REVERSE AUCTION BIDDING – BID ARRIVALS ANALYSIS

A Thesis

by

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ABSTRACT

Reverse Auction Bidding (RAB) is a recently developed procurement method that can be used by the construction industry. The technique is different from a traditional auction system, since RAB system uses a bidding activity method that is completed anonymously by prequalified bidders during a fixed auction time. The basic premise for the auction is that the current best auction price is available for viewing during the whole auction process by both bidders and owner. The apparent incentive is for noncompetitive bidders to lower the price. There are however controlling factor beyond the reach of owners, such as market demand, lending restrictions, stakeholder expectations and risk tolerance levels, that impact on price levels. However, owners continue to attempt to drive down prices using this technique.

A study into the mechanics of RAB was launched at Texas A&M University in 2004. This ongoing study of RAB continues to this time with eighteen case studies. This nineteenth study looks at the time series bid data from some of the prior work. Nine case studies were selected from the previous case studies. These nine studies provided untainted data with 6674 RAB bid arrivals by prior investigator actions. This study concerns the statistical process of bid arrivals with time.

The hypothesis to be tested is that the RAB bid arrivals timing can be modeled with a statistical process. The analysis reviewed the fit for several types of distribution, including Gaussian and Poissionian. The best fit was modeled by non-homogeneous Poisson process (NHPP). The first conclusion from the analysis is that RAB bid arrivals follows a Poisson process, termed non-homogeneous Poisson process (NHPP). The second conclusion is that

the controlling Poissionian process has a square root factor. The NHPP model for RAB provides a tool for future studies of RAB in real time. Future work is suggested on the inter-time periods for the bidding.

DEDICATION

In memory of my grandfather, Xilin Zhu.

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NOMENCLATURE

Definitions

Theses standard definitions come from prior case studies.

- **Reverse Auction Bidding:** "Reverse auction bidding is a type of auction in which the roles of buyers and sellers are reversed. In a regular auction (also known as a forward auction), buyers compete to obtain a good or service, and the price typically increases over time. In a reverse auction, sellers compete to obtain business and price decrease over time" (Machado, 2009).
- **Game Theory:** "A formal analysis of conflict and cooperation among intelligent and rational decision makers" (van Vleet, 2004)
- **Bidders Personality:** "The dictionary defines personality in several ways. One definition emphasizes the public, social stimulus, or behavioral characteristics of a person that are visible to other people and make an impression on them. Another definition stresses a person's private, central, inner core. Included within this private core are the motives, attitudes, interests, believes, fantasies, cognitive styles and other mental processes of an individual. Some definitions of personality emphasize its "person" quality, personal existence, or identity features. Other meanings of personality are associated with specific disciplines or professions" (Panchal, 2007).
- **Responsive Bidder:** "A bidder whose bid satisfies all the terms and conditions of bidding, delivery requirements, detailed specifications is called a responsive bidder" (Machado, 2009).

- **Aggressive Bidder:** "Aggressive bidders are the bidders who attain highest overall returns in the entire bidding process" (Chouhan, 2009).
- **Average Bidder:** "Average bidders are bidders who attain average distribution of returns in the entire bidding process" (Chouhan, 2009).
- **Poor Bidder:** "Poor bidders are bidders who attain below average distribution of returns in the entire bidding process".
- **Economically effective bidder-** "The bidder who attains highest overall returns in the form of profits from the entire bidding process" (Machado, 2009).
- **Economically ineffective bidder-** "The bidder who attains lowest overall returns in the form of profits from the entire bidding process" (Machado, 2009).
- **Economic Winner-** An individual who generated the highest average returns. Panchal (2007) coined this term to indicate a more successful player in the game. An economic winner makes no direct difference to the game for the player where the player has an objective of minimizing the average bid for the game. The player sees the average price for purchases and a distribution of prices (Guhya, 2010a).
- **Economic Loser**: An individual who generated the lowest average returns. Panchal (2007) coined this term to indicate a less successful player in the game. An economic loser makes no direct difference to the game for the player where the player has an objective of minimizing the average bid for the game (Guhya, 2010a).
- **Game:** a series of jobs for the construction of a reinforced concrete floor slab, each game lasts approximately 8 to 10 weeks in game play time, with each round of the game modelling a week and occurring in a 20 minute period, with 15 minutes of bid time and 5 minutes of build time (Guhya, 2010).

- **Traditional bidding:** In this type of auction all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is assumed to be awarded at the price submitted provided no other contracts opened on the decision process (Boser, 2000).
- **Bid arrival:** a record when bid activity occurs and creates a bid track on online bidding system. This record includes bidding information like price, bidder information, bid time, etc.,
- **A widget-** a good to be purchased by the buyer.

Game Definitions

The following list contains terms associated with the reverse auction bidding game. These terms were defined by van Vleet (2004), Chaudary (2000), Panchal (1995) and Guhya (2010).

λ player	This represents the bidder group, treated as a single entity for the purpose of game analysis.
λ_i player	The i^{th} bidder in the bidding group.
υ player	This represents the purchaser.
α game	The postulated sub-game played between bidders in seeking economic advantage over the remaining bidders. This game almost always disadvantages the υ player, but the υ player created the system and so is responsible for the υ player's economic losses as a result.
ω game	The postulated sub-game played within the Reverse Auction Bidding game between the purchaser and the

bidders. In terms of this analysis, it is deemed to effectively reduce to a two-player game, with competition implications for all players. The υ player in reality sees only the average of all won bids.

τ — Bid time allowed for each round of play in the game.

δ — Period between bid time τ that represents the work time in the game.

B_j — ith bid

B_v — Accepted bid for each job.

K — This variable is a fixed dollar sum, representing the υ player's base price, although in this game K is a vector of costs.

Γ — This variable is a fixed dollar sum, representing the υ player's maximum incremental price above K

Ξ — This variable is normally defined by the set of numbers $\{\Xi \mid 0 < \Xi \leq 1\}$, although negative values of Ξ are permitted by the Reverse Auction Bidding system. Ξ is used to normalize the profit data. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. This type of play is discouraged as the assumption in the game is steady state economic conditions in the outside economy. Future studies may look at a failing market, but that is beyond this study.

Type ξ	A stronger player
Type ζ	A weaker player
Type ϕ	Exists and who is within the middle of the profit range

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

Background

Reverse auction bidding (RAB) is an innovative procurement method. Its name indicates its distinct feature, the reversed roles of buyers and sellers. It is used in the procurement of materials and services of commercial goods as well as construction procurement. A number of private and government agencies in construction industry are utilizing RAB as their method of procurement. This study continues a long running study into the process and features of Reverse Auction Bidding at TAMU.

Prior Reverse Auction Bidding Studies and Reverse Auction Bidding

Eighteen studies have been completed at TAMU into the Reverse Auction Bidding system. These studies have firstly collected a large data source of bids on a single contract type, a reinforced concrete slab, and secondly provided an approach for research studies to look at issues of personality, bidding patterns, and bid times. A number of the studies do not fit the standard pattern as various elements of the RAB system were studied by the research group. The prior studies identified the phenomena that the rate of bidding increased through the 15-minute bid period, but none identified the process of the underlying statistics.

Nine studies have clean data were used for this study. The prior analysis and researches were discarded for this work. The analysis solely relies on a fresh analysis of the complete raw data set for nine studies.

RAB is a different bidding system from the sealed hard bid, the traditional procurement method used in construction up until the early 1990s. In the traditional sealed hard bid, the lowest price is still the major criterion for awarding bid. However, all sellers only have a single opportunity to bid the project and all bid prices are sealed in the bid package prior to the opening of the tenders. The traditional sealed bid process creates an antagonistic framework between the seller and the buyer. The antagonism stems from the sellers concentration on price. Other systems have been developed to overcome this problem for the construction industry.

Prior to a RAB round, all sellers should go through a prequalification selection stage, so that final bid selection is solely on submitted price. Only those who are prequalified can be involved in RAB. During the auction process, prequalified sellers can bid multiple times anonymously. The TAMU Web based system uses anonymous login names for each bidder to ensure a fair system.

The current lowest bid, which could be seen through an online auction system provided by the buyer or the third party, is the foundation of their future bidding. At the end of Reverse Auction Bidding, the seller who provides the lowest bid typically wins the bid or wins the chance to step into the final negotiation. Rogers (Rogers, 2010)provided an explanation of the game theory. This is two games, one termed to game between buyer (γ) and seller (λ) as to the price range and then among individual buyer (λ_i) as to returns from the total price available. The two games outlined earlier, that if considered from the perspective of a single buyer and a small seller group, clearly place the seller at a disadvantage as has been shown by Guhya (2010).

RAB was introduced in the mid-1990s as Business-to-Business (B2B) online Reverse Auction Bidding (Schoenherr & Mabert, 2007). Initially used by a Fortune 100 company and the Naval Supply Systems Command , it brought “perceived” remarkable saving for those companies, according to the published literature from the time. As a result, reverse auction then attracted attention from both academic researchers and industrial users.

In terms of the feasibility of Reverse Auction Bidding, it caused fierce debate because of the similarity of the system to bid shopping. The debates always focused on following points:

- posited savings it brought to buyers by driving down the profit margin of sellers
- what are suitable items for this type of procurement
- related legal issues of the procurement process and the awarded contract
- relationship between buyers and sellers affected by RAB

The strongest complaint of course against RAB is the emphasis on price over every other attribute. This is considered on ethical issue by some researchers and sellers. In the end, it does not engender the development of a serious partnership between the buyer and seller.

The real issue is one of widgets. The bigger and more complex the widget, the clearer the need is for simple and direct communication between the buyers and seller. The RAB process has a place for a small widget, such as pencils or telegraph poles. However, it is problematic for larger items, where price uncertainty can provide a significant advantage to the canny seller and unwary buyer.

A study of the process of Reverse Auction Bidding occurs at TAMU. This research commenced with the work of van Vleet (2004). Van Vleet developed a simple web based system to test the performance of people in a simulated Reverse Auction Bidding system. The web-based system's development, since van Vleet's development of the Microsoft Access based system (Wellington, 2006), includes migration to SQL Server and security upgrades.

In this RAB data study, 6432 bid data points from nine case studies, provides the data to complete a statistical analysis of bid arrival timing. This data is a clean data set that clearly follows the strict roles outlined by van Vleet (2004).

Objective of the Study

Eighteen case studies completed previously at TAMU and using from three to nine bidders provide a database of information on bidding patterns for Reverse Auction Bidders. Nine of these cases studies were suitable for this work; constraints on the other studies precluded their use in this work. This study used only the data and data set and did not rely on the previous analysis work. The study will review a number of statistical models to ensure that the model with best fit it selected.

The quality of data available to this study is finally reaching an acceptable statistical data set for a statistical; analysis. This process provides a model for this RAB data set.

The objectives of this study are

- to investigate alternative statistical models that may fit this data and select a model;

- to determine the parameters for the model using a suitable goodness-of-fit test.

Hypothesis

The hypothesis is that a suitable statistical process models can be found to model the arrival time data for bidding from the nine TAMU.

Significance

Amongst all characteristics of online Reverse Auction Bidding (RAB), bid arrivals is a crucial one for analyzing bidding dynamics, bidders' performance in order to reveal bidding strategies hiding behind those datasets. With the identified statistical model, some special phenomena like "early bidding" and "bid sniping" can be examined in future studies.

Limitations and Delimitation

The limitations noted in the prior case studies are:

- The experiment of this study was restricted to construction science students from the Department of Construction Management at Texas A&M University
- There was no industry professionals involved in the experiments
- The experiment process was carried out in a controlled setting
- The risk and variables was restricted compared to real life
- Some bidders, but not all bidders were selected for personality type using the Keirsey Temperament Sorter Test
- Errors and invalid data such as clerical and miscalculations occurring during the bidding game process will not be removed from final dataset

The delimitations are:

- The professional procurement is not a requirement and using professionals from the industry is beyond the scope of this research
- All individual participants were randomly selected with different educational, professional background and personal history in order to provide as equal a representation of various personality and behavior types as possible. This request limited the number of available case studies
- All participants had no reverse auction experience before each case study
- All participants were trained by researcher on RAB in prior to the experiment, which made sure that all participants were on the same level in terms of the knowledge on Reverse Auction Bidding system prior to the data collection period for each study

CHAPTER II

LITERATURE REVIEW

Introduction

This literature review presents a summary of:

- Traditional Types of Auctions
- English Auctions
- Dutch Auctions
- Sealed First Price Auctions
- Vickrey Auction
- Other Types of Auctions
- Reverse Auction Bidding
- Posited Savings for RAB
- Procured Items
- Legal Issues
- Buyer to Seller Relationship
- Personality Testing
- Personality Types and the Importance in Reverse Auction Bidding
- A brief summary of the RAB System used for the study work
- Poisson Process
- Poisson Process for Online Auction Bidding
- Bid Arrivals

- Summary

Traditional Types of Auctions

An auction is one method to procure goods and services using a simple bidding mechanism. Traditional auctions are based on long-standing theoretical foundations and tested empirical work (Parente, 2008) . There are different kinds of traditional auctions and Klemperer (1999) classified four main types of auctions. These four auctions are English auctions, Dutch auctions, sealed first price auctions and the Vickrey auctions. There are also other types of auctions, including the Japanese auctions, the Take-it-or-leave-it auctions, and the Candle auctions, to list some of the variants. An auction is perceived as providing an economically transparent method to procure goods and services.

English Auctions

English auction, also known as forward auctions or ascending auction is the most commonly used form of auction. It is suitable for limited supplied goods or unique sold items (Wamuziri, 2009). In English auctions, the bidding process starts with the lowest acceptable price for seller, usually but not always the reserve price. Each bid after must exceed this price. As a result, seller could keep the item from selling for less than this reserves price, by setting it at the beginning of the auction. Bidders then begin bidding for the items against each other by placing higher price than the last bid. The auction terminates when no more bidders are willing to announce a higher price. Usually the auctioneer counts three to sign a clear end, again economically transparent. Moreover, the item sells at the highest bid. Seller will hold the items, if the final bid price does not exceed the reverse price. The notable characteristic of English auction is that each bidder knows the level of the current best bid during the whole auction process (McAfee & McMillan, 1987). This type of auction is used to sell antiques, artworks, and houses. It is fair and clear provided that collusion, usually illegal, does not occur.

Dutch Auctions

Dutch auction, also called multiple items auctions or open descending price auction (Krishna, 2009), is named for the Dutch tulip auctions. It is a converse type of auction when compared to the English auction. The seller initially calls a very high price. Seller will constantly lower the price through each round of bid until a bidder is finally willing to accept this price. The Dutch auction relates the price paid to the time of the auction. Namely, the longer the auction goes on, the lower the price.

In a Dutch auction, as for all sales, rational bidders always have their own clearly acceptable valuation of the item for sale. The auction begins with a price, which is inevitably over this valuation, while the bidder keeps waiting. Once the successively lowered sale price comes down and reaches this amount, a buyer may accept this offer but obtain a zero profit. Waiting longer to bid a lower price will increase the bidder's profit. However, this behavior comes with the economic risk that the bidder may end up losing the item to another bidder (Wamuziri, 2009). The entire process balances risk and return.

So Dutch auctions force bidders to think about their own valuation of the item before the auction and act decisively while bidding. This type of auctions is often used for perishable items (McAfee & McMillan, 1987) like flowers in the Netherland, fish in Israel, tobacco in Canada, and used furniture.

Sealed First Price Auctions

Sealed first price auction is different from English auction, all bidders most simultaneously submit only one bid (Krishna, 2009). Like the English auction, the item goes to the highest bidder. Sometimes, a seller will choose the winner randomly from those who name the same highest bid, if there is a tie. The fundamental rule of sealed first price auction is that all bidders could not know the bids information of other competitors before the end of the auction and also couldn't adjust their own bids according to other's bids (McAfee & McMillan, 1987).

In sealed first price auction, the bidder gets three options. They are

- to bid their full valuation
- to bid a shaded value of the full valuation
- to bid considerably under the valuation (Wamuziri, 2009).

The third option may lead the bidder to losing the bid to their competitors, while the first option could gain the bidder no profit if their bid was successful. As a result, rational bidding strategy for sealed first price auction should be bidding with a shaded value of the full valuation. With this approach, the bidder could make a profit and win the bid at the same time. The bidder gains more profit with a higher shaded value. Nevertheless, as noted, too higher shaded value may increase the risk of losing the bid. So, this kind of auction forces bidders to guess the valuation of others' and bid a little more than this amount (Wamuziri & Abu-Shaaban, 2005). Some UK construction procurement uses this type of auctions.

Vickrey Auction

Sealed second price auction is similar to sealed first price auction, where all bid will be sealed and revealed at the same time. What makes them different is that the winner of this kind of auction only needs to pay the second highest price bid other than the highest one. It is also called Vickrey auction to commemorate the economist who first put forward that this type of action as it pushes each bidders to bid their true valuations (Wamuziri, 2009). Overall, the best strategy of sealed second price auction is to bid the true value, which is identical to English auction. However, they have different information transparency (Wamuziri, 2009), since sealed second price auction needs information transparency. In addition, each bidder is in a passive condition. As a result, sealed second price auction is seldom used in practice. A sealed second price auction is a very good tool to model bidder‘s behavior, since bidder needs to bid their true value.

Vijay (Krishna, 2009) pointed out that sealed second price auction is in some ways similar to proxy bidding system, which is used by Internet auction site like eBay. In eBay, a bidder who bids the highest is awarded the bid by actually paying the current highest bid plus the current bidding increment (Krishna, 2009).

Other Types of Auctions

Besides those four types of auction mentioned above, there are still some other types, like Japanese auction, Take-it-or-leave-it auction and Candle auction. In a Japanese auction, the price rises up through each round of bid. Each bidder shows if they are willing to stay at the current price level for each round. Once a bidder quits, the bidder will not reenter the auction. In Take-it-or-leave-it auction, the seller announces the price of each project, and bidder can choose accept (“take”), which leads the end of auction, or reject (“leave”) the bid, after which seller goes to the next item. The clear advantage of this type of auction is that protect the private valuation information (Wamuziri, 2009). In Candle auction, the bid is awarded to the last bid price before a candle burns out (Wamuziri & Abu-Shaaban, 2005). This is similar to the RAB where a timer runs out.

Reverse Auction Bidding

Reverse Auction Bidding is a relatively new type of procurement method, which has its bidder and seller reversed. It is an innovative type of auction that was introduced in the mid-1990s as Business-to-Business (B2B) online Reverse Auction (Schoenherr & Mabert, 2007). Its name comes from one of its remarkable characteristics, which are the reversed roles between bidder and seller. In addition, unlike the traditional auctions with paper-based submission, the auction process is usually via a web-based system.

