On Interactive Search and Computer Assisted Planning – State of the Art and Future Research Directions

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Production planning and scheduling are notoriously difficult problems that have to be solved on a daily basis in industrial environments. Due to the complexity of these problems, methods from operations research/computer science are often used to assist the human planner.

The article reviews interactive search and computer assisted planning approaches, giving an overview about selected recent scientific developments from fuzzy modelling and multi criteria decision making. Based on the insight gained in the structure of these approaches and problems, we describe an intelligent system for the resolution of production scheduling problems. The system has been successfully implemented and tested on several benchmark problems.

Keywords: computer assisted planning, interactive optimisation, scheduling

1 Introduction

In many practical cases, the planning of industrial problems has to simultaneously take into consideration numerous aspects or ‚points of view' [Roy 1996] of a particular decision maker. Certain activities should be completed as soon as possible, while the utilization of involved resources should e.g. be maximized or levelled over time. Approaches from multi-criteria decision making (MCDM) meet this circumstance by formulating models which allow the consideration of multiple criteria at once.

The resolution of these problems is based on the formal definition of a quantitative model which acts as a surrogate for the real world situation while the optimal solution of this model is then applied to the actual situation. In the case of conflicting criteria, a whole set of equally Pareto-optimal alternatives exists under which the selection of a most preferred solution has to be made, usually supported by techniques from multi-criteria decision aid. Consequently, two aspects are of relevance. First, the identification of Pareto-optimal solutions, which in many cases already is NP-hard [Brucker et al. 1999]. Second, the choice of a solution that reflects the decision maker's preferences to a maximum extend.

Different ways of combining these two steps of problem resolution exist, and numerous approaches have been proposed for the resolution of project planning and scheduling problems [Herroelen 2005]. In most cases however, research focuses on particular isolated aspects rather than developing holistic approaches that tackle the entire real world situation. As a consequence, existing (commercial) implementations of project scheduling systems [which acts as a surro], which equally have to deal with problems of differing characteristics, lack several functionalities that are otherwise well-established in the research literature (an example being the possibility to define maximum time lags between activities [Zimmermann et al. 2006]).

The motivation of the article is threefold. First, we aim to present and discuss general principles in planning and optimization. The particular chosen aspects are fuzzy and multi criteria approaches, two areas of research which have drawn considerable interest in past years. Second, future research directions are described based on the limitations observed with existing methods, and third, an exemplary production scheduling system is presented which combines some ideas of interactive, computer-assisted planning. The presentation and discussion of the system is done in the light of the previously described developments, and the implementation is evaluated from a critical perspective.

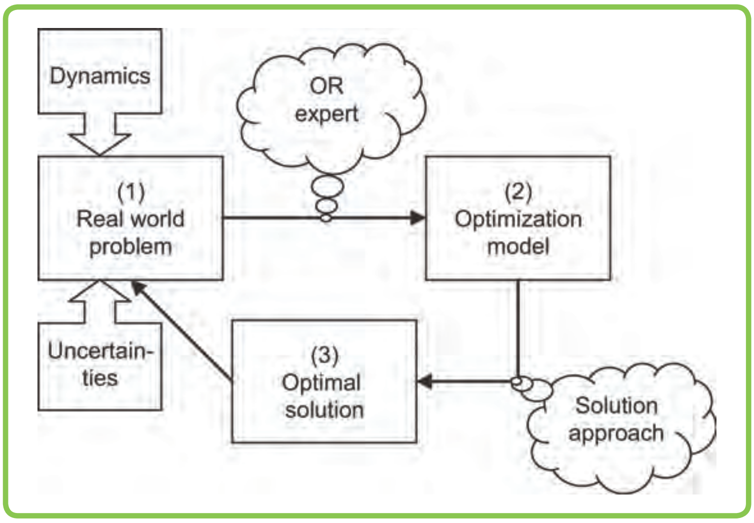

Figure 1: Resolution of Real World Optimisation Problems in OR

The article is organized accordingly. Section 2 gives an overview about the principles of solving real world optimization problems in Operations Research (OR). Shortfalls of classical approaches are discussed, and different ways of overcoming these are presented. Recent scientific developments are described in the following Section 3, and an intelligent production scheduling system based on the provided discussion is presented in Section 4. Conclusions are presented in Section 5.

