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A multi-objective fuzzy genetic algorithm for job-shop scheduling problems

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Analysis and modelling

ABSTRACT

Purpose: Many uncertain factors in job shop scheduling problems are critical for the scheduling procedures. There are not genetic algorithms to solve this problem drastically. A new genetic algorithm is proposed for fuzzy job shop scheduling problems.

Design/methodology/approach: The imprecise processing times are modeled as triangular fuzzy numbers (TFNs) and the due dates are modeled as trapezium fuzzy numbers in this paper. A multi-objective genetic algorithm is proposed to solve fuzzy job shop scheduling problems, in which the objective functions are conflicting. Agreement index (AI) is used to show the satisfaction of client which is defined as value of the area of processing time membership function intersection divided by the area of the due date membership function. The multi-objective function is composed of maximize both the minimum agreement and maximize the average agreement index.

Findings: Two benchmark problems were used to show the effectiveness of the proposed approach. Experimental results demonstrate that the multi-objective genetic algorithm does not get stuck at a local optimum easily, and it can solve job-shop scheduling problems with fuzzy processing time and fuzzy due date effectively.

Research limitations/implications: In this paper only two objective functions of genetic algorithm are taken into consideration. Many other objective functions are not applied to this genetic algorithm.

Originality/value: A new multi-objective fuzzy genetic algorithm is proposed for fuzzy genetic algorithm. The genetic operations can search the optimization circularly.

Keywords: Artificial intelligence methods; Scheduling; Genetic algorithm; Multiple objectives

1. Introduction

Many researchers assume that processing times are fixed and deterministic in job shop scheduling problems (JSSPs). This assumption may be realistic if the operations under considerations are fully automated. However, whenever there is human interaction, this assumption may present difficulties in applying the schedule or even invalidating it. Unfortunately, those uncertainties have not received enough attention [1].

In the paper a genetic algorithm is presented to optimizing fuzzy JSSPs. The due dates are modeled as trapezium fuzzy numbers [2]. The satisfaction of clients can be denoted by the area which overlapped by the processing time and due date [1]. Under these circumstances, on the basis of the agreement index of fuzzy due date and fuzzy completion time, we formulate multi-objective job shop scheduling problems which maximize both the minimum agreement and maximize the average agreement index [2]. The final objective is to maximizing the satisfaction of clients.

We assume that decision maker may have a fuzzy goal for each of the objective functions. Two benchmark problems are used to demonstrate the effectiveness of the proposed method [3].

2. Problem definition

The JSSP can be stated as follows: a set of n jobs have to be processed on a set of m machines. Each job consists of a chain of operations and the operation order on machines has been planed

[3].The goal for this problem is to the satisfaction of clients that maximize objective function.

In JSSP, using a shifted triangular fuzzy number to model the uncertainty is very realistic. The fuzzy due date is represented by the degree of satisfaction with respect to the job completion time, and denoted by trapezium fuzzy numbers.

For the fuzzy completion time for each job expressed as $\tilde{C}$, as an index showing the portion of $\tilde{C}$ that meet the fuzzy due date $\tilde{D}_i$, it is convenient to adopt the agreement index AI of the fuzzy completion time $\tilde{C}$ with respect to the fuzzy due date $\tilde{D}_i$. Here, as shown in Fig. 1, the agreement index AI is defined as value of the area of membership function intersection divided by the area of the $\tilde{C}$ membership function [4].

$$\mathrm{AI} = (\mathrm{area}\tilde{\mathrm{C}}_i \cap \tilde{\mathrm{D}}_i)/(\mathrm{area}\tilde{\mathrm{C}}_i) \tag{1}$$

