UNIVERSITÉ DE MONTRÉAL

TIMBER AUCTION SIMULATION AND DESIGN

FARNOUSH FARNIA

DÉPARTEMENT DE MATHÉMATIQUES ET DE GÉNIE INDUSTRIEL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

THÈSE PRÉSENTÉE EN VUE DE L'OBTENTION

DU DIPLÔME DE PHILOSOPHIÆ DOCTOR

(GÉNIE INDUSTRIEL)

AVRIL 2015

UNIVERSITÉ DE MONTRÉAL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

Cette thèse intitulée :

TIMBER AUCTION SIMULATION AND DESIGN

présentée par : FARNIA Farnoush

en vue de l'obtention du diplôme de : Philosophiae Doctor

a été dûment acceptée par le jury d'examen constitué de :

GAMACHE Michel, Ph. D., président

FRAYRET Jean-Marc, Ph. D., membre et directeur de recherche

BEAUDRY Catherine, ing., Ph. D., membre et codirectrice de recherche

LEBEL Luc, Ph. D., membre et codirecteur de recherche

ROUSSEAU Louis-Martin, Ph. D., membre

WANG Chun, Ph. D., membre externe

DEDICATION

To Maya Rose,

Masoud,

Tahereh & Mohammad

ACKNOWLEDGEMENT

I would like to take this opportunity and greatly thank my co-supervisors, Professor Jean-Marc Frayret and Professor Catherine Beaudry from École Polytechnique de Montréal and Professor Luc Lebel from Laval University for their supports and direction. Prof. Frayret was a great advisor that continuously supported me in many ways during my studies. I am highly grateful for all his non-stop supports and efforts.

I would like to thank FORAC consortium for supporting me in their professional environment. I am so honored to be affiliated with FORAC during my PhD studies, too many advantages to count. I would also like to thank FORAC staff for their support, especially Catherine Levesque for her kind support during these years. I am also thankful the Ministry of Natural Resources in Quebec (MRNF) specially Vincent Auclair for sharing the information and to being criticized.

My special thanks goes to my husband, Masoud Kalantari and my little sweetheart, Maya Rose Kalantari. My motivation for my PhD doubled from the second Maya entered my life. Masoud encouraged and supported me all the times during PhD study until I finish it.

The last but not least, I would also like to express my profound gratitude to my mother Tahereh Dadrasi, my father Mohamed, my sisters, Farnaz and Fatemeh. Words simply cannot express my deepest love to my family, specially, my mother who always encouraged me during my studies.

At the end, I would like to thank École Polytechnique de Montréal and its staff for giving me the opportunity to continue my PhD study.

Montreal, Quebec, Farnoush Farnia
April 22, 2015

RÉSUMÉ

La commercialisation sous forme de vente aux enchères publique du bois provenant de forêts, comme dans la province de Québec, est une tâche difficile. En effet, il est crucial de déterminer les prix représentatifs de la vente aux enchères de bois dans toutes les régions du Québec afin de permettre à plus d'acheteurs potentiels d'accéder au marché. De même, il est également important de concevoir un système d'enchères qui est bénéfique pour les entreprises forestières et les gens de Québec. La vente unitaire, dans lequel les utilisateurs de bois autorisés à soumissionner pour le lot entier, est actuellement appliquée comme une méthode de vente aux enchères. Dans ce système de vente aux enchères du bois, les utilisateurs de bois sont responsables de la récolte de la totalité du lot et pour la revente espèces ligneuses indésirables à d'autres utilisateurs.

Dans ce projet, nous analysons d'abord différentes configurations d'enchères à rondes multiples de type premier prix sous pli scellé, tel que proposé par le ministère des Ressources naturelles du Québec, afin de mieux comprendre la dynamique et les facteurs dominants de la réussite de ce type de mécanisme d'allocation de bois. Pour cela, nous utilisons la simulation à base d'agents pour modéliser et simuler des ventes aux enchères, en proposant notamment des comportements de soumissionnaires réalistes, incluant des stratégies d'adaptation et d'apprentissage, qui ont été simulées et comparées dans diverses configurations. Les comparaisons ont été menées en mesurant notamment le taux de succès de gagner l'enchère et le prix unitaire remporté en $\$/m^3$. Cette étude suggère également des configurations de paramètres permettant maximiser les recettes pour le commissaire-priseur.

À l'étape suivante de la recherche, cette thèse présente la simulation de la vente de plusieurs sortes de bois rond en utilisant une méthode d'enchères combinatoires. Dans ce processus de vente, les soumissionnaires peuvent avoir besoin d'une combinaison des produits. En utilisant l'approche par simulation, les résultats montrent que les revenus générés par enchère combinatoire peuvent être plus élevés que le revenu de l'enchère unitaire. Afin d'effectuer une analyse de sensibilité, les expériences sont répétées et testés avec diverses combinaisons de quatre paramètres de configuration. Les résultats de l'analyse permettent d'évaluer dans quel contexte l'enchère combinatoire peut faire mieux que l'enchère unitaire, et cela dans différents marchés.

Enfin, cette thèse présente un système d'enchères combinatoires qui alloue le bois aux soumissionnaires afin d'améliorer la coordination des dépendances entre les soumissionnaires retenus dans les zones forestières mixtes (c'est à dire avec plusieurs types de produits et utilisateurs potentiels). Pour supporter la coordination des opérations et améliorer la fraicheur du bois, nous proposons une vente aux enchères combinatoire, qui permet aux soumissionnaires d'ajuster la valeur des offres en fonction du temps, via une sorte de calendriers. Cette enchère combinatoire permet ainsi au commissaire-priseur de trouver les meilleures combinaisons de soumissions gagnantes maximisant ainsi les préférences temporelles des soumissionnaires. Pour cela, nous définissons un nouveau problème de détermination du vainqueur (WDP) qui utilise ces fonctions de valeur. Afin de comparer l'impact de diverses préférences temporelles, une analyse de sensibilité est menée.

