STRATEGIC PETALS: A MODEL FOR COST-EFFECTIVE PROCUREMENT IN THE FLOWER INDUSTRY'S DUTCH AUCTIONS

by

Tetiana Stasiuk

A thesis submitted in partial fulfillment of the requirements for the degree of

MA in Business and Financial Economics

Kyiv School of Economics

2024

Thesis Supervisor: ______________________________ Professor Konstantin Sonin

Approved by ____
Head of the KSE Defense Committee, Professor

____

____

____

Date ____

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

CAGR Compound Annual Growth Rate

NGO Non-Governmental Organization

LP Linear Programming

MILP Mixed-Integer Linear Programming

DSS Decision Support System

CHAPTER 1. INTRODUCTION

Dutch auctions have become very important in the flower industry, especially within the borders of the Netherlands. From the original concept of the Dutch auction that happened in Holland in the 1600s, the style of purchase has developed into the dominant method for the flower trade, taking about 60% of the global plant trade (Florists' Review, 2023). These are auctions in which the bidding starts high and then decreases at a fixed rate until someone accepts the current price. In comparison with the more common English auction in which prices ascend, this method introduces quite distinct strategic challenges and opportunities for bidders.

The Dutch auction is more than its background and its broad practice in the flower industry. Trading companies such as Royal Flora Holland and Landgard have emerged as global centers where several million flowers are sold on a daily basis. Their productivity is vital to the proper running of the worldwide flower market, affecting price determination, supply chain logistics, and the availability of flowers and their cost to consumers worldwide.

Procurement strategies currently being utilized by firms in such auctions lead to suboptimal spending. The lack of transparency related to other people's bidding strategies puts the bids in a high-stakes environment. Flower companies and wholesalers have to procure flowers from these auctions at the best possible price, ensuring the quality needed for their business. The inherent complexity requires the development of more sophisticated procurement strategies that better enhance cost-effectiveness and operational efficiency.

Improving the effectiveness and economy of procurement with the required quality is quite essential in Dutch auctions. The percentage of suboptimal procurement spending results from the dynamic nature of the pricing mechanism and often the blind nature of the strategies that other bidders may have adopted. Flower shops and wholesalers function within a very competitive market where effective procurement strategies are key to sustaining profitability. Ineffective approaches result in increased operational costs and, therefore, decreased general business performance.

The study gives the model of procurement planning, improving the ability to make accurate purchasing decisions regarding the amount of flowers to be bought with a view to meeting the demand without excessive risk of overspending money. Thus, the procurement model provides the company with a competitive advantage in procuring quality flowers at the best prices, hence improving the positioning of the company in the market.

The implementation of the optimization model would improve risk management since it identifies the possibility of market fluctuation and supports an appropriate sourcing strategy to mitigate these risks.

Advanced optimization models take advantage of the upward trend in economic efficiency. Companies will not overpay for the flowers, and occasions of overbuying will be reduced by making fact-based procurement decisions. This procurement methodology will make sure that the procurement gets locked in with the actual demand, hence reducing the carrying costs. Its advantages go beyond immediate cost savings into long-term strategic gains, where improved supplier relationships mean a better ability to respond agilely to market changes.

The research is motivated by collaboration with an industrial company that regularly takes part in auctions for the procurement of flowers.

This analysis will go on to enhance the procurement strategy for the company within the Dutch auctions by optimizing lot selection and procurement decisions for cost-effectiveness, efficiency in operations, and sustainable development. These improvements would benefit the company along with its consumers.

The study is methodologically based on a mixed-integer linear programming method that determines an optimal procurement plan in view of the company's demand

and information about lots available before the auction. The model does not take into account transaction costs because transportation, storage, pre-cooling, packing, etc., are normally made by third-party companies; moreover, it highly depends on the types of flowers and their quantities.

The developed model provided satisfying results and, at the same time, managed to procure at the least cost the fulfillment of the demand for the various types of flowers. For each product, the status reached "Optimal," which means the model is robust and effective enough to choose from a host of procurement options that would provide the least cost under the given constraints.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

2.1. Industry Overview

The floriculture industry is comprised of flowers and ornamental plants that are grown for distinctive aesthetic appeal and decorative use. These include: cut flowers, produced mainly to be used as fresh flowers in bouquets and floral arrangements; treated cut flowers, preserved mainly for continuous use beyond the natural life of the flowers; foliage plants, grown mainly for their ornamental foliage; flower bulbs, which are grown mainly to be planted by the consumer; and ornamental plants, such as flowering pot plants and ornamental grasses. We will be focusing mainly on cut flowers since these are the specialization of the company we are working with.

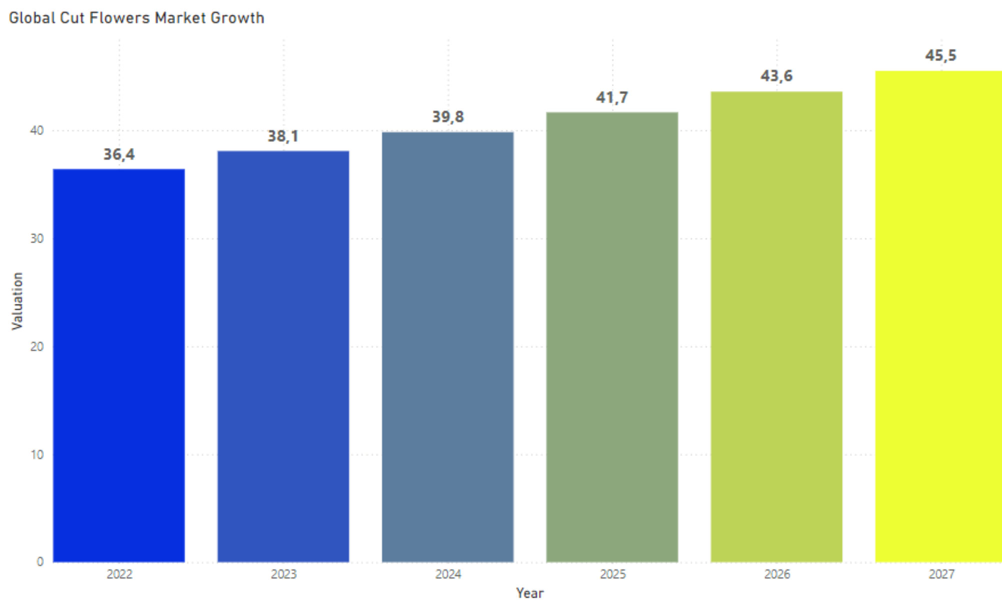
Cut flowers are, in some ways, an unusual agricultural product. Certainly, like most farming products, they are perishable; still, the value of flowers is such that they are very different from most other crops. While most commodities derive functional utility from their potential to feed or fuel, the flower is an almost completely aesthetic and emotive commodity. They act as messengers of the deepest sympathy to the purest joy.

Commercial production of cut flowers began in the Netherlands in the 1600s when the first greenhouse was built, allowing out-of-season plant production and sale. Initially, greenhouses were located around cities. However, when air transport and refrigerated trucks became available, the producers were able to move to areas with better climates and less expensive production.

The flowers are usually categorized into traditional or specialty, while specialty flowers encompass many ornamental flora, and roses, carnations, and chrysanthemums represent the top-selling flowers of the traditional flower category in the global market (Yue & Hall, 2010).

The global cut flower market, valued at USD 36.4 billion in 2022, is expected to reach USD 45.5 billion in 2027, which will reflect a Compound Annual Growth Rate (CAGR) of 4.6% during the same period of time (Markets and Markets, 2023).

