Operational performance of two-stage food production systems

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CHAPTER 6

Reduction of Product Losses

Introductory note

The degree of connectivity between two production stages is an important aspect in the management of operations. Differences and volatility of production speeds have more influence on performance if two stages are more strongly connected. This especially concerns packaging speed, as packaging equipment is more prone to disturbances and will therefore be more volatile.

In the previous chapters, simulation results were presented for two-stage production systems with intermediate storage. In the production systems that were studied, the intermediate storage decoupled the processing and packaging stage to a large extent. For the production system in this chapter, the decoupling is only minor, or in other words: the two production stages are strongly connected.

Production disturbances are an important aspect in our research framework. For any situation, the analysis of disturbances is relevant in the reduction of product losses. But due to the strongly connected production stages, their impact becomes even bigger; the time between a disturbance in the packaging stage and a resulting effect in the processing stage is relatively small.

The strong connection is therefore also the main reason for developing the simulation tool presented in this chapter. The tool simulates production on the operational level, because this is the level where the process interactions occur that lead to the realization of product losses. Even for managerial decisions made on a higher level (tactical/strategic), the simulation of operational interactions is therefore necessary.

Although the research framework is applicable for a wide range of production systems, the importance of the production disturbances is partly dependent on the degree of connectivity between the production stages. Especially for strongly connected production systems (like the case study presented in this chapter), the resulting decision support tool can be valuable in the analysis and reduction of product losses.

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Abstract

In food-processing industries, reduction of product losses is important for improving profitability and sustainability. This paper presents a decision support tool for analyzing the effects of planning decisions on the amount of product losses in the food-processing industry. We created a research framework to collect and analyze data, supporting the development of an Excel-based decision support tool that helps to evaluate different scenarios for the planning decisions and production parameters. The tool was developed in co-operation with and implemented in a real-life dairy plant, where the tool was able to reduce the planning-related losses by nearly 20%. But an equally important result is the insight gained on the interactions between processing, packaging, and intermediate storage. The framework and tool can easily be implemented in other situations.

6.1 Introduction

In the process industries, waste and product losses are important due to environmental and economical requirements. In the food-processing industries, due to low margins, and high value of raw materials, product losses can be an interesting starting point for reducing costs and improving profitability. It will lower the amount of raw materials used, decrease the amount of rework and improve the quality of the end product. Furthermore, environmental performance is also becoming a means for gaining competitive advantages (see *e.g.*, Bansal and Roth, 2000; Faulkner *et al.*, 2005). For the food-processing industry, reduction and reuse of organic residues are the two major environmental challenges recently identified by Maxime *et al.* (2006).

Concerning product losses, we can differentiate between planning-related losses and unpredictable losses. The type of production process we present in

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this paper concerns a very common two-stage process with a processing and packaging stage (and intermediate storage). Unpredictable losses are caused by production stops due to disturbances; planning-related losses are caused by stops due to setups, intermediate cleaning operations, full intermediate storage tanks (stops the processing stage), and tanks running empty (stops the packaging stage). The amount of losses is not that obvious, because of the capacitated intermediate storage tanks; the interactions between processing and packaging are not straightforward (see also Van Dam *et al.*, 1993).

For production management, it is specifically interesting to know or estimate product losses before production starts. Due to the interactions between processing equipment, intermediate storage tanks, and various packaging lines, prediction of product losses is not straightforward. A large variety in stock-keeping units (SKUs) and batch sizes, combined with interactions between process parameters like capacitated intermediate storage tanks and production speeds of the processing and packaging stage, create a situation where the impact of planning decisions on product losses is not clear to production management. The possibility to estimate these losses allows production managers to change production parameters like batch sizes and sequences to be able to evaluate its effect on product losses. To the best of our knowledge, studying product losses from a planning perspective has not been presented before in the literature.

The objective of this paper is to develop a decision support tool to analyze product losses in the food-processing industry. This includes the development of a research framework, which also yields valuable results by itself. The decision support tool is designed to estimate the product losses for a period of planned production (*i.e.*, choice of batch sizes, capacity assignments) and facilitates scenario analysis. We also applied the proposed decision support tool in a case study to show its potential for reduction of losses.

