An Adaptive Evolutionary Algorithm for Production Planning in Wood Furniture Industry

J.C. Vidal, M. Mucientes, A. Bugarín and M. Lama

Abstract— **This paper describes an Adaptive Evolutionary approach to the problem of the production planning task in the wood furniture industry. The objective is to schedule new incoming orders and to regenerate the scheduling for already existing orders when necessary. Complexity and uncertainty of this task promotes the use of an hybrid solution that combines Evolutionary Algorithms (EAs) and Fuzzy Sets. On one hand, EAs allow an efficient and flexible use of large number of parameters involved in the scheduling task and to reduce its computation time. On the other hand, Fuzzy Sets improve the confidence in the evaluation of the solutions when uncertain knowledge is used. This evolutionary approach to the production planning task is a part of a knowledge-based system that manages the product design life cycle of wood-based furniture and is being currently implemented on a wood furniture industry.**[1]

I. Introduction

Custom furniture industry is facing unprecedented levels of competitiveness that forces organizations to increment their productivity and to reduce their costs, since customers expect quickly customized higher-quality products at lower cost. A way to achieve some of these objectives is the improvement of the processes related to the product design and assembly [2]. As a part of the product life cycle, production planning plays an important role to get these objectives [12], since an accurate time estimation and an optimal assignment of resources improve the organization productivity, logistics and storage capacity requirements.

The problem of production planning and scheduling in the furniture industry is not new. Conventional search and optimization techniques are hard to apply for scheduling of large-scale custom furnitures. On one hand jobs, resources and the variety of constraints and preferences configure a huge and complex search space that cannot be timely solved in practice by traditional techniques. On the other hand, the schedule must be frequently updated in response to changes in the jobs priority or the availability of resources. However, in real-world production environments, efficiency and optimization must be balanced and results close to the optimum but achieved in a reasonable amount of time are often sufficient. Evolutionary Algorithms (EAs) are well suited to such problems due to their adaptability and their effectiveness at searching large spaces [8]. In this field EAs are a useful tool for only analysing a small number of possible solutions in order to find an acceptably optimized plan. In this sense, the time required to schedule the production plant is drastically reduced.

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An important feature for planning in the wood furniture industry is the difficulty to estimate its manufacturing times. Unlike other planning domains, humans still have much influence on the furniture manufacturing processes. Computer-Aided Manufacturing (CAM) products estimate the time of machinery from Computer-Aided Designs (CAD) designs. However, these products do not take human influence into account and do not provide the capacity to estimate non-machinery time. In practice, most of estimations are based on experts knowledge and are therefore uncertain. For this reason, the planning task must be endowed with the capability to deal with the uncertainty of time estimations the schedules are based on.

In this paper, we describe the module in charge of the production planning task as a part of a Knowledge-Based Business Process Management System (BPMS) [27] in the wood furniture industry that solves the product design task by means of knowledge-enriched workflows [25]. The module is implemented by means of an adaptive EA that selects a number of suitable production options taking into account the jobs to be done and the resources available for them to be done (current workload of the industry, availability of the resources centres, ...). The planning module includes a fuzzy rule based system for improving the planning task in order to also take into account the uncertainty due to bad time production estimations and other non-foreseable factors thus allowing plans with lower levels of uncertainty to be considered. The BPMS is based on a framework [27] that combines the Unified Problem-solving method Modelling Language (UPML) [6] with workflows to define and reuse both static and dynamic knowledge in process-oriented view. Parts of the BPMS have been implemented and tested at a wood furniture industry, whilst other are currently under development.

The paper is structured as follows: section II describes the scheduling problem which custom furniture industry faces. Based on this description, section III describes the modelling approach to solve the problem and its implementation. Finally, section IV present the conclusions and the future trends of this work.

II. Wood-based Furniture Manufacturing

This section describes the most elementary concepts of the production planning task in the custom wood-based furniture manufacturing industry and provides the basis for the approach presented in the following sections. We must remark that some of the task features described in this section are attached to the characteristics of the industry the system is being developed

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for. However, experience tells us that most of companies of this field face similar troubles when promoting the automation of the production planning task and therefore, could take advantages of the solution herein described.

