OPTIMAL PRODUCTION SCHEDULING FOR DAIRY INDUSTRIES

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ABSTRACT

During the few last years, the profile of the food industry has changed greatly. Local, small-sized plants have given their place to large, national or multinational-scale food processing units. Furthermore, the effort of the industry to respond to consumer demands for greater product variety has increased the number of production tasks significantly. For the above reasons, the production planning and scheduling process has become very complex and the available equipment is often used close to its maximum capacity.

The dairy industry in particular produces an increasing variety of products that differ in 'internal' features like fat content, flavor, the type of whey etc., or 'external', like the size of the container and the language of the label (for exportable goods). Moreover, there are restrictions regarding the suitability of a machine for a production task (i.e. some products can only be produced on some machines) as well as restrictions in the production sequence, which are directed by product properties. These constraints are translated into specific scheduling rules; for example, if skimmed milk is used for the production of zero-fat yogurt, it should be processed before low-fat or full-fat milk in order to achieve lower setup times and product losses due to changeovers. The presence of these restrictions, together with the need to maintain high quality standards in food production and the short shelf-life of dairy products, further complicate the scheduling process.

Production tasks are handled within the factory through production scheduling, which refers to the strategies of allocating equipment, utility and manpower resources over time to execute the processing tasks required to manufacture one or several products in time (Pinto & Grossmann, 1998). Obviously, the development of tools that can help the industry to increase its flexibility and the utilization of available resources emerges as a necessity.

Sales forecasting is another critical factor for the efficient operation of a food manufacturer. If an efficient sales forecasting system is available, it will be possible to prepare ahead of sudden surges or plunges in demand and reduce the amount of lost sales or excess production. That is important for the food industry in general, but especially for the dairy industry it is of great significance due to the short shelf-life of its products. Dairy products are particularly perishable and customers require that food is as fresh as possible. They are purchased several times within the week and their sales show intense fluctuations due to factors like price, promotions, changing consumer preferences or weather changes (Van der Vorst et al.,

1998). Because of these characteristics, when demand is less than expected, because of i.e. promotional activities of an antagonist, the unsold quantities will gradually become less likely to be preferred by consumers, as there are fresher products available. At the end of a brief life-cycle, unsold quantities have to be discarded, burdening the industry with extra cost for transportation and environmentally sound disposal. On the other hand, an underestimation of the demand creates a lost sales cost. Clearly, the accuracy of the sales forecast determines to a great extend the profitability of the company. However, companies are still in the development phase as far as forecasting methodologies are concerned. In a recent initiative 48% of companies were identified as poor at forecasting (Adenbajo & Mann, 2000).

In this work, a complete two-level framework for use in food and in particular dairy industries is proposed. The specific characteristics of the dairy industry have been taken into consideration, in terms of the behavior of food sales over time and the special requirements in the production phase. At the scheduling level, an MILP (Mixed Integer Linear Programming) model of the system was developed, using a continuous representation of time. The solution of the MILP problem provides a complete production schedule, which establishes in a precise manner the products to be produced on each machine, the respective quantities, and the starting and finishing time of each task. The model uses a detailed representation of events and their timing, in order to ensure that all the timing restrictions imposed by machine or feeding limitations, or even internal company requirements are respected. For example, in the case of a common feeding line, production must be coordinated across all machines. The proposed model allows incorporation of sequence-dependent transitions between products and calculates the respective setup time and cost. Furthermore, the produced schedule meets the production sequence limitations in terms of fat content, flavor, product whey and added ingredients.

At the forecasting level, a time-series model was developed based on the implementation of the Radial Basis Function (RBF) neural network architecture trained and the fuzzy means training algorithm (Sarimveis et al. 2002). Neural networks were preferred over linear models in order to capture the nonlinear elements of the dairy sales time series and were found to perform better compared to other methods that were tested. Furthermore, in order to optimize the performance of the forecasting model, a genetic algorithm approach was followed for the proper selection of input information. Forecasts are used as input to the scheduling methodology.

Application of the two-level framework on real data taken from the leading dairy product manufacturer in Greece illustrated the efficiency of the proposed method.

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