The paper is structured as follows. First, we address the research framework and relate this to existing literature. Then, we explain the methodology applied in the case study. Subsequently, the development of the decision support tool is presented in detail. Next, we describe the deterministic simulation study we performed with the decision support tool. Finally, we discuss the findings, their implications and limitations, and the opportunities for further research.

6.2 Theoretical background

So far, product losses have been studied mainly from a point of view of reducing waste and reducing the environmental pressure. Especially, the reduction and re-use of wastewater has had quite some attention in the literature, mainly from a more engineering-oriented perspective (see *e.g.*, Mann and Liu, 1999; Puigjaner *et al.*, 2000). For the food-processing industry, approaches are also mostly geared towards biological and technical improvements, for instance in the case of beer production as recently surveyed by Fillaudeau *et al.* (2006).

Within the production management literature, waste management in process industries has been largely ignored: most work has been done in the manufacturing and remanufacturing of discrete products (see *e.g.* Guide *et al.*, 1999; Guide, 2000). Flapper *et al.* (2002) and French and LaForge (2006) are among the first to systematically explore a specific aspect of waste management in the process industries: reuse. Next to the reuse of product losses, the reduction of losses is a major challenge in the food-processing industry (Maxime *et al.*, 2006).

We believe the reduction of product losses through improved planning decisions to be a promising direction in this field of research. First of all, this directly reduces losses, but as a secondary effect, a larger percentage of the remaining losses can be reworked within the quality boundaries, due to additional planning insights.

In process industries, a significant part of product losses is related to setups of equipment when changing from one product to another (see also Flapper *et al.*, 2002). This would advocate a situation where the number of setups is minimized —and batch sizes chosen as large as possible. However, in recent years, there has been a trend towards smaller production batches to improve Just-In-Time (JIT) practices. Although, most of these studies concern discrete processes, Mehra *et al.* (2006) found that this also applies to process industries. This trend might result in more product losses and it makes losses an important issue to consider.

6.2.1 Research framework

The research framework we developed for this study is presented in Figure 6.1. The approach chosen in this paper is related to the approach by Van Donk *et al.* (2005) for the make-to-order versus make-to-stock decision. The main points in the framework we present are to study the production characteris-

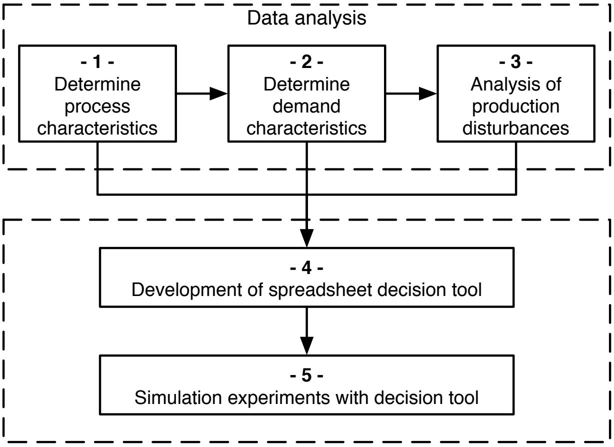

Figure 6.1. Research framework for the creation of a decision support tool for product losses.

tics, investigate the demand, and to make an in-depth analysis of production disturbances and breakdowns. These results are used in the development of a deterministic spreadsheet simulation of the production system, which is subsequently used to study the effect of various planning decisions on product losses. We can, for instance, analyze different parameter settings with regards to efficiency, planning period and the production system configuration.

First, we identified process characteristics, consisting of the structure of the production process and the task of production control (Akkerman and Van Donk, 2006a). This analysis is the basis for understanding and improving production control. The necessary data were gathered from process diagrams, existing information systems (*e.g.*, Enterprise Resource Planning (ERP) systems), and interviews with production planners and process engineers.

Secondly, we analyzed demand characteristics. To analyze this, we used procedures based on the approach of D'Alessandro and Baveja (2000), where demand variability and average demand were used to create product segments. Historical demand data can normally be retrieved from information systems at production or sales departments. In their study, the authors created product segments to decide between make-to-order and make-to-stock strategies for each of the segments. They did this graphically by plotting average weekly demand on the x-axis and its coefficient of variance on the y-axis. Furthermore, they used the results to reassign products to different plants. In this paper, demand variability and average demands were relevant in the realization of batch sizes and the number of changeovers. For product losses, the number of changeovers was a very important variable; starting and stopping production is one of the main causes for product losses. Compared to D'Alessandro and Baveja, we focused more on regularity of demand, to be able to show possibilities for combining batches. This also meant we slightly changed the graphical method. Here, we used the average time between two orders for the same recipe (which we labeled inter-arrival time) as a measure for regularity on the y-axis. Also, because average weekly demand gave an unrealistic idea of batch sizes for recipes that are not ordered every week, we changed the variable on the x-axis to the average order size.

