A simulation- and optimisation-based decision support system for an uncertain supply chain in a dairy firm

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Abstract: Supply Chain Management (SCM) refers to the problems where the decisions of supply, production and demand are integrated in a single framework. A typical supply chain faces uncertainty in terms of supply, production and demand. Therefore, SCM is largely about managing uncertainty and risks. This paper introduces a simulation- and optimisation-based decision support system that helps the scheduler in a dairy firm to schedule milk tankers and production in order to (1) meet the market demand, (2) minimise the difference between supply and demand, and (3) minimise the overall trip cost for collecting raw milk from milk farmers.

Keywords: Decision Support System; DSS; Supply Chain Management; SCM; scheduling; simulation; optimisation.

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1 Introduction

A supply chain is defined as the flow of goods and information from initial sourcing all the way through to delivery to the end user. A supply chain is a highly dynamic environment that is subject to supply availability and market fluctuation. A typical supply chain faces uncertainty in terms of supply, production and demand. Supply Chain Management (SCM) is concerned with planning, coordinating and integrating the sourcing, procurement, production and distribution activities involved in the supply chain. SCM activities take place within a framework of complexity and uncertainty, dealing with changes in both upstream and downstream market conditions, as well as internal contingencies. The goal of SCM is to provide maximum customer service at the lowest possible costs (Chu, 2003). SCM uses advanced technology, information management and operations research to plan and control an expanding complexity of factors to better produce and deliver products and service.

This paper describes a simulation- and optimisation-based decision support system, called SCManager, that captures the combinatorial complexity and uncertainty dimensions associated with a real-world supply chain. Our research was motivated by a complex supply chain facing a dairy firm. This paper is based upon an actual situation encountered by the dairy firm. The information has been disguised and some details have been omitted to maintain confidentiality while retaining the important characteristics of the situation. The dairy firm is a small milk-processing company that runs two factories. Factory A produces three types of fresh milk products to satisfy daily demand in the local market, and Factory B produces dried milk for the nationwide market. The technology in the dairy industry is stable and the products are homogeneous. Firms in the industry are price-takers. They bear all the market risks. Their customers are obligated to purchase only what they need.

This dairy firm faces complex challenges, such as fluctuating market conditions, aggressive competition from larger companies, pricing pressures, and rising transportation and production costs. Competition in the local dairy market is fierce. The dairy firm operates at minimal profit margins. It is therefore crucial that the firm’s operation is cost-effective. After some efforts of reengineering its production, the firm shifts its attention to the performance of the supply chain as a whole. However, the difficulty of capturing supply chain value with better supply chain planning and operational scheduling is significant owing to the uncertainties in the supply chain.

The firm faces uncertainties in three separate but tightly coupled areas: supply, production and demand. Therefore, the firm must make the scheduling decisions under great uncertainty. The firm operates a fleet of milk tankers to collect milk from milk farms. It has contract with about 130 farmers to supply raw milk daily. The amount of milk provided by each supplier has seasonal and daily variations. The farmers are serviced by the tankers over two shifts each day. The farmers are grouped together into a trip – a sequence of farmers that are visited by a tanker in a specific order. The morning shift consists of a set of trips that collect milk and deliver it to Factory A. The trips in the afternoon shift collect milk from the farmers who are not visited by the morning shift and deliver the milk to Factory B. The trips must be scheduled so as to satisfy the local market demand first.

Factory A delivers the fresh dairy products to local grocery stores, convenience stores, supermarkets, restaurants and hotels through a contract truck company. Each customer order consists of different quantities of the three product types. Because of high uncertainty in consumer demand, most customers do not order milk from Factory A in advance. Instead they place their orders on site when the delivery truck comes to their stores, and the quantities of their orders vary daily. Therefore the firm faces uncertain daily demand. For the firm, the nature of the production process can be uncertain because of the uncertain production yield losses. The three fresh milk products go through different production lines with independent yield-rate distributions. Because of the yield losses, the firm produces a random fraction of the raw milk for each product.

Before implementing the SCManager system, two full-time schedulers manually developed weekly schedules for the milk tankers and production. During the scheduling process, they used the simple moving-average method to estimate raw milk supply and local demand for each milk product. Based on the supply and demand estimates, the schedulers created schedules for the milk tankers and production in Factory A. In their scheduling process, the schedulers typically modelled the firm's supply chain process in terms of 'average' scenarios. The decisions on supply and production were based on the average demand, supply and yield rate. This method can lead to systematic errors known as the 'flaw of averages', in which the decisions are made in an environment where the system itself is trying to 'defeat' the decision maker (Savage, 2002). If actual demand exactly equals its average, then there are no costs associated with overproduction and underproduction. However, the actual rarely equals the average. If actual demand is less than the average, then there will be spoilage costs since the firm disposes unsold perishable milk products. If demand is greater than the average, there will be cost related to the lost sales. Unsatisfied demand frequently results in the loss of sales to a competitor. It also results in the decrease of future demand. Therefore, the firm always faces the costs associated with overproduction and underproduction. Because of volatile demand and supply as well as short product life, matching actual supply with actual demand becomes an important strategic decision for the firm. On the other hand, crew costs (drivers and truck costs) account for a large portion of the firm's operating expenses. Because dairy products are low-value products, material and transportation costs play a significant role in the economics of production. The firm faces rising milk-collection costs, which motivates the schedulers to pursue an improvement in the milk tanker deployment in order to minimise the crew cost.

As a result, the firm wanted to exploit any possible efficiency improvement opportunities offered by technology. The firm recognised the need to build a Decision Support System (DSS) that respects the complexity and uncertainties in its supply chain. The promise of a simulation- and optimisation-based DSS is particularly appealing to the firm where the scheduling decision must be made under great uncertainty. The firm organised a project team and developed the SCManager system. After the firm implemented the SCManager, improvements have been realised in terms of reducing the operation cost, reducing the gap between supply and demand, and improving customer service metrics.

The rest of this paper is organised as follows. In the next section, we review existing research and approaches on the issues related to supply chain management. In Section 3, we first discuss the firm's supply chain problem, and then describe the SCManager system. We also present the observations from the implementation of the system. Our conclusions are provided in the final section.