Reverse Auction Bidding starts with a company sending out a request for quotation (RFQ) with clear definition of the bid goods/services. All bidders log into the online system at the same time without knowing whom they are competing against, although an economically intelligent bidder will be aware of the main competition. They can adjust their bid strategy on their next bid by analyzing the relationship between the current best quote and their own bid. Each bidder is able to submit bid multiple times until the end of auction. The competition during this dynamic process is very dyadic since bidders need to offer their own bid as low as possible while making sure that they still have some profit margin. However, this type of auction helps buyer discover the true market price of the goods/service and benefits buyer with the lowest price, although recent work suggests this is not necessarily the case (Gupta, 2010)

Among the available published articles, articles studying RAB dynamics and corresponding bidders' performance are rare, however research pertaining to eBay online auction shows that the non-homogeneous Poisson process (NHPP) model fits the bid arrival time data for the eBay auctions (Shmueli, Russo, & Jank, 2004).

Reverse Auction Bidding, first used in 1997 by a Fortune 100 company "Global Co," for procurement with the stated goals of reducing costs, saving processing time and paper (Mabert & Skeels, 2002). This practice was continuously used throughout 2001.

A few years later, in May 2000, Navy Activity, a part of the Naval Supply Systems Command, tried its first Reverse Auction Bidding (Mabert & Skeels, 2002). During almost the same time period, a number of large companies listed in Fortune 1000 began to test this new method of procurement (Emiliani & Stec, 2001). Because of its perceived considerable cost and time saving, the popularity of Reverse Auction Bidding rose among corporations, governments and other organizations. And accordingly, some online systems, like FreeMarkets, eBreviate and Procuri (Mabert & Skeels, 2002), were established to offer Reverse Auction Bidding services as third parties. These companies conducted millions of auctions.

The current debate on Reverse Auction Bidding focuses on savings, procured items, legal issue, and buyer-seller relationship. There are no clear answers now.

Posited Savings for RAB

Proponents of RAB offer the followings comments in support of the system. RAB leads to some direct benefits especially in cost and time saving. The saved cost comes not only from the measurable direct cost saving of paper, transportation, ordering and other purchasing cost by using online auction system, but also from the reduced price offered by the bidder because of competitive auction. For example, through thirty Reverse Auctions, Global Co, reported over $20 million saving (near 11% in average) out of $207 million contracts (Mabert & Skeels, 2002). Those contracts covered different areas, such as transportation, steel, loose fill and bulk bags, construction materials and services, and control panels etc.

Navy Activity saved 17% out of $119 million with twenty four Reverse Auctions (Mabert & Skeels, 2002). These two cases were not exclusive ones. With 10 to 20 percent below historical prices, the reported saving seemed to be quite significant (Beall, 2003). This however is a far from proven point. As Nichols (2009) observed, there is very limited published data on these types of auction systems. The old adage "it is to good to be ture" appears to be protectant relevant to this type of hyped system. Clearly, it is a good system for small goods with a limited price range, preference of Gaussian distribution at where the buyer and seller relationship is non-existent beyond a standard warranty. As Guhya (2010) and others show with the TAMU RAB studies, a good set of bidders will establish a non-Gaussian distribution and the best players, termed Type ξ, will obtain excellent returns. The basic game is flawed for uncertain pricing (Nichols, 2009).

However, this major benefit raised negative comment for Reverse Auction Bidding. Reverse auction was blamed as “price only auction” (Schoenherr & Mabert, 2007), because the low bid won and value added by non-price element, such as quality, reputation etc. seemed to be ignored. Some researchers pointed that the saving cost brought by Reverse Auction Bidding came from lowering the margin of seller, (Hartley, Lane, & Yunsook, 2004), which actually impaired sellers’ profit. And some studies showed that sellers always participated in Reverse Auction Bidding due to the coercion from buyer (Engel & Emiliani, 2007). It also indicated that rising stock prices led by saving of buyers’ company was actually not as promising as it seemed to be, as for internal controls and the accuracy of financial reporting. Also, the length of time period for the savings from procurement was also questioned (Wamuziri, 2009). Researchers pointed out that the saving would not be conspicuous once the “real market price” was discovered (Mabert & Skeels, 2002).

As a method for establishing market prices for goods, the RAB system is not that good, due to inherent flaws in the system’s design and in human behavior in bidding (Gupta, 2010; Nichols, 2009).

Procured Items

The discussion, which questioned the feasibility of Reverse Auction Bidding of all kinds of products, has never stopped. Some researchers (Mabert & Skeels, 2002) studied some cases and concluded that Reverse Auction Bidding could not be suitable for every purchasing contract. Products, like strategic items and direct inputs, are not that accessible to Reverse Auction Bidding due to their long-term contract requirement or oligopoly among sellers, (Schoenherr & Mabert, 2007). The suitable ones included complex and highly-engineered items (Wagner & Schwab, 2004) or standard projects. Jap (2002) put forward that the only suitable products should be commoditized products.

Schoenherr & Mabert (2007) explore this myths that Reverse Auction Bidding is commodities-products-only auction. They suggested having Reverse Auction Bidding for non-commodities products by refining the RFQ order, conducting market research and analysis, defining detailed and specific attributes of projects, and using specialized third-party consultant.

In the end, the objective of the negotiation period is to determine a fair quantum for the cost and the capability of the bidder to complete the scope of work. Major buyers place significant emphasis on reviewing the ability of the bidder after bids are submitted. This offer takes the form of a graduated scale over several items. However, the task is simple as a question:

- Can they do the work?
    - If yes, allow to bid.
    - If no, decline to bid.

However, in a restricted market, the buyer wants to keep down prices and procure on market rates. So allowing marginal bidders into the process, who will never win under the "review system," is not seen as a direct cost to the buyer.

Of course, this is not true. A typical engineering firm can spend up to eight percent of costs on bid preparation.

Legal Issues

As a new modern method of procurement, Reverse Auction Bidding attracts more and more attention from manufacturing and service sector business and government agencies. Its popularity also raised the concern of its legal and contractual issues. Research dealing with legal issue indicated that there was some unfair trade practice (Engel & Emiliani, 2007) during Reverse Auction Bidding. The unfairness came from the unequal positions of buyer and sellers. Sellers may be facing a form pf coercion in Reverse Auction Bidding. Horlen, Eldin, & Ajinkya (2005) analyzed the future legal challenges of Reverse Auction Bidding in terms of some legal grounds, like Federal Trade Commission, Anti-Dumping Act of 1916, Robinson-Patman Act, Clayton Antitrust Act and Business Method Patents.

Reverse auction was banned by the Federal Acquisition Regulation (48 CFR 245.610 and 48 CFR 15.610), because of some flaws in legal performance (Merson, 2000), however, the prohibition was later removed. Though legal challenges existed in Reverse Auction Bidding awarded contract, Reverse Auction Bidding is still appealing to public buyer, like large international companies and government. The state of Texas, Pennsylvania, Kansas, New York State, Missouri, Minnesota, and Wisconsin (Horlen et al., 2005) had approved the legislation to allow Reverse Auction Bidding.

There are no real legal or economic implement to a successful RAB, except that the basic game is flawed, that the flaw is against the buyer is interesting but as it is self-inflicted the sellers cannot be blamed legally or economically. Buyers will continue to believe they got a good deal.

Buyer to Seller Relationship

Since price is the decisive element in Reverse Auction Bidding process, the expected side effect is the negative impact Reverse Auction Bidding might bring to the buyer-supplier relationship. It is possible that buyer will not care about the non-price elements like reputation, quality and previous partnerships. This may result in deterioration of previous seller-buyer partnership. People question whether Reverse Auction Bidding can be used in procurement, which requires long-term seller-buyer relationship. Reversed auction was recognized to bring new business to new sellers who could offer lower price, while making current seller annoyed at losing the hard-won long-term business (Emiliani & Stec, 2005). Due to its price oriented characteristic, Reverse Auction Bidding could lead to profit margin erosion (Emiliani & Stec, 2004) and coercion to sellers (Engel & Emiliani, 2007). In construction industry, seller-buyer partnership could be impaired when contractors, who won the contract with lowest price in Reverse Auction Bidding, would charge higher prices for change orders and extra work if client ordered, in order to keep their profit margin (Wamuziri, 2009).

While some researchers tried to refute by putting forward the idea that Reverse Auction Bidding could potentially benefit both sellers and buyers at the same time. Some researchers suggested that buyers, who need collaborative and long-term relationship sellers, can use Reverse Auction Bidding as a process improvement tools to check market price instead using it as a price weapon (Smart & Harrison, 2003). Also, the buyer-seller relationship can be kept fair to all by prequalifying bidders with non-price elements, detailing RFQ, providing education, training and assistance to bidders during Reverse Auction Bidding process (Schoenherr & Mabert, 2007).

An important economic observation is when all things are equal the prices should be the determining factor (Hartford, 2005) for projects funded by shared equity. In the end, the game has major flaws. The flaws will always benefit the λ player at the expense of the ω player, as the γ player starts the game. This is a self-inflicted problem. The insensitive observation is that this is not generally visible to the ω player, but is clearly visible to the λ player.

Personality Test

An important observation in the TAMU case studies is the impact of personality on the returns to the bidders or the λ_i player. Rogers (2010) originally suggested the use of the Keirsey Temperament Sorter Test to look at the difference in personality between a *Type* ξ and *Type* ζ types. The temperament sorter test has 71 questions, although issues exist with scoring methods being less than transparent in the case of ties.

Chouhan (2009) used the Keirsey Temperament Sorter test to review personality types and compare performances. The Keirsey Temperament Sorter identifies 16 types of personalities that fit into four groups

- SJ - The Guardians,
- SP -The Artisans,
- NT –The Rationals
- NF-The Idealists.

Different Personality Types

Table 1 shows the Keirsey Temperament Sorter Test Summary.

Table 1

Keirsey Temperaments

	Temperament	Role	Role Variant
Introspective (N)	Idealist (NF) *Diplomatic*	Mentor (NFJ) *Developing*	Teacher (ENFJ): *Educating*
			Counselor (INFJ): *Guiding*
		Advocate (NFP) *Mediating*	Champion (ENFP): *Motivating*
			Healer (INFP): *Conciliating*
	Rational (NT) *Strategic*	Coordinator (NTJ) *Arranging*	Field marshal (ENTJ): *Mobilizing*
			Mastermind (INTJ): *Entailing*
		Engineer (NTP) *Constructing*	Inventor (ENTP): *Devising*
			Architect (INTP): *Designing*
Observant (S)	Guardian (SJ) *Logistical*	Administrator (STJ) *Regulating*	Supervisor (ESTJ): *Enforcing*
			Inspector (ISTJ): *Certifying*
		Conservator (SFJ) *Supporting*	Provider (ESFJ): *Supplying*
			Protector (ISFJ): *Securing*
	Artisan (SP) *Tactical*	Operator (STP) *Expediting*	Promoter (ESTP): *Persuading*
			Crafter (ISTP): *Instrumenting*
		Entertainer (SFP) *Improvising*	Performer (ESFP): *Demonstrating*
			Composer (ISFP): *Synthesizing*

Table 2 shows the individual components in the temperament scale. The issue is of course the equal scores between groups, which are assigned to one arbitrary category.

Table 2

Summary of the Individual Components of the Different Personality Types

#	Name	Meaning
E	Extraversion	Feel motivated by interaction with people. Tend to enjoy a wide circle of acquaintances, and *gain* energy in social situations
N	Intuition	More abstract than concrete. Focus attention on the big picture rather than the details, and on future possibilities rather than immediate realities
F	Feeling	Value personal considerations above objective criteria. In making decisions, often give more weight to social implications than to logic
J	Judgment	Plan activities and make decisions early. Derive a sense of control through predictability
I	Introversion	Quiet and reserved. Generally prefer interacting with a few close friends rather than a wide circle of acquaintances, and *expend* energy in social situations
P	Perception	Withhold judgment and delay important decisions, preferring to "keep their options open" should circumstances change
T	Thinking	Value objective criteria above personal preference. When making decisions, generally give more weight to logic than to social considerations
S	Sensing	More concrete than abstract. Focus attention on the details rather than the big picture, and on immediate realities rather than future

Personality Types and the Importance in Reverse Auction Bidding

Personality does not form part of this study. A future study is recommended for this issue. However, the impact of personality in returns in the game study is clear (Gupta, 2010).

A Brief Summary of the RAB System Used for the Case Study Work

van Vleet Study

A website using ASP programming was developed by van Vleet (2004) to simulate the online RAB game and run the bidding game process. This website now uses a Microsoft SQL Server and data set to collect the bid and time data. This web-based system allows the bidders to input their bid information, which is simultaneously stored in the database.

The bidding process basis is several 15-minute bidding section, each followed by a five-minute break. Independent variables like rain delay, travel and delivery charges, and delays due to distant projects are in the study to provide a rational and realistic game environment. Each bidder is in the game is to generate maximum profit level.

Specifics

The specific features of the games are:

- The total duration of the game will be a maximum of nine consecutive weeks.

- All bidders initially have an equal dollar amount of $40,000 available in their bank accounts.
- The original cost for every job is estimated to be $10,000 excluding the travel costs and the delivery costs. The values of these costs are posted along the job site address.
- The duration for completing each job is assumed to be five days, excluding the rain delay. The work week is assumed to be five days long i.e. from Monday to Friday.
- Initially, every bidder will only be allowed to work on three jobs in a week. If a bidder decides to undertake more than three jobs in a week, then the bidder will have to take a loan from the bank. The additional charge for each loan is $500 and this will be automatically charged irrespective of a win or less in the bid.
- Since the base cost for all jobs is $10,000, and the default duration is five days, the cost accumulated is $2000 per day for all jobs. The travel expenses and the delivery charges would also be summed up on a daily basis accordingly depending upon the location. In the game, this provides a check on a player being bankrupt. Only one player is the last decade was declared bankrupt in one game and removed.
- The location of the owner is assumed to be located in Sugar Land, Texas and thus the additional expenses for travel and delivery are assumed on

the basis of the proximity of the job site from this place. The offices of the subcontractors are also assumed to be in Sugar Land, Texas.

- The minimum acceptable return on investment derived from long term construction industry standards is 10%. However, this would not be tested during the game and the players would be cautioned of this condition.
- Payment for work is scheduled to be delivered at the completion of 5th construction day.
- The primary objective of all the bidders is to maximize their profits while maintaining bank assurance and satisfactory liquidity.

Rain Delay

Houston has relatively high rainfall from May to July every year. The game was assumed to be played during this period. Delay caused by rainfall was taken into accounted in this game. National Oceanic and Atmospheric Administration (NOAA, 2010) provides the data on the statistical information for the probability of rain in Houston for the months of May, June and July. Figure 1 depicts the rain distribution for this area.

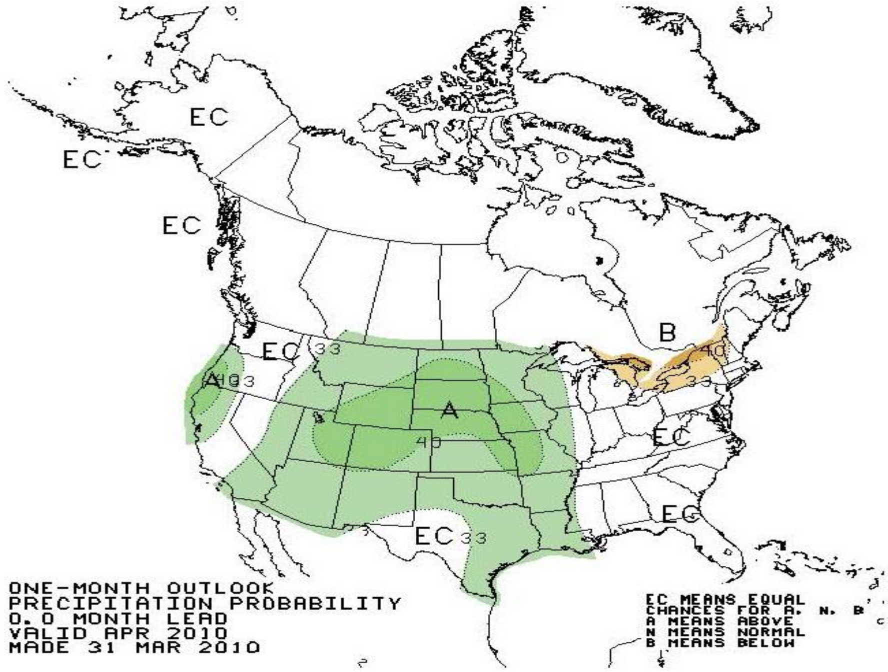


Figure 1 Rain Probability in USA (after NOAA, 2010)

The aspect of rain delay would affect the bidding process, escalating the costs due to travel and delivery charges and the overall cost of construction. Since all the jobs are expected to finish in five days, any job experiencing a rain delay is termed as an incomplete job.

Table 3 represents the form of the rain delay matrix on each of the site location used in the case studies. "1" denotes enough rainfall to cause a delay in construction, whereas "0" denotes no rainfall. Currently there is no correlation between the site locations and the amount of rainfall in that vicinity.

Table 3

Rain Delays for Week One

Day	Site					
	One	Two	Three	Four	Five	Six
Monday	1	0	0	0	1	0
Tuesday	0	1	1	0	0	0
Wednesday	0	0	0	0	0	0
Thursday	0	0	1	0	0	1
Friday	1	0	0	0	1	1
Saturday	0	0	0	0	0	0

Site Locations

All the locations in the RAB are located around Sugarland, Texas as intended by the developer of the RAB game, van Vleet (2004). The locations can be seen on the map in Figure 2.