Finally, production disturbances on the packaging lines are studied based on machine failure codes retrieved from production control software. As these (stochastic) disturbances are the cause of the unpredictable losses, an analysis of all production disturbances is a necessary third step in the analysis.

The decision support tool we developed is designed for determining the amount of product losses for a capacity assignment provided by the user. This means we are not aiming at automating any planning decisions, but only at providing insights into the effect of these decisions on product losses. In the process, it also results in a better understanding of the production process and the interaction between different production units. According to Olhager and Persson (2006), this last issue is one of the main reasons for using simulation studies in manufacturing environments. Olhager and Persson further stated that a thorough understanding of the nature of the manufacturing operations is one of the factors in the search for operational excellence. With the decision support tool presented in this paper, we specifically aim at improving this understanding.

The implementation of the decision support tool is performed in the spreadsheet program Microsoft Excel using the Visual Basic programming language. We feel that this greatly improved user acceptance, as virtually all possible users have experience with the software. Thiriez (2004) argues that better user acceptance is caused by the availability of Excel on most computers and by the fact that the user can see (at least partially) how the model works, which makes her/him feel closer to the model and less reluctant to actually use it.

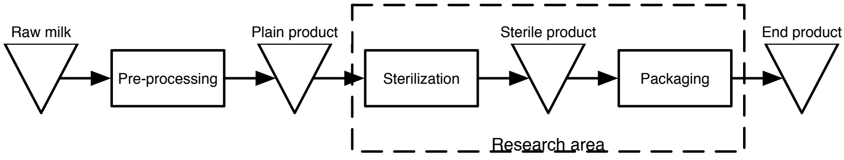

Figure 6.2. Outline of the production system in the case study (including the main research area).

6.3 Case study

The case study discussed in this paper concerns a dairy plant, which weekly uses 3-4 million litres of raw milk in the production of over 200 different SKUs for a variety of consumer markets. The main characteristics of the SKUs are recipe and package size. These two characteristics also determine (to a large extent) the required processing and packaging steps.

Initial results from the data analyses, as well as the final results from the simulation study, were presented on a regular basis to a project group consisting of operations management and operations research (OM/OR) faculty, production planners, process engineers, the plant manager, and other relevant parties. This close cooperation ensured the validation of our research findings and gave opportunities for data triangulation to ensure internal validity (see *e.g.*, McCutcheon and Meredith, 1993).

6.3.1 Process characteristics

In this paper, we do not describe the full process analysis in our case study, but limit the contribution to some general points that are necessary for discussion in the remainder of the paper.

The three main steps in the production process are pre-processing, sterilization, and packaging (as illustrated in Figure 6.2). For the product flow through the plant, this means conversion from raw milk collected from farmers to end products that are shipped to retailers. Before and after the sterilization process, intermediate storage tanks are present to hold prepared recipes and sterile products.

Because the focus of this research was on the reduction of product losses from a planning perspective, we also identified all the places where product losses occurred, how much losses occurred in each situation (determined by taking samples), and whether these losses were in any way influenced by planning decisions. This analysis resulted in a focus on a specific part of the plant (shown in Figure 6.2), where 75% of the losses occur and where most of the planning decisions are made. The resulting part of the production system concerns the sterilization and packaging of products. An important remark is that these two production stages are quite different in the way they handle products. The sterilization process is a batch process, producing sterile products for transfer into the intermediate (sterile) storage tanks. The packaging process consists of several packaging lines that can each package a certain package size. In general, the sterilization process can be considered as the bottleneck and is therefore, a leading factor in production planning. Normally, several packaging lines are connected to each sterilization process, to balance production speeds and to be able to produce various packaging sizes.

