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 applications. This is due to three reasons: The uncertainty in the production process, combinatorial complexity of the search space, and conflicting objectives for production optimizing. Knowledge-based techniques, especially approximate reasoning and constraint relaxation, are promising candidates to solve these problems.

We use a case study to demonstrate how knowledge-based scheduling with the desired capabilities could work. The applied knowledge representation technique covers the uncertainty inherent in the problem domain by using fuzzy set theory. Based on this knowledge representation, the importance of jobs is defined. This classification of jobs supports the straightforward generation of a schedule.

We introduce a control strategy which comprises several types of constraints, namely organizational, spatial, and chemical ones. This strategy supports the dynamic relaxation of conflicting constraints in order to improve the schedule.

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1 Introduction

Planning, and thus scheduling of factory processes involves the simultaneous consideration of jobs to be performed and resources which those jobs require. Usually, a job is identified with a deliverable product which has to meet a certain quality. Hence, each job is correlated to some formal specification of the intended product.

Resources are typically those materials, tools, units, and individuals, which are in the factory to be consumed, to be used, or to work for the production process. Each resource is associated with some formal specification of its characteristics and capabilities.

The planner's task is to correlate these specifications, and to generate a set of operations called a process plan which leads to the production of the desired product. Additionally, it leads to a set of explicit constraints concerning the sequence of operations, and a set of resource requirements for the operations.

When a number of jobs has to be executed together, the composition of their resource requirements imposes additional constraints on the sequence of operations. These constraints prohibit simultaneous use of non-sharable resources. A planner (scheduler) has to consider both the explicit constraints concerning the sequence of operations imposed by the plans, and the implicit constraints concerning the sequence of operations, which are determined by the availability of the resources. The scheduler must also take into account expected delivery and maintenance dates, as well as human factors.

The task of scheduling jobs and resources in a factory is difficult for at least three reasons. First, we have to deal with the combinatorial complexity due to multiple ways of job accomplishment [7, 8]. Second, conflicting objectives may hinder the definition of an undisputed optimality measure [17]. Finally, there is uncertainty in the execution of jobs due to the lack of knowledge about the exact physical facts underlying the production process. Often, reactive scheduling is proposed as a solution to this problem [16]. Thus, it becomes senseless to compute exact scheduling solutions. To illustrate these problems, we describe an existing scheduling task.

In a joint project between the Alcatel-Elin Research Center Vienna and the Christian Doppler Laboratory for Expert Systems in Vienna, an expert system was developed. It supports the technical staff of the steelmaking plant of Böhler Company in Styria (Austria) in generating schedules for steel heats for one week [3].

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 about 2000 different kinds of steel, with 42 chemical elements varying in their specification for each kind. The requirements concerning their quality are very strong.

The steelmaking plant consists of four electric arc furnaces, a ladle-refining equipment with several aggregates to enable chemical reactions, casting cranes, moulds, slots for moulds, and a horizontal continuous casting unit. The first operation on a heat is melting the steel in an electric arc furnace. This process takes between two and five hours. The melted steel is emptied into ladles and a heat treatment is performed in a ladle furnace. The duration is comparable to the one in the electric arc furnace. After this step, special treatments may be performed in the vacuum decarburation unit or in one of the vacuum oxygen decarburation units of the plant. The following step is the processing of the steel in a horizontal continuous caster, to form slabs or billets, or alternatively the casting of the steel into moulds to form ingots. In the latter case, space in the teeming bay is required, where ingots can solidify in their moulds. The solidification process may take up to 24 hours, dependent on the ingot size. A team of workers is needed to set up and strip off the moulds. About 70% of the jobs are cast into ingots despite the higher costs of this process when compared to the casting process with a continuous caster. The process plan itself is known already in advance for every kind of steel and needs not to be computed.

The production is order-oriented, which means that only few stocks exist and almost no production for stocks is made. If a client orders a special steel quality, the company can in many cases not guarantee delivery dates. Actually, about 15% of the delivery dates cannot be met. This delay is due to the amount of different steel qualities and constraints in the technical process, like chemical incompatibilities between jobs.

