

# REAL-TIME SUPPORT FOR AUCTIONEERS TO DETERMINE OPTIMAL CLOCK START FOR MULTI-UNIT SEQUENTIAL DUTCH AUCTIONS

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## Abstract

*In this paper we explore the issue of starting price in subauctions and provide theoretically motivated guidance to provide online real-time support for auctioneers within the Dutch Flower Auction (DFA), a well established business-to-business (B2B) auction platform. A key contribution of this study is the design of starting price increments mechanism such that the equilibrium points with higher revenue structures become identifiable and feasible. In our analysis, we first empirically show that the relationship of clock starting price and the winning bid in a previous auction is indeed an important factor in determining future prices. Then we develop an analytical model for optimizing the subplot starting point from the perspective of maximizing revenue to generate normative insights. We then use the data to demonstrate how the auctioneers' choice of using a static starting point may result in loss of revenue. Our analysis indicates that the existing rule to determining the starting price may be adequate for auctions that generate small prices but the rule may generate too small revenue for auctions with higher prices. These findings lead to the need of online real-time support that is able to do dynamic starting price setup in correspondence with the auction characteristics.*

**Keywords:** Auction theory, decision support system, Dutch auction, multi-item auctions

## 1. Introduction

In this research we focus on providing technology based real-time decision support mechanism for fast paced Dutch Auctions. Our work is in the tradition of developing decision support systems for knowledge workers, for example, by automating trivial tasks like data entry businesses can decrease the corresponding error rates (Taylor & Raden, 2007). Advances in technology provides many opportunities to support organizational information needs by utilizing systems that provide more accurate and more timely information to aid managerial decision making (Eckerson, 2006).

The context for our research is the Dutch flower auctions (DFA) (Kambil & Van Heck, 1998). The DFA play a vital role in maintaining the Netherlands's leadership in this industry; they serve as efficient centers for exchange of flower products between suppliers and buyers. The suppliers in the DFA are the growers (often family businesses), while the buyers include both large and small wholesalers and retailers. The auctioneers act on behalf of growers, while the bidders act on behalf of the buyers. In DFA auctions, the auctioneers set initial prices, reserve prices, minimum lot sizes, and clock speeds; while the bidders decide which and how many flowers to bid on and at what price. In 2008, FloraHolland – a cooperative of growers that operate six auction houses strategically located throughout the country – reported trades of over 44.8 million cut flowers and 5.1 million potted plants per day, generating over 4 billion Euros in sales per annum<sup>1</sup>. The DFA are held on weekday mornings between the hours of 6 and 10. Up to 40 auctions can occur simultaneously, with each lasting 3 to 5 seconds on average. In total, roughly 125,000 transactions occur daily.

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<sup>1</sup> <http://www.flora.nl/en/AboutFloraHolland/Cooperative/Documents/Kengetallen%20EN.pdf>

The mechanism of choice in the DFA is *clock trade*, an open-cry descending price auction, colloquially known as a *Dutch* auction. A Dutch auction (for a single good) initiates with a high price (100 units) that progressively falls until a buyer bids by announcing that he is willing to accept the current price. If the current price is above the seller's *reserve price* – the price below which the seller is unwilling to sell – the auction then *clears*, with that buyer winning the good at the current price. The DFA are multi-unit auctions where buyers bid by pressing a button indicating the portion of the overall lot being auctioned that they would like to buy. The first buyer to bid wins and the clock is stopped. If the winning bidder does not select the entire remaining quantity, the clock restarts at a higher price as compared to the previous subplot winning price and the auction reruns. The starting point for the subplot auction is determined by adding a fixed number of units to the current price (at present auctioneers add 19 units) regardless of the price level in a given auction. This process repeats until the entire lot is sold.

Realizing the opportunities offered by dynamic pricing in maximizing revenue (Zhao & Zheng, 2000), we explore the issue of starting price setup within subauctions. In order to maximize the revenue gain, we believe that the auctioneer should move from the current practice of static starting price setup to the practice of applying dynamic starting price by the assistance of real-time support system. In response, to define the rationale of the support system, our work is focused on determining the optimal starting price for DFA sublots and relates to finding the auction ending prices in Yankee auctions by (Bapna et al. 2008) in terms of maximizing auctioneer's revenue by considering bidders' willingness to pay. The key difference is that in our case each bid results in a sale, whereas in Yankee auctions (Bapna et al. 2008) each interim bid provides an indication of final valuation for a bidder.