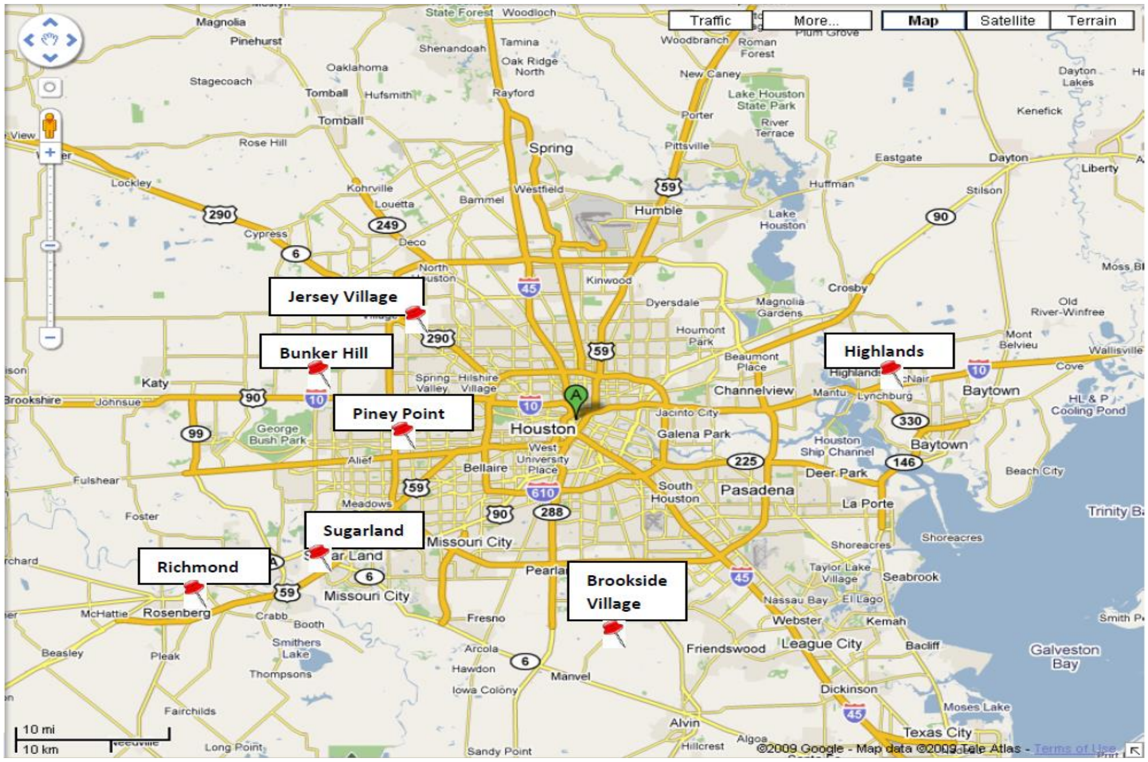


Figure 2 Construction Site Locations in Houston (Google Maps, 2010)

Brookside Village, Piney Point Village, Highlands, Jersey Village, Bunker Hill Village and Richmond were the six construction sites selected by van Vleet (2004). The overhead expenses of travel and delivery to these sites are directly proportional to the distance of these site locations from Sugar Land, Texas where the owner's office is situated. The intent is to introduce variable costs into the game to provide realism.

Table 4 indicated the locations of the sites, their distance from the owner's office in Sugar Land, Texas and the travel and delivery costs associated with each location.

Table 4

Location of the Construction Sites in Houston

Site #	Location of Development	Distance from Sugarland (Km)	Travel Cost ($)	Delivery Cost ($)	Total Cost ($)
Site 1	Brookside Village	67.6	858	624	1482
Site 2	Piney Point Village	38.6	495	360	855
Site 3	Highlands	112.6	1452	1056	2508
Site 4	Jersey Village	64.37	825	600	1425
Site 5	Bunker Hill Village	43.45	561	408	969
Site 6	Richmond	22.53	297	216	513

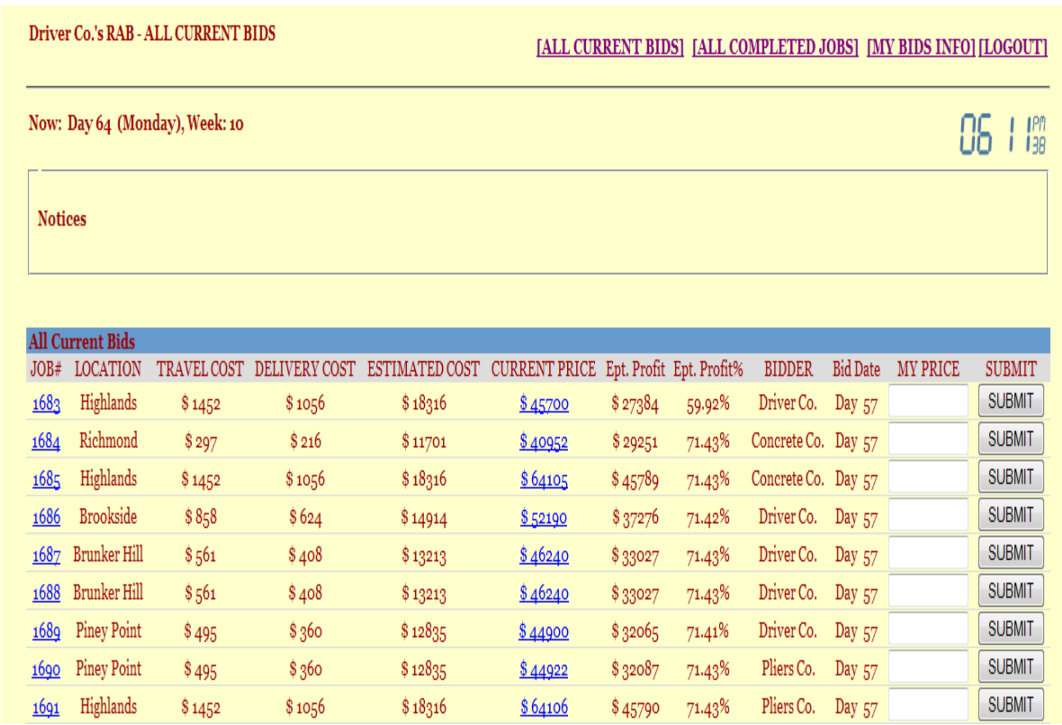
The number of jobs offered each week is decided by a probability of two dice rolls.

Data Collection

The website used for the RAB game to run simulations was developed by van Vleet (2004) using Microsoft Access and ASP programming (Kim, 2004; Kingsley-Hughes, Kingsley-Hughes, & Read, 2004). Data gathered during the game is originally collected in a Microsoft Access database and is later used to analyze the bidding process. To solve the problem of multiple bidding and Access constraints on limited open list, Wellington (2006) changed the game to use Sequential Query Language (SQL) and a SQL Server database. Every participant of the RAB game was assigned a unique username and password to access the site. The usernames typically assume random company names, such as :

- Driver Co.
- Pliers Co.

All the information related to bid process such as the cost of the job, all current bids, and the bidder's company name were made available to the bidders once they logged into the website using their unique usernames. The level of transparent information is high. Upon logging on to the server, the participants were directed to the All Current Bids screen as shown in Figure 3.



Driver Co.'s RAB - ALL CURRENT BIDS

[ALL CURRENT BIDS] [ALL COMPLETED JOBS] [MY BIDS INFO] [LOGOUT]

Now: Day 64 (Monday), Week: 10

06 : 11 PM 38

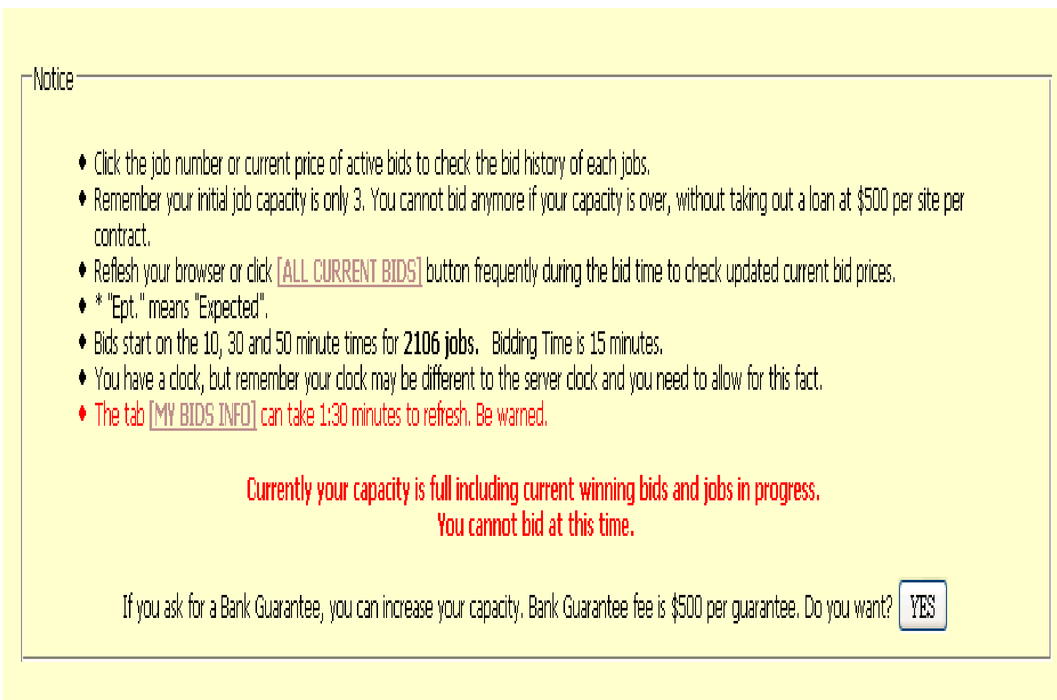
Notices

All Current Bids

JOB#	LOCATION	TRAVEL COST	DELIVERY COST	ESTIMATED COST	CURRENT PRICE	Ept. Profit	Ept. Profit%	BIDDER	Bid Date	MY PRICE	SUBMIT
1683	Highlands	$ 1452	$ 1056	$ 18316	$ 45700	$ 27384	59.92%	Driver Co.	Day 57		SUBMIT
1684	Richmond	$ 297	$ 216	$ 11701	$ 40952	$ 29251	71.43%	Concrete Co.	Day 57		SUBMIT
1685	Highlands	$ 1452	$ 1056	$ 18316	$ 64105	$ 45789	71.43%	Concrete Co.	Day 57		SUBMIT
1686	Brookside	$ 858	$ 624	$ 14914	$ 52190	$ 37276	71.42%	Driver Co.	Day 57		SUBMIT
1687	Brunker Hill	$ 561	$ 408	$ 13213	$ 46240	$ 33027	71.43%	Driver Co.	Day 57		SUBMIT
1688	Brunker Hill	$ 561	$ 408	$ 13213	$ 46240	$ 33027	71.43%	Driver Co.	Day 57		SUBMIT
1689	Piney Point	$ 495	$ 360	$ 12835	$ 44900	$ 32065	71.41%	Driver Co.	Day 57		SUBMIT
1690	Piney Point	$ 495	$ 360	$ 12835	$ 44922	$ 32087	71.43%	Pliers Co.	Day 57		SUBMIT
1691	Highlands	$ 1452	$ 1056	$ 18316	$ 64106	$ 45790	71.43%	Pliers Co.	Day 57		SUBMIT

Figure 3 All Current Bids Screen from RAB Web Site

The All Current Bids screen all the information about the jobs such as the estimated cost, travel cost, delivery cost, approximate profit and profit percentage. It also contained the “My Bids” column, within this column the bidder would insert his bid amount and click on submit to place that bid. This information was available to all the bidders. Each bidding session went on for 15 minutes and nine such bidding sessions took place with a five-minute break between each session. Bidders were unable to place bids before the commencement of the bidding and after the end of the sessions. As mentioned earlier, each bidder was constrained to bid on only three jobs within a given week. To bid on more than three jobs each participant had the option of taking a loan from the bank, for which a fee of $500 was deducted from the bidder’s available balance. Figure 4 provides the bidder the option of accepting a bank loan.



Notice

- Click the job number or current price of active bids to check the bid history of each jobs.
- Remember your initial job capacity is only 3. You cannot bid anymore if your capacity is over, without taking out a loan at $500 per site per contract.
- Reflesh your browser or click [ALL CURRENT BIDS] button frequently during the bid time to check updated current bid prices.
- * "Ept." means "Expected".
- Bids start on the 10, 30 and 50 minute times for **2106 jobs.** Bidding Time is 15 minutes.
- You have a clock, but remember your clock may be different to the server clock and you need to allow for this fact.
- The tab [MY BIDS INFO] can take 1:30 minutes to refresh. Be warned.

Currently your capacity is full including current winning bids and jobs in progress.
You cannot bid at this time.

If you ask for a Bank Guarantee, you can increase your capacity. Bank Guarantee fee is $500 per guarantee. Do you want? YES

Figure 4 Bank Guarantee Web Form

Figure 5 demonstrations the upper limit rules of the reverse auction process. In the RAB game, the bidder is only allowed to bid lower than an already placed bid, as it is a reverse auction. If the bidder places a bid that is an amount higher than the current bid, the following notification appears on their screen.

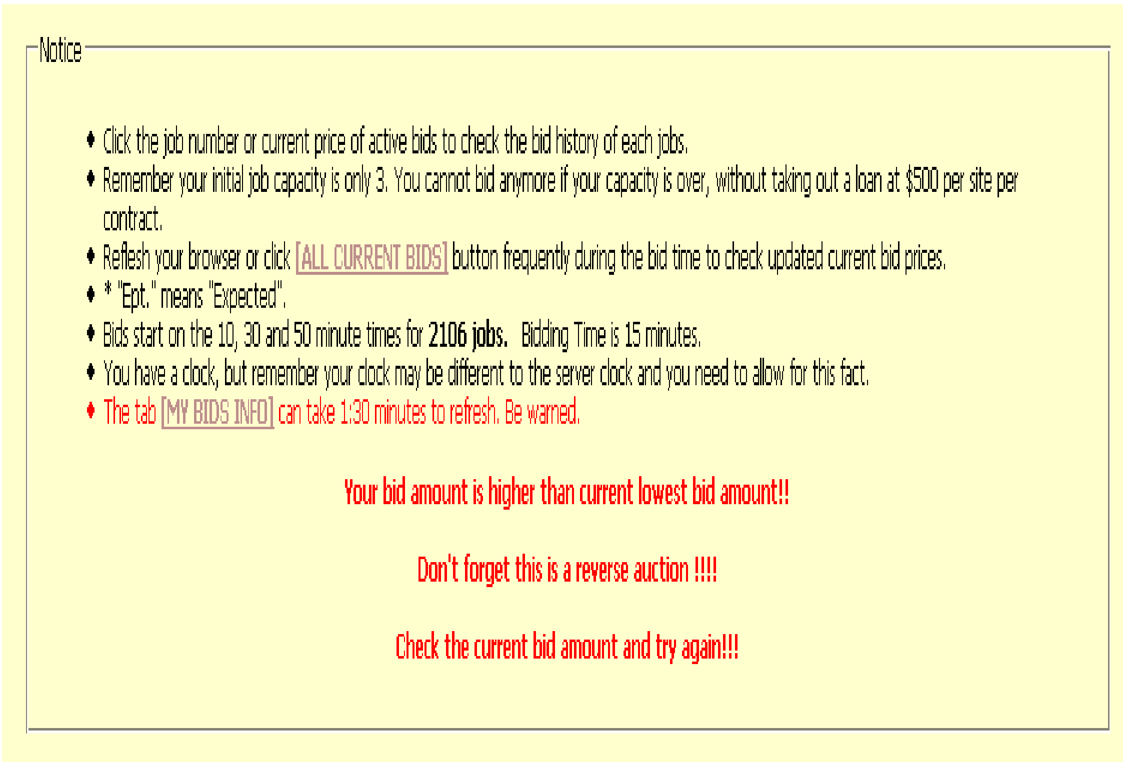
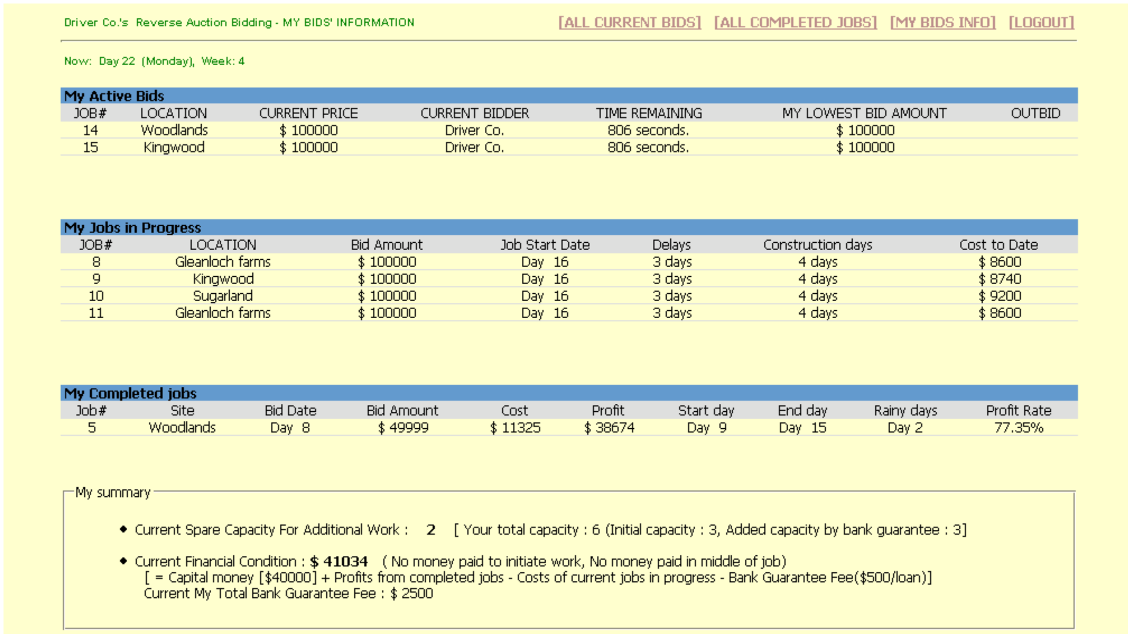


Figure 5 Higher Than Acceptable Bid Web Statement

After the end of each 15 minute, bidding session the jobs award to the lowest bidder for each job. To see information regarding, what jobs have been won by a bidder, the bidder can go to the “my bid info” page which provides the relevant information about the jobs won as seen shown in Figure **6**.