Mots-clés: enchères du bois, enchères séquentielles, la stratégie d'apprentissage, systèmes multi-agents, l'affectation enchères combinatoire, la coordination, la fraicheur du bois, et de problèmes de détermination du vainqueur

ABSTRACT

The marketing of wood obtained from forests in public auction, such as in the province of Québec, is a challenging task. Indeed, it is crucial to determine representative prices of the wood auction in all regions of Quebec in order to allow more potential buyers to access the market. Similarly, it is also important to design an auction system that is beneficial for forest companies and the people of Québec. Single-unit auction, in which timber users allowed to bid on the entire lot, is currently applied as a method of auction. In this timber auction system, timber users (i.e., winners) are responsible for harvesting the entire lot and for reselling unwanted timber species to other users.

In this project, we first analyze various configurations of the multiple-round first-price sealed-bid auction of wood as proposed by the Québec Ministry of Natural Resources to better understand the dynamics and the dominant factors of success of this type of wood allocation mechanism. To do so, we use agent-based simulation to model and simulate auctions with realistic bidders' behavior. Different bidding patterns including adaptive and learning strategies are then simulated and compared in various setup configurations. The comparisons have been conducted on the success rate of winning the auction and the winning price per m^3. This study also suggests parameter configurations to maximize revenue for the auctioneer.

In the next step of research, in the last part, this thesis presents the simulation of multiple-round timber combinatorial auction as the bidders may need variety of species and the size of timber companies may be different. Using simulation approach, the results shows the revenue generated by combinatorial auction can be higher than the revenue of a single unit auction. In order to do sensitive analysis of the comparison, the experiments are repeated and tested with different setup configuration of four parameters. The results of analysis help to evaluate how combinatorial auction can perform better than single auction in different markets.

Finally, we intend to present an auction system, which allocates wood to bidders in order to improve the coordination of the dependencies between winning bidders in mixed forest areas (i.e., wood lots with multiple users). To achieve the coordination of procurement operations and improve the freshness of the wood, we propose an auction, by allowing the value of bids to be expressed as a function of time, via some sort of timetables, and by using a combinatorial auction that will allow the auctioneer to find the best combinations of winning bids. In order to do that, we define a new winner determination problem (WDP) that use these value functions for coordination procurement and delivery operations and wood freshness. In order to compare the proposed time-based combinatorial auction with combinatorial auction a sensitive analysis is conducted. The comparison is done according to bidders' and seller's time flexibility.

Keywords: timber auction, sequential auction, learning strategy, multi agent system, allocation combinatorial auction, coordination, wood freshness, and winner determination problem

TABLE OF CONTENTS

DEDICATION iii

ACKNOWLEDGEMENT iv

RÉSUMÉ v

ABSTRACT vii

TABLE OF CONTENTS ix

LIST OF TABLES xiii

LIST OF FIGURES xiv

LIST OF SYMBOLS AND ABBREVIATIONS xvi

INTRODUCTION 1

CHAPTER 1 : RESEARCH PROBLEM AND METHODOLOGY 3

1.1 Problem description and objective: 3

1.2 Research methodology 4

1.2.1 Methodology of timber auction design and simulation (Paper 1 & 2) 4

1.2.2 Multiple round single-unit auctions 4

1.2.3 Multiple-round combinatorial auctions 5

1.3 Methodology of time-base combinatorial auction (Paper 3) 6

1.4 Structure of thesis 6

CHAPTER 2 : CRITICAL REVIEW OF THE LITERATURE 7

2.1 Introduction 7

2.1.1 Forms of auctions 7

2.2 State of the art of timer auction design and simulation ... 8
2.2.1 Auction design in natural resources ... 8
2.2.2 Auction design aspects ... 10
2.2.3 Multi-agent simulation and auction design ... 12
2.3 Research opportunities ... 13
2.4 Contributions of the research thesis ... 14
CHAPTER 3 : ARTICLE 1 : MULTIPLE-ROUND TIMBER AUCTION DESIGN AND SIMULATION ... 15
3.1 Introduction ... 15
3.2 Theoretical background ... 17
3.3 Multiple-Round Timber Auction Model ... 20
3.4 Agents' model ... 22
3.4.1 Auctioneer ... 22
3.4.2 Bidders ... 23
3.5 Experiments ... 30
3.5.1 Methodology of experiments ... 30
3.5.2 Random parameters and common elements ... 31
3.5.3 Synthesis of the experiments ... 32
3.6 Results and discussion ... 33
3.6.1 Experiment 1 ... 33
3.6.2 Experiment 2 ... 36
3.6.3 Experiments 3 ... 38
3.7 Conclusion ... 43
3.8 Acknowledgement ... 43
3.9 Annexes ... 44
3.10 References: ... 46