To operationalize the study, we first empirically show that the relationship of clock starting price and the winning bid in a previous auction is indeed an important factor in determining future prices. Then we develop an analytical model for optimizing the subplot starting point from the perspective of maximizing revenue to generate normative insights. We then use the empirical data to demonstrate how the auctioneers' choice of using a static starting point may result in loss of revenue. Our results indicate that the current static rule for determining the starting price may be adequate for auctions that generate small prices but the rule may generate too small revenue for auctions with high prices and higher variability.

## 2. Related Literature

Currently, the studies in the area of auction decision support system and intelligent agent move in a fast pace. Many of the studies are developed for a specific type of market mechanism such as, double auction (Gode & Sunder, 1993; Friedman & Rust, 1993), English auction (Anthony et. al. 2001), and Vickrey auction environment (Ockenfels & Roth, 2006). However, the study within Dutch auction mechanism has received less attention so far. Moreover, the Dutch auction design theories are not nearly as well understood as the others. Most of the research related to Dutch auctions has dealt with auctions with slow clock movement where auction may take several hours or even days (Carare & Rothkopf, 2005); whereas we look at rapid-fire Dutch auctions lasting seconds. In addition, the auctions we consider are multi-round sequential auctions for multiple units. Moreover, DFA is different from traditional sequential auctions where a defined number of units are auctioned sequentially (Bernhardt & Scoones, 1994) in pre-specified number of sequential auctions. Considering the unique properties of the DFA as multi-unit multi sequential Dutch auction, a thorough understanding of the relationships between auction design parameters and the market performances (e.g. revenue) is an important step in creating a successful expert system.

Recall that in our case the DFA auctioneers represent the growers. As such, their main objective is to realize high prices. Secondly, it is also important that they achieve quick turnaround, since flowers are perishable goods. In Dutch auctions the auctioneers are able to influence the dynamics of an auction by controlling the initial auction prices, reserve prices, minimum lot sizes, and clock speeds. Our work is focused on determining the optimal starting price for DFA sublots and relates to finding the auction

ending prices in Yankee auctions by (Bapna et al. 2008) in terms of maximizing auctioneer's revenue by considering bidders' willingness to pay. The key difference is that in our case each bid results in a sale, whereas in Yankee auctions (Bapna et al. 2008) each interim bid provides an indication of final valuation for a bidder.

### 3. Empirical Motivation

To provide a motivation for our research, we provide empirical evidence from the DFA transaction data logs over 5 working days of April 2009. For expositional clarity and to avoid a variety of different factors that influence the prices, we use data for a single flower from a single grower so that fixed effects due to flower type and growers are not a consideration. Our objective is to show that starting clock price has an effect on realized price in a round, especially as it relates to relatively different levels (high, low) of prices. We chose winning bid value ( $b_t$ ) as our dependent variable. The auctioneers use a static value of 19 units for the clock restarting value. To see the relative impact of this factor, we use the ratio of new clock start price and the winning bid in the previous round (WinningBidRatio) as our main variable of interest. Although the increment is constant, the ratio changes based on the value of winning bid in the previous auction round.

Since the prices of a flower are affected by many other factors, we use several control variables. We consider two variables related to the supply and demand dynamics (minimum purchase unit and total remaining unit); a variable that captures the effects due to auction timing (auction sequence); and two variables which indicate the flower characteristics (length and weight). The regression results are shown in Table 1. All variables are highly significant at the significance level of less than 0.01. The model provides an excellent fit with the  $R^2$  of 0.703 with an adjusted- $R^2$  of .702, indicating very little collinearity as also indicated by very low Variance Inflation Factor values (VIF). All the signs in the regression are as expected and this parsimonious model has extremely good fit with excellent diagnostic indicators.

