MOOPPS: An Optimization System for Multi Objective Production Scheduling

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1 Introduction

The resolution of multi objective optimization problems is twofold: First, the set of Pareto-efficient alternatives \( P \) with respect to the defined objective functions has to be determined. Second, an alternative \( x^* \in P \) has to be chosen by the decision maker. Obviously, practical problems require that both aspects are addressed within a solution concept.

In the current paper, we present an optimization system solving multi objective production scheduling problems (MOOPPS). The identification of Pareto optimal alternatives or at least a close approximation of them is possible by a set of implemented metaheuristics. Necessary control parameters can easily be adjusted by the decision maker as the whole software is fully menu driven. This allows the comparison of different metaheuristic algorithms for the considered problem instances. Results are visualized by a graphical user interface showing the distribution of solutions in outcome space as well as their corresponding Gantt chart representation.

The identification of a most preferred solution from the set of efficient solutions is supported by a module based on the aspiration interactive method (AIM) [5]. The decision maker successively defines aspiration levels until a single solution is chosen.

After successfully competing in the finals in Ronneby, Sweden, the MOOPPS software has been awarded the European Academic Software Award 2002 (http://www.easa-award.net/, http://www.bth.se/llab/easa_2002.nsf).

2 Multi objective production scheduling

Production scheduling can be characterized as the assignment of jobs \( J = \{J_1, \ldots, J_n\} \), each of which consists of a set of operations \( J_j = \{O_{j1}, \ldots, O_{jo_j}\} \) to a set of machines \( M = \{M_1, \ldots, M_m\} \). Processing of operations on the machines is done involving a nonnegative processing time \( p_{jk} \) for each operation \( O_{jk} \). A schedule \( x \) defines starting \( s_{jk} \) times of the
operations \( O_{jk} \) on the machines. Based on this assignment, completion times \( C_j \) of the jobs \( J \) are derived.

Typical side constraints that have to be taken into consideration are precedence constraints among operations of jobs and release dates \( r_j \) of jobs \( J \). Also, due dates \( d_j \) may be present for each job \( J \). An overview is given e. g. in [6].

The schedule identified for a given problem should be of overall maximum quality from the perspective of a so called decision maker/planner/scheduler. Often, multiple aspects or ‘points of view’ [9] are of relevance that formally can be expressed by a set of optimality criteria. For each schedule \( x \), a vector of objective function values \( G(x) = (g_1(x), \ldots, g_k(x)) \) determines its quality. Important objective functions include the maximum completion time or makespan \( C_{\text{max}} = \max(C_j) \) of the jobs \( J \), the sum of the completion times \( C_{\text{sum}} = \sum C_j \), the maximum tardiness \( T_{\text{max}} = \max(T_j) \) with \( T_j = \max(C_j - d_j, 0) \) and the number of tardy jobs \( U = \sum U_j \) with \( U_j = 1 \) if \( C_j > d_j \), 0 otherwise. Without loss of generality, we assume in the further explanations that all considered objective functions have to be minimized.

The goal of a multi objective optimization problem can be formulated as to

\[
\text{“min” } G(x) = (g_1(x), \ldots, g_k(x))
\]

\( x \in \Omega \) as a solution of the problem and belongs to the set of all feasible solutions \( \Omega \). As often conflicting objective functions \( g_k(x) \) are considered, minimization does not lead to a single optimal solution but is understood in the sense of efficiency (or Pareto optimality) [12].

**Definition 1 (Pareto dominance)** An objective vector \( G(x) \) is said to dominate \( G(x') \), if \( g_i(x) \leq g_i(x') \forall i \in \{1, \ldots, k\} \land \exists i \in \{1, \ldots, k\} \mid g_i(x) < g_i(x') \). We denote the domination of a vector \( G(x) \) to the vector \( G(x') \) with \( G(x) \prec G(x') \).

**Definition 2 (Pareto optimality, Pareto set)** A solution \( x \in \Omega \) is said to be efficient or Pareto optimal, if \( \nexists x' \in \Omega | x' \prec x \). The set set of all solutions fulfilling this property is called the Pareto set \( P \).

