A DSS for Production Planning and Scheduling in the Paper Industry

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ABSTRACT: We present a decision support system for paper production planning and scheduling. The global problem is described, and a hierarchical model is proposed that integrates solutions for demand forecasting, order acceptance, capacity planning and scheduling, and the cutting problem. This approach allows for a better coordination between marketing and production decision-making procedures, leading to a reduction of conflicts. We present a general description of the models and the solution procedures developed. These were integrated in an interactive and easy to use environment, allowing for the use of an advanced tool, without the need for a complete understanding of the underlying mathematical concepts. The system is physically installed in different functional areas, and data sharing is accomplished through the company’s central information system.

KEY WORDS: Production Planning and Scheduling, Hierarchical Planning, Forecasting, Decision Support Systems
1. Introduction

This work results from a cooperation project between Portucel Industrial (a major Portuguese paper producer) and ICAT – a Portuguese R&D Institute. The project’s end goal was the design and development of a Decision Support System (DSS) for production planning at the Cacia production centre of Portucel Industrial. This mill produces paper rolls in a production to order policy, although production to stock is acceptable, namely when demand is low. A hierarchical model with two levels of decision-making was developed integrating the subproblems of demand forecasting, order acceptance, capacity planning and scheduling, and cutting.

Production planning and capacity scheduling is a very complex problem, where decisions must take into account many different constraints, several conflicting objectives, and the dynamics of the production system. The Hierarchical Production Planning – (Hax and Meal, 1975) and (Bitran and Tirupati, 1993) – is a classical approach, where the global problem is divided into several interconnecting subproblems. By changing from a multi-objective situation to several decision levels and through information stratification in different levels of aggregation, a computational approach is possible. Decision levels are established to efficiently coordinate the functional areas, assuring consistency of the resulting interdependencies. On the other hand, the implementation of decisions at the operational level is postponed as much as possible, so reducing the uncertainty level.

Some other approaches for automated scheduling in the paper industry have been proposed. In (Kojima et al., 1991), an expert system incorporating three subsystems, is described. A DSS developed for Naheola Mill is presented in (Pickard and Yeager, 1997). In (Keskinocak et al., 1998) and (Murthy et al., 1999), an agent-based DSS, following a multi-criteria optimisation approach, is described. The problems tackled include allocation of orders to paper machines, sequencing of orders in each machine, scheduling cutting decisions and vehicle loading.

The main advantages of our DSS rely on using a demand forecasting module; on assuring the consistency of the solution schedules (due to an integration of the cutting decisions in the capacity planning algorithms); and, on supporting order acceptance, thus improving the coordination between marketing and production.

The system's forecasting module supports marketing decisions by monitoring the evolution of paper demand, as well as decisions related to production planning, cutting, and inventory management. Potential benefits include: lower opportunity loss costs — which are due to the refusal of orders at times when the production maximum capacity is attained — better usage of the plant capacity when demand is low; reducing lead times; and, reducing cutting waste, by suggesting a larger number of alternatives to explore in the production plans.

The global problem is briefly described in the next section. In section 3, a hierarchical decomposition is identified, establishing the relations between the different subproblems. Section 4 is devoted to the presentation of the models, to a
2. Problem description

Clients order quantities (in tonnes) of paper rolls specifying a combination of the attributes: paper type, paper basic weight, rolls diameter and rolls width. We consider an aggregation of the final items into families, (Hax and Meal, 1975). Each pair of the attributes paper type and paper basic weight defines a given family.

The manufacturing process is organised into two stages continuously repeated. Firstly, the paper machine produces a large stream of paper of a given family. This stream is wounded originating a reel. Secondly, each reel is cut to obtain a given set of widths, as figure 1 shows. Set-ups occur in both stages. Global production capacity is defined on the first stage (cutting is faster). Final items are packaged for shipping or temporary storage. The stock consists of items not assigned to any order.

