Fuzzy Approach for Modeling Multiple Criteria in the Job Grouping Problem

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Abstract

In flexible manufacturing systems (FMS) jobs (or products) are grouped in order to improve productivity. Usually the goal is to minimize the set-up size or the number of set-up occasions, whereas other criteria are regarded less important and, consequently, omitted from the objective function. In this paper we discuss fuzzy multiple criteria optimization of the job grouping problem in printed circuit board (PCB) assembly. We review briefly the theoretical background of the problem in question and the applied modeling method. The importance of the criteria is prescribed by weighting, and poorly satisfied criterion can be compensated by other criteria. We also show how the criteria affect the solution. The presented method is implemented in our production scheduling system designed for electronic industry and is currently in everyday use.

Keywords: printed circuit boards, job grouping, multiple criteria, fuzzy scheduling, group technology, production planning

TUCS Research Group
Algorithmics

1 Introduction

The construction of a production planning system begins with building a model which represents the production environment. This model, however, is always an idealization of the actual problem: a coarse model may be easier to understand but it may lack some important aspects, whereas a detailed model may be a more accurate representation but harder to understand. Because of this duality there are two approaches for using the model: If there is uncertainty about the accuracy of the model we may want to grant the final decision to a human user, and in this case the model is used to point out the important aspects of the actual problem and possibly for suggesting some solutions. An alternative approach is to solve the problem by using an algorithm which utilizes an objective function based on the model for evaluating the solutions. Figure 1 illustrates the role of the model in this scheme. A system biased on visualization allows the production planner to interact and analyze the schedule, whereas an algorithm driven system solves the given problem efficiently and independent from the user (see [25] for a production planning system based on visualization and [38] for an algorithmical approach to the present problem). Although both approaches have their benefits, extremes should be avoided when designing a production planning system: An algorithm is capable of solving a combinatorial problem inexhaustibly, whereas human tends to try only few possible solutions before choosing one. Instead, human usually has some “outside” knowledge about the reality concerning the problem, whereas the algorithm “sees” nothing but the model. Therefore, the usability of a production planning system, in essence, depends on the balance between these two points of view: the computer should provide the user with sufficient support for making the actual decision (e.g., generate good schedules from which the user chooses—and possibly refines—one for the production). Ammons *et al.* express similar view in [2] (see also [35]): “an ‘optimal’ real-time scheduling system is one that effectively combines computer scheduling algorithms and artificial intelligence methodologies within the context of the versatile capabilities of the human supervisor”.

In this paper we describe a model for *job grouping* problem [8]. In its simplest form the problem can be stated as follows: A set of jobs are processed on a machine. During the processing the machine performs one or several operations on the jobs, and each operation requires one or more tools. Tools are stored in a magazine which can hold a limited number of different tools (i.e., it has a certain capacity). Our task is to determine a loading strategy (i.e., a specification of the contents of the tool magazine at the beginning of the processing of each job) with a minimum total set-up time which depends

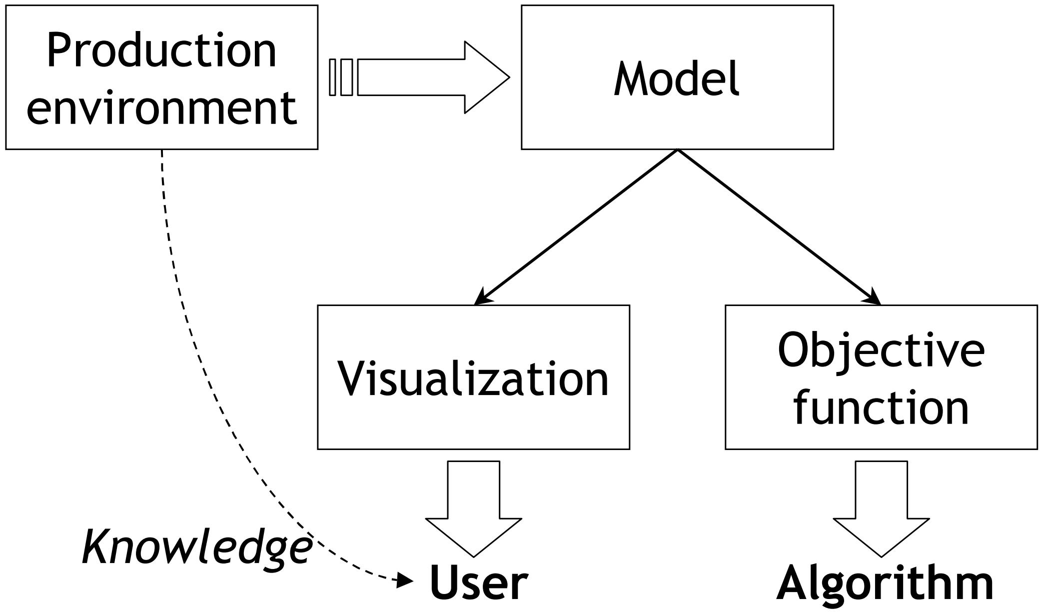


Figure 1: A model of the production environment can be used as a basis for visualization or for calculating an objective function

linearly on the number of *tool switching instants*. As a result, the set-up for the whole *job group* is done on one switching instant and after that all the jobs in the group are processed successively. This set-up problem and family set-up strategies in general are addressed in [27, 41, 30, 3, 29, 1, 38]. Crama *et al.* [7, 9] give a solid theoretical background for the tool management problems and prove that job grouping problem is $\mathcal{NP}$-hard.