From the description of the multi objective optimization problem in Expression (1) we derive in combination with the Definitions 1 and 2 the final goal to find all \( x \in P \). Finally, the decision maker is able to select a most preferred solution \( x^* \in P \).

### 3 A decision support system for multi objective scheduling

#### 3.1 System description

For the resolution of multi objective production scheduling problems, the integrated system MOOPPS has been implemented. As illustrated in Figure 1, the system consists of different components for the resolution of the problem.

A method database contains a set of heuristics approaches for solving multi objective scheduling problems:

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1. Priority rules [4], based on the early work of Giffler and Thompson [3] for generating active schedules.

2. Local search neighborhoods [8] within a multi-point hillclimber.

3. Multi objective evolutionary algorithms [1], incorporating elitist strategies and a variety of crossover neighborhoods like e.g. uniform order based crossover, order based crossover, two point order crossover, and partially mapped crossover.

4. The ‘MOSA’ multi objective simulated annealing algorithm of Teghem et al. [11].

5. A module based on the ‘AIM’ aspiration interactive method [5] for an interactive search in the obtained results.

The model instance database stores the data of the problem instances that have to be solved. General job shop as well as flow shop scheduling problems can be formulated. Besides newly generated data sets, well-known test instances from literature [2] have been included. Solutions are obtained by linking model instances with methods. This allows the reuse of specific metaheuristics for a range of problem instances as well as the comparison of results obtained from different heuristic approaches. A graphical user interface as given in Figure 2 links the modules described above into a single system.

### 3.2 Optimization and decision making

The resolution of multi objective scheduling problems is supported by a procedure consisting of two stages. First, Pareto optimal alternatives or an approximation $P_a$ of the Pareto set $P$ are computed using the chosen metaheuristics. Second, an interactive search in the obtained results is performed by the decision maker.

During this interactive decision making procedure, aspiration levels $A = \{a_{g_1}, ..., a_{g_k}\}$ for each of the optimized objective functions $G(x) = (g_1(x), \ldots, g_k(x))$ are chosen. As shown in Figure 3, the elements of the approximation $P_a$ of the Pareto set $P$ are accordingly divided into two subsets, the subset $P_{as}$ of the alternatives fulfilling the aspiration levels $g_i(x) \leq a_{g_i} \forall i = 1, \ldots, k$. 

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1, ..., k) and the subset $P_{-as}$ of the alternatives that do not meet the aspiration levels. It is obvious that $P_{as} \cup P_{-as} = P_{a}$ and $P_{as} \cap P_{-as} = \emptyset$.

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The initial values of the aspiration levels $a_{g_i}$ are set to the worst values in $P_a$: $a_{g_i} = \max_{s \in P_a} g_i(x) \forall i = 1, ..., k$ and as a consequence, $P_{as} = P_a$. The decision maker is allowed to modify the values of the aspiration levels and successively reduce the number of elements in $P_{as}$ until $|P_{as}| = 1$. The remaining alternative in $P_{as}$ is the desired compromising solution $x^*$ as the fixed aspiration levels are met by this alternative.

As Figure 4 demonstrates, the decision maker does not only have to rely on the choice of aspiration levels but is able to visualize the corresponding Gantt chart of a particular schedule.

4 Conclusions

A decision support system for multiple objective scheduling problems has been presented. It incorporates a set of metaheuristics that can be adapted to specific problems instances. As the user interface is highly visual, nonexperienced users are able to solve scheduling problems under multiple objectives with comparably little knowledge.

After an approximation of Pareto optimal alternatives has been obtained, an interactive decision making module based on the aspiration interactive method allows the identification of a most preferred schedule. The system may also be used to compare different approximation results of various metaheuristic approaches in terms of their approximation quality. It is therefore suitable for demonstrating the use, adaptation and effectiveness of metaheuristics to
complex combinatorial optimization problems using the example of machine scheduling under multiple objectives.

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