An information entropy based artificial immune algorithm for the flexible job shop problem with transportation time

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Abstract

In the field of job shop scheduling, including canonical flexible job shop problem (FJSP), the transportation time between machines is generally ignored. To fill this gap, a FJSP considering energy consumption and transportation time constraints are proposed. A sequence-based mixed integer linear programming (MILP) model based on the problem is established, and the weighted sum of maximal completion time and energy consumption is optimized. In the framework of the artificial immune algorithm (AIA), the expected reproduction probability (ERP) is introduced to ensure the diversity of the population, which is determined by the antigen affinity and the antibody concentration obtained by calculating the information entropy between antibodies. Meanwhile, a simulated annealing (SA) algorithm is combined to accelerate the convergence of solutions, and an improved artificial immune algorithm (IAIA) is proposed. According to the computational comparison with other efficient meta-heuristic algorithms, the IAIA has a better performance for solving the FJSP with different problem scales.

1 Introduction

In recent years, increasing numbers of enterprises have been paying more attention to the problem of how to optimize the scheduling of workshop to maximize the interests of efficiency. [Oddi *et al.*, 2011] Therefore, the job-shop problem (JSP) has become one of the most popular research topics in the literature due to its potential to dramatically decrease costs and increase throughput [Jones *et al.*, 2001].The flexible job shop problem (FJSP), as an extension of JSP, has received widespread attention because of its flexibility and realistic. [Brandimarte, 1993]. However, literature review shows that several assumptions in canonical FJSP being considered are unreasonable, e.g., each operation can be processed after it is finished in the previous machine [Karimi *et al.*, 2017]. Most researchers omitted the intermediate process of transportation time between two machines while the transportation of jobs requires the participation of cranes, automatic guided vehicles or other tools, which is essential in actual industrial scheduling [Junqing *et al.*, 2018]. Therefore, a FJSP considering transportation time and energy consumption is proposed and a hybrid meta-heuristic algorithm is proposed to solve this problem, which is a combination of AIA and simulated annealing (SA) algorithm, taking the maximum completion time (makespan) and energy consumption as the objective function, and assigning different weight coefficients to each objective. In the proposed hybrid meta-heuristic algorithm, an information entropy theory is applied to obtain better antibodies and some potential high quality antibodies are searched from the point of view of global search. Furthermore, four kinds of mutation operators based on machine-selection (MS) part and operation-sequence (OS) part are used to perform further local search in the neighborhood structure. In order to verify the validity of the model, the MILP model is constructed by CPLEX.

2 Problem description

The FJSP-T model is improved on the basis of the classical FJSP, which can be defined as follows. There are a set of jobs $\{J_1, J_2, \dots, J_n\}$ to be executed on a set of machines $\{M_1, M_2, \dots, M_m\}$, in which each job j consists of a sequence of op_j operations and each operation $O_{j,l}$ is carried out on one of a subset of eligible machines $M_{j,l} \subseteq M$. In terms of transportation times, every operation $O_{j,l}$ of each job j has their own transportation time $t_{j,k,i}$ of transferring from machine k to another machine i. In addition, the energy consumption generated when jobs processed on machines is taken into account. When jobs are processing in machines, they will produce disparate energy consumption $ec_{j,i}$ in per unit time.

$$min\, \alpha \cdot C_{max} + (1-\alpha) \cdot E \tag{1}$$

$$E = \sum_{j=1}^{N} \sum_{l=1}^{op_j} \sum_{i=1}^{m} \sum_{k=1}^{m} Y_{j,l,i,k} \times p_{j,l,i} \times ec_{j,i} \tag{2}$$

$$C_{j,l} \geq C_{j,l-1} + \sum_{i=1}^{m} \sum_{k=1}^{m} Y_{j,l,i,k}(p_{j,l,i} + t_{j,k,i})\ \forall j, l > 1 \tag{3}$$

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$$C_{j,1} \geq \sum_{i=1}^{m} Y_{j,1,i,k}(p_{j,1,i} + t_{j,0,i}) \quad \forall j \tag{4}$$

$$C_{max} \geq C_{j,n} \quad \forall j \tag{5}$$

Constraint set (1) summarizes the objective function that aims to minimize the weighted sum of makespan and energy consumption, and the α denotes their respective weight coefficients. The constraint set (2) is to calculate the total energy consumption of all operations when they are being processed on the machines, in which the variable $Y_{j,l,i,k}$ is a binary variable that takes value 1 if $O_{j,l}$ processes on machine i and $O_{j,l-1}$ on machine k. The constraints set (3) guarantee that the beginning of each operation is after the completion time and transportation time of the previous operation. Constraint set (4) forces that the first operation of each job is transported from a virtual machine 0 to other machines. Constraint set (5) determines the value of the makespan by considering the completion time of the last operation of all the jobs.