![Diagram of the cutting process](image)

**Figure 1. The cutting process**

Cutting reels of a given family and a given diameter originates items of that family and diameter. A cutting pattern (or pattern) is a set of item widths, each of which to be cut a given number of times. A cutting pattern is feasible if it is technically possible to cut a reel into the correspondent combination of widths. A cutting solution is a set of feasible patterns, each of which to cut a given number of reels. The Cutting Stock Problem consists of determining a cutting solution, producing a given set of items with minimum waste. Assigning items in a cutting solution to client orders originates a cutting plan. The Capacity Planning and Scheduling Problem consists of assigning capacity to families’ production over a planning horizon (1 to 3 months). The resulting plan – the aggregated plan – determines the quantities to be produced of each family and the correspondent production sequence. There are set-up times dependent on the family sequence.
3. The hierarchical decision making model

Production planning and scheduling is positioned between different management levels, connecting the overall goals of the company and the constraints of the shop floor. Cooperation and functional coordination are fundamental aspects for a successful planning system. Marketing makes the interface between the clients and the company, and has to deal with order acceptance. Marketing is concerned with maximising revenues, and their decisions are made first, establishing the demanded quantities and the correspondent delivery dates. Production is then required to fulfil the demand, minimising costs. The hierarchical model on figure 2 describes the decision making process, using the notation of the (Schneeweiss, 1999) framework.

![Hierarchical dependencies on the decision making process](image)

Our decision making model consists of two levels, each of which including a human decision maker (DM). Order acceptance is the decision function of the Middle Management Decision Maker (MMDM) on the Top Level (TL). At the Base Level (BL), the Low Management Decision Maker (LMDM) has to plan and schedule the shop floor. Pricing and promotion issues are excluded from our approach. The decision criterion on the TL is maximising capacity exploration, satisfying client requests to the largest extend. The MMDM interacts with the capacity planning and scheduling model to evaluate the impact of accepting a given order. In this interaction he is not concerned with how the items are produced but when the production is concluded. Capacity is limited and part of it is also used to produce paper that will be wasted during cutting. Therefore, cutting issues influence the maximisation of the capacity usage. Our capacity planning and scheduling model (sec. 4.1) integrates the cutting stock optimisation model (sec 4.2). In a capacity
surplus situation, the MMDM interacts with the forecasting model to determine which items are more likely to be ordered. Generating produce-to-stock orders, anticipates production of items, leading to a more effective exploration of capacity.

The LMDM is responsible for the operational planning. The BL optimising criterion is the minimisation of production costs. The decision functions include determining aggregate plans and establishing the cutting plans (sec 4.2) to be executed on the shop floor. The TL establishes the demand to be produced giving down this information as instructions to the BL; the BL reacts and responds with feedback to the TL. Although with different perspectives, both decision makers interact with the capacity planning and scheduling model. The LMDM is concerned with the planning and scheduling of product families and also interacts with the cutting stock optimisation model to determine cutting plans. He also interacts with the forecasting model to have insights about items that are most likely to be ordered in the short term. Economies of scale and waste reduction may be achieved by anticipating the production for some of these items. Final cutting plans are given down as instructions to be implemented by the shop floor. The Information System (IS) receives the outputs of the shop floor, and performs the corresponding updates. Both management levels access the updated information.

4. The DSS Model base

4.1. Capacity planning and scheduling

Assigning stock items to client orders. This function supports the computation of effective demand and precedes any planning/scheduling process. We use a priority heuristic rule following the *Earliest Due Date* criterion. Orders are handled on non-decreasing order of delivery date. The procedure looks for stock items with appropriate attributes and performs the largest possible assignment. The user is shown a report of all the assignments and can accept it, refuse it or accept part of it, cancelling the undesirable assignments.

Order acceptance - Effective capacity/Aggregate demand ratio analysis. This function is a first step to evaluate the impact of accepting a given proposed order. It is totally dependent on the rational model of the DM. He introduces a value for the expected lost of capacity (trim waste plus set-up waste) and the system computes the cumulative effective capacity and compares it with aggregated cumulative demand over a discrete time horizon. The system analyses accepted orders and, if capacity lacks, suggests a list of changes with minimal impact, including postponing delivery dates or correcting demanded quantities. The DM interactively accepts or refuses changes until cumulative capacity is sufficient to produce cumulative demand.