The aim of production planning is to schedule a finite set of client orders $O = \{O_o, 1 \leq o \leq NO\}$ in the manufacturing workload. A finite set of resources $R = \{R_r, 1 \leq r \leq NR\}$, both human as well as machines (cutting machine, horizontal band saw, two side thickness planner, abrasive finishing machine, etc.) is in charge of performing the different manufacturing operations $MO = \{MO_m, 1 \leq m \leq NMO\}$ (cut, shape, assemble, finish, etc.) of a production plant. Client orders must be sorted according to a given priority and its delivery date. Orders are subdivided in a set of jobs $J_i = \left\{J_i^k, 1 \leq k \leq NJ_i\right\}, O_i \in O$ with a specific manufacturing operation MO_m to be done. Jobs inherit the client order precedence but are also sorted according to the operation dependencies. These dependencies are defined by means of predefined manufacturing routes which are assigned to a furniture manufacturing based on its CAD design specification. For example, the use of a type of joint may require to assemble the furniture before the finishing, thus increasing the manufacturing, packaging and/or shipping costs.

A special feature of the planning task in this field is that jobs are not directly related to resources. A job is assigned to a resource centre C_c ($C = \{C_c | 1 \leq c \leq NC\}$) which is in charge of dividing the work among its resources. In this sense, the resource centre has the capability to assign the job to an individual or a group of resources. For this purpose, a set of strategies $S = \{S_s | 1 \leq s \leq NS\}$ has been defined to group resources. Basically, three type of strategies have been defined: *(i)* a single one, *(ii)* a percentage or *(iii)* all the available resources belong to the group that will perform the job. However, the association of operations is made at a resource level and thus centres can only perform those operations that can be carried out by their resources. Moreover, resource assignment to centres may vary along the time. In a certain sense, resources define time slots that are assigned to a centre. Thus, the time slots for resource R_r can be defined as $TS_r = \left\{TS_r^t, t = ([t_{in}, t_{out}], J_i^k)\right\}$ where t represents the resource assignment to perform a job J_i^k in the time interval $[t_{in}, t_{out}]$ in resource R_r. Initially, all the resources are available, i.e. they have no schedules assigned $J_i^k = \phi$ for $k = 1, ..., NJ_i$ and $i = 1, ..., NO$.

Let us suppose a client order O_1 composed of one hundred office desks. The office desks may consists of different kinds of materials such as metal, wood and wood-based products, plastic, melamine foils, laminate, PVC, and so on. Based on the CAD designs of the desks, specific manufacturing, and assembly rules related to the kind of material the furniture will be made of, the manufacturing operations to be performed and thus its jobs J_1^k for $k = 1, ..., NJ_i$. In order to define a manufacturing plan, each job must be assigned to a resource centre. For example, job J_1^1 (e.g. in charge of cutting the melamine panels) may be assigned to the cut centre C_1 which assigns two cutting machines (R_1 and R_2) to perform this job.

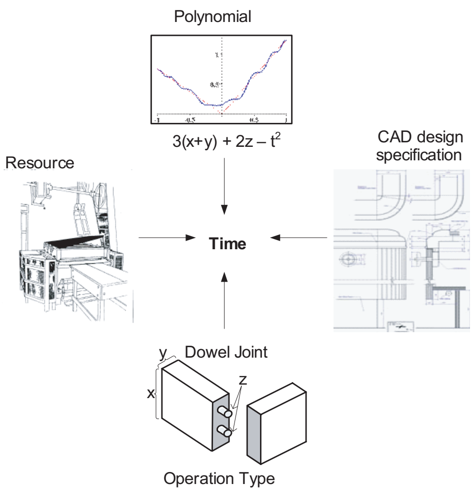

Fig. 1. Time estimation of a resource manufacturing operation is built from a polynomial equation

As regards the manufacturing plan, this assignment means that the free time slots of the R_1 and R_2 resources are assigned to the job.

