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Uncertainty Management by Relaxation of Conflicting Constraints in Production Process Scheduling

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Abstract

Mathematical-analytical methods as used in Operations Research approaches are often insufficient for scheduling problems. This is due to three reasons: The combinatorial complexity of the search space, conflicting objectives for production optimization, and the uncertainty in the production process. Knowledge-based techniques, especially approximate reasoning and constraint relaxation, are promising ways to overcome these problems.

A case study from an industrial CIM environment, namely high-grade steel production, is presented to demonstrate how knowledge-based scheduling with the desired capabilities could work. By using fuzzy set theory, the applied knowledge representation technique covers the uncertainty inherent in the problem domain. Based on this knowledge representation, a classification of jobs according to their importance is defined which is then used for the straightforward generation of a schedule.

A control strategy which comprises organizational, spatial, temporal, and chemical constraints is introduced. The strategy supports the dynamic relaxation of conflicting constraints in order to improve tentative schedules.

1 Introduction

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 [6]. Second, conflicting objectives may hinder the definition of an undisputed optimality measure [11]. 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 [10]. To illustrate the situation, an existing scheduling task is described in the following.

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 was 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. The compatibility rule is effective for all 42 chemical elements, but usually only 8 main elements are considered, since the others generally are not expensive, do not vary significantly, or have no great impact on the steel quality. 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.

2 Uncertainty Management

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

No.	Name	Time	Type	Ni	Cr	Co	Mn	Fe	V	W	Mo
h_0	M100	5am		.1	1.2	.005	1.3	95	.1	.005	.005
h_1	A101			12.0	17.8	.25	1.8	69	.005	.005	2.8
h_2	S600			.2	4.3	.0005	.35	78	1.9	6.7	5.2
h_3	K460	11am	CC	.1	.6	.0005	1.15	94	.1	.15	.005
h_4	A506			8.0	17.5	.005	2.0	69	.005	.005	0.05
h_5	M238		BEST	1.2	2.1	.005	1.6	90	.005	.005	.25
h_6	M238		BEST	1.2	2.1	.005	1.6	90	.005	.005	.25
h_7	K116			.1	12	.0005	.4	83	.005	.005	.005

Table 1: Characteristics of given heats in the example

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 [8, 12]. Since [9], and as recently as in [1], fuzzy logic has been successfully applied to knowledge-based scheduling. Our approach generalizes these former ones to include, beside temporal constraints, other kinds like chemical or organizational constraints.

In section 2.1, we propose a method how the given constraints may be represented by fuzzy sets and how an evaluation for a complete schedule is computed. Section 2.2 explains the generation of a preliminary schedule and the search for a better schedule. Such a schedule can only be found if constraints are relaxed, because many constraints are antagonistic. This relaxation will again be based on fuzzy sets.

A small example of the application is described to illustrate the used techniques. The example is restricted to one furnace and the planning horizon is only several hours. Additionally, only a subset of the given constraints is considered in order to reduce the complexity of the example. The existance of a schedule until 5am is assumed. The input is a list of jobs that should be scheduled. The first heat h_0 in the list is the latest job scheduled from the last scheduling process. The main ingredients of each order are given in table 1.

Three heats of table 1 have special characteristics that imply their classification as very important jobs. Heat h_3 is processed on the continuous caster (CC) and has a delivery date. The delivery date is 4pm, the overall treatment takes about five hours, and therefore the processing should start at 11am. Heats h_5 and h_6 shall be cast into big ingots with a special BEST[1]-treatment. This implies that they cannot be produced immediately one after the other. Instead, there should be a time interval of at least ten hours between them.

[1]BEST stands for Böhler Electro Slag Topping.

2.1 Qualitative Representation and Evaluation of Constraints with Fuzzy Logic

The constraints of the given application can be divided into three categories: Constraints on a particular job, temporal constraints, and constraints on the compatibility of jobs.

Constraints on a particular job are constraints based on required resources or aggregates. They are used to describe the importance of jobs. This importance of jobs is used later to control the generation of a preliminary schedule by scheduling the most important job first. In our sense, this importance is a combination of the difficulty to schedule a job in general and its urgency, that is to schedule it for the actual planning horizon. A job that requires a bottle-neck resource like the continuous caster is usually difficult to schedule. A job with a certain delivery date is important, because it must be scheduled in the planning horizon in which the delivery date falls. Jobs that are not important may be shifted to the next planning horizon. To schedule a shifted job eventually, it is necessary that the importance of the job increases over time. The range of fuzzy linguistic variables to represent importance is: *urgent*, *very important*, *important*, *medium*, and *not important*.