Capacity planning and scheduling problem. The problem is decomposed into two subproblems considering different time scales, (Captivo et al., 2000). In the first
one, we determine the quantities to produce over a discrete time horizon divided into production periods, assuming each order to be produced during the period preceding its due date. Family production quantities are determined by obtaining a cutting solution for each family. Given a cutting solution, each pattern is disaggregated into a set of jobs each cutting a minimum set of orders. The second subproblem regards time disaggregation, and consists of one machine batching and scheduling with family sequence dependent times, (Potts and Van Wassenhove, 1992). A batch is a sequence of reels of the same family to be produced continuously, defining a family production quantity. A job consists of cutting a set of reels, with items assigned to a given set of orders. The optimising criterion is the minimisation of late jobs. The problem is NP-hard and we developed a heuristic solution procedure. For each family, jobs are ordered in non-decreasing order of due date (Monma and Potts, 1989). Family batches are built by grouping sub-sequences of jobs whose due date is in a given time window, the length of which equals a half production period. Batch sequencing uses Schutten’s priority rule (Schutten, 1996), considering a parameter for the relative value of the set-up time. By varying this parameter, different sequences are generated. The best sequence is updated whenever a new one is found either improving the total processing time, or the number of late jobs.

The correspondent aggregate plan displays for each production run the beginning time, the processing time, the end time, the quantity, the cutting waste, the set-up waste and the earliest and latest due dates. It also presents the relevant aggregated values and several economic parameters. The procedure also generates the correspondent disaggregated solutions.

4.2. Determining cutting plans

*Cutting Stock Problem.* To determine a cutting plan the DM selects a set of orders to cut (or partial orders) of a given family and diameter. Orders for a common width are aggregated and, the effective demand for each width is computed. We consider an Integer Linear Programming model, based on the one of (Gilmore and Gomory, 1961), including a tolerance parameter defining upper and lower bounds for the fulfilment of the demand constraints, (Captivo et al., 2000). We solve the LP relaxation by implicit column generation. Due to the tolerance, rounding the final LP solution by an appropriate procedure is a near optimal cutting solution.

Technical constraints define pattern feasibility. The total width cut by a pattern must be within two given limits and there are bounds on the total number of items cut and on the number of items smaller than a given value. Columns are generated solving a knapsack with additional constraints, using a dynamic programming algorithm – (Gilmore and Gomory, 1963) – modified to verify these constraints.

The DM is offered a set of functionalities to test different scenarios, generating new solutions and improving a given solution. Introducing new items in the plan may not increase the number of reels, thus achieving economies of scale. This
procedure is especially helpful if some patterns cut a large waste. In this process, the DM uses the forecasting functionalities to determine the most adequate item widths. Figure 3 presents an example of improving a cutting solution by DM interaction.

**Figure 3. Improving cutting solutions**

In the first solution, a pattern is cutting a waste of 50cm for 69 reels. Using the forecasting module, the DM decides to produce-to-stock 15 items of that width. For each of the remaining reels (54) the waste is used to cut 4 items of width 12cm. The waste of 20cm on the pattern cutting 41 reels is also used to cut items of width 12cm. These improvements lead to the second solution.

**Assignment of items to client orders.** Given a cutting solution, items are assigned to client orders aiming order spread minimisation. A heuristic iteratively determines a minimum cardinality set of orders that might be cut using a given pattern. Assignment is performed, updating the number of “not yet assigned” items. Priority is given to assignments that fulfil or are “close to fulfil” the maximum number of orders. Short runs and out runs may occur, as a consequence of computing non-exact optimal cutting solutions. The DM controls short runs while generating cutting plans, and interactively handles out runs during the assignment process. The system suggests possible assignments and the DM chooses the most appropriate.