Böhler itself comprises several plants. Hence, the steelmaking plant receives orders from other plants, like the rolling mill or the forges to produce slabs, billets, or ingots of certain qualities. Compatible orders are used to form jobs, and a list of jobs for one week is worked out. The task of the expert system is then to find a possible sequence of these jobs which violates as few constraints as possible.

In the course of a schedule construction several constraints have to be taken into account. These constraints are often vague and moreover, they conflict with each other. Human experts have no pretension to generate an optimal schedule, because they know that the uncertainty in the execution of the schedule would break this optimality anyway. Human experts can decide that some schedules are better than others, but they can not give straightforward algorithms to construct the optimal schedule. They regard the following constraints:

- **Chemical Constraints**

  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 very rare and therefore expensive, that it will be wasted, and money is lost. For example, if a job requires a high percentage of an expensive element like Cobalt (Co), the subsequent jobs should use as much of the residual as possible. 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. This general rule nevertheless has some exceptions that have to be handled separately.

- **Temporal Constraints**

  For some steel qualities, it is necessary that the steel is still hot after casting for subsequent treatments like forging. In this case, there will be an appointment between the steelmaking plant and the subsequent plant. This appointment must be kept within a variation of ± 2 hours. The average number of jobs with appointments is about 10%. For some jobs no appointments are made, although their subsequent treatment should be done immediately after casting. These jobs should not be scheduled at the end of the week, because the subsequent plants are not working throughout weekends. Some jobs with difficult treatments should be performed during day shifts, because an engineer should supervise these jobs. Usually, the treatments in the aggregates behind the electric arc furnace are shorter than the duration of the melting. Sometimes the duration in the ladle furnace is longer. This duration has to be observed, too.

- **Work Load Constraints**

  If a heat should be cast in many small ingots, the burden for the workers that set up und strip off the moulds is larger than for a few large ingots, because the handling of every mould takes approximately the same time. One objective of the expert system is to achieve a uniform distribution of the burden over the planning interval, also called planning horizon in the literature, for these workers.

- **Spatial Constraints**

  Further constraints for the scheduling process are restrictions on and among the aggregates. The duration of the solidification of big ingots (50 tons) is about one day. Only one ingot can be produced per day, because there exists only one place for such an ingot. Since there is only one continuous casting unit, only one furnace melts steel which is cast for this unit in a certain period of time, in order to be independent of delays in the execution of jobs. If two following heats of one furnace that should be cast both on the continuous caster are of almost the same steel quality, the caster should operate continuously. These jobs are called serial castings. It must be observed that as few delays of the subsequent jobs as possible occur. If an amount of steel is ordered that does not make a full heat, it can be coupled with another one of compatible steel quality forming a double- or triple-casting. In this case, only a part of the heat is poured in the refinement ladle. Durations of treatments in the refinement and casting process will be shorter in this case.

One important aspect and problem we have mentioned is the uncertainty in the production process itself. Often, a certain amount of scrap iron is used for economical reasons for some heats. Scrap iron is classified regarding its presumed ingredients. For a given job, scrap iron that contains already some desired elements is chosen. Unfortunately, these ingredients can only be identified approximately. If a specification for a heat exists, it is not certain whether the actual heat fulfils these requirements. Sometimes additional treatments have to be performed after the scrap is melted in the furnace. Hence, the overall duration of a job as well as the actual steel quality are uncertain.

The second problem we want to cope with is the complexity of the scheduling process. There are about 45 jobs with different steel quality requirements for every furnace for one week. There are 45! or more than $1.19622211 \times 10^{56}$ permutations how the jobs could be scheduled without observing the constraints. Clearly too many to try to evaluate and compare them all. Unfortunately, constraints mainly reduce pairs of possible subsequent jobs and can only be applied if some jobs have already been scheduled. In many cases, the first jobs scheduled will not necessarily ideally fit in the preliminary schedule, and therefore they are likely to become candidates for backtracking. Applying chronological backtracking would re-

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 jobs in the example

sult in an exponential problem that could not be solved in reasonable time. Further complexity arises from interactions between the four furnaces which cannot be discussed in this paper.

