

A Relative Comparison between BAP and JSSP using Two Heuristics AFSA and ACO

K.Sumangala¹, S. Sulthani Begum²

¹Assistant Professor, Department of Computer Science and Applications
Vellalar College for women, Erode-12, Tamilnadu, India
sumangala555@gmail.com

²Research Scholar, Department of Computer Science
Vellalar College for women, Erode -12, Tamilnadu, India
sulthanizahir@gmail.com

Abstract: Scheduling is the allocation of shared resources over time to competing activities. Job Shop Scheduling Problem (JSSP) and Berth Scheduling or Berth Allocation Problem (BAP) is two of NP-Complete problems in Operations research. BAP can be modeled as an unrelated parallel machine-scheduling problem (Pinedo, 2002), where a vessel is treated as a job and a berth as a machine. Thus JSSP and BAP are related with each other and solved using two different Meta heuristics. The Ant colony Optimization (ACO) is used to solve JSSP and Artificial Fish Schooling Algorithm (AFSA) is used to solve BAP. The experimental results are compared. The performance evaluation shows, the AFSA converges more quickly than ACO.

Keywords: JSSP, BAP, ACO, AFSA.

1. Introduction

The BAP is one of the parallel machine scheduling problems. A job and a machine can be treated as a ship and a berth, respectively. The Static BAP reduces to a classical assignment problem that is known to be polynomially solvable (Pinedo, 1995). Bean et al. (1991) and Norman and Bean (1999) deal with the machine scheduling problems where each job has a release time that corresponds to a ship arrival time in the Dynamic BAP. Norman and Bean [6] treat the parallel machine scheduling; however they assume identical machines in parallel whereas Imai et al.,[1] deals with unrelated machines in parallel. Therefore, it is apt to compare the performance of Dynamic BAP and a JSSP.

1.1 Relating BAP with JSSP

The Number of berths in BAP is related with number of Machines in JSSP. The Number of Ships i.e. Vessels in BAP is related with number of Jobs in JSSP. The Main Objective of BAP is to minimize the total flow time incurred by the vessels i.e. sum of the waiting time and the service time of the vessels. The Main Objective of JSSP is to minimize the make span i.e., time difference between the start and finish of a sequence of jobs or tasks.

Table 1.1 Similarities between BAP & JSSP

BAP	JSSP
No. Of Berths	No Of Machines
No. Of Vessels i.e. Ships	No Of Jobs
Objective: Minimize Flow time	Objective : Minimize Makespan

The Gantt-Chart is a convenient way of visually representing a solution of the JSSP and BAP.

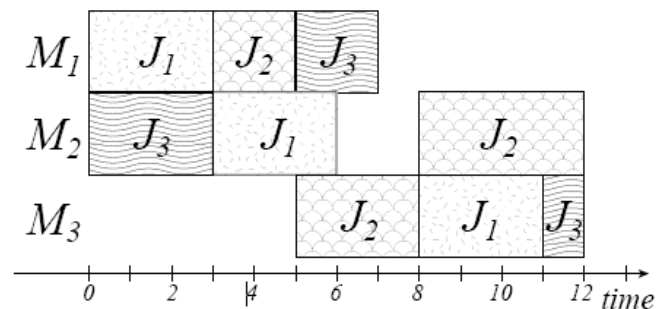


Figure 1.1 Gantt-Chart representation of a solution for a 3 X 3 problem

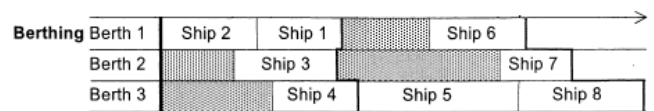


Figure 1.2 Gantt-Chart representation of allocation of 8 ships in 3 berths

2. Job Shop Scheduling used by an Ant System

Sjoerd van der Zwaan et al., [6], referred to a standard model of the n-job,m-machine job shop problem, denoted by:n/m/G/Cmax, The parameter G indicates that jobs are connected with technological production rules, describing their processing order of machines. This order is specified in the technological matrix T. An example for T could be:

$$T = \begin{bmatrix} M1 & M2 & M3 \\ M2 & M3 & M1 \end{bmatrix}$$

A row of the matrix represents a job, specifying the sequence of machines to be scheduled. Each element of the matrix T is referred to as an operation. The processing time of each operation is specified by matrix P:

$$P = \begin{bmatrix} t(O_{11}) & \dots & t(O_{1m}) \\ t(O_{21}) & & t(O_{2m}) \\ \vdots & & \vdots \\ t(O_{n1}) & \dots & t(O_{nm}) \end{bmatrix}$$

The matrices T and P together define a job shop problem. The parameter Cmax stands for the minimum make-span of the job-shop and indicates the performance measure used to minimize (the so called evaluation function). Given some solution of a job shop problem, the value of Cmax is then equivalent to the production time that it takes to finish all the jobs, taking into account the imposed restrictions of machine occupation.