2 Literature review

In the literature related to supply chain management, much research has been conducted in the areas of machine scheduling, logistics scheduling and inventory control (Chang and Lee, 2004; Cheng and Kovalyov, 2001; Li *et al*., 2005; Potts and Kovalyov, 2000; Potts and Van Wassenhove, 1992; Qi, 2005). Machine scheduling models concern allocating limited machine time to jobs. Logistics scheduling deals with job delivery and transportation issues. To support logistics activities, researchers have developed both tactical planning and operational scheduling tools to address resource allocations, inventory policies, customer segmentation and customer product consumption forecasting. In most existing models, inventory cost is a significant portion of the total cost, and production and distribution are indirectly linked through inventory. The purpose of inventory control is to reduce the total inventory cost for the demands from all customers. Traditional approaches to these problems focus on three major variables: delivery time, cost and quality. Efficiency and competitiveness are the main preoccupations.

Uncertainty is a multidimensional concept and has been considered as one of the most important factors in the management field (Milliken, 1987; Sutcliffe and Zaheer, 1998). Uncertainty in the supply chain is one of the characteristics that make the supply chain optimisation problems challenging and important. While routine planning and control decisions in static supply chains are now relatively well understood, this is not case for uncertain supply chain environment.

Analytic models reflecting uncertainty in the form of a random supply variable were first explored by Arrow *et al.* (1958), where the amount received from an agricultural harvest is based on some probability distribution that is completely independent of the order quantity. Since then, many researches have focused on four major problems:

1 the random yield problem
2 suppliers diversification problem
3 the assembly problem
4 the random demand problem.

The traditional approach to addressing variability of the demand is to improve forecasting. Safety inventories are used to mitigate the variability of lead times. Safety capacity is used to maintain a sufficient capacity to process customer orders.

In a standard production–inventory problem with demand uncertainty only, the production decision for the single-period problem is made by using the news vendor solution (Nahmias, 2004) and the components are ordered to meet the production requirement. However, with supply uncertainty, the delivered quantity of the components may not be sufficient to realise the chosen production goal. Anupindi and Alella (1993) discuss diversification under supply uncertainty for a single component in a two-suppliers case with random demand and derive conditions under which diversification will occur. Gurnani *et al.* (1996; 2000) consider an assembly system where a firm faces random demand for the final product and uncertainty in the delivery timing of the components. They formulate the cost function where the decision variables are the target level of the finished product to assemble and the order quantities of the components from the suppliers.

In the literature on issues related to uncertain yield, Yano and Lee (1995) present a comprehensive review of articles on lot sizing with random yield. Sepehri *et al.* (1986) create a variable yield model and develop a heuristic solution from a dynamic programming formulation, in a situation where multiple production runs are available to meet a demand. Gerchak and Parlar (1988) address the issue of diversification across *n* suppliers in an Economic Order Quantity (EOQ) setting with random yield. Gerchak *et al.* (1988) consider a single-period model with random yield and random demand and show that the optimal order point is unaffected by the yield distribution. Lee and Yano (1988) propose a multiple-production stage, single-time period model with an external, deterministic demand made only on the final production stage. The amount produced at each stage depends on a random yield-rate fraction multiplied by the order quantity. Tang (1990) studies a multistage production system with uncertainty in output rate and demand and analyses the impact of varying yield rates and demand on the production–inventory policy. Gerchak *et al.* (1994) use an innovative approach to address the assembly problem with random yield at the component and at the assembly stage. Yao (1998) considers an inventory model where the objective is to minimise the cost of procuring components subject to a given probability of achieving a fixed target yield from the assembly stage.

Some research models address joint scheduling decisions of procurement, production and distribution. Zipkin (1986) considers the combined inventory and production problem and develops evaluation models for the inventory and production steps. Potts (1985) and Woeginger (1998) study a model in which orders are first processed in a single plant and then delivered to their customers. The objective is to minimise the maximum order lead time. Since transportation cost is not considered as a part of the objective in their model, each order is delivered as a separate shipment immediately after it is processed. Chen (1996), Wang and Cheng (2000), and Hall and Potts (2003) consider a different set of models that treat both delivery lead time and transportation cost as part of the objective, but assume that the order delivery is done instantaneously without any transportation time. Bassok and Akella (1991) study an aggregate production planning problem in a manufacturing facility with a critical raw material. The raw material supply is unreliable owing to stochastic lead time or stochastic quality, and the demand for each of the products is stochastic and uncorrelated. They jointly optimise production and component ordering decisions and demonstrate the savings by using an integrated model. Lau and Lau (1994) study the procurement and sourcing problem faced by a buyer who has to choose between a low-cost/long-lead-time supplier and a high-cost/short-lead-time one in the environment where demand is deterministic while procurement lead-times are stochastic. Ciarallo *et al*. (1994) discuss the aggregate planning problem for a single product with random demand and random capacity and incorporate the uncertainties into the production process. Lee and Chen (2001) consider a similar model but with the restriction that there are a limited number of vehicles that deliver the completed orders from the plant to the customers. Hall *et al*. (2001) investigate a model with the restriction that there are a fixed set of delivery dates at which the completed orders can be delivered. Chen and Vairaktarakis (2005) study a model with both delivery lead-time and transportation cost as part of the objective function and with non-zero delivery times.

As firms attempt to increase supply chain performance, there is a critical need to gain a deeper understanding of the processes in the supply chain. Supply chain problems are usually very large and complex owing to the interaction between the entities, dynamics of the processes, and stochastic nature of the demand and supply. Simulation has been found to be one of the popular and suitable mechanisms for modelling supply chain and evaluating the performance of a supply chain (Kumar *et al*., 1993; Venkateswaran and Son, 2004). There have been a number of simulation tools developed for analysing supply chain processes (Swaminathan *et al.*, 1998) or for studying specific research issues such as the well-known ‘bullwhip effect’ (Lee *et al*., 1997). Towill *et al*. (1992) use simulation techniques to evaluate effects of various supply chain strategies on demand amplification. Tzafestas and Kapsiotics (1994) utilise a combined analytical/simulation model to analyse coordinated supply chains control. Chang and Makatsoris (2001) address the necessity for developing the simulation model for the supply chain management and discuss the requirements for supply chain simulation modelling. Chopra and Meindl (2006) introduce the software simulation of the ‘Beer Game’. The Beer Game supply chain consists of four stages (producer, distributor, wholesaler and retailer) with a single player operating at each stage, and allows the players to experience the well-known ‘bullwhip effect’, or the amplification of downstream demand fluctuations as they propagate upstream to distributors, manufacturers and their suppliers. Kleijnen (2005) provides a survey of simulation in supply chain management. The author reviews four types of simulation, namely, spreadsheet simulation, system dynamics, discrete-event simulation and business games. However, these simulation tools have focused on significantly simpler scenarios than those likely to be found in practical supply chain trading environments.