Concerning the scheduling process, the most important information is that scheduling is performed on a weekly basis, mainly based on orders received from the centralized planning department of the business unit. The orders are received on SKU level, where package sizes, labels, and recipes are differentiating elements. For the production scheduling, the orders are aggregated on recipe level. The major changeover efforts are between recipes. The required package sizes only determine which packaging lines can be assigned (can be more than one line for a recipe). Changing between labels can be done inline, and is relatively effortless.

The setups are very important in determining the amount of product losses. When changing between recipes, piping is emptied, the equipment must be sterilized and the new production started. During these steps significant product losses are incurred. Next to the losses occurring during changeovers, losses can also occur during production when:

- The intermediate storage tank is full and the sterilization process has to be stopped and restarted;
- The intermediate storage tank is empty and packaging lines have to be stopped and restarted;
- The sterilization process or one of the packaging lines reaches its maximum running time and the equipment has to be cleaned and again sterilized to ensure product quality.

In all of these cases, product losses are incurred, which we labeled as planning-related losses. The amount of these losses is hard to predict, because it is partly dependent on the realized efficiency of the packaging lines, which mainly depends on the production disturbances, which have also been studied in detail and are discussed below. For instance, if a certain packaging line has a low realized efficiency, products will accumulate in the intermediate storage tank until the tank is full and the sterilization process has to be stopped and restarted. Later in this paper, we present a spreadsheet simulation of the production system to estimate these planning-related losses.

6.3.2 Demand characteristics

For analyzing the demand characteristics, we collected historical order data from existing information systems. This data consists of one year of weekly order sets on SKU level. This was coupled with the classification of products to gain information on a recipe level.

Initially, we performed the analysis as suggested by D'Alessandro and Baveja (2000), plotting weekly average demand for recipes on the horizontal axis and the coefficient of variance on the vertical axis. By analyzing one full year of order data, it was clear that three clusters of recipes were produced:

- Recipes with high average weekly demand and relatively low variability;
- Recipes with intermediate average weekly demand and a medium variability;
- Recipes with low average weekly demand and high variability.

One of the main determinants for the coefficient of variance is the number of weeks in which there is no demand for a certain recipe. For the three clusters found, this means that the low-variability recipes are ordered every 1–2 weeks, the medium-variability recipes every 1–2 months, and the high-variability recipes once or twice a year.

As described in the research framework, we propose a slightly different graphical method than D'Alessandro and Baveja. The result is shown in Figure 6.3; the vertical axis has been cut off at 6 weeks, as any recipe with a longer interval is incidental. In this way, we feel we can show the potential improvement by combining batches. For instance, if a certain recipe has small order sizes, but is received almost every week (the lower left corner of the figure), it is useful to see whether it is possible to combine some of these orders to increase batch sizes. In our case study, this was not always possible due to the shelf life of the product. However, for some products (with longer shelf life), it was possible to combine these orders to form larger batches. The general expectation is that this will lead to a decrease in product losses, but this

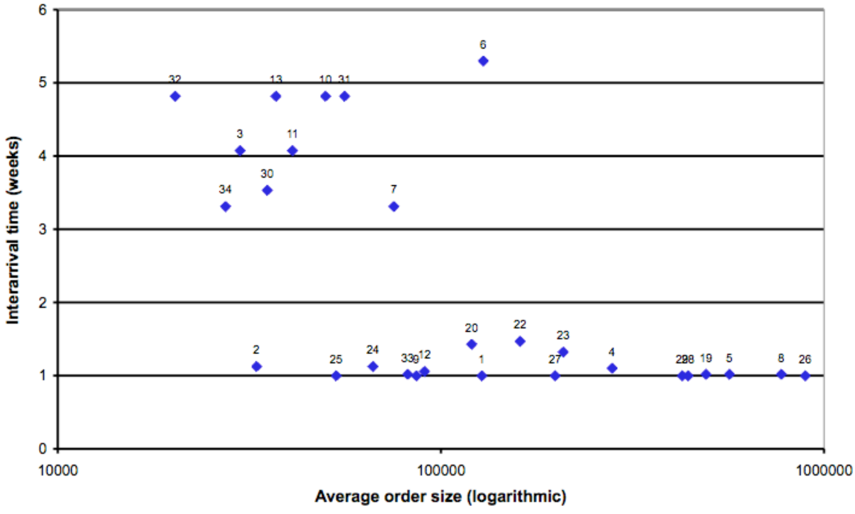

Figure 6.3. Analysis of demand variability. By plotting the time between two orders for the same recipe against the average order size, the figure provides insight in the regularity of demand and the opportunities for combining batches.

is difficult to quantify. Therefore, we chose to add the spreadsheet simulation to our study.