Driver Co.'s Reverse Auction Bidding - MY BIDS' INFORMATION [ALL CURRENT BIDS] [ALL COMPLETED JOBS] [MY BIDS INFO] [LOGOUT]

Now: Day 22 (Monday), Week: 4

My Active Bids

JOB#	LOCATION	CURRENT PRICE	CURRENT BIDDER	TIME REMAINING	MY LOWEST BID AMOUNT	OUTBID
14	Woodlands	$ 100000	Driver Co.	806 seconds.	$ 100000	
15	Kingwood	$ 100000	Driver Co.	806 seconds.	$ 100000	

My Jobs in Progress

JOB#	LOCATION	Bid Amount	Job Start Date	Delays	Construction days	Cost to Date
8	Gleanloch farms	$ 100000	Day 16	3 days	4 days	$ 8600
9	Kingwood	$ 100000	Day 16	3 days	4 days	$ 8740
10	Sugarland	$ 100000	Day 16	3 days	4 days	$ 9200
11	Gleanloch farms	$ 100000	Day 16	3 days	4 days	$ 8600

My Completed jobs

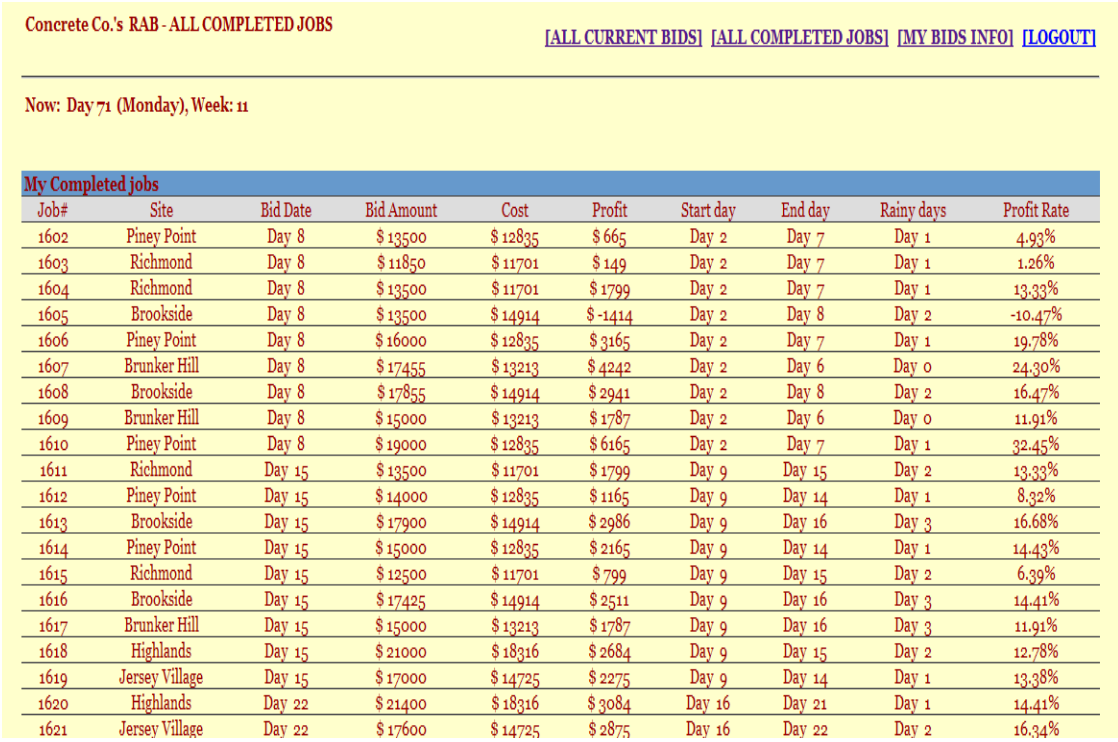
Job#	Site	Bid Date	Bid Amount	Cost	Profit	Start day	End day	Rainy days	Profit Rate
5	Woodlands	Day 8	$ 49999	$ 11325	$ 38674	Day 9	Day 15	Day 2	77.35%

My summary

- Current Spare Capacity For Additional Work : **2** [Your total capacity : 6 (Initial capacity : 3, Added capacity by bank guarantee : 3]
- Current Financial Condition : **$ 41034** (No money paid to initiate work, No money paid in middle of job)
  [= Capital money [$40000] + Profits from completed jobs - Costs of current jobs in progress - Bank Guarantee Fee($500/loan)]
  Current My Total Bank Guarantee Fee : $ 2500

Figure 6 My Bid Info Web Page

The "all completed jobs" tab as shown in Figure 7 displays information regarding the completed jobs. The bidder can view the status of the jobs they have won, whether the jobs are completed or are still running due to rain delays from this page.



Concrete Co.'s RAB - ALL COMPLETED JOBS

[ALL CURRENT BIDS] [ALL COMPLETED JOBS] [MY BIDS INFO] [LOGOUT]

Now: Day 71 (Monday), Week: 11

My Completed jobs

Job#	Site	Bid Date	Bid Amount	Cost	Profit	Start day	End day	Rainy days	Profit Rate
1602	Piney Point	Day 8	$ 13500	$ 12835	$ 665	Day 2	Day 7	Day 1	4.93%
1603	Richmond	Day 8	$ 11850	$ 11701	$ 149	Day 2	Day 7	Day 1	1.26%
1604	Richmond	Day 8	$ 13500	$ 11701	$ 1799	Day 2	Day 7	Day 1	13.33%
1605	Brookside	Day 8	$ 13500	$ 14914	$ -1414	Day 2	Day 8	Day 2	-10.47%
1606	Piney Point	Day 8	$ 16000	$ 12835	$ 3165	Day 2	Day 7	Day 1	19.78%
1607	Brunker Hill	Day 8	$ 17455	$ 13213	$ 4242	Day 2	Day 6	Day 0	24.30%
1608	Brookside	Day 8	$ 17855	$ 14914	$ 2941	Day 2	Day 8	Day 2	16.47%
1609	Brunker Hill	Day 8	$ 15000	$ 13213	$ 1787	Day 2	Day 6	Day 0	11.91%
1610	Piney Point	Day 8	$ 19000	$ 12835	$ 6165	Day 2	Day 7	Day 1	32.45%
1611	Richmond	Day 15	$ 13500	$ 11701	$ 1799	Day 9	Day 15	Day 2	13.33%
1612	Piney Point	Day 15	$ 14000	$ 12835	$ 1165	Day 9	Day 14	Day 1	8.32%
1613	Brookside	Day 15	$ 17900	$ 14914	$ 2986	Day 9	Day 16	Day 3	16.68%
1614	Piney Point	Day 15	$ 15000	$ 12835	$ 2165	Day 9	Day 14	Day 1	14.43%
1615	Richmond	Day 15	$ 12500	$ 11701	$ 799	Day 9	Day 15	Day 2	6.39%
1616	Brookside	Day 15	$ 17425	$ 14914	$ 2511	Day 9	Day 16	Day 3	14.41%
1617	Brunker Hill	Day 15	$ 15000	$ 13213	$ 1787	Day 9	Day 16	Day 3	11.91%
1618	Highlands	Day 15	$ 21000	$ 18316	$ 2684	Day 9	Day 15	Day 2	12.78%
1619	Jersey Village	Day 15	$ 17000	$ 14725	$ 2275	Day 9	Day 14	Day 1	13.38%
1620	Highlands	Day 22	$ 21400	$ 18316	$ 3084	Day 16	Day 21	Day 1	14.41%
1621	Jersey Village	Day 22	$ 17600	$ 14725	$ 2875	Day 16	Day 22	Day 2	16.34%

Figure 7 All Completed Jobs Screen

The SQL database provides data on the bids to the nearest second, as collected in the web-based game.

Poisson Process

The Poisson process is a special type of Markov process that happens in a fixed consecutive time period (Boxma & Yechiali). It is named after the French Mathematician Siméon-Denis Poisson (Ott & Longnecker, 2010). As a continuous-time process, it is a mathematical model of a completely random series of events (Cox & Lewis, 1966). Poisson process counts the numbers of occurring events along the timeline and the time of the occurred events in a certain time interval. According to its characteristics, it is also a type of point process of the real half line.

There are some important probability distributions, such as Poisson distribution, exponential distribution, and gamma distribution developed based on the Poisson process. There are five major properties of the Poisson process(Cox & Lewis, 1966). as research applications:

- distribution of number of events
- distribution of duration between events
- order statistics for the exponential distribution
- conditional property of the Poisson process
- time-dependent Poisson process

The first two properties mentioned above can be used to model RAB bidding process and study bidding strategies behind RAB. As one of the most important stochastic processes in probability theory, it is used to model random events in time and space (Kingman, 1993), such as the times of radioactive emissions, the calling times from customers at a service center, and the positions of flaws in a piece of material. Poisson process is very common in our life.

The property of distribution of number of events is used to test if the number of occurred events over a certain time period follows a Poisson distribution (Kingman, 1993; National Institute of Standards and Technology (U.S.), 2003). Another critical property of the Poisson process focuses on the duration between events. Through empirical data, it has been shown that the time duration between events follows exponential distribution of a specific parameter λ for some processes. To be specific, the durations between events are independent and exponentially distributed with random variables with mean 1/ λ (Boxma & Yechiali). In different conditions, the time duration can be defined in different way. And its distribution won't be affected, because any occurred event in any section of a Poisson process is independent in the preceding sections of process (Cox & Lewis, 1966).

Poisson Process for Online Auction Bidding

Since RAB is still a relatively new type of auctions, most of studies that pertained it focus on the advantages and disadvantages of its feasibility for application, like savings, item & services procured buyer-seller relationship, and its application in specific industries. In addition, there is just few published article discussing the model of bidding dynamics and strategies, such as bid arrivals model and bids duration model for RAB so far. However, as a special type of online auction, RAB shares some characteristics in bidding procedures with other online auction, such as eBay auction. Like other online auctions, the bidders in RAB can bid multiple times anonymously till the end of bidding section.

Many researchers had been involved in the study of online auction bidding strategy and bidders' performance through bid duration and bid arrival research. Among those researchers, Gneezy (2005) used the data from the online auction of some specific industries, like the interbank foreign exchange market, and other type of auction, including first- and second-price common-value sealed-bid auctions. Most of them (Borle, Boatwright, & Kadane, 2006; Russo, Shyamalkumar, Shmueli, & Jank, 2004; Shmueli et al., 2004; Shmueli, Russo, & Jank, 2007; J. Zhang & Zhang, 2011) studied the online auctions through real eBay auction data.

The online English Auction is the default and the most commonly used format among those several types of auction formats that eBay marketplace offers, (Hu & Bolivar, 2008). In the eBay auction, the bid would be awarded to the very last, also the highest price auction, after multiple times of bidding within fixed time period (Roth & Ockenfels, 2002). Whether for eBay auction or RAB, each bid will indicate a record of the bid time to the online auction system during the online auction process. The record is bid arrival, while the waiting time between bids is bid duration. The bid arrival and bid duration are crucial characteristics to understand the bidding dynamics and bidding strategies, bidding process, and outcomes of auction (Shmueli et al., 2004; J. Zhang & Zhang, 2011). The bid arrival here is equal to the word "event" that we mentioned in Poisson process, while the bid duration is equal to the word "event duration" above. These two topics raised increasing attention in model the dynamics and strategies behind the online auction. They are also the essential concerns of this research of RAB.

Bid Arrivals

Bid arrivals are an essential attribute of online auction bidding. This word refers to the bid time records returned to the online auction system. They are a very good tool to model bidding process in order to study bidder behavior and bidding strategies. Many researchers studied "early bidding," "bid sniping" or "last minute bidding" phenomenon through analysis bid arrivals. Early bidding refers to the behavior of bidders who bid any time during the auction period (Mizuta & Steiglitz, 2000). In addition, bid sniping or last minute bidding refers to the bidding behavior of bidders who wait until the last few seconds of the auction to place their bids.

Many researchers tried to model the bid arrivals for online auction bidding. However, there has been no accurate developed model which could approximate bid arrivals process with all its feature included (Shmueli et al., 2007). A popular assumption in these literatures is that Poisson process could be an approximation. Most of those literatures assumed that the bid arrivals process follows Homogeneous Poisson Process (HPP) (Russo et al., 2004).

Non-homogeneous Poisson process (NHPP), also called inhomogeneous Poisson process, is defined as a variation of Poisson process. Its name comes from its varied λ over different time periods. In NHPP, λ can be a piecewise function as equation 1. During time period $(t_a, t_b]$, the expected times of events would be:

$$\lambda = \lambda_{\mathrm{t_a,t_b}} = \int_{\mathrm{t_a}}^{\mathrm{t_b}} \lambda\,(\mathrm{t})\mathrm{dt} \tag{1}$$

Then, with the dependent variable r defined in equation 2

$$\mathrm{N}(\mathrm{t_b}) - \mathrm{N}(\mathrm{t_a}) = r \tag{2}$$

it has the probability formula as the listed in equations 3.

$$\mathrm{P}\big[\big(\mathrm{N}(\mathrm{t_b}) - \mathrm{N}(\mathrm{t_a})\big)\big] = \frac{\mathrm{e}^{-\lambda\cdot\Delta\mathrm{t}}(\lambda\cdot\Delta\mathrm{t})^{\mathrm{r}}}{\mathrm{r}!}, \qquad \mathrm{r} = 0, 1, 2, \ldots, \tag{3}$$

Mizuta & Stieglitz (2000) introduced simulations of the online second-price auction bidding process, with fixed and continuous bidding period. In this research, they modeled two types of agents for early bidders and bid snipers to study the interactions between the two types of bidders their bidding strategies. The results turned out to be that early bidders could win with lower price while the bid sniping strategy is more effective. In one bid sequence model and bid arrivals models research, they point out that the Poisson arrival model need specific length of the time interval between bids (A. Zhang et al., 2002).

Self-similar process were found by Roth and Ockenfels during the empirical studies of the online bidding process based on bid arrivals data during a close end auction (Roth & Ockenfels, 2000). They studied the second price online auction in consecutive periods with the Amazon and eBay data. They found that the bid sniping (last minute bidding) in a fixed period came at the equilibrium point in auction, which has private values or unknown, dependent values. The equilibrium point here is the moment when there is a motivation for bidders not bid too high before knowing other's reaction. At this point, bidders prefer to waiting, in order to evade a bidding war (Ockenfels & Roth, 2006) that will raise the expected final awarded price. Then the advantages brought by bid snipping are shut out. Then some researcher moved their focus to other Poisson process to fit and simulate the bid arrivals data better. In the research of Vakrat and Seidmann (2000) introduced a non-stationary Poisson process of bidder's arrivals. In this model, the intensity function $\lambda(x)$ within auction duration t was defined as shown in equation 4

$$\lambda(\mathrm{x};\mathrm{t}) = \lambda_a e^{-\frac{x}{t}},\ \ 0 \leq x \leq t \tag{4}$$

λ_a here is the measurement of web site traffic in the auction. They found out that the number of units being offered had a positive impact on the number of bidders. A class of 3-stage non-homogenous Poisson processes were put forward (Shmueli et al., 2004) to fit, interpret and model bid arrivals from the eBay online auction data . Russo et. al., (2004) discussed the descriptive models based on features of real online auction bid data and the model for bidder arrivals that leads to the bid arrivals process. These authors also presented the model for BARISTA (Bid ARrivals In STAges) process (the bid arrivals process).

Most research uses Poisson distribution as the testing model to fit the data. Some minor work looked at non-Poisson distributions. In the research, which studied the distribution of waiting times between bids on the interbank foreign exchange (FX) market, it was assumed that the randomly and independently arrived bids follow a Poisson process at the very beginning (Aurell & Hemmingsson, 1997). However their empirical observation of bid arrivals turned out to fall in exponential distribution, which proved that the duration between bids in the interbank foreign exchange (FX) market actually follows a power-law. The results may however be skewed by the LIBOR scandal (Ma, MacNamara, Bouchard, & D'Arminio, 2012).

Summary

As a new procurement method, Reverse Auction Bidding is a fiercely debated topic. The published articles mainly discuss the external and observable effects of Reverse Auction Bidding, such as posited savings, suitable items for procurement, related legal issues, and effects for the relation between buyers and seller. The dynamics, biding strategies and bidders’ performance presents a fertile research area to understand the bidding process from the large amount of transparent data available from recent studies.

A study of the process of Reverse Auction Bidding was launched at TAMU by van Vleet II (2004). An online website based on SQL Server datasets was developed to simulate the bidding process and test contractors' (bidders') performance in Reverse Auction Bidding. Eighteen Reverse Auction Bidding studies completed at TAMU reveal the dynamics and in part explain some elements of the bidders' performance of RAB. This prior research looked at areas of game theory, tacit collusion among bidders, the significance of personality, the RAB game for the role variants of guardians in different types of industrial and some specific cases studies.

The published article studying RAB dynamics and corresponding bidders' performance is rare, but such studies on eBay online auction exist. Some researchers modeled the eBay bid arrivals with certain type of distribution, such as the non-homogeneous Poisson process NHPP model (Shmueli et al., 2004). This model appears suited to the RAB data on bid timing and sufficient data exists to provide a tolerable approximation to the complete data set.

CHAPTER III

METHODOLOGY

Introduction

This chapter outlines the study methodology, including a brief discussion on the available process models and summarizes the alternative analysis methods used for this study.

Study Methodology

The study fits a statistical model to a point-based data set as follows:

<u>Data Set</u>

- assembled of the data set;
- reviewed the data set and removed of suspect data;
- presented of the data in a format suitable for analysis purposes.

<u>Statistical Review</u>

- compared the data set to arrange of standard statistical distributions to ;detect the model that can be tested for goodness-of-fit;
- undertook a goodness-of-fit test for each model to determine the best fit;
- undertook a review of the residual data from the fitted model to look for other features that may control the data set;
- established the key parameter for the model.

<u>Future Work</u>

- outlined the uses of the model and future research work on the RAB.

Poisson Process Models

Poisson Theory

Named after the French Mathematician Siméon-Denis Poisson (Ott & Longnecker, 2010) Poisson process is a process that "count" events till a specific point of time. Each occurred event of Poisson process jumps up to a higher state. Therefore, Poisson process is sometimes a "jump" process. As one of the most important stochastic process in probability theories, it is used to model random events in time and space (Kingman, 1993), such as the times of radioactive emissions, the calling times from customers at a service center, rainfall and the page view requests to a website. As a continuous-time process, it is a mathematical model of a completely random series of events (Cox & Lewis, 1966). Poisson process counts the numbers of the continuously and independently occurring events along the timeline and the time of the occurred events in a certain time interval. According to its characteristics, it is also a type of point process of the real half line(Last, 1991).

Poisson process is very important and common in our life, since it generates some important probability distributions, such as Poisson distribution, exponential distribution, and gamma distributions. There are five major properties of the Poisson process as research application: distribution of number of events, distribution of intervals between events, order statistics for the exponential distribution, conditional property of the Poisson process, and time-dependent Poisson process (Cox & Lewis, 1966).

Statistical Definition of Poisson Process

- A Poisson process $[\mathrm{N(t)}, \mathrm{t} \geq 0]$ is a counting process with the following additional properties(Cox & Lewis, 1966; Kingman, 1993). The process has stationary and independent increments. With dependent variable r defined in equation 5,

$$\mathrm{N(t)} = r \tag{5}$$

the statistical definition can be shown in equation 6 and 7:

- $\mathrm{N}(0) = 0$ (6)
- $\mathrm{P}(r) = \frac{\mathrm{e}^{-\lambda \mathrm{t}}(\lambda \mathrm{t})^{\mathrm{r}}}{\mathrm{r}!}, \;\; \mathrm{r} = 0, 1, 2, \ldots,$ (7)

When $\mathrm{N(t)}$ is number of occurred event, the independent process, λ is the intensity of this function, and t is the time when event occurred.