CHAPTER 4 : ARTICLE 2 : AGENT-BASED SIMULATION OF MULTI-ROUND TIMBER COMBINATORIAL AUCTION 50

4.1 Introduction 50

4.2 Theoretical background and research objectives 52

4.3 Research objectives 54

4.4 Multiple-round timber combinatorial auction 54

4.4.1 Bidding approach 56

4.4.2 Winner determination 59

4.5 Results and discussion 61

4.5.1 Experiment 1 – Price per m^3 in combinatorial auctions 62

4.5.2 Experiment 2 – Target achievement of bidders in combinatorial auctions 64

4.5.3 Experiment 3 – Price per m^3 – comparison between combinatorial and single-unit auctions 67

4.5.4 Experiment 4 – Target achievement of bidders – comparison between combinatorial and single-unit auctions 68

4.6 Conclusion and future studies 73

4.7 Acknowledgements: 74

4.8 References: 75

CHAPTER 5 : ARTICLE 3 : TIME-BASED COMBINATORIAL AUCTION FOR TIMBER ALLOCATION AND DELIVERY COORDINATION 77

5.1 Introduction 78

5.2 Theoretical background 81

5.3 Time-based combinatorial auction 83

5.3.1 Auction system description 83

5.3.2 Bids structure 86

5.4 Winner Determination Problem 88

5.4.1 Mathematical model: 89

5.4.2 Timber freshness and delivery coordination 91

5.5 Methodology of experiments 92

5.5.1 Bidders' behaviour 93

5.6 Experiments 94

5.7 Results and discussion 96

5.8 Conclusion: 99

5.9 Acknowledgement: 100

5.10 References: 101

CHAPTER 6 : GENERAL DISCUSSION AND CONCLUSION 105

6.1 Multiple-round single unit timber auctions 105

6.2 Multiple-round combinatorial timber auctions 107

6.3 Time-based combinatorial timber auctions 108

6.4 Industrial impact of scientific contributions 109

6.5 Conclusion 111

6.6 Future work 112

BIBLIOGRAPHY 113

LIST OF TABLES

Table 3–1. Defining five configurations by assigning different α and β 31

Table 3–2. Experimental design specificities 33

Table 3–3. Analysis of variance of Price per m3 44

Table 3–4. Analysis of variance of Target Achievement.. 45

Table 4–1: Sets and indexes of the model... 57

Table 4–2: Analysis of variance for price per^3 from the combinatorial auctions 63

Table 4–3: Analysis of variance for the target achievement of bidders with combinatorial auctions 65

LIST OF FIGURES

Figure 3–1. Examples of adaptive approach behaviour 28

Figure 3–2. Average sale price per m3 of four approaches in different setup configuration 34

Figure 3–3. Average target achievement of four approaches in different setup configurations 35

Figure 3–4: Average target achievement of five approaches in different setup configurations 37

Figure 3–5. Average sale price of five approaches in different setup configuration 38

Figure 3–6. Comparative analysis of target achievement and sale price (Part 1) 40

Figure 3–7: Comparative analysis of target achievement and sale price (Part 2) 42

Figure 4–1: Price per m^3 from the combinatorial auctions; (a) impact of the number of auctions; (b) impact of the lot size; (c) impact of the number of bidders. 63

Figure 4–2: Comparative analysis of the price per m^3 from the combinatorial auctions: combined effect of number of auctions and lot size 64

Figure 4–3: analysis of the target achievement of bidders from combinatorial auctions: (a) effect of the number of auctions; (b) effect of periodicity; (c) effect of lot size; (d) effect of the number of bidders.. 66

Figure 4–4: Comparative analysis of the target achievement of bidders from combinatorial auctions: combined effects of each two parameter. 67

Figure 4–5: percentage change (combinatorial auction over single-unit auction) in price per m^3 as a function of (a) the number of auctions (b) lot size (c) the number of bidders, and (d) periodicity 68

Figure 4–6: percentage change (combinatorial auction over single-unit auction) in target achievement as a function of (a) the number of auctions (b) lot size (c) the number of bidders, and (d) periodicity 69

Figure 4–7(part 1): Comparative analysis of the impacts on sale price and target achievement (Part 1). (a) Price per m^3: combined effects of number of bidders and number of auctions. (b) Target achievement: combined effects of number of bidders and number of auctions. (c) Price per m^3: combined effects of number of bidders and lot size. (d) Target achievement: combined effects of number of bidders and lot size. (e) Price per m^3: combined effects of number of bidders and periodicity. (f) Target achievement: combined effects of number of bidders and periodicity. 71

Figure 5–1. Time-based good and bid definition 85
Figure 5–2: Time-dependant valuation of goods 87
Figure 5–3: Bid structure 87
Figure 5–4. Time management example 92
Figure 5–5. Examples of different time value function 94
Figure 5–6. Average loss of revenue (in percent of average revenue of combinatorial auction without time management) 96
Figure 5–7. Revenue for time-based combinatorial auction (TBCA) for different Ks and Variances 98

LIST OF SYMBOLS AND ABBREVIATIONS

WDP	Winner Determination Problem

INTRODUCTION

Recently, several issues caused decrease in timber sales in Quebec. Environmental issues have led to the modification of forest management practices on public land. Forest products markets collapse in the United States caused significant reduction in industrial activity. Following this reduction, drastic changes in forest management in the province of Quebec, Canada, also led to reduction in timber supplies under the Québec forest regime, which was based on an exclusive long-term licencing system. Moreover, the licensing system made it difficult to establish a fair price for timber transactions. All these changes resulted in the reduction of revenue for the government and the reduction of raw materials for local mills. Therefore, the government decided to sell part of supplies (25% of available timbers) through auction to determine the representative prices of the wood in all regions of Quebec, and to allow access to the timber market to more potential buyers. The buyers are interested in having the supplies according to the evaluation of their market. Selling wood through auction can help buyers to access supplies according to the value of their forest products market.

It is complicated to design an auction system along with stabilizing a certain level of guaranteed supplies. The design should consider different goals such as offering a certain level of stability to traditional user, offering opportunities to new entrepreneurs, and assuring a fair financial return for a public asset. It is important for the seller to know how to design an auction to maximize the benefit in different market conditions.

The sealed-bid auction is desirable since this type of auction is applicable in all forms of timber sales. Although theoretically from an economic point of view, the first-price sealed-bid auction is not the most effective auction, it is interesting especially for areas where there would be a low level of competition (Cramton, 1998). Indeed, there is no exchange of the information of prices that allow players to reassess their bidding values with the flow information. Thus, according to Cramton (1998), the first-price bid is preferable in a situation of information asymmetry and low level of competition. Using agent-based technology, simulation and design of the multiple-round single-unit auction can be investigated.