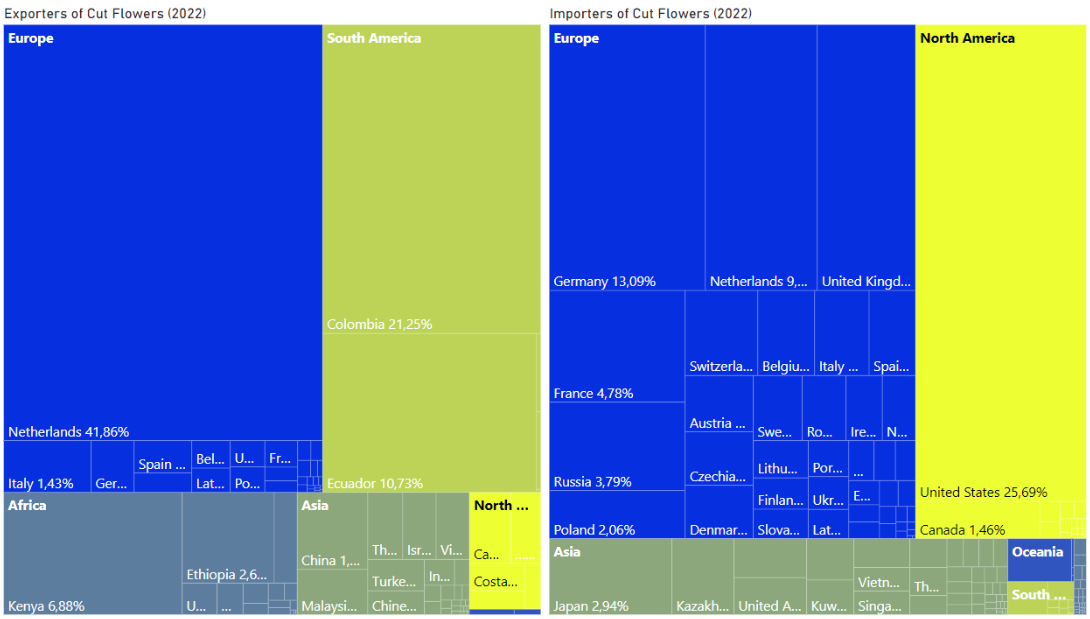
Figure 1. Global Cut Flowers Market Growth, 2022-2027



Source: Own presentation based on data from Markets and Markets, 2023

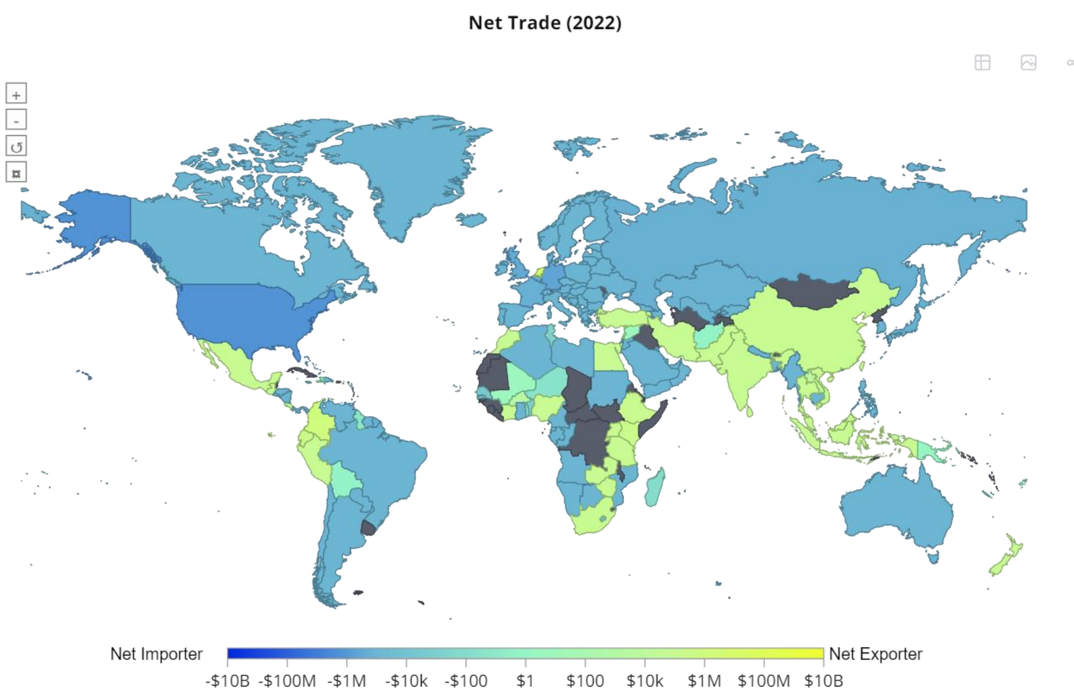
Like many other industries, the cut flower industry is based on its key exporters and importers. As illustrated in Figure 2 below, the Netherlands maintains more than 40% of the world market and is particularly renowned for its flower auctions. Put together, Colombia and Ecuador control more than 30% of the market; Kenya and Ethiopia, in total, have less than 10%. On the import side, the United States leads by importing almost 26% of all cut flowers, while Germany, the Netherlands, the United Kingdom, and France together cover approximately 35%. Figure 3 shows a better understanding of the world trade flow; it describes the net flow of cut flowers by country in 2022 and points out the most important net exporters and importers of the products concerned (oec.world, 2023).

Figure 2. Exporters and importers of cut flowers, 2022



Source: Own presentation based on data from oec.world, 2023

Figure 3. Net Trade of cut flowers, 2022



Source: oec.world, 2023

In this context, global trade has developed primarily in the context of auction houses. They provide growers with a central market from which they sell flowers to wholesalers and retailers through a competitive-bid process.

In this manner, Royal Flora Holland, based in the Netherlands, is reportedly the largest auction cooperative today, selling about 95 percent of all flowers and plants sold in the Netherlands.

It was formed in 2008 through the merger of the world's two biggest flower-auction centers. Actually, this was a merger with the aim of combating threats brought about by business competition from the opening of new international flower markets in Mumbai and Dubai. This cooperative has constructed a centralized auction system, offering an efficient and large-scale transaction platform that has touched the global growers and buyers in such a business-essential way. Apart from Royal Flora Holland, other leading companies like Dümmen Orange and Selecta One have contributed a lot to the marketplace of cut flowers, organizing activities in the sphere of breeding and propagation. All these companies, therefore, invest much in research and development to produce new cultivars suitable for the preferences of consumers. As identified earlier, all varieties of plants are supplied to the world market from large flower farms primarily located in the Netherlands, Colombia, Ecuador, Kenya, and Ethiopia.

The market structure also includes a network of wholesalers and distributors like FleuraMetz, Florca, etc., who use the latest logistics and supply chain management practices to ensure freshness and quality maintenance. Into the same breadth, companies like Bloom & Wild and The Bouqs Company disrupted retail with an online marketplace to reach out to consumers for an overall convenience factor in online shopping and home delivery services. Thus, today's cut flower market is typified by its technology at each stage, from breeding and growth to distribution and retail. Various reasons have influenced this market to grow noticeably.