Successful supply chain management requires many decisions relating to supply chain strategy, design, planning and operation. These decisions have strong impact on overall profitability and success. In the broader literature of SCM, a tremendous amount of research has been done on various strategic and tactical problems. However, there are some researches that address decision support issues at practical operational level. Joines *et al*. (2002) present a simulation methodology for optimising supply chain employing a supply chain simulator and genetic algorithms for the sourcing problem of general merchandise from a supplier to a retailer. Van der Zee and van der Vorst (2005) conduct a literature survey with the aim of listing simulation model qualities essential for supporting successful decision making on supply chain operation. Basnet and Foulds (2006) developed a vehicle-scheduling decision support system, called FleetManager, that addresses the milk tanker routing problem in the New Zealand dairy industry.

The system incorporates vehicle routing and judgemental models to help the vehicle schedulers of a dairy company build the schedules using their experience and preferences. However, this system focuses only on the vehicle-scheduling problem. It does not incorporate uncertainties into its decision-making process. In our paper, we describe a simulation- and optimisation-based decision support system that considers uncertainties in demand, supply and production and uses simulation and optimisation techniques to help the scheduler in a dairy firm make daily operational decisions on the supply, vehicle routing and production.

3 The SCManager system

The purpose of the SCManager system is to help the schedulers make scheduling decisions on the trips and production to meet the customers' daily demand efficiently. The system utilises Monte Carlo simulation and an optimisation methodology that employs a heuristic search algorithm. The SCManager optimises the firm's supply chain and satisfies the customer demand by searching for better trips and by simulating the whole process of milk collection, production and customer demand. The following subsections describe the supply chain problem, the methodology used by the system, the components of the system, and the system implementation results.

3.1 The problem

We can define our problem mathematically and introduce some optimality properties. We are given N suppliers and M customers. The supply is stochastic for a variety of reasons. Supplier i ($i = \{1, \dots, N\}$) provides random quantity s_i of raw milk with a certain probability distribution. The firm collects total raw milk S from n ($n \subset N$) suppliers through h trips in the morning shift. Factory A divides the collected milk S into $S_1, \dots, S_k$ to produce k different types of products. The production is a stochastic process. The production line j produces the quantity Q_j of product j from raw milk S_j with random yield rate α_j ($j = \{1, \dots, k\}$). The demand is also stochastic. Customer w has a random demand d_j^w for product j ($w = \{1, \dots, M\}$; $j = \{1, \dots, k\}$) with a certain probability distribution. The supply chain problem is to schedule the trips and production so as to optimise objective functions that take into account crew costs and supply–demand match.

Figure 1 provides a high-level overview of the supply chain processes for the dairy firm. The decisions on trips and production are afflicted by uncertainties that turn supply and production into random variables. Production is to meet an uncertain demand that can be represented by a random variable with a probability distribution. The uncertainty present in the production process can be modelled by a yield rate that is a second random variable with a probability distribution. Finally, the supply decision must incorporate the effect of uncertainty on the output of milk farmers. Given the random demand, random yield rate and random supply, our problem can be defined as to find trips and production schedules such that the gap between demand (D) and quantity produced (Q) is minimised and the total travelling distance of the trips (C) is also minimised:

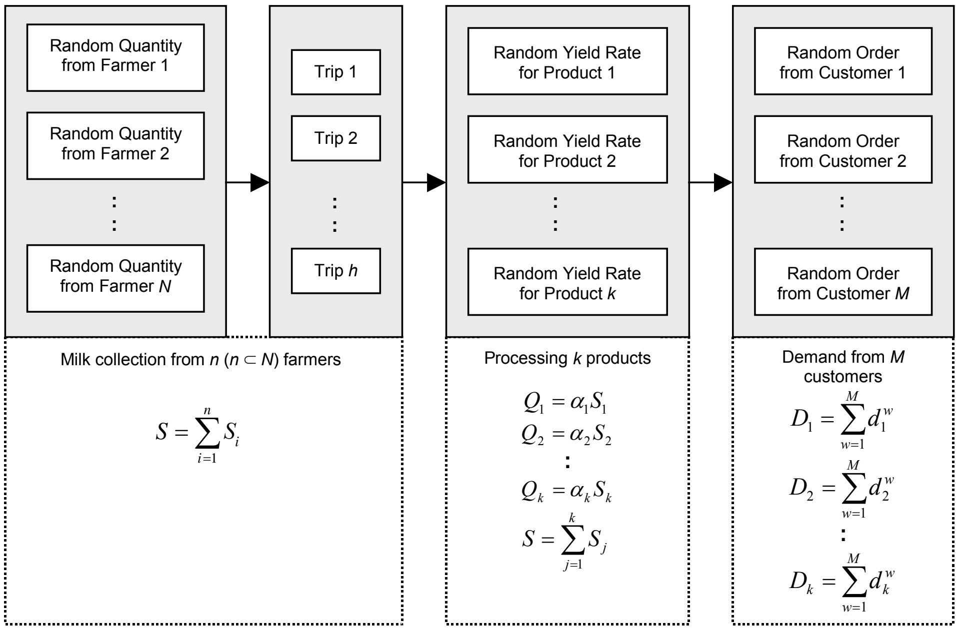
$$\min \ \gamma = \sum_{j=1}^{k} | D_j - Q_j \ | \ \text{and } C = c_{\text{trip1}} + c_{\text{trip2}} + \dots + c_{\text{trip}h}$$

where:

D_j = demand for product j
Q_j = quantity of product j produced.

Clearly the firm would like the demand–supply gap γ to be as small as possible, preferably $\gamma = 0$. The issue is to collect raw milk S from farmers in such amount that minimises the gap γ and total travelling distance C.