Homogeneous Poisson Process

There are different types of Poisson processes. Among these Poisson process, Homogeneous Poisson process (HPP) is the most general one. In the HPP, λ, also known as the intensity, is a constant with the dimensions of the reciprocal of time (Cox & Lewis, 1966). It measures the expected times of events during the certain time period. If the number of events in given time interval $[t, t + \Delta \mathrm{t}]$ with $\Delta \mathrm{t}$ as a time increment, N(t) follows a sample Poisson process, then $\left(\mathrm{N}(\mathrm{t} + \Delta \mathrm{t}) - \mathrm{N}(\mathrm{t})\right)$ has a Poisson distribution of mean shown as equation 8:

$$\mu = \lambda \cdot \Delta \mathrm{t} \tag{8}$$

With this mean value, $\mathrm{N(t)}$ as a non-negative integer, and dependent variable r defined in equation 9

$$\mathrm{N(t + \Delta t) - N(t)} = r \tag{9}$$

The probability distribution is given in equation 10:

$$\mathrm{P}[r] = \frac{\mathrm{e^{-\lambda \cdot \Delta t}(\lambda \cdot \Delta t)^r}}{\mathrm{r!}}, \qquad \mathrm{r} = 0, 1, 2, \ldots, \tag{10}$$

Non-Homogeneous Poisson Process

Non-homogeneous Poisson process (NHPP), also called inhomogeneous Poisson process, is a variation of Poisson process. It got its name, because its λ varies during different times. In NHPP, λ can be a piecewise function as equation 11. During time period$[t_a, t_b]$, the expected times of events would be:

$$\lambda_{\mathrm{t_a, t_b}} = \int_{\mathrm{t_a}}^{\mathrm{t_b}} \lambda\,(\mathrm{t})\mathrm{dt} \tag{11}$$

Then, with dependent variable r defined in equation 12

$$\mathrm{N(t_b) - N(t_a)} - r \tag{12}$$

it has the probability formula as the shown in equations 13.

$$\mathrm{P}\big[\big(\mathrm{N(t_b) - N(t_a)}\big)\big] = \frac{\mathrm{e^{-\lambda \cdot \Delta t}(\lambda \cdot \Delta t)^r}}{\mathrm{r!}}, \qquad \mathrm{r} = 0, 1, 2, \ldots, \tag{13}$$

In this research, the 3-step NHPP model (Shmueli et al., 2004) used another model fitted to the data. The original continuous intensity functions of 3-step NHPP model are listed below as equations 13, 14, and 15:

$$\lambda(s) = c\left(1 - \frac{d_1}{T}\right)^{\propto_2 - \propto_1}\left(1 - \frac{s}{T}\right)^{\propto_1 - 1}, \qquad 0 \le s \le d_1 \tag{14}$$

$$\lambda(s) = c\left(1-\frac{s}{T}\right)^{\propto_2-1}, \qquad d_1 \le s \le T-d_1 \qquad (15)$$

$$\lambda(s) = c\left(1-\frac{d_2}{T}\right)^{\propto_2-\propto_3}\left(1-\frac{s}{T}\right)^{\propto_3-1}, \qquad T-d_1 \le s \le T \qquad (16)$$

Here, s is the order number of time interval dependent variable. T is the total number of time intervals. d_1 is the point of time when the intensity λ begins changing non-homogeneously. $\propto_1, \propto_2 \propto_3$ are all calculable parameter. The $\propto_3$ is expect to be close to 1, and $\propto_2 > 1$ $\propto_1 \neq 0$ to represent the early surge in bidding. And c is the calculable parameter which is a constant. The random variable $\mathrm{N(t)}$, which counts the number of arrivals until time T follows a Poisson distribution with mean formula as equation 17, 18 and 19:

$$\mathrm{m(s)} = \mathrm{K}\left(1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right), \qquad 0 \le \mathrm{s} \le \mathrm{d_1} \qquad (17)$$

$$\mathrm{m(s)} = \left(1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right) + \frac{\mathrm{Tc}}{\propto_2}\left(1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right), \qquad \mathrm{d_1} \le \mathrm{s} \le \mathrm{T}-\mathrm{d_1} \qquad (18)$$

$$\mathrm{m(s)} = \mathrm{K}\left(1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right) + \frac{\mathrm{Tc}}{\propto_2}\left(1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right) + \frac{\mathrm{Tc}}{\propto_3}\left((\frac{\mathrm{d_2}}{\mathrm{T}})^{\propto_2-\propto_3} 1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_3}\right),$$

$$\mathrm{T}-\mathrm{d_1} \le \mathrm{s} \le \mathrm{T} \qquad (19)$$

In addition, the parameter K can be calculated by equations 20:

$$\mathrm{K} = \frac{\mathrm{Tc}}{\propto_1}\left(1-\left(1-\frac{\mathrm{d_1}}{\mathrm{T}}\right)^{\propto_2-\propto_1}\right) \qquad (20)$$

If we have parameter C been figured out with equation 21 and 22:

$$\mathrm{C} = \frac{\mathrm{c}}{\mathrm{m(T)}} \qquad (21)$$

$$\mathrm{C} = \frac{\propto_1\propto_2\propto_3/\mathrm{T}}{\left(1-\frac{\mathrm{d_1}}{\mathrm{T}}\right)^{\propto_2} \propto_{3(}\propto_{1-}\propto_2) + \propto_3\propto_3\left(1-\frac{\mathrm{d_1}}{\mathrm{T}}\right)^{\propto_2-\propto_1} - \left(\frac{\mathrm{d_2}}{\mathrm{T}}\right)^{\propto_2} \propto_1 (\propto_{3-}\propto_3)} \qquad (22)$$

Then the cumulative function of this 3-step Poisson process is given by equations 23, 24 and 25:

$$\mathrm{F(s)} = \frac{\mathrm{CT}}{\propto_1}\left(1-\frac{\mathrm{d}_1}{\mathrm{T}}\right)^{\propto_2-\propto_1}\left[1-\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}\right], \qquad 0 \le \mathrm{s} \le \mathrm{d}_1 \quad (23)$$

$$\mathrm{F(s)} = \frac{\mathrm{CT}}{\propto_1\propto_2}[(\propto_1-\propto_2)\left(1-\frac{\mathrm{d}_1}{\mathrm{T}}\right)^{\propto_2}+\propto_2\left(1-\frac{\mathrm{d}_1}{\mathrm{T}}\right)^{\propto_2-\propto_1}-\propto_2\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_1}, \mathrm{d}_1 \le \mathrm{s} \le \mathrm{T}-\mathrm{d}_1 \quad (24)$$

$$\mathrm{F(s)} = 1-\frac{\mathrm{CT}}{\propto_3}\left(\frac{\mathrm{d}_2}{\mathrm{T}}\right)^{\propto_2-\propto_3}\left(1-\frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto_3}, \qquad \mathrm{T}-\mathrm{d}_1 \le \mathrm{s} \le \mathrm{T} \quad (25)$$

Besides Homogeneous Poisson process (HPP), Non-homogeneous Poisson processes (NHPP), there are some other variations, such as Spatial Poisson process, Space-time Poisson process, and Separable space-time Poisson process. They are not going to be introduced and used in this research.

Gaussian Distribution

Gaussian distribution, also known as normal distribution is continuous distribution (Miller, Freund, & Johnson, 2000). It is one of the most important probability distribution in the natural and social science. Its symmetric bell-shaped density curves has only one single peak when the dependent variable is close to the mean μ. The standard deviation σ shows the spread of the bell curve (Miller et al., 2000). With different value of μ & σ, Gaussian distribution generates different shape of bell curve, which is controlled by the normal density. The equation of the density of Gaussian distribution with random variable x is shown as equation 26:

$$f(x;\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma}}e^{-(x-\mu)^2/2\sigma^2} \qquad (26)$$

A standard Gaussian distribution fit will be used in test the model of RAB bid arrival process.

Power-law Distribution

Power distribution is also a very important probability distribution in natural and social phenomena, such as the population of cities, the intensities of earthquakes, and the decay of radioactive element(Clauset, Shalizi, & Newman, 2009). It shows the relationship between two quantities. As a type of long tail distribution, power-law has no characteristic value(Ott & Longnecker, 2010). The general function of power-law distribution with random variable x is shown in the equation 27:

$$P(x) = Cx^{-a} + \varepsilon \tag{27}$$

C here is a constant, a is the exponent which is greater than 1. ε is the deviation(Clauset et al., 2009; Miller et al., 2000; Ott & Longnecker, 2010). In this research, a standard power-law distribution fit will be utilized for RAB bid arrival model regression test.

Goodness of Fit Tests

For the counted data with the number of occurred events in a fixed period, Chi-Square Test is used to check if the data fits an exact probability model within accept limits. This test is called Chi-square goodness-of-fit test or Pearson's Chi-square test. It is the Chi-square goodness-of-fit statistic that can be used to test to fit a set of data (Ott & Longnecker, 2010). And the Chi-square can be estimated by equation 28:

$$\chi^2 = \sum_{i=1}^{k} \left[\frac{(n_i - E_i)^2}{E_i}\right] \tag{28}$$

In this statistic, the quantity n_i stands for the number of bid arrivals in section i, and E_i is the expected number of bid arrivals in section i if the proposed model fits the data.

With $n = n_1 + n_2 + \cdots + n_k$ and $E_i = n_i p_i$, where p_i is the probability of a bid arrival occurring in the ith section using the NHPP model. The degree of freedom (df) in this test is in equations 29:

$$df = k - 1 \tag{29}$$

where k is the number of sections.

In the Chi-square test of this research, the actual number of bid arrivals, E_a, are compared to the theoretically expected bid arrivals, E_e, to check if the data followed the model. A comparison between the calculated χ^2 and the critical value of Chi-square distribution table with the same degree of freedom provides the data for the hypothesis being tested that the data fit the model.

Data Analysis Methods

The data analysis methods were:

- collecting all data into timed sections;
- fitting data in the proposed methods;
- testing data-fit-in with model regression;
- further testing data-fit-in condition with goodness-of-fit test.

CHAPTER IV

RESULTS

Introduction

This chapter can be summarized as:

- data set and analysis
- statistical review
- summary and potential future work

Reverse Auction Bidding has been studies by nineteen researchers at TAMU in the past decade. These researchers have studied a variety of issues concerning RAB. This study is the first major study of an aggregated data set from a selection of the nineteen studies.

Data Set and Analysis

Introduction

All data in this research came from the previous RAB research experiments among Texas A&M University (TAMU) students. Van Vleet II (2004) designed the repeatable experiment. TAMU students involved in the experiments acted as construction bidders. It was assumed that all bidders taking part in these auctions had passed the prequalification selection of the experience and qualifications. In addition, all bidders were on the same educational level of RAB. Each bidding section was held in a 15 minutes section. A summary of the nineteen studies is shown in Table 5.

Table 5

Summary of Nineteen Case Studies

Study Number	Name	Date	Topic
1	Van Vleet	Jul-04	First Study to establish system, no controls on price
2	Shankar	Jul-05	Duplicated Van Vleet's study
3	Gregory	Dec-06	Multi-game study
4	Gujarathi	Nov-07	tacit collusion game study
5	Panchal	Nov-07	Standard Study
6	Chouhan	Aug-09	Bidder's personality impact study
7	Chaudhari	Dec-09	Owners Interference study
8	Machado	Nov-09	Bidder's personality significance study
9	Petersen	May-10	Performance of poor economic performer
10	Guhya	May-10	Statistical Analysis of First Case Study
11	Saigonkar	May-10	Personality significance and impact on returns
12	Billing	Aug-10	Graph Theory Study
13	Gupta	Aug-10	Role Variants of Guardians in the Facilities Management Industry
14	Patel	Aug-10	Significance of Personality Types on the Impact of Returns
15	Somani	Aug-10	Role Variants of Guardians in the Construction Industry
16	Plumber	Aug-10	bidders' Personality Type
17	Bedekar	Dec-10	bidding strategy pattern of first time bidders
18	Bhalerao	Aug-11	Statistical Study in profit percentage
19	Xun	Aug-12	Multi Group Study, repeat study 3
20	Shu	Aug-13	Bid Arrival study

As for the general online RAB, each bidders could bid multiple times until the bidding time period ended. Bidders must bid lower than the current best bid. Thus, the final lowest bid would be accepted in the final negotiation process. During the bidding process, all bidding actions, including cost, time, contractor, bid order etc., were recorded by an online RAB system. The website for the online RAB system was created by Kim (2004), and then redeveloped with SQL Server by Wellington (2006). With this system, experimental data, including project, bid time, section time period, bidders information, were stored in the SQL dataset. Nine experiment datasets fitted the requirements for this research. The other data sets had been designed to test specific matters were considered not suitable for this research work.

The data sets were eliminated for several reasons including:

- a change in the bid time period, one attempt to use a ten minute bid period proved to be problematic as insufficient time elapsed for the bidding to stabilized;
- one study included a bidder who drove the bid prices down modeling owner interference in the project;
- very short games;

Table 6 provides a sample of the bid details table from the database.

Table 6

Original Access Dataset Sample 1 (Bid Table)

bidID	jobID	ctrID	bidAmount	bidDate	bidTime
5	1	4	$12,999.00	1	7:01:02 PM
19	1	4	$12,400.00	1	7:02:21 PM
88	1	4	$12,150.00	1	7:11:48 PM
105	1	7	$12,149.00	1	7:13:27 PM
2	1	8	$13,000.00	1	7:00:22 PM
11	1	8	$12,500.00	1	7:01:39 PM
22	1	8	$12,200.00	1	7:02:52 PM
1	1	9	$15,000.00	1	7:00:20 PM
115	1	9	$12,000.00	1	7:14:16 PM
62	2	4	$12,999.00	1	7:09:30 PM
89	2	4	$12,450.00	1	7:11:52 PM
95	2	4	$12,200.00	1	7:12:22 PM
104	2	4	$12,100.00	1	7:13:20 PM
8	2	7	$13,500.00	1	7:01:29 PM

Table 6 shows the identified used in the database. The data shown in the table is:

- bidID - a unique sequential number assigned to each bid
- jobID - a unique sequential number assigned to each job
- ctrlID - - a number cosigned to each bidder
- bidAmount - the amount bid for this offer
- bidDate - a day code for the game in data set (1, 2, 3, …, n day)
- bidTime - the actual time when the bid record occurs in the system

Table 7 shows a sample of the job details table from the database.

Table 7

Original Access Dataset Sample 2 (Job Table)

jobID	siteID	jobPrice	ctrID	jobBidStartTime	jobBidEndTime
1	6	12000	9	5/4/04 7:00 PM	5/4/04 7:15 PM
2	5	12100	4	5/4/04 7:00 PM	5/4/04 7:15 PM
3	5	11999	7	5/4/04 7:00 PM	5/4/04 7:15 PM
4	5	12000	9	5/4/04 7:00 PM	5/4/04 7:15 PM
5	6	11750	8	5/4/04 7:00 PM	5/4/04 7:15 PM
6	4	11999	7	5/4/04 7:00 PM	5/4/04 7:15 PM
7	3	12300	9	5/4/04 7:00 PM	5/4/04 7:15 PM
8	4	11999	4	5/4/04 7:00 PM	5/4/04 7:15 PM
9	3	12499	7	5/4/04 7:00 PM	5/4/04 7:15 PM
10	1	12300	8	5/4/04 7:00 PM	5/4/04 7:15 PM
11	1	12000	9	5/4/04 7:00 PM	5/4/04 7:15 PM
12	1	12300	8	5/4/04 7:00 PM	5/4/04 7:15 PM
13	2	10900	6	5/4/04 7:00 PM	5/4/04 7:15 PM
14	4	12000	4	5/4/04 7:20 PM	5/4/04 7:35 PM
15	4	12450	4	5/4/04 7:20 PM	5/4/04 7:35 PM

The additional data shown in

Table 7 is:

- siteID –the unique integer identified each site;
- jobPrice –the winning bid;
- jobTimes – the start and end time for the bidding sessions.

Time is an interesting problem for online auction and bidding systems. One of the first changes made to the web system was the inclusion of a clock on the pages to allow bidders to keep track of the time.

Data Transformation

The data from the nine data sets provided the input to a single data set. The key characteristics of the data set are:

- A new and unique identification numbers was given to all participants.
- A count of the number of bidders yields 76.
- A count of the number of experiments yields nine.
- A count of the number of bidding weeks yields 97.
- A count of the number of projects yields 916.
- A count of the number of bids yields 6432 valid bids from 6647 bids.

The data shown in the table is:

- Case Study ID – Assigned ID of case study follow the chronological order
- Number of Bidder – Total number of involved bidder for the related case study
- Number of Section – Total number of 15-minute section recorded for the related case study
- Number of Project – Total number of involved project for the related case study
- Number of Bids - Total number of bid arrival record for the related case study

Table 8 provides a summary of the bid and record data for the nine case studies. The data shown in the table is:

- Case Study ID – Assigned ID of case study follow the chronological order

- Number of Bidder – Total number of involved bidder for the related case study
- Number of Section – Total number of 15-minute section recorded for the related case study
- Number of Project – Total number of involved project for the related case study
- Number of Bids - Total number of bid arrival record for the related case study

Table 8

Bid and Record Data Summary

Experiment Date	Case Study ID	Number of Bidder	Number of Section	Number of Project	Number of Bid
4-May-2004	1	5	8	86	773
29-May-2006	2	4	25	118	192
4-Jun-2006	3	9	13	156	1077
5-Nov-2007	4	4	5	43	346
6-Apr-2010	5	5	8	54	804
3-Apr-2010	6	37	10	179	776
8-Jun-2010	7	4	10	97	865
10-Jun-2010	8	4	9	92	759
11-Jun-2010	9	4	9	91	1082
Total		76	97	916	6674

The typical game involved for players van. Vleet (2004) looked at the issue of collusion of the players. The Herfindahl Index is a potent measurement of the chance of collusion. A HI for 4 to 5 players provides a reasonable competitive level. As can be observed is the data shown in the table is:

- Case Study ID – Assigned ID of case study follow the chronological order

- Number of Bidder – Total number of involved bidder for the related case study
- Number of Section – Total number of 15-minute section recorded for the related case study
- Number of Project – Total number of involved project for the related case study
- Number of Bids - Total number of bid arrival record for the related case study

From Table 8, it is shown that some games used more than five players to test while the interest competition drove down pricing.

Table 9 shows the sample of the number of bids during each section within the overall data set. Table 9 only shows the critical number of bid arrivals during each of 97 assigned 15-minute bidding sections. The data was filtered with Excel to present the sections having more than 100 bid arrivals to avoid some zero bid arrivals sections. Each data point was reviewed to prove that it met the roles of the some and game and that it was completed. Data that did not meet this criterion were eliminated.

