Optimization of the Production Planning and Trade of Lily Flowers at Jan de Wit Company

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Jan de Wit Company implemented a decision-support system based on linear programming as a production-planning and trade tool for the management of its lily flower business. The LP maximizes the farm’s total contribution margin, subject to such constraints as market-defined sales limits, market requirements, characteristics of the production cycle duration, technical requirements, bulb inventory, and greenhouse limitations. The main decision variable to be calculated is the number of flower beds in a specific greenhouse, from a specific bulb batch, of a specific variety, for a specific purpose, taking into consideration planting and expected harvesting weeks. Between 1999 and 2000, company revenue grew 26 percent, sales increased 14.8 percent for pots of lilies and 29.3 percent for bunches of lilies, costs fell from 87.9 to 84.7 percent of sales, income from operations increased 60 percent, return on owner’s equity went from 15.1 to 22.5 percent, and best quality cut lilies jumped from 11 to 61 percent of the quantities sold. The system also suggested changes in the product mix.

(Industries: agriculture, food. Programming: linear, applications.)

Like most industrial sectors, the ornamental plant and flower industry has experienced the effects of globalization. In Brazil, this has meant an increase in competition; greater production in such traditional areas as the municipality of Holambra in São Paulo State; the creation of new regional production areas; the installation of national and international companies to supply seedlings and seeds; government grants for the production of flowers and plants, helping to increase the incomes of small- and medium-sized nurseries and exporters; imports of natural and artificial flowers and plants; and exaggerated promotions of flowers. The increased competition has caused price reductions, which are seen as a measure of quality.

The farmers cannot ignore the current market changes and the need to use tools to help them make decisions, which will lead to closing good deals, increasing profits, reducing costs, and improving quality. We developed a computer program using mathematical optimizing models to help a lily producer from the Holambra region to make such decisions.

The Problem

Producer Johannes Petrus W. de Wit, general manager and owner of Jan de Wit Company, had good reasons for celebrating the coming of 2001. By the end of 2000, Jan de Wit Company, Brazil’s largest producer of Oriental and Asian lily flowers, had increased revenues by 26 percent in comparison with 1999. It achieved this
gain in a well-cultivated area that occupies two hectares (20 thousand square meters) in Holambra, the City of Flowers, 160 kilometers from Sao Paulo, in Brazil.

The firm’s gains resulted from its investment in computerized production planning based on a mathematical model developed specially for its many needs. Producing about 420,000 pots and 220,000 bunches of lilies per year, Jan de Wit Company had trouble planning production manually. So many parameters were involved that the company had to split the planning to control the productive process.

The final customer is the main agent of the lily business (Figure 1); Brazil’s 180 million inhabitants spend US$ 1.1 billion per year on flowers, mostly at the retail level (exports of Brazilian flowers are not significant yet).

The flower retailers, mainly flower shops, supermarkets, and garden centers, number around 10,000. They purchase flowers from distributors, about 400 companies. At the six wholesale marketplaces in Brazil, around 3,600 flower producers (occupying 4,500 hectares) bring their flowers to sell to the distributors.

To produce the lily flowers Jan de Wit Company needs bulbs—vegetative propagation structures—normally furnished by bulb wholesalers in Holland. These wholesalers offer many varieties of bulbs, which they acquire from bulb producers, most also located in Holland.

Bulb supply is a critical aspect in the lily business chain. It takes two years to produce a bulb big enough to produce flowers. The bulb grows underground at the base of the lily plant. Normally each plant produces one bulb, which also acts as a storage organ that holds carbohydrates, nutrients, and water for the next-generation plant. From the bulb, the flower develops.

Brazil currently does not cultivate great quantities of bulbs. Jan de Wit Company gets 95 percent of its bulbs from Holland, where it also stores its bulb stock. The company annually imports 3.5 million bulbs of approximately 50 varieties of potted lilies (to be sold as flowering plants) and cut lilies (to be sold in bunches). Every month, as scheduled, the Dutch suppliers send part of this stock. The entire stock and the contents of each shipment are divided into batches. Each batch contains a determined number of bulbs, furnished by a specific bulb producer, from a specific harvesting year, variety, and bulb size. Jan de Wit traces all bulb batches from the moment of purchase until the moment the lilies are harvested.

Jan de Wit Company began working with lily flowers on a small scale in 1992, when it practically started the culture in Brazil. In 2000, it reached 18,745 square meters of greenhouses, a shed of 1,500 square meters, 1,032 square meters of cold-storage rooms, and a team of around 30 employees.

Jan de Wit Company uses Veiling Holambra, the largest flower wholesale marketplace in Brazil and Latin America, as its only sales vehicle. In 2000, Veiling Holambra had an annual revenue of US$ 80 million (38 percent of the Brazilian flower market at the producer level). Approximately 250 of the 400 distributors purchase at Veiling Holambra.
The Veiling uses two main trading systems: auction and intermediation. The auction is a daily cash market. In the auction room, distributors can buy the flowers passing in front of them under the conditions shown on an electronic panel. Quantities and prices may oscillate considerably. Half of Jan de Wit Company’s sales occur at the auction, which provides transparent and market-driven prices. Intermediation is like the futures market. Specialized agents close buy-and-sell contracts between distributors and producers for the short, medium, and long term. The other half of Jan de Wit Company’s sales is made through intermediation, which entails less risk in terms of quantities and prices.

The Veiling also defines the market requirements, for instance, the selling unit, the minimum number of buds and stems per bunch or per pot, quality standards for top quality flowers (no qualifying remarks) and second and third quality flowers (depending on the qualifying remarks, for example, “some spots on the leaves”).

Based on daily contact with its clients at Veiling Holambra, on sales history, on current fashion trends, and on the economic environment, the company identifies market opportunities in terms of weekly sales quantities and prices for each lily variety.

To select the best market opportunities, those it will exploit, the company must consider the technical and operational restrictions on its production process.

Oriental and Asian lily flowers are temperate-climate flowers suited to colder regions, and growing them in Brazil is not easy, requiring a special process to produce good-quality flowers. Before planting, the bulbs must be held for about two months at the right temperature (bulb preparation); after that, they may be planted or stored frozen at less than 2°C. After planting, the bulbs remain in a 12°C environment for two weeks until the stem roots form (bulb rooting), and then they are moved to the greenhouse (bulb spacing), which has a temperature of 25°C.

Fundamental to the business is buying the right bulbs and volumes during the three month period of the Dutch bulb harvest. The company must cross-check its market opportunities and its technical and operational restrictions to determine an optimal sales and production plan and to calculate the number of bulbs of each variety and each of three different sizes to buy.

It is also critical to plant the bulbs during the right week. Depending on the variety, the bulb size, and the planting week, the production cycle can vary from six to 16 weeks. Basically, to transform the optimal sales and production plan into reality, Jan de Wit Company must plant the right bulbs during the right week.

To make efficient use of its greenhouses, the company must have very strict and accurate planning. It must take into consideration the seasonal pattern of the flower market, with its peaks at specific dates, such as Mother’s Day, Easter, All Soul’s Day, and Christmas. In addition to these seasonal characteristics, the flower market is also affected by trends for certain varieties and colors, which means that the producer must be alert to the market’s moods at the moment of planning.

The problem to be solved can be stated as follows: How can Jan de Wit Company best exploit market opportunities, respecting technical and operational restrictions, managing the trade and production cycle, and optimizing its financial results?

The Role of Operations Research

The history behind this project is very interesting. In February 1997, Caixeta-Filho published a short article, “Modeling, through operations research, in agribusiness systems,” in a student journal of the University of São Paulo. This article attracted the interest of Swaay-Neto, a flower-business management consultant who had not previously been familiar with operations research. Swaay-Neto phoned Caixeta-Filho to discuss the use of operations research models in the flower business. He ended up becoming one of Caixeta-Filho’s students in a class on linear programming, offered to graduate students in applied economics at University of São Paulo. He concluded the course by presenting a final paper entitled “Gladiolus bulb production planning.” After that, Swaay-Neto invited Caixeta-Filho to develop more accurate modeling approaches to applying mathematical programming to
some flower-sector problems. They did further work on the “gladiolus case” (Caixeta-Filho et al. 2000), with the help of Ricardo Lopes, who improved the model and developed an Excel worksheet with user-friendly interfaces for data input. This model was implemented at Terra Viva Company. That implementation opened other doors, including that of the lily case.

We started the project in July 1998. The first practical results came in the last quarter of 1998. During the first semester of 1999, we focused on developing an interface for the user capable of generating data for the model from sales and production input. Next, during the second half of 1999, we made the solution found by the model more user friendly. Also during 1999, we consolidated the pertinent database. Since January 2000, Jan de Wit Company has been using the system fully, and its benefits are visible.