The timber auction system could also evolve into a combinatorial auction. A combinatorial auction allows the buyer to bid on any lot or combination of lots. This type of auction can significantly improve market efficiency when the value of a combination of lots is greater than the sum of individual lots' value (i.e., additive values).

If forest stands are mixed (i.e., several lots in one stand), the winners of a combinatorial auction must coordinate harvest operations. This can be a challenge for both the seller and the winners. If winners cannot reach an agreement regarding the period of harvest, timber freshness can be affected. Therefore, for a combinatorial auction to be implemented in the context of the Quebec natural forest, harvest operations coordination must be addressed.

This thesis proposes to study the performance of different configurations of first-price sealed-bid auctions and combinatorial auctions in the context of the Quebec natural forest. Both studies aim to identify the right auction configuration to use according to different possible auction design objectives. Next, an auction mechanism is proposed in order to address directly coordination issues during the combinatorial auction.

CHAPTER 1 : RESEARCH PROBLEM AND METHODOLOGY

This Ph.D. thesis is composed of three journal articles. These papers address the problems that were described in introduction of the thesis. These papers are as following.

1) Farnia. F., J.M. Frayret, L. LeBel, C. Beaudry, 2013 "*Multiple-Round Timber Auction Design and Simulation*", International Journal of production economics, 146(1), 129-141.

2) Farnia. F., J.M. Frayret, L. LeBel, C. Beaudry, 2014 "*Agent-based Simulation of multi-round timber combinatorial auction",* submitted to Canadian Journal of Forest Research.

3) Farnia. F., J.M. Frayret, C. Beaudry, L. LeBel, 2014 "*Time-Based Combinatorial Auction for Timber Allocation and Delivery Coordination*", Forest Policy and Economics, 50(1), pp 143–152.

This thesis consists of two main methodologies. The first main methodology is to simulate two different timber auctions using agent-base simulation platform (article one and article three). The second main methodology is based on developing and designing timber auction model called time-base combinatorial auction.

1.1 Problem description and objective:

The research problem consists of the design and simulation of timber auctions, which are applicable in the studied context, suggests solutions, and explain how the models are working in different market situations and auction parameters.

The objectives of the thesis are defined in order to build a solution for the general problem. The objectives are:

1) Propose a model in order to study the effects of the market situations and auction parameters on the outcome of the multiple-round single-unit timber auctions.
2) Propose advanced bidding patterns to the bidders on how they can get more advantage from the auctions.
3) Propose a model that can compare combinatorial timber auctions with single-unit timber auctions and addresses the situations in which one is better than the other.

4) Propose a solution to develop an auction that can determine the winners considering the coordination among multiple bidders in a given area to deliver high quality woods (fresh woods).

1.2 Research methodology

This part includes two main methodologies, which are applied to accomplish the problem objectives. The first methodology is designing and simulating multiple-round timber auctions including parameters analysis using agent-based simulation (first and second papers). The second methodology presents an auction method (time-base combinatorial auction), which overcomes the problems within current timber auctions (third paper).

1.2.1 Methodology of timber auction design and simulation (Paper 1 & 2)

The first methodology of the thesis includes design and simulation of multiple round timber auctions. The simulations are based on multi agent systems. The model consists of the seller, the buyers, and the auctioneer. In this methodology, the auctioneer announces several auctions periodically to the market. When the auctions are announced, bidders must decide whether or not they participate in auction and how much they want to bid.

The auction system includes several decision variables and parameters. There is a set of items with random parameters. The simulation model also contains three different types of agents according to their needs. The bidders contain several parameters including bidding pattern. After announcing items and collecting bids, the auctioneer chooses the winner(s). In order to allow the model to be dynamic, the bidder agents update their needs and their mill's capacity.

The simulation model includes several parameters such as the number of bidders, the average lot size, the auction periodicity, and the number of auction per year to study the impacts of different auction configuration.

1.2.2 Multiple round single-unit auctions

This methodology is used in paper 1, which is described in Chapter 3. The auctions that are announced in the multiple round auctions are first-price single-unit auctions. The items that the seller wants to sell are lots, which consists of four different types of products. In this model, after receiving bids, the auctioneer chooses the winner that has offered the highest price for each individual item.

This model allows the bidders to decide which item(s) they want to send their bids according to their need and the characteristics of the lot. In this model, the bidders also can decide their bid amount using their bidding pattern. To find the optimum bidding pattern, five bidding patterns are proposed: random bidding, fixed behaviour, adaptive, learning, and adaptive learning approaches.

To achieve the objectives of the first two contributions, three experiments have been conducted. In the first two experiments, different bidding patterns are compared in four different simulated scenarios. Each scenario is a combination of a number of potential bidders and an average lot size. These scenarios simulate the competitiveness of the market and the average wood supply amount in the market. In the first experiment, the four scenarios are compared where there are an equal number of bidder agents using each type of bidding patterns. In the second experiment, we compared the same four scenarios with five configurations of hybrid bidder agents of adaptive learning approach. Finally, in the third experiment, we used a factorial design plan as the combinations of three levels of each auction parameter in order to investigate the effects of auction configurations.

1.2.3 Multiple-round combinatorial auctions

In this methodology, combinatorial auctions are used at each round of auction. The advantage of using combinatorial auction is that it allows the bidders to bid on any combination of the four products of a lot. Therefore at each round, the bidder can bid on both the entire lot, or any subset of the lot. In this simulation model, the auctions that are announced are combinatorial auctions. For each auction the bidders bid on any combination according to their need using adaptive learning approach.

