Fitness landscape analysis and tabu search for the Flexible Job shop Scheduling Problem with Transportation

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1 Introduction

Metaheuristics are often used to solve optimization problems including workshop scheduling problems. They are made of several components such as encoding schemes, neighborhood operators, search strategies, objective functions, scheduling engines, etc. The choice of these components is usually random or based on intuition [7]. However, a good choice of component would lead to better performance of heuristics. The impact of solution representation (encoding) in search spaces was announced in [4]. In this study, emphasis is lain on encodings schemes and neighborhood operators. We use fitness landscape analysis to characterize search spaces according to different pairs of encodings and neighborhoods for the problem of Flexible Job shop Scheduling Problem with Transportation (FJSPT). The properties of these spaces are confronted with the performance of a tabu search to make a comparative analysis of 15 encoding-neighborhood pairs. This study is an extension of a previous work carried out for a classical Job shop Scheduling Problem (JSP) [6].

2 Problem description

The Flexible Job Shop Scheduling Problem with Transportation (FJSPT) is defined by a set of n jobs, a set of m multifunctional machines and a set of r identical transportation resources. Each job i is composed of n_i ordered O_{ij} operations, such that $j = \{1,2,\dots,n_i\}$. Each operation O_{ij} is executed non-preemptively on a machine k chosen from the candidate machines defined for the operation with a processing time p_{ijk}. A machine can only process one operation at a time. Each job requires several transportations, first from a loading unit to the first machine to process the job, then from one machine to another depending on the operations of each job, then to an unloading unit. Each job transportation requires one of the transportation resources. The selected transportation resource may be required to make an empty trip from its current location to the location where the job is to be picked up, unless these two locations are the same. From this second location, a loaded trip is performed to transfer the job to its next location (machine/unloading unit). Empty and loaded trips may have different durations. The objective is to simultaneously determine machines' assignment and operations' sequence in addition to transportation resources' assignment and transportation tasks sequence', while minimizing the total execution time (C_{max}).

3 Fitness landscape and tabu search

In combinatorial optimization, a fitness landscape is a triplet where we denote a set of solutions (S), a neighborhood relationship between solutions (N) and a solution evaluation function (f). S is defined by an encoding scheme while N is described by a neighborhood operator and f induces a scheduling engine. Fitness landscape analysis helps to represent and study the structure of search spaces for scheduling problems. It is used to explain the behavior of algorithms, to predict their performance and to guide their design and tuning [8]. Three of the multiple landscape properties [3] are investigated in this study: ruggedness, neutrality and evolvability. Ruggedness measures the size and the distribution of local optima; it is commonly calculated with the *correlation length* metric. Neutrality is interested in neighbor solutions having the same fitness; it is measured with the *neutrality rate* metric. Evolvability is the capacity to evolve in the landscape toward better fitness; it is measured with the *accumulated escape probability* metric. The different FJSPT landscapes targeted in the experiments, depending on the couples encoding-neighborhood, are confronted to tabu search performances in order to find out correlations with the results of the landscapes analysis. The current tabu search is a single solution metaheuristic, inspired by [5].

4 Experiments and results

Five encoding schemes are considered [1,2,6]: job list encoding (*job*) which represents a solution by a list of integers of size Σn_i, each element corresponding to a job number; operation list encoding (*ope*) which is an ordered list of all operations; machine list encoding (*mch*) with a list of m operation lists assigned for each machine; operation sequence and machine assignment encoding (*osma*) which represents a solution by an operation sequence like *job* and a list of machine numbers corresponding to operations in first list; matrix encoding (*tnm*) which adds a complementary list to *osma* for transportation resource assignment. To each of these encodings, three classical neighborhood operators have been associated: insertion (*ins*), swap (*swp*) and reverse (*rev*). For *mch*, operators are adapted to take machine reassignment into account. For representations which do not encode machines or transportation resources assignments, the scheduling engine applies a *first best machine* C_{max} rule followed by a *first best transportation resource* C_{max} rule. We use 89 instances taken from [2] with n = [2,3,4,5,6,7,8,9,10,11,12,15,20], m = [2,3,4,5,6,7,8,10,11,12,13, 15,16,17,18] and r = 2. For each of the landscapes generated by the encoding-neighborhood pairs, over 20 random walks of 1000 iterations among the feasible solutions, we measure ruggedness and the neutrality. To measure evolvability, for each encoding and its neighborhood operators, and each instance, we uniformly generate 1000 solutions and 100 neighbors for each solution (*mch* is not considered, because its uniform solution generation is hard). We compute the results of 10 runs of the tabu search; the results are ranked for each encoding and its neighborhood operators and the best one is kept for each instance and each run.