The project team was composed of Caixeta-Filho, who developed the mathematical model; Swaay-Neto, who acted as project leader and business analyst, oversaw the modeling and programming activities, made tests, and worked on data gathering and project implementation together with Jan de Wit Company; and Wagemaker, who programmed the software and supported the analysis and implementation. Jan de Wit Company provided the financial investment.

The main initial difficulties we faced were related to the communication process as a whole and to the fact that the traditional approach to flower business management did not use operations-research-based models. We had to make the executives of Jan de Wit Company believe our promises (“how can these guys think that a mathematical tool may give better results than ours . . .“) and understand linear programming (we gave them some formal theoretical classes), and we had to convince them to invest in a completely new project instead of investing in a new greenhouse or irrigation system. During the conceptual development and implementation phases, we had to help the executives understand the process as a whole and redesign their business. We overcame—or at least mitigated—the initial executive resistance by comparing past manually created and inferior solutions with those resulting from feeding the same historical input data into the optimization model.

Initially we concentrated on developing planning tools, and then we looked at questions associated with control. To make this work possible, we formulated a linear programming model to optimize planning and developed a production-control application to facilitate handling of input data and the model results.

We programmed this decision-support system, compatible with Windows, using Visual Basic and supporting it with an Access databank. The system required a minimum configuration of a Pentium 233 MHz with 32 MB of RAM.

The final linear-programming model, developed in GAMS language (Brooke et al. 1992), used as its objective function an expression of the total contribution margin of the producer. The maximization of this objective should be subject to the following restrictions: upper and lower market-defined sales limits; market requirements (selling unit, minimum number of buds, and minimum number of stems per bunch or pot); characteristics of the production cycle’s duration (depending on the variety, this constraint takes into consideration bulb size, bulb origin, sprout length, and planting week); technical requirements (number of bulbs per pot or box and their spacing); bulb inventory; and usage limitations for each type of greenhouse.

The key decision variable to be calculated using this optimization model is the number of flower beds in a specific greenhouse, originated from a specific bulb batch, from a specific lily variety, for a specific use (for example, potted lily or cut lily), taking into consideration the pertinent planting week and the expected harvesting week. The general matrix dimensions involved 120,000 rows, 420,000 columns, and 1,300,000 nonzero elements (Appendix).

**The Implementation Process**

The starting point in production planning is to estimate the quantity range of lilies that can be traded each week, detailing the contractual minimum quantities and the maximum and possible quantities to be sold, and the average price for each variety. The producer
had to make this estimate based on knowledge of the market. This market-driven practice reduces the difference between production and sales and between over- and underproduction.

We took into consideration the fact that the producer has full control over the whole production system. This means that the company can calculate, among other things, the cycle of production, how many flowers each bulb will produce, physical losses, productivity, and costs. These parameters can vary according to such factors as the variety, the time of year, the type of greenhouse, and the environment.

The first stage of planning is to cross-check the estimated sales with the production cycle, identifying all the possible combinations within that time period. The mathematical model is able to recognize these combinations and suggests an optimized production plan, respecting the technical viability and production operational limits. The production plan suggests what, when, where, and how many to plant.

The control functions of the decision-support system should ideally work as aids for the production manager. The production notes and annotations should be minimal but should contain all the information necessary for planning and control.

One of the things the system does is calculate the availability of the flower beds week by week, assuming the company will not plant anything else. The system’s primal task is to try to occupy the areas as they become available in the best possible way.

With this drill, we cross-check every theoretically possible planting using the sales forecast and cycle of each variety, resulting in a huge series of combinations. The system indicates which is the optimal combination, maximizing the total contribution margin and considering the occupation of the greenhouses. So, if the company begins growing a six-week-cycle variety on week 41, it is already known at week 41 that the area will be occupied until week 47. We add every possibility of occupation until we go beyond the available area and have to discard a few combinations. And which ones do we discard? The ones with the lowest profitability.

For the model to process the information, data must be input from the company data bank regarding lily variety; planting area; estimated sales; cycle; greenhouse type; bulb stock; bulb price; production costs; minimum number of buds and stems; and lots already planted and their characteristics, such as number of bulbs, plant type (cut lilies or potted lilies), date of planting, allocated beds, and estimated harvest.

The main results from the system are the information generated by the linear programming model, such as financial results, sales, levels of greenhouse use, stock utilization, and harvest.

The decision-support system (Figure 2) has been used weekly, usually by company’s production and sales management team.

In practice, the company can estimate future sales by product and by week, based on daily contact with customers and their individual sales history, as well as

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Return on equity went from 15.1 percent to 22.5 percent.

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fashion trends and the economic scene. Inputting the sales forecast to the system is the beginning of the planning process. Next, the mathematical model is run. After the model produces the optimal solution and its economic result, the company analyzes how the solution meets sales per product, what greenhouses will be used, the consumption of bulbs, and the corresponding dual values. Based on these data and on what it can negotiate with its clients, Jan de Wit Company starts changing the sales per product (minimum and maximum quantities or price) and rerunning the model to improve the result. Before committing to the sales and production plan, the company closes deals with the customers, aiming at a 50 percent presale.

The main subprocesses within production planning are bulb preparation, planting, spacing, and harvesting. The system controls the stage of each batch, issuing production orders, data-collection cards, reports to follow production, and stickers to identify the end products. These tools help management and the operational team to communicate and warrant the execution of each subprocess and the collection of control data, such as the batch of bulbs planted, the quantity of bulbs planted, the type of substrate, the type of packing, the spacing date, the flower bed, the harvesting date, and the number of pots or stems harvested.
The system is used throughout the entire process, forcing integration throughout the enterprise and confirming what is usually emphasized in operations research theory. The system’s implementation made it possible to redesign and standardize processes, create history in a consistent database, and eliminate the old procedures based only on spreadsheets. Tracing batches is a great strength of the system, because it enables the company to select the suppliers with the best-quality bulbs.

The project was laborious, but the team worked well together. Thanks to the active participation of the top management leaders of the company and the gradual transparency of the results, the other members of Jan de Wit Company accepted the project very well.

**Financial Results**

To analyze the impact on the client’s business, we defined and calculated key performance indicators based on real data from 1999 and 2000, as well as on the expectations for 2001.
During these three years, revenue grew 26 percent in 2000, reaching the level of R$3,229,542.00. We expect a further increase of 32 percent in 2001. Sales totaled 484,722 pots and 285,088 bunches in 2000, a positive change of 14.8 percent and 29.3 percent, respectively, in comparison to 1999. Forecasted for 2001 are sales of 986,000 pots and 205,000 bunches, with the company departing from a strategy that focused on potted lilies and on Oriental cut lilies, facing its main competitor which focuses on Asian cut lilies.

The average prices at Veiling Holambra were the same in 1999 and 2000 for potted lilies, R$3.39 per pot, and varied from R$ 5.14 to R$ 5.56 per bunch for cut lilies. For 2001, the expected average prices are R$ 3.59 per pot and R$ 7.97 per bunch. The company expects to get a much higher price per bunch because of its strategy of producing only Oriental cut lilies, which are more expensive than Asian.

Variable costs represented 64.1 percent of sales in 1999 and 62.4 percent of sales in 2000. In 2001, the company expects to reduce variable costs to 53.8 percent by using cheaper growing practices and suffering lower production losses, which in 2000 reached 11.8 percent for potted lilies and 13 percent for cut lilies.

The firm’s contribution margin (total sales less variable costs) increased 32 percent in 2000 compared to 1999. This can be considered a direct result of the system, which maximizes the value of this variable.

Fixed costs were R$ 613,140.00 in 1999 and R$ 718,373.00 in 2000, with estimates of R$ 801,500.00 for 2001, a small R$ 83,000.00 absolute growth compared to 2000. Sales and production levels are growing without significant new fixed costs, characterizing an operational leverage suggested and made possible by the system.

Income from operations was R$ 309,546.00 in 1999 and R$ 495,243.00 in 2000, a 60 percent increase. The forecast for 2001 is for R$ 1,160,000.00, a growth of 134 percent in comparison to 2000. Regarding return on owner’s equity, it went from 15.1 percent in 1999 to 22.5 percent in 2000.

The number of employees increased from 30 in 1999 to 31 in 2000, with the sales per person increasing from R$ 85,586.00 to R$ 104,178.00. For 2001, the company expects to employ a working team of 33 people with an average of R$ 128,787.00 in sales per person.