6.3.3 Production disturbances

Concerning the production disturbances, we used information from an information system that registers all production stops with accompanying reasons. These data sets were used to study how the failures were distributed among the production units, and to what extent these stops can be related to planned production. Ideally, this would result in a direct relationship between the production stops and planning characteristics like the amount of SKUs produced in a certain period or the runtime of the production units. For instance, the number of production failures can be expected to be higher when starting equipment for a new batch, and therefore, the number of production stops could decrease as average batch sizes increase.

In our case study, production failures were present on the packaging lines. Here, a large array of equipment for packaging, labeling, wrapping, etc. causes frequent production stops. For the sterilization processes and the intermediate storage tanks, production failures do not exist. Unfortunately, it was not possible to compare failure behaviour and planned production on a detailed level. Therefore, we resorted to regression analysis to identify relationships between a number of aggregate measures, such as the total number of stops per week. From the information available, the expectation is that the main contributing factors in the number of stochastic stops are the production volume and the number of SKUs produced within this volume. The production volume determines the amount of production time, and thereby, affects the number of expected (stochastic) breakdowns. The number of SKUs is included because the expectation is that production failures would be more likely to happen after a minor changeover on the packaging line (to change product labels or tray sizes).

Using multivariate regression analysis, we determine that only the production volume has a significant effect and thus can be used to estimate the amount of product losses. Interestingly, no significant relation between the number of SKUs and the amount of production stops was found. The estimate can be implemented by an average number of disturbances per time unit for each of the packaging lines, which is a simple but intuitive procedure. In the decision support tool presented in the following sections, the final overview of product losses shows this estimate next to the calculated number of planning-related losses. In this way, the tool was able to provide an overview of all product losses within the research focus.

6.4 Spreadsheet decision tool

The tool is basically a deterministic spreadsheet simulation, implemented in Visual Basic for Microsoft Excel. It consists of four steps (outlined in Figure 6.4), which use company data. In the first two steps, user input is necessary. The general outline can be summarized as follows. First, a set of production orders in inserted on SKU level. Secondly, these orders are aggregated on recipe level. Here, batches are formed and capacity assignments are made (user input). The third step is the actual deterministic simulation, where the expected realized production is depicted in Gantt charts. The fourth step includes the calculations of the expected planning-related product losses based on all the starts and stops of the production units shown in the Gantt charts.

Since we were specifically not intending to develop a scheduling tool, the batching and capacity assignments were included as user input. In this way, the model can be used to perform *what-if* analyses for different scheduling decisions. In the following sections, the four building blocks of the decision support tool are described in more detail.

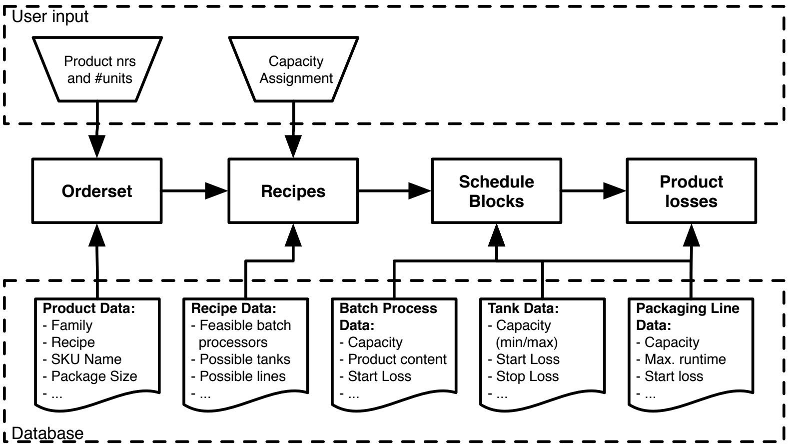

Figure 6.4. Structure of the decision support tool, consisting of four steps: (1) production orders, (2) capacity assignment on the recipe level, (3) the graphical representation of the simulated production, and (4) the calculation of expected product losses. User input and company data are a necessary input throughout the process.