Figure 1 The supply chain processes for the dairy firm



3.2 The methodology

Operations Research and Computer Science communities have developed efficient problem-solving techniques for a variety of problems, such as job shop-scheduling problem, resource constraint project-scheduling problem, and vehicle routing problem. It is a common practice to model new problems as instances of an existing classical problem (Beck *et al*., 2006). If a problem can be modelled as a classical problem, there exist techniques that are very likely to be able to solve the problem reasonably well. By their very nature, however, classical models are a simplification of real-world problems and often based on limiting assumptions. A real-world problem is seldom a perfect match for a classical optimisation problem studied in the literature. The challenge in our case is to address those real-world features that are not considered in the classical models. Besides the complexity of the problem, there is the additional challenge of not being able to model. The mathematical modelling is unable to deal with the uncertainty nature of the problematic situation. It is unlikely to find an efficient exact algorithm to handle the complexity and uncertainty involved in our case.

Uncertain quantity is what mathematicians call a random variable. To our dairy firm, the uncertainty is an objective feature of its supply chain over which the firm has no control. It is generally false to assume that the supply associated with average demand is the average supply. The best we can do to estimate a random variable *a priori* is to estimate its probability distribution. Planning for an uncertain future calls for a shift in information management – from single average number to a probability distribution – in order to correct the 'flaw of averages' (Savage *et al*., 2006). Under uncertain conditions in our case, the supply, demand and yield rate are no longer fixed values, rather they are random variables whose exact numerical values are unknown but can be represented in terms of probability distribution. Supply chain performance can significantly benefit from effectively using the probability distribution in decision-making processes.

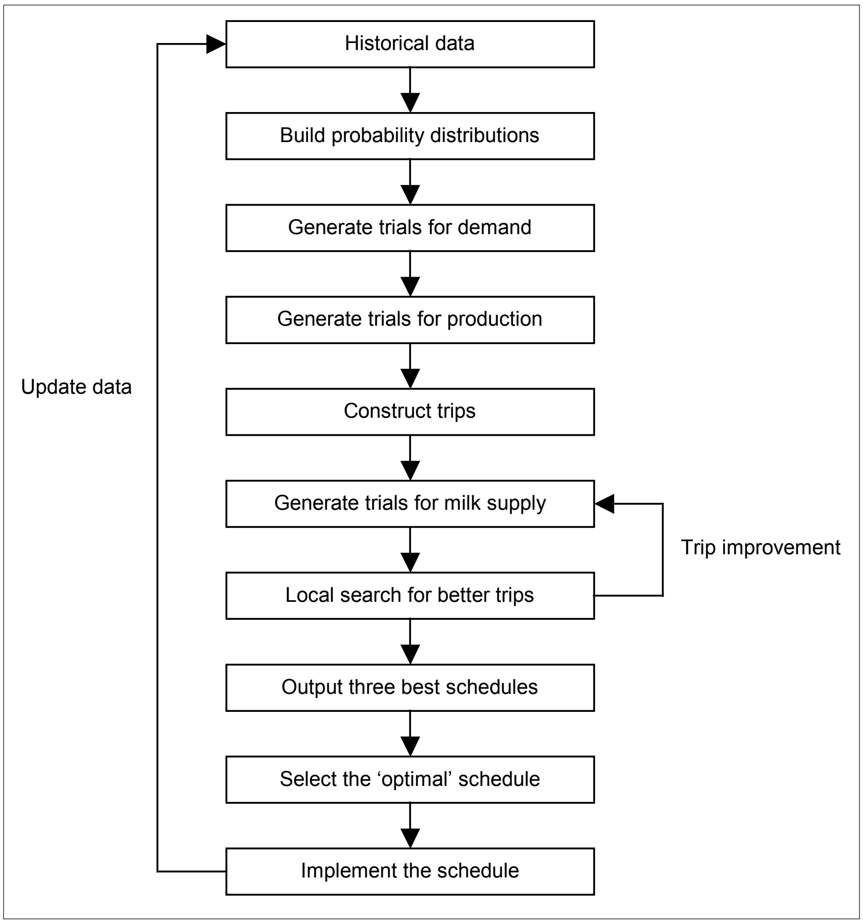
This dairy firm problem with random demand, random yield rate and random supply is difficult to solve analytically. It is probably impossible to extend any optimal approach used in the literature to this more complex problem. With so many uncertainties, our case is just a perfect application for simulation. Simulation means any sort of stochastic analysis based on modelling probability distribution through sampling. Computer simulation is a methodology that can be used to directly model the complexities of an entire system without the limiting assumptions. A simulation model seeks to 'duplicate' the behaviour of a system by studying the interactions among its components. The output of the simulation model is presented in terms of selected measures that reflect the performance of the system. Obviously, the creation of a simulation-based DSS is necessary in this context.

Simulation systems usually are not constructed in the framework of an optimisation process. A simulation system merely measures the output of a system for predetermined values of the decision variable. In our case, there is a need to combine optimisation with the power of simulation system. The implementation of a simulation process within the context of optimisation can be achieved by systematically changing the values of the decision variables and then measuring the output by making proper simulation runs. The combination of simulation and optimisation can become a powerful tool for allowing us to both quantify and observe the supply chain dynamics.

This dairy firm stores rich historical data about milk supply from each farmer, demand order from each customer, and production yield rate for each product. The probabilities can be extracted from these data. A probability profile that lists all the possible outcomes with their probabilities provides complete specification of the uncertain situation. The probability distributions of these random variables are assumed to be independent across the supply chain. Once we know the probability, we can manage the schedule by adjusting trips to increase the chance of a desirable outcome.

Figure 2 illustrates the framework of the SCManager system. The most basic problem here is to characterise the properties of the inherent uncertainties in the supply, production and demand. This framework acknowledges that these uncertainties have a definite impact on the cost of supply chain decisions. A DSS that recognises the variation in supply, demand and production processes will invariably lead to less chaotic results. By modelling these uncertainties in an aggregate fashion, the interaction of these uncertainties is revealed.

Figure 2 The framework of the SCManager system



The Monte Carlo simulation method is used in the system. Monte Carlo simulation is a well-established method for handling uncertainties and associated risks in computer simulation models. It essentially involves generating hundreds or thousands of replications of a model where uncertain variable is replaced with numbers generated from an appropriate distribution to represent the form of uncertainty of the particular variable.

