A Fuzzy Evolutionary Algorithm for Scheduling in Wood-based Furniture Manufacturing

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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 if necessary regenerate the scheduling for already existing orders. 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 the great amount 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.

Keywords: fuzzy production planning, evolutionary algorithms, wood furniture industry.

1 Introduction

The problem of production planning and scheduling in the furniture industry [8] is not new. Conventional search and optimization techniques are hard to apply for scheduling of large-scale custom furniture. 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 [7]. For detailed short/medium term scheduling, EAs can get good solutions in a reasonable amount of time, when compared with classic techniques [5, 6].

An important feature of 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. Although some Computer-Aided Manufacturing (CAM) products which estimate the time from Computer-Aided Designs (CAD) designs are available, most of estimations are based on experts knowledge and are therefore uncertain. For this reason, the planning task must be able to manage the uncertainty of time estimations the schedules are based on.

In this paper, we describe the module for production planning as a part of a Knowledge-Based Business Process Management System (BPMS) [4] in the wood furniture industry that solves the product design task by means of knowledge-enriched workflows [3]. 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 resource workload, resources centers availability, ...). The EA is adapted along the search process using a Fuzzy Rule-Based System (FRBS) in order to avoid premature convergence and increase the search speed, modifying the tradeoff between exploration and exploitation.

The paper is structured as follows: Section 2 presents the scheduling problem in custom furniture industry. Then, Section 3 describes the proposed approach, and Section 4 its implementation. Finally, in Section 5, conclusions and future work are pointed out.

2 Wood-based Furniture Manufacturing

This section describes the most elementary concepts of the production planning task in the custom wood-

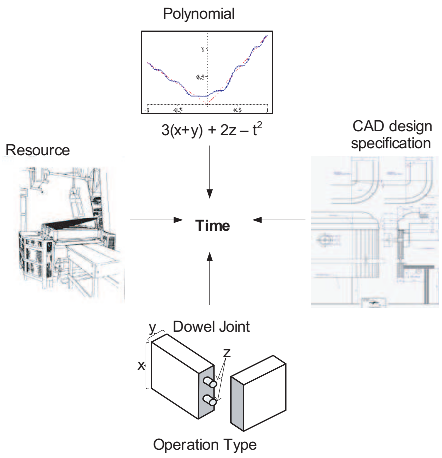

Figure 1: Time estimation of a resource manufacturing operation is built from a polynomial equation

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 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.) have to perform 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 center 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 center has the capability to assign the job to an individual or a group of resources. For this purpose, a set of strategies $S = \{S_s | 1 \leq s \leq NS\}$ have been defined to group resources. Basically, three type of strategies have been defined: *(i)* only 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 centers can only perform those operations that can be carried out by their resources. Moreover, resource assignment to centers may vary along the time. In a certain sense, resources define time slots that are assigned to a center. 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 center. For example, job J_1^1 (e.g. in charge of cutting the melamine panels) may be assigned to the cut center C_1 which assigns two cutting machines (R_1 and R_2) machines to perform this job. As regards the manufacturing plan, this assignment means that the free time slots of the R_1 and R_2 resources are assigned to 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 are 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