Variable	Adjusted $R^2$	Coefficients (Standard Error)	Standardized Coefficients	VIF
Constant		55.765 (2.415)		
WinningBidRatio	.473	-17.846 (.840)	-.358	1.595
Length	.596	.665.534 (.020)	.418	1.362
Weight	.655	-1.099 (.058)	-.300	1.409
NormalizedAuctionSequenceNumber	.665	-7.108 (.948)	-.112	1.259
NormalizedRemainingUnits	.691	-7.541 (.932)	-.138	1.632
NormalizedMinPurchaseQty	.702	-74.975 (9.917)	-.138	1.869

The result in Table 1 shows that the winning bid ratio has a negative and significant effect on prices in the current round. The winning bid ratio accounts for 43.7% variance in the value of predicted bids for the current round. Besides winning bid ratio, the flower stem length (variable Length) has the largest impact and explains 15.8% variance. Overall the regression model provides excellent support for our research goal that starting price is an important variable and, since it is under the control of auctioneer, could be optimized to enhance revenues.

#### 4. Theoretical Model, Results and Discussion

Empirical analysis in the previous section indicates that the relative starting price with respect to previous price, for a given lot, has a significant impact on the realized price in the following subplot auction. Given the significant negative coefficient, one implication of the result is that a static addition of a fixed amount to the clock may be detrimental to the realized prices when the price in a previous auction is relatively small. However, given that our data only contains static addition to prior round prices to determine the new starting clock price, the coefficient on the ratio only implies that when prices in previous round are small, the current round price is going to be smaller as compared to when price in the previous round were higher. How can, then, we provide an insight into starting auction prices to an auctioneer?

To provide insights into the problem we develop an analytical model for expected revenue for the remaining lot. For expositional purposes, we assume that there are  $I$  bidders with demand that exceeds the supply  $N$ . Without loss of generality, we assume that each bidder has a demand for one unit of the flowers being sold in a lot. Let the bidders' willingness to pay follow a discrete probability density function  $f(b)$  with support  $(r, b_u)$  where  $r$  is the commonly known reserve price<sup>2</sup> and  $b_u$  is bidders' maximum willingness to pay. Given the support, the Cumulative density function  $F(b)$  is simply defined as  $\sum_{m \in b} f(m)$ . The auctioneer chooses a starting clock price  $(b^{t-1} + x)$  in a new sub-auction, where  $b^{t-1}$  is the realized winning bid in the previous round and  $x$  is the chosen increment for the new sub-auction. Note that if  $(b^{t-1} + x) > b_u$ , then  $f(b^{t-1} + x) = 0$  and if  $(b^{t-1} + x) < b_u$ , then  $f(b^{t-1} + x) = \sum_{m=(b^{t-1}+x)}^{b_u} f(m)$ . We can now define the expected price in the current round can be represented by the average bid  $E(b)$  as:

$$E(b) = \sum_{m=r}^{(b^{t-1}+x)} mf(m) \text{ if } (b^{t-1} + x) < b_u \text{ or}$$

$$E(b) = \sum_{m=r}^{b_u} mf(m) \text{ if } (b^{t-1} + x) \geq b_u \quad (1)$$

Since this is a multi unit auction, the support and probability density functions need to be updated after each round and expected bid can be generated for each round. The total expected revenue can then be generated by summing over the expected price in each round  $j$  where the support and resulting probability distribution has to be evaluated at the upper bound of support at  $(E(b)_{j-1} + x)$ . This problem can be easily solved computationally for any distribution and, in the future, we plan to create a simulation model seeded by the real data from the DFA to solve the problem endogenously. However, given the expression for expected bid  $E(b)$ , we can generate some insights into the general problem by approximating the revenue using the following expression:<sup>3</sup>

$$E(R) = N * E(b) \quad (2)$$

Let us now explore the properties of  $E(R)$  with respect to the clock starting price  $(b^{t-1} + x)$ . The following proposition summarizes the result.

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<sup>2</sup> In the DFA, the reserve price is determined once a year and is common to all auctions regardless of quality or quantity variations; these are well known by buyers and, thus, a buyer that has a valuation of less than the reserve price will not participate in the auction.

<sup>3</sup> The expression is equivalent to assuming that the clock continues to run for the bidders who have not bid until the lot is exhausted. This mechanism provides an upper bound for revenue in sequential Dutch Auctions, especially due to the observed declining prices in Dutch auctions (van den Berg, et al. 2001).

**Proposition 1:**

- i) The expected revenue will monotonically increase with the increase in  $x$  as long as  $(b^{t-1} + x) < b_u$ .
- ii) The expected revenue remains the same for any value of  $x$  when  $(b^{t-1} + x) \geq b_u$ .