In the SCManager system, the overall scheduling process is divided into four steps. The first step is to determine the target level of raw milk supply. The system generates Monte Carlo trials for demand and production yield rate. Then based on the trials, the system calculates the target level of raw milk supply. We recognise that simulation is a statistical experiment and its results will reach steady state only after the experiment is repeated a sufficiently large number of times. As a result, in order for the output of the system to be representative of what would be expected in the long run, we allow the system to generate 'large enough' trial samples to ensure that steady-state conditions prevail. Clearly, making simulation runs very long in order to bypass the transient state is costly, as it may involve long nonproductive use of computing time.

The second step constructs the initial feasible trips for the morning shift, using the Nearest Insertion algorithm (Cook *et al.*, 1998). Each trip is constrained by the capacity of a tanker. The output of a farmer cannot be split between tankers. In each construction step, the next farmer to be added to the trip is determined by its distance and expected output. The system generates a set of trips with the objective of achieving cost minimisation. The cost factor is represented by the total distance of the trips. Then the system simulates the supply chain process. Upon the completion of the simulation, the output is the configuration of the trips with five values: total distance of the trips (C), expected gap γ, maximum gap γ_m, minimum gap γ_{min}, and standard deviation for the gap γ_{SD}.

During the third step, the system uses the local search heuristic to improve the trip schedule. An initial trip obtained in the construction stage is improved by swapping farmers with neighbouring trips or unselected farmers, based on certain optimisation rules and practical constraints, such as the probability of collected milk exceeding the tank capacity for a trip is less then 3%. Then the system performs the simulation on the new trip schedule. This stage repeats until a predefined number of iterations are performed. The system keeps the three best overall schedules.

In the last step, the scheduler evaluates the three best schedules. It is a multiobjective optimisation situation. With the objective of minimising the total travel distance C and minimising the gap γ, it is essential for the scheduler to measure and compare different schedules in order to select a satisfactory schedule. The system provides the scheduler with a summary of the schedules. The system interface displays these values in charts to present the consequences of these options. The scheduler selects the optimal schedule, based on the business goals and his personal preferences. Once a schedule is selected, the system outputs the schedule details for the trips and production.

After implementing the schedule, the scheduler enters the actual numbers for farmers' supplies, customers' orders, and production yield rates into the system. The system automatically updates the relevant probability distributions.

3.3 The SCManager system

The SCManager system incorporates uncertainties in supply, production and demand as well as embeds the simulation model and optimisation heuristic within IT application. It contains three major components: the database, the rule-set and the scheduling component.

3.3.1 The database component

This database is an essential part of the DSS and provides the scheduler with necessary inputs for the decision-making process. The database includes several data files. The Supplier file records the daily amount of milk provided by each farmer. The Customer file contains data about the order from each customer each day. The Production file includes the daily production yield rate for each product. The Probability files contain 60-day moving probability distribution for each farmer, customer and yield rate. Each day when the scheduler updates the Supplier, Customer and Production files, the probability distributions for supply, demand and yield rate are automatically recalculated and stored in the Probability files. Therefore, the probability distributions are updated on a daily basis. The Trial files contain the matrixes of pre-generated Monte Carlo trials for farmers, customers and yield rates. The scheduler can choose to generate 1000, 1500, or 2000 Monte Carlo trials for each random variable. The Distance file contains a matrix that records the distance between each pair of farmers and between each farmer and the factory. Finally, The Schedule file contains the most recently selected trip schedule. The scheduler has an option to retrieve the schedule and use it as initial trips for the optimisation process, by which the scheduler can save trip-construction time. All files in the database can be interactively updated through the user-friendly scheduler interface.

3.3.2 The rule-set component

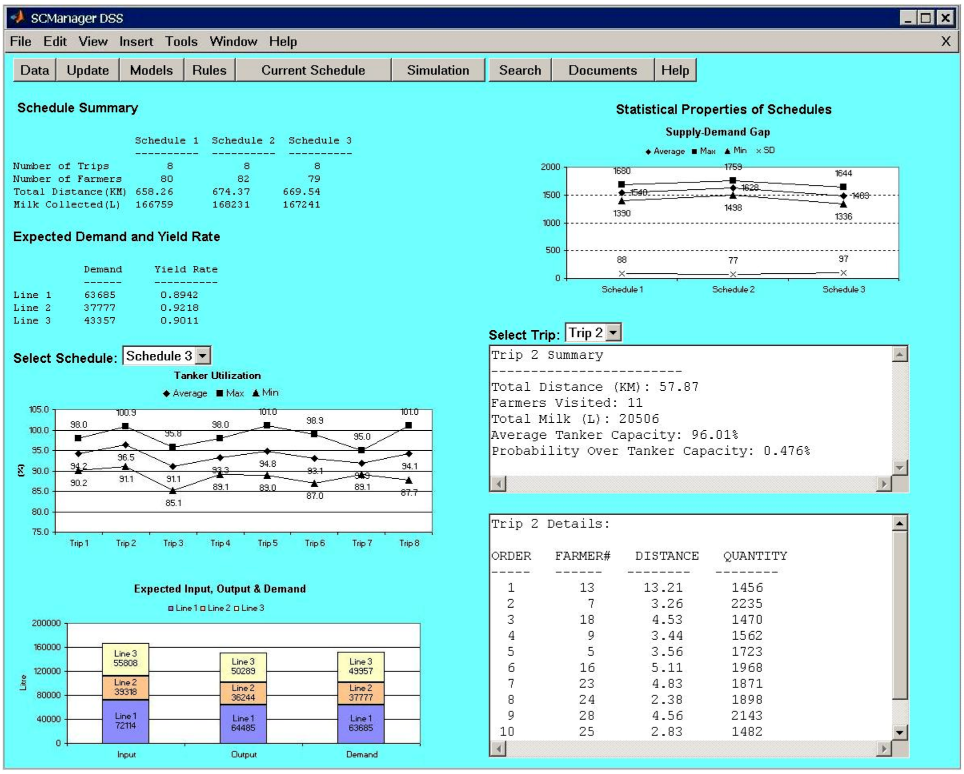
The scheduler set up the rules through dialogue boxes. By offering step-by-step guidance, the rule-set component is designed to help the scheduler establish a set of rules and criteria that will be used in the simulation and optimisation process. The rule set stores the following elements:

- The overall schedule decision flow model that help the scheduler understand the decision-making procedure and logic behind the system. The model follows the following decision-making process framework that enables the scheduler to critically review the decision-making process that leads to a decision. The first step involves generating alternatives. The second involves optimisation search in order to arrive at a small set of solutions that are implementable. The final step is to analyse these solutions under a scheduler's lens. The scheduler reviews tradeoffs among criteria to decide which solution best aligns with the business strategy or objectives.
- A series of constraint rules (such as the capacity of a milk tanker and number of available tankers for a particular day) and priority rules devised from the practical realities of supply chain process. These rules are used in the simulation process.
- A set of criteria for heuristic search algorithm, which are used in the optimisation process.
- A scheduling guideline that helps the scheduler to select the optimal schedule according to the firm's policies and business goals.