2 Uncertainty Management

Our approach to solve the problems mentioned in the introduction is as follows: A first schedule is generated straightforward by considering most important jobs first. In order to cope with the given complexity, the schedule is constructed without chronological backtracking. The importance of jobs is fuzzy and dynamic, which means that the importance of one job may grow over time. The preliminary schedule may not contain all jobs and still violate some constraints. In such a case, 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, we need an evaluation function that is based on the given constraints. We use fuzzy logic for modeling this evaluation. Since we cannot discuss pros and cons of fuzzy logic in this paper, we refer to [14, 18].

In the following subsection, it is shown how the introduced constraints may be represented by fuzzy sets and how an evaluation for a complete schedule can be computed. In subsection 2.2, the generation of a preliminary schedule is explained. Subsection 2.3 describes the search for a proper schedule. Such a schedule can only be found if constraints are relaxed, because many constraints are antagonistic. This relaxation will be based again on fuzzy sets.

We describe a small example of our application to illustrate the used techniques. We restrict the example to one furnace and the planning horizon to one day. Additionally, we consider only a subset of the given constraints in order to reduce the complexity of the example. We assume that there exists already a schedule until 5am. Our 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 jobs 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

[1]BEST stands for Böhler Electro Slag Topping.

immediately one after the other. Instead, there should be a time interval of at least ten hours between them.

2.1 Qualitative Representation and Evaluation of Constraints with Fuzzy Logic

The constraints of the given application can be put into three main groups: 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, the importance is a combination of the difficulty to schedule a job in general and the importance 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. As a matter of fact, jobs that are not that important may be shifted to the next planning horizon. To get such a shifted job ever scheduled, it is necessary that the importance of the job increase over time. The range of fuzzy values to represent this 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. If many large ingots are produced, these orders are difficult to schedule, because there is not enough space for the solidification process.

The inverse strategy is necessary with chemical ingredients: 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.

One objective of our 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, with N the number of jobs:

$$importance(S) = \bigcap_{i=1}^{N} importance(H_i)$$

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. We can identify the following values: *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 values are mapped onto three values: *in time*, *nearly in time*, and *not in time*. From these values a schedule can be evaluated with respect to its temporal constraints:

$$timeliness(S) = \bigcap_{i=1}^{N} timeliness(H_i)$$

Representation of temporal constraints with fuzzy sets is discussed in detail in [1, 4, 5, 15]. We therefore do not further investigate this aspect.

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 high*, *high*, *medium*, *low*, *very low*, and *no* compatibility. The latter is a special case, since a sequence being classified incompatible can

- IF the percentage of Nickel in heat H_0 is the *same* as in heat H_1,
  THEN the Nickel-compatibility of heat H_0 preceding heat H_1 is *very high*.
- IF the percentage of Chromium in heat H_0 is *less* than in heat H_1,
  THEN the Chromium-compatibility of heat H_0 preceding heat H_1 is *medium*.
- IF the percentage of Tungsten in heat H_0 is *slightly more* than in heat H_1,
  THEN the Tungsten-compatibility of heat H_0 preceding heat H_1 is *high*.
- IF the percentage of Vanadium in heat H_0 is *much more* than in heat H_1,
  THEN the Vanadium-compatibility of heat H_0 preceding heat H_1 is *low*.
- IF the percentage of Cobalt in heat H_0 is *just below* the physical limit
  imposed by the specification of an upper limit for Cobalt in heat H_1,
  THEN the Cobalt-compatibility of heat H_0 preceding heat H_1 is *very low*.
- IF the burden of workers in heat H_0 is *very high*
  and the burden of workers in heat H_1 is *low*,
  THEN the work-load compatibility between heat H_0 and heat H_1 is *very high*.