Carmon *et al.* [6] divide traditional approaches to reduce set-up times into two categories: reducing set-up frequency by enlarging the lot sizes, and Group Technology (GT). In GT efficiencies in manufacturing are realized by grouping similar tasks (e.g., according to shape, dimension or process route) and dedicating equipment for performing these tasks [28]. A significant advantage of applying GT principles in scheduling is that the set-up time and, consequently, the set-up costs are reduced. Kulkarni and Kiang [26] categorize the approaches to GT as follows:

1. Conventional approaches:

    (a) *Mathematical programming formulation* tries to minimize the total distance measures between parts within families and gives an optimal solution.

   (b) *Graph theoretic method* uses cliques of the machine-graph as means of classification.

   (c) *Matrix formulation* represents part-part, part-machine or machine-machine relationships in a matrix form (this has been the most extensively studied approach in literature).

2. Artificial Intelligence (AI) related approaches:

   (a) *Syntactic pattern recognition* treats the machine sequences as strings which are then used to form part families.

   (b) *Expert systems* use a knowledge-base and clustering algorithms interacting closely with each other; heuristic decisions are made according to 3–4 meta-constraints and the knowledge-base handles violations.

   (c) *Fuzzy mathematics* is used in quantifying imprecise and uncertain relationships (e.g., by using a matrix formulation with non-binary values).

   (d) *Neural networks* involve pattern recognition and feature memorizing as well as learning in order to give a representation of the problem.

For a review of the relevant literature of the job grouping problem, see [38]. An extensive review of different approaches to GT and cellular manufacturing in general is provided by Heragu in [18].

In this paper we extend the job grouping problem by considering also other criteria in addition to the tool set-up. Minimizing the number of switching instants is still the primary (or hard) criterion, but we want to find among the feasible solutions the ones which fulfill best the other (soft) criteria (see figure 2). Fuzzy techniques are used for modeling the soft criteria and for evaluating the solutions. Furthermore, fuzzy approach provides us with means for building an intuitive user interface. Consequently, it has proved to be useful in both aspects—visualization and objective function—of the production planning system.

This paper is organized as follows: We begin with a brief introduction to fuzzy scheduling in section 2. In section 3 we describe an existing production environment, which forms the basis of our research, and discuss the modeling process. Moreover, we describe some technical details of the production environment that affect the model and, therefore, cannot be overlooked. An analysis of the experiences of the system is presented in section 4. Concluding remarks appear in section 5

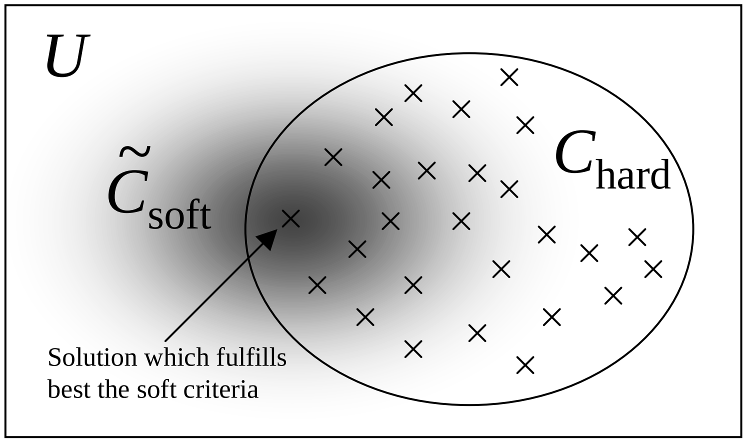


Figure 2: Soft criteria are used for selecting the best solution within a crisp set of feasible job grouping solutions. Darkened area illustrates the region where the soft criteria is satisfied.

2 Theoretical Background

Multiple criteria decision making (MCDM) refers to making decisions in the presence of multiple and possibly conflicting criteria. Hwang and Yoon [21] classify MCDM problems into two categories: *multiple objective decision making* (MODM) and *multiple attribute decision making* (MADM). MODM is associated with the problems where alternatives are not predetermined, and the thrust of the model is "to design the best alternative by considering the various interactions within the design constraints which best satisfy the decision making by way of attaining some acceptable levels of a set of some quantifiable objectives". Alternatively, the MADM problem has usually a limited number of predetermined alternatives, which have an associated a level of achievement of the attributes, and the final decision is made based on these attributes. Thus, MODM is associated with *design* problems and MADM with *selection* problems. Accordingly, the job grouping problem with multiple criteria considered in this paper belongs to the class of MADM problems.

Depending on how the computation and the decision processes are combined in the search for compromise solutions, Fonseca and Fleming [14] identify three classes of multiobjective methods:

1. *A priori articulation of preferences*: Decision maker chooses an aggregating function that combines individual objective values into a single utility value, which makes the problem single-objective prior to optimization.

2. *A posteriori articulation of preferences*: Optimizer presents the decision maker a set of candidate solutions from which the compromise solution is then selected.

3. *Progressive articulation of preferences*: Decision making and optimization occur at interleaved steps. At each step, decision maker supplies preference information to the optimizer, which, in turn, generates better alternatives according to the information received.

Fuzzy decision making in general concerns deciding future actions based on vague or uncertain knowledge. The problem in making decisions under uncertainty is that the bulk of the information we have about the possible outcomes, about the value of new information, about the way the conditions change dynamically with time, about the utility of each outcome-action pair, and about our preferences for each action is typically vague, ambiguous and otherwise fuzzy [33]. In this respect, fuzzy scheduling can be viewed as a branch of fuzzy decision making in which fuzzy logic is applied to one or more features of the "traditional" scheduling problems (e.g., due-dates, job precedence relations, machine-part matrices or processing times, see [17, 22, 40, 31, 10, 20]). A survey of relevant literature of fuzzy decision making in general is provided by Fullér and Carlsson in [15].