Figure 1 presents, from left to right, correlation length and neutrality rate results grouped by encoding-neighborhood pairs for family instances. For the correlation length measure, *ope* generally gives the highest lengths regardless of operators while *job-rev* gets the lowest; portraying that *ope* landscapes are quiet smoother than the others. We also observe that the correlation length increases with the size of instances. The neutrality rate for the different pairs varies depending on family instances and instances sizes. *tnm* shows neutrality below 20% for *dn*, *exf* and *mt10t* family instances. *ope* globally shows the highest neutrality except for *mt10t*, *setb4t*, *seti5t* instances where *mch-rev* exceeds *ope* and approaches 100%. We notice that neutrality of *mkt* instances seems to be strongly influenced by encodings and neighborhood operators. Although neutrality differs in our landscapes for the different encoding-neighborhood pairs, the way instances are generated impacts the measures. To assess the landscape evolvability, we calculate accumulated escape probability that shows some slight differences from one pair to another. However, *job* and *tnm* probabilities are almost always greater compared to *ope* and *osma*. These evolvability results match those of neutrality.

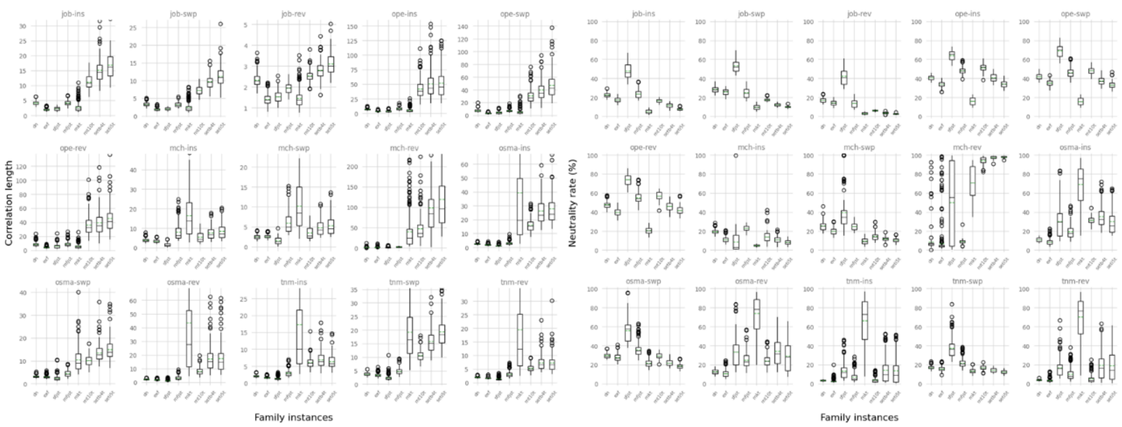

Figure 1: Correlation length and neutrality rate by family instances.

The number of times each encoding-neighborhood pair gives the best C_{max} over four execution times with our tabu search is shown in Figure 2. We observe a predominance of *job* on all execution times. With 10s, regardless of the associated operator, *job* obtained at least 300 times the best C_{max} over 890 runs. The tabu search on 120s propels the *job-ins* radically in the lead. It got 533 times the best fitness when *mch-swp* comes last reaching them only 41 times.

5 Conclusion

Encoding schemes and neighborhood operators affect FJSPT landscapes. However, the features of these landscapes also depend on instances properties. Aside search space analysis, the encoding-neighborhood pairs investigated in this study were also tested on a tabu search. *job-ins* specifically, and *job* globally obtained the best results. But unfortunately, no obvious correlation can be deduced from the properties of the landscapes and the performance of our tabu search.

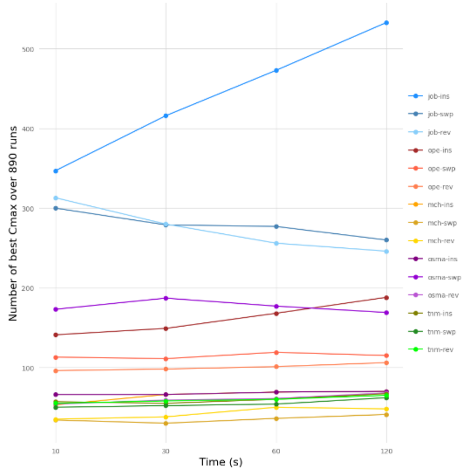

Figure 2: Number of best C_{max}

The results of classical JSP fitness landscape analysis in the aforementioned study [6] are somewhat different from those of the FJSPT. Adding flexibility and transportation to JSP changes the structure of the search spaces generated by the encoding schemes and neighborhood operators. Nevertheless, *job-ins* produced the best performance with a tabu search for both cases.

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