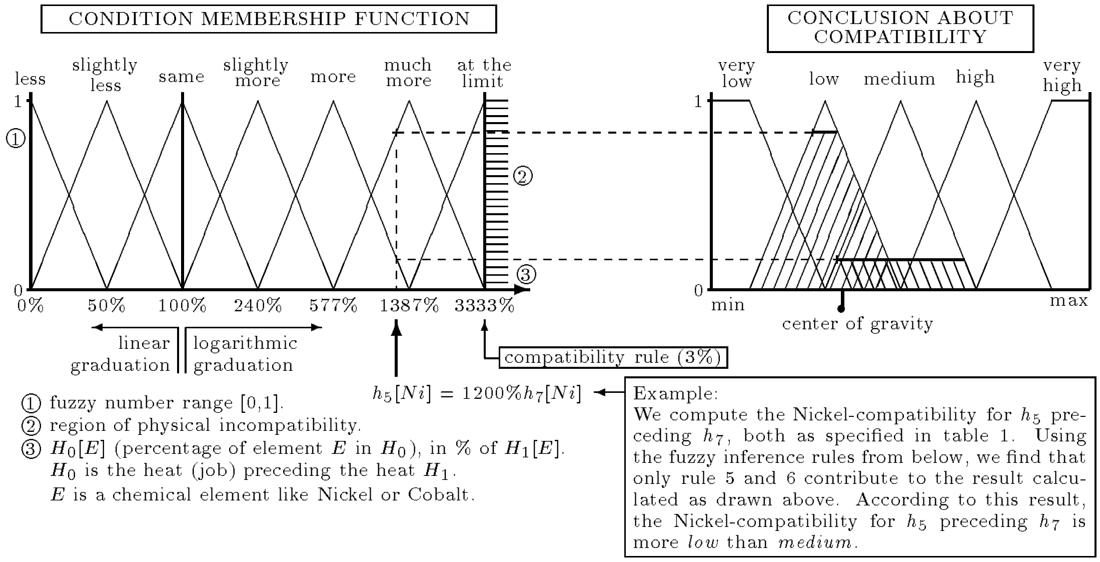
Table 2: Some rules to compute the compatibility of two jobs

never be scheduled in this order because of hard chemical constraints to be observed.

In table 2, several rules defining this compatibility measure for different factors have been listed. The specification of the ingredients are sometimes upper limits and sometimes nominal values. These rules can be interpreted directly as fuzzy inference rules. For example, the compatibility calculation of the percentages from the chemical element Nickel for a sequence of two heats is shown in table 3. In this case, only the two rules 5 and 6 from table 3 contribute to the result, as explained in the box about the example in table 3. The condition parts of the rules 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 now, considering only Nickel, whether the sequence h_5 preceding h_7 is allowed or not, and if yes, how good this sequence is compared to other sequences. To decide this with the given fuzzy inference rules, somehow the linguistic variables and numeric values must be matched. This is done with a fuzzy membership function as defined in table 3, both for the condition and for the conclusion part. In our 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 rules 5 and 6, two membership functions $low_{[Ni]}(h_5, h_7)$ and $medium_{[Ni]}(h_5, h_7)$ appear as a result of the calculation. Their combination

$$comp_{[Ni]}(h_5, h_7) = \max(low_{[Ni]}(h_5, h_7), medium_{[Ni]}(h_5, h_7))$$

is a new membership function defining the Nickel-compatibility of h_5 preceding h_7, which is generally speaking more low than



The fuzzy inference rules with fuzzy linguistic variables:

