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Thanh-Do Tran, Inés González-Rodríguez, El-Ghazali Talbi

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Thanh-Do Tran[1], Inés González-Rodríguez[2], and El-Ghazali Talbi[1]

[1] DOLPHIN Team, Inria Lille – Nord Europe and LIFL, Université Lille 1, France
[2] Department of Mathematics, Statistics and Computing, University of Cantabria, Spain
Emails: thanh-do.tran@inria.fr, ines.gonzalez@unican.es, and el-ghazali.talbi@lifl.fr

1 Context

In recent years, much work has been expended on addressing job-shop scheduling problems (JSP) with uncertain information. There are two primary approaches to uncertainty handling, i.e. using probability theory and possibility theory. In the probabilistic school, a statistical model is used to quantify uncertainty. Thus, the prior existence of complete information regarding the uncertainty is implicitly assumed. In the possibilistic school, conversely, no prior statistical data nor underlying models are required. Indeed, vague perception and imprecise knowledge regarding the uncertainty may still be sufficiently usable. Possibility theory is thus rationally applicable to practical JSP.

This work lies in the possibilistic category. Specifically, we deal with JSP where uncertain processing times are modeled by triangular fuzzy numbers (TFNs). Following the pioneering work by Fortemps [4], a memetic algorithm that includes a specialized local search was applied to minimizing fuzzy makespans [1]. While local search really helps improve solution quality, the use of expectation model might cause a leak of uncertainty information during the optimization, especially when asymmetric TFNs get involved. To overcome this issue, in recent work [3], the authors proposed a multiobjective genetic approach that uses all three defining points of an approximate triangular fuzzy makespan to drive the optimization. The multiobjective approach puts more pressure for minimizing the *whole* fuzzy makespan than the single-objective approach. The lack of a specialized local search, however, hinders the multiobjective approach from searching for well qualified schedules. And this is where a multiobjective memetic approach comes into play.

This paper examines the incorporation of the local search proposed in [2] into the multiobjective genetic approach introduced in [3]. The incorporation results in a simple multiobjective memetic algorithm that is based on the NSGA-II and the $\mathcal{N}_2$ neighborhood structure for individual improvement in the Lamarckian learning procedure. An extensive experiment was conducted to confirm the superiority of the algorithm compared to both the single-objective memetic and multiobjective genetic methods. The new analysis scheme also shows that, regardless of the expert's attitude toward uncertainty quantification, the proposed approach would consistently find statistically better schedules in terms of expected makespan.

2 Multiobjective Memetic Approach to Fuzzy JSP

Given a crisp JSP instance (i.e. matrices $\mathbf{p}$ for task processing times and $\mathbf{v}$ for machine allocation) and a certain task processing order σ, we need to propagate the problem's constraints to compute the makespan $C_{\max}(\sigma, \mathbf{p}, \mathbf{v})$ associated with that σ. The makespan is the maximal completion time over all jobs. In propagating constraints, we need the addition and maximum operations. The objective of this problem is to find an optimal order σ^* such that $C_{\max}(\sigma^*, \mathbf{p}, \mathbf{v})$ is minimal. When fuzzy processing times involve, the makespan becomes fuzzy as well. If TFNs are used in $\mathbf{p}$, the fuzzy makespan is unfortunately not triangular anymore due to fuzzy maximum operations. However, an approximate fuzzy maximum operator can be used to make its result triangular, and so is the makespan. The objective now is to find an optimal σ^* that minimizes the fuzzy makespan.

Following the work in [3], we continue to use NSGA-II to minimize the three defining points of triangular fuzzy makespans. These three values are taken as the three objectives to be minimized simultaneously in NSGA-II. The genetic algorithm comprises the permutations-with-repetition encoding scheme in which each task is codified only by its job number. Accordingly, an advanced decoding procedure is required. In this case, we employ the extended Giffler and Thompson algorithm to decode candidate solutions from its genotype to phenotype. Also, the job order crossover and simple swap mutation are used to generate genetic material for the evolution.