Fuzzy optimization originates from ideas proposed by Bellman and Zadeh in their seminal paper [4]. They introduced the concepts of fuzzy constraints, fuzzy objective and fuzzy decision, which have been later applied to many optimization problems. Herrera and Verdegay [19] address four special topics of fuzzy optimization: fuzzy mathematical programming, fuzzy set based models of combinatorial optimization, meta-heuristic techniques and fuzzy scheduling. Furthermore, they give an extensive literature review of the research done in these areas.

Fuzzy sets have also been proposed for extending constraint satisfaction problems (CSP) so that partial satisfaction of the constraints is possible. Dubois *et al.* [11] view the scheduling problem as an extension of CSP, where constraints are *more or less relaxable* or *subject to preferences*. These flexible constraints are either *soft* constraints, which express preferences among solutions, or *prioritized* constraints, that can be violated if they conflict with constraints with higher priority [12].

In the fuzzy constraint satisfaction problem (FCSP) [16, 5, 37, 32] both types of flexible constraints are regarded as local criteria that gives a (possibly partial) rank orderings to instantions and can be represented by means of fuzzy relations. A fuzzy constraint represents the constraints as well as the criteria by the fuzzy subsets C_i of the set S of possible decisions. If C_i

is a fuzzy constraint and the corresponding membership function μ_{C_i} for some decision $s \in S$ yields $\mu_{C_i}(s) = 1$, then decision s totally satisfies the constraint C_i, while $\mu_{C_i}(s) = 0$ means that it totally violates C_i (i.e., s is unacceptable). If $0 < \mu_{C_i}(s) < 1$, s satisfies C_i only partially. Hence, a fuzzy constraint gives a rank ordering for the feasible decisions much like an objective function. FCSP is a five-tuple

$$P\langle V, C_\mu, W, T, U\rangle$$

which comprise the following elements:

V	a set of variables
U	a set of universes (domains) for each variable in V
C_μ	a set of constraints where each constraint is a membership function μ from the value assignments to the range $[0, 1]$ and has an associated weight w_c representing its importance or priority
W	a weighting scheme (i.e., a function that combines a constraint satisfaction degree $\mu(c)$ with w to yield the weighted constraint satisfaction degree $\mu^w(c)$)
T	an aggregation function (e.g., a t-norm that, given C_μ, produces a single partial order on value assignments)

An *instantion* is a solution of the partial constraint satisfaction problem P iff it is a maximal element of the partial order $T(C_\mu)$.

In fuzzy scheduling there are two main constraint types:

1. constraints defining the space of admissible solutions (e.g., release dates, operation durations, precedences, transfer and set-up times, resource availability and resource sharing)

2. constraints characterizing the quality of scheduling decisions (e.g., due-dates, productivity, frequency of tool changes, inventory levels and shop stability)

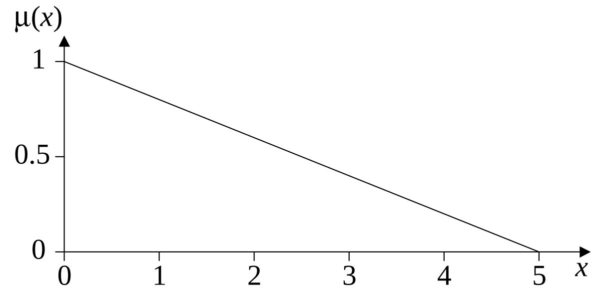
The former can be viewed as uncertainty of the actual process, whereas the latter describe user's preferences which can be relaxed. For example, due-dates describe user's preferences (i.e., jobs *should be* finished by duedate) whereas processing time is subject to uncertainty of the process (i.e., the exact duration of machine operations is *not known beforehand*). Some constraints must be satisfied for schedule to be valid, while others may not always be satisfied and might need to be relaxed. Therefore, a good schedule *satisfies hard constraints* and *relaxes selectively soft constraints to optimize performance.*

The job grouping problem considered in this paper can essentially be regarded as an instance of fuzzy multiple criteria optimization problem. All the criteria can be taken into account by representing each of them as a fuzzy set and aggregating them together to give an overall optimality measure of the solution. The task is to search for a grouping which has the maximum degree of satisfaction of the specified goals and constraints, both of which may be subject to imprecision.

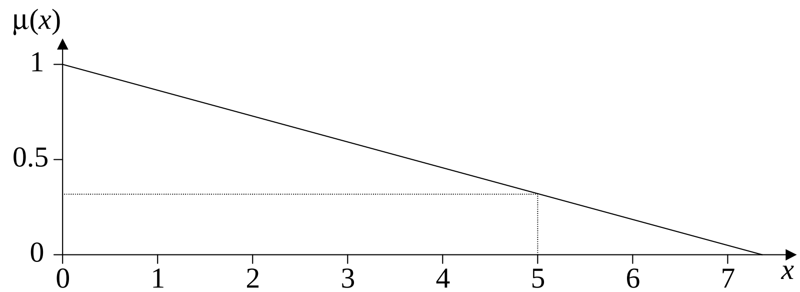
Next, we discuss three distinct aspects of a model based on FCSP: defining the criteria as membership functions, prioritizing the criteria with weights and aggregating the weighted criteria to measure of the optimality of the solution.