Using Ant System for Job Shop Scheduling, it is necessary to define the problem into a graph. To do so, consider the technological matrix T given in the previous section. An idea is proposed for how to define the job shop into a graph. This is illustrated in the following figure, for the example of the 2/3/G/Cmax job shop defined by T.

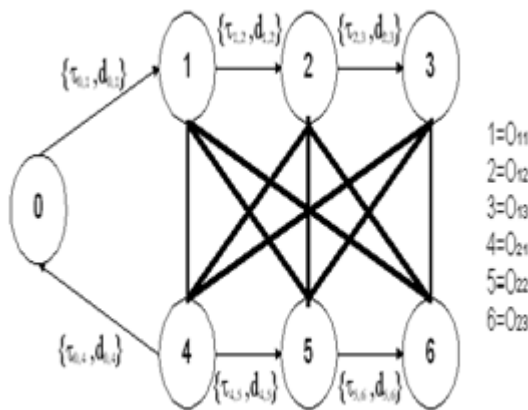


Figure 2.1 Definition of a 2/3/G/Cmax job shop problem into a graph.

The nodes of the graph represent the operations given by matrix T (e.g. O11 indicates element T11 and equals machine M1). The nodes belonging to the same job are connected by the unidirectional horizontal edges, respecting the technological order of processing a job. The rest of the edges are bidirectional. The maximum number of nodes of a n*m job shop is given by: Nodes= (n*m) +1.

3. BAP using AFSA

3.1 Basic principle of AFSA

In water sources like sea, lake and Pond following other fish, a fish can always find food at a place where there are a lots of food, hence generally the more food, the more fish. According to this phenomenon, AFSA builds some artificial fish (AF), which search an optimal solution in solution space (the environment in which AF live) by imitating fish swarm behavior.

Three basic behaviors of AF are defined as follows:

- a) Prey: The fish perceives the concentration of food in water to determine the movement by vision or sense and then chooses the tendency.
- b) Swarm: The fish will assemble in groups naturally in the moving process, which is a kind of living habits in order to guarantee the existence of the colony and avoid dangers.
- c) Follow: In the moving process of the fish swarm, when a single fish or several fish find food, the neighborhood partners will trail and reach the food quickly.

3.2 Notations used in Mathematical Model

B: set of berths.
V: set of vessels.

i: i=(1,..., I)∈B.

j: j=(1,..., J)∈V.

bj: the starting time of the service for the jth vessel.

Aj: the arrival time of the jth vessel.

Cij: the service time of the jth vessel at the ith berth.

Xij: indicated that if the jth vessel was serviced at the ith berth, Xij was equal to 1, otherwise it was equal to 0.

Si: the number of vessels at the ith berth.

S: the total number of arrival vessels.

Pi: the quay length of the ith berth.

Lj: the length of the jth vessel including the horizontal safety length.

$$\text{Objective: Minimize } \sum_{i \in B} \sum_{j \in V} (b_j - A_j + C_{ij}) X_{ij} \quad - (1)$$

Equation (1) minimized the total of flow time incurred by vessels.

$$\text{Subject to: } \sum_{i \in B} S_i = S \quad - (2)$$

Equation (2) ensured that the total number of arrival vessels was equal to the sum of vessels at berths.

$$\sum_{i \in B} X_{ij} = 1 \quad - (3)$$

Equation (3) ensured that each vessel should be serviced once and exactly once at any berth.

$$b_j - A_j \geq 0 \quad - (4)$$

Equation (4) ensured that vessels should be serviced after their arrivals.

$$(P_i - L_j) X_{ij} \geq 0 \quad - (5)$$

Equation (5) ensured that the length of the jth vessel did not exceed the quay length of the ith berth.