3 The proposed algorithm

This section list the main components of the proposed IAIA. The AIA is inspired by the human immune mechansim, in which the antibodies is an encoded solution, and the affinity represents quality of each soltuion. In this study, the AIA, based on information entropy theory, is used to implement global search, taking the reciprocal of the makespan as the criterion of affinity evaluation.[Zeng and Wang, 2018] The similarity of the chromosomes is evaluated and the antibody concentration is determined on the basis. Then, the population is sorted according to two criteria, antigen affinity and antibody concentration, antibodies, with antibodies of quality then selected for further local search based on SA and an immune suppression operation[Lin and Ying, 2013]. The framework of IAIA is described in Algorithm 1.

Algorithm 1 IAIA framework

Input: FJSP data set, parameters
Output: a near optimal solution

Initialize
  a) Initialize the parameters (α, N_c, etc.)
  b) Initialize the population with the MSOS chromosome representation [Karimi *et al.*, 2017]
Evaluate the affinity of each antibody in current population by $affinity = \frac{1}{makespan}$
while not termination condition **do**
  Select the best N_c antibodies with the highest affinity
  Clone the N_c antibodies from the selected antibodies
  Exert mutation to $N_c(N_c + 1)$ cloning antibody
  Calculate the expected reproduction probability (ERP) of the mutated antibodies and sort them with cloning antibodies by descending order
  Update the original population by suppression process
  Mutated the best N_c antibodies with highest affinity in the population by SA algorithm
end while
return result

4 Computational results

In order to verify the effectiveness of the proposed IAIA, three other efficient heuristic algorithms were selected to compare with the IAIA, including imperialist competitive algorithm(ICA)[Karimi *et al.*, 2017], enhanced genetic algorithm(EGA)[Dai *et al.*, 2019] and variable neighborhood search(VNS) algorithm[Amiri *et al.*, 2010]. The first and second comparison algorithms have been proved to have clear advantages in solving this problem, and the VNS algorithm is also widely accepted because of its effective local search ability. Each algorithm runs 30 times independently and 30 seconds for each time, and the average value is used for comparison. As shown in Table 1, all the algorithms are compared on several instance with different scales, and the performance of the algorithm are measured by relative percentage increase (RPI) value, in which $RPI = \frac{f_{Current} - f_{Best}}{f_{Best}} \times 100$. As shown in Figure 1, multifactor analysis of variance (ANOVA) is applied to evaluate the performance of each algorithm. The p-value=7.33585e-12 which is far less than 0.05, showing that the four compared algorithms have significant differences. The Figure 2 shows the convergence curve of a instance, in which 20 jobs are processed on 6 machines. Both of figures prove that the proposed IAIA has a better performance on this problem.

Table 1: Comparison with other heuristic algorithms

Inst	Best	Fitness				RPI			
		ICA	EGA	VNS	IAIA	ICA	EGA	VNS	IAIA
10-5	179.17	181.25	186.63	179.17	179.49	1.15	4.00	**0.00**	0.18
10-6	206.78	211.05	217.87	210.59	206.78	2.02	5.09	1.81	**0.00**
20-5	333.71	342.68	356.46	343.97	333.71	2.62	6.38	2.98	**0.00**
20-6	411.49	434.67	450.51	441.36	411.49	5.33	8.66	6.77	**0.00**
50-5	747.41	763.98	783.79	757.58	747.41	2.17	4.64	1.34	**0.00**
50-6	979.18	1014.15	1039.07	1009.34	979.18	3.45	5.76	2.99	**0.00**
Average	476.29	491.30	505.72	490.34	476.34	2.79	5.76	2.65	**0.03**

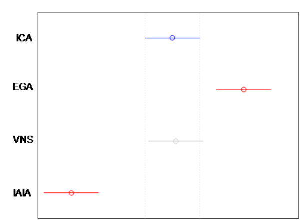

Figure 1: ANOVA result for compared algorithms

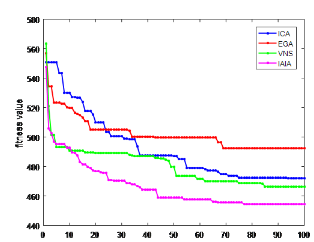

Figure 2: Convergence curves for compared algorithms

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