The trend of giving flowers as gifts for different occasions and consumers' new consciousness has made constant demand for cut flowers. Besides, people's views on flowers have changed from just being a gift item to also a home decor item. The ease of online trade also created convenience for consumers in accessing various types of flowers, apart from other attached services such as delivery. In addition, with industry expansion, out-of-season flowers locally or those not available in a particular region yet highly available elsewhere in the world become accessible to consumers. This is further evidenced in the growth of floral tourism with increases in visitors to gardens, flower shows, and festivals. However, the industry is further burdened with a number of threats and issues as well. For example, flowers are extremely perishable products that require much in terms of fresh maintenance during transportation and storage. The importation of an exotic variety of flowers also ultimately forces the selling price up to a rate unaffordable by some consumers. The lack of standardization throughout the industry makes it incredibly cumbersome to compare prices and quality among the many providers.

On the other hand, an area of growth in the cut flower market includes the demand for green products. In this direction, considering the increased awareness developed during the last years regarding sustainability issues, manufacturers started to focus worldwide on sustainable flower growth; hence, the number of sustainable cut flowers available in the market is quite large.

The world flower industry is peculiarly different from any other industry due to its wide array of product offerings and openness to international trade. Due to the uniqueness, limited supply, and other origin-related factors, each and every flower possesses certain attributes. Not only sociocultural factors but technological development have also made the floricultural industry take over as a global phenomenon.

2.2. Related studies

The recent studies have focused mainly on the optimization of the production and procurement of different commodities, such as natural gas, flowers, and flower bulbs.

Caixeta-Filho et al. (2000) developed a linear programming model to optimize the production planning of Gladiolus bulbs in Brazil. It had been designed to optimize the grower's gross economic result by finding optimal quantities of bulblets to plant with regard to sales, prices, stock, and planting area. It has been implemented by a representative bulb grower and resulted in optimal combinations of bulblet types and spacing and yielded a 15% gain in gross economic results during its first year of use.

Caixeta-Filho et al. (2002) applied a linear programming-based decision-support system for the management of lily flower production. The model had the objective of maximizing the total contribution margin of the farm, considering sales limits set by the market, requirements of the market, characteristics of the production cycle, and greenhouse limits. Implementation of this system yielded a revenue increase of 26%, an increase of 14.8% in lily pot sales, and an increase of 29.3% in lily bunch sales from 1999 to 2000. More than that, the operational costs were reduced inside the company, and the quality of its flowers increased considerably.

Mandl and Minner (2020) developed a nonparametric data-driven approach to optimize natural gas procurement in the face of uncertain prices. Instead of relying on a parametric price model, as is common in much previous research, this approach uses historical and real-time data of procurement decisions via mixed integer linear programming. Significant cost savings are shown empirically, along with improved procurement strategies, based on machine learning techniques that reduce overfitting and generalization errors.

Chenu et al. (2017) presented two mixed-integer-programming models of multidimensional-combinatorial and volume-discounting-auctions with the purpose of enhancing procurement efficiency for an international NGO. Regardless of the number of suppliers, there was a 10% or more decrease in the procurement cost, while in a combinatorial and volume discount auction, the figure stood at 15%.

In this respect, Giacon et al. (2020) focused on NGO procurement efficiency through cost reduction and finding the right seller. The authors identified three optimization models related to integer linear programming. Indeed, the findings showed that 9-20 percent increased efficiency in procurement was much better compared to any regular strategy through choosing the lowest price.

The current literature on this topic can also provide information on a set of optimization techniques, especially variants of linear programming and machine learning methods applied within different contexts, such as energy procurement and various types of auctions. These studies would, therefore, form the basis on which similar models, if possible, may be developed by taking into consideration the requirements of the flower industry at the Dutch auctions.

This shortcoming can be met by developing a strong linear programming model that optimizes the flower procurements. A decision support system with an integrated model can provide procurement recommendations and thus help the company to decide in a better and less expensive way.

CHAPTER 3. METHODOLOGY

Most commodity procurement optimization papers, such as Mandl & Minner (2020), Chenu et al. (2017), and Giacon et al. (2020), and production planning, such as Caixeta-Filhoa et al. (2000) and Caixeta-Filhoa et al. (2002), considered linear programming or its variants to develop the model. The methodology in this paper is based on the approach developed in the study on cost procurement reduction with multidimensional auctions by Chenu et al. (2017).

Generally speaking, linear programming (LP) is a branch of mathematical programming that studies methods for finding the extrema of linear functions subject to constraints in the form of linear equations or inequalities.

The mathematical formulation of any LP problem is as follows:

$$Z = c_1x_1 + c_2x_2 + \cdots + c_nx_n \rightarrow \max\ (min) \tag{1}$$

Under the following conditions:

$$\begin{cases} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n\{\leq, \geq, =\}b_1; \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n\{\leq, \geq, =\}b_2; \\ \cdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n\{\leq, \geq, =\}b_m; \end{cases} \tag{2}$$

$$x_1 \geq 0, x_2 \geq 0, \ldots, x_n \geq 0. \tag{3}$$

Function 1 is the target function or objective function. In economical optimization problems, the objective function characterizes efficiency of functioning and development of an economic system. For example, one objective function may be such a requirement as to maximize profit due to production of some product under given constraints on available resources.

System (2), (3) - is the system of constraints (or the system of conditions) of a linear programming problem. It describes the internal technological and economic processes of the functioning and development of the production and economic system, and also the processes of the external environment, which influence the results of the activity of the system. It believes the values $\mathrm{b}_j, c_j, a_{ij}$ are pre-defined and predetermined at a preliminary analysis stage of the real situation.

In our case, one of the variants of LP-MILP is used. This is such a kind of LP where some variables are restricted to become integers, specifically including binary variables in optimization problems.

We have a set of k kinds of flowers. For each type of flower $k \in [1; K]$, there is a demand for Q^k units of the type of flower. There are suppliers $i \in [1; N]$, which provide those flowers. Also, there is a list of M^k price-quantity pairs for each type of flower indexed by j, $\left\{\left(P_1^k, \left[Q_{i1_{low}}^k; Q_{i1_{high}}^k\right]\right), \dots, \left(P_j^k, \left[Q_{ij_{low}}^k; Q_{ij_{high}}^k\right]\right)\right\}$. Each price-quantity pair defines the price P_j^k that the company in the industry is willing to pay per unit of lot k, while the number of units available on the auction is in the interval $\left[Q_{ij_{low}}^k; Q_{ij_{high}}^k\right]$. Let c be a fixed commission paid to the auction house if the company participated in the clock auction and bought something in any quantity.

To every price-quantity pair $\left(P_j^k, \left[Q_{ij_{low}}^k; Q_{ij_{high}}^k\right]\right)$, there is a corresponding binary decision variable x_j^k that equals to 1 if some number of units of the lot is bought in the auction within a defined interval at a wanted price per unit; takes the value 0 in other cases.

The capacity of boxes in which flowers are sold during auctions differs according to their type. Associated with each price-quantity pair, there is a continuous variable b_j^k that precisely specifies how many boxes of the lot the buyer needs to purchase at auction.

C^k – box capacity; w_{over} and w_{under} – two custom weights that are introduced within the model. Those binary variables let the model choose if it is better to buy a bit more or less than the demand level. This forms an important part of decision-making, as flower demand is seasonal and also varies with trends. Hence, the ability to further sell the flowers depends on it too. Weights are set manually for every type of flower; for instance, w_{over} with the value 1 signals to the model that if we cannot buy the exact number of flowers, it's all right to buy a bit more. w_{under} works the opposite way, and the model would try to buy slightly less.