3.2 Algorithm Design for the BAP

Notations used in the algorithm

X: the current status of an artificial fish swarm. $X = (X_1, X_2, \dots, X_n)$, where X_i ($i=1, \dots, n$) represents the current status of the i th AF, i.e., the searched solution. This is the berthing sequence assigned to vessels.

For example, $X_i = (1,3;4,2)$ expressed that vessels S1,S3 were assigned to berth1 in the order of 1,3; vessels S2,S4 to berth2 in the order of 4,2.

Y_i : the value of function (1) corresponding to X_i , i.e., the value of fitness function $Y_i = f(X_i)$.

According to Nan Du et al.,[3]

Definition 1: $D(X_i, X_j)$, the distance between two fish is defined as

$$D(X_i, X_j) = |X_i - X_j| + |X_j - X_i|,$$

D_{ij} : the distance between the i th AF and the j th AF.

It was the number of different elements between X_i and X_j .

For example, if $X_i = (1,3;2,5;6,4)$ and $X_j = (1,3;6,2;5,4)$, then $D_{ij} = 3$.

Visual: the visual range of the AF.

Definition 2: $N(X, \text{Visual})$, the visual-neighbors of AF. X whose distance with X is in the Visual,

$$N(X, \text{Visual}) = \{X^* | D(X, X^*) < \text{Visual}\},$$

Where each X^* is a neighbor of X . (or)

$$N(X_i, \text{Visual}) = \{X_j, D_{ij} \leq \text{Visual}\}$$

Definition 3: Nan Du et al., X_c , the center of AF set X_1, X_2, \dots, X_n ,

$$C(X_1, X_2, \dots, X_m) = \bigcup_{i=1}^m \bigcup_{j=1, j \neq i}^m (X_i \cap X_j).$$

δ : congestion degree, $0 < \delta < 1$.

FishNum: the population size of an artificial fish swarm.

Maxgen: maximum iterations.

Trynumber: the number of prey iteration.

3.3 Algorithm Procedure

The algorithm procedure of the BAP was described as follows

Step1: Initialization. Set FishNum, Maxgen, Trynumber, Visual, δ ; input the expected arrival time and service time of vessels; randomly generate an artificial fish swarm with the population size FishNum, i.e., initialize $X = (X_1, X_2, \dots, X_i, \dots, X_{\text{FishNum}})$. $NC = 0$.

Step2: For each X_i , execute follow behaviour; if found a better solution X_j , replace X_i with X_j then go to Step7; otherwise go to Step3.

Step3: Rounded Visual * (1-NC/MaxGen) to the closest integer Visual2; if Visual2 > 0, go to Step 4 using Visual2; otherwise go to Step5.

Step4: For X_i , execute prey behavior; if found a better solution X_j , replaced X_i with X_j then go to Step7; otherwise go to Step5.

Step5: For X_i , execute swarm behavior; if found a better solution X_j , replace X_i with X_j then go to Step 7; otherwise go to Step6.

Step6: For X_i , execute move behavior. If found a better solution X_j , replaced X_i with X_j then go to Step7; otherwise go to Step8.

Step7: $NC = NC + 1$; update the optimal solution on the bulletin board.

Step8: If $NC = \text{Maxgen}$, output the current optimal solution, the end; otherwise, go to Step2.

4. Comparison of Rate of Convergence between ACO and AFSA

ACO in 6/6/G/Cmax Muth- Thompson,[8] a benchmark JSS Problem is taken for comparison. Average number of cycles to reach optimum is taken over five runs of the 6/6/G/C max Muth-Thompson problem.

Parameters used are;

Maximum number of cycles $NC_{\text{max}} = 1000$

$$\alpha = 10$$

$$\beta = 10$$

$$\rho = 0.01$$

AFSA is applied in BAP. Average number of iterations to reach optimum is taken over five runs of the proposed AFSA.

Parameters used are;

Maximum number of iterations $\text{Maxgen} = 20$

$$\text{Trynumber} = 10$$

$$\text{Congestion Degree} = 0.8$$

$$\text{Visual} = 4$$

$$\text{No. of Berths} = 6$$

$$\text{No. of Vessels} = 10$$

$$\text{No. of Vessels/berth} = 2$$

The Experiment is conducted with the same Number of Fish and Ant. The rate of convergence is compared and the Figure 4.1 shows that AFSA converges more quickly than ACO.