2.1 Criteria as Membership Functions

Each criterion associated to the problem can be fuzzified by defining a membership function which corresponds to the intuitive "rule" behind the criterion. However, for some criteria the membership function cannot be defined absolutely because it varies according to some variable. For this reason we apply *extension principle* to the criteria: the membership function corresponding to a criterion is defined by using some specific situation as a foundation, which can then be generalized to cover the whole domain by scaling the membership function [45]. To put it more formally, assume that X and Y are two crisp sets and let f be a mapping from X into Y, $f : X \to Y$, such that for each $x \in X$, $f(x) = y \in Y$. Further, assume that A is a fuzzy subset of X. Now we can define $f(A)$ as a fuzzy subset of Y such that $f(A) = \bigcup_x \{A(x)/f(x)\}$ (N.B., notation $A(x)/f(x)$ means that the element x has a membership grade $A(x)$ in the fuzzy subset A). For example, the fuzzy set which corresponds to criterion "the width of boards within a group should be the same" (see section 3) can be formulated for a specific case where there are ten batches in a group: when all the batches have equal widths (i.e., they are either wide or narrow), the criteria is fully satisfied (i.e., $\mu(0) = 1$), whereas an even distribution (five narrow and five wide boards) yields $\mu(5) = 0$. The membership function of figure 3a connects these two points linearly. Let us now assume that there are 15 batches in the actual group and five of them are narrow. The membership value can be calculated by using the extension principle: the membership function is scaled to correspond the actual situation (figure 3b) and after that the membership value can be derived.



a) A fuzzy set representing the criterion for the case of 10 batches. The value of x is the number of boards with the less common width: $0 =$ all boards are narrow or wide; $5 =$ half of ten boards are wide and the other half narrow.



b) The membership function after applying the extension principle when 5 batches out of 15 are narrow.

Figure 3: Extension principle is used when the fuzzy set representing the criterion "the width of boards should be the same" is extended from an initial case.

2.2 Weighting

The priorities of the criteria must also be considered. This prioritization can be done by *weighting* the corresponding fuzzy sets. Weights ensure that the more important criteria have a greater effect on the objective function than the less important ones. The poorly fulfilled criteria affect the aggregated result more than the criteria with higher membership values. Therefore, weighting can be based on an interpretation of the fuzzy implication as a boundary which guarantees that a criterion has *at least* a certain fulfillment value. Let us assume that a fuzzy criterion $\widetilde{C}_i$ has a weight $w_i \in [0, 1]$ where a greater value w_i corresponds to a higher priority. Thus, the weighted value of a criterion is obtained from the implication $w_i \rightarrow \widetilde{C}_i$. This operation can be defined either classically as $A \rightarrow B \iff \neg A \vee B$ or with any other method proposed in the literature (see [23] for a list of possible implementations for fuzzy implication).

In the system described in this paper we use the following weighting scheme (see [43]) where the weighted membership value $\mu_C^w(x)$ of a criterion C is defined as:

$$\mu_C^w(x) = \begin{cases} 1, & \text{if } \mu(x) = 0 \text{ and } w = 0, \\ (\mu_C(x))^w, & \text{otherwise.} \end{cases}$$

In this case when $w = 0$ the criterion is "turned off" because the corresponding weighted membership value always equals 1 (i.e., it does not affect the overall aggregated result).

However, applying weights in this fashion is quite unintuitive for the user. Therefore, the utilization of the weights has been simplified by introducing the concept of *relative importance* which represents the priorities among the criteria [34]. For example, if a criterion C_1 has relative importance 1 and the relative importance of a criterion C_2 is 5, then C_2 is considered to be five times more important than C_1. Furthermore, if a criterion C_3 has relative importance 5, then it is equally important to C_2. Moreover, the relative importance can be assigned with linguistic attributes (e.g., 1 means equal importance, 3 weak importance of one over another, 5 essential or strong importance, 7 very strong or demonstrated importance and 9 absolute importance) which are easier for the human expert to specify. For example, the "Criteria Equalizer" window in figure 5 gives the user an idea of how relative importances affect the solution. The importance measures can be mapped to fuzzy weights simply by defining that the criterion with the greatest importance has a weight of 1 and scaling the rest accordingly.

2.3 Aggregation

Any fuzzy conjunction operation can be used to aggregate the criteria together. However, it would be preferable if the aggregator had also compensatory properties. Then the effect of one poorly satisfied criterion would not be so drastic on the result of the aggregation, as it is the case with fuzzy conjunction operators (i.e., t-norms). Mean-based or averaging operators are often used because they possess this property. The OWA operator (*ordered weighted averaging*), proposed by Yager in [44], is suitable in this case because the amount of compensation of the operator can be adjusted freely.

An OWA operator of dimension n is a mapping $F : \mathbb{R}^n \rightarrow \mathbb{R}$, that has an associated weight vector $W = (w_1, w_2, \ldots, w_n)^T$ where each weight $w_i \in$

$[0,1]$, $1 \leq i \leq n$, and $\sum_{i=1}^{n} w_i = 1$. Furthermore, $F(a_1, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j$ where b_j is the jth largest element of the bag $\langle a_1, \ldots, a_n \rangle$ (wherefore the operator is called ordered). A fundamental aspect of this operator is the re-ordering step. An aggregate a_i is not associated with a particular weight w_i but rather a weight is associated with a particular ordered position of aggregate (see [46] for further details on OWA operators).