**Proof:**

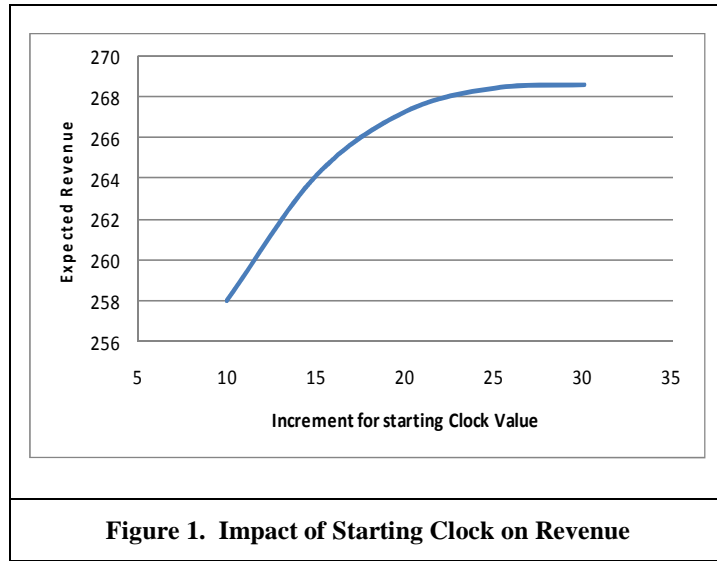
- (i) From equation 1, for any value  $x_1 < x_2 < b_u$

$$E(b_1) = \sum_{m=r}^{(b^{t-1}+x_1)-1} mf(m) + (b^{t-1} + x_1) \sum_{m=(b^{t-1}+x_1)}^{b_u} f(m) \tag{3}$$

$$E(b_2) = \sum_{m=r}^{(b^{t-1}+x_1)-1} mf(m) + (b^{t-1} + x_1) f(b^{t-1} + x_1) + (b^{t-1} + x_1 + 1) f(b^{t-1} + x_1 + 1) + \dots + (b^{t-1} + x_2) \sum_{m=(b^{t-1}+x_2)}^{b_u} f(m) \tag{4}$$

$$E(b_2) - E(b_1) = f(b^{t-1} + x_1 + 1) + 2f(b^{t-1} + x_1 + 2) + \dots + (x_2 - x_1) \sum_{m=(b^{t-1}+x_2)}^{b_u} f(m) > 0 \tag{5}$$

This implies that  $E(b_2) > E(b_1)$ . Since  $E(R) = N * E(b)$ , it follows that  $E(R(b_2)) > E(R(b_1)) \forall x_1 < x_2 < b_u$ .  
 (ii) This can be proven similarly to (i). Since there is no probability mass on getting a price higher than  $b_u$ , the expected price remains the same and hence there is no change in revenue.