The MILP formulation is as follows:

$$\sum_{k \in K} \sum_{j \in M^k} (b_j^k C^k P_j^k + x_j^k c) \rightarrow min \quad (4)$$

Subject to

$$x_j^k Q_{ij_{low}}^k \leq b_j^k \leq x_j^k Q_{ij_{high}}^k \quad (5)$$

$$\sum_{j \in M^k} x_j^k \leq 1, \forall k \in K \quad (6)$$

$$\sum_{j \in M^k} b_j^k C^k \geq Q^k \ if \ w_{over}^k = 1, \forall k \in K \quad (7)$$

$$Q^k - C^k \leq \sum_{j \in M^k} b_j^k C^k \leq Q^k \ if \ w_{under}^k = 1, \forall k \in K \quad (8)$$

$$x_j^k \in \{0; 1\}, \forall j \in M^k, \forall k \in K \quad (9)$$

$$w_{over}^k, w_{under}^k \in \{0; 1\}, \ \forall k \in K \quad (10)$$

$$b_j \geq 0, j \in M^k \quad (11)$$

Constraint (5) states that when purchasing a certain quantity of a lot k at price P_j^k, this quantity must fall within the quantity interval $\left[Q_{ij_{low}}^k; Q_{ij_{high}}^k\right]$. Constraint (6) means that for each winning bid, only one price-quantity pair can be chosen. Constraints (7) and (8) force the model to meet the demand as much as possible, depending on the values of the weights. Constraint (9) described that the decision variable x_j^k can only be binary. Likewise, constraint (10) describes that weights shall also be binary. Finally, Constraint (11) is the non-negativity condition.

The MILP model developed in this context picks up the quantity to be purchased from specific lots. In fact, it is structured to take maximum benefits from the given form of the auction by selecting an optimal price-quantity combination from the available suppliers.

It corresponds to the Dutch auction mechanism, which optimally designs the procurement strategy concerning the price-quantity pairs. In this regard, the model allows the buyer to make appropriate purchasing decisions by considering constraints like meeting demands and supplier capacities. Thus, the MILP model acts like a DSS in order to help go through the Dutch action to minimize costs and satisfy the procurement requirements.

Testing in the simulated environment needs to be done to ensure that the developed model is efficient. The behavior of such a complex system can be simulated using the Monte Carlo method.

The simulation modeling method is based on the creation of algorithms and programs that could imitate a real system and its main features. Considering our research, it was necessary to develop the optimization model, which will be able to create an accurate procurement plan. Simulation modeling gives us the ability to try how fluctuations of variables happen to the overall cost of procurement.

By definition, simulation is a computer experiment. The main difference between such an experiment and a real one consists in the fact that it is conducted not with the system the subject of our research (an auction) but with its simplified formal equivalent, a model. Conduction of a real experiment without knowing in advance the capabilities created by the optimization model is expensive and impracticable. Machine simulation is the only reliable way to test the developed optimization model before any real-world implementation.

Another important benefit of using a Monte Carlo simulation involves the way it can show possible vulnerabilities in optimizing the model through stress-testing thousands or hundreds of generated scenarios. In each of these scenarios, variables take on a wide range of values based on a given distribution. Through those values, the optimization model recalculates the procurement plan and shows the possible outcome of each scenario.

In summary, it is explained that the Monte Carlo method permits the verification of how this model would act under different conditions other than the base scenario, adding a degree of confidence to its reliability with a view to minimizing risks when it comes to real-world application.

CHAPTER 4. DATA

For this purpose, the data provided by the industrial company include lots to be auctioned and, on the other side, the needs of the firm. Thus, it is necessary that the provided data contain the product name, available boxes, box capacity for each product, demands, and price per unit for a specific auction date.

Another important observation was that there might be a number of lots for the same product from one of many suppliers, with different lot characteristics like variable number and capacity of boxes.

The capacity of boxes varies since the types of flowers vary, as they are different in size and some require special ways of packaging. It is these differences that make procurement a challenging task as this calls for careful planning and logistics in ensuring effective and economical transportation and delivery. In practice, these capacities determine how many cases must be purchased to satisfy the demands, so this is crucial information about buying as cheaply as possible. Variations in capacity are usually because of variations in packaging. Since the model does not consider transaction costs, the most frequent capacity across lots of the same product was used for the construction of the model.

Table 1 also contains the pre-specified weights of each flower type. Only one weight is set to 1 (either w_{over} or w_{under}) for each product. That is to say, if the demand could not be satisfied in a predefined value, the model would choose either over-purchasing or under-purchasing of the specific type of flower. Because the weights are set by the flower's popularity in certain seasons, it would mean that peonies are most in demand in June and chrysanthemums in October. This will be controlled through weights as to whether the model tries to exceed the demand level or stay below, hence aligning better with the purchases to fit the market needs.

Table 1. Flower Procurement Data

Product	Price/Unit	Demand	Box Capacity	w_over	w_under
R GR CELEB	0.31	700	60	1	0
R GR CHAPEAU	0.31	800	40	1	0
R GR CHARMANT	0.31	600	40	1	0
R GR CHERRY-O	0.35	400	50	1	0
R GR CHIC WHITE	0.35	200	20	1	0
R GR CHIFFON	0.33	150	20	1	0
R GR CLARENCE	0.33	600	40	1	0
R GR COMANCHE	0.33	400	80	1	0
R GR CONFIDENTIAL	0.33	800	50	1	0
LI LA SCANSANO	0.64	300	60	0	1
LI LF WHITE HEAVEN	0.64	300	60	0	1
LI OT MALDANO	0.64	400	40	0	1
LI OT ZAMBESI	0.64	250	40	0	1
CHR S AAA KRISSI	0.46	400	75	1	0
CHR S AAA BOUNCER	0.46	200	75	1	0
CHR S AAA AURINKO	0.46	500	75	1	0
CHR S AAA EDVALDO	0.46	300	75	1	0
CYMB T GLADYS	4.40	300	6	1	0
CYMB T COCKTAIL	4.40	200	6	1	0
CYMB T GEM	4.40	200	9	1	0
GE MI ALIX-NOOR	0.16	200	80	1	0
GE MI AMELIE	0.16	400	80	1	0
GE MI BELLA	0.16	400	80	1	0
ZANT CAPT VENTURA	0.48	100	60	1	0
CALLA ARUNA	0.48	100	40	1	0
CALLA MANILA	0.48	100	40	1	0
ALSTR ANNABELLE	0.26	100	80	1	0
ALST AMITY	0.26	200	40	1	0
ALST FL CAMPARI	0.26	200	50	1	0
ALST FL CHARME BLANC	0.26	300	50	1	0
ALST FL CHARME WHITE	0.26	250	50	1	0
ALST FL DYNAMITE	0.26	250	50	1	0
ANTH A ACROPOLIS	0.53	300	10	1	0
ANTH A ADINA	0.53	200	20	1	0
LIM S ROSA SUN BIRDS	0.28	100	50	1	0
LIM SIN TIFFANY DIAM	0.28	100	50	1	0
TU EN STRONG GOLD	0.19	100	150	0	1

Table 1. Flower Procurement Data

Product	Price/Unit	Demand	Box Capacity	w_over	w_under
HYP COCO CASINO	1.47	250	80	1	0
HYP COCO TANGO	1.47	200	150	1	0
EUS G ALISSA PUR WHI	0.63	220	40	0	1
EUS G ROSI RED	0.63	100	40	0	1