1. IF the percentage of chemical element E in heat H_0 is *less* than in heat H_1,
   THEN the E-compatibility of H_0 preceding H_1 is *medium*.
2. IF the percentage of chemical element E in heat H_0 is *slightly less* than in heat H_1,
   THEN the E-compatibility of H_0 preceding H_1 is *high*.
3. IF the percentage of chemical element E in heat H_0 is the *same* as in heat H_1,
   THEN the E-compatibility of H_0 preceding H_1 is *very high*.
4. IF the percentage of chemical element E in heat H_0 is *slightly more* than in heat H_1,
   THEN the E-compatibility of H_0 preceding H_1 is *high*.
5. 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*.
6. 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*.
7. IF the percentage of chemical element E in heat H_0 is *just below*
   the physical limit imposed by the element's presence in H_1,
   THEN the E-compatibility of H_0 preceding H_1 is *very low*.
8. IF the percentage of chemical element E in heat H_0 is *over*
   the physical limit imposed by the element's presence in H_1,
   THEN there is *no compatibility* for H_0 preceding H_1.

Table 3: Fuzzy inference to compute chemical compatibility between two heats

$H_0 \setminus H_1$	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 4: Compatibility matrix for heat sequences

medium. 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.

As one observes, 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 for the compatibility problem of minor interest, 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 be at least 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 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.

Table 4 shows this matrix for our example. It will be used for the construction of the preliminary schedule and during the improvement process. To evaluate schedules during improvement steps, it is necessary to compute an evaluation function for the

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 5: Preliminary schedule for example heats

compatibility of the entire schedule. This can be achieved with a fuzzy and-operator. For a given schedule S with N jobs, the evaluation function is given by:

$$comp(S) = \bigcap_{i=1}^{N-1} comp(H_i, H_{i+1})$$

2.2 Generating a Preliminary Schedule

To generate a preliminary schedule, the jobs are classified regarding their importance. Then they are scheduled in the sequence of their importances. The *urgent* and *very important* jobs are scheduled first. To be scheduled means that a temporal interval is assigned to them. These intervals are spread over the entire planning horizon because of temporal and resource constraints. During this 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 having a duration of approximately one job are created, they are filled with compatible jobs as soon as possible.

During this scheduling process, the compatibility matrix as shown in table 4 is used. If for a heat H_0 only one heat H_1 has a good compatibility value, then the two heats can be interpreted as one job consisting of two heats. H_1 is the definitive successor of H_0. If one of these heats is scheduled, the other one is scheduled automatically, too. If a heat H_0 has two possible successors, H_1 and H_2, and H_1 is scheduled after another heat, the heat H_2 will be assigned as the definitive successor of H_0. Jobs with *no* sequence-compatibility are not scheduled one after the other.

This scheduling strategy can be interpreted as a constraint satisfaction problem (CSP). The objects in this CSP are the heats and for every heat a set of possible successors exist. With constraint propagation the set of successors can be reduced. If one job is the only possible successor of a job, it cannot be any more the successor of another job.

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. Instead of backtracking the last scheduling decisions, we try to repair or improve such a preliminary schedule.

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. We choose h_5 to be the successor of h_0. The other is scheduled at the end of our planning horizon. Then a job to close the empty interval between h_5 and h_3 is looked for. The best job is h_7. Heat h_2 is another difficult job for the actual week, 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 be-

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 6: Intermediate schedule for example heats

hind 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, we schedule h_1 between h_2 and h_6. Heat h_4 remains for the next planning horizon. This preliminary schedule is illustrated in table 5.

2.3 Improving the Schedule by Relaxation of Constraints

To improve a schedule, we need a measure for schedules that evaluates which schedule of two is the better one. The first attempt would be to count violated constraints as well as correctly scheduled jobs. Unfortunately, the violation of constraints has 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 great financial damage. On one hand, we must consider hard constraints that may not be relaxed, and on the other hand constraints may 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, we need an evaluation function based on the introduced fuzzy values.

We call the actual schedule the "currently best schedule". This "currently best schedule" is usually not that good. To improve a given schedule, we look for a potential constraint violation that could be improved. In the example, such a violation is found between heat h_2 and h_1. We will therefore take one of them out of the schedule. If we take h_1, no other heat is found in the whole list that would fit better. Therefore we take h_2 out of the schedule and look for another heat that fits better here. We can replace h_2 by h_4 and get the schedule shown in table 6 which is the "current best schedule", because our evaluation function based on fuzzy sets assigns a better value to this schedule than to the old one.