The main difficulty related to the planning task is that the time to perform a job depends on *(i)* the resource that will perform it, *(ii)* the manufacturing operation to be performed, and *(iii)* the furniture specification (specially related to material). This scenario implies that the job time must be estimated for each manufacturing plan generated along the planning process. We use an estimation method based on influence parameters in order to determine a polynomial approach for estimating the time of resource operations. Once these parameters were identified by means of regression equations (over a set of well balanced examples that were timed), the coefficients of these polynomials are calculated. Following with the office desk example, suppose the drying kiln operation J_1^1. The polynomial that obtains the job time for this process should take into consideration relevant parameters such as the intended use of the product (inside or outside use), the product volume, or the moisture content among other aspects. As it is depicted in Fig. 1, time estimation requires to relate the resource and its polynomial equation with the CAD specification of the furniture purpose of the evaluation. Since time recordings are not available for all future productions, and the relevant parameters for them may also be different from previous ones, time estimations are always associated to a degree of uncertainty that is inherent to the production problem.

III. An Adaptive Fuzzy Evolutionary Approach to the Production Planning Problem

This section describes our approach to develop the production planning task described in section II. Since some of the features of the BPMS influenced the planning module solution, it is worth to briefly mention them: the BPMS is modelled as a workflow specially designed to cover the product design in the wood furniture industry within a new

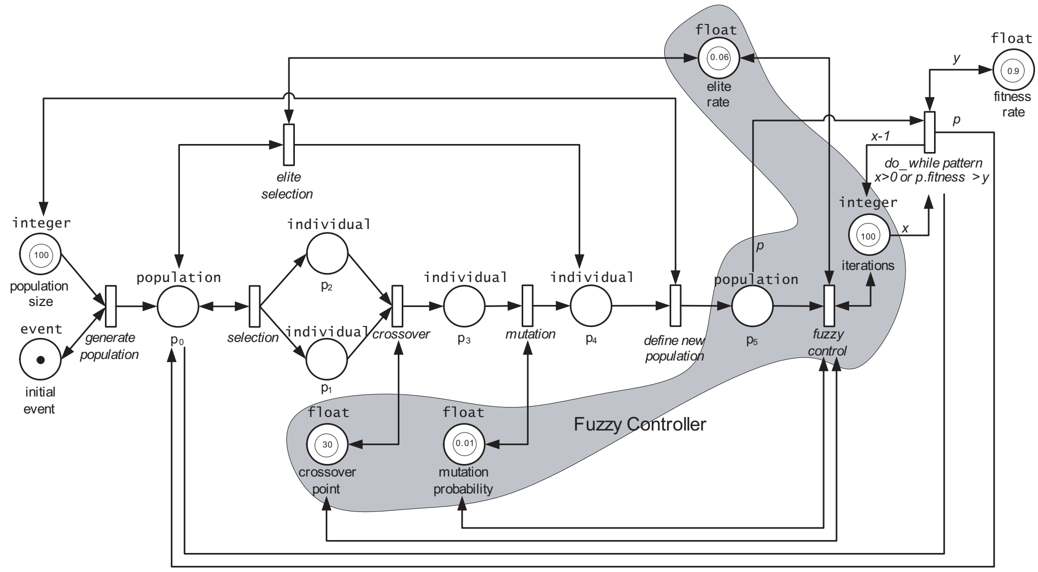

Fig. 2. HLPN of the adaptive fuzzy evolutionary algorithm

workflow framework [27] which is based on both workflow [1] and UPML frameworks [6]. The workflow layer in this framework is used to define the control flow of business processes. Within this layer, a *propose, revise and update* composite method for dealing with the EA has been defined through a High Level Petri Net (HLPN) [16]. Through the HLPN formalism, the workflow specification models tasks by means of transitions, conditions by means of places and cases by means of coloured tokens. Complex tasks, represented by substitution transitions [16], will be solved through composite methods.