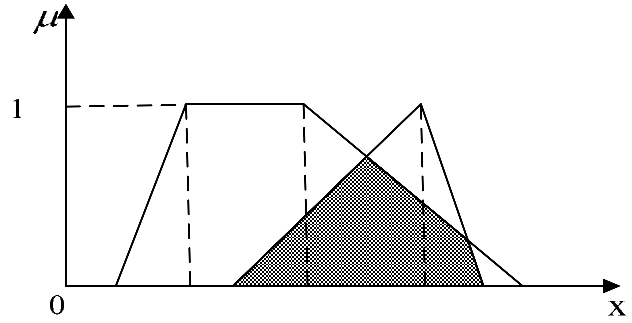

Fig. 1. Agreement Index

3. BI-criteria optimization

In this paper, to reflect real-world situations adequately, we formulate multi-objective fuzzy job shop scheduling problems as two-objective ones which maximize both the minimum agreement and maximize the average agreement index. It should be emphasized that these objective functions z1 and z2 respectively denote average agreement index, minimum agreement index [4].

$$\max\mathrm{imize}\ z_1 = \frac{1}{n}\sum_{i=1}^{n} \mathrm{AI}_i \tag{2}$$

$$\max\mathrm{imize}\ z_2 = \mathrm{AI}_{\min} = \min_{i=i,\dots n} \mathrm{AI}_i \tag{3}$$

Now, considering the imprecise nature of the decision maker's judgments, these fuzzy goals can be quantified by eliciting the corresponding membership functions [5].

This two-objective function will maximize the minimum agreement and maximize the average agreement index. Therefore, the new objective function can be defined as where w is the weight of the spread in the bi-criteria objective function [6].

$$\min z = z_1 + \omega z_2 \tag{4}$$

4. Genetic algorithm

In this GA, the scheme is the operation-based representation which is a direct approach. This representation encodes schedule as a sequence of operations [4, 6]. To ensure a feasible schedule from any possible permutation of genes, all operations for a job have the same symbol.

4.1. Crossover operation

Crossover operator is used to generate new individual and it can retain good features from the current generation. The partial schedule exchange crossover is modified in this algorithm as follows [7]:

We use the following symbols in our crossover operator [8]. PA and PB: parent chromosomes. CA and CB: child chromosomes. Point and Nextpoint: crossover points. BlackA and BlackB: partial chromosomes between PA and PB in each parent.

1) Randomly pick a value from 5 to length-10 as crossblack, length is the length of the chromosome.
2) Pick a position in parent PA randomly. The second position will be equal to the first position plus the value of crossblack. Then, crossblackA is formed with the genes between and including the first and second positions.
3) To form crossblackB, repeat step 2 for parent PB.
4) Find out the exceeded genes from children PA and PB by comparing the crossbackB and crossblackA and set genes to 0.
5) Move all the genes which value is 0 to the front o.
6) Exchange the partial schedules which gene value is 0 with crossblackB and crossblackA to generate children CA and CB. Figs. 2 and 3, 4 illustrate the crossover process.

		Black A	
PA	4 2 1 1 3 5 5 4 4	3 2 4 4 3 2 3 5 5 1	1 5 2 3 2 1
		pointA	NextpointA
		BlackB	
PB	3 1 5 4 1	5 3 4 5 4 2 1 3 1 3	2 4 5 2 4 5 2 3 1 2
		pointB	NextpointB

Fig.2. Select cross point and cross black

4.2. Mutation operation

An exchange order mutation operator will be used in this genetic algorithm [7] [8]. That is, partial genes (operations) are chosen randomly and then their positions are exchanged in reverse order as shown in Fig. 5. The mutate operator can be summarized as follows [7]:

1) Randomly pick a value of mutate black from 3 to length-1.
2) Randomly pick a position in parent PA. The second position will be equal to the first position plus mutate black. Then, mutate black is formed with the genes between and including the first and second positions.
3) Make mutate black in reverse order to create new gene black, and replace mutate black make in step 2. The new chromosome M1 is child chromosome.