3.3.3 The scheduling component

The scheduling component performs the entire scheduling process. The scheduler communicates with the component through the scheduler interface. The interface is simple and interactive, and is composed of a limited set of controls and displays. The scheduling component retrieves the trials from the database, performs the simulation, and heuristically searches for better schedules. It generates different schedules and enables the scheduler to evaluate them and decide on the most satisfactory one. The major output of the DSS consists of several scheduling charts and tables that provide the scheduler with a summary of the morning shift schedule and production schedule (see Figure 3). The statistical properties of the results are immediately apparent through the charts. The scheduler would choose one alternative among several alternatives based on their estimated cost, measured performance and other managerial criteria that could not be modelled in the system.

Figure 3 Outputs of SCManager system



3.4 The implementation results

The SCManager project team consisted of a SCM consultant, a system analyst, two programmers, a scheduler and a manager. The team started to develop the DSS system with an eye on simplicity of use rather than computing power. The design philosophy therefore was to provide a DSS that allows the scheduler to have robust, consistent answers without deep knowledge of statistics or operations research.

The team also focused on the scheduler interface, that is, on how the scheduler could interact with the system. This is particularly difficult when the output of the system is probabilistic. Schedulers have so much difficulty to understand and communicate uncertainty in the supply chain. After all, how does a scheduler interact with a probability distribution? The team developed the system using a prototyping approach. They identified the linkage between supply, production and demand, and then developed a prototype of a simple tool for describing probability, simulation or optimisation. They obtained feedback from the schedulers and managers on the perceived usefulness of the tool. The systematic testing assured that each process was error-free and user-friendly before the next layer of complexity was added. The team worked on both the model building and the interface between the user and system.

All the components of the system were initiated with proof of concept prototypes that enabled the team to get validations from the top management before going into full-scale software development. The top management made the major strategic decisions on the system development, so that the DSS could follow crystal clear and undisputed directions in the decision-making process and optimisation objectives. For instance, it was stated that in production scheduling, the satisfaction of customer orders outweighs cost optimisations. When using the system to schedule the trips, a scheduler must first answer the question "Does the total amount of collected milk correspond to the customer orders?", and then the next question "Are the trips cost-effective?"

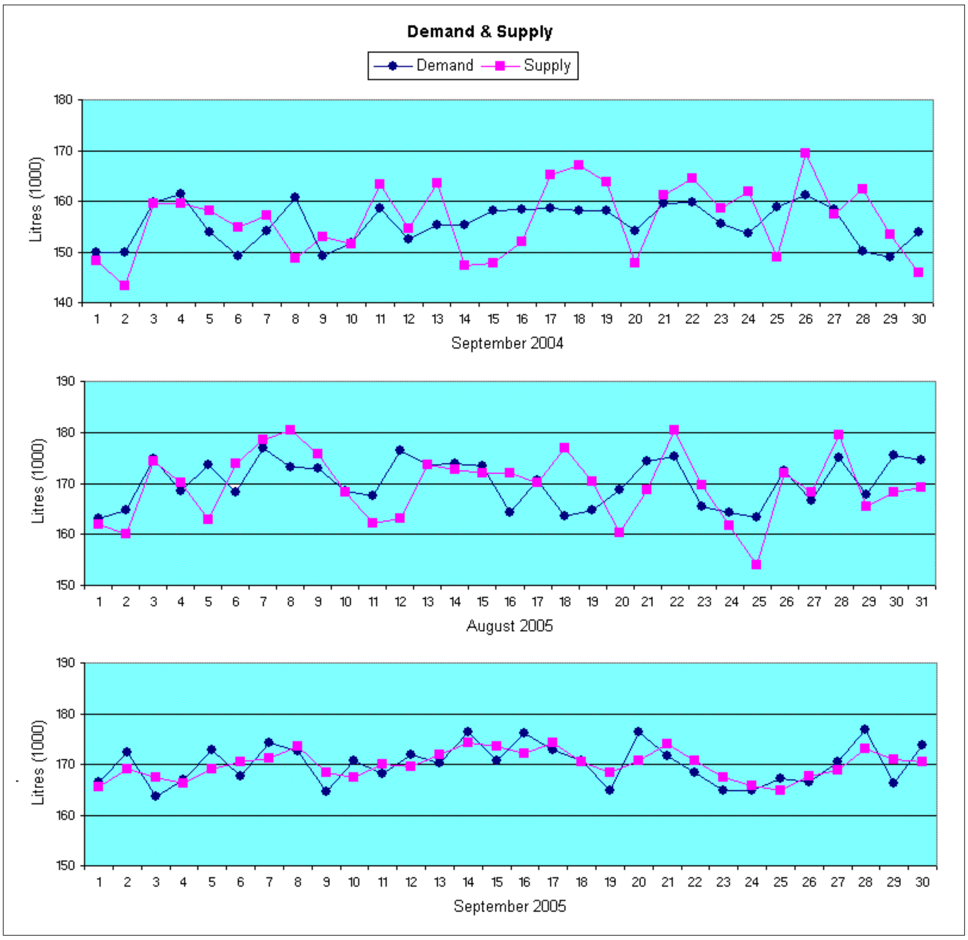
The team implemented an algorithm using the MATLAB 6.5 language. The SCManager system was conducted on a SUN 420R Server, running the Solaris 8 operating system.

