the same time.
- Machines are never breakdown during the schedule. Machine cannot process the job more than one at the same time.

Mathematical Model

$$\text{Min } Z = \alpha\, C_{max} + \beta\, N_t \qquad (3.11)$$

$$\alpha + \beta = 1 \qquad (3.12)$$

If the value of $C_j - d_j$ is positive then $N_t = 1$, the value of $C_j - d_j$ is negative then $N_t = 0$.

where,

C_{max} : Makespan.

N_t : Number of tardy jobs.

α & β : Weight factor for makespan and number of tardy jobs.

Z : Combined objective function

C_j : Completion time of the job

d_j : Due date of the job

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

III. PROPOSED METHODOLOGY

Artificial Immune System Algorithm is an adaptive system inspired by function of immune system. The immune system is a collection of defense mechanisms in a living body. It protects the body from disease by detecting, identifying, killing pathogens and tumor cells. Antigens are of two types. They are self antigen and non self antigen. Self antigens are harmless to the body, whereas non self antigens are disease causing elements. The immune system of vertebrates protects living bodies against the attack of various foreign substances (called antigens or pathogens) such as viruses, harmful bacteria, parasites and fungi.Antibodies are molecules which are present in the body cells. If the number of the antigen is more than the antibody, then the foreign organisms (antigens) such as virus, bacteria etc. affect the immune system. Antibody affinity value is increased by replica and mutation process. The good affinity value antibody is selected as parent. It produces multiple offspring due to proliferation. More number of antibodies is increased by cloning process for neutralizing the antigen. If the fitness value of offspring is improved when compared to parent then replace parent antibody with offspring. The worst antibodies are replaced by new antibodies. This process is called receptor editing. This process is used to escape from local optima. This process will be repeated until the maximum number of iteration is reached. AIS algorithm is applied to constrained Multiobjective nonlinear optimization problems (Zhuhong Zhang 2007). AIS algorithm is used to solve Linear and loop layout problems in flexible manufacturing systems (Satheesh Kumar et al. 2009). AIS algorithm is adopted to solve Resource availability cost problem (Peteghem & Vanhoucke 2013), Blocking flow shop (Lin & Ying 2013), Multi-objective job shop scheduling (Gopinath et al. 2015), Forward Reverse Logistics Multi-Period Model (Kumar et al. 2016) and Optimal Sitting of Distributed Generators in a Distribution Network (Meera & Hemamalini 2017).

Procedure for Hybrid Artificial Immune System Algorithm

In the method, dispatching rules are used to produce seed sequences. Dispatching rules are best seed sequences give good results. HAIS algorithm is developed to produce the seed sequence in Table 1. The Variants of HAIS algorithm is developed based on Shortest Processing Time (HAIS1), Longest Processing Time (HAIS2), and Earliest Due Date (HAIS3). The initial population consists of seed sequence and (p – 1) randomly generated sequence. The seed sequence is generated by HABC algorithm.

Step 1: Generate the initial population randomly.

Step 2: Objective function value is calculated for randomly generated sequence. Calculate the affinity value of each sequence (antibody).

Affinity = 1/objective

Step 3: To select the best sequence based on the affinity value for cloning. The rate of cloning is calculated using Equation (5.2)

Rate of cloning=(Affinity value of a solution × population size)/(Total of affinity values of solutions in the population) (5.2)

Step 4: Two phase mutation is carried out for each sequence. They are Inverse mutation and Pair wise mutation.

Step 5: To update and stored the improved affinity values after cloning and mutation process.

Step 6: Replace the low affinity value R % sequence with new randomly generated R % sequence.

Step 7: The updated and new randomly generated sequence is input sequence for next cycle.

Step 8: The above process is continued until the maximum criteria reached. The flow chart of AIS algorithm is represented in Figure 1.