A. Adaptive Fuzzy Evolutionary Algorithm Description

The EA algorithm defined for our scheduling task is depicted in Fig. 2. The usual structure of the EA has been upgraded in order to support a fuzzy control over the EA behaviour (grey box over the HLPN in Fig. 2). Production scheduling in the wood furniture industry is based on the human experience and empirical information and its results have a certain degree of uncertainty. In this sense, it is necessary to control the degree of confidence of the solutions obtained in each EA iteration. For this purpose, a fuzzy controller supervises the new populations and modifies the selection, mutation and crossover rates in order to improve the quality of the solutions and to avoid premature convergences.

The initial marking of the HLPN EA defines the initial values for the fitness, selection, crossover and mutation rates and sets a population size of N individuals. Population size plays an important role in the correct behaviour of this solution. Although the domain-specific control knowledge reduces the complexity of our task, planning is extremely hard to solve. Population size adjusts the quality of the solution at the expense of task time consuming. Large populations obtain better work plans but demand more computation. The same happens with the fitness rate and the number of iterations of the EA. With a small number of iterations or a wrong fitness rate, the EA may get results away from the optimal solution.

1) Problem Encoding: The encoding of our scheduling problem is depicted in Fig. 3. The chromosomes contain all the orders that must be manufactured. Specifically, a chromosome contains a sequence of orders scheduled according to its priority and delivery date. This kind of arrangement assigns a higher priority to jobs based on the client order precedence and allow those jobs to choose their resources and reserve their free slot times in advance.

Jobs of the chromosome are ordered based on the manufacturing route selected to perform a client order. This kind of sorting, jointly with the precedence constraints of client orders, define a unique jobs configuration. In fact, a job position is the same in all the chromosomes of a population. The genes that compose the chromosomes are defined by three elements: a job identifier, a resource centre identifier and a resource assignment strategy identifier. A gene defines the centre that will perform a job and its resource assignment strategy.

It should be noted that this EA does not allow the definition of incorrect chromosomes. Both the generation of the initial population and the mutation operations define only correct chromosomes.

2) Fitness Function: The fitness function herein described evaluates the goodness of each of the individuals of the population. This evaluation is very hard because of the simplicity of the chromosome. In a certain sense, the iterations in the EA define the assignment of resources to jobs and the configurations of resources within the same resource centre. Although this information restricts the scheduling, it does report nothing about the workload of the resources or the manufacturing time. In fact, it is necessary to compute the work plan from the chromosome information before the fitness

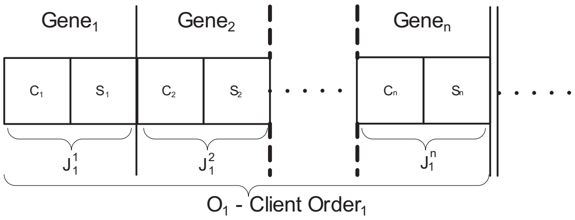

Fig. 3. Chromosome and gene representation

function can evaluate it.

The method that solves this task defines the following steps for each job J_i^k of a client order O_i:

- Select all the resources R_r of the resource centre C_c that can perform the job J_i^k.
- Compute the time and the percentage of work performed for the operation type MO_m per minute of work for each R_r.
- Get the free time slots of each R_r based on *(i)* the manufacturing strategy of the O_i ("as soon as possible", "as late as possible", "no strategy"), on *(ii)* its delivery date and *(ii)* on the jobs dependencies.
- Define the resource groups of the C_c that can perform J_i^k according to the grouping strategy S_s in the chromosome.
- Select the most suitable group based on the free slot assignment and the time worked by each resource.

Fitness function formulae for a plan defined in the time interval $[t_{in}, t_{out}]$ can be defined as follows where $\alpha, \beta, \delta, \gamma \in \mathbf{R}$ are weight coefficients:

$$\alpha\left(\sum_{r=1,\dots,NR} wl_r^{[t_{in},t_{out}]}\right) - \beta\left(\sum_{\substack{r=1,\dots,NR\\ [t_1,t_2]\in[t_{in},t_{out}]}} ol_r^{[t_1,t_2]}\right) + \delta\left(\sum_{i=1,\dots,NO} ctime_i\right) + \gamma\left(\sum_{i=1,\dots,NO} ccost_i\right)$$