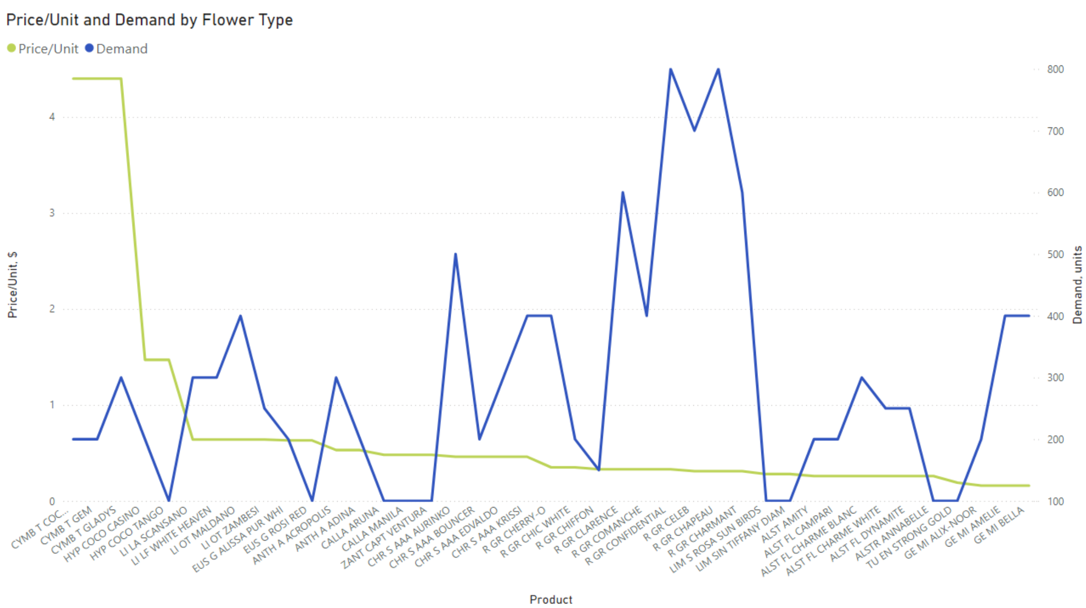
Source: provided by the company in the industry

The variation in this dataset includes flowers, which are normally in demand, such as roses and chrysanthemums, and the more specialized variety, like cymbidium.

Information for the selected lots is the name of the supplier, product name, and number of available boxes. In all, there are 102 lots with 41 unique flower types in the dataset. It is enough to make a solid procurement plan for the company using the developed model; on the other hand, this is still a tiny fraction of floricultural products because one auction usually holds 16-19 thousand lots.

From the table below, it shows that demand is complementary depending on the flower types and generally, demand is usually high at low prices per unit. The relatively cheap flowers like roses and gerbera have relatively high demand as compared to relatively expensive flowers like cymbidium and hypericum, whose demand is low.

Figure 4. Demand and Price/Unit by Flower Type



Source: Own presentation based on data from Table 1

One of the important constraints in the model involves the lower and upper bounds on the number of boxes that can be procured for each variety of flower. The lower bound usually remains stable at 1-2 boxes, whereas the upper bound varies immensely, reaching a maximum of 64 in Table A.1.

The setup of the model commences with the listing of price-quantity pairs. This list for each product gives the price the company is prepared to pay per unit lot and the number of boxes of units available at auction. In our case, the number of price-quantity pairs ranges from 1 to 7 for different products.

Since there is no volume discounting by the auction houses, the price per flower is independent of the number of boxes bought.

The constant price makes it easy to develop a buying decision, as the cost per unit depends on nothing. Correspondingly, the fixed costs are constant for all types of flowers at a value of €2 per transaction, acting like a commission to the auction house for every transaction that occurs during the auction. While fixed costs are minimal, they are part of the model in order to complete the cost calculation.

With all this information at hand, the model runs individually for each type of flower in order to find an optimum solution for a particular product. The model has been developed in Python and solved by means of the PuLP library – an LP modeler written in Python. The choice of this tool was because it is fast and easy to work with. The results for all products were obtained in several seconds and are presented in Chapter 5.

CHAPTER 5. RESULTS

5.1. Procurement Model Results

This chapter presents the results of the procurement optimization model developed in the simulated environment.

The model is built using the data presented in Chapter 4, which contains information on various cut flowers, like different types of roses, tulips, and chrysanthemums. The objective function would seek to minimize the cost while meeting a certain specified level of demand for each flower type. It highlighted the quantity of boxes that each type of flower should purchase from each lot to achieve the required demand, or the quantity closest to it, at the lowest cost.

Table 2. Optimal Procurement Quantities by Flower Type

Product	Status	Total Cost	Over Purchased	Under Purchased	l_1	l_2	l_3	l_4	l_5	l_6	l_7
R GR CELEB	Optimal	227.2	20	0	4	8	0	0			
R GR CHAPEAU	Optimal	250.0	0	0	0	0	0	0	0	20	0
R GR CHARMANT	Optimal	188.0	0	0	0	15	0				
R GR CHERRY-O	Optimal	142.0	0	0	0	8	0				
R GR CHIC WHITE	Optimal	76.0	0	0	0	4	4	2			
R GR CHIFFON	Optimal	54.8	10	0	8						
R GR CLARENCE	Optimal	200.0	0	0	15	0					
R GR COMANCHE	Optimal	134.0	0	0	0	5	0				
R GR CONFIDENTIAL	Optimal	266.0	0	0	0	0	16	0	0		
LI LA SCANSANO	Optimal	155.6	0	60	4						
LI LF WHITE HEAVEN	Optimal	155.6	0	60	0	4					
LI OT MALDANO	Optimal	232.4	0	40	0	9					
LI OT ZAMBESI	Optimal	157.6	0	10	0	3	3				
CHR S AAA KRISSI	Optimal	209.0	50	0	0	0	6				
CHR S AAA BOUNCER	Optimal	105.5	25	0	3						
CHR S AAA AURINKO	Optimal	243.5	25	0	0	0	0	7			

Table 2. Optimal Procurement Quantities by Flower Type

Product	Status	Total Cost	Over Purchased	Under Purchased	l_1	l_2	l_3	l_4	l_5	l_6	l_7
CHR S AAA EDVALDO	Optimal	140.0	0	0	0	0	4				
CYMB T GLADYS	Optimal	1322.0	0	0	50						
CYMB T COCKTAIL	Optimal	899.6	4	0	34						
CYMB T GEM	Optimal	912.8	7	0	23	0					
GE MI ALIX-NOOR	Optimal	40.4	40	0	0	0	0	0	3		
GE MI AMELIE	Optimal	66.0	0	0	5	0					
GE MI BELLA	Optimal	66.0	0	0	5						
ZANT CAPT VENTURA	Optimal	59.6	20	0	0	2	0				
CALLA ARUNA	Optimal	59.6	20	0	3	0					
CALLA MANILA	Optimal	59.6	20	0	0	3	0				
ALSTR ANNABELLE	Optimal	43.6	60	0	0	2					
ALST AMITY	Optimal	54.0	0	0	0	5					
ALST FL CAMPARI	Optimal	54.0	0	0	4						
ALST FL CHARME BLANC	Optimal	80.0	0	0	6						
ALST FL CHARME WHITE	Optimal	67.0	0	0	5	0					
ALST FL DYNAMITE	Optimal	67.0	0	0	5						
ANTH A ACROPOLIS	Optimal	163.0	0	0	7	23					
ANTH A ADINA	Optimal	108.0	0	0	10						
LIM S ROSA SUN BIRDS	Optimal	30.0	0	0	2	0	0	0			
LIM SIN TIFFANY DIAM	Optimal	30.0	0	0	2						
TU EN STRONG GOLD	Optimal	0.0	0	100	0	0	0	0	0		
HYP COCO CASINO	Optimal	472.4.0	70	0	0	4	0				
HYP COCO TANGO	Optimal	443.0	100	0	2						
EUS G ALISSA PUR WHI	Optimal	128.0	0	20	5	0					
EUS G ROSI RED	Optimal	52.4	0	20	2	0	0				

Source: Own calculation based on data from Chapter 4

The application of the procurement optimization model to the data set gave the best solutions for each flower type from the various suppliers and lots at a total cost of €8,215.2. The result of the analysis shows that the procurement cost differs by flower type, depending on a specific lot choice. For example, the cymbidium flower varieties represented the highest procurement cost; in the dataset, they are considered the most expensive, and their box capacity is relatively small. Unlike the gerbera, which have lower prices per unit and much higher box capacity, a large number of boxes need to be bought in order to cover the demand.