Table 9

Bid Arrivals during Each Section (Filtered Sample)

Section ID	Total Number of Bid Arrivals During Each Section
1	130
5	117
6	109
41	123
42	174
43	217
44	149
45	115
48	119
51	140
52	155
53	214
54	237
56	205
57	147

The next stage of the data transformation included:

- calculating the relative bid arrival time based on the section start time and actual bid time for each bid.
- transforming the relative bid arrival time from hour-minute-second into second type.
- analyzing this second type of relative bid time is the bid arrival record that this research using standard statistical techniques.

Data Errors and Correction

The experiment rules requires that all bidding activities should be performed with 15 minute bidding section, which means that bid arrivals' value in seconds should not exceed 900. However, there was some bid arrivals' value exceeding 900 due to some unknown flaw of the TAMU RAB website or SQL Server dataset. This flaw should be corrected for future case studies. The bid arrivals' times were checked and the invalid data were marked for deletion. The invalid data was removed from the bid arrivals' data set to provide final set, which was to be used in the statistical analysis. Table 10 shows a summary of the valid 6432 bid arrivals used for further statistical analysis. In Table 10, the data were ranked by "Bid Time" column. The first five columns show the basic bid arrival data from prior case studies. The "relative bid time" comes from the subtraction "Section Start" from "Bid Time". The hour-minute-second type of relative bid time was transformed to second-only type and became bid arrival, which was then used for statistical analysis. The last column was used to mark the invalid bid arrival data, which was then removed from the final data set. After validation process, there are 6432 bid arrival records being taken in to final data set for statistical analysis. The method used is to plot of bid arrival records from nine case studies. Each one shows the plot of all bid arrival time record from case study. Each bid arrival record point carried its value of its bid arrival order number (value of x axis) and the time point in second (value of y axis) when this bid arrival occurred.

Table 10

Completed Bid Data Set Characteristics

Bid ID	Project ID	Bid Time (PM)	Section Start (PM)	Section End (PM)	Relative Bid Time	Bid Arrivals	Validation
1	1	4:05:06	4:00:00	4:15:00	0:05:06	306	594
4	1	4:05:43	4:00:00	4:15:00	0:05:43	343	557
2	2	4:05:19	4:00:00	4:15:00	0:05:19	319	581
13	2	4:15:10	4:00:00	4:15:00	0:15:10	910	10
3	3	4:05:27	4:00:00	4:15:00	0:05:27	327	573
5	4	4:06:19	4:00:00	4:15:00	0:06:19	379	521
12	4	4:14:24	4:00:00	4:15:00	0:14:24	864	36
10	5	4:11:14	4:00:00	4:15:00	0:11:14	674	226
11	5	4:11:22	4:00:00	4:15:00	0:11:22	682	218
9	6	4:10:36	4:00:00	4:15:00	0:10:36	636	264
7	7	4:10:04	4:00:00	4:15:00	0:10:04	604	296
8	7	4:10:27	4:00:00	4:15:00	0:10:27	627	273
6	8	4:08:59	4:00:00	4:15:00	0:08:59	539	361
15	9	4:21:52	4:20:00	4:35:00	0:01:52	112	788

Figure 8 shows the bid arrival data for the first case study.

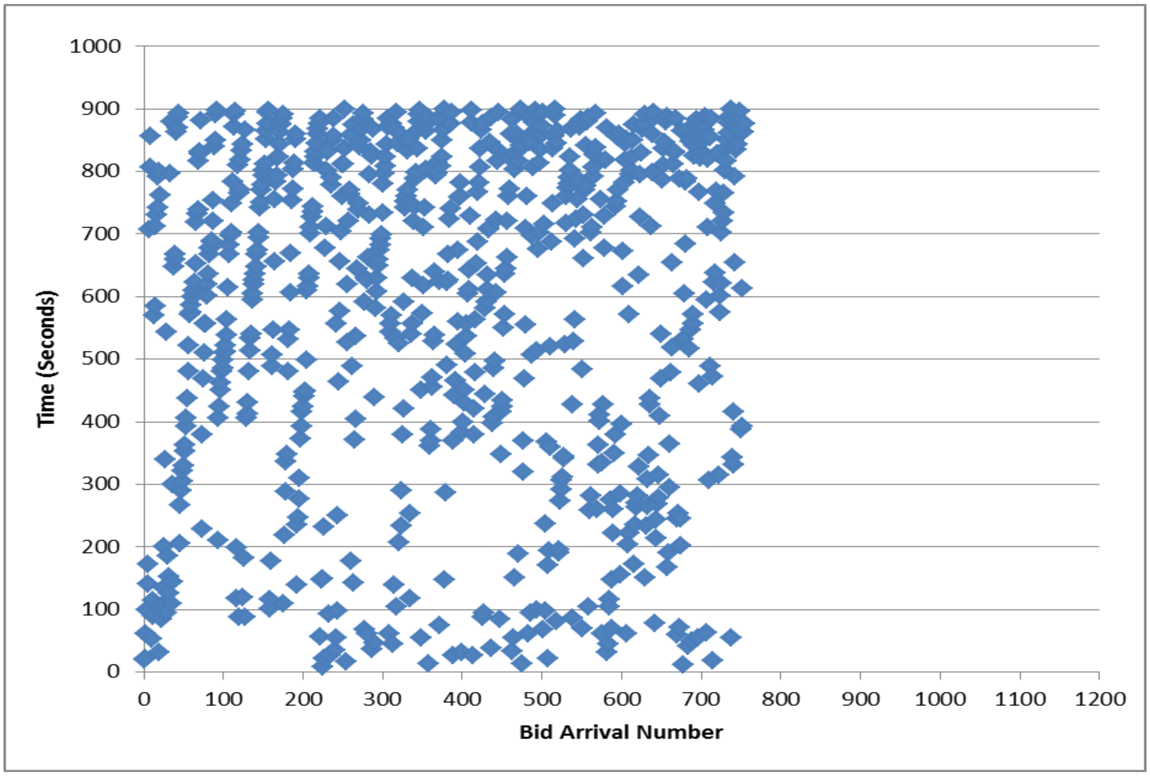


Figure 8 Bid Arrival Time Data for Case Study One

From Figure 8, it is hard to figure out the trend that the potential statistical distribution for the bid arrival data. The homogeneous plotted bid arrivals records show that bid activities happened with no rule and all bidders in case study one bided randomly over 15-minute section. This situation can be explained as “early bidding” phenomenon.

Figure 9 shows the bid arrival time for the ninth case study.

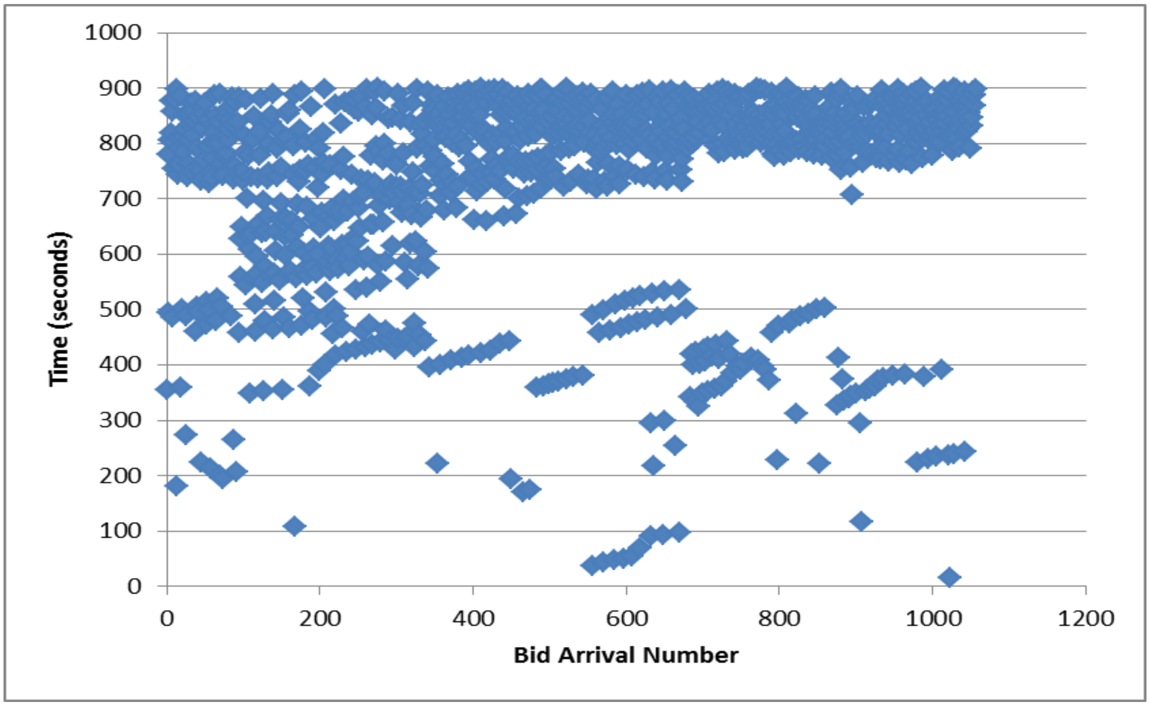


Figure 9 Bid Arrival Time Data for Case Study Nine

From Figure 9, it is clear to see that most of bid arrival record occurs when time is approaching the last 200 seconds (700-900). The bidding activity became much more fierce when the auctions were closed to the end. This situation is a very good sample to show "bid sniping" phenomenon. The last two figures are plotted at the same scale for comparison purposes.

Different conclusions were derived from those two samples of case study bid arrival plots, so as the plots from seven other case studies. Figure 8 and Figure 9 shows the problem of trying to determine the statistical properties from a limited data set. The data shows some patterns but is too limited to show an overall statistical pattern. A number of the previous research studies looked at this problem but failed to reach a reasonable conclusion (Billing, 2010; Chaudary, 2009; Chouhan, 2009; Gregory, 2006;

Guhya, 2010a; Gupta, 2010; Machado, 2009; Panchal, 2007; Saigaonkar, 2010; Shankar, 2005; van Vleet, 2004). This problem may result from limited size of data sample, which only focused on the data set from single case study. Therefore, the author enlarged the data sample size, in order to figure out the specific statistical process that RAB bid arrival follows. The bid arrival data is put together for analysis.

Bid Time Analysis

This RAB experiment was designed to be repeatable (Fisher, 1971) and each section with similar virtual construction projects was linearly independent. Hence, each bid arrival is considered to be an independent value. Hence, all bid arrivals from the nine experiments are collected and placed into a 15-minute summary section.

Table 11 provides a summary of a sample of the bid data in five-second increments. This complete set of data in the 15-minute section was divided into 180 time intervals with chronological order, which covers five second each. The number of bid arrivals and cumulative number of bid arrivals over each time interval were counted for each five-second interval.

Table 11

Sample of the Bid Data in Five Second Increments

Time Interval ID	Number of Bid Arrivals (5 Sec)	Cumulative Number of Bid Arrivals (5 Sec)
1	0	0
2	4	4
3	17	21
4	20	41
5	16	57
6	25	78
7	23	105
8	24	129
9	24	153
10	24	177
11	33	210
12	14	224
13	29	253
14	26	279

Figure 10 shows the tendency plot of RAB bid arrivals for time-continuous 15-minute section for the complete data set for five-second intervals. The x-axis plots the order of time interval, and the y-axis plots the number of bid arrivals during the corresponding time interval.

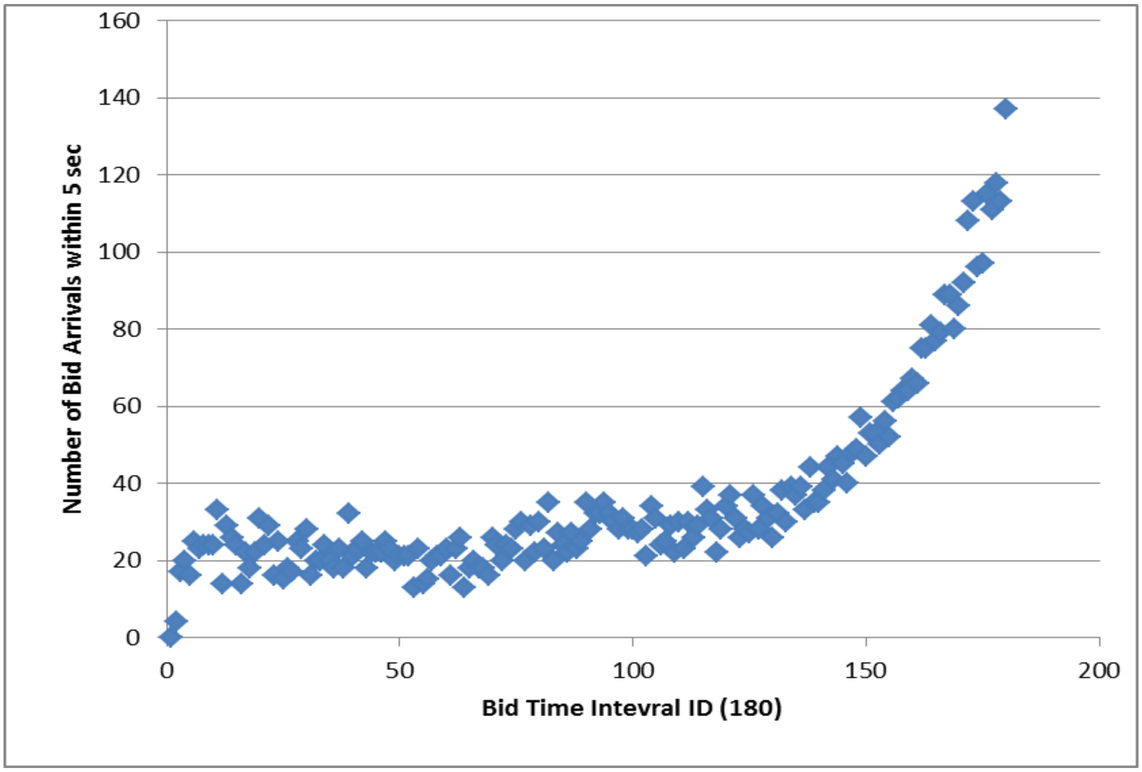


Figure 10 Bid Arrivals for Complete Set

Figure 10 shows a tolerably stable pattern. It is significantly more stable than the pattern observed by (Guhya, 2010) in the first cash study. Guhya postulated the third order polynomial provided to fit to this data. He characterized each player as “constant” “variable”, “low rate aggressive” and “aggressive”. This matter is a future research issue to determine if bidders do bid at different rates.

The phenomena of “early bidding”, “bid sniping” or “last minute bidding” are obvious in this plot. During the first 600 seconds, the plot shows low density of bid arrivals, which indicates “early bidding”. The number of RAB bid arrivals then rockets significantly when the bidding time getting close to the end. The RAB bid arrivals typically experience a mass amount of ‘last minute bidding”. The heterogeneity in RAB bidding dynamics is quite similar to the situations of eBay online auction that were mentioned by other researchers (Shmueli et al., 2004; Shmueli et al., 2007).

Figure 11 shows the cumulative number of bid arrivals of 180 time intervals for the summary 15-minute section.

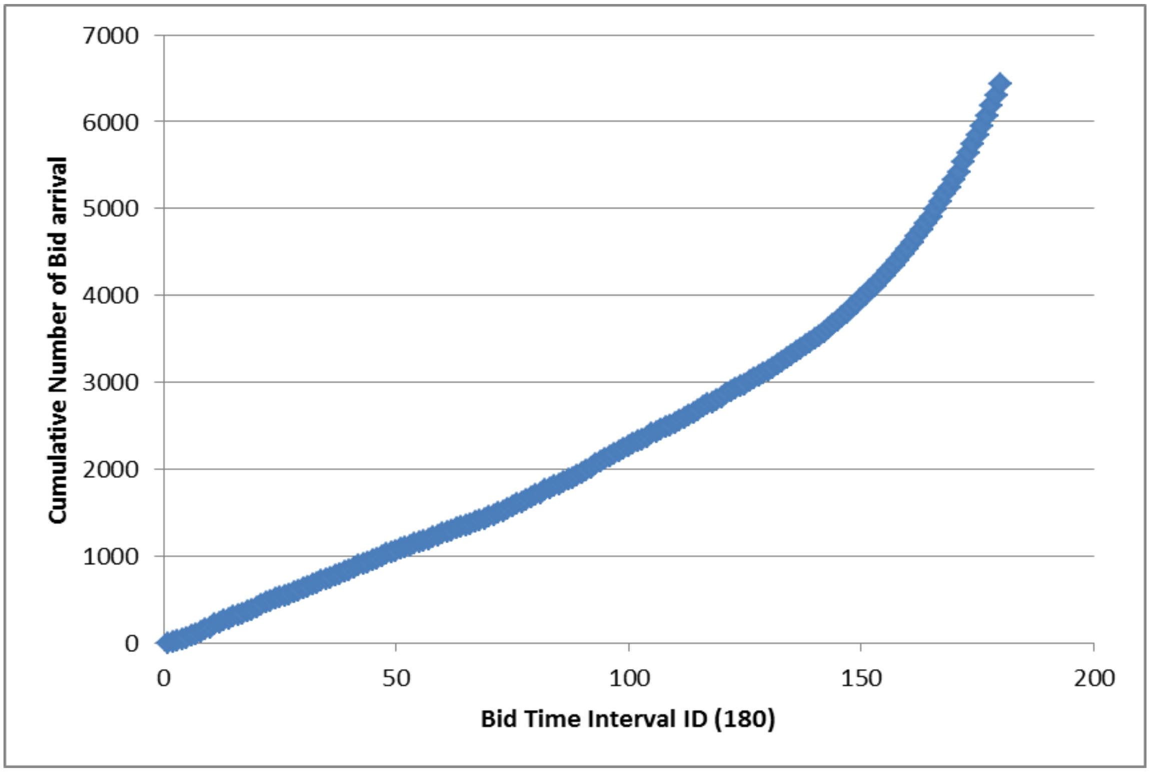


Figure 11 Cumulative Bid Arrivals for Complete Set

Figure 11 shows the tendency plot of cumulative number of RAB bid arrivals for continuous 15-minute section. The x-axis stands for the order of time interval, and the y-axis stands for the cumulative number of bid arrivals during the corresponding time interval. The curve rises smoothly. This result is similar to the research that modeled the eBay online auction bid arrivals (Shmueli et al., 2004).

Figure 12 shows the linear regression fit. Clearly the data is not linear in time.