Several experiments have been conducted in order to achieve the objective of this thesis. First, the revenue of combinatorial auction is compared to the revenue of single-unit auction at each round of the auction, in order to evaluate the effect of combinatorial auction on revenue. Other experiments are repeated and tested with different setup configurations of four parameters, i.e., various numbers of auctions per year, periodicity, lot size, and number of bidders. The analysis of variance of the parameters on the timber price is also presented. To verify the results, the comparison of combinatorial auction and single unit auction is tested with different setup configurations. The comparison helps to evaluate whether combinatorial auction can outperform single-unit auction in certain conditions. Similar studies have been conducted to investigate the target achievement of bidders in combinatorial auction and comparison of both single and combinatorial auctions.

1.3 Methodology of time-base combinatorial auction (Paper 3)

This methodology includes the development of an auction, which considers coordination of harvest operations. In this methodology, first the concept of time-based combinatorial auction is presented. In this auction model, the bidders can also present their preferred combinations of goods at their time preferences. The winner determination problem (WDP) of time-base combinatorial auction is proposed. In this model, the seller can decide how flexible he can be on the duration of harvesting operation.

Several experiments have been conducted in this methodology. First, a sensitive analysis is performed in order to compare the proposed time-based combinatorial auction with a combinatorial auction. To investigate the effect of this model on the outcome of the auction, both models are compared according to bidders' and seller's time flexibility. The difference between the revenue of both combinatorial auction and time-based combinatorial auction associates with cost of coordination. This cost can be used as an upper bound of the cost of coordination.

1.4 Structure of thesis

This thesis proceeds as follows. The critical review of timber auction design and simulation is explained in Chapter 2. Article 1 is "Multiple-Round Timber Auction Design and Simulation", which is presented in Chapter 3. Next, Chapter 4 includes the article 2 describing "Agent-based Simulation of Multi-round Timber Combinatorial Auction". "Time-Based Combinatorial Auction for Timber Allocation and Delivery Coordination" which is the article 3 is also presented in Chapter 5. Finally, general discussion of the thesis is presented in Chapter 6, followed by a conclusion and future works (Chapter 7).

CHAPTER 2 : CRITICAL REVIEW OF THE LITERATURE

2.1 Introduction

The literature of the design and simulation of timer auctions consists of several main research areas. The first area of research includes the auction design in scarce natural resources. The other areas consist of auction design issues in general auction design such as multiple-round auctions, multi-agent simulation, bidding strategies, and combinatorial auction. Studying these areas led to the development of a state-of-the-art auction system for natural resources.

Some documentation is available on the allocation mechanisms in the timber sale system. In British Columbia, experts have determined that 20% sale on the open market of wood and 80% of wood sale under license would be sufficient to ensure a fair allocation. The statistical value of sales obtained by the British Colombia Timber Sale will be considered robust when nearly 20% of the public forest timber will be sold at auction (Athey *et al*. 2002). The study by British Colombia Timber Sale system shows that at least 40% of timber sales on the open market is used to allow a fair allocation (Crowe, 2008). Other research works suggest similar market allocations, which are discussed in more details in the upcoming chapters.

2.1.1 Forms of auctions

There are several types of auctions to consider for the sale of timber in Quebec: the English auction (the price goes up to the highest bid), the Dutch auction (the price goes down to the last time), the first price sealed bid auction, the Vickrey auction (the highest bid wins, but the winner pays the second price), simultaneous multiple auctions (all items offered at the same time), and combinatorial auction (a bid can be placed on an item or combination of items).

In this thesis, all the auctions that are applied in timber market are sealed-bid auctions. In this auction, the bidders cannot adjust their bids to others bids, since the information are not public. According to Milgrom (1989), the sealed-bid auctions are more suitable for governmental contracts and allocating natural resources.

2.2 State of the art of timer auction design and simulation

In this section we are introducing several aspects of the design and simulation of the auction. To better understand the literature review, we listed several topics, which are related to our research problem.

2.2.1 Auction design in natural resources

Oil, mineral, radio spectrum, and timber rights are limited natural resources where allocating and pricing the resources are important areas of research. The allocation of natural resources can be done through formal and informal processes. Auctions are formal process while generating research interest in economic, marketing and consumer behaviour fields. There are several reasons why auction is appropriate for allocating natural resources to companies (Cramton, 2007). Because auction is a competitive and transparent method for allocating natural resource while maximizes the revenue.

According to analyses of Cramton (2007), a selection of auction models are applicable for auctioning oil rights. The level of competition and structure of bidder preferences are two main factors of auction design. When the bidders have additive values and competition is low, first-price sealed-bid auction can be more appropriate. If bidders have almost additive values and competition is higher, then an open auction is applicable. These approaches can result in best-selling price and can decrease bidder uncertainty.

The main disadvantage of open auctions is that it is more vulnerable to tacit collusion; bidders can send signals during open auction. For example, companies can arrange not to compete against each other and consider punishment when they don't observe the agreement at the time of auction. However, in sealed bid auction signaling and punishment cannot be performed. Therefore, sealed-bid auction is preferable when collusion is an issue (Cramton and Schwartz, 2000).

Several auction models have been investigated to solve the timber allocation problem, considering different aspects of timber auction: (Mead (1967), Hansen (1985), Paarsch (1991), Elyakime et al. (1994, 1997), Baldwin et al. (1997), Athey and Levin (2001), Haile (2001), Athey et al. (2011). Auction is a competitive method of allocation while it maximizes the revenue for the seller. Auction design is crucial since it can make an efficient assignment of rights to bidders, and also maximizes revenue for the government (Cramton, 2007). Athey and Levin (2001) described that bids in timber auctions are multidimensional.