In the system described in this paper we use "soft-and" compensation [36] in which the weight vector is defined

$$w_i = \frac{2i}{n(n+1)},$$

where n is the number of criteria to be aggregated together. This weight distribution yields a fair compensation, which in our case is considered to be more desirable than imposing strict rules on the evaluation of the optimality of the job grouping.

3 Modeling the Production Environment

In this section we describe an actual production environment for printed circuit board assembly (Teleste Corporation, Nousiainen, Finland). An assembly line for automatic component printing usually comprises several successive work phases; in our case it consists of three phases: In the first phase, an initially empty PCB passes a glue dispenser which inserts a glue dot at each onsertion locus or draws adhesive paste over the whole board in order to fixate the electric components. In the second phase the actual printing is done by an onsertion machine. In the third phase the PCB visits an oven which heats it in order to harden the glue/paste. After these phases the PCBs wait in a buffer storage and finally pass a manual insertion phase in which some large components are inserted and soldered.

Although there are several subsequent phases, we concentrate on the *surface mount device* (SMD) machine which is used for the component printing in the second phase [42]. The reason for this is that the set-ups and component printing of the SMD machine consume most of the production time and, therefore, it is the bottleneck of the whole production line. The machine gets surface mount components from four carriage modules of the feeder unit comprising in total six carriage modules. Components can be loaded to two outermost carriage modules while the other four are used in printing.

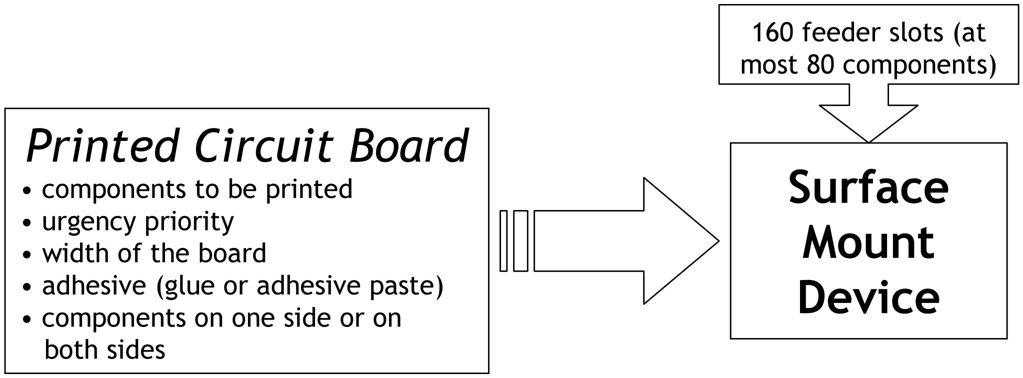


Figure 4: Features affecting the job grouping problem

3.1 Identifying the Aspects of the Production

If we look at the different jobs (PCB batches) which are processed on the line, we notice that their total number is very high but the amount of PCBs in a job is usually small. The daily production program includes typically 4–10 different *products* (PCB types). The set-up times form a significant part of the total production time (it can be as much as 50 percent). Therefore, our main objective is to minimize the set-up times by grouping the products efficiently. Normally the due dates are considered the most important restriction, but in this case they are managed by a two-level priority classification: products are either *urgent* or *non-urgent*. The *widths of the PCBs* vary, and the change of the conveyor width causes an interrupt in the printing process. Also, some PCBs require component *printing on both sides*, and in order to avoid unnecessary storaging, the other side should be printed as soon as possible after the first side. The last feature that affects the production is that the oven must be heated or cooled if *the type of the adhesive* changes. In figure 4 the aforementioned aspects of the production environment are summarized.

Because the total number of different component types in a PCB is significantly smaller than the capacity of the feeders in the machine, we can quite freely choose an appropriate input organization. In our earlier work [38] we developed several methods (e.g., heuristic algorithms) for solving the grouping, but our solutions lacked a measure which takes into consideration the various aspects of the actual production environment. By using a "classical" objective function we were able to find a grouping with a minimal number of groups and control somewhat the distribution between the groups. The aforementioned aspects—urgencies, conveyor widths, oven temperatures, the management of the double sided PCBs and the size of the set-up—were all ignored. Although the original heuristics improved the actual production, further refinements were still needed.

3.2 Defining the Criteria

To sum up the discussion of the previous section, we give now a more accurate description of the criteria present in the environment:

- Track widths: The conveyor track widths of the PCBs in a group should be equal.
- Double-sided PCBs: Opposite sides of a double-sided PCB should be processed in the same group.
- Set-up size: The number of different components needed for the group set-up should be minimal.
- Urgency: Jobs belonging to the same urgency class should be in the same group.
- Oven temperature: A group should comprise only glued or pasted boards.
- Number of groups: The number of groups should be minimal.
- Total set-up: The sum of set-up sizes of all the groups should be minimal.

The primary objective is minimizing the number of groups since the set-up times are considered to be the bottleneck of the production. This can be done by modeling also this goal as a soft criterion. However, the difficulty with this approach is that the relative importance of the criterion must be set so high that it dominates the solutions. That in turn narrows the effective range of the other criteria, and their contribution to the solution diminishes. Alternatively, we can use some heuristic method to compute an initial solution and then improve it by applying the other criteria. Consequently, the distribution of weights becomes more even and the effect of the less important criteria becomes notable when evaluating different solutions. Nevertheless, the Number of groups criterion can be reinstated by changing its role: the number of groups can decrease, if it enhances the optimality of the solution, but it can never increase. This ensures that this criterion cannot get worse regardless the weight associated with it.