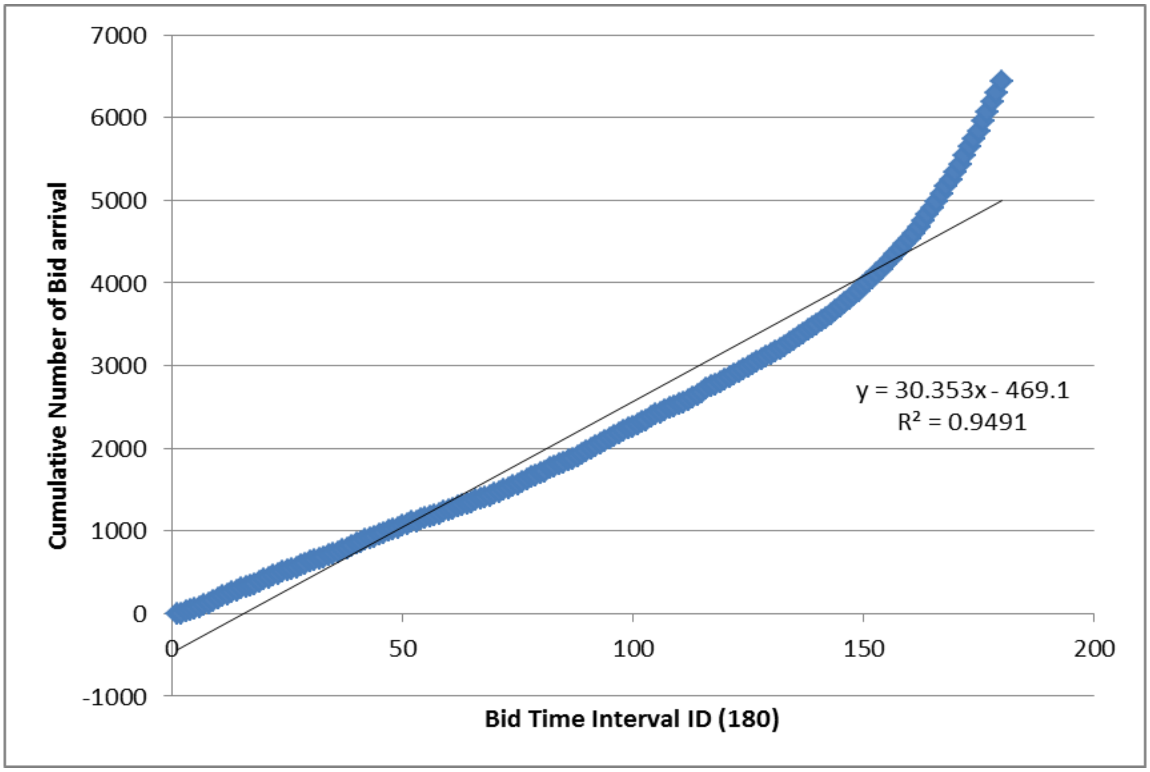


Figure 12 Cumulative Bid Arrivals for Complete Set (Linear Fit)

Figure 13 shows a polynomial fit.

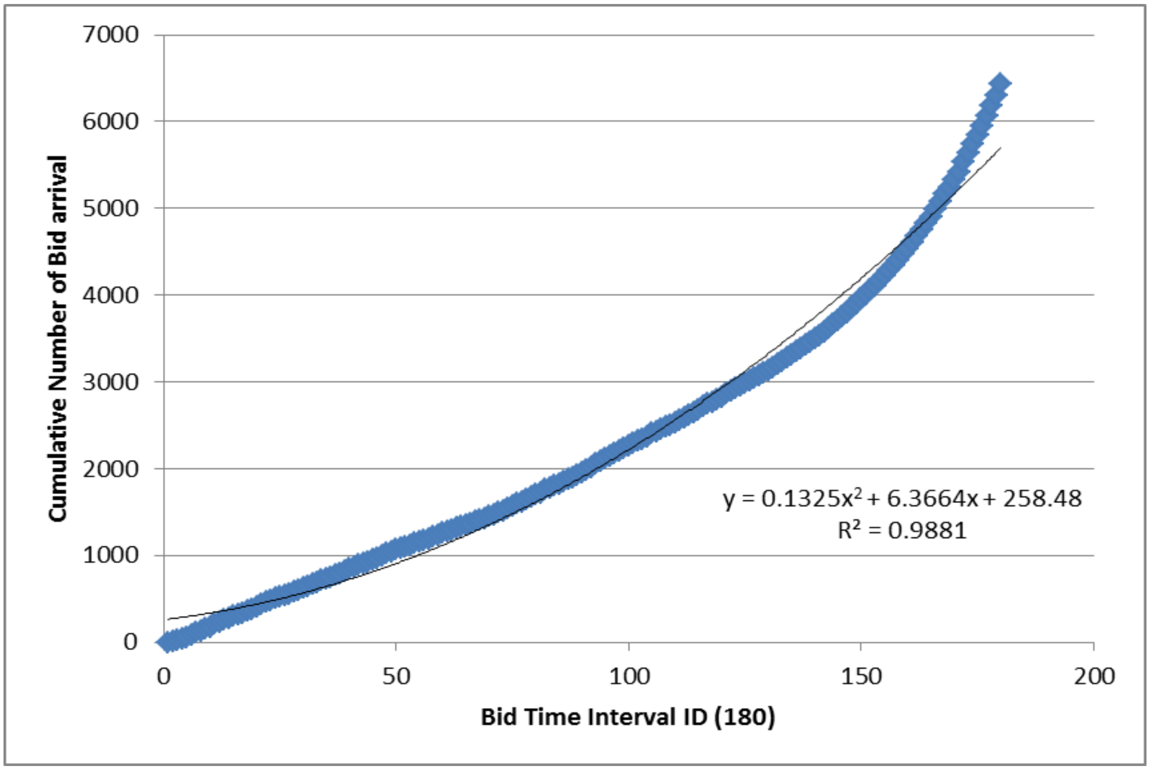


Figure 13 Cumulative Bid Arrivals for Complete Set (Polynomial Fit)

Figure 11, Figure 12 and Figure 13 provide a summary of the data for completing the statistical data fit. The first step in the process is to fit equations to the data with standard linear regression model available in Excel. Fitted equations are shown on Figure 12 for a linear regression. Figure 13 shows a polynomial fit.

Clearly, the data is not linear or polynomial fit. The second stage is to fit and check the various distributions. A Gaussian distribution yields an unacceptable error in the fit and is not considered further. A Power-law distribution yields an unacceptable error in the fit and is not considered further. A Homogeneous Poisson Process (HPP) yields tolerable fit, but deviations at the start, middle and end of the data suggests that time has an impact on the data and the inhomogeneous process it more likely to fit this data as for the eBay auction did.

Model Regression

Human behavior can be modeled via standard statistical distributions. The Non-homogeneous Poisson Process (NHPP) model is a complex statistical model, so the fitting steps were:

- determining the data for the fitting model for each time interval;
- comparing the fitted data to the experiment data and determining χ^2 estimates for goodness-of-fit test;
- reviewing the χ^2 estimates and the residual data using Fast Fourier transformation techniques (Brigham, 1988) to see if a cyclic pattern exists within the primary statistical model residual data

<u>Formulas and Definition</u>

The NHPP model is different from a normal Poisson process, since its intensity is a function of time. If bids arrive during $[0, T]$ in line with a NHPP $N(t), 0 \leq t \leq T$, the intensity function is the equation 30.

$$\lambda\,(s) = \mathrm{c}\left(1 - \frac{\mathrm{s}}{\mathrm{T}}\right)^{\propto - 1} \quad 0 < \propto < 1 \text{ and } \mathrm{c} > 0 \text{ (constant)} \tag{30}$$

if $\propto$ was assumed as 0.5, the intensity function could be presented as equation 31 to show a simple form to the standard equation 11.

$$\lambda\,(\mathrm{s}) = \frac{\mathrm{c}}{\sqrt{1 - \frac{\mathrm{s}}{\mathrm{T}}}} \quad \mathrm{c} > 0 \text{ (constant)} \tag{31}$$

This function shows that $\lambda (s) \rightarrow \infty$ when $s \rightarrow T$, which means that the bid arrivals' density becomes higher and higher towards the end. This characteristic simulates the "bid sniping" well. Human are not automatous, as happening when a Poisson distribution controls a machinery process. Human beings do not switch on automatically at the beginning of a game, do take breaks for human reasons, and have a quick, but limited reaction time to input data. All of these issues will act to introduce residual errors into the data set. As with other such as data, a Fast Fourier transform analysis of the residual data will provide insight with the human elements in the underlying model.

NHPP Model Test Fit

In the simplest form, it is possible to use the linear regression to demonstrate that the rate of bid arrival in the game period. A regression coefficient variance or R^2 from results is a tolerable indication of this pattern. However, a better fit can be tested with χ^2 statistic. The technique used for this study is:

- fitting the NHPP model data with α as variable;
- determining the χ^2 statistic for each fitted bid arrival record in terms of α;
- varying the period of the time steps to look at change in the χ^2;
- determining the time step of α that minimizing the χ^2 statistic for the data;
- assuming fit model has the same number of bid arrivals as the experiment data.

In order to assure the veracity, the 15-minute section was cut into wider time interval pieces, so that the statistical analysis results would not be affected by unknown singularities. Then the number of bid arrivals of 20 time intervals within the 15-minute section was calculated for testing the NHPP model. Table 12 shows the RAB bid arrivals NHPP model testing process.

Table 12

NHPP Model Regression

Time interval ID (s)	s/T	1-s/T	λ=(1-s/T)^(α-1)	No. of bid arrivals (experiment)	No. of bid arrivals (NHPP model)
1	0.0500	0.9500	1.0260	153	149.1260
2	0.1000	0.9000	1.0541	204	193.5314
3	0.1500	0.8500	1.0847	197	181.6250
4	0.2000	0.8000	1.1180	194	173.5189
5	0.2500	0.7500	1.1547	204	176.6692
6	0.3000	0.7000	1.1952	189	158.1287
7	0.3500	0.6500	1.2403	179	144.3144
8	0.4000	0.6000	1.2910	173	134.0052
9	0.4500	0.5500	1.3484	229	169.8309
10	0.5000	0.5000	1.4142	238	168.2914
11	0.5500	0.4500	1.4907	276	185.1464
12	0.6000	0.4000	1.5811	247	156.2165
13	0.6500	0.3500	1.6903	263	155.5929
14	0.7000	0.3000	1.8257	270	147.8851
15	0.7500	0.2500	2.0000	295	147.5000
16	0.8000	0.2000	2.2361	356	159.2080
17	0.8500	0.1500	2.5820	442	171.1859
18	0.9000	0.1000	3.1623	567	179.3011
19	0.9500	0.0500	4.4721	748	167.2579
20	1.0000	0.0340	5.4233	1008	185.8660

For an α of 0.5 is a square rood factor for twenty time interval, which is 45 seconds each. Table 13 shows the RAB bid arrivals NHPP model testing result. For an α of 0.5 is a square rood factor for twenty time interval, which is 45 seconds each.

Table 13

NHPP Model Regression Result

α	Mean	SD	CV	C (NHPP model)
0.50	165.2101	16.0718	9.73%	30.6000

In this model test process, T is 20, which is the total number of time intervals of the 15-minute section. Each time interval ID (s) was substituted into the standard function to get the intensity λ estimates. From Table 12, the $1-\frac{s}{T}$ of time interval 20 would be 0 with $\frac{s}{T}$ =1, so that the corresponding λ would become an imaginary number. In case of that situation, the parameter of $1-\frac{s}{T}$ for the λ of time interval 20 was set as 0.0034, which approaches 0.

The number of bid arrivals of the NHPP model could be estimated by dividing the experimental number of bid arrivals by the corresponding intensity (Table 12). The mean, standard deviation and coefficient of variation were also gotten using Excel. The mean of estimated number of bid arrivals is 165. The standard deviation is 16.1. The estimated constant C is 30.6. In addition, the coefficient of variation is 9.7%, which is a relatively small coefficient of variation. The smaller this coefficient of variation, the more stable the actual experimental number of bid arrivals regression to the NHPP model.

The Excel model provided the tool to minimizing χ^2. α was varied from 0 to 1, for periods of 30, 45 and 60 seconds. The minimum χ^2 was found for an α of 0.5 ± 0.005 as for 45 second interval. Any movement away for 45 seconds either up or down in time, increased χ^2 did change to α. The conclusion is that a NHPP model is best fitted at 45 second interval for an α of 0.5.

<u>Chi-square (X^2) Test</u>

Figure 14 shows a plot of the experiment data against to NHPP fit for 45-second at $\propto$ of 0.5.

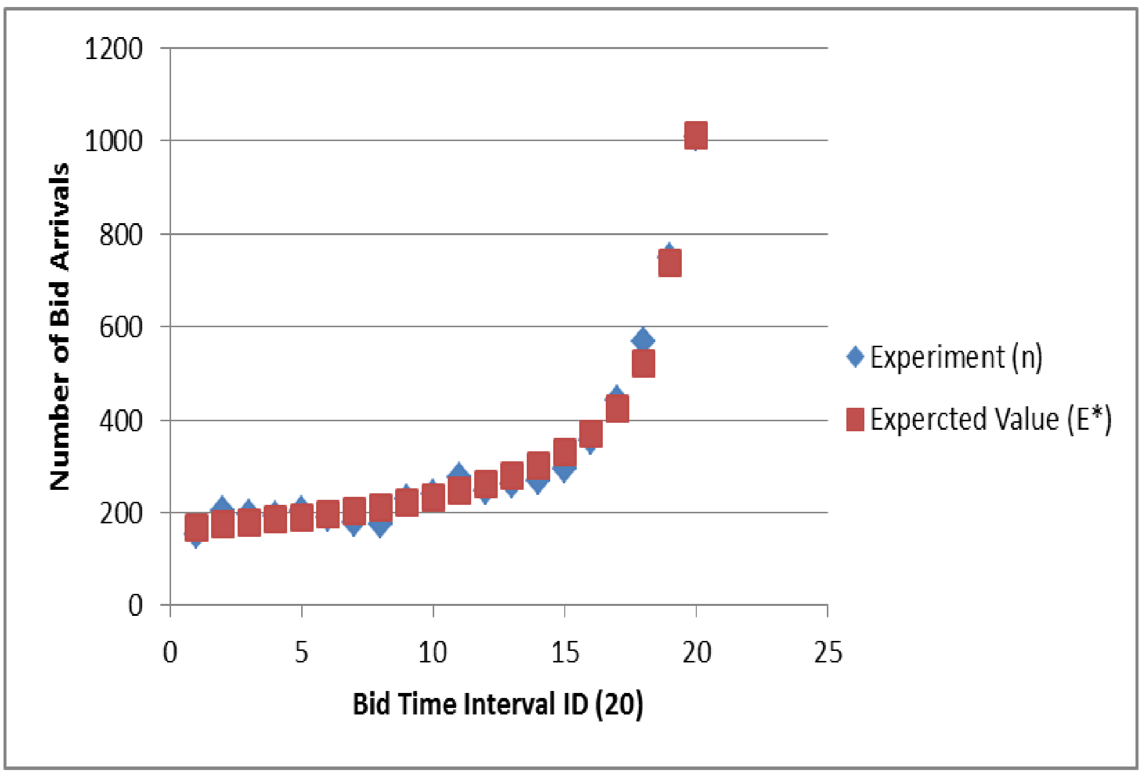


Figure 14 Number of Bid Arrivals: Experiment vs NHPP Model

Figure 14 fits to the experiment data. Table 14 shows the Chi-square test process and result for α of 0.5 at 45-second intervals.

Table 14

Chi-square Test

Time interval ID (s)	No. of bid arrivals (experiment) (n)	s/T	λ^*	No. of bid arrivals (E^*)	Residuals ($n-E^*$)	χ^{2*}
1	153	0.0250	1.0127	166.6109	-13.6109	1.1119
2	204	0.1000	1.0541	173.4141	30.5859	5.3946
3	197	0.1500	1.0847	178.4416	18.5584	1.9301
4	194	0.2000	1.1180	183.9334	10.0666	0.5509
5	204	0.2500	1.1547	189.9656	14.0344	1.0368
6	189	0.3000	1.1952	196.6331	-7.6331	0.2963
7	179	0.3500	1.2403	204.0558	-25.0558	3.0766
8	173	0.4000	1.2910	212.3880	-39.3880	7.3046
9	229	0.4500	1.3484	221.8321	7.1679	0.2316
10	238	0.5000	1.4142	232.6594	5.3406	0.1226
11	276	0.5500	1.4907	245.2446	30.7554	3.8570
12	247	0.6000	1.5811	260.1211	-13.1211	0.6619
13	263	0.6500	1.6903	278.0812	-15.0812	0.8179
14	270	0.7000	1.8257	300.3620	-30.3620	3.0691
15	295	0.7500	2.0000	329.0301	-34.0301	3.5196
16	356	0.8000	2.2361	367.8669	-11.8669	0.3828
17	442	0.8500	2.5820	424.7761	17.2239	0.6984
18	567	0.9000	3.1623	520.2423	46.7577	4.2024
19	748	0.9500	4.4721	735.7337	12.2663	0.2045
20	1008	0.9735	6.1430	1010.6080	-2.6080	0.0067

Table 15 shows the Chi-square test process for α of 0.5 at 45-second intervals.

Table 15

Chi-square Test Result

α	Total No. of bid arrivals (experiment)	Total λ	Total No. of bid arrivals (expected value)	χ^2
0.5	6432	39.0967	6432.0000	38.4764

The χ^2 statistic for the best fit was 38.5 and to $\chi^2_{0.005}$ value for 19 degree of freedom is 38.7. The NHPP provides a tolerable fit to the data. It is recommended that this data be refitted when more bid data becomes variable. The next step is the analysis is to determine the residual data.

Human Element to the Bid Data

From Figure 15 Residuals, the author found that the experimental value did not fit NHPP model perfectly, the author then plotted the Residuals and χ^2* to analyze the contractors' performance during RAB process. The residuals curve waved over time. The author tried to analyze and hypothesize the bidding dynamics behind this curve.

Figure 15 shows the Residuals plot in 15-minute section.