The classification of jobs in the list is dependent on the situation in the actual planning horizon. For instance, if for the actual planning horizon many jobs with a high chromium-nickel-alloy exist, then a high percentage of nickel (Ni) is no problem. On the other hand, when there are only few jobs with high nickel percentages, these jobs can be difficult to schedule.

Temporal fuzzy values can be used to describe that jobs are too early or too late. The fuzzy value describes a degree of uncertainty in both direction. One can identify the following linguistic variables: *very early*, *early*, *in time*, *late*, *very late*. For the evaluation of a schedule it makes no difference whether jobs are too early or too late. Therefore, the five variables are mapped onto three: *in time*, *nearly in time*, and *not in time*. Representation of temporal constraints with fuzzy sets is discussed in detail in [1, 3, 4, 9].

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. Accordingly, we define six fuzzy sets for the global as well as for each restricted compatibility: *very*

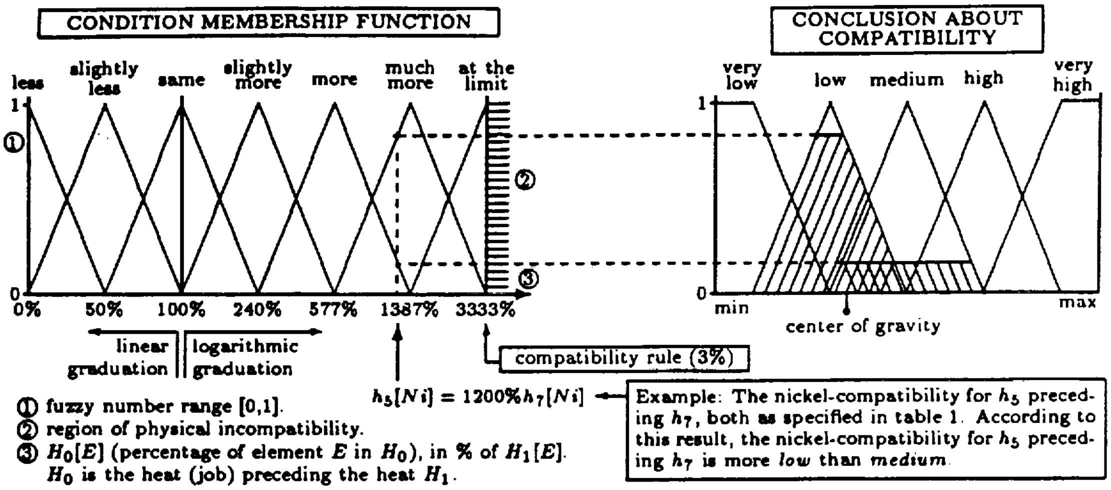

Table 2: Fuzzy inference to compute chemical compatibility between two heats

high, *high*, *medium*, *low*, *very low*, and *no* compatibility. The latter is a special case, since a sequence being classified incompatible can never be scheduled in this order because of hard chemical constraints to be observed.

The compatibility calculation for nickel is shown in table 2. The condition parts of the fuzzy inference rules used for this calculation contain statements about the percentage of some chemical element in the first heat compared to the following heat. In the example taken from table 1, the heat h_5 must contain $h_5[Ni] = 1.2\%$ of the chemical element nickel, whereas heat h_7 should contain only $h_7[Ni] = 0.1\%$. The relative percentage of $h_5[Ni]$ is therefore 1200% of $h_7[Ni]$. The question is, considering only nickel, whether the sequence h_5 preceding h_7 is allowed or not, and if yes, how good this sequence is. To decide this with the given fuzzy inference rules, the linguistic variables and numeric values must be matched. This is done with a fuzzy membership function as defined in table 2, both for the condition and for the conclusion part. In the example, the numeric input of 1200% relates more or less with the linguistic variables *more* and *much more*. Following the dotted lines to the conclusion membership functions for such rules as "IF the percentage of chemical element E in heat H_0 is *more* than in heat H_1, THEN the E-compatibility of H_0 preceding H_1 is *medium*" or "IF the percentage of chemical element E in heat H_0 is *much more* than in heat H_1, THEN the E-compatibility of H_0 preceding H_1 is *low*", membership functions $low_{[Ni]}(h_5, h_7)$ and $medium_{[Ni]}(h_5, h_7)$ appear as a result of the calculation. Their combination is a new membership function defining the nickel-compatibility of h_5 preceding h_7. In order to compare the result with other compatibilities, it must be defuzzified. This can be done by calculating the center of gravity of the surface and then taking the value of its x-coordinate as the result, a standard method in fuzzy calculation [8].