These results are remarkable given that the Brazilian flower market as a whole in 2000 had a very clear excess of supply, making selling more difficult than it had been in 1999. A comparison of the auction and intermediation prices at Veiling Holambra confirms this situation: In 1999, for instance, average prices were higher at auction than at intermediation, and the opposite was the case in 2000. A related indicator is the value of the quantities that could not be sold at the auction compared to the total sale value: 1.6 percent in 1999 and 4.8 percent in 2000. For 2001, the company expects behavior more like that in 1999.

The trading conditions offered by the Veiling reward the producers that best respond to the needs of their clients, the flower distributors. With the system, Jan de Wit Company managed to balance the needs of its clients and its own restrictions. By improving its planning and control, the company will be able to increase its short-, medium- and long term supply agreements from about 50 percent of its production in 1999 and 2000 to 60 percent in 2001. Thus, the company will lock in the sale price and guarantee its profit on that part of its production. It sells the remainder on the daily cash market, where considerable price oscillations may occur.

Technical Impacts

The system suggested changes in the product mix. Of the top 10 lily varieties in 2000, only six were in the top 10 in 1999. The company cut the number of varieties it produced from 50 in 1999 to 40 in 2000. It dropped 22 varieties for various reasons (because they were money losers, were unavailable at the bulb market, and so forth) and is testing 12 new varieties for future sales. The market demands a wide range of varieties and is always looking for something new. On the other hand, more varieties mean more complexity in the production process. The system helps Jan de Wit Company to determine the right balance.

Ninety-three percent of the potted lilies the company...
sold in both 1999 and 2000 were of the best quality. Its cut lilies went from 11 percent best quality in 1999 to 61 percent in 2000, with this 50 percent improvement responsible for the better-than-average sale prices in 2000.

Using the system, the company has increased its production and simultaneously improved quality. The production manager can dedicate more time to production itself and less to planning and administration; he has better control over the production process and subprocesses (for example, bulb preparation, planting, spacing, harvesting). The system indicated varieties to plant, the bulb sizes, and planting weeks; it also supported the selection of bulb suppliers in 2000, tracking results from the bulbs supplied in 1999. Bulb quality improved in 2000 over 1999, with bulb losses before planting going from 1.6 percent in 1999 to 0.5 percent in 2000.

It has already been adapted to other flower types.

The Time-Saving Impact
Prior to implementing the decision-support system, Johannes de Wit planned production himself and took several days to plan for a six-month period. Furthermore, the results were less consistent. With the system, he delegates this function in a professional manner. Jan de Wit Company now has fast answers with which it can better negotiate its clients' orders, an important differential in the market.

In the days of the old process, the company relied on creating Excel spreadsheets to help it handle all the variables, an increasingly impossible task. The company doubted that the plan produced would bring the best-possible economic results. Later in the control stage, inconsistencies and questionable data used to surface. Nowadays, with the new tool, the company manages, in a short time compared to the past, to optimize planning, considering all the variables and maximizing economic results. Jan de Wit Company has also greatly reduced the differences between planned results and reality.

Because of uncertain events, climatic or technical problems, the actual production plans do not always materialize. In those instances, the system again shows its value, giving the company an opportunity to take corrective action. Based on the available data, when it has excess production, the company can encourage increased throughput through promotions or refrigerate flowers to sell days later, when it expects a shortage. In case of shortage, Jan de Wit Company can warn its clients in advance.

These measures enhance the company’s image and help it to develop a market for products with the Jan de Wit brand. They increase clients’ satisfaction and reduce loss of capital and other problems in the whole chain.

Concluding Remarks
Jan de Wit’s improved results in 2000 were not due to a better-behaved market, which was weaker in 2000. They were also not related to any technical changes in the production process. They can only be the consequences of better management at Jan de Wit Company, whose chief new tool is the DSS we developed.

The executives of Jan de Wit Company testify that they are convinced that the optimization system is their main working tool for managing both trade and production processes. Clients of the company, the distributors, also realize significant benefits because they can buy and sell their products in advance, ensuring volumes, prices, and margins. Their clients, the retailers, also benefit because their orders are guaranteed. This improves results throughout the chain, from retailer to producer.

Jan de Wit Company can now make important investments in the continuity of its business and the improvement of its product’s quality, for example, by cooling the sorting and packing area.

The company faces growing competition, with decreasing margins, requiring greater professionalism from all the companies in the business. According to testimony from Johannes Petrus W. de Wit, “companies in the flower business that don’t wake up to planning and control systems risk almost unsurpassable capital losses, endangering their continuity and damaging the market.”
Regarding further developments, we envisage possibly adjusting report formats and eventually the modeling structure. Portability deserves special attention in further developing the system. The gladiolus bulb model (Caixeta-Filho et al. 2000) was the seed for this lily model. The lily model is much bigger and more comprehensive, and it has already been adapted to other flower types (chrysanthemum flowers, for instance). Recently, we were asked to evaluate how the modeling structure could be applied to lettuce greenhouses.

Appendix: General Linear Program Formulation

The goal of the linear programming model is to maximize the farm’s total contribution margin, taking into consideration the pertinent constraints related to such factors as upper and lower market-defined sales’ limits; market requirements (selling unit and minimum number of bulbs and minimum number of stems per bunch or pot); bulb inventory; characteristics of the production cycle’s duration; technical requirements (number of bulbs per pot or box and their spacing); usage limitations for each type of greenhouse.

The mathematical formulation of the model follows.

Indices Related to the Main Sets

\( j \) stands for each bulb batch;
\( v \) stands for each lily variety;
\( g \) stands for the specific use of the lily (potted lily or cut lily);
\( l \) stands for each lily variety;
\( i \) stands for the planting week in the year; and
\( t \) stands for the expected harvesting week in the year.

Main Parameters (Data)

\( \text{PRECO}_{vg} \) = expected price for the lily variety \( v \), from group \( g \), in the harvesting week \( l \);
\( \text{VMAX}_{vg} \) = maximum sales level for the lily variety \( v \), from group \( g \), in the harvesting week \( l \);
\( \text{CPREV}_{vg} \) = expected harvests for the lily variety \( v \), from group \( g \), in the harvesting week \( l \);
\( \text{VMIN}_{vg} \) = minimum sales level for the lily variety \( v \), from group \( g \), in the harvesting week \( l \);
\( \text{PERDA}_{vg} \) = level of physical loss for the lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{BOTOES}_{vgj} \) = number of buds for the lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{DENS}_{vgj} \) = density measure adopted for the lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{ESPAC}_{vgj} \) = spacing measure adopted for the lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{FV}_{vgj} \) = binary value that identifies whether lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \), belongs to the potted lily group;
\( \text{FC}_{vgj} \) = binary value that identifies whether lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \), belongs to the cut lily group;
\( \text{QLSP}_{vgj} \) = binary value that identifies whether lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \), is compatible with the plane greenhouse with temperature and luminosity control (QLSP);
\( \text{QLS}_{vgj} \) = binary value that identifies whether lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \), is compatible with the inclined greenhouse with temperature and luminosity control (QLSI);
\( \text{PF}_{vgj} \) = binary value that identifies whether lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \), is compatible with the plane greenhouse (PF);
\( \text{BULB}_{j} \) = availability level of bulb batch \( j \);
\( \text{CBULB}_{j} \) = cost to purchase bulb batch \( j \);
\( \text{CCANT}_{vgj} \) = costs associated with the flower beds to be used by lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{MINBOTOES}_{vgj} \) = minimum quantity of buds to be accepted for lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{MINHASTE}_{vgj} \) = minimum quantity of stems to be accepted for lily variety \( v \), from bulb batch \( j \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{OEOEQLSP}_{i} \) = availability of flower beds in greenhouse type QLSP at week \( t \);
\( \text{OEOEQLSI}_{i} \) = availability of flower beds in greenhouse type QLSI at week \( t \);
\( \text{OEOF}_{i} \) = availability of flower beds in greenhouse type PF at week \( t \).

Main Decision Variables

\( \text{RBRU} \) = gross economic result;
\( \text{REC} \) = total revenue;
\( \text{CTOT} \) = total costs;
\( \text{CB} \) = bulb costs;
\( \text{CF} \) = cut lily costs;
\( \text{CFV} \) = potted lily costs;
\( \text{QT}_{j} \) = quantity of bulbs from batch \( j \), for lily variety \( v \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{QTGRUPO}_{vgj} \) = quantity of potted lilies or cut lilies obtained from bulbs from batch \( j \), for lily variety \( v \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{NUMCANT}_{vgj} \) = total flower beds occupied by bulbs from batch \( j \), for lily variety \( v \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{NUMCANT}_{1v} \) = total flower beds in greenhouse type QLS, occupied by bulbs from batch \( j \), for lily variety \( v \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
\( \text{NUMCANT}_{2v} \) = total flower beds in greenhouse type QLSI, occupied by bulbs from batch \( j \), for lily variety \( v \), from group \( g \), planted in week \( i \), and with expected harvest in week \( l \);
NUMCANT3,pgal = total flower beds in greenhouse type PF, occupied by bulbs from batch j, for lily variety v, from group g, planted in week i, and with expected harvest in week 1;

EQLSP,pgal = total flower beds used in greenhouse type QLSP in week t, occupied by bulbs from batch j, for lily variety v, from group g, planted in week i, and with expected harvest in week 1;

EQLSI,pgal = total flower beds used in greenhouse type QLSI in week t, occupied by bulbs from batch j, for lily variety v, from group g, planted in week i, and with expected harvest in week 1;

EPF,pgal = total flower beds used in greenhouse type PF in week t, occupied by bulbs from batch j, for lily variety v, from group g, planted in week i, and with expected harvest in week 1.

Mathematical Modeling Structure (mostly defined for combinations of sets related to viable production cycle’s durations):
Maximize the objective function

\[ RBRU = REC - CTOT \]  

subject to the following constraints:

Bulb inventory:

\[ \sum_{v} \sum_{g} \sum_{j} \sum_{i} QT_{,pgal} \leq BULB_{j} \]  

Accounting procedures for potted lilies, discounting physical losses and taking into consideration only the lilies with the minimum number of buds:

\[ QTGRUPO_{,pgal} = \frac{(QT_{,pgal} \times (1 - PERDA_{,pgal}))}{DENSP_{,pgal}} \]  

\[ \geq MINBOTES_{,pgal} / DENSP_{,pgal} \]  

\[ QTGRUPO_{,pgal} = 0 \text{ for } QLSP_{,pgal} = 1 \text{ and } BOTES_{,pgal} \]  

\[ < MINBOTES_{,pgal} / DENSP_{,pgal} \]  

Accounting procedures for cut lilies to discount physical losses and take into consideration only the lilies with the minimum number of buds and minimum number of stems:

\[ QTGRUPO_{,pgal} = \frac{(QT_{,pgal} \times (1 - PERDA_{,pgal}))}{MINHASTE_{,pgal} \text{ for } FC_{,pgal} = 1 \text{ and } BOTES_{,pgal}} \]  

\[ \geq MINBOTES_{,pgal} / MINHASTE_{,pgal} \]  

\[ QTGRUPO_{,pgal} = \frac{(QT_{,pgal} \times (1 - PERDA_{,pgal}))}{MINBOTES_{,pgal} / BOTES_{,pgal} \text{ for } FC_{,pgal} = 1} \]  

\[ \text{and } BOTES_{,pgal} < MINBOTES_{,pgal} / MINHASTE_{,pgal} \]  

Revenue structure:

\[ REC = \sum_{v} \sum_{g} \sum_{i} \sum_{l} PRECO B_{,lag} \times QTGRUPO_{,pgal} \]  

Cost structure:

\[ CTOT = CB + CFC + CFV, \]  

\[ CB = \sum_{v} \sum_{g} \sum_{j} \sum_{i} CBULB_{j} \times QT_{,pgal} \]  

\[ \text{CFC} = \sum_{j} \sum_{v} \sum_{g} \sum_{l} CCANT_{,pgal} \times NUMCANT_{,pgal} \text{ for } FC_{,pgal} = 1, \]  

\[ \text{CFV} = \sum_{j} \sum_{v} \sum_{g} \sum_{l} CCANT_{,pgal} \times QTGRUPO_{,pgal} \text{ for } FV_{,pgal} = 1. \]  

Sale level limits:

\[ \sum_{j} \sum_{v} QTGRUPO_{,pgal} \leq VMAX_{,lag} - CPREV_{,lag} \]  

\[ \sum_{j} \sum_{v} QTGRUPO_{,pgal} \geq VMIN_{,lag} - CPREV_{,lag} \]  

Accounting procedures for determining the number of flower beds:

\[ NUMCANT_{,pgal} = QT_{,pgal} / (ESPAC_{,pgal} \times DENS_{,pgal}) \]  

\[ EQLSP_{,pgal} = NUMCANT_{,pgal} \text{ for } QLSP_{,pgal} = 1, \]  

\[ i < l, \ t \geq i, \ t \leq l, \]  

\[ EQLSI_{,pgal} = NUMCANT_{,pgal} \text{ for } QLSI_{,pgal} = 1, \]  

\[ i < l, \ t \geq i, \ t \leq l, \]  

\[ EPF_{,pgal} = NUMCANT_{,pgal} \text{ for } PF_{,pgal} = 1, \]  

\[ i < l, \ t \geq i, \ t \leq l, \]  

\[ NUMCANT_{,pgal} = NUMCANT_{,pgal} + NUMCANT_{,pgal} + NUMCANT_{,pgal}. \]  

Avoiding occupations that are not permitted for each type of greenhouse:

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} EQLSI_{,pgal} = 0 \text{ for all } t \text{ and } QLSI_{,pgal} \neq 1, \]  

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} EQLSP_{,pgal} = 0 \text{ for all } t \text{ and } QLSP_{,pgal} \neq 1, \]  

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} \sum_{i} EQLSI_{,pgal} = 0 \text{ for all } t \text{ and } QLSI_{,pgal} \neq 1, \]  

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} \sum_{i} EQLSP_{,pgal} = 0 \text{ for all } t \text{ and } QLSP_{,pgal} \neq 1, \]  

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} EPF_{,pgal} = 0 \text{ for all } t \text{ and } PF_{,pgal} \neq 1, \]  

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} \sum_{i} EPF_{,pgal} = 0 \text{ for all } t \text{ and } PF_{,pgal} = 1, \]  

\[ i < l, \ t < i, \ t > l, \]  

Respecting the weekly availability of flower beds for each type of greenhouse:

\[ \sum_{j} \sum_{v} \sum_{g} \sum_{l} EQLSP_{,pgal} \leq OOEQLSP_{,pgal} \text{ for all } t \]
Illustrating the Model

Taking the lily variety named Orange Pixie as an example, we present the main types of input data used by the system in Tables 1 to 5 and the main results obtained by the model in Table 6.

### Table 1: The company could use the designated flower beds for the lily variety named Orange Pixie.

<table>
<thead>
<tr>
<th>Flower bed code range</th>
<th>Corresponding greenhouse</th>
<th>Unavailability period</th>
</tr>
</thead>
<tbody>
<tr>
<td>101–110</td>
<td>PF</td>
<td>01/01/1999–30/06/1999</td>
</tr>
<tr>
<td>201–210</td>
<td>QLSI</td>
<td>—</td>
</tr>
<tr>
<td>211–220</td>
<td>QLSI</td>
<td>—</td>
</tr>
<tr>
<td>301–310</td>
<td>QLSI</td>
<td>01/05/1999–30/09/1999</td>
</tr>
</tbody>
</table>

### Table 2: The lily variety named Orange Pixie has these general characteristics.

<table>
<thead>
<tr>
<th>Bulb size</th>
<th>Flower group</th>
<th>Planting week</th>
<th>Cycle (days)</th>
<th>Buds/stem</th>
<th>Physical loss (%)</th>
<th>Density</th>
<th>Spacing</th>
<th>Greenhouse compatibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>Potted</td>
<td>45</td>
<td>55</td>
<td>3</td>
<td>3</td>
<td>3 bulbs/pot</td>
<td>1.000 pots/flower bed</td>
<td>QLSI or PF</td>
</tr>
<tr>
<td>16</td>
<td>Cut</td>
<td>46</td>
<td>53</td>
<td>5</td>
<td>3</td>
<td>16 bulbs/box</td>
<td>160 boxes/flower bed</td>
<td>QLSI, QLSI or PF</td>
</tr>
</tbody>
</table>

### Table 3: The lily variety named Orange Pixie has these costs.

<table>
<thead>
<tr>
<th>Bulb costs</th>
<th>Lily production</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>Value (R$)</td>
</tr>
<tr>
<td>12</td>
<td>0.25/bulb</td>
</tr>
<tr>
<td>16</td>
<td>0.30/bulb</td>
</tr>
<tr>
<td>Flower group</td>
<td>Minimum quantity of buds</td>
</tr>
<tr>
<td>Potted</td>
<td>9</td>
</tr>
<tr>
<td>Cut</td>
<td>24</td>
</tr>
</tbody>
</table>

### Table 4: In 2000, the lily variety named Orange Pixie had these trade figures.

<table>
<thead>
<tr>
<th>Bulb batch code</th>
<th>Lily group</th>
<th>Period of time in which the bulbs can be planted</th>
<th>Available quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>98320919</td>
<td>Potted</td>
<td>07/01/1999—16/01/2000</td>
<td>17,150</td>
</tr>
<tr>
<td>98323929</td>
<td>Cut</td>
<td>25/09/1999—01/02/2000</td>
<td>52,500</td>
</tr>
</tbody>
</table>

### Table 5: The company maintains these inventory levels for bulbs used in producing the lily variety named Orange Pixie.

<table>
<thead>
<tr>
<th>Bulb batch code</th>
<th>Lily group</th>
<th>Bulbs to be planted</th>
<th>Planting week</th>
<th>Harvesting week</th>
<th>Number of flower beds</th>
<th>Quantity to be sold</th>
<th>Expected revenue (R$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>98320919</td>
<td>Potted</td>
<td>12,371</td>
<td>45/1999</td>
<td>01/2000</td>
<td>4 in a QLSI greenhouse</td>
<td>4,000 pots</td>
<td>10,960.00</td>
</tr>
<tr>
<td>98323929</td>
<td>Cut</td>
<td>10,227</td>
<td>46/1999</td>
<td>02/2000</td>
<td>4 in a QLSI greenhouse</td>
<td>1,240 bunches</td>
<td>7,440.00</td>
</tr>
</tbody>
</table>

Table 6: The example of the results generated by the optimization model shows the production of the lily variety named Orange Pixie.
The presentation during the Edelman competition included the following executive endorsements:

Johannes Petrus W. de Wit, general manager and owner of Jan de Wit Company, said, “I receive the finished production plan. It is the soul of my business, the basis for cost and investment budgeting. Based on the quantities to be produced, I can extrapolate the supplies needed. Based on bottlenecks identified by the sensitivity analysis, I can direct investments. The system also forecasts the revenue influx, to which I endeavor to match my payments. The budget became trustworthy. I can now dedicate more of myself to the management of my business.”

Marcelo Moraes, production and sales manager of Jan de Wit Company, said, “My team is more motivated because in the beginning of 2000, having exceeded estimated results for 1999, all participated in the profits, receiving individual bonuses equivalent to a month’s salary. Based on the system’s planning, I now manage my team better, delegate more responsibility and have improved result evaluation. I dedicate less time to check and control and more time to plan and analyze. Last month I was on a holiday, and I had never been on a holiday with such a confidence.”

References
Managing the Seed-Corn Supply Chain at Syngenta

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Each year, Syngenta Seeds, Inc. produces over 50 seed-corn hybrids and the following year markets over 100 hybrids under the NK brand name. The fact that growing seed corn is a biological process dependent upon local weather and insect conditions during the growing season complicates production planning. In addition, customers’ experiences with a particular hybrid during a given year strongly influence demand for that hybrid during the next year. To help mitigate some of these yield and demand uncertainties, Syngenta (and other seed companies as well) take advantage of a second growing season for seed corn in South America, which occurs after many of the yield uncertainties and some of the demand uncertainties have been resolved or reduced. To better manage this production-planning process, Syngenta and the University of Iowa developed and implemented a second-chance production-planning model. A trial of the model showed that using it to plan 2000 production would have increased margins by approximately $5 million. Today, Syngenta uses this model to plan production for those varieties that account for 80 percent of total sales volume.

(Inventory: production, uncertainty. Industries: agriculture, food.)

Each spring, farmers (consumers of seed corn) decide how to allocate their land among a variety of possible crops, one of which is corn, at least in many areas including the Midwest. After deciding how much of their land to plant in corn, farmers must decide which hybrid(s) to purchase and plant. There are literally hundreds of different hybrids produced either by one of eight firms (including Syngenta) that account for approximately 73 percent of the total United States market of approximately $2.3 billion or by one of the over 300 smaller regional firms that account for the remaining 27 percent. These hybrids differ in their resistance to certain diseases and insects as well as their performance under different soil and climatic conditions. Certain hybrids, for example, are optimized for the shorter, cooler northern corn belt while others are optimized for the longer, hotter southern corn belt. The choices particular farmers make are, therefore, highly dependent upon their locations.

In addition, farmers’ decisions may be heavily influenced by their experience during the previous growing season. Suppose, for example, a farmer happened to choose a particular hybrid intended for a cooler, less humid climate. If the weather happened to be abnormally hot and humid in that growing season, the farmer would likely have a much lower yield than he or she expected and hence would be less inclined to purchase that particular hybrid again. Conversely, if the hybrid chosen happened to be optimized for the growing conditions as they actually occurred, the situation would be reversed. If the hybrid were new and hence not thoroughly tested, very few growers would be inclined to make large plantings. Instead they would tend to make small test plantings to evaluate...
the hybrid’s performance under their local growing conditions.

Because seed corn cannot be produced instantaneously but instead must be produced over a long summer growing season, Syngenta and other seed companies must rely on their inventories of seed corn produced in previous growing seasons to fill farmers’ demands for the current growing season. The production of hybrid seed corn can be briefly described as follows. A hybrid is the genetic cross of two genetically different parent inbreds plants. To produce the genetic cross (or hybrid) that will be sold as seed corn, the seed company or its contractor grows these two parent inbreds in the same field in alternating rows. As the plants mature, the tassels from one of the parents (called the female plant) are removed in a labor-intensive “detasseling” operation, thereby insuring that the only pollen available to pollinate the female plant must come from the other parent (called the male plant). The resulting corn that matures on the female plant is, therefore, a genetic cross of its two parents. Once corn from the female matures, the seed company picks it and transports it to processing plants where it is dried, sorted, treated with antifungal or other coatings, bagged, and stored in anticipation of the upcoming selling season.

Thus, production to meet the demand for seed corn for the 2002 growing season actually occurs in 2001 (or earlier) during one of two growing seasons: the North American growing season in which seed-corn parent stock is planted in the spring and harvested in late summer or the South American growing season which is offset by approximately six months.

Syngenta plans for 2001 seed-corn production prior to the time when it actually knows the final demands for 2001 seed corn. But, when it plans 2001 production, Syngenta knows the following with a fair degree of certainty:

—Inventory on hand to meet 2001 demands,
—Production costs for North American production,
—and
—Production costs for South American production.

What it does not know with certainty are the following:

—Demand during 2001,

—Average yields for 2001 North American production of seed corn,
—Average yields for 2001 South American production of seed corn, and
—Demand during 2002.

Much of the variability of seed-corn demand in any year is due to the variability of experiences with particular hybrids during the previous growing season. When it plans 2001 production, Syngenta knows about those experiences (which affect demand during 2001) for the year 2000. Thus, for the 2001 planning process, demand during 2001 may be regarded as far more certain than the demand that will exist during 2002 (Figure 1). During this first phase of the planning process, prior to spring planting, Syngenta determines, for each hybrid, how much acreage to plant for the 2001 North American production period and makes a contingent 2001 production plan for South America.

In the second phase of the planning process later in the year, it updates and finalizes the production plan for South America. At this point, Syngenta knows the final 2001 demand and the average yields from North American production; the only significant uncertainties remaining are the average yields from any planned South American production and the demand during the 2002 sales period.

Inputs to the first-stage planning process include:

—Information about on-hand inventories of seed corn,
—Projected demand during 2001,
—The distributions of yield in both North and South America,
—The distribution of demand during the year 2002,
—The selling price of seed corn, and
—The costs of both North and South American production.

In the planning process, planners decide about how much acreage to devote to producing each variety of seed corn in both North and South America.

In recent years, competition from other firms and research leading to new proprietary genetics have combined to shorten product life cycles. As a result, each year fewer hybrids have a long, stable demand history that would make forecasting demand easy. Instead, more hybrids are either beginning their life cycles with little certainty regarding their demand or
ending their life cycles with predictable but declining demand. Because of the shortened product life cycles, production planning has become more crucial to the success of the company and simultaneously more challenging.

**Modeling**

The impetus for studying and modeling the seed-corn planning process came from a conversation between one of the University of Iowa researchers and a student in the evening MBA program. That evening’s class had included a discussion of the single-period news-vendor model in which there is a single chance to order or produce a product to meet a subsequent random demand (Figure 2). The instructor mentioned planning seed-corn production as a possible application for such a model, suitably modified to incorporate the fact that production yield is a random variable. After class a student who worked for one of the largest seed-corn producers in the world mentioned that planning for seed corn was actually a more complicated process. During the ensuing conversation, the student explained that the process was complicated primarily because South American production, offset by approximately six months, provides the company with a second chance to produce seed corn for sale in the next marketing season.

After some initial modeling efforts, the University of Iowa researchers contacted Syngenta to see if the company had any interest in pursuing a joint research effort aimed at better understanding and modeling the seed-corn planning process. Syngenta agreed to provide information on the seed-corn industry, its crop growing practices, and specific data regarding demand distributions, yield distributions, seed-corn prices, and production costs. In return for providing this information and for serving as a beta test site, Syngenta obtained the right to use any resulting software and models for its own production planning.

The university team modeled the seed-corn planning process as a two-stage (corresponding to North...
American and South American planting decisions) dynamic programming problem, the objective of which is to maximize expected gross margin. Jones et al. (2002) illustrate the value (increase in expected margin) of two production opportunities versus one. Figure 1 is a graphical representation of the model developed with one exception; a certain demand equal to the expected demand replaces the first random demand. The primary reason for this change is that the first stage of the planning process takes place just before spring demand occurs, and by that time, most of the original uncertainty regarding that demand has been resolved. As a result, we found that incorporating the spring demand as a random variable rather than as a certain demand complicated the model and enlarged its data requirements without providing any significant benefits.

To be very specific, the model requires the following pieces of information:
—The sales price per unit (unit = 80,000 kernels) of seed corn,
—The shortage cost per unit of seed corn,
—The salvage value per unit of unsold seed corn,
—The cost per unit of processing and shipping seed corn (for both North and South America),
—The cost per acre of planting, managing, and harvesting seed corn (for both North and South America),
—The probability distribution for next year’s demand for seed corn, and
—The probability distribution of seed corn yield (based on units per acre for both North and South America).

Most of these data items are quite straightforward and were obtained by examining historical financial, accounting, and production data. Three of these items, however, required some effort: shortage cost, salvage value, and demand distribution. Determining the appropriate shortage cost required input from the finance, accounting, and marketing groups at Syngenta. After much discussion and analysis, we approximated shortage cost as the lost profit from two years’ worth of sales. Thus, if the profit per unit sold is $x, the shortage cost is $2x. Leftover seed corn can be stored and used to meet demand the following year. Salvage value, therefore, is closely approximated by the expected cost of producing seed corn less the cost of storing it until the next year. Seed corn, however, can be carried in inventory for a limited number of years because seed that is too old has a very low germination rate. We estimated the demand distribution from historical data. To do this, we obtained data records that provided 207 observations of forecasted demand and actual demand for different hybrids. First, we normalized the data by dividing, in each case, the actual demand by the forecasted demand, providing us with a total of 207 ratios. We then estimated a distribution of these ratios (the normalized demand distribution) by constructing a histogram from the 207 ratios. This histogram shows, for example, what percentage of the time actual demand was between 90 percent and 100 percent of forecasted demand. To obtain the actual demand distribution used in the model, we then multiplied forecasted demand, a datum, by the distribution of ratios (the normalized demand distribution). Because we used linear programming to model the problem, we used discrete approximations for both demand and yield distributions. We chose all the data used in constructing the normalized demand distribution for years and for hybrids for which actual inventory was left on hand after the sales period. This is important because otherwise we would not have been able to say with certainty what actual demand was—had ending inventory been zero, all we could have said is that demand exceeded supply.

In applying the model, the analyst first runs it prior to spring planting using the best estimates of demand and yield distributions available at that time. The outputs for each hybrid variety from this initial application are recommendations on
—How many acres to plant for the North American growing season, and
—For each possible value of North American yield, how many acres should be planted for the South American growing season.

At the end of the North American growing season just prior to planting in South America, the analyst also runs a simplified single-growing-season version of the
model. At the time of this second run, Syngenta knows North American yield and, based on information accumulated during the current growing season, can update estimates of South American yield and next year’s demand prior to running the model. The output from this second model run is a recommendation on how many acres to plant in South America.

The objective for both stages in the dynamic programming recursion is to maximize expected gross margin: expected revenue from seed-corn sales less expected costs of production, holding, and shortage. The objective function is either a sum or an integral of concave functions, depending upon whether or not the probability distributions are discrete or continuous. As a result, the objective function itself is concave, so the model is well posed. However, we pose the problem as a linear program and solve it using the What’s Best! add-on to Microsoft Excel.

Our model treats each hybrid independently of others. Although one might suspect that some production constraint (land availability, for example) would link the different hybrids, this is not the case. Syngenta has enough opportunities to contract out the production of seed-corn to outside producers that availability of land and availability of other production inputs are not constraints.

Implementation

Syngenta’s original production planning process was iterative: First, the marketing group collected estimates of next year’s sales from its sales force and used them to develop an aggregate demand forecast. Typically, senior managers imposed production constraints and financial constraints that precluded producing everything Marketing wanted. To resolve the differences, marketing representatives and their counterparts from Production, Finance, and Accounting usually held many meetings in which they negotiated to arrive at a yearly production plan. Typically, they regarded South American production only as a reactionary rescue event to help overcome a shortfall resulting from an unexpectedly poor yield in North America. They drew up the typical North American production plan, therefore, under the assumption that North American production would have to cover demand.

Because formal modeling procedures, at least those based on optimization methods, were new to Syngenta’s production planning process, Syngenta insisted on validating the model and its results before using it in practice. To do this, Syngenta selected four hybrid varieties that company representatives believed to represent the range of typical varieties and for which detailed information was available regarding

—Production costs,
—Yield estimates at the time production decisions were made,
—Demand estimates at the time production decisions were made,
—Actual (realized) yields, and
—Actual (realized) product demands.

In the study, we ran the model for each of the four hybrids in each of the two years of the study (Tables 1 and 2). The idea was to compare what Syngenta actually did to what would have happened if it had used

One major benefit is the reduction in forecasting bias.

the model and followed its recommendations with no modification. For each model run, we used the yield distributions and demand distribution that Syngenta could have used at the time it made the acreage decisions. Yield distributions and cost data were different for North America and South America. Once the model-computed planting acreages were available, we made the assumption that realized yields for the model scenario would have been the same as the yields that were actually observed. It should be noted that Syngenta recorded forecasted demand to the nearest 1,000 units and recorded sales to the nearest 100 units while recording acres, actual production, and inventories to the nearest unit. The results adopt the same reporting convention (Tables 1 and 2).

To go into this in more detail, we will consider Hybrid A for year 1 of the study period. The seed company forecasted a demand of 67,000 units in year 1 for this particular hybrid. It expected a yield, based on prior harvest data, of 41.2 units per acre and actually planted 1,507 acres in North America (in the summer
Table 1: This table shows the model results versus the actual results for Hybrids A and B. Although the model does not outperform decisions actually taken in every case, using the model would have improved margins over the two-year period by approximately 12 percent for Hybrid A and by 28 percent for Hybrid B. The entries for inventory carryover are the number of units after sales carried into the next year. Entries in bold represent higher margin outcomes.

<table>
<thead>
<tr>
<th>Year 1</th>
<th>Actual</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial inventory</td>
<td>28,678</td>
<td>28,678</td>
</tr>
<tr>
<td>Forecasted demand</td>
<td>67,000</td>
<td>67,000</td>
</tr>
<tr>
<td>Acres planted</td>
<td>1,507/0</td>
<td>1,844/0</td>
</tr>
<tr>
<td>Production</td>
<td>69,322</td>
<td>84,824</td>
</tr>
<tr>
<td>Sales</td>
<td>72,000</td>
<td>72,000</td>
</tr>
<tr>
<td>Inventory carryover</td>
<td>26,000</td>
<td>41,502</td>
</tr>
<tr>
<td>Margin</td>
<td>$3,836,480</td>
<td>$3,197,713</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial inventory</td>
</tr>
<tr>
<td>Forecasted demand</td>
</tr>
<tr>
<td>Acres planted</td>
</tr>
<tr>
<td>Production</td>
</tr>
<tr>
<td>Sales</td>
</tr>
<tr>
<td>Inventory carryover</td>
</tr>
<tr>
<td>Margin</td>
</tr>
</tbody>
</table>

Table 2: This table shows the model results versus the actual results for Hybrids C and D. Although the model does not outperform decisions actually taken in every case, using the model would have improved margins over the two-year period by approximately 12 percent for Hybrid C and by 36 percent for Hybrid D.

<table>
<thead>
<tr>
<th>Year 1</th>
<th>Actual</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial inventory</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Forecasted demand</td>
<td>43,000</td>
<td>43,000</td>
</tr>
<tr>
<td>Acres planted</td>
<td>780/0</td>
<td>587/0</td>
</tr>
<tr>
<td>Production</td>
<td>28,392</td>
<td>21,372</td>
</tr>
<tr>
<td>Sales</td>
<td>31,000</td>
<td>8,807</td>
</tr>
<tr>
<td>Inventory carryover</td>
<td>32,792</td>
<td>3,580</td>
</tr>
<tr>
<td>Margin</td>
<td>– $295,848</td>
<td>$876,607</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial inventory</td>
</tr>
<tr>
<td>Forecasted demand</td>
</tr>
<tr>
<td>Acres planted</td>
</tr>
<tr>
<td>Production</td>
</tr>
<tr>
<td>Sales</td>
</tr>
<tr>
<td>Inventory carryover</td>
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<tr>
<td>Margin</td>
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prior to the year 1 sales period) and 0 acres in South America. The actual planting decision of 1,507 acres, when multiplied by the expected yield of 41.2 units per acre, results in an expected production of 62,088 units. When added to initial inventory of 28,678 units, the expected total supply would have been 90,766 units. The firm planned for overproduction because the costs of shortages are much larger than the costs of overproduction (because excess inventory can be carried over for sale the next year). The company has a financial incentive to weight its decisions towards avoiding shortages rather than avoiding excess inventory. Its actual yield was 46 units per acre for a total production of 69,322 units. Its total supply (including inventory carried over) was 98,000 units.

For the model run for this problem, we used a yield distribution that ranged from 31.2 to 51.2 units per acre, with an expected yield of 41.2. We generated the demand distribution by multiplying 67,000 (forecasted demand) by the normalized distribution. Using the model, the production plan for North America was 1,844 acres. If the company had planted this many acres and had obtained the same yield of 46 units per acre, the total production would have been 84,824 units. Because the actual North American yield of 46 units per acre was much larger than the expected yield of 41.2 units per acre, the model’s second-period production plan, computed after period 1 yield is known, called for 0 acres in South America. Combined with carryover, using the model’s production plan would have given Syngenta a total supply of approximately 113,502 units. Because actual demand was 72,000 units, the company actually carried over 26,000 units to the next year. Using the model’s production plan would have led to a carryover of about 41,502 units.

In both cases, supply was sufficient to meet demand, so revenue was the same. To determine margin, we subtracted planting and harvesting costs as well as...
carryover costs from revenues. In this case, the model’s production plan incurred extra planting and harvesting costs as well as extra inventory carrying costs, so the year 1 actual margin realized by the company was greater than what it would have earned had it used the model.

Continuing on to year 2 with the same hybrid, the company forecasted a demand of 164,000 units, planted 4,697 acres in North America and eventually sold 146,000 units. The model’s production plan called for 3,687 acres to be planted in North America. The model called for lower second-year acreage partly because the carryover from year 1 would have been larger using the first period acreage it specified. Had the company used the model’s suggested acreage decision in year 1, its year 1 margin would have been lower than it actually obtained. By using the model in year 1 and year 2 for this hybrid, however, it would have obtained an overall (over the two-year interval) margin increase of approximately 12 percent.

For Hybrid B, the seed company forecasted a demand of 275,000 units in year 1. It expected a yield, based on prior harvest data, of 59.6 units per acre in North America and 45 units per acre in South America. The company actually planted 4,827 acres in North America and 1,009 acres in South America. Its actual yield was 63.6 units per acre in North America and 32.1 units per acre in South America for a total production of 339,386 units. Its total supply (including inventory carried over) to face year 1 demand was 461,000 units.

For the model run for this problem, we used a yield distribution that ranged from 39.6 to 79.6 units per acre, with an expected yield of 59.6 for North America (the corresponding numbers for South America were 23, 69, and 46 respectively). We generated the demand distribution by multiplying 275,000 (expected demand) times the normalized demand distribution. Using the model, the production plan for North America was 4,264 acres. If the company had planted this many acres, using the realized 63.6 units per acre figure, the total production would have been 271,198 units. Because the actual North American yield of 63.6 units per acre was larger than the expected yield of 59.6 units per acre and there was a substantial carryover from the previous year, the model’s South American production plan called for zero acres in South America.

Combined with carryover, the yield based on using the model’s production plan would have given Syngenta a total supply of 392,812 units. Because actual demand was 396,000, Syngenta actually carried over 65,000 units to the next year. Had it used the model’s production plan, Syngenta would have had a shortage of 3,188 units.

To determine margins, we subtracted planting and harvesting costs and carryover and shortage costs from revenues. In this case, the model’s production plan incurred lower planting and harvesting costs and lower inventory carrying costs than the company had actually incurred, so the year 1 actual margin realized by the company was substantially less than what it would have earned had it used the model.

Continuing on to year 2 for Hybrid B, the company forecasted a demand of 409,000 units, planted 9,992 acres in North America (no South American acres), and eventually sold 229,000 units, leaving an inventory carryover of 492,474 units. The model’s production plan called for 8,465 acres to be planted in North America, which would have led to a production level of 556,136 units and an inventory carryover of 327,135 units. In summary, using the model’s suggested acreage decision in year 1 instead of the company’s actual decision would have led to an increase (relative to what the firm actually realized) in year 1 margin of about $3,000,000. The additional improvement that would have occurred in year 2 for this hybrid would have given it an overall (over the two-year interval) margin increase of about $7 million.

The actual results versus the model results for Hybrids C and D are documented in Table 2. As with Hybrids A and B, the model does not always outperform decisions actually taken, but on an aggregate basis it would have improved performance. In fact, aggregating results for the four hybrids over the two-year study period shows that margins would have improved by more than 24 percent while inventory carryover would have been reduced by 27 percent.

These data, limited though they are, suggest that using the model would indeed produce production plans quite different from those the company actually adopted. On average, the model’s production plans produce less inventory carryover and greater margin
than those actually adopted. Also, the model tended to plant a smaller acreage than Syngenta actually did.

Although the results of this experiment appeared promising, the production plans the model recommended were quite different from those Syngenta produced by using its current production-planning process. The senior managers decided that the model would have to prove itself further before they would adopt it as part of the planning process. To test the model further, they decided to use the model to develop an independent production plan in parallel to their ongoing processes for planning production for 2000 to produce seed corn to sell in 2001. Syngenta first developed production plans for 18 of its top hybrids using its normal procedures. These production plans were the ones actually implemented in 2000.

Afterwards, we ran the model on the same 18 hybrids using the same demand, yield, and cost data that had been inputs to the normal procedures. Syngenta kept track of actual production yields and actual year 2001 seed-corn demands for these 18 hybrids. In June 2001, after sales results for 2001 were finalized, it could therefore compare what actually happened with what would have happened if it had followed the model’s recommendations. This side-by-side comparison showed that, by using the model and implementing its recommendations, Syngenta would have planted fewer acres, would have had less inventory to carry over, and could have increased its margins by approximately $5 million on these 18 hybrids.

The final results of the 2000 production-planning experiment were not known until June 2001, well after the 2001 production plan had to be implemented, but preliminary results from the experiment had indicated margin improvements in the same range as actually occurred. As a consequence, Syngenta regarded the 2000 production planning experiment as a successful test of the model and decided to use the model beginning in 2001 to help plan production of hybrids in three classes:

- Top selling hybrids comprising 80 percent of its total sales volume,
- New hybrids with high demand uncertainty, and
- Late life cycle hybrids with established but declining demand.

Based on historical data, we developed different demand distributions for the hybrids in each of these three classes, using the modeling procedure described earlier.

Currently, the vice president of supply management runs the model with input from marketing, production, and inventory managers. A team of managers from these three areas decides whether to follow the model outputs. Each year, Syngenta modifies certain model parameters (yield distributions, demand forecasts, and normalized demand distributions) to account for the most recent information. It takes several weeks to accumulate the required model inputs, but actually running the model and analyzing its output takes only one to two days. It performs first runs of the year (two-period model) in late February or early March to allow adequate time for production contracting. It performs second runs of the model (one-period model) in late August or early September to confirm the South American production decisions.

Impact

In developing and implementing the model, we clearly demonstrated the existence of systematic bias in the demand forecasts. Specifically, we found that the historical demand forecasts Syngenta had produced using the traditional aggregation or roll-up methods overestimated demand 73 percent of the time. By using the model to analyze various realistic scenarios, we found that eliminating the bias in forecasting procedures could produce substantial benefits. This has spurred Syngenta to thoroughly review and modify its forecasting process. For 2002, it organized a team dedicated solely to forecasting and inventory management with the goal of reducing the inventory-to-sales ratio.

Using the model has changed the way Syngenta thinks about and values a second chance at production in South America. Before we developed the model, it saw South American production merely as a high cost tool for adjusting inventory. Now, it sees the second-chance opportunity in South America as a viable inventory-management tool and plans for it, making it an integrated event rather than a reactionary rescue event. Even when Syngenta does not use South American production, the fact that it is an available option
enables it to reduce the acreage in North America it devotes to seed-corn production. As a result, Syngenta has been able to reduce its working capital while still meeting customer demands for seed corn.

A key example of Syngenta’s change of thinking is that it now contracts for South American production in advance. As a result, Syngenta has been able to choose better growers at reduced prices, allowing it to better predict yield, to reduce production costs, and to come close to its inventory goals.

Since implementing the model, Syngenta has analyzed industry benchmarks to investigate how its leading competitors use the second-chance production opportunity in South America. It found that on average, seed-corn companies sell only 60 percent of the seed corn they produce in South America each year, storing the remaining 40 percent until the next year. By using the model, Syngenta has improved its use rate of seed grown in South America to 80 percent. Since producing seed corn in South America is a costly option, Syngenta believes that improving the South American use rate is a key indicator.

The final results for the production plans Syngenta developed and implemented during the calendar year 2001 will not be available until late spring or early summer of 2002 when it has its final sales figures. Syngenta estimates, however, that using the model to help plan 2001 production will increase margins by several million dollars.

Senior managers in Syngenta have stated that, although the margin improvements are very beneficial, the major benefits of the model and its implementation lie elsewhere. Specifically, senior managers think the major benefits are

— The different thought process driving improvements in forecasting demand that have reduced the systematic bias in demand forecasts,
— The opportunity to reduce working capital while still meeting customer needs, and
— The recognition that using modeling helps them to be proactive in developing planning tools in a changing business environment.

One major benefit is the reduction in forecasting bias. In comparing the normalized demand distributions for 1998–1999 and 2000–2001, we found that the forecasts overestimated demand 73 percent of the time in 1998–1999 and only 59 percent of the time in 2000–2001 (Figure 3). The ideal number is 50 percent.

Syngenta’s business is changing. Customers are increasingly demanding a wider variety of multiple seed treatments (fungicide, pesticide, and so forth) on multiple hybrids. Research on genetically modified organisms (GMOs) has led to new varieties that resist depredation from the dreaded European corn borer, tolerate applications of Roundup herbicide, and tolerate corn root worm. These new genetic varieties and combinations and the growing number of possible
seed coatings imply an explosion in the number of end products. This growth in the number of end products will increase demand uncertainty at the stock-keeping-unit (SKU) level. Syngenta cannot delay customization (via GMO type) until it has resolved demand uncertainties because it must produce the seed corn it sells for one growing season in a previous growing season. Although theoretically it can delay customization (via seed-coating type), doing so would necessitate making huge investments in treating equipment to be able to treat seeds rapidly enough to provide an acceptably short lead time to customers.

To meet such customer demands in a fairly flat sales market without making unacceptably high investments in working capital, Syngenta will need better planning processes than it has previously used. We are working to develop tools to help plan production in this increasingly challenging environment. Syngenta also needs production-planning tools for other seed products, such as soybeans. We are trying to develop production-planning models for these products as well. According to Ed Shonsey, president of Syngenta Seeds, North America,

The efforts associated with developing the model and the use of the derived analysis tool have already paid huge benefits to our company. They have changed the way we think about uncertainty and risk and have forced us to rethink the way we do business. I am convinced that the use of the model and similar decision-support tools will assist us in being successful in the future.

Appendix

In modeling the production-planning problem for seed corn, we make use of the following cost parameters, distribution functions, and decision variables. Period 1 refers to the first North American growing season, and period 2 refers to the second growing season in South America.

Cost Parameters

\( p \) — the selling price per unit (unit = 80,000 kernels).

\( \pi \) — the shortage cost per unit for unmet demand.

\( v \) — the salvage value per unit for any unsold seed at the end of period 2.

\( c_i \) — cost per unit of processing seed at the end of period \( i \) (includes holding or shipping as applicable).

\( K_i \) — cost per acre in period \( i \).

Distribution Functions

\( f(D) \) — distribution of demand at the end of period 2. (We allow for the possibility of updating this distribution as the selling season nears.)

\( g_i(y_i) \) — distribution of yield in period \( i \), \( i = 1, 2 \).

Decision Variables

\( Q_1 \) — number of acres to plant during period one (first growing season).

\( Q_2 \) — number of acres to plant during period two (second growing season).

We denote \( w_i \) as the number of units available at the beginning of period \( i \). At the beginning of period 1, the producer has \( w_1 \) units available, which is the quantity of product carried over from the previous year. At the beginning of period 2, the producer has \( w_2 = w_1 + Q_{1,v1} \) units available. Finally, after second-period production and demand \( D \) has occurred, the producer has \( w_3 = \max(0, w_2 + Q_{2,y2} - D) \) units which it will carry over to the following year.

We showed (Jones et al. 2001) that under very reasonable conditions the problem can be formulated as a dynamic programming problem and furthermore that the resulting dynamic programming problem is well posed. To solve the dynamic programming problem in practice, we generated discrete approximations to the yield and demand distribution functions and then formulated the problem as a linear program. Thus we let

\[
g_i(y_i) = \{ g_{i,1}, g_{i,2}, \ldots, g_{i,v}, \ldots, g_{i,m} \},
\]

where \( \prob(y_i = y_{i,v}) = g_{i,v} \)

\[
g(y_2) = \{ g_{2,1}, g_{2,2}, \ldots, g_{2,v}, \ldots, g_{2,m} \},
\]

where \( \prob(y_2 = y_{2,j}) = g_{2,j} \)

and

\[
f(D) = \{ f_1, f_2, \ldots, f_{r}, \ldots, f_p \}
\]

where \( \prob(D = D_k) = f_k \).

Given the following decision variables:

\( Q_1 \) = first-period acreage choice,

\( X_i \) = second-period acreage choice when \( y_1 = y_{1,v} \)

\( i = 1, \ldots, m, \)

\( Z_{ijk} \) = dummy variable that reflects [sales revenue + salvage − shortage penalty] when \( y_1 = y_{1,v}, y_2 = y_{2,j} \)

and \( D = D_k \) for all \( i, j, k \), we have the linear program
Maximize $-K_i Q_i - \sum_{i=1}^{m} g_{1i} c_1 Q_i y_{i1} - \sum_{i=1}^{m} g_{1i} K_{2i} X_i - \sum_{i=1}^{m} g_{3i} \left( \sum_{j=1}^{n} g_{2j} c_j X_j y_{2j} \right) + \sum_{i=1}^{m} g_{1i} \left( \sum_{j,k} g_{2j} f_{i j k} Z_{i j k} \right)$ \hspace{1cm} (1)

subject to

$Z_{i j k} \leq p (w_1 + Q_i y_{i1} + X_i y_{2i}) - \pi(D_k - (w_1 + Q_i y_{i1} + X_i y_{2i}))$ for all $i, j, k$, \hspace{1cm} (2)

$Z_{i j k} \leq p D_k + v(w_1 + Q_i y_{i1} + X_i y_{2i} - D_k)$ for all $i, j, k$, \hspace{1cm} (3)

$Q_i \geq 0$, \hspace{1cm} (4)

$X_i \geq 0$ for all $i$, \hspace{1cm} (5)

$Z_{i j k} \geq 0$ for all $i,j,k$. \hspace{1cm} (6)

The first term in the objective function is the first-period planting cost. The second term captures the expected cost of processing the first-period harvest. The third term is the expected second-period planting cost, and the fourth term gives the expected cost of processing the second-period harvest. Finally, the fifth term gives the expected value of (revenue + salvage – shortage cost), which can be calculated once the seller has realized demand.

In the constraints, every triple $(i,j,k)$ appears in each of constraints (2) and (3). Constraints (2) are tight when demand is greater than or equal to supply, while constraints (3) are tight when demand is less than or equal to supply. Finally, constraints (4), (5), and (6) are the usual nonnegativity conditions on the variables. The implemented linear program has approximately 1,500 variables and 1,500 constraints.

To guarantee that the linear programming problem has a feasible, finite, and nontrivial solution, we make two assumptions regarding the problem parameters, where $E(\cdot)$ is the expected value:

\begin{align*}
(i) \quad & \frac{K_i}{E(y)_i} + c_i \leq 1, 2, i, \\
(ii) \quad & \frac{K_i}{E(y)_i} + c_i \leq 1 + \pi \text{ for at least one } i \in \{1, 2\}.
\end{align*}

Assumption (i) states that the salvage value of seed must be less than or equal to its expected cost of production. In the absence of this assumption, the producer’s expected profits would be unbounded. This condition must hold for both period 1 and period 2 if a feasible, finite solution is to exist.

Assumption (ii) states that the expected per-unit cost of production must be less than or equal to the total gain (avoidance of penalty cost plus revenue) that the producer can earn from selling seed. Violation of this assumption would imply that the producer’s optimal choice would be to not produce. This condition must hold for at least 1 of the 2 periods or the trivial (nonproduction) solution would be optimal.

References