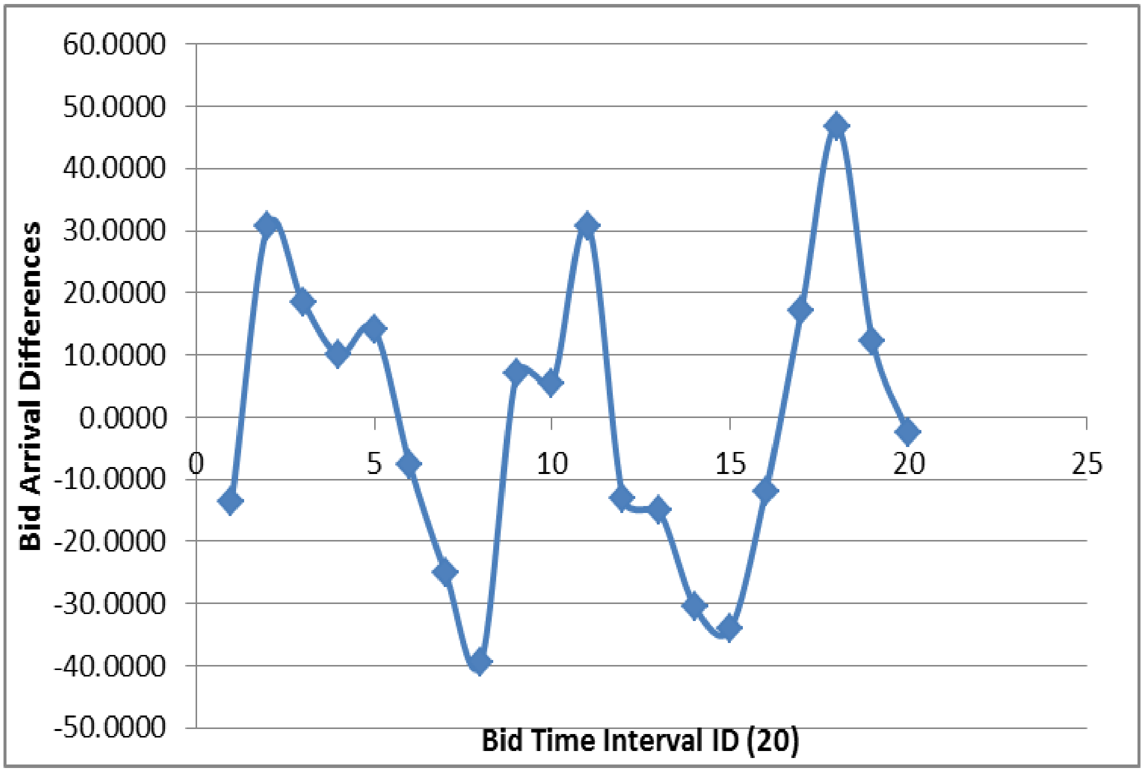


Figure 15 Residuals

Figure 15 shows the absolute value of residual data, which is the difference between the fitted model and the experiment data. Figure 15 shows the χ^{2*} plot. Figure 16 shows the χ^{2*} result data plot for the fitted model. The residual data should be randomly scattered for a model with the optional fit. As is often observed in human data, there is cyclic pattern to the residual data.

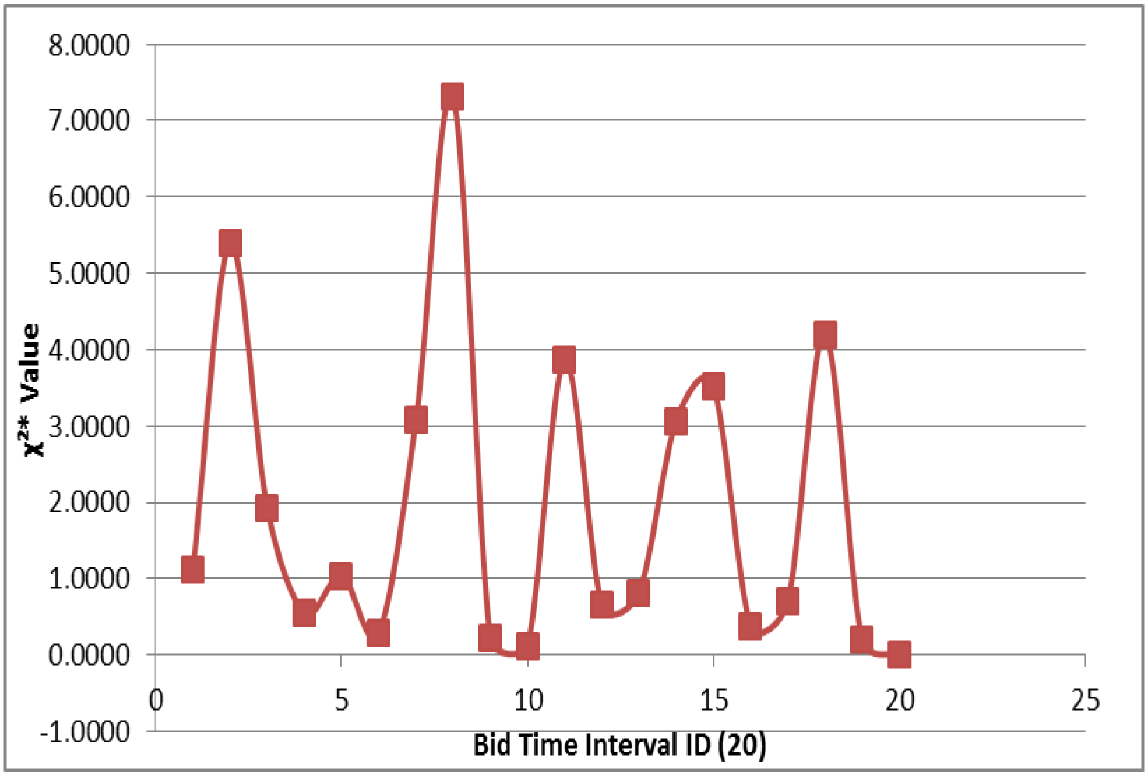


Figure 16 χ^2 Test Results

A Fast Fourier transform analysis of residual data expanded to include necessary zeros, as required for the analysis yields a cyclic pattern to the residual results. From a simple thought experiment, the following factors most likely play into creating the cyclic pattern. These factors are:

- a start time is a bit variable to human, so game play does not commence at exact zero second. If this is true, the data should show a negative residual for the first period and higher residual for next few periods to corporation for the lost time. This is observed.
- the end bidding rate is limited by the response time in types of human when presents with this data. In order to confirm this assumption, a small reaction time

counting experiment was set up. In this one-minute experiment, there were two students involved, A and B. Once student A typed a three-digit number on her screen A on her screen, student B typed the three-digit number B on his screen, which valued number A plus1. For the second round, the two students switched their screens. After several rounds of tests, the average time for reaction and typing was counted as 30 numbers per minute. Therefore, on the condition of limited reaction and typing time of human as well as the limited data exchange volume of the RAB system, it is reasonable that the bid arrivals did not keep rising as the model showed.

- boredom in the middle, there is a peak in the FFT at about 5 minutes, we opine that human becomes bored with the game and slow the bidding rate, a important observation is that bidding in the middle reduces for available profit, which is not in the best interval of the λ player. The players as group, λ player, will try the maximizing their profit and by default return the best overall profit to the group. The second is a consequence of the first. Slowing the rate of bidding in the middle achieves this objective although usually affects the data bid of jobs.

This simple thought experiment does not prove that the cyclic pattern is caused by these three problems. Future research is recommended on this issue. A simple review of the intervals of successful bids at industrial site will provide this information.

Summary

In this part, the author used model regression to test if RAB bid arrivals data fits NHPP model. The further model regression significance test was done via goodness-of fit test. As the significant evidence, the testing results shows that RAB bid arrivals data can fit NHPP model. In addition, the changing of model residuals was explained by considering human behavior at games.

CHAPTER V

CONCLUSIONS

This is the twentieth Reverse Auction Bidding research in Texas A&M University. The research series were initiated by Mr. Robert G. Van Vleet II in 2004, who was introduced the tacit collision in bidding and bid shopping. Since that first study, nineteen studies have gathered data, or completed analysis of earlier studies. Guhya (2010) developed a significant number of the analysis techniques used for subsequent studies. Chouhan (2009) developed the study of personality related to returns in the game.

Sufficient case study data exist now to complete longitudinal studies of the bid data. This is the first of these studies; the objective of the study is to examine the statistical properties of the bid arrival time data. Shmueli et. al, (2004) postulated a non-homogeneous Poisson process model as the standard process for eBay online auction data.

A review of the bid arrival data against four statistical models, Gaussian, Power-law, homogeneous Poisson process and NHPP showed that the NHPP provided the best statistical fit to the bid arrival data. This result matches the findings from the eBay data. Although the common assumption is that a Reverse Auction Bidding is different to a normal auction in terms of price movement, the alternative objective remains of setting prices for goods and services. As with almost all economic transactions, that involves at least two players, a buyer and a seller. A simple two part games explain the RAB system.

Nine TAMU studies were established for development as an aggregate data set. A total of 6674 entries were reviewed to fit the model of the game play, about 242 were discarded. The data was binned in a different of time steps. A five- second interval plot showed evidence of the underlying Passion process.

The NHPP model was developed that matched the number of bids in the experiment data, as the first fit point. A statistical study, varying the time interval width from 30 to 60 second each, showed that a 45-second time interval of the data, with a model parameter $\propto$ of 0.5 ± 0.005 yielded the lowest χ^2 aggregate for the data.

Fast Fourier transformation analysis of the residual data showed that a few cyclic patterns were evident in the residual data. A number of minor human behaviors affects in a minor manner the results set. These concerns are a slowness to start bidding, a slight over compensation, just a start to catch up, boredom in the middle of the bidding period at 15-minute section and "bid sniping" at the end. The Fast Fourier transformation analysis indicated these minor cyclic patterns.

Reverse Auction Bidding studies provide a powerful tool to understand human behaviors in bidding, to see the underlying statistics is some detail and to gather a lot of fundamental data. The same statement is not true for other bidding system where limited data is available. This study confirms the hypothesis that a statistical distribution is existing to model the bid arrival times for a RAB game. The model with the best fit is a NHPP model as postulated for eBay online auction bid arrivals.

Future research concerns are:

- bid arrival time related to personality type;
- bid arrival time related to number of bidder;

- bid cost step by bidders;
- rate of return.

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APPENDIX A

THE KEIRSEY TEMPERAMENT SORTER

For each question, decide on answer a or b and put a check mark in the proper column of the answer sheet. Scoring directions are provided. There is no right or wrong answers since about half the population agrees with whatever answer you choose.

1. When the phone rings do you
   a. hurry to get to it first
   b. hope someone will answer
2. Are you more
   a. observant than introspective
   b. introspective than observant
3. Is it worse to
   a. have your head in the clouds
   b. be in a rut
4. With people are you usually more
   a. firm than gentle
   b. gentle than firm
5. Are you more comfortable in making
   a. critical judgments
   b. value judgments
6. Is clutter in the workplace something you
   a. take time to straighten up
   b. tolerate pretty well
7. Is it your way to
   a. make up your mind quickly
   b. pick and choose at some length
8. Waiting in line, do you often
   a. chat with others
   b. b. stick to business
9. Are you more
   a. sensible than ideational
   b. ideational than sensible
10. Are you more interested in
    a. what is actual
    b. what is possible
11. In making up your mind are you more likely
    a. to go by data
    b. to go by desires
12. In sizing up others do you tend to be
    a. objective and impersonal
    b. friendly and personal
13. Do you prefer contracts to be
    a. signed, sealed, and delivered
    b. settled on a handshake

14. Are you more satisfied having
    a. a finished product
    b. work in progress
15. At a party, do you
    a. interact with many, even strangers
    b. interact with a few friends
16. Do you tend to be more
    a. factual than speculative
    b. speculative than factual
17. Do you like writers who
    a. say what they mean
    b. use metaphors and symbolism
18. Which appeals to you more:
    a. consistency of thought
    b. harmonious relationships
19. If you must disappoint someone are you
    a. usually frank and straightforward
    b. warm and considerate
20. On the job do you want your activities
    a. scheduled
    b. unscheduled
21. Do you more often prefer
    a. final, unalterable statements
    b. tentative, preliminary statements
22. Does interacting with strangers
    a. energize you
    b. tax your reserves
23. Facts
    a. speak for themselves
    b. illustrate principles
24. Do you find visionaries and theorists
    a. somewhat annoying
    b. rather fascinating
25. In a heated discussion, do you
    a. stick to your guns
    b. look for common ground
26. Is it better to be
    a. Just
    b. merciful
27. At work, is it more natural for you to
    a. point out mistakes
    b. try to please others
28. Are you more comfortable
    a. after a decision
    b. before a decision
29. Do you tend to
    a. say right out what's on your mind

b. keep your ears open

30. Common sense is

    a. usually reliable

    b. frequently questionable

31. Children often do not

    a. make themselves useful enough

    b. exercise their fantasy enough

32. When in charge of others do you tend to be

    a. firm and unbending

    b. forgiving and lenient

33. Are you more often

    a. a cool-headed person

    b. a warm-hearted person

34. Are you prone to

    a. nailing things down

    b. exploring the possibilities

35. In most situations are you more

    a. deliberate than spontaneous

    b. spontaneous than deliberate

36. Do you think of yourself as

    a. an outgoing person

    b. a private person

37. Are you more frequently

    a. a practical sort of person

    b. a fanciful sort of person

38. Do you speak more in

    a. particulars than generalities

    b. generalities than particular

39. Which is more of a compliment:

    a. "There's a logical person"

    b. "There's a sentimental person"

40. Which rules you more

    a. your thoughts

    b. your feelings

41. When finishing a job, do you like to

    a. tie up all the loose ends

    b. move on to something else

42. Do you prefer to work

    a. to deadlines

    b. just whenever

43. Are you the kind of person who

    a. is rather talkative

    b. doesn't miss much

44. Are you inclined to take what is said

    a. more literally

    b. more figuratively

45. Do you more often see

    a. what's right in front of you

    b. what can only be imagined

46. Is it worse to be

a. softy

b. hard-nosed

47. In trying circumstances are you sometimes

    a. too unsympathetic

    b. too sympathetic

48. Do you tend to choose

    a. rather carefully

    b. somewhat impulsively

49. Are you inclined to be more

    a. hurried than leisurely

    b. leisurely than hurried

50. At work do you tend to

    a. be sociable with your colleagues

    b. keep more to yourself

51. Are you more likely to trust

    a. your experiences

    b. your conceptions

52. Are you more inclined to feel

    a. down to earth

    b. somewhat removed

53. Do you think of yourself as a

    a. tough-minded person

    b. tender-hearted person

54. Do you value in yourself more that you are

    a. reasonable

    b. devoted

55. Do you usually want things

    a. settled and decided

    b. just penciled in

56. Would you say you are more

    a. serious and determined

    b. easy going

57. Do you consider yourself

    a. a good conversationalist

    b. a good listener

58. Do you prize in yourself

    a. a strong hold on reality

    b. a vivid imagination

59. Are you drawn more to

    a. fundamentals

    b. overtones

60. Which seems the greater fault

    a. to be too compassionate

    b. to be too dispassionate

61. Are you swayed more by

    a. convincing evidence

    b. a touching appeal

62. Do you feel better about

    a. coming to closure

    b. keeping your options open

63. Is it preferable mostly to

    a. make sure things are arranged

    b. just let things happen naturally

64. Are you inclined to be

    a. easy to approach

    b. somewhat reserved

65. In stories do you prefer

    a. action and adventure

    b. fantasy and heroism

66. Is it easier for you to

    a. put others to good use

    b. identify with others

67. Which do you wish more for yourself:

    a. strength of will

    b. strength of emotion

68. Do you see yourself as basically

    a. thick-skinned

    b. thin-skinned

69. Do you tend to notice

    a. disorderliness

    b. opportunities for change

70. Are you more

    a. routinized than whimsical

    b. whimsical than routinized

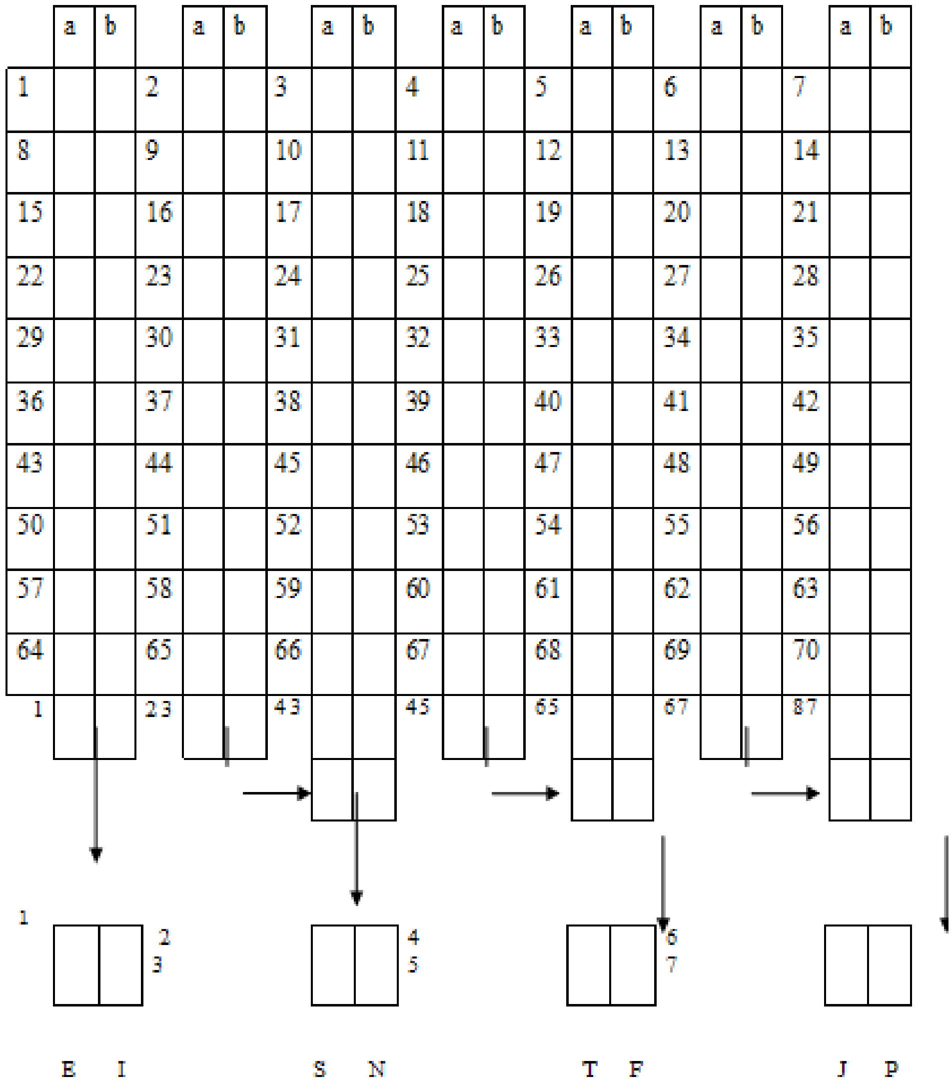

Figure 17 Sample Score Card