6.4.1 Step 1 — Orderset

Here, order data can be inserted on SKU level, which is also the way the data are currently delivered from the central planning department. Because of links to the product database that contains all relevant product information, such as recipe, package size, etc., the SKU name can be added automatically when entering a product number. Automatically, the SKU amounts are transformed into uniform measures like litres or kilos.

6.4.2 Step 2 — Recipes

After product data are obtained on the SKU level, an aggregation is performed to obtain data on the recipe level. These recipe orders have to be scheduled on the various production units (batch processors, the intermediate storage tanks, and the packaging lines). Here, we come to the final and most important user inputs. Batching decisions and production unit assignments can be made for each recipe. If necessary, recipes can be split into several batches (*e.g.*, if batch sizes would otherwise be too large). Figure 6.5 shows how the assignment can be easily done in the decision support tool. On the left, the product amounts are shown for the different package sizes. On the right, the various production units are shown. As can be seen, certain assignments are not possible (grey areas) because of recipe requirements

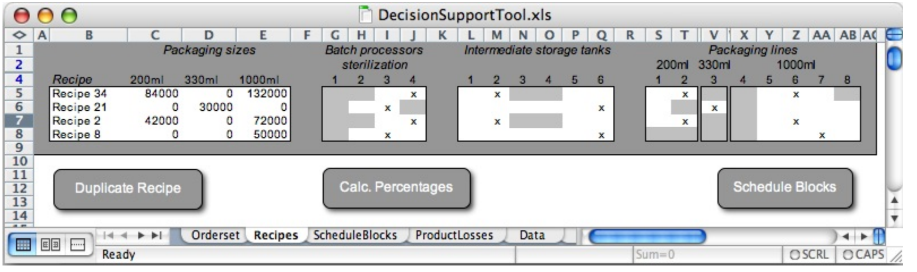

Figure 6.5. Example of the recipe overview and production unit assignments. On the left, recipes and required volumes for different packaging lines are shown (automatically derived from the production orders of Step 1). The remaining part of the screen is used for the assignment of the recipe batches to the various production units (where not all assignments are possible). For example, recipe 34 is to be produced in two different packaging sizes (200ml and 1000ml), and is assigned to batch processor 4, storage tank 2, and packaging lines 2 and 6.

(*e.g.*, a product needs to have a certain treatment in the batch process or can only be stored in a tank which has an agitator). Several additional features are available through buttons below the recipe table.

6.4.3 Step 3 — Schedule blocks

Figure 6.6 shows the result of a deterministic simulation example, based on recipe data, production unit characteristics, and the capacity assignments made in Step 2. The expected realized production is depicted in Gantt charts for each of the recipes, which we call schedule blocks. This includes setups, intermediate cleaning, and stops due to full or empty storage tanks. As this concerns a deterministic simulation study, the production stops of the packaging lines were not modelled with stochastic procedures. To model the efficiency of the packaging lines in a deterministic way, we adjusted the packaging capacity for its average efficiency (for each of the packaging lines). Using these adjusted capacities, the decision support tool creates expected production results.

It is important to note that sequencing decisions were not made in the process to create these so-called schedule blocks. These can affect reuse possibilities for product losses, and should therefore, be considered during the scheduling of the production batches.

We also added the possibility to create a graphical representation of the expected storage level in the intermediate storage tank. This gives additional opportunities to gain insight into the characteristics and interactions of the production process and on the impact of the capacity assignments that were