2 Solving Optimisation Problems – Principles and Shortfalls

2.1 General Problem Resolution

As already sketched above, the resolution of real world problems by means of techniques from Operations Research involves the steps given in figure 1. First, a model (2) of the actual problem (1) is derived, often involving an OR specialist. This surrogate ideally should reflect the described situation as closely as possible. Then, the model is solved and the optimal or most-preferred Pareto-optimal solution (3) is implemented in the real world situation. Due to the complexity of most problems, heuristic or meta heuristic approaches [Loukil et al. 2005] are used in this context.

While traditional approaches define a single optimization function for which the problem is solved to optimality, it can be noticed that practical problems often involve several aspects that simultaneously have to be taken into consideration when solving the problem at hand. Two ideas of dealing with this circumstance are reported in the literature:

1. Fuzzy approaches integrate the preferences of the decision maker into the evaluation of the alternatives [Fortemps 2000; Geiger, Fuzzy, 2006]. When solving the optimization problem, the preferences are implicitly maximized, leading as a result to a most-preferred solution.
   The direct representation of the decision makers' preferences using fuzzy approaches is an advantageous way of modelling the evaluation of alternatives, as it closely represents the subjective view of the decision maker. It can be expected that the resolution of the fuzzy model therefore leads to a most-preferred solution, making a further choice of an alternative or adaptations of the solution unnecessary. On the other hand, strong requirements have to be made with respect to the definition of the fuzzy model. The decision maker must be able to closely define the fuzzy membership functions and the implemented fuzzy logic. If he/she is not able to give these specifications, or simply if the available time for modelling is insufficient, simplifying assumptions have to be made that reduce the proximity of the fuzzy model to the actual problem.
2. Multi-criteria approaches define a set of objective functions that describe the alternatives in terms of different aspects at once. Given the property that the chosen set of objective functions is exhaustive [Bouyssou 1990], the set of Pareto-optimal alternatives contains a ost-preferred solution which can then be selected. Three general principles are known in this context:
   (a) A priori approaches combine the set of criteria into a single evaluation function, reflecting the associated utility of the decision making with a particular solution. Similar to fuzzy approaches, a detailed knowledge of the preferences of the decision maker is needed in order to implement this approach. Only in cases where such information can be obtained, a priori approaches may be implemented, reducing the problem to a mono criterion optimization problem.
   (b) A posteriori approaches first identify the entire set of Pareto-optimal alternatives and then perform an interactive search in the Pareto set. As the computation of the Pareto-optimal alternatives can be done without the immediate participation of the decision maker ("offline"), a considerable amount of computing time may be allocated to this task. Also, no particular preference information is needed in this step. The identification process of a most-preferred alternative can then be done based on the results of the preceding identification phase. However, the results are usually discarded to a large extent as the decision maker is only interested in a single alternative, not a possibly huge set of Pareto-optimal solutions.
   (c) Interactive approaches combine the search for optimal solutions with the successive articulation of the preferences of the decision maker. Trying to bring together the advantages of the previously mentioned approaches, interactive methods enable the decision maker to progressively articulate his/her preferences, thus directing the search process in particular (preferred) regions. However, only very limited time for the computation of the alternatives is available here. The decision maker needs to be integrated in the search process, and he/she is usually only willing to wait for some few minutes or even only seconds. In result, this may limit the quality of the obtained solutions.

2.2 Open Issues

Especially multi-objective approaches are of increasing popularity and importance in scientific research [Hoogeeven 2005]. It has to be mentioned however, that for large and complex optimization problems, such as project scheduling and planning problems, and with increasing number of objective functions, the number of Pareto-optimal solutions grows exponentially. While this increases the computationally necessary effort when identifying the Pareto set, it also leads to problems most-preferred solution by the decision maker. Rather than presenting possibly thousands of solutions to the decision maker, a representative subset has to be chosen beforehand, discarding a large percentage of the Pareto set.

More recent approaches propose ideas to overcome this problem. The concept of dimensionality reduction [Deb & Saxena 2006] aims to reduce the number of objectives, keeping only a small subset of the most anti-correlated objective functions. Investigations of test problems indicate that this concept is able to successfully reduce the computational effort for problems with many objectives. From a multicriteria decision making perspective it however formulates a contradiction as it automatically discards objectives which have been considered to be of importance when modelling the problem. While this is a feasible decision for the decision maker, it appears to be a critical action for an automated approach.

Another idea of dealing with large multi-objective optimization problems is the focus on particular regions of the Pareto front, so called ‚knee regions' [Rachmawati & Srinivas 2006]. These regions are defined by maximum marginal rates of return and describe solutions for which the improvement in one objective is accompanied by a severe degradation in another. By reducing search to this particular region, the computational complexity may be reduced. It has to be mentioned however, that up to now no we are not aware of any empirical evidence indicating that these regions are of particular interest to a decision maker.

Two other issues of real world problems further complicate the resolution of real world planning problems:

1. Dynamics. As real world situations often change over time, models and their optimal or most-preferred solution become obsolete and have to be adapted to the new circumstances.
2. Uncertainties. Many aspects of actual situations are not precisely known and can therefore only described using stochastic or fuzzy approaches [Herroelen & Leus 2005].

As a result, the formal, approximate model often lacks the necessary accuracy, and the computed optimal solution is not applicable to the real world situation.

A way to overcome this problem is formulated by systems which allow the interactive, manual modification of the obtained solution by the decision maker [Foulds & West 2006,T'kindt et al. 2005]. This is however considered to be a corrective procedure only and does not include a true interaction with the optimization system as the optimization model as such remains untouched.

3 Recent Developments

A considerable progress in the development of quantitative approaches to planning problems can be observed in the literature. Coming from single-objective models, increasingly advanced ideas have successfully been tested in numerous situations, leading to multi-objective formulations, among others. With respect to real world situations, a gap becomes clear when comparing highly effective specialized optimization procedures and the lacking accuracy of the defined models. Due to the dynamics and uncertainties of many problems however, a higher accuracy may however not be achievable.

The following recent research developments aim to address these issues.

3.1 Interactive Optimisation

Interactive optimization procedures may overcome several problems that are present in non-interactive methods. First, the decision maker does not have to state his/her preferences as opposed to a priori methods, which may as well not be a priori possible. Second, no search has to be performed in a Pareto-set of huge cardinality. Given the fact that the decision maker only selects a single, most-preferred Pareto-optimal solution, the computation of a large number of other alternatives is not unnecessarily performed.

In order to achieve this, the integration of preferences in the definition of solution algorithms for planning problems becomes necessary. We acknowledge the work that has been carried out in the area of multi-criteria decision aid (see e.g. [Vincke 1992]) and the upcoming ideas of integrating interactive procedures in evolutionary meta heuristics [Phelps & Köksalan 2003]. It remains however open, how dynamics and uncertainties may be handled in this context, and how changes of preferences affect the identification of a most-preferred solution.

While many advantages of interactive methods exist, a serious disadvantage is the very limited available time when carrying out computations. Solution approaches and the available hardware therefore have to be as fast as possible.

3.2 Open Models

Modelling an actual problem can often only be done in an approximate way [Clark 2002]. While some characteristics of the problem are emphasized, others are simplified or even left out. Especially in engineering, where the optimization of certain technical systems is confronted with complex interdependencies of the decision variables, simplifications have to be accepted in many cases [Vankan & Maas 2002].

In addition to the interactive articulation of preferences and the guidance of the optimization procedure towards the most-preferred solution, the decision maker should therefore be enabled to modify the model during search [Geiger & Petrovic 2004]. This includes the introduction and the discarding of optimality criteria, as well as the possibility to add constraints to the model, e. g. fixating the starting times of certain activities. While the initially proposed formal description of the real world situation may only be of limited preciseness, the accuracy successively increases. Especially for commercial implementations of quantitative methods addressing a large market share this may be beneficial, as often a qualified OR expert is not present when decision makers model the actual problem.

Contrary to existing approaches where it is possible to ‚fine-tune' obtained results only, the optimization procedure should be allowed to continue with the added constraints until a satisfactory solution has been identified.

4 An Intelligent Production Scheduling System

4.1 Elements of the System

In the light of the discussion provided above, an intelligent productions scheduling system has been proposed [Geiger, Solving, 2006]. The system integrates computational intelligence methods for the construction of optimal production schedules with a user interface, allowing the interaction of the production planner with the system.

The main components of the system comprise:

Model-Builder
A model-builder, allowing the definition of machines, jobs, operations, release dates, due dates, and the relevant optimality criteria.

Solver-Subsystem
A solver-subsystem that computes production schedules for the current situation. This element provides numerous computational intelligence techniques to solve the problem at hand, ranging from multi-objective evolutionary algorithms to simple local neighbourhood search. Extensive parameter settings allow the adaptation of the system to specific situations, thus tuning the algorithms to the current problem.

Visual User Interface
A visual user interface, displaying the production schedules to the human planner [Geiger, Teaching, 2006]. Two types of different visual outputs are available.

1. A plot of the production schedules in outcome space, comparing the objective values of the alternatives and showing the trade-off between different schedules in terms of their evaluation. An example of such a plot is given in figure 2. Different Pareto-fronts are visualized and made comparable.
2. A Gantt-chart, clearly stating a particular alternative in decision space. In this visual

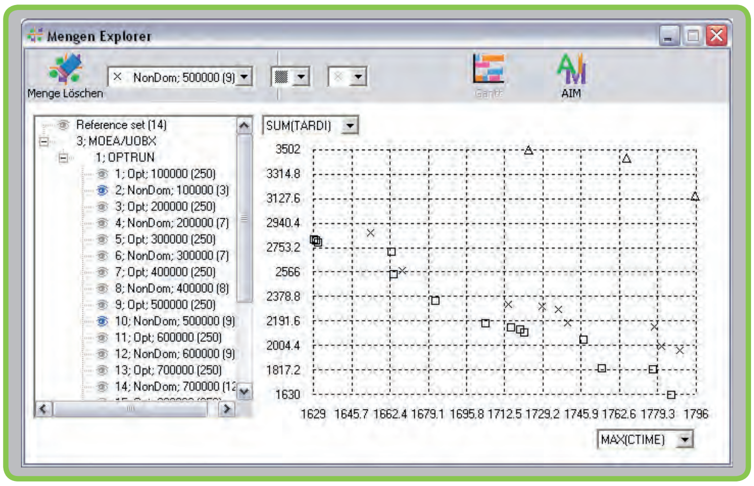

Figure 2: Visualisation of the Production Schedules in Outcome Space

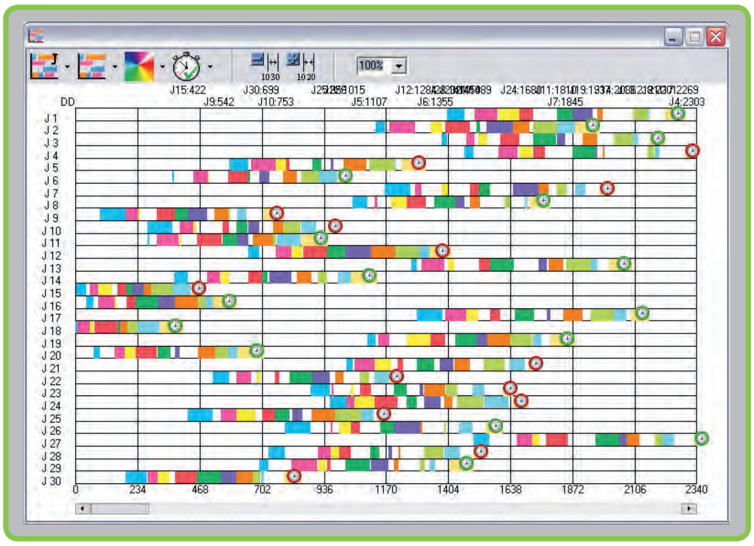

Figure 3: Visualisation of the Production Schedules in Alternative Space

elements, each operation is given as a rectangle whose length corresponds to the required production time. Figure 3 gives an example of such an interface.

4.2 The Problem Resolution Process

The resolution of production scheduling problems follows the previously discussed logic of a posteriori approaches. We first compute an approximation of the Pareto-optimal alternatives using the computational intelligence techniques provided by the solver-subsystem. The obtained approximation is then presented to the human planner by means of the elements of the visual interface.

Based on the interactive component of the system, the human planner may choose to select a particular solution from the approximation set. This may be done by comparing the evaluations and the corresponding trade-offs of different alternatives in outcome space. The selection process is equally supported by the visualization of the solutions in alternative space, as the precise production schedule is visualized using Gantt-charts.

During the problem resolution process, it may occur that the results obtained by the system are not satisfactory to the human planner. This may be the case due to an insufficient approximation of the Pareto-set, or due to a lacking accuracy of the defined model. In these situations, the human planner may modify/clarify the underlying objective functions and/or the parameters of the computational intelligence techniques, rerunning/continuing the computational methods to improve the obtained solutions.

4.3 Evaluation of the System

The proposed system for production scheduling has been evaluated with respect to two aspects: performance and usability. While the quality of the obtained results can be judged using production scheduling benchmark instances taken from the literature, the systems usability can only be determined by experienced software experts.

Computational investigations of the implemented computational intelligence techniques on benchmark instances demonstrate the applicability of the system for the targeted problem domain. Numerical results are reported in [Geiger, Solving, 2006]. In brief, the implemented heuristics led to competitive results, improving one benchmark instance from the literature.

A panel of international software experts evaluated the user interface of the system. Even in its' preliminary version, the software has been honoured with the European Academic Software Award in Ronneby, Sweden. The system allows an indirect interaction of the decision maker with the results as he/she may select schedules by clicking on their image (their objective function values) in outcome space and display the actual plan using Gantt charts. The decision maker is therefore given the opportunity to compare alternatives with different characteristics and evaluations, leading to the final choice of a most-preferred solution.

Assuming the completeness of the optimality criteria in the quantitative model, the decision maker is able to identify a most-preferred solution using the system. However, in cases where criteria change over time, it may be relevant to the decision maker to modify the underlying model or even directly interact with a solution by rescheduling certain jobs manually. Clearly, limitations of typical production scheduling systems can be identified here, including the presented multi-objective production scheduling system. Interaction with the system is usually only allowed on a higher level such as the outcome space, while the formal model is kept unchanged during the problem resolution process.

5 Conclusions

The article first presented a review of existing approaches to optimization and decision making in planning problems. Different approaches have been identified, each of which possess different disadvantages, particularly when solving practical problems. To overcome existing limitations, we proposed the further integration of interactive procedures into the resolution of these problems. This includes the successive articulation of preferences, as well as the modification of models during search.

Based on the initial discussions, an intelligent production scheduling system has been proposed, allowing the resolution of complex planning problems under multiple objectives. The system includes several elements, such as computational intelligence techniques and visualization components, that assist the human planner in an actual planning situation.

A certain disadvantage of the interactive combination of search and decision making however is, as already mentioned above, the limited available time for computations. This has to be taken into account when following the here derived research directions. Interactive methods rely on the availability of fast computer hardware. With the increasing performance of cheap personal computers however, the development of these approaches becomes more and more feasible.

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