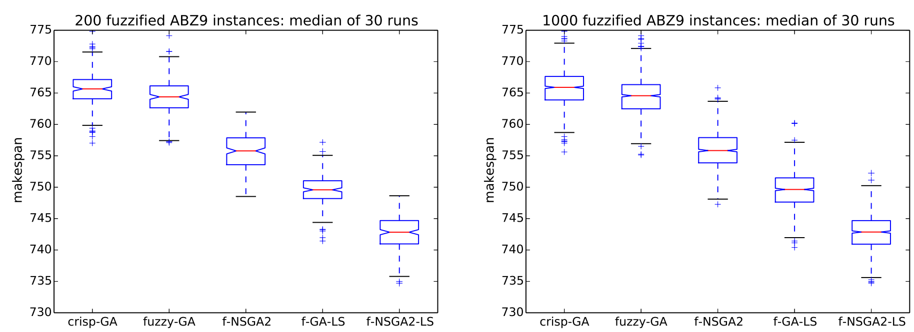
An efficient local search (LS) may help boost the search performance of NSGA-II. Indeed, such a LS, if properly incorporated into the genetic algorithm, may introduce valuable genetic material to the population through individual learning. A local search in the fuzzy problem may also make a joint effort to look for schedules that minimize makespans across the three solution graphs (corresponding to the three defining points of TFNs) in parallel. One of such handy LS algorithms was proposed in [2], in which a reduced neighborhood structure called $\mathcal{N}_2$ was introduced[3]. This LS is quite efficient as it considers reversing only critical arcs at the extreme of critical blocks, thus may reduce the neighbourhood size.

The integration of LS into genetic algorithm however requires due consideration. For example, when and to which solutions individual learning should be applied are often of great concern. For the Lamarckian-evolution-style memetic algorithm in this study, we empirically propose applying LS only to the 25% top-quality individuals of the population, and individual learning is activated only after the first 5% of the whole budget is consumed. The idea is to allow some diversification at the early stage of the evolution and not to spend much effort in improving non-potential individuals.

3 Experimental Results

Twelve popular crisp JSP instances were used to evaluate the multiobjective memetic approach: FT10, FT20, LA21, LA24, LA25, LA27, LA29, LA38, LA40, ABZ7, ABZ8, ABZ9. Many of these instances are considered challenging with interesting properties. For each crisp instance, we respectively sampled 200 and 1000 fuzzy instances in such a way that their triangular fuzzy processing times have the min, modal, and max values lying randomly in the ranges [75%, 95%], (95%, 105%), and [105%, 125%] of the original crisp processing times, respectively. We have compared the proposed approach (denoted as f-NSGA2-LS) against the single-objective genetic algorithm (GA) that works only on the modal value of TFNs (denoted as crisp-GA), GA optimizing the expected value of fuzzy makespans (fuzzy-GA), GA with local search optimizing the expected value (f-GA-LS), and the multiobjective approach without local search (f-NSGA2) introduced in [3]. All the algorithms were run 30 times on each of the fuzzy instances with a population size of 400 up to 10^5 evaluations.

For each algorithm, the best solution in terms of expected makespan, $\mathrm{E}[A] = \frac{1}{4}\left(a^1 + 2a^2 + a^3\right)$, was recorded for comparison. A sample result for the instance ABZ9 as shown in Fig. 1 suggests that the proposed multiobjective memetic approach performs significantly better than all other methods. Note that similar patterns are also consistently observed over all other problem instances.



(a) 200 fuzzy samples (b) 1000 fuzzy samples

Fig. 1. Distributions of expected makespans of five algorithms solving 200 and 1000 randomly sampled fuzzy instances from the instance ABZ9. The median of 30 final expected makespans from the 30 runs of an algorithm on a fuzzy sample is used as the algorithm's output on that fuzzy instance. Thus, each box consists of 200 or 1000 median results. Note, notches display an approximated 95% confidence interval for the box medians; without a formal test, non-overlapping notches indicate a strong evidence that values in the boxes come from different distributions, i.e. the difference in the box medians is statistically significant.

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