The most interesting observation in Table 2 is that no lots were chosen for tulips, specifically TU EN STRONG GOLD. Because this type of flower has a box capacity of 150 units per box, the predefined demand is 100, and the under-purchase weight is 1. This is because tulips are trending most during spring and are not as popular during the fall season. It makes more sense not to procure the product at all since that helps to avoid unnecessary spending and probable waste.

Sometimes, the model spreads the procurement quantities among lots, as in the products R GR CELEB and R GR CHIC WHITE, the demands of which were satisfied by 2 and 3 lots, respectively. This is most likely to reflect some optimization problem between pricing and availability of boxes. Most of the time, the model procured a full quantity of flowers from a single lot. This would hint that, in some cases, the pricing or availability from one lot could provide the most cost-efficient solution. Other products reflected the same: by concentrating orders in fewer transactions, fixed commission costs associated with multiple purchases were avoided.

The advantage of the strategy relying on single-lot procurement is rather obvious: it keeps the fixed costs down. That means a model-optimized procurement mainly selected the cost of multiple transactions of the same product, which was considered higher. However, in cases when pre-determined specifications called for purchases from lots that were different, the approach was to pool the orders for general best returns.

The results indeed distribute the procurement quantities into several lots efficiently. This is the case with various high-demand products where no lot can be large enough to cover the full need, whereas low-demand products normally use one lot for procurement. It could run such a procurement plan that the total cost would be reduced to the barest minimum while meeting all the constraints.

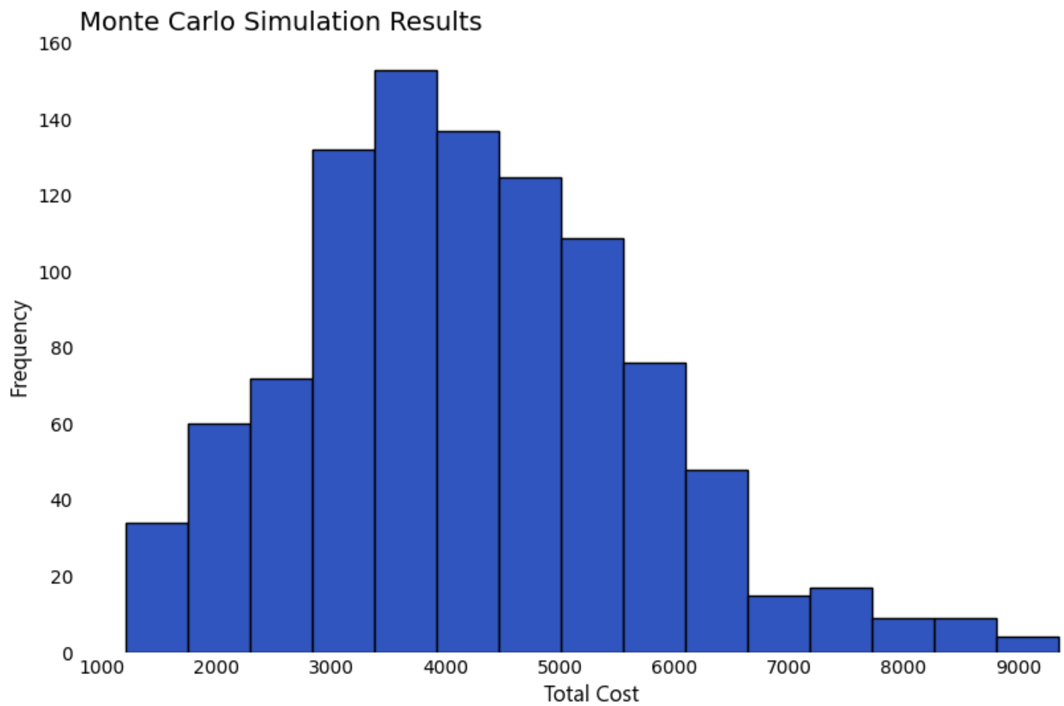
5.2. Monte Carlo Simulation Results

Accurately forecasted costs are of utmost importance during the decision-making process when it comes to procurement optimization. However, in real life, proper cost prediction is not that easy, considering the randomness of demand and prices.

The Monte Carlo simulation with 1,000 trials on the sensitivity of total procurement cost to demand and price volatility. On each iteration, random values of demand and prices were generated based on the normal distribution, where the standard deviation of demand was 10% due to high volatility in the flower market because of seasonal factors and changes in consumer preferences, among others; variation of prices was 5% because that is the average value of the standard deviation of the prices for the most popular types of flowers during the last 6 years. Also, over- and under-purchasing weights were generated randomly and had values of either 0 or 1.

The simulation modeling approach is more comprehensive as it allows the modeling of possible real-life situations where demands and prices are not constant but vary within some range. Similarly, the optimization model calculated the value of the total procurement cost over the generated values in each iteration.

Figure 5. Monte Carlo Simulation Results



Source: Own presentation based on the Monte Carlo Simulation

Most overall procurement costs fall between about €3,000 and about €5,500. The distribution of total procurement costs is a little right-skewed; this means that while lower costs are more common, there are occasions when the total costs rise. Still, the tail of the distribution does indicate that higher cost outcomes may occur, just like the one that appeared in Chapter 5.1. The histogram shows the variation in total cost outcomes from the variations in demand and price. This gives a general picture of the cost expectations and risks.

The summary statistics from the Monte Carlo simulation show the fluctuation in total procurement cost due to fluctuating demand and prices.

Table 3. Summary Statistics of Monte Carlo Simulation

	Total Cost
count	1000
mean	4230
std	1476
min	1207
25%	3218
50%	4077
75%	5176
max	9352

Source: Own calculation based on the Monte Carlo Simulation

The average total cost, as one can see from the summary statistics, is €4,230, which would mean that over scenarios, the expected procurement cost should be about the same. The standard deviation of €1,476 measures the uncertainty in potential outcomes. The lowest observed cost is €1,207, while the highest is €9,352, indicating the wide range of possible cost outcomes and substantial risk of realizing high costs under particular conditions. The interquartile range tells the position of the bulk of procurement costs, as 50% falls between €3,218 and €5,176.

The Monte Carlo simulation shows the possible range of procurement costs. Most of the procurement costs are going to fall around the mean. The distribution is rightward-skewed; while the lower costs are more frequent, in a number of scenarios, costs could go significantly higher. The big standard deviation and a wide gap between minimum and maximum costs point to the existence of great dispersion in procurement variability. Thus, the procurement strategies should be able to deal with both lower and higher-cost scenarios.