TEST Engineering & Management
March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

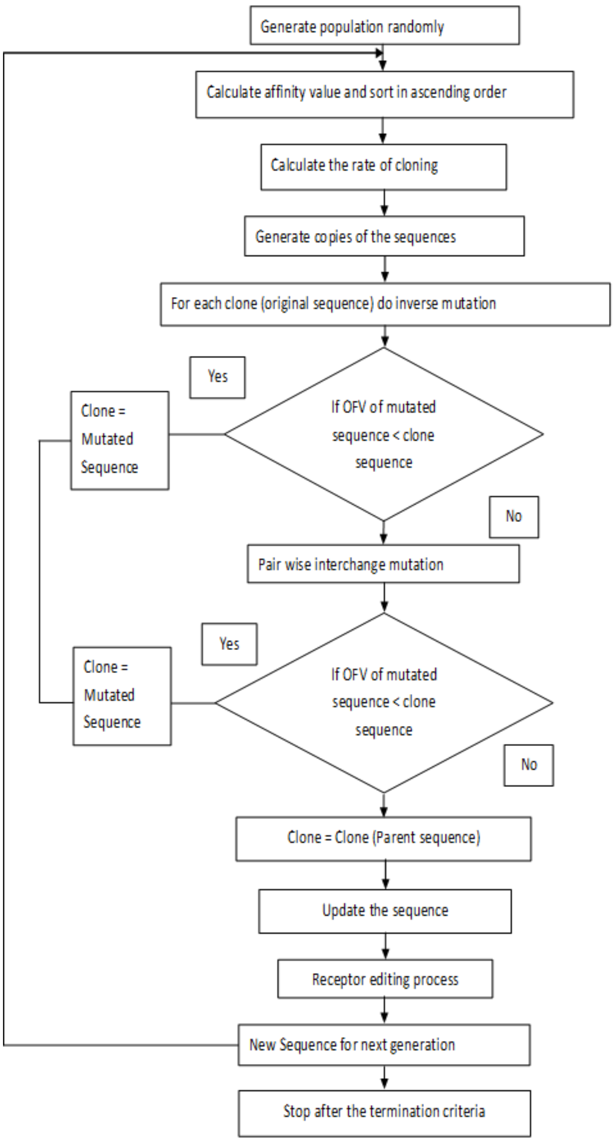

Figure 1. Flow chart for AIS algorithm

Numerical Illustration

AIS algorithm is proposed to solve 5 jobs 2 machines problems in SDST Permutation Flow Shop Scheduling with Due Date. The processing time is given in Table1. Setup Times with Due dates are considered. Setup Times are given in Table 2 and Table 3. Due dates are represented in Table 4.

Table 1. Processing time for SDST shop with due date

Jobs	Machines	
	M1	M2
1	19	5
2	11	1
3	8	2
4	30	35
5	69	17

Table 2. Setup time on machine 1 for due date shop

Sj1k	1	2	3	4	5
1	-	16	12	13	19
2	20	-	15	17	18
3	22	19	-	17	14
4	22	20	17	-	20
5	5	10	2	18	-

Table 3. Setup time on machine 2 for due date shop

Sj2k	1	2	3	4	5
1	-	9	17	6	14
2	23	-	8	10	24
3	12	20	-	24	25
4	20	24	25	-	9
5	22	4	18	5	-

Table 4. Due dates for each job

Jobs	Due dates (dj)
1	36
2	82
3	132
4	175
5	217

Step 1: The initial population is generated randomly. The population size (P) is 5. Each antibody is assumed to be each sequence. Calculate the Objective Function Value (OFV) for each sequence. It is represented in the Table 5.25.

Table 5. Initial sequence and its objective value

Initial sequence	Objective Function (Z)
4-1-2-3-5	110
5-2-4-1-3	109.5

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

1-5-2-4-3	120
2-3-4-1-5	114.5
3-4-5-2-1	105

Step 2: Arrange the sequence in ascending order based on objective function and calculate the affinity value f (xi) for each antibody in Table 5.26.

Table 6. Affinity value of antibody

Initial sequence	Objective Function (Z)	Fitness Value (f (xi) = 1/Z)
3-4-5-2-1	105	0.009524
5-2-4-1-3	109.5	0.009132
4-1-2-3-5	110	0.009091
2-3-4-1-5	114.5	0.008734
1-5-2-4-3	120	0.008333

Step 3: Calculate the rate of cloning. It is represented in Table 5.15. The sequence selection for cloning is directly depends on its affinity value.

Table 7. Rate of cloning

Initial sequence	Objective Function (Z)	Fitness Value (f (xi) = 1/Z)	Rate of cloning
3-4-5-2-1	105	0.009524	1.062614
5-2-4-1-3	109.5	0.009132	1.018878
4-1-2-3-5	110	0.009091	1.014304
2-3-4-1-5	114.5	0.008734	0.974472
1-5-2-4-3	120	0.008333	0.929732

This procedure gives more clones of sequences that have lower OFVs than those with higher OFVs. It raises a temporary population of clones(C).