In the next step, we find that the compatibility of h_7 preceding h_3 is low. Therefore we look for a job that would be a better predecessor of h_3. Heat h_5 is the best fit. We thus have two possibilities: We can look for a heat that can be processed between h_0 and h_5, or we simply shift h_3 in time. Regarding only the compatibility constraints, the best solution would be to exchange h_5 and h_7. This would result in the schedule in table 7. Unfortunately, another constraint is violated in this case: The interval between the heats h_5 and h_6 should be at least 10 hours. Therefore we try to shift heat h_3. Since delivery dates may be shifted up to two hours, we can start with heat h_3 at 9am and start heat h_7 after h_3. The result is the schedule shown in table 8.

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 [9, 10] a technique called TABU search is described that can be used to overcome this problem.

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

Table 7: Schedule that violates a temporal constraint

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 8: Final schedule for example heats

The search will end if no further constraint violations can be detected any more, 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 we have such a distance function, we can restrict the search effort 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 the highly unreliable knowledge and conflicting objectives in scheduling applications, mathematical-analytical methods as used in Operation Research approaches are in many cases insufficient. 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.

Our applied knowledge representation technique, namely fuzzy sets, covers the uncertainty of problem domain knowledge and supports the straightforward generation of a schedule based on the importance of the jobs considered. However, due to this ad hoc generation of schedules, some jobs usually remain unscheduled. In order to utilize the compatibility of jobs, we have proposed a control strategy which comprises several types of constraints (organizational, spatial, chemical), and supports the dynamic relaxation of conflicting constraints.

This control strategy can be used to handle emergency cases, too. Hence, it becomes possible to react to events in the course of job execution. In particular, improper conditions for subsequent jobs, require immediate and dynamic adaptation, i.e. reactivity in scheduling. We have achieved this adaptation by supporting the human expert in relaxing those conditions which may solve the case at hand. Using this approach, it becomes possible to evaluate possible scenarios before actual activities are performed. We call this kind of problem solving ‘what-if’ games. Such a simulation prevents the human expert from causing more troubles by an improper decision. Finally, the decision process is more transparent and thus, tracable.

However, in order to support the evaluation and experimentation with chemical element constellations as well as production constraints we have to develop a sophisticated interaction concept. In particular, the condition membership function for inference rules as shown in table 3 should remain under complete control of the human expert. The

- compatibility rule
- element constellation
- shape of the membership functions
- weights of the fuzzy inference rules

should be considered in the course of what-if games with the schedule to support estimates of schedule modifications. The condition membership functions in table 3 for example are to be adapted for each element in two ways. First, their general shape can be altered in order to get sharper or softer transitions from one linguistic variable to the next. Second, the compatibility rule can be changed for one element from 3% to 2.5%, which would mean that this latter element does not remain in the furnace as a residual to the same extent as the other. Additionally, the relative weights of the fuzzy inference rules can be changed to better represent the relative importance of the playing factors, e.g., the work load constraint could be classified more important and thus receive higher weights than chemical constraints. All these adaptations need a lot of fine tuning, therefore the engineers should have the opportunity to experiment with the system in order to be able to match their own way of decision making more accurately. An enriched, spreadsheet-like environment seems to be the proper interaction technique for this type of correlated information. In such an environment, the change of one dimension can be traced simultaneously with the remaining dimensions. This immediate feedback enhances considerably the way the engineers can experiment with their assumptions in order to find better values for the system's parameters.

We intend to build a general fuzzy-scheduling environment to support the development of other expert systems in the domain of industrial production scheduling. We believe that, using the described techniques, the development cycle for scheduling expert system becomes shorter and the knowledge representation easier. Moreover, we assume that with the given techniques, better schedules can be generated.

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