The conditions of the fuzzy inference rules consider only relative values for the percentage of elements like nickel in the two compared heats. Absolute values are of minor interest for the compatibility problem, but could easily be modeled by introducing more complex three-dimensional membership functions. We chose a half-logarithmic graduation to be able to handle those relative values. Since the compatibility rule is asymmetric and only restricts the second heat to a minimal value for a certain chemical element, which must at least be present in this heat, the graduation is asymmetric, too, and only logarithmic on the right half. Beside simplifying the visualization, this logarithmic scale has an additional positive effect, since positions on the right side of the 100% mark that are still near the center, are preferred and get more attention per unit than positions more close to the physical limit on the far right. This reenforces the natural meaning of the fuzzy linguistic variables positively.

The fuzzy inference rules like those used in table 2 give several fuzzy judgements how compatible the heats are. These judgements in form of membership functions can be simplified to the linguistic variable to which the judgement mainly pertains. 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. After defuzzifying the matrix, numeric values that can be rematched with the original fuzzy linguistic variables can be written in the matrix.

Table 3 shows the matrix for the example. It will be used for the construction of the preliminary schedule and during the improvement process. To evaluate

$H_0 \setminus H_1$	h_1	h_2	h_3	h_4	h_5	h_6	h_7
h_0	low	medium	high	low	high	high	medium
h_1	–	very low	very low	very high	low	low	very low
h_2	very low	–	very low	low	very low	very low	very low
h_3	medium	high	–	medium	high	high	high
h_4	high	very low	very low	–	medium	medium	medium
h_5	medium	high	high	medium	–	very high	medium
h_6	medium	high	high	medium	very high	–	medium
h_7	medium	medium	low	medium	medium	medium	–

Note: H_0 precedes H_1, e.g., the compatibility of heat h_3 preceding h_2 is *high*, whereas h_2 preceding h_3 is *very low*.

Table 3: Compatibility matrix for heat sequences

compatibility:	high	medium	low	high	very low	low	
	h_0	h_5	h_7	h_3	h_2	h_1	h_6
time:	5am	7am	9am	11am	1pm	3pm	5pm

Table 4: Preliminary schedule for example heats

schedules during improvement steps, it is necessary to compute an evaluation function for the compatibility of the entire schedule. This can be achieved with a fuzzy and-operator.

2.2 Generating a Schedule

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.

In the list of jobs given in table 1, job h_3 has a delivery date. It will be scheduled first. Thereafter, jobs h_5 and h_6 will be scheduled, because they are very difficult jobs. They include a special treatment and therefore need a long time span between each other. Fortunately, one of them fits well after h_0. h_5 is choosen to be the successor of h_0. The other is scheduled at the end of the planning horizon. The job h_7 is scheduled between h_5 and h_3 to close the empty interval between them. Heat h_2 is another difficult job for the actual planning horizon, because most heats have high percentages of nickel (Ni) and chromium (Cr), and h_2 has only small amounts of both. Moreover, h_2 has large amounts of vanadium (V) and tungsten (W). The best place for h_2 is behind heat h_3. An empty interval remains between h_2 and h_6. There exists no heat in the given list that fits between h_2 and h_6. To fill the interval, h_1 is scheduled between h_2 and h_6. Heat h_4 remains for the next planning horizon. This preliminary schedule is illustrated in table 4.

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.

The actual schedule is called the "currently best schedule". To improve a given schedule, a potential constraint violation that could be improved is searched. In the example, such a violation is found between heat h_2 and h_1. Therefore one of them is taken out of the schedule. If h_1 is taken, no other heat is found in the whole list that would fit better. Therefore h_2 is taken out of the schedule and another heat that fits better is searched. h_2 can be replaced by h_4 and one gets the schedule shown in table 5 which is the "current best schedule", because the evaluation function based on fuzzy sets assigns a better value to this schedule than to the old one.