Black A 3 2 4 4 3 2 3 5 5 1 Black B 5 3 4 5 4 2 1 3 1 3

PA 4 2 1 1 3 5 5 4 4 3 2 4 4 3 2 3 5 5 1 1 5 2 3 2 1

PB 3 1 5 4 1 5 3 4 5 4 2 1 3 1 3 2 4 5 2 4 5 2 3 1 2

PA 0 0 0 0 0 0 0 0 4 0 2 4 4 0 2 3 5 5 1 1 5 2 3 2 1

PB 0 0 0 0 1 0 0 4 5 0 0 1 0 1 3 0 4 5 2 4 5 2 3 1 2

PA 0 0 0 0 0 0 0 0 0 0 4 2 4 4 2 3 5 5 1 1 5 2 3 2 1

PB 0 0 0 0 0 0 0 0 0 0 1 4 5 1 1 3 4 5 2 4 5 2 3 1 2

Fig.3. Delete exceeded genes

CA 5 3 4 5 4 2 1 3 1 3 4 2 4 4 2 3 5 5 1 1 5 2 3 2 1

CB 3 2 4 4 3 2 3 5 5 1 1 4 5 1 1 3 4 5 2 4 5 2 3 1 2

Fig.4. Legalizing CA and CB

Black

P1 4 2 1 1 3 5 5 4 4 | 3 2 4 4 3 2 3 5 5 1 | 1 5 2 3 2 1

Point1 Point2

M1 4 2 1 1 3 5 5 4 4 1 5 5 3 2 3 4 4 2 3 1 5 2 3 2 1

Fig.5. Reverse mutation operator

5. Experimental results

The parameter values of genetic algorithm in Table 1 are found through a lot of experiences, which are used in each of the trials of GA. All of the trials of GA are performed 5 times for each problem [4, 6]. The Experimental results are shown in Table2.

As can be seen in Figs. 6 and 7, the convergence curves obtained through this genetic algorithm are very stable. Moreover, this genetic algorithm can get the best result in several generations for 6×6 scheduling problem. It can also get the optimization solution for difficult 10×10 problem fleetly.

Table 1
Parameter Values of GA

Problem	Population size	Number of generation	Crossover rate (%)	Mutation rate (%)	Parameter w
6×6	20	30	80	20	2
10×5	50	50	80	20	2

Table 2
Experimental Results

Problem	Best result	Average time /s	Number of trial
6×6	0.857	45	5
10×5	0.963	381	5

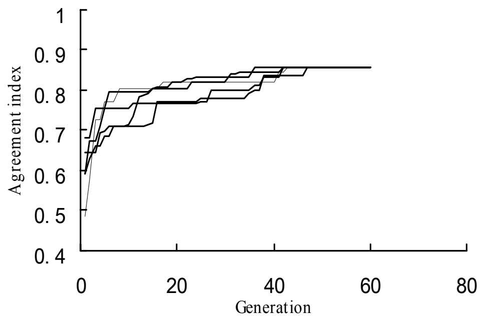

Fig. 6. Convergent curve of genetic algorithm(6×6)

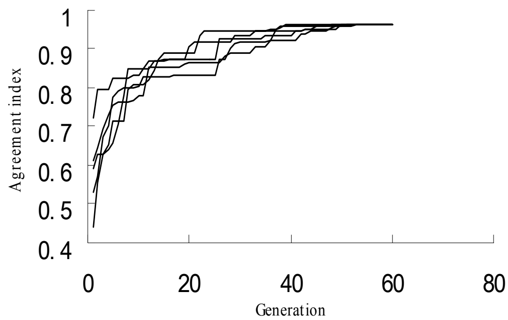

Fig. 7. Convergent curve of genetic algorithm(10×10)

6. Conclusions

This bi-criteria genetic algorithm approach is proposed to solve fuzzy job shop scheduling problems. Since processing times were modeled as triangular fuzzy numbers, the makespan is a triangular fuzzy number as well. We formulate multi-objective job shop scheduling problems with fuzzy due date and fuzzy processing time as two-objective ones which maximize both the minimum agreement and maximize the average agreement index. Moreover, by considering the imprecise nature of human influence, we assume that the decision maker may have a fuzzy goal for each of the objective functions. After eliciting the linear membership functions through the interaction with the decision maker, we adopt the fuzzy decision for combining them. As illustrative numerical examples, we consider both 6×6 and 10×10 two-objective job shop scheduling problems with fuzzy due date and fuzzy processing time, and demonstrate the feasibility and effectiveness of the proposed method.

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