**4.3. Demand forecasting**

The forecasting module filters any new input data about demand, and updates and processes several auxiliary files, to create an internal memory of all order requests for over 10 years, but computes forecasts only for the items, of item groups, with higher demand in recent years. It gives the decision maker the opportunity of visualising, through different kinds of graphs and tables, any of the time series or its corresponding forecasts. Moreover, it automatically produces an output file with suggested produce-to-stock orders, giving indication, through appropriate performance indexes, of the relative expected accuracy of the underlying forecasts.
Demand for an item along time is represented by a sequence of bivariate observations, \( \{ (t_k, y_k) \} \): \( y_k \) units of the item were ordered (but possibly not produced) at time index \( t_k \) (expressed as the number of days since a predefined base date). Aggregated time series were also considered, by including all order records for items in a given class — namely, items corresponding to the same paper type and basic weight. In order to define criteria for the creation of the individual time series and for the choice of the forecasting models to use, extensive data mining of the raw data was carried out, and careful preprocessing procedures were set up.

To compute forecasts, supervised neural networks were first considered, as nonlinear autoregressive models applied to the sequences of bivariate records \( \{ (t_k, y_k) \} \), where \( \Delta t_k = t_k - t_{k-1} \). Several forecasting objectives were investigated, given data up to \( t_N \): (i) to estimate \( (x_{N+1}, y_{N+1}) \); (ii) to estimate the total demand between \( t_N \) and \( t_N + \Delta \); (iii) to estimate the time horizon corresponding to a total demand of \( z \) units of the item. Despite the quality of the forecasts produced by these neural models, the forecasting module put into usage eventually included only simpler models and methods, based on exponential smoothing of the data. These are more efficient, but reasonably robust and accurate, and enabled an easier, autonomous, adaptive and optimised updating of the model parameters, on a daily basis, for hundreds of time series (Carmo and Rodrigues, 2002).

Figure 4 shows, as an example, one type of graph which is particularly useful for decision support: for a given item, past demand for the last 9 months, and expected total demand along the following 3 months are simultaneously displayed (in different scales). Time index “zero” refers to the current date, when the system is consulted. Apart from easily assessing the evolution of demand in the recent past, and the total demand forecasts in the short and medium terms, the user can easily notice the approximate timing and size forecasted for the next order.

Figure 4. Past demand and expected cumulative demand for a given item
5. Implementation

The DSS runs locally, on personal computers, exchanging data with the company Information System (IS). The user calls local processes to perform the following data extracting and the corresponding file import: historic records of orders; records of accepted orders or proposed orders (on analysis); and records of stock items. These data files are updated daily and also by user request. The interaction between the decision makers ensures acknowledgment of major changes (e.g., a large order cancelled) that can harm the current plan. Following user requests, the system generates local files for cutting plans, assignment of stocks to client orders, and changes on active orders or proposed orders. Local processes export these files to the SI, allowing for the databases update. The cutting machine, on the shop floor, also receives the information exported on the cutting plan files.

The DSS supports the user interaction with the models providing several data management functionalities: information searching, extracting and ordering, according to different criteria and levels of aggregation; order partitioning allows the building of different scenarios for generation and evaluation of cutting solutions; changing order records (quantities and due dates) is helpful to perform “what-if” analysis on order acceptance and capacity planning decision processes; monitoring and updating the DSS parameters and the production system parameters.

6. Conclusions

The DSS presented is an interactive easy to use tool, with the usual database management functions, and also with the capacity to quickly generate and evaluate alternative solutions, enabling the DM to take advantage of his knowledge and expertise. Based on alternative solutions with improved quality, the act of deciding is much more rational. Additionally, it also allows for a high degree of coordination between the different phases of the global problem and promotes cooperation between marketing and production – functional areas with conflicting objectives.

The benefits for the company are a global production cost reduction: immediately, due to improving solutions quality, and speeding up their generation; and, on the long term, due to a better organization of the information regarding the production, a better coordination of the planning process, reductions in lead times and an improvement of costumer service.

References