Demand and price fluctuations make the procurement cost estimate more realistic. Such an approach would help derive one of the prominent benefits that would lead the decision-makers to plan for normality and extremity scenarios, hence enabling resilient and cost-effective procurement strategies against the wind of market volatility.

Cost variability implications have to be put into perspective for strategic planning. The spread shown in Figure 5 indicates the possible procurement costs that the organization could use to its advantage by developing adaptive procurement strategies that can respond flexibly to changes in demand and price. The rightward skew in the distribution shows that while mid-range costs are more probable, there are enough examples of high-cost outcomes that would beg caution. Because of this, it is considered necessary that procurement managers make provisions for such risks through contingency budgeting so that the impact of such sudden increases in quoted prices is reduced.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

In this respect, the research focuses on the flower market and aims to enhance the procurement planning strategies for the Dutch auction using the optimization model. In developing the approach here, it is ensured that there will be improved cost efficiency along with operational efficiency for the company in the contextual backdrop of the industry. The floral industry, owing to its peculiar nature, demands effective procurement strategies. The international scope of the industry makes flower procurement hard for companies due to the peculiar properties of each flower. In this respect, we provide a comprehensive solution that could be applied in procurement planning by businesses.

Floriculture is a complex and, to some extent, a thriving industry carried out on a wide scale in most parts of the world. Floriculture depends mainly on seasonality, climatic changes, and consumer trends. The Netherlands holds the lead position in the global floriculture market. It hosts the biggest flower auctions in the world; known as the Dutch auction. It employs a reverse auction mechanism whereby the prices start declining until a bid is placed. It follows that the buyer has to respond to fast-moving auctions with an optimum price-quality balance in a competitive and challenging environment. In other words, businesses are expected to make quick decisions while optimizing cost and timely delivery within the framework of international trade regulations.

There are some related studies in procurement, auctions, and optimization whose insights might also be helpful in floriculture. The optimization techniques they applied were so promising in developing the efficiency of procurement within other industries dealing with energy and agricultural commodities. They noted that the main enablers in trying to handle price fluctuation, supplier selection, and demand volatility were based on mathematical modeling.

In spite of the huge amount of literature on auctions and procurement optimization, few are related to floriculture in reality, let alone referring to the Dutch auction.

The developed MILP model takes into account the bidding system of the Dutch auction, in which there is a continuous fall in price until one bids. This is a decision-support system, the MILP model, which gives the buyer the capability to readjust the procurement plan with the most optimal lot selection. In the model, various lots are considered for different characteristics of box capacity and number of boxes. Each type of flower has its best procurement strategy. This will better capture the nuances of individual lots, especially when working with a variable product base, as is typical in the flower industry.

Another advantage of the MILP model is its tendency to try to cover the procurement needs with the smallest possible number of lots. Such is the case with flowers that are in great demand, no lot can fulfill the whole order, so the model will distribute procurement quantities effectively over the lots. This keeps the procurement strategy flexible and scalable. In the case of low-demand products, for instance, it was intended to consolidate procurement into one lot to minimize operational complexity.

The study has considered the need to take care of risk mitigation at the procurement stage. Cost prediction is a very difficult but vital component of procurement planning. Companies should consider such uncertainties since variations in demand and price significantly affect the overall procurement costs. Throughout the research, model testing was mentioned; the Monte Carlo simulation was selected in order to examine the strength of the MILP model. Running it in a simulated environment can give the decision-makers an idea of how this model is going to behave by simulating conditions that may arise from changing market conditions.

Further research might concern more improvements that could be made in the proposed model, like embedding more variables and constraints-underlining, for instance, the seasonal pattern of the auction prices-thus developing a responsive approach towards it. Another point that could be developed within the model is considering transportation and supply chain costs since this would give a wider approach to procurement, connecting auction decisions with logistics and delivery costs. That would give the companies a scope to optimize the total cost of acquiring and delivering the products. Various studies can provide more predictive analytics and machine learning algorithms that could be used in the procurement model.

Such predictive models analyze auction outcomes from the company's side, market trends, and seasonality of historical data, and thus can offer even greater solutions for demand forecasting and price prediction. The procurement system would then factor in the market fluctuation, and its responses to further refine the cost-saving measures and operational efficiency. This would replace the current approach with a data-driven one, which is far more robust and better equipped to handle real-world complexities. The research provides an overview of the world floriculture market, defining the best procurement strategies in Dutch auctions by the use of a Mixed-Integer Linear Programming model.

The peculiarities of this industry, like the seasonality of the products, high perishability, and volatility of the market, ensure that this MILP model is a valid decision support system for companies to choose the most optimal lots that can satisfy the demand and supply constraints. That is, the flexibility of the model, allowing strategic procurement decisions for high-demand products requiring procurement from various lots, enables low-demand products to benefit from a reduced number of transactions. Besides, applying Monte Carlo justifies the application of the model in realistic conditions of auctions with the purpose of reducing risks that might come about through fluctuations in price and demand. These will be further enhanced in future research by adding more variables to the model; for example, the addition of transportation costs, enhancement in demand forecasting and price prediction using predictive analytics by machine learning.

Practical solutions that might help in cost efficiency and operational effectiveness in flower procurement are discussed, although there is scope for wider applicability.

REFERENCES

Abernethy M., 2018. Getting To Know Dutch Auctions. Optimal Auctions. https://www.optimalauctions.com/getting-to-know-dutch-auctions.jsp

Caixeta-Filhoa J. V., van Swaay-Netob J. M., Lopes R. L. (2000), Linear programming applied to the flower sector: a Gladiolus bulb production case study, *International Transactions in Operational Research* 7: 525-537. https://doi.org/10.1111/j.1475-3995.2000.tb00215.x

Caixeta-Filhoa J. V., van Swaay-Netob J. M., Wagemaker A. de P. (2002), Optimization of the Production Planning and Trade of Lily Flowers at Jan de Wit Company, *Interfaces* 32(1): 35-46. https://doi.org/10.1287/inte.32.1.35.13

Chenu M., de Brito I. J., Yoshizaki H. T. Y. (2017), Supplier Selection and Cost Procurement Reduction with Multidimensional Auctions, In. Rio de Janeiro: ABEPRO. https://doi.org/10.14488/ENEGEP2017_TN_STO_238_379_34557

Florists' Review. 2023. Flower Auction Royal Flora Holland Explained. Florists' Review. https://floristsreview.com/flower-auction-royal-floraholland-explained/

Geeks for Geeks. (2024). Linear Programming. https://www.geeksforgeeks.org/linear-programming/

Giacon, J., de Brito, I. and Yoshizaki, H. (2020), "NGO's Supplier Selection and Procurement Cost Reduction with Multi-dimensional Auctions", Yoshizaki, H.T.Y., Mejia Argueta, C. and Mattos, M.G. (Ed.) *Supply Chain Management and Logistics in Emerging Markets*, Emerald Publishing Limited, Leeds, pp. 41-59. https://doi.org/10.1108/978-1-83909-331-920201003

Mandl C., Minner S. (2020), Data-Driven Optimization for Commodity Procurement Under Price Uncertainty, *Manufacturing & Service Operations Management* 25(2): 371-390. https://doi.org/10.1287/msom.2020.0890

Markets and Markets, 2023. Cut flowers market by Type, Application, Distribution Channel - Global Forecast to 2027. Markets and Markets. https://www.marketsandmarkets.com/Market-Reports/cut-flowers-market-18187231.html

Observatory of Economic Complexity. (2022). Cut flowers. https://oec.world/en/profile/hs/cut-flowers?disaggregationValue=value2&filterSelector=valueFilter0&countryComparisonMeasureSelector=Trade+Value

The International Statistics Flowers & Plants Yearbook 2023, Volume 71
[ISSN: 2313-7126. ISBN: 978-1-7391918-1-8]

Yue, C., & Hall, C., 2010. Traditional or specialty cut flowers? Estimating U.S. consumers' choice of cut flowers at noncalendar occasions. *HortScience*, *45*(3), 382–386.