Athey Levin, and Seira (2004), studied bidding patterns in sealed bid and open timber auctions with various kinds of bidders. They observed US forest service timber to find out the comparative outcome of open and sealed bid auctions. Their key finding is that sealed bid auctions are better for timber market by virtue of attracting more small bidders, allocating more products to these bidders, and in some cases making higher revenue.

The structure of oil rights auction and spectrum auctions are comparable in type of auction design. The important differences of timber auction with these two auctions are the product of the auction and the structure of auction design is from dynamic and static aspects. In oil rights auction and spectrum right auction, the oral or open auction is more appropriate because of the degree of competition among bidders. In contrast, in timber auction the sealed bid or closed auctions are attractive (Athey Levin, and Seira, 2004). A disadvantage of open bidding is that the bidding process discloses information of others valuations (Milgrom and Weber, 1982). Furthermore, in oil rights auction and spectrum right auction the bidders are more interested in the entire oil right than in entire a timber right. In fact, in timber licenses, the bidders are not interested in all species in a specific area.

One of the common characteristics in all three auctions is that they encourage simultaneous auctions rather than sequential auction. A disadvantage of sequential auctions is that the auctions limit the information available to bidders and limit how the bidders can respond to information. In sequential auctions, the bidding pattern is complicated since bidders must predict what prices will be in upcoming auctions when defining bids in the current auction. However, sequential auction can be better in a case where there are many auctions.

Cramton (2009) declared that the concerns of the auction design are almost similar in all scarce natural resources. Generally, when the competition of the market is weak and the bidders have additive values, a simultaneous first-price sealed-bid auction can be the best allocation method.

Timber market includes a low degree of competition. The first reason is that the forest companies may not be interested in all species in the lot. Second, the cost of transportation from the lot to the bidder’s mill affects the number of participating bidders. Consequently, the timber auction is significantly different from the other applications of natural resource auctions, because of the complexity of the problem (distance and species composition).

2.2.2 Auction design aspects

Before considering design issues, it is important to think first about the bidders' preferences. There are three standard bidding valuation methods: private values, common values, and interdependent values. In private values, each bidder's value does not rely on the private market's information of the other bidders. Common values are situations where items have the same value to all bidders. Interdependent values are valuation functions in which each bidder's value of a product depends on his and other bidders' private information (Cramton 2009).

Auction design consists of several steps. The first step is to identify the objectives of the auction, what is the maximize revenue. The government wants to gain the maximum revenue over the long duration from its resources.

Other than the objective, it is essential that the auctioneer introduce a familiar method of explanation of bids to winners. The bids can be one-dimensional, or multi-dimensional bids. The next step is defining the product —what items should be sold in the auction. These products might be different in every kind of auction. The lot size, volume, and location are some example for product definition.

In the next step a number of basic design issues should be considered:

- Sequential vs. simultaneous sale with set of lots sold one after another or all at once
- Dynamic vs. static auctions by an ascending auction process or a single sealed bid
- The information for the bidders to know when they should send their bids
- Reserve prices or the minimum selling prices

One of the main issues of auctioning set of items is how to introduce the items in the market. Multiple-round auctions include set of auctions, which announce multiple goods consequently or concurrently (Grossklags et al., 2000). Bidder's behaviour can be analysed and predicated at the time of auction design to get more advantage of the multiple-round auction. The reason is that the behaviour of a bidder in an auction can change when there are other auctions in the market. Kagel (1995) studied and analyzed the bidding behavior of multiple-round auctions. More specially, Bidding in multiple-round online auction is investigated in many studies (Anthony and Jennings 2002, Shehory 2002, Airiau and Sen 2003, Greenwald and Boyan 2005, Gerding 2008, Yue et al. 2010).

Weber (1983) and Menezes (1993) compared the advantages and disadvantages of sequential auction and simultaneous auction. Zeithammer (2004) studied the bidders' behaviour, which considers forward auctions in sequential auctions. In forward-thinking behaviour, bidders bid lower if there are other auctions to be announced by the seller in upcoming auction. Ashenfelter (1989) also investigated that the selling price of each item drops consequently in auctioning multiple items. Ganuza (2004) concluded that in a round of an auction, the auctioneer should publish less information to the bidders in order to have more competition. Pinker et al. (2000) and Karuga et al. (2005) studied "the number of auctions" to be introduced at each round of an online sequential auction. Besides, Lange et al. (2011) considered the bidding behavior changing in multiple-round auction with resale option.

Bidding strategies is one of the main aspects that have been considered in different kind of auctions. Bidding strategy is a guideline to manage bidding in order to achieve the goal of the bidder. Zero-Intelligence-Plus (ZIP) strategy (i.e, agents adjust their offer prices with the market activity) is one of the simplest strategies (Gode and Sunder 1993, Cliff and Bruten 1997). ZIP Bidding strategies using history of past auctions (learning strategies) is studied by Boutilier et al. (1999) and Tesauro and Bredlin (2001). Various strategies can be used by bidders using mathematical functions to find the optimal bidding value. It is crucial to find the best strategy according to the situations of the auction.

Timber combinatorial auction is a way of allocating timber products to buyers. The timber products can be species or part of a lot and bidders can bid on any combination of these products (Cramton et al., 2006). The winning bid is the combination with the highest combined value of the bids. In resource allocation problem, when the resources are different, combinatorial auction is a practical technique (i.e. Rassenti et al., 1982; Ghassemi Tari and Alaei, 2013; Wang and Dargahi, 2013). In scheduling problems also combinatorial auction is proper method (i.e. Brewer, 1999; De Vries and Vohra, 2003; Cramton et al., 2006; Jung and Kim 2006).