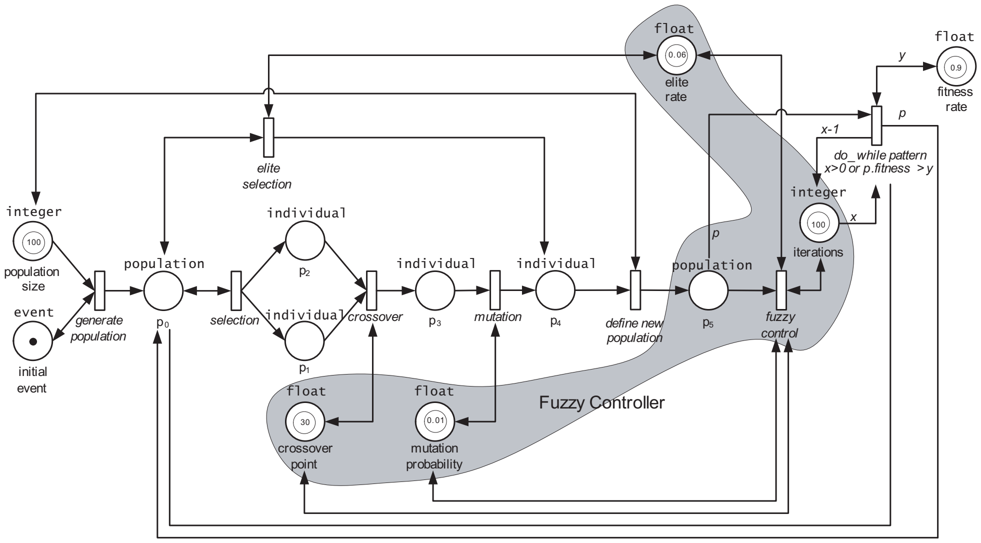

Figure 2: High Level Petri Net of the adaptive fuzzy EA

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.

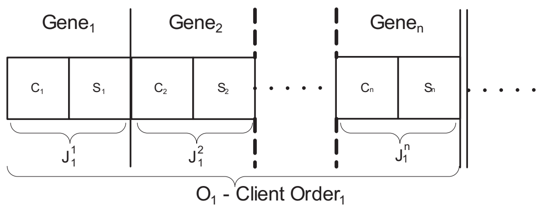

Figure 3: Chromosome and gene representation

3 Adaptive Evolutionary Approach to Production Planning

The EA 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 behavior (grey box in Fig. 2). Production scheduling in the wood furniture industry is based on the human experience and empirical information to a great extent 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 elitism, mutation and crossover rates in order to improve the quality of the solutions and to avoid premature convergence.

3.1 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 allows 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 center identifier and a resource assignment strategy identifier. A gene defines the center that will perform a job and its resource assignment strategy.

3.2 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, an individual defines the assignment of resources to jobs and the configurations of resources within the same resource center. 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 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 center 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 and 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 *(iii)* 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 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. Resource work load is based on the usage of a resource and on its availability in a time interval.

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 $workload_r > 0.9$ and other resources R_k for $k = 1, .., NR$ and $k \neq r$ in the same center have a $workload_k < 0.9$ for the same manufacturing operations. It should be noted that the minimum period of time to define an overload is fixed in 1 hour.

The last two aspects taken into account are the time and cost related to the orders manufacturing. 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 same procedure has been used to compute the cost comparison. In this case, the time slots of each resource are multiplied by the resource cost per minute and compared against the cost estimate.

3.3 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. 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 center that will perform the manufacturing operation or the resource assignment strategy. In both cases, the number of mutations is restricted to the centers that have a resource with the ability to perform the job and the grouping strategies defined in the environment, respectively.

3.4 FRBS for EA adaption

The fuzzy control system modifies the elite, mutation and crossover rate values according to a fuzzy evaluation of the population. The objective of this control is the dynamic adaption of the algorithm in order to improve its behavior, 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 systems 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.

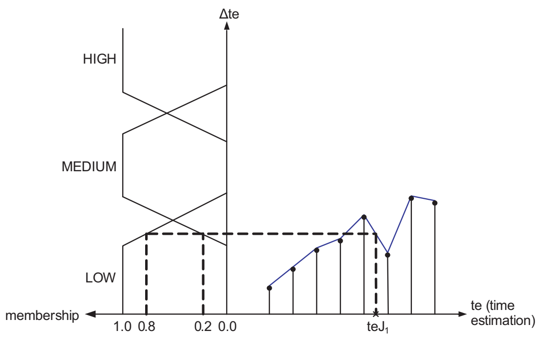

Figure 4: Calculation of uncertainty for a job

- 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 percentage 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.

Using the information coming from the fitness function and the uncertainty of each plan, a FRBS has been implemented in order to modify the crossover and mutation probabilities, and the elitism rate. Adaptive EAs [1, 2] can improve conventional EAs, 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 (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 underlying 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) with high crossover rate and low mutation probability. But when the solutions improve and the uncertainty is reduced, this rates are changed to approach the genetic algorithm to an Evolution Strategy (lower crossover rate and higher mutation rate).