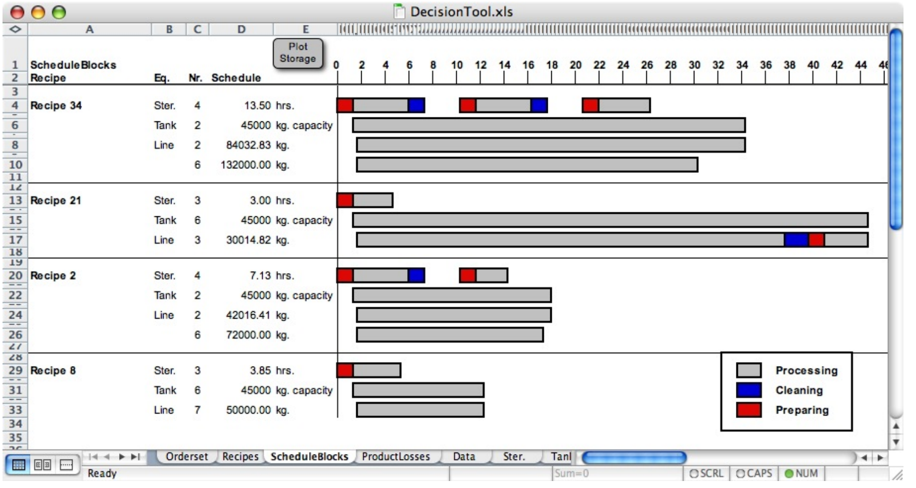

Figure 6.6. Schedule blocks: Gantt charts showing the expected realized production for each of the recipes. This graphically represents the effects of the planning decisions on the expected realized production.

made.

6.4.4 Step 4 — Product losses

Based on the schedule blocks from Step 3, the planning-related amount of product losses can be calculated. From the simulated production runs determined in Step 3, the expected amount of stops and starts of equipment can be calculated and the amount of losses resulting from these is determined. This is summarized in two ways. First, the losses are summed for each of the production units. As mentioned before, the losses calculated are combined with an estimation of the stochastic part of the losses based on the operational time, to create a good overview of the total amount of expected losses. Secondly, the losses are also summed for each of the recipes produced and also combined with an estimation of the stochastic part. This results in a loss percentage per recipe, which can be a very useful insight in the costing aspect of the plant.

6.5 Simulation experiments

Using the decision support tool, we were able to perform simulation studies or what-if analyses to estimate the effects of changes in *e.g.*, scheduling procedures, setup losses, cleaning times, efficiencies, additional capacity, etc.

Based on the current situation in the case study company, we were particularly interested in the effects of an extended planning horizon and the effects of increasing packaging line efficiencies[2].

The experiments described in this section were performed with several weeks of data. Starting from actual schedules, the effects of parameter changes were simulated. In all experiments, close cooperation with the production manager was sought. This was also necessary in some cases, as he would be able to make new production schedules in the experiments concerning the extended planning horizon.

6.5.1 Planning horizon

Currently, production is scheduled on a weekly basis. In the case study company, there was a strong feeling that an extended planning horizon would lead to more efficient batch sizing and would therefore, reduce setups. However, they were not able to quantify this due to the complex interactions in the production system. Larger batches would definitely reduce product losses due to setups, but to what extent it would influence intermediate production stops was unclear.

In our simulation study, we compared a planning horizon of 1, 2, and 4 weeks. We used actual weekly schedules as inputs for the study, and combined these schedules into schedules for 2 weeks and 4 weeks. Due to best-before dates on the end products, a significant number of products is still produced on a weekly basis, even though this results in small, inefficient batches.

To comply with confidentiality, we indexed the results, where the average weekly product loss is set to 100. Figure 6.7 shows that going from a planning horizon of one week to a horizon of two weeks results in a reduction of product losses of nearly 20%. Considering the fact that there were only a few possibilities to combine batches due to the best-before date restrictions, this result is remarkable. Changing the planning horizon to four weeks resulted in an additional 14% improvement, but four weeks might be an unrealistic target in the current competitive environment in the food-processing industry.

[2]Here, efficiency is defined as the total effective time divided by the total production time, where the latter includes unexpected stops, and possible production at lower speeds. Together with the theoretical capacity of the packaging lines, the efficiency is used to determine the total expected production time.

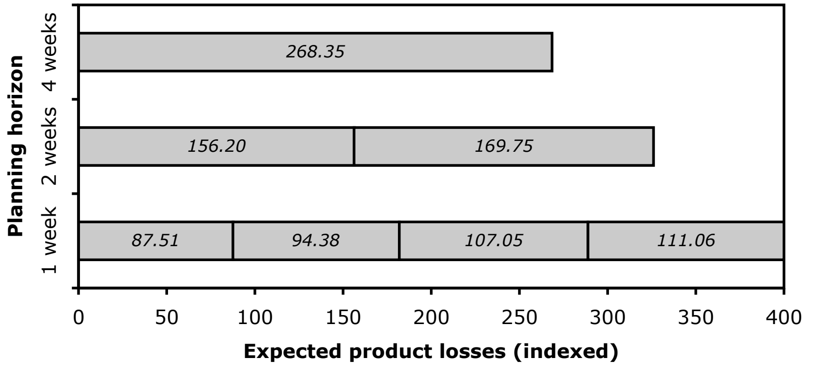

Figure 6.7. Resulting product losses for different planning horizons (average weekly loss is indexed at 100).