In the next step, the compatibility of h_7 preceding h_3 is found low. Therefore a job that would be a better predecessor of h_3 is searched. Heat h_5 is the best fit. There are two possibilities: a heat that can be processed between h_0 and h_5 can be searched, or h_3 can be simply shifted in time. Regarding only the compatibility constraints, the best solution would be to exchange h_5 and h_7. Unfortunately, another constraint is violated in this

compatibility:	high	medium	low	medium	high	low
	h_0	h_5	h_7	h_3	h_4	h_1	h_6
time:	5am	7am	9am	11am	1pm	3pm	5pm

Table 5: Intermediate schedule for example heats

compatibility:	high	high	high	medium	high	low
	h_0	h_5	h_3	h_7	h_4	h_1	h_6
time:	5am	7am	9am	11am	1pm	3pm	5pm

Table 6: Final schedule for example heats

case: The interval between the heats h_5 and h_6 should be at least 10 hours. Therefore heat h_3 will be shifted. Since delivery dates may be shifted up to two hours, heat h_3 can start at 9am and heat h_7 started after h_3. The result is the schedule shown in table 6.

Every exchange of jobs in the schedule can be interpreted as one operator in a search process. The search for better schedules can be guided by heuristics based on our evaluation function. This heuristic search is a kind of hill climbing method. Unfortunately, the disadvantage of a hill climbing method is that it can be caught in local maxima. In [7] a technique called TABU search is described that can be used to overcome this problem.

The search will end if no more constraint violations can be detected, or no further improvement can be achieved. It is not that easy to say that no further improvement can be achieved. Here it makes sense to define a distance function between an optimal schedule where all compatibilities would be very high, and all the other constraints would be observed too. If there is such a distance function, the search effort can be restricted by a ratio between distance and search effort. It would be fruitless to invest much more search effort if only a small distance exists. On the other hand, if the distance is large, one should search longer for a better schedule.

3 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. We 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.

We 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.

References

[1] G. Bel, E. Bensana, D. Dubois, J. Erschler and P. Esquirol: "A Knowledge-Based Approach to Industrial Job-Shop Scheduling" In: *Knowledge-Based Systems in Manufacturing, Andrew Kusiak (ed.),* Taylor & Francis, pp 207–246, 1989.

[2] Jürgen Dorn and Reza Shams: "An Expert System for Scheduling in a Steelmaking Plant" In: *Proceedings of the World Congress on Expert Systems, Orlando Fla.,* Pergamon Press, 1991.

[3] Didier Dubois: "Fuzzy Knowledge in an Artificial Intelligence System for Job-Shop Scheduling" In: *Applications of Fuzzy Set Methodologies in Industrial Engineering, Gerald W. Evans et al. (eds.),* Elsevier, pp 73–89, 1989.

[4] Didier Dubois and Henri Prade: "Processing Fuzzy Temporal Knowledge" In: *IEEE Transactions on Systems, Man, and Cybernetics, Vol. 19, No. 4,* pp 729–744, July/August 1989.

[5] Mark S. Fox: *Constraint-Directed Search: A Case Study of Job-Shop Scheduling.* Pitman, London, 1987.

[6] Mark S. Fox and Norman Sadeh: "Why Is Scheduling Difficult? A CSP Perspective" In: *Proceedings of the European Conference on Artificial Intelligence,* pp 754-767, 1990.

[7] Fred Glover: "Tabu Search–Part I" In: *ORSA Journal on Computing, Vol. 1, No. 3,* pp 190–206, 1989.

[8] Constantin V. Negoiţă: *Expert Sytems and Fuzzy Systems.* Benjamin/Cummings 1985.

[9] Henri Prade: "Using Fuzzy Set Theory in a Scheduling Problem: A Case Study" In: *Fuzzy Sets and Systems, Vol. 2, No. 2,* pp 153–165, April 1979.

[10] Patrick Prosser: "A Reactive Scheduling Agent" In: *Proceedings of the Eleventh International Joint Conference on Artificial Intelligence,* pp 1004–1009, 1989.

[11] Stephen F. Smith, Mark S. Fox and Peng Si Ow: "Constructing and Maintaining Detailed Construction Plans: Investigations into the Development of Knowledge-Based Factory Scheduling Systems" In: *AI Magazine 7(4) Fall,* pp 45–61, 1986.

[12] Lotfi A. Zadeh: "Knowledge Representation in Fuzzy Logic" In: *IEEE Transactions on Knowledge and Data Engineering, Vol. 1, No. 1,* pp 89–100, March 1989.