2.2.3 Multi-agent simulation and auction design

Multi agent system is a computerized system that consists of intelligent agents which are interacting in an environment. The intelligent agents can sense and react in interaction with other agents without the direct interference of a user. The software agents also are able to manage their actions and goal-directed behaviours (Wooldridge and Jennings, 1994).

Recently, multi-agent simulation has been used to simulate and study auction systems (Vidal, 2007). Multi-agent simulation is an effective method to simulate and analyze auction systems while studying the complex interactions among different kinds of agents. Researches have analyzed the interaction among different agents with large-scale data. Specially, when the simulated auction is complex and there are many agents involves, multi-agent simulation handles the bidders' interactions and bidding strategies. Using multi-agent simulation, mathematical analyses do not need to be simplified and economic methods such as Bayesian Nash equilibrium are not assumed (Mehlenbacher, 2007). These advantages lead us to use multi-agent system for simulation and study multiple-round timber auctions.

Autonomous agents are used to analyze different bidding strategies in different applications. Artificial adaptive agents are used to implement some experiments in learning in auctions (Andreoni and Miller, 1995). Bapna et al. (2003) simulated auctions using multi-agents in order to maximize the profit for both seller and buyer. To combine three different bidding strategies, they suggested hybrid bidding strategies.

Combinatorial auction includes large-scale data, which can be easily done in Multi-agent simulation. Multi-agent simulation platform can handle both bidder's behavior and winner determinations (Vidal, 2007). The randomness of the parameters of the simulated auction model is a challenge in designing and simulating auction system (Shoham and Leyton-Brown, 2009). Combinatorial auction is investigated and simulated in several research works including Kutanglui and Wu (2001), where an autonomous distributed scheduling model is applied.

2.3 Research opportunities

Considering the need of government about implementing a proper auction system and analyzing the critical literature review guided us to several research ideas about simulating and designing timber auctions.

First, considering the literature review, it is an opportunity to simulate and analyze both sequential and simultaneous auctions simultaneously. Although the literature sometimes encourages simultaneous auctions due to complicated bidding pattern, this study considers both sequential and simultaneous since there are lots of auctions that should be announced. This study also proposes advanced bidding patterns to guide bidders how to bid in sequential auction to gain more profit.

Then, the bidders' behavior and bidding strategies in multiple-round timber auctions have not been studied in the literature. Although the methods of adaptive learning are hard to investigate in auctions, it does not take into account the time pressure and many other factors that should be considered in the context of timber auctions. For example, the bidders should consider the pressure of time in multiple-round of auctions since as time passes without wining on auction, the profit of running mills decreases due to fixed costs. Therefore, the bidders should change their bidding strategies as time passes.

Next, in timber auction the bidders may be interested in a part of a lot, which is different from other natural resources. Hence, when they win all species, they re-sell some species after they totally harvest the entire area. This may cause some problems in wood quality, such as wood deteriorating. Also, the winner would delay harvesting the area if it does not find a good buyer for some species in the area. Therefore, it seems that it is better to also study combinatorial auction, as the simulation of this kind of the auction has not been investigated yet.

Finally, synchronizing the forest operation planning among the winners in the same area is important for winner determination, as it cannot be described in combinatorial auction. The Lack of this kind of auction guided us to present time-base combinatorial auction. All of these parameters together make this kind of auction more complicated than the other auction applications in natural resource.

2.4 Contributions of the research thesis

This research thesis proposes three different contributions, which are presented in three papers.

The first paper proposes the design and the simulation of multiple-round single-unit timber auction. Using agent-based simulation, simultaneous sequential timber auctions are simulated. A mathematical linear programing model is developed to determine the best set of items to bid at each round of the auction. This paper suggests different bidding patterns including adaptive and agent-learning methods. This study presents parameter configurations of the model to maximize revenue for the auctioneer. This paper has been accepted in June 2013 for publication in the International Journal of Production Economics (submitted in January 2013)

The second paper proposes the design and the simulation of multiple-round timber combinatorial auction. The paper shows that the combinatorial auction can generate more revenue for the government comparing single unit auction in many different market situations. The markets conditions in which combinatorial auction can outperform single-unit auction are presented. This paper has been submitted to Canadian Journal of Forest Research.

The third paper proposes an auction system, referred to as time-based timber combinatorial auction. The contribution of this auction model is including time, which is used to valuate the good for sale with respect to expected delivery period in combinatorial auction. This system allocates multiple goods in mixed forest stand, to multiple winners, and to address the coordination of timber deliveries to winners while considering the freshness of wood. Moreover, the winner determination problem of time-base combinatorial auction is presented for the auctioneers who want to use this auction in their model. Finally, the model contributes on delivery coordination while it may impact total revenue due to loss of value when time preference is not fully satisfied. This paper has been submitted in December 2013 and accepted in July 2014 for publication in Forest Policy and Economics.

CHAPTER 3 : ARTICLE 1 : MULTIPLE-ROUND TIMBER AUCTION DESIGN AND SIMULATION

Abstract:

This paper presents a multiple-round timber auction simulation, developed in order to study various configurations of auction design. In this study, simultaneous sequential timber auctions are modelled and analyzed using agent-based simulation. As there are many individual items in the auction to be sold, the auction designer defines several rounds that are sequential at pre-defined intervals. At each round, the auction designer announces several simultaneous auctions. Since bidders are offered different items at each round, a mathematical linear programming model for selecting the best set of items to bid for is presented. Different bidding patterns are simulated and compared in various setup configurations. The most advanced of these strategies are adaptive and use agent-learning capability. The comparisons include the success rate of winning the auction and the winning price per m^3. This study suggests an efficient bidding pattern for bidders to bid in order to achieve to their goal and increase their profit. Similarly, in order to increase profit, the auctioneer (i.e., the government) needs to control several auction parameters including the number of auctions per year, the lot size, the auction periodicity, and the number of bidders. This study also suggests parameters configurations that to maximize revenue for the auctioneer.