APPENDIX A

DATA TABLE

Table A.1. Information on Selected Lots

ID	Supplier	Product	Boxes Available
1	Omang	R GR CELEB	8
2	Omang	R GR CELEB	8
3	Omang	R GR CELEB	5
4	Omang	R GR CELEB	7
5	Bloomingdale Roses	R GR CHAPEAU	21
6	Bloomingdale Roses	R GR CHAPEAU	12
7	Bloomingdale Roses	R GR CHAPEAU	61
8	Diya	R GR CHAPEAU	16
9	Lolomarik / Fresco	R GR CHAPEAU	25
10	Lolomarik / Fresco	R GR CHAPEAU	64
11	Lolomarik / Fresco	R GR CHAPEAU	24
12	QualiRosa	R GR CHARMANT	32
13	QualiRosa	R GR CHARMANT	21
14	QualiRosa	R GR CHARMANT	3
15	Lolomarik / Fresco	R GR CHERRY-O	37
16	Lolomarik / Fresco	R GR CHERRY-O	55
17	Lolomarik / Fresco	R GR CHERRY-O	25
18	Klumpet Roses	R GR CHIC WHITE	2
19	Klumpet Roses	R GR CHIC WHITE	4
20	Klumpet Roses	R GR CHIC WHITE	4
21	Klumpet Roses	R GR CHIC WHITE	3
22	Vip Roses by Sassen	R GR CHIFFON	13
23	Berg RoseS	R GR CLARENCE	56
24	Berg RoseS	R GR CLARENCE	59
25	Zuubier & Co Int.	R GR COMANCHE	6
26	Zuubier & Co Int.	R GR COMANCHE	16
27	Zuubier & Co Int.	R GR COMANCHE	6
28	Bliss	R GR CONFIDENTIAL	8
29	Bloomingdale Roses	R GR CONFIDENTIAL	7
30	Bloomingdale Roses	R GR CONFIDENTIAL	48
31	Bloomingdale Roses	R GR CONFIDENTIAL	11
32	Bloomingdale Roses	R GR CONFIDENTIAL	6
33	Bloem kw. C.P.M. c an Dijk	LI LA SCANSANO	10

ID	Supplier	Product	Boxes Available
34	Blo emkw. C.P.M. can Dijk	LI LF WHITE HEAVEN	1
35	Jos van Sante	LI LF WHITE HEAVEN	25
36	Bloemkw. C.P.M. can Dijk	LI OT MALDANO	6
37	Bredefleur	LI OT MALDANO	13
38	Bloemkw. C.P.M. can Dijk	LI OT ZAMBESI	1
39	Bredefleur	LI OT ZAMBESI	3
40	Kwekerij Power	LI OT ZAMBESI	3
41	van Helvoort Company	CHR S AAA KRISSI	27
42	Hans&Ruud Hendriks	CHR S AAA KRISSI	3
43	Hans&Ruud Hendriks	CHR S AAA KRISSI	8
44	Hans&Ruud Hendriks	CHR S AAA BOUNCER	3
45	Hans&Ruud Hendriks	CHR S AAA AURINKO	22
46	Hans&Ruud Hendriks	CHR S AAA AURINKO	1
47	van Helvoort Company	CHR S AAA AURINKO	18
48	Funny Santini	CHR S AAA AURINKO	26
49	van Helvoort Company	CHR S AAA EDVALDO	33
50	van Helvoort Company	CHR S AAA EDVALDO	10
51	Hans&Ruud Hendriks	CHR S AAA EDVALDO	58
52	SPECIAL ORCHIDS	CYMB T GLADYS	53
53	SPECIAL ORCHIDS	CYMB T COCKTAIL	50
54	SPECIAL ORCHIDS	CYMB T GEM	40
55	Sunshine Orchids	CYMB T GEM	39
56	Summit Den Houter Gerbera	GE MI ALIX-NOOR	18
57	Summit Den Houter Gerbera	GE MI ALIX-NOOR	16
58	Summit Den Houter Gerbera	GE MI ALIX-NOOR	17
59	Batist Westmade	GE MI ALIX-NOOR	17
60	Batist Westmade	GE MI ALIX-NOOR	22
61	Van der Wilt Gerbera's	GE MI AMELIE	18
62	Van der Wilt Gerbera's	GE MI AMELIE	30
63	Van der Wilt Gerbera's	GE MI BELLA	23
64	J.H. Meiland	ZANT CAPT VENTURA	12
65	J.H. Meiland	ZANT CAPT VENTURA	46
66	Zandvoort Flowers	ZANT CAPT VENTURA	28
67	J.H. Meiland	CALLA ARUNA	32
68	J.H. Meiland	CALLA ARUNA	22
69	J.H. Meiland	CALLA MANILA	32
70	J.H. Meiland	CALLA MANILA	40
71	J.H. Meiland	CALLA MANILA	16

Table A.1. Information on Selected Lots

ID	Supplier	Product	Boxes Available
72	H.M. Tesselaar	ALSTR ANNABELLE	7
73	H.M. Tesselaar	ALSTR ANNABELLE	63
74	Kisima / Fresco	ALST AMITY	61
75	Kisima / Fresco	ALST AMITY	59
76	Together2Grow	ALST FL CAMPARI	30
77	Together2Grow	ALST FL CHARME BLANC	11
78	Together2Grow	ALST FL CHARME WHITE	18
79	Together2Grow	ALST FL CHARME WHITE	19
80	Together2Grow	ALST FL DYNAMITE	24
81	Jan van Velden & Zn.	ANTH A ACROPOLIS	21
82	Jan van Velden & Zn.	ANTH A ACROPOLIS	23
83	Jan van Velden & Zn.	ANTH A ADINA	21
84	Samore	LIM S ROSA SUN BIRDS	24
85	Samore	LIM S ROSA SUN BIRDS	18
86	Samore	LIM S ROSA SUN BIRDS	17
87	Samore	LIM S ROSA SUN BIRDS	18
88	Mijo Flowers MKS	LIM SIN TIFFANY DIAM	9
89	Black Label Laan Tulips	TU EN STRONG GOLD	8
90	Triflor	TU EN STRONG GOLD	8
91	Triflor	TU EN STRONG GOLD	11
92	Triflor	TU EN STRONG GOLD	9
93	Triflor	TU EN STRONG GOLD	12
94	Florius BV	HYP COCO CASINO	12
95	Florius BV	HYP COCO CASINO	60
96	Florius BV	HYP COCO CASINO	58
97	Florius BV	HYP COCO TANGO	16
98	Sunrise Holland Big Sun	EUS G ALISSA PUR WHI	55
99	Sunrise Holland Big Sun	EUS G ALISSA PUR WHI	45
100	Berglisianthus	EUS G ROSI RED	21
101	Berglisianthus	EUS G ROSI RED	22
102	Berglisianthus	EUS G ROSI RED	6

Source: provided by the company in the industry