Preference-driven tabu search for multiobjective scheduling problems

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1 Introduction

Many real-life decision problems involve the simultaneous consideration of several, often conflicting, criteria. In most cases, a single solution that satisfies all these objectives at the same time is not feasible, hence the search for compromise solutions, called *efficient solutions*. Depending on the stage at which the decision-maker (DM) participates in the solution process, several strategies can be distinguished for solving a multi-objective optimization problem. We focus on the *a priori* and *a posteriori* strategies which make use of a preference model that is extracted from the DM. The first uses this model directly in the optimization process, while the second solves the problem classically, constructing the set of Pareto optimal solutions, which it then filters using the preference model.

In this work, we consider the *Flexible Job Shop problem (FJSP)*, which consists of ordering several jobs involving operations, in its multiobjective form. This problem is NP-Hard [1]. We focus on the integration of the DM's preferences in the optimization process when considering three criteria : makespan (f_1), total machine processing time (f_2) and balanced machine utilization (f_3). We assume that the DM is able to identify reference performance levels, but that the heterogeneity of the criteria scales makes it difficult to use compensatory models. We use the Ranking using Multiple Profiles [3] (RMP) model embedded in a hybrid Tabu Search method. Lastly, we compare the *a priori* and *a posteriori* strategies.

RMP is a multiple criteria method that ranks alternatives, defined on a set of m criteria, by comparing them to reference profiles instead of each other. RMP contains the following parameters : P, the set of reference profiles ordered based on the dominance principle ; w the set of criteria importance weights ; σ, the lexicographic order in which the profiles are used.

An alternative a is considered to be preferred to another alternative b according to profile p_k if the set of criteria on which a is at least as good as p_k is more important that the set of criteria on which b is at least as good as p_k, i.e. $\sum_{\substack{j\in 1..m \\ a_j \geq p_{k,j}}} w_j > \sum_{\substack{j\in 1..m \\ b_j \geq p_{k,j}}} w_j$. When these sums are equal, profile p_k cannot discriminate between a and b, hence the following profile according to σ is used. This process is repeated until a profile is able to discriminate between a and b, giving the relation between the two alternatives, while when no profile is able to achieve this, the alternatives are considered as equivalent.

2 Preference-driven tabu search

We encode a solution using two variables : x and y, where x is an assignment of operations to different machines, and y is the order of each operation on the machine to which it is assigned.

We define an additional metric that we use within the proposed resolution approach as $\delta(F(x,y),P) = \min_{p_k < f_k(x,y)} f_k(x,y) - p_k, \forall k \in 1..m$. This measure indicates the smallest improvement on any criterion between a solution encoded by x and y and any reference level, normalized w.r.t to the closest two bounding reference levels. This measure is used instead of the distance to the utopian point within the classical Hybrid Tabu Search (HTS) approach [2]. We therefore prioritize solutions that require smaller improvements on any criterion in order to move within a more preferred category w.r.t. the preference model, and hence our DM.

We define the RMP-score function $\Phi(F(x,y),P,\sigma,w)$ that takes its values in the interval $[1, (h+1)^k]$. Solutions that compare in the same way to all reference profiles may be considered as equivalent w.r.t. the preference model. We may hence consider RMP as an ordered classification model containing up to $(h+1)^m$ classes. We use this classification as a scoring function where a higher value corresponds to a more preferred solution.

The main steps of this method are summarised as follows :

Initialization : generate P_{size} solutions using multiple rules, Tabu_List = $\emptyset$

Exploration : perform a local search in the neighborhood of the current solution.

Selection : sort the set $\{N(x,y) \setminus Tabu\_List\}$ by descending RMP score. After that, we choose $\overline{(x,y)} = \underset{(x,y)\in \arg\max \Phi(F(N(x,y)),P,\sigma,w)}{\arg\min} \delta(F(N(x,y)),P)$

Update and repeat : add the current solution to Tabu_List, then consider $\overline{(x,y)}$ as the current solution. We repeat this process until the stopping condition is reached.

3 Conclusion

In order to test the proposed approach, we have used well-known public instances and compared them with the proposed procedure in [2]. The results show that the proposed algorithm focuses its search on regions within the search space corresponding to solutions that achieve better levels of DM aspiration than the HTS algorithm, leading to a faster discovery of better solutions from the DM's perspective. Further experiments on more instances are needed to validate this claim.

Références

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