Step 4: Two phase mutation is carried out for each sequence. They are Inverse mutation and Pair wise mutation. Inverse mutation is represented in Table 5.16.

Table 8. Inverse mutation

Sequence	OFV	Inverse mutation	OFV
3-4-5-2-1	105	4-3-5-1-2	97
5-2-4-1-3	109.5	2-5-4-3-1	114 (Not improved)
4-1-2-3-5	110	1-4-2-5-3	109.5
2-3-4-1-5	114.5	3-2-4-5-1	102
1-5-2-4-3	120	5-1-2-3-4	114.5

After inverse mutation, if the OFV of the mutated sequence is less than the original sequence, then the original sequence is replaced by the mutated sequence. Otherwise pair wise mutation is carried out on the original string. The pair wise mutation is represented in Table 5.17.

Table 9. Pair wise mutation

Input sequence (US1)	OFV	Pair wise	OFV
5-2-4-1-3	109.5	4-2-5-1-3	107 (improved)

Step 5: To update and store the improved affinity values after cloning and mutation process. It is represented in Table 5.18.

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

Table 10. Updated sequence and its OFV

Update sequence (N)	OFV
4-3-5-1-2	97
4-2-5-1-3	107
1-4-2-5-3	109.5
3-2-4-5-1	102
5-1-2-3-4	114.5

Step 6: Replace the low affinity value R % sequence with new randomly generated R % sequence. If R= 40 % then replace high OFV sequence with randomly generated new sequence in Table 5.19.

Table 11. New sequences for next cycle

Update sequence (N)	OFV	New sequences for next cycle
4-3-5-1-2	97	5-1-2-3-4
4-2-5-1-3	107	1-4-2-5-3
1-4-2-5-3	109.5	Rand sequence 1
3-2-4-5-1	102	3-2-4-5-1
5-1-2-3-4	114.5	Rand sequence 2

Step 7: The updated and new randomly generated sequence is input sequence for next cycle.

Step 8: The above procedure is repeated upto the termination criterion is reached. After completion of first cycle, we can get a best sequence. The best sequence for 5 jobs 2 machines SDST PFSS with due date problem is given in Table 5.30. Gantt chart is represented in Figure 5.4.

Table 12. Results of SDST PFSS with due date problem

Final Best Sequence	4-3-5-2-1
Cmax	203
Nt	2
Z	102.5

From this problem, high fitness value sequences are stored as best. The best sequence is the input sequence for the next cycle. Gantt chart is represented in Figure 5.7.

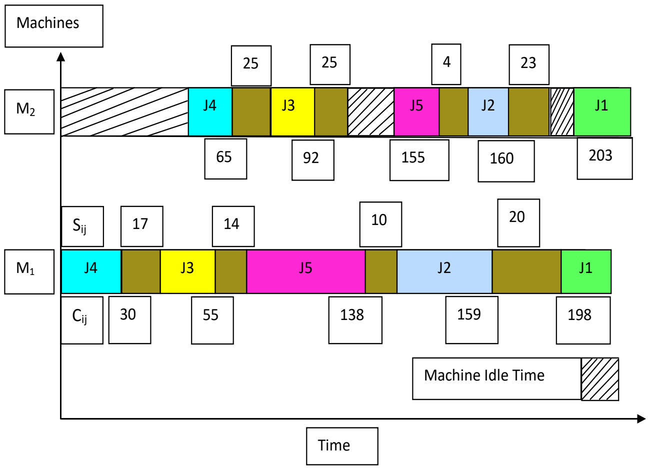

Figure 2. Gantt chart for SDST PFSS with due date problem

Computational Result

In this research paper, Hybrid AIS algorithms are implemented in java environment. The algorithms are tested with Taillard benchmark problems. HAIS algorithms are used to minimize makespan and number of tardy jobs. The performance of HAIS algorithms is represented in terms of Average Relative Error Percentage (AREP). It is represented in Table 13. For 20 job 5 machine problems, AREP value of HAIS3 is low. HAIS3 algorithm produced low relative error when compare to the HAIS1 and HAIS2. For 20 job 10 machine problems, HAIS2 produced best result. HAIS1 performed worst result when compare to the well HAIS1. For 20 job 20 machine problems, HAIS3 produced best result. There is a large relative error percentage difference

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

between HAIS1 and HAIS2. The AREP value for combined objective is represented in the Figure 3.