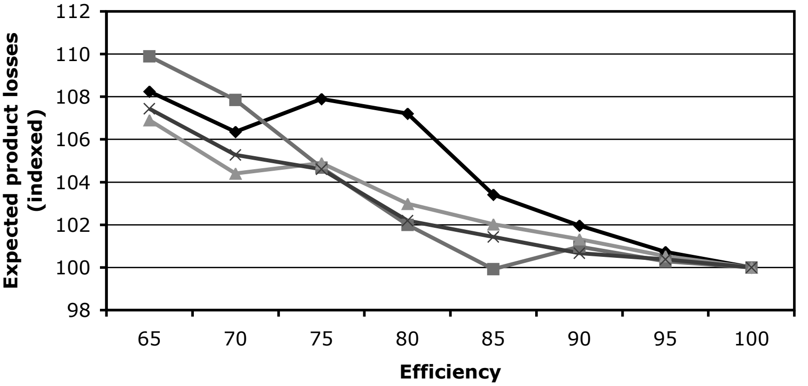

Figure 6.8. Resulting product losses for different efficiencies for four weeks (100% efficiency is indexed at a product loss of 100).

6.5.2 Packaging line efficiency

Here, the expectation of production management is that an increasing efficiency will reduce the number of production stops due to full intermediate storage tanks. However, due to the interactions between the processing and packaging stage, this is not clear. To gain insight into these effects, we simulated four weeks of production under various levels of efficiency. We range the efficiency from 65-100%, to have an extensive range of possible efficiencies. We again indexed the results, and used the results for 100% efficiency as the benchmark value.

The results are shown in Figure 6.8. Experiments show that there is indeed an overall tendency towards less product losses at higher efficiency, but sometimes an increase in efficiency can also lead to an increase of product losses. This is caused by replacing a few long stops of the sterilization process with a larger number of short stops; resulting in more losses due to starting and stopping.

6.6 Conclusions and discussion

This paper discusses the development of a decision support tool for reduction of product losses in the food-processing industry. We created a research framework to collect and analyse data, supporting the development of the tool, and providing insights in the possible scenarios for deterministic simulation studies. The research framework and the development of the decision support tool are illustrated by an application in a dairy processing company.

The current paper is one of the first papers that starts with the idea of reducing the product losses by explicitly relating them to planning decisions. It is also original in the development of a concrete decision support tool that helps to achieve better planning and therefore, helps to prevent or reduce losses. The theoretical value is that the paper helps in better understanding the complexities underlying waste and product losses in food-processing and process industries. Reduction of product losses through improved planning is a fruitful way to improve both the profitability and sustainability of production processes in the food-processing industry.

In the case study, one of the obvious findings is that larger batches, achieved by longer planning horizons, tend to reduce the production losses. However, the relationship turns out to be more subtle then expected due to the interaction effect between packaging lines and their breakdown behaviour, processing lines and the intermediate storage. A longer planning horizon is beneficial for reducing the planning-related amount of product losses. All in all, the tool is able to help the corporate managers to reduce the planning-related losses by nearly 20% by combining only a relatively small amount of batches. But maybe a more important result is the insight gained on the interactions between processing, packaging, and intermediate storage.

In the current application, we limited our focus to a more or less deterministic approach of product losses. Future work might include the stochastic breakdown behaviour of the packaging lines to analyze the effect of strong variation in the amount of product losses and their effects on reusability of the product.

The method as applied in this paper offers a systematic tool to assess the performance of a plant with respect to product losses and the relationship with demand pattern, production batch sizes and planning. It might be obvious that the Excel-tool implementation is case-specific. However, it can easily be adapted to similar production systems and it is built to facilitate use in other situations. We strongly believe that the approach is also applicable for other factories and companies. The research framework and tool structure presented in this paper can be used as guidelines for the case-specific development of decision support tools for reduction of product losses.

In the future, the production manager will also have access to the tool, and will be able to utilize it to evaluate his planning and scheduling decisions. For this, the tool needs some additional development to improve its usability, and then only brief training will be necessary (the implementation in Microsoft Excel greatly improves user acceptance and understanding).

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