The SCManager system was a successful decision support application of incorporating the simulation tools, optimisation features and scheduler's preferences. The firm has been using the DSS for two years. The managers and the schedulers expressed satisfaction with the DSS. More specifically, the firm benefited from the SCManager in the following ways:

- The SCManager facilitates the scheduling task. The time spent by the schedulers in preparing the schedules has been cut significantly and the boredom of the task has been reduced. The system reduced the number of schedulers from three to one, thus freeing the other schedulers for other creative tasks. The system has greatly simplified the work of the scheduler by eliminating paperwork, by simplifying the data management and by reducing the overall time dedicated to scheduling.
- The system has contributed in many ways to increasing the firm's efficiency by reducing its scheduling costs and by improving supply chain management. The trips generated by the system have proven to be more logical and operationally efficient and have resulted in significant savings. The cost per kilogram of milk collected from the farmers was reduced by more than 15%.
- Implementation of the DSS dramatically improves cost performance. The benefit of the DSS can be graphically demonstrated by comparing the gap γ between two periods. The firm started using the SCManager in September 2005. Figure 4 compares the gap γ between September 2004 and September 2005 and between August 2005 and September 2005. After implementing the system, the monthly mean gap γ was reduced by at least 30% and the standard deviation of mean gap by at least 45%. The firm estimates that the SCManager saves more than \$100,000 annually owing to smaller γ. Since developing the system cost the firm about \$210,000, the payback period was just a little more than two years.
- The customers, suppliers and production details have been systemised and incorporated into the system database, which has greatly improved the information management aspect of the firm's operations.
- The system provides schedulers with a better understanding of the scheduling process, supply chain operations and resource management. The system has been able to improve the visibility of the supply chain and its associated processes to the decision makers.

In conclusion, the SCManager system has made a major contribution to overhauling the firm's supply chain. The firm does see the benefits of the system: cost reduction, cost-based decision making, operational optimisation, and last but not least, better coordination between supply, production and demand.

Figure 4 Comparing the gap γ between September 2004 and September 2005 and between August and September 2005



4 Conclusion

This paper describes the characteristics of a simulation- and optimisation-based DSS that supports scheduling decisions in an uncertain supply, production and demand context. There is little doubt that supply chain is one of the key functional areas where costs can be significantly improved. The challenge in this case is how to model the underlying statistical relationship between the suppliers, production and customers in this uncertain supply chain. If we ignore the uncertain portions of supply chain, significant supply chain value may remain hidden, and therefore unexploited. Successfully conceptualising, planning, scheduling and executing a supply chain involve recognising and effectively managing a wide range of uncertainties.

With the simulation modelling and optimisation technique, we brought a new approach to the supply chain management. This study identifies an important area of simulation research that has fundamental connections to scheduling and optimisation applications. This case shows how a simulation model can communicate and quantify probability concept in an uncertain context.

However, there are some drawbacks with the SCManager. First, this system is currently too slow from a computational standpoint to qualify as interactive in a decision-making setting. The development of the system focuses on simplicity of use rather than power. A whole scheduling process takes several hours of CPU time to complete. So, it has room to improve computing efficiency by redesigning the algorithm and technique on simulation and optimisation. Secondly, the system does not provide the schedule manipulation functions to allow the scheduler to edit the trips. The system automatically creates the suggested trips. Sometimes it causes a problem. When a schedule is disrupted by an exception event, the scheduler must then modify it by adding a new supplier to a trip, removing a supplier from a trip, and swapping of suppliers between different trips. A DSS must provide the flexibility to schedule to cope with unexpected situations.

There are a lot of research opportunities in the field of supply chain management. It should leverage technology in innovative ways to unlock performance improvements across the supply chain. Based on the current model, efficient heuristic algorithms are desired to handle large-scale problems.

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References

Anupindi, R. and Alella, R. (1993) 'Diversification under supply uncertainty', *Management Science*, Vol. 39, No. 8, pp.944–963.

Arrow, K.J., Karlin, S. and Scarf, H. (1958) *Studies in the Mathematical Theory of Inventory and Production*, Stanford, CA: Stanford University Press.

Basnet, C. and Foulds, L. (2006) 'Fleet manager milks efficiency out of dairy company', *OR/MS Today*, Vol. 32, No. 6, pp.36–42.

Bassok, Y. and Akella, R. (1991) 'Combined component ordering and production decisions in manufacturing systems with supply quality and demand uncertainty', *Management Science*, Vol. 37, No. 12, pp.1556–1574.

Beck, J.C., Prosser, P. and Selensky, E. (2006) 'A case study of mutual routing scheduling reformulation', *Journal of Scheduling*, Vol. 9, No. 5, pp.469–491.

Chang, Y. and Makatsoris, H. (2001) 'Supply chain modeling using simulation', *International Journal of Simulation*, Vol. 2, No. 1, pp.24–30.

Chang, Y.C. and Lee, C.Y. (2004) 'Machine scheduling with job delivery coordination', *European Journal of Operational Research*, Vol. 158, No. 2, pp.470–487.

Chen, Z.L. (1996) 'Scheduling and common due date assignment with earliness-tardiness penalties and batch delivery costs', *European Journal of Operational Research*, Vol. 93, No. 1, pp.49–60.

Chen, Z.L. and Vairaktarakis, G.L. (2005) 'Integrated scheduling of production and distribution operations', *Management Science*, Vol. 51, No. 4, pp.614–629.

Cheng, T.C. and Kovalyov, Z. (2001) 'Single supplier scheduling for multiple deliveries', *Annals of Operations Research*, Vol. 107, No. 1, pp.51–63.

Chopra, S. and Meindl, P. (2006) *Supply Chain Management – Strategy, Planning, and Operations*, 3rd ed., Englewood Cliffs, NJ: Prentice Hall.

Chu, E. (2003) 'A review of simulation studies on supply chain management', *Journal of the Academy of Business and Economics*, Vol. 2, No. 1, pp.22–27.

Ciarallo, F.W., Akella, R. and Morton, T.E. (1994) 'A periodic review production planning model with uncertain capacity and uncertain demand: optimality of extended myopic policies', *Management Science*, Vol. 40, No. 3, pp.320–332.

Cook, W.J., Cunningham, W.H., Pulleyblank, W.R. and Schrijver, A. (1998) *Combinatorial Optimization*, New York: John Wiley & Sons.

Gerchak, Y. and Parlar, M. (1988) 'Yield randomness/cost tradeoffs and diversification in the EOQ model', *Naval Research Logistics*, Vol. 37, No. 3, pp.341–354.

Gerchak, Y., Vickson, R.G. and Parlar, M. (1988) 'Periodic review production models with variable yields and uncertain demand', *IIE Transactions*, Vol. 20, No. 2, pp.144–150.

Gerchak, Y., Wang, Y. and Yano, C.A. (1994) 'Lot sizing in assembly systems with random component yields', *IIE Transactions*, Vol. 26, No. 2, pp.19–24.