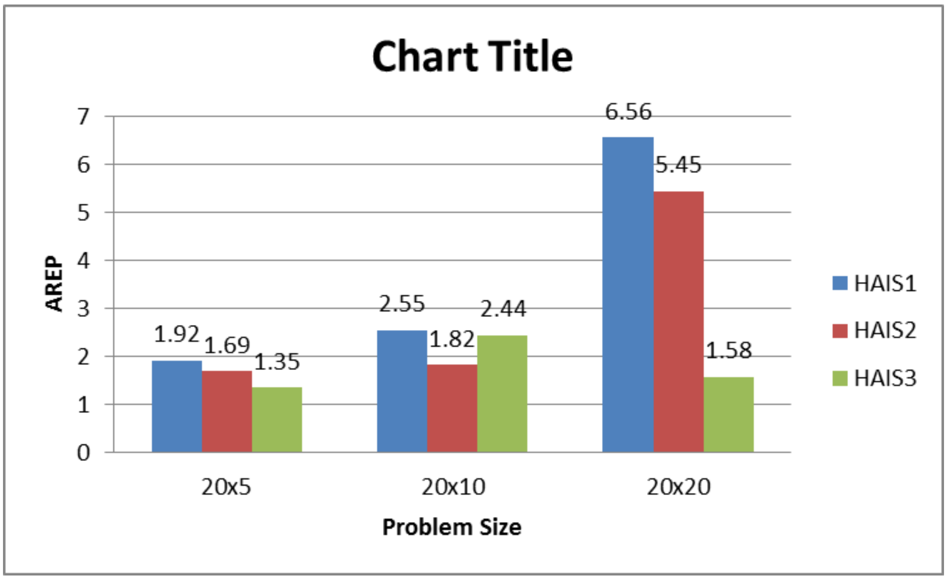

Figure 3. AREP values for PFSS with setup time and due date

AREP value of MGELS is low. MGELS algorithm produced better results when compare to the AIS and ABC.

Table 13. Performance of the algorithms for PFSS with setup time and due date

Instance Size	Problem No	HAS1	HAS2	HAS3
20x5	Tai_20x5_1	0	4.291498	0.566802
	Tai_20x5_2	9.054163	0	2.164179
	Tai_20×5_3	0	4.335793	2.013423
	Tai_20×5_4	1.472995	0	1.956182
	Tai_20×5_5	2.100457	0	3.145695
	Tai_20×5_6	0	2.378929	1.274427
	Tai_20×5_7	3.656716	0.565885	0
	Tai_20×5_8	0.461255	0	1.342282
	Tai_20x5_9	0.782473	0	1.06383
	Tai_20x5_10	1.655629	5.352987	0
20x10	Tai_20×10_1	5.96693	2.139037	0
	Tai_20×10_2	3.028264	0	1.495581
	Tai_20×10_3	2.933673	1.590909	0
	Tai_20×10_4	0	5.231689	2.039429
	Tai_20×10_5	3.938115	6.394558	0
	Tai_20×10_6	1.187215	0	5.663305
	Tai_20×10_7	4.353741	0	3.542781
	Tai_20×10_8	0	2.803738	4.068117
	Tai_20×10_9	1.828411	0	5.316285
	Tai_20×10_10	2.272727	0	2.232143
20x20	Tai_20×20_1	6.950673	8.906692	0
	Tai_20×20_2	4.068117	0	7.899716
	Tai_20x20_3	27.77778	25	0
	Tai_20x20_4	8.169597	5.32575	0
	Tai_20x20_5	2.677165	0	4.88189

March-April 2020
ISSN: 0193-4120 Page No. 3080 - 3088

	Tai_20x20_6	2.789256	5.371901	0
	Tai_20x20_7	3.521127	4.979879	0
	Tai_20x20_8	3.734876	1.735928	0
	Tai_20x20_9	2.887606	0	3.065304
	Tai_20x20_10	3.056995	3.212435	0

CONCLUSION

Hybrid Artificial Immune System algorithm produced better result for various size of problems. Earliest Due Date based Artificial Immune System algorithm relative error percentage difference value is low when compared to other approaches. In future, it can be applied to solve other problems.

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