Fitness evaluation is based on four criteria. The first one, is related to the resources work load. In this sense, a high degree of work load indicates a good use of resources.

$$wl_r^{[t_{in},t_{out}]} = \frac{usage_r^{[t_{in},t_{out}]}}{availability_r^{[t_{in},t_{out}]}}$$

Resource work load is based on the usage of a resource in a time interval. The usage formulae for the resource R_r and the time interval $[t_{in}, t_{out}]$ can be defined as follows, where $J_i^k \neq \phi \ \forall k = 1, ..., NJ_i$, $i = 1, ..., NO$, and $[t_1, t_2] \in [t_{in}, t_{out}]$:

$$usage_r^{[t_{in},t_{out}]} = \sum_{TS_r^{[t_1,t_2],J_i^k} \in TS_r} (t_2 - t_1)$$

Computation of availability is similar, and has also includes the free time slots of the resource ($J_i^k \in (J_i \cup \phi)$).

The second criterion looks for overloads and possible bottlenecks in the production plant. This is a negative property of a plan. A resource R_r for $r = 1, .., NR$ is overloaded for a certain period of time $[t_{in}, t_{out}]$ where $t_{in} + 60 < t_{out}$ if the $wl_r^{[t_{in},t_{out}]} > 0.9$ and other resources R_k for $k = 1, .., NR$ and $k \neq r$ in the same centre have a $wl_k^{[t_{in},t_{out}]} < 0.9$ for the same manufacturing operations. It should be noted that the minimum period of time to define an overload is fixed in 1 hour.

Time and cost related to the orders manufacturing are also taken into account. This evaluation compares the time and cost needed to perform a client order manufacturing in relation to the time and cost set in its price estimate. For example, the use of a certain resource may reduce the production time but increase the price of the manufacturing. The formulae for the time comparison between the estimate TE and the manufacturing order O_i for $i = 1, ..., NO$ time estimation in the client order time interval $[t_{in}, t_{out}]$ can be defined as follows where $i = r, ..., NR$, $k = 1, ..., NJ_i$, $[t_1, t_2] \in [t_{in}, t_{out}]$, and $J_i^k \neq \phi$ for $k = 1, ..., NJ_i$:

$$ctime_i = \frac{\sum_{TS_r^{[t_1,t_2],J_i^k} \in TS_r} (t_2 - t_1)}{TE}$$

The same procedure has been used to compute the cost comparison. In this case, the time slots of each resource is multiplied by the resource cost per minute $cost_r$ and compared against the cost estimate CE:

$$ccost_i = \frac{\sum_{TS_r^{[t_1,t_2],J_i^k} \in TS_r} (t_2 - t_1) \cdot cost_r}{CE}$$

3) Selection, Crossover and Mutation Functions: Although the operators used in this EA are quasi-standard, some of them introduce some differences because of the chromosome encoding. As we previously mentioned, incorrect chromosomes are not allowed in our scheduling process. For this reason, both crossover an mutation operators define a special behaviour. The scheduling task uses a crossover operator that randomly defines one crossover point. However, this point cannot cut a gene. As regards mutations, a random mutation operator is defined with the ability to perform two kind of changes. It is possible to change the centre that will perform the manufacturing operation or the resource assignment strategy. In both cases, the number of mutation are restricted to the centres that have a resource with the ability to perform the job and the grouping strategies defined in the environment, respectively.

4) Fuzzy Rule Based System for EA adaption: The fuzzy control task modifies the elite, mutation and crossover rate values according to a fuzzy evaluation of a population. The objective of this control is the dynamic adaption of the algorithm in order to improve its behaviour, also considering less uncertain plans. The fuzzy evaluation of the population and the control of the EA is performed in several steps:

- In a previous off-line step, experts are requested to linguistically define the significant terms for evaluating the quality or reliability of the estimation times provided by the regression equations for every job. This is done by a fuzzy partition involving three terms (HIGH, MEDIUM, LOW) that refer to the uncertainty of the estimation times.