Gurnani, H., Alella, R. and Lehoczky, J. (1996) 'Optimal order policies in assembly systems with random demand and random supplier delivery', *IIE Transactions*, Vol. 28, No. 8, pp.865–878.

Gurnani, H., Alella, R. and Lehoczky, J. (2000) 'Supply management in assembly systems with random yield and random demand', *IIE Transactions*, Vol. 32, No. 8, pp.701–714.

Hall, N.G., Lesaoana, M. and Potts, C.N. (2001) 'Scheduling with fixed delivery dates', *Operations Research*, Vol. 49, No. 1, pp.134–144.

Hall, N.G. and Potts, C.N. (2003) 'Supply chain scheduling: batching and delivery', *Operations Research*, Vol. 51, No. 4, pp.566–584.

Joines, J.A., Gupta, D., Gokce, M.A., King, R.E. and Kay, M.G. (2002) 'Supply chain multi-objective simulation optimization', *Proceedings of the 2002 Winter Simulation Conference*, pp.1306–1314.

Kleijnen, J.P.C. (2005) 'Supply chain simulation tools and techniques: a survey', *International Journal of Simulation and Process Modeling*, Vol. 1, Nos. 1–2, pp.82–89.

Kumar, A., Ow, P.S. and Prietula, M.J. (1993) 'Organizational simulation and information systems design: an operations level example', *Management Science*, Vol. 39, No. 2, pp.218–240.

Lau, H.S. and Lau, A.H.L. (1994) 'Coordinating two suppliers with offsetting lead time and price performance', *Journal of Operations Management*, Vol. 11, No. 4, pp.327–337.

Lee, C.Y. and Chen, Z.L. (2001) 'Machine scheduling with transportation considerations', *Journal of Scheduling*, Vol. 4, No. 1, pp.3–24.

Lee, H.C. and Yano, C.A. (1988) 'Production control in multi-stage systems with variable yield losses', *Operations Research*, Vol. 36, No. 2, pp.269–278.

Lee, H.L., Padmanabhan, V. and Whang, S. (1997) 'The bullwhip effect in supply chains', *Sloan Management Review*, Vol. 38, No. 3, pp.93–102.

Li, C.L., Vairaktarakis, G. and Lee, C.Y. (2005) 'Machine scheduling with deliveries to multiple customer locations', *European Journal of Operational Research*, Vol. 164, No. 1, pp.39–51.

Milliken, F. (1987) 'Three types of perceived uncertainty about the environment: state, effect, and response uncertainty', *Academy of Management Review*, Vol. 12, No. 12, pp.133–143.

Nahmias, S. (2004) *Production and Operations Analysis*, 5th ed., New York: McGraw-Hill/Irwin.

Potts, C.N. (1985) 'Analysis of a heuristic for one machine sequencing with release dates and delivery times', *Operations Research*, Vol. 28, No. 6, pp.1436–1441.

Potts, C.N. and Kovalyov, M.Y. (2000) 'Scheduling with batching: a review', *European Journal of Operational Research*, Vol. 120, No. 2, pp.228–249.

Potts, C.N. and Van Wassenhove, L.N. (1992) 'Integrating scheduling with batching and lot-sizing: a review of algorithms and complexity', *Journal of the Operational Research Society*, Vol. 43, No. 5, pp.395–406.

Qi, X. (2005) 'A logistics scheduling model: inventory cost reduction by batching', *Naval Research Logistics*, Vol. 52, No. 4, pp.312–320.

Savage, S., Scholtes, S. and Zweidler, D.D. (2006) 'Probability management', *ORMS Today*, Vol. 33, No.1, pp.20–28.

Savage, S.L. (2002) 'The flaw of averages', *Harvard Business Review*, Vol. 80, No. 11, pp.20–21.

Sepehri, M., Silver, E.A. and New, C. (1986) 'A heuristic for multiple lot sizing for an order under variable yield', *IIE Transactions*, Vol. 18, No. 1, pp.63–69.

Sutcliffe, K.M. and Zaheer, A. (1998) 'Uncertainty in the transaction environment: an empirical test', *Strategic Management Journal*, Vol. 19, No. 1, pp.1–23.

Swaminathan, J.M., Smith, S.F. and Sadeh, N.M. (1998) 'Modeling supply chain dynamics: a multiagent approach', *Decision Science*, Vol. 29, No. 3, pp.607–632.

Tang, C.S. (1990) 'The impact of uncertainty on a production line', *Management Science*, Vol. 36, No. 12, pp.1518–1531.

Towill, D.R., Naim, M.M. and Wikner, J. (1992) 'Industrial dynamics simulation models in the design of supply chains', *International Journal of Physical Distribution and Logistics Management*, Vol. 22, No. 5, pp.3–13.

Tzafestas, S. and Kapsiotics, G. (1994) 'Coordinated control of manufacturing/supply chains using multi-level techniques', *Computer Integrated Manufacturing Systems*, Vol. 7, No. 3, pp.206–212.

Van der Zee, D.J. and van der Vorst, J.G.A. (2005) 'A modeling framework for supply chain simulation: opportunities for improved decision making', *Decision Science*, Vol. 36, No. 1, pp.65–95.

Venkateswaran, J. and Son, Y.J. (2004) 'Design and development of a prototype distributed simulation for evaluation of supply chains', *International Journal of Industrial Engineering*, Vol. 11, No. 2, pp.151–160.

Wang, G. and Cheng, T.C.E. (2000) 'Parallel machine scheduling with batch delivery costs', *International Journal of Production Economics*, Vol. 68, No. 2, pp.177–183.

Woeginger, G.I. (1998) 'A polynomial-time approximation scheme for single-machine sequencing with delivery times and sequence-independent batch set-up times', *Journal of Scheduling*, Vol. 1, No. 2, pp.79–87.

Yano, C.A. and Lee, H.L. (1995) 'Lot sizing with random yield: a review', *Operations Research*, Vol. 43, No. 2, pp.311–324.

Yao, D.D. (1998) 'Optimal run quantities for an assembly system with random yields', *IIE Transactions*, Vol. 20, No. 4, pp.399–403.

Zipkin, P. (1986) 'Models for design and control of stochastic multi-item batch production systems', *Operations Research*, Vol. 34, No. 11, pp.91–104.