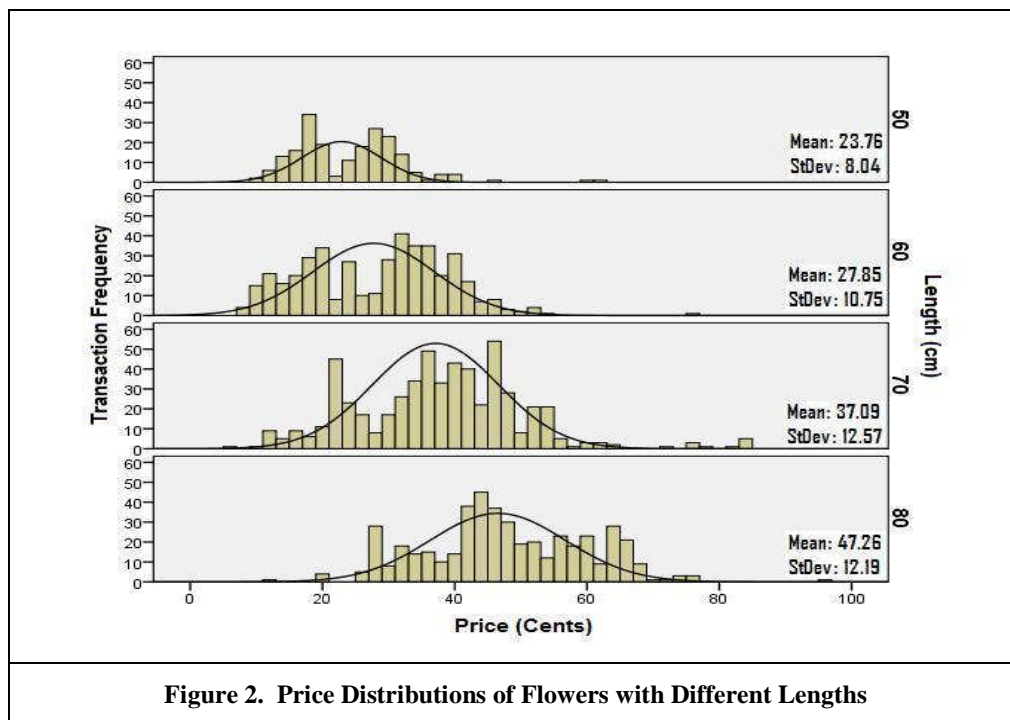


Let us clarify these results with a simple example. Suppose the  $f(b)$  follows a triangular distribution with a support of  $[10, 60]$ , the prior auction round price was 30 and the remaining lot size is 40 units of flowers. Figure 1 provides the impact of choosing different values for the starting price increment  $x=10 \dots 30$ , on the expected revenue based on Equation 2.

The implication for the auctioneer is that, from the revenue perspective, having a higher starting price may be better than a lower price. However, since the auctioneers in DFA are also concerned about the time it takes to auction a lot, it is not optimal to start all auction clocks at the maximum possible price of 100 units. To gauge the potential benefits of changing the starting clock, we further explore the price distributions by one of the most important factor that determines a flower's price – the stem length of a flower. The distributions of auction prices are shown in Figure 2 for different length of Roses. The distribution provides an important insight.

For example, the mean price of flowers with a stem length of 50 is 23.76 with a standard deviation of 8.04. Assuming the normal distribution 99% of the valuations will be within approximately  $x=19$  price units (or about a price of 42), as shown by the figure. Therefore, if an auctioneer was to use the rule of using  $x=19$ , on average that should provide optimal revenue. On the other hand, for the stem length of 80, the standard deviation is 12.19, with an  $x=19$  almost 6 percent of the bidders may have bid higher than the clock starting price on average and, hence, 19 may be too small for an increment to the previous round price resulting in a lower revenue for the auctioneer.

Understanding the relationship among the starting price increments, flower characteristics (e.g. length), and flower price, a proper decision rule could be assigned to auctioneers' real time support system. In each auction, for each flower type (considering all of the flower's characteristics e.g. length, weight, etc.), the support system will retrieve the historical transaction data and will make an inference regarding the bidders' valuation distribution. Based on the valuation inference, the optimal starting price increment value could be easily calculated by using the analytical model. However, considering that each auction operates within strictly limited time (3-5 seconds per auction), and considering that DFA auctions hundreds types of flower having unique characteristics, it is reasonable to build an automated real-time support system that can ease the auctioneers' task in determining optimal starting price.



**Figure 2. Price Distributions of Flowers with Different Lengths**

## 5. Conclusions and Future Work

In this paper, we provided motivation for studying the problem of setting the starting price in subauctions for Dutch flower auctions. Our results indicate that the current practice of using a fixed increment of 19 units to the winning bid in prior auction round may be optimal for smaller price auctions but leaves potentially significant amount of money on the table by starting the auction at a price well below the willingness to pay for some bidders. The conclusion is that for different flower types the auctioneer should adjust the starting price increment value dynamically to ensure highest revenue. Considering wide arrays of flower types and short transaction time per-auction, a decision support system that would give the auctioneer a recommendation regarding the starting price in a real-time manner would benefit the auctioneers in gaining more revenue.

In this work we developed a theoretical model that will be embedded to the support system decision rule. We have also shown that differences in the market's characteristics, in this case flower's length, could lead to different valuation distributions, and consequently different opportunities in extracting extra revenue for the auctioneers. However length is just one of many attributes that influences the revenue, a full understanding of the revenue dynamics considering all the important market factors (previous price, length, weight, and other quality indicators including growers' reputation) is required. In response, we are currently doing the fixed affect model analysis. Moreover, in the future, we will consider also the transaction time factor to the model. Determining the optimal starting clock value that will consider the tradeoff between increased time and potential revenue for these auctions is also in an important task in building a reliable dynamic support system (Ketter et. al. 2009).

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