- Historical information of all the previous time estimations and the actual production times for all jobs is collected. This allows the sytems to calculate, for every job with estimated time te_J, its mean percentage error Δte_J. This error will be the key information for calculating the reliability of future time estimations. If no previous history exists for te, the value provided by a linear interpolation among the previously existing te is used.
- The first on-line step evaluates the quality of the time estimations of each job J_i of the work plan, using the previously indicated historical information. A percentage error Δte_{Ji} is obtained for job J_i and their membership degree to the three linguistic labels that define its quality. These three degrees are the measure of the uncertainty of the estimation times for each new job.
- The second step computes the global work plan evaluation. Once the particular degrees of uncertainty are calculated for each job in the plan (as stated before) the total uncertainty measures are calculated by means of simple t-conorm operations between the uncertainty of each job in the plan.
- Finally both the total time estimation for the plan and its uncertainty measure are used twofold:
  1) It is used as the input to the fuzzy control system that will improve the EA parameters.
  2) It is forwarded to the expert as an indication of the quality of the plan. In order to make it more understandable a linguistic approximation process is applied for giving such information only in terms of the relevant linguistic labels HIGH, MEDIUM, LOW and all the linguistic formulae including them (i.e., all the AND, OR, NOT combinations of these terms), thus considering all expressions that may be informative to experts.

Let us see this by means of an example. Figure 4 graphically describes the process. The historic of percentual deviations of previous jobs is depicted in $te - \Delta te$ axis, whilst linguistic labels defined by the expert are depicted in $membership{-}\Delta te$ axis. For a new job J_i, time estimation te_{J_i} is previously calculated using the regression model for that operation. The corresponding error mean percentage error Δte_{J_i} and its associated uncertainty are obtained. For the example in Fig. 4 uncertainty for job J_i is $(LOW_{0.8}, MEDIUM_{0.2}, HIGH_{0.0})$. For a plan involving just this job J_i and another job J_k $(LOW_{0.0}, MEDIUM_{0.4}, HIGH_{0.6})$, the total uncertainty will be described as $(LOW_{s(0.8,0.0)}, MEDIUM_{s(0.2,0.4)}, HIGH_{s(0.0,0.6)})$, where s is the t-conorm operator used for aggregation.

The global uncertainty (reliability) information for every plan is of great help for experts to select the most adequate plan at every moment. This critical decision is always done manually by experts and therefore the system is only requested to provide them with information on the plan duration, its schedule proposal and uncertainty associated. Decision is usually made on the total time criteria, but it may be the case that the uncertainty criteria be considered for discarding some plans.

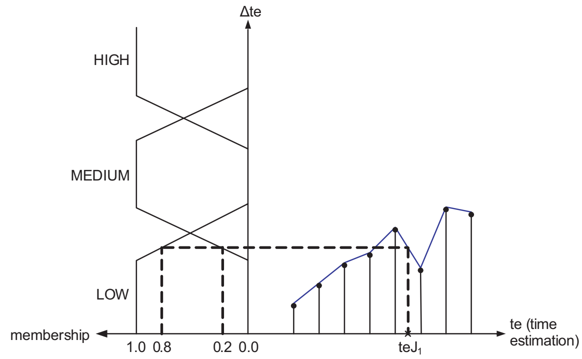

Fig. 4. Calculation of uncertainty for a job

Using the information coming from the fitness function and the uncertainty of each plan, a fuzzy rule-based system (*FRBS*) has been implemented in order to modify the crossover and mutation probabilities, and the elitism rate. Adaptive evolutionary algorithms [30], [31], [32] can improve conventional evolutionary algorithms, for example avoiding the premature convergence and increasing the search speed.

In this application, it is quite important to obtain reasonably good solutions (plans) in a short time (a few minutes). For this reason, an adaptive balance between exploration and exploitation of the search space helps in speeding up the search process. The main idea underlaying the *FRBS* is to explore the search space when the obtained solutions are not good and have a high uncertainty. This is done with a regular genetic algorithm (GA), but when the solutions improve and the uncertainty is reduced, the GA evolves into an Evolution Strategy, (1, 1)-ES. In a (1, 1)-ES the best individuals of the population are mutated and replace the worst individuals, exploiting the search space in the most promising areas.