In addition to the aforementioned objectives, we also considered Similarity criterion (the amount of common components of PCBs in the same group should be maximal) and Evenness of groups criterion (group sizes should be as even as possible), but they were rejected later. Because the similarity between two batches and the similarity between two groups are not commensurable, the former criterion is hard to implement. Although an even distribution of batches is a somewhat desirable goal, the benefits gained by applying the latter criterion are negligible.

The criteria are defined as membership functions (see figure 3). The expression "should be" (as in "the conveyor track widths of the PCBs in a group *should be* equal") is interpreted so that the more the situation resembles the ideal case, the higher membership value it gets. For example, a homogenous group comprising only wide or narrow boards is ideal for Track widths criterion and, therefore, has a membership value 1, whereas in the worst case the group has the same amount of both board types and this fifty-fifty case gets a membership value 0. When these two extremes are connected linearly, we get a preference for homogenous groups (which is our interpretation of "should be"). The membership functions for the other criteria are defined in a similar fashion.

4 Test Results and Observations

The model presented in this paper is implemented in our integrated machine scheduler system (see figure 5) [24]. System features include an interactive graphical user interface, which provides the production planner with a clear visualization of the situation, a set of possible operations for affecting the grouping (e.g., fixing jobs to a certain group), warning in exceptional situations (e.g., component starvation), numerical information (e.g., estimated printing times) and tight integration with other software (e.g., printing order optimization). These features are discussed in length in [39] along with an analysis of the improvements in efficiency observed in the production plant.

In this section we present test results for a set of actual production data. Table 1 represents a typical test case of the size of 30 jobs The columns of the table describe the characteristics of the board: urgency indicates whether the board is urgent or not, width discerns wide and narrow boards, adhesive glue and paste boards, and the reverse side of the board (if it exists) is indicated in the last column.

The optimization algorithm used in the test runs is local search heuristic which performs repair based operations. This methods allows the hard constraints to be violated occasionally in order to broaden the scope of search

Board	**Urgency**	**Width**	**Adhesive**	**Reverse side**
ASU4021	Non-urgent	Wide	Glue	RIE9309E
AXF60065	Non-urgent	Wide	Paste	—
AXR15850	Non-urgent	Narrow	Paste	—
AXT245	Urgent	Wide	Paste	—
CAF9517B	Non-urgent	Wide	Paste	—
CAG963BB	Non-urgent	Narrow	Paste	CAG963BT
CAG963BT	Non-urgent	Narrow	Paste	CAG963BB
COR231E	Non-urgent	Wide	Paste	—
COT23XC	Urgent	Wide	Glue	—
CRT212	Non-urgent	Wide	Glue	—
CWA230C	Non-urgent	Wide	Paste	—
CVD201G	Urgent	Wide	Glue	—
D2187B1	Non-urgent	Wide	Paste	D284A1
D2484A1	Non-urgent	Wide	Glue	D2187B1
DOT113GB	Non-urgent	Narrow	Glue	—
DOT21365	Urgent	Narrow	Glue	—
DOT213PR	Urgent	Narrow	Paste	—
DPS230	Non-urgent	Wide	Paste	—
DTC800EN	Non-urgent	Wide	Glue	—
DXT802EN	Non-urgent	Wide	Paste	—
GHA001D1	Non-urgent	Wide	Glue	—
M3156A	Urgent	Wide	Glue	M3159A1
M3156A1	Urgent	Wide	Glue	M3159A
M7113A1	Non-urgent	Wide	Paste	—
M9212B1	Urgent	Wide	Glue	—
MHE6104	Non-urgent	Wide	Paste	—
RIE9309E	Urgent	Wide	Glue	ASU4021
S1109B1	Non-urgent	Wide	Paste	—
S3510	Non-urgent	Wide	Glue	—
TTC810	Non-urgent	Wide	Glue	—