Keywords: timber auction, sequential auction, learning strategy, multi agent system, and allocation.

3.1 Introduction

Environmental pressure to reform forest management practices on public land, as well as drastic reduction in industrial activity following forest products markets collapse in the United States, have led to a net decrease in timber sales. At the same time, successful mills or entrepreneurs complained that access to wood supply was impossible under the Québec forest regime, which was based on an exclusive long-term licensing system. Moreover, this licensing system made it difficult to establish a fair price for transactions. In response to these issues, the Québec government decided to make a portion of the annual wood supply (25%) available through an auction system, as soon as 2013. With wood available through auction, buyers can access supplies according to the value of their own forest products market. In such a context it is complex to design an auction system while preserving a certain level of guaranteed supplies. Different goals are pursued such as offering a certain level of stability to traditional user, offering opportunities to new entrepreneurs and assuring a fair financial return for a public asset.

In this paper the sealed first-price Auction protocol is considered as the interaction protocol between the auctioneer agent (i.e., a government agency) and the bidder agents (i.e., forest products companies). In this type of auction, bidders submit their sealed bids, all at the same time, without disclosure of the bid content to competitors. After evaluation, the bidder with the highest bid is announced to pay the proposed price and own the lot. This method of auction is different from the English auction method, in which each bidder can only bid once at each time. Further, bidders cannot adjust their proposed bid, since they do not have information about their competitors' bid. It is therefore more appropriate in this context to use sealed technique in tendering, such as in mining leases and governmental contracts (Milgrom, 1989).

Timber auctions aim at selling timber lots via a bidding process. The multiple-round timber auction is a process, in which the auctioneer announces several different items (i.e., wood lots) periodically to the bidders. The design of a simulation platform of a wood procurement system based on a multiple-round auction requires a framework that captures the basic dynamics of that system. Therefore, agent-based simulation is used in this study to design and simulate realistic agents' behaviours and bidding patterns in the context of a multiple-round timber auction.

In this paper, different combinations of bidding patterns and auction design parameters are simulated and compared in order to better understand the impacts of various factors of the auctions outcomes. The results show the combined influence of several auction design parameters and bidding patterns over both bidders' capacity to achieve procurement target and the seller's total profit.

The remaining of the paper proceeds as follows. Section 2 presents the literature review. The simulation multiple-round auction model is presented in Section 3, followed by the models of the agents' bidding patterns in Section 4. Section 5 presents the results of experiments designed to compare and validate the various bidding patterns. Next, Section 6 presents and discusses the results of experiments designed to specifically study the influence of various auction configurations. Finally, Section 7 concludes and presents the limitations of this research.

3.2 Theoretical background

Allocating and pricing limited natural resources, such as oil, mineral rights, spectrum, and timber, are two important questions. In order to solve timber allocation problems, many auction models have been used (Mead (1967), Hansen (1985), Paarsch (1991), Elyakime *et al*. (1994, 1997), Baldwin *et al.* (1997), Athey and Levin (2001), Haile (2001), Athey *et al.* (2011)). In practice, formal and informal processes are used to determine the allocation of natural resources. Auctions are an example of formal process for allocating and pricing natural resources. They have generated research interest in economic, marketing and consumer behaviour fields. Auction maximizes the revenue for the seller, while being transparent and competitive method of allocation. An efficient auction design can achieve both an efficient assignment of rights to bidders, and maximizes revenue for the seller (Cramton, 2007).

The auction process contains three main elements: auction issues, auction protocols, and auction strategies. The bidders apply the auction protocols to express clear rules and procedures. These rules are used to send bids, accept or reject proposals, as well as decide when the auction starts and ends. The bidders' preference and the need of the bidder at the time of auction are part of the auction strategies (McAfee and McMillan, 1987).

Multiple-round auctions usually consist of a number of auctions that are announced consecutively or concurrently, dealing with multiple goods (Grossklags *et al*., 2000). One of the important aspects of analysing this type of auction is to attempt to analyze and predict bidders' behaviour. To achieve this goal, different theoretical and empirical studies have been developed (Kagel, 1995). Many of the studies on bidding in multiple-round auctions involve online auction (Anthony and Jennings 2002, Shehory 2002, Airiau and Sen 2003, Greenwald and Boyan 2005, Gerding 2008, Yue *et al.* 2010).

Similarly, several studies have compared the advantages and disadvantages of sequential auction over simultaneous auction (Weber, 1983, Menezes, 1993). In sequential auctions, Zeithammer (2004) investigated the bidders' forward-looking behaviour. In forward-looking behaviour, bidders intend to underbid if they expect another auction by the seller to happen in the next round of the auction. Along the same line, Ashenfelter (1989) concludes that in selling multiple items through the auction, the selling price of the each item drops accordingly. Ganuza (2004) studies the sale item information to be revealed by auctioneer in a round of the auction. This study shows that to have more competition, the auctioneer should publish less information to the bidders. By using data from Internet auction sites, Pinker *et al*. (2000), and Karuga *et al*. (2005) study the number of items to be sold in each round of a sequential auction. However, in these studies, they did not consider both sequential and simultaneous auction. Furthermore, auction with resale is one of the aspects that can be considered in multiple round auctions. Lange *et al.* (2011) investigate changing in the biding behavior in timber auction with resale compare to the auction without resale option.

Similarly, bidding strategies have been studied in various kinds of auction systems. One such strategy is Zero-Intelligence-Plus (ZIP) strategy (Gode and Sunder 1993, Cliff and Bruten 1997). However the advantage of ZIP strategy is unknown over other strategies. In sