Fuzzy Constraint Relaxation Techniques for Knowledge-Based Scheduling*

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Abstract: Mathematical-analytical methods as used in Operations Research approaches are often insufficient for real-world applications. This is due to three reasons: The imprecise informations in the real-world applications, combinatorial complexity of the search space, and conflicting objectives for optimizing. The combination of several knowledge-based techniques, especially approximate reasoning and constraint relaxation, is a promising way to handle these problems.

I attempt to give an overview on existing fuzzy constraint relaxation techniques, focusing on

- the type of problems handled,
- the techniques used, with examples,
- advantages,

and then proceed to compare these techniques with other constraint relaxation techniques.

Special emphasis will be given to the industrial scheduling domain, as this is a very prominent real-world application area for constraint satisfaction methods.

I Introduction

Constraint relaxation is necessary when problems are overconstrained or too difficult to solve completely, but it is acceptable to settle for a "good enough" solution. This applies to many problems encountered in practical manufacturing situations. Constraint relaxation as in [4] aims at finding values for a subset of problem describing variables that satisfy a subset of the constraints. Constraints are "weakened" to permit additional acceptable value combinations. For practical as well as theoretical reasons, approximate reasoning methods as those examplified by [10] are a very elegant way to weaken these so-called "soft" constraints. [3] correctly point out that this method allows to represent in the same framework priorities between the constraints. In this present paper, a small example taken from a real-world application illustrates the easiness and elegance arising from the use of fuzzy constraint relaxation techniques.

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II Knowledge-Based Scheduling

The task of scheduling jobs and resources in a factory is difficult for mainly three reasons. First, one has to deal with the combinatorial complexity due to multiple ways of job accomplishment. Second, conflicting objectives may hinder the definition of an undisputed optimality measure [9]. Finally, there is uncertainty in the execution of jobs due to the lack of knowledge about the exact physical facts underlying the production process. Thus, it becomes senseless to compute exact scheduling solutions. Often reactive scheduling is proposed as a solution to these problems [7]. To illustrate the situation, an existing scheduling task is described in the following (see [8] for further reading).

In a joint project between the Alcatel-Elin Research Center Vienna and the CD-Laboratory for Expert Systems, an expert system was developed. It supports the technical staff of the Böhler steelmaking plant in generating weekly schedules for steel heats [2]. Side conditions are the same as for the approach proposed in this paper, with the difference that no attempt to handle uncertainty has been made in this first expert system. Böhler is one of the most important European producers of high-grade steel. The plant produces tool steel, high-speed steel, and stainless steel. There are hundreds of different kinds of steel, with 42 chemical elements varying in their specification. The requirements concerning steel quality are very strong.

One problem in scheduling is that residuals of one heat in the electric arc furnace may pollute the next heat. As a general rule of thumb, it can be said that 3% of a chemical element in a heat remain on the electric arc furnace's wall, and 3% of the difference of this element in the first heat and the second heat will be assimilated by the second heat. Two heats that have similar shares of the element in question pose no problem. However, if the second heat has a much smaller percentage than the preceding one, the pollution by the residual from the first becomes too large to be compensated by decreasing the amount added to the second heat. This either means that the quality of the second heat will be badly influenced, or if the polluting element is expensive, that it will be wasted, and money is lost. In the following these two constraints are called compatibility rule. Uncertainty arises because exact values for the chemical elements can very often not be mesured. Further constraints for the scheduling process are temporal, distribution control, spatial, and resource restrictions on and among the aggregates.

III Fuzzy Constraint Relaxation

One objective of the presented strategy is to schedule as many jobs as possible. In order to get the most important jobs scheduled, the evaluation function for an entire schedule must contain a factor representing the importance of jobs. Hence, an evaluation function is defined to assign an importance value to a schedule by adding up the importance values for each job in the schedule. These latter values are calculated by considering the resource requirements, due dates and various other attributes of individual jobs.

A first schedule is generated straightforward by considering most important jobs first. The first schedule may not contain all jobs and still violate some constraints. In these cases, jobs in the schedule will be exchanged to find a proper schedule. A hill climbing search method is used to control this exchange. To compare solutions, an evaluation function based on the given constraints is needed. Fuzzy logic is a sound AI-technique to manage uncertainty as present in this problem [10]. Since [6], and as recently as in [1] or [5], fuzzy logic has been successfully applied to knowledge-based scheduling. This approach generalizes these former ones to include, beside temporal constraints, other kinds like chemical or organizational constraints.

The compatibility of two jobs integrates several factors: Different chemical elements, and the work load of workers. The compatibility between two jobs is calculated by first evaluating the compatibility for each factor separately, in order to get restricted compatibility measures, using six fuzzy sets for the global as well as for each restricted compatibility: *very high*, *high*, *medium*,

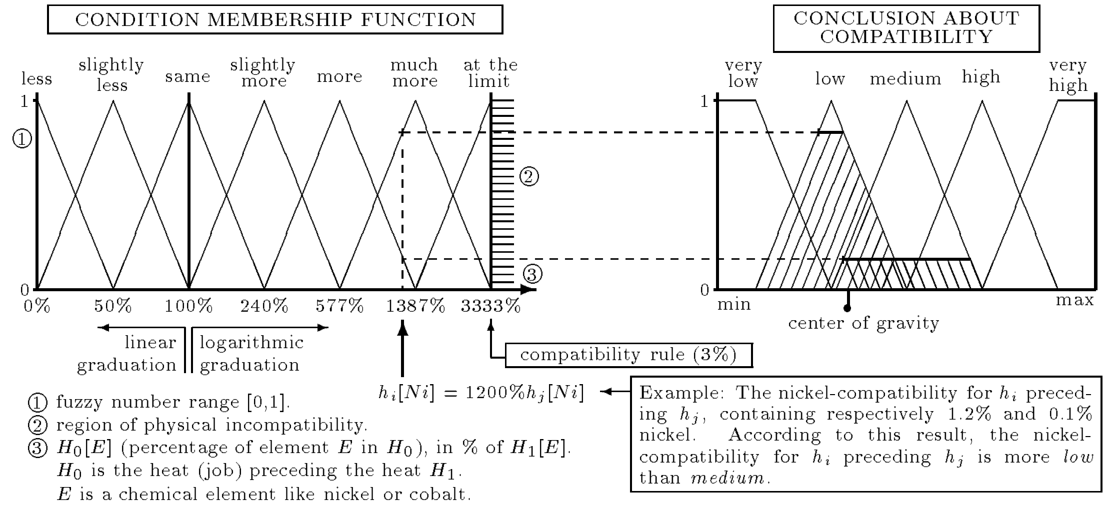

Figure 1: Fuzzy inference to compute chemical compatibility between two heats

low, *very low*, and *no* compatibility. In figure 1, an example compatibility calculation for nickel is shown. The condition parts of the rules contain statements about the percentage of some chemical element in the first heat compared to the following heat. To decide about compatibilities with fuzzy inference rules, the linguistic variables and numeric values must be matched. This is done with a fuzzy membership function as defined in figure 1, both for the condition and for the conclusion part, using standard fuzzy calculation rules.

The resulting fuzzy-values can all be combined by computing a weighted mean of the defuzzified values to get one overall value for the two heats:

$$comp(H_i, H_j) = \sum_{E \in \{Wl, Ni, Cr, \ldots\}} g(E) comp_{[E]}(H_i, H_j)$$

In this formula, $g(E)$ is the normalized weight of a rule and E is a member of the set of all factors influencing the compatibility, namely work load (Wl) and the 42 chemical elements like nickel or chromium. This computation is done for every pair of jobs that may be scheduled. The result is a matrix of fuzzy values where the fuzzy values describe how compatible the sequence of the job of a column after the job in a row is according to all rules.

IV Discussion

To generate a preliminary schedule, the jobs are classified regarding their importance. Then they are scheduled in the sequence of their importances. Scheduling a job means assigning a temporal interval to it. These intervals are spread over the entire planning horizon because of temporal and resource constraints. During the scheduling process, empty intervals are created between scheduled jobs. The compatibilities with the jobs before and behind this empty interval are not considered. If empty intervals with a duration of approximately one job are created, they are filled with compatible jobs as long as there are some available.

Usually, some jobs can not be scheduled, because no interval exists where they would not violate some compatibility constraints. In addition, some empty intervals remain in the schedule, and the compatibility between the jobs adjacent to this interval is usually bad. In order to cope with the given complexity, instead of backtracking to the last scheduling decisions, such a preliminary schedule is repaired or improved by exchanging jobs.

To improve a schedule, a measure for schedules that evaluates which schedule of two is the better one is needed. Unfortunately, the violation of constraints can have far-reaching consequences. The violation of a temporal constraint can cause the need for more resources such as additional energy, or rescheduling in subsequent plants. The violation of chemical compatibility can result in the loss of a heat which would be a heavy financial damage. On one hand, one must consider hard constraints that may not be relaxed, and on the other hand constraints must be relaxed to a certain degree in order to get a feasible schedule with as many jobs as possible. In order to evaluate all these antagonistic constraints, an evaluation function based on the introduced fuzzy values is needed.

V Conclusion

Due to highly unreliable knowledge and conflicting objectives in scheduling applications, mathematical-analytical methods as used in Operation Research approaches are insufficient in many cases. I have illustrated this very problem for a steelmaking plant. In order to overcome this deficiency we have developed a solution which combines two sound AI-techniques for problem solving: Approximate reasoning and constraint relaxation.

I believe that, using the described techniques, the development cycle for scheduling expert system becomes shorter, the knowledge representation easier, and better schedules can be generated compared to earlier used techniques.

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