Table 1: Characteristics of the boards in the example problem

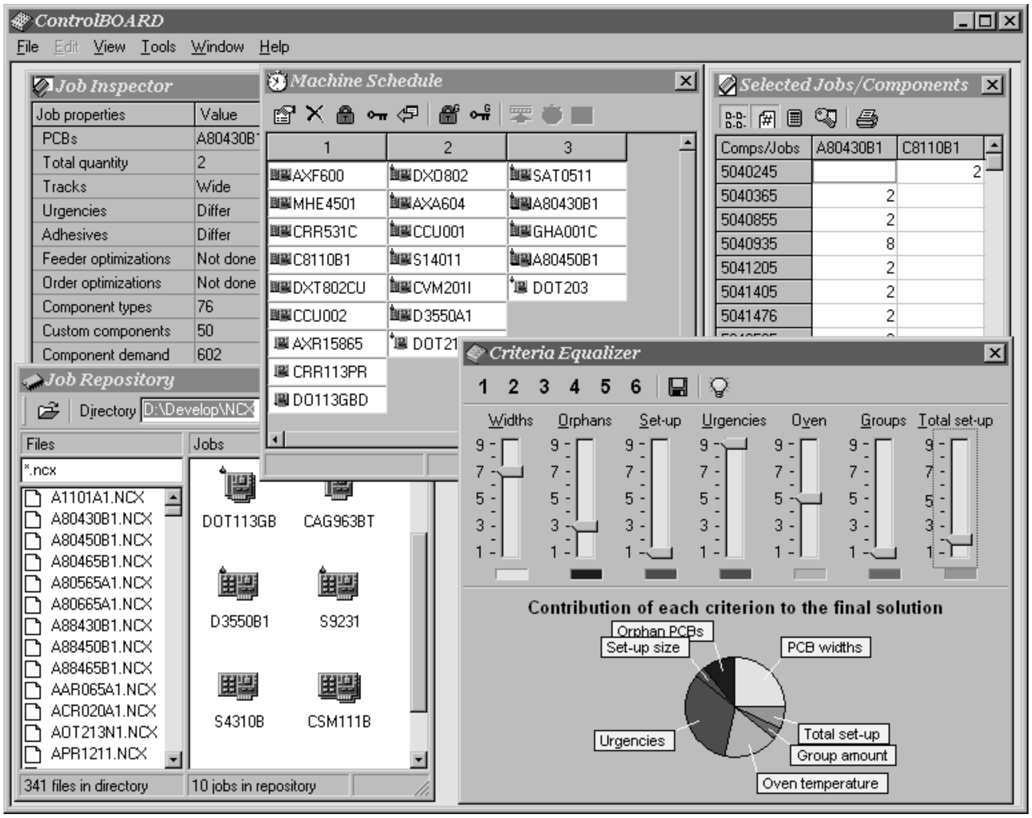


Figure 5: A screenshot from the ControlBOARD integrated machine scheduler system

after which the repair operations are used to bring the search back to the set of feasible solutions. The algorithm can be stopped at any time and the currently best solution is available to the user. See [38] for a more detailed description of the search heuristics.

The fulfillment of the criteria in different weight configurations is presented in table 2. The tests were made on a PC with a 266 MHz processor, and in each case (excluding the initial allocation) the optimization algorithm ran until one minute had elapsed. The rows of the table describe the following configurations:

- *Initial allocation* shows the situation after the initial heuristic (see [38]) which considers only the set-up sizes when forming the groups.

- *Equal weights* represents a grouping where equal weights have been assigned to all the criteria.

	Group size				Urgencies (%)				Widths (%)				Oven (%)				Orphans				Set-up size			
Situation	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*
Initial allocation (clustering heuristic)	4	12	2	12	75	75	50	83	50	75	100	92	50	58	100	50	1	0	1	0	121	150	104	142
Equal weights (W1:O1: S1:U1:V1:G1:T1)	12	10	4	4	92	80	75	75	82	100	100	75	100	80	100	75	1	3	1	1	144	154	138	129
Only urgency	16	4	6	4	100	100	83	100	88	100	67	50	69	100	67	50	1	2	0	1	159	130	155	157
Only oven	4	8	9	9	50	88	67	67	100	88	89	56	100	100	100	78	0	1	2	3	158	148	144	154
Only width	6	2	7	15	67	50	57	87	100	100	100	100	67	100	86	67	0	1	1	0	129	148	144	155
Only orphans	10	10	7	3	80	80	57	67	80	80	71	100	60	60	57	67	0	0	0	0	159	151	150	147
Only set-up size	2	13	9	6	50	85	67	50	100	85	78	67	50	62	56	50	0	0	2	2	50	158	158	133
Set-up size and total set-up	5	1	13	11	60	100	85	73	60	100	85	82	60	100	54	55	1	1	0	0	129	52	158	158
Width and urgency	5	6	3	16	60	67	100	88	100	100	100	100	80	67	100	63	1	0	2	1	152	129	142	159
Width, urgency and oven	13	7	6	4	85	100	50	100	92	100	83	100	92	100	50	100	2	2	2	2	158	148	157	130
Width, urgency, oven and orphans	5	4	13	8	60	100	92	88	80	100	85	100	60	100	100	100	1	1	1	1	151	155	156	152
Width, urgency, oven and orphans	6	13	4	7	50	85	100	100	83	92	100	100	67	85	100	100	1	1	2	2	159	146	130	148
All criteria (W9:O4:S2: U7:V5:G1:T1)	7	5	2	16	57	60	100	88	100	100	100	94	86	80	100	63	0	0	0	0	156	117	130	157

Table 2: A summary of different criteria configurations and the fulfillment of the criteria in each group

- *Only urgency* (*oven*, *width*, *orphans* or *set-up size*) represents a grouping where only urgency (oven, widths, orphans or set-up size) criterion is considered.

- *Set-up size and total set-up* minimize both the set-up size of each group and the total sum of the set-up of the whole grouping.

- *Width and urgency* considers these two criteria weighting them equally.

- *Width, urgency and oven* considers these three criteria weighting them equally.

- *Width, urgency, oven and orphans* considers these four criteria weighting them equally.

- *Width, urgency, oven and orphans (W7:03:U1:V9)* considers these four criteria with the following weights: width = 7, orphans = 3, urgency = 1 and oven = 9.

- *All criteria (W9:O4:S2:U7:V5:G1:T1)* represents a grouping where the criteria have the following weights: width = 9, orphans = 4, set-up size = 2, urgency = 7, oven = 5, groups = 1 and total set-up = 1.

In each case the algorithm forms four groups from the 30 jobs. Sizes of these groups are presented in the respective subcolumns in the group size column, and the fulfillment of the criteria of each individual group are presented in a similar fashion. Urgencies, widths and oven columns show the percentage of the jobs with the more common property of the whole group (e.g., 75 in the urgency column means that 75 percent of the jobs in the group have the same urgency). Therefore, 50 corresponds to the worst case (in which half of the jobs have one property and the rest another), whereas 100 describes an ideal situation (where all the jobs in the group share the same property). Orphans column shows the number of the orphan boards (i.e., boards that do not have the reverse side in the same group). In order to satisfy the orphans criterion the number of orphans should be as low as possible. Set-up size column shows the amount of feeder slots required by the group (maximum 160 slots). In order to satisfy the respective criterion the set-up size should be as small as possible—but in practice the set-up sizes tend to reside near the upper limit of the capacity.