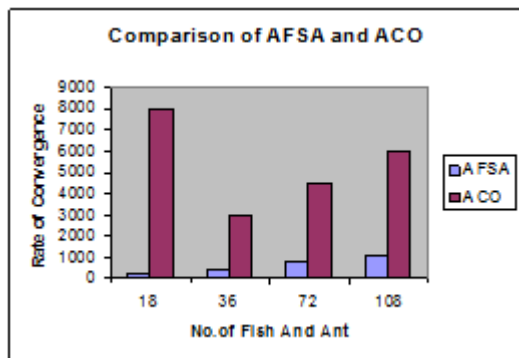


Figure 4.1 Comparisons of AFSA and ACO

Table 4.1 Influence of Species in Convergence rate of AFSA and ACO

No. of Species (Ant & Fish)	Rate of Convergence		No. of Cycles	
	AFSA (BAP)	ACO (JSSP)	AFSA (BAP)	ACO (JSSP)
18	198	8000	11	444
36	396	3000	11	83
72	720	4500	10	62
108	1080	6000	10	55

5. Conclusion and Further Research

The experimental results show rate of convergence is very low in AFSA used in BAP compared to ACO used in JSSP. The AFSA can adjust the searching range adaptively by four search behaviors. The computational time and the quality of solutions depend on parameter selection. Experimental results verified the validity and feasibility of the proposed algorithm and show that the algorithm has better convergence performance i.e. AFSA converges 45% quicker than ACO in JSSP. In AFSA the parameter selection can be generalized with the help of some advanced techniques in future.

References

[1] Akio Imai, Etsuko Nishimura and Stratos Papadimitriou, "The dynamic berth allocation problem for a container port" Transportation Research Part B 35 (2001) 401-417

[2] K.H. Kim, K.C. Moon, "Berth scheduling by simulated annealing," Transportation Research Part B, Vol. 37, pp.541-560, July 2003

[3] X.L. Li, Z.J. Shao, and J.X. Qian, "An optimizing method based on autonomous animals: Fish-swarm Algorithm", System Engineering Theory and Practice, Vol. 22, pp.32-38, November 2003.

[4] Nan Du, Supriya D Mahajan, Bindukumar B Nair, Stanley A. Schwartz, Chiu Bin Hsiao and Aidong Zhang, "An artificial fish swarm based supervised gene rank Aggregation algorithm for informative genes studies", Proceedings of the IASTED International Conference Computational Intelligence and Bioinformatics (CIB 2011)November 7 - 9, 2011 Pittsburgh, USA.

[5] E. Nishimura, A. Imai, and S. Papadimitriou, "Berth allocation planning in the public berth system by

genetic algorithms", European Journal of Operational Research, Vol. 131, pp. 282-292, June 2001.

[6] Norman, B.A., Bean, J.C., 1999. A genetic algorithm methodology for complex scheduling problems, Naval Research

[7] Saeed Farzi, "Efficient Job Scheduling in Grid Computing with Modified Artificial Fish Swarm Algorithm", International Journal of Computer Theory and Engineering, Vol. 1, No. 1, April 2009.

[8] Sjoerd Van Der Zwaan and C Marques," Ant Colony Optimization for Job Shop Scheduling "- Proceedings of Third Workshop on Genetic Algorithms and Artificial Life, 1999.

[9] D.Teodorovic, and M. Dell'Orco, Bee colony optimization –A cooperative learning approach to complex transportation problems, In Advanced OR and AI Methods in Transportation, pp.51-60,2005

[10] C Tong, H Lau, A Lim, "Ant colony optimization for the ship berthing problem", in Advances in Computing Science - ASIAN'99, P.S. Thiagarajan and R. Yap, Eds. Thailand: LNCS1742,1999, pp. 359-370.

[11] Weijun Xia, Zhiming Wu, "An effective hybrid optimization approach for multi-objective flexible job-shop scheduling problems", Computers & Industrial Engineering, Volume 48,Issue 2, pp 409-425, March 2005.

[12] Ying Wu, Xiao-Zhi Gao, and Kai Zenger, "Knowledge-based artificial fish-swarm algorithm", Preprints of the 18th IFAC World Congress Milano (Italy) August 28 - September 2, 2011

[13] Yong PENG, "An improved artificial fish swarm algorithm for optimal operation of cascade reservoirs", Journal of computers, Vol. 6, No. 4, April 2011.