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). As outputs, the system will modify the crossover and mutation probabilities (p_c, p_m), and the elitism rate (e_r). As an example:
$If\ AF\ is\ low\ and\ AU\ is\ high\ and\ div\ is\ low$
$Then\ p_c\ is\ high\ and\ p_m\ is\ medium\ and\ e_r\ is\ low$

In this situation the individuals have a low fitness value, the uncertainty of the plans is high, and the diversity is low, so the EA must maintain a high crossover rate to continue the exploration of the search space, keep a low value for the elitism (as the average fitness is low), but the mutation probability must be medium in order to increase the diversity of the population.

4 System implementation

In order to test the behavior of our solution we have designed a set of five small client orders. Each of these orders is composed of five jobs with different manufacturing operations: wood and wood-based panels cutting, varnishing, assembly, etc. The results described in this section were simulated with the following production plant configuration:

- 25 resource centers.
- 10 resources per center.
- 3 resource assignment strategies.

This produces a search space of size 10^{46}. The fact that each scheduling lasts approximately 2 seconds for each plan, makes the complete exploration of the search space impossible in a reasonable amount of time with a conventional algorithm.

The FRBS for the adaptation of the EA has three input and three output variables with the following characteristics:

Variable	Labels	Universe of discourse
AF	2	[1.0, 2.0]
AU	2	[0, 1]
div	2	[0.33, 0.66]
p_c	3	[0.4, 1.0]
p_m	3	[0.01, 0.05]
e_r	2	[0.06, 0.12]

Table 1: Characteristics of the data base of the FRBS

The other parameters of the EA are a population of 50 individuals and 100 iterations.

The proposed system will help in the near future in the decision making for scheduling in the wood furniture industry. For this reason, it provides the human decision maker with information related to the uncertainty of the proposed plan. This information must be also considered during the execution of the evolutionary algorithm in order to focus in areas of the search space with both high fitness and low uncertainty. The main advantage of the proposed adaptive EA over a usual EA is its capability to model all this information with a FRBS in a easier and more intuitive way.

5 Conclusions and Future Work

Although a prototype of the planning model is still currently being validated at a wood furniture industry, two conclusions can be derived 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 task. 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 this sense, a fitness and uncertainty measure helps experts to have a vision of the plan that is closer to the reality. Moreover, the fuzzy labels facilitates the understanding of the plan evaluations.

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References

[1] F. Herrera and M. Lozano. Adaptive genetic operators based on coevolution with fuzzy behaviors. *IEEE Transactions of Evolutionary Computation*, 5(2):149–165, 2001.

[2] F. Herrera and M. Lozano. Fuzzy adaptive genetic algorithms: Design, taxonomy and future directions. *Soft Computing*, 7(8):545–562, 2003.

[3] J.C. Vidal, M. Lama, A. Bugarín and S. Barro. Problem-Solving Analysis for the Budgeting Task in Furniture Industry. In *Seventh International Conference on Knowledge-Based Intelligent Information & Engineering Systems*, volume 2774 of *LNAI*, pages 1307–1313, Oxford, UK, 2003. Springer-Verlag.

[4] J.C. Vidal, M. Lama, and A. Bugarín. *Integrated Intelligent Systems for Engineering Design*, chapter Integrated Knowledge-based System for Product Design in Furniture Estimate. IOS Press, to be published in 2006.

[5] S. Kreipl and M. Pinedo. Planning and scheduling in supply chains: An overview of issues in practice. *Production and Operations Management*, 13(1):77–92, 2004.

[6] T. Löhl, C. Schulz, and S. Engell. Sequencing of batch operations for highly coupled production process: Genetic algorithms versus mathematical programming. *Computers and Chemical Engineering*, 22:S579–S585, 1998.

[7] M. Gen and R. Cheng. *Engineering Design and Automation*. John Wiley & Sons Inc., 1997.

[8] P. O'Grady and R.E. Young. Issues in Concurrent Engineering Systems. *Journal of Design and Manufacturing: The Research Journal of Concurrent Engineering*, 1:1–9, 1991.