The *FRBS* uses as input variables the average fitness of the population (AF), the diversity of the population (div), and the average uncertainty of the plans (AU). Sometimes, it is also needed the fitness and uncertainty of the best solution (F_b and U_b). As outputs, the system will modify the crossover and mutation probabilities (p_c, p_m), the elitism rate (e_r) and also the posibility of reinitializing the population keeping the best individuals. As an example:

$$If\; AF\; is\; good\; and\; AU\; is\; low$$
$$Then\; p_c\; is\; low\; and\; p_m\; is\; high\; and\; e_r\; is\; medium$$

In this situation the individuals have a good fitness value and the uncertainty of the plans is low, so the evolutionary algorithm can exploit the most promising areas of the search space increasing the mutation probability and elitism rate, and reducing the crossover probability.

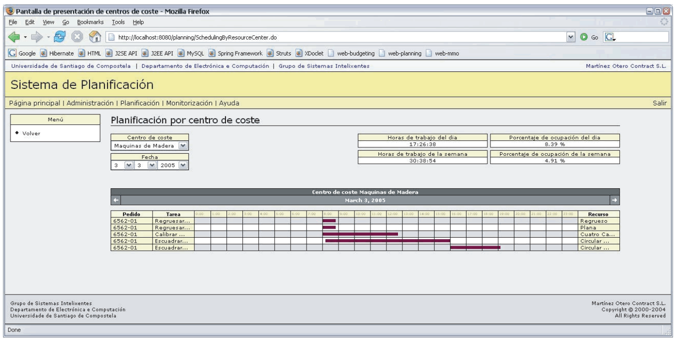

Fig. 5. Woodworking machinery center work plan

B. System Implementation and Validation

As previously mentioned, this development is part of a project that deals with the product design life cycle in the wood furniture industry. Our solution has been implemented as a part of a Workflow Management System enriched with knowledge-based capabilities [27] (Fig. 5). Both the product design and specifically the production planning tasks have been modelled as workflows. The control flow depicted in Fig. 2 is the core of our workflow although other tasks have been defined for the planning automation to be assessed and validated by a human expert. In this way, the scheduling complements the design for manufacturing and assembly. For example, once the manufacturing plans are computed by the EA, the three best plannings options in terms of cost, together with their durations and degree of uncertainty, are offered to the human expert for validation. This information is useful for users to finally decide on the plan to be moved to real production of to ask the system for more reliable plannings. If none of the plans are considered to be valid by the expert, then the expert defines the changes or constraints that new plans should fulfil. These new parameters can affect previous steps of the product design workflow, e.g. changes in the materials composition, designs, manufacturing route, or resources calendars, and will require a new scheduling.

IV. Conclusions and Future Work

Although a prototype of the planning moduel is still currently being validated at a wood furniture industry, two conclusions can yet be inferred from the results obtained. Firstly, our solution considerably reduces the time needed to compute manufacturing plans. In fact it fulfils all the requirements to perform a future dynamic re-scheduling. Secondly, even though some time estimations are far from the obtained in the production plant, the approach for dealing with uncertainty has proved to be useful for experts plan validation. In these sense, a fitness and uncertainty measure helped experts to have a vision of the plan closest to the reality. Moreover, the fuzzy labels facilitates the understanding of the plan evaluations.

In parallel other tasks of the product design workflow are still under development. For example, a refinement of the polynomials for time production estimation. Following with the example described in section II, the time two cutting machines need to cut one hundred office desks melamine panels has been estimated in 6h20min while the real time of manufacturing was 8h35min (26% error). The evaluation of this discrepancy defines a LOW level of confidence and affects the final confidence of the plan. Thus, the validation stage of the production planning task is influenced by external factors. In order to avoid this drawback, the feedback of this stage and the information extracted from the plans are used to improve time estimations. In fact, estimations and real time measures must be constantly compared. For example, the workload of the ”wood machinery” resource centre for a given day must be compared with what was previously planned. In a near future, this refinement should be automatically made by a learning from previous examples module.

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