Figure 6 illustrates the results of table 2. The aforementioned weight configurations are listed along the horizontal axis, and the vertical axis represents the percentage of the fulfillment of the criteria. Orphans criterion is scaled by setting 100 to correspond a situation in which there are no orphans

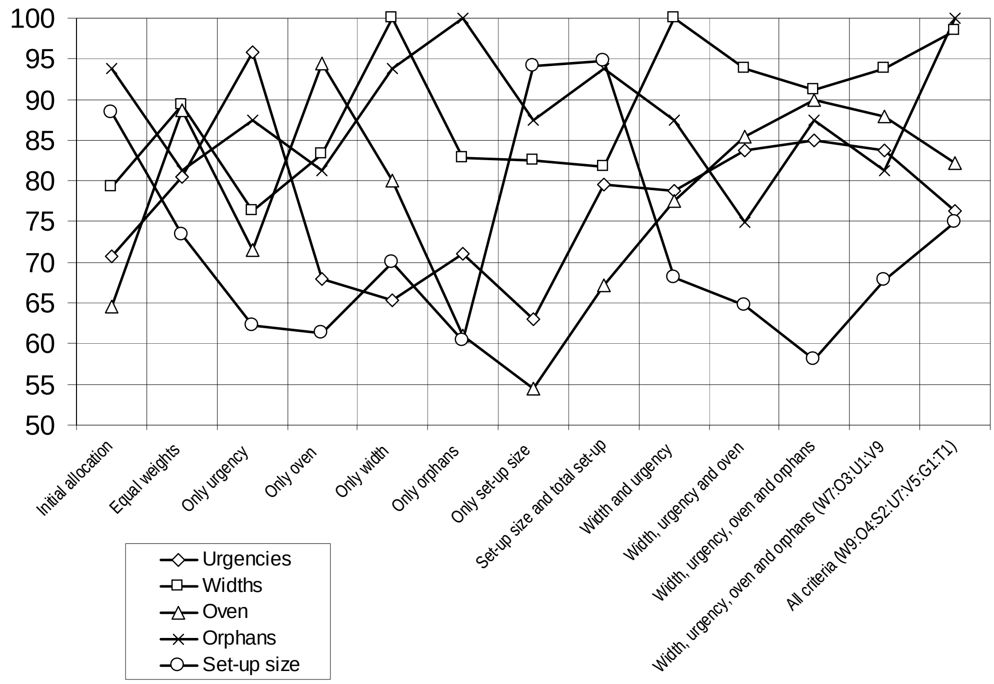


Figure 6: Fulfillment of the criteria

and 50 the worst case where all eight double-sided boards are orphans. Similarly the set-up size criterion is scaled so that 80 slots represent an optimal case and 160 the worst case. The points in the graph represent the averages over the four groups in each case and the purpose of the lines connecting the points is merely illustrative.

The initial allocation considers only the set-up size criterion while the rest are scattered on a large area. When we optimize this grouping with equal weights, we can see that the fulfillment of the other criteria is compensated by a notable decrease in the set-up size criterion. Furthermore, because of the compensation, the criteria are more tightly together than in the initial grouping. This is further illustrated when we apply only the urgency criterion: urgency criterion becomes well fulfilled at the cost of the other criteria. Similar tendencies can be observed when optimizing only oven, widths or orphans (in the last two cases the grouping manages to completely fulfill the criterion in question). Because reverse sides have always the same width, in the case of only width the orphan criterion is also high, and, conversely, when we consider only orphans, the other criteria drop very low because the reverse sides of a board may have dissimilar characteristics. When we apply only set-up size criterion, the set-up size gets better than in the initial grouping, and it improves further when total set-up criterion is also applied. A grouping in which we apply both width and urgency criterion can be contrasted with the case in which only width is considered: in both cases width criterion is completely satisfied but urgency criterion is noticeably better when it is applied whereas the rest of the criteria are then more poorly satisfied. The idea of compensation is illustrated when oven criterion is added to the situation: the increase in both oven and urgency criteria is compensated by the decrease of the width criterion, and when orphans criterion is added, the compensation further decreases the width criterion while the rest of the criteria increase. In this case the weights of the four criteria are equal and their fulfillments are packed together tightly. Next, we distribute the weights and observe that the criteria are not as close together as in the previous case. A similar phenomenon can be seen in the last grouping, in which all the criteria have distributed weights: there are two peaks (widths and orphans) pointing out of the "pack" but they are compensated by the other three criteria (compare this setting to the grouping with equal weights).

5 Concluding Remarks

In this paper we discussed the job grouping problem. We studied an actual production environment for electronic assembly and presented a model which uses fuzzy sets for defining the soft constraints present in the production process. This model is now an integral part of an production planning system and it has provided flexibility and interactivity that the previous version of the system lacked. In addition, we showed that the prioritization scheme presented in this paper has the desired effect on the solutions provided by the search algorithm. Further research on the effect of different OWA weight vectors—especially on parametrized variants such as ME-OWA (maximum entropy) and S-OWA (for details, see [45]) and exponential OWA introduced in [13]—and their integration to the user interface is currently under work. Also, new implementations are developed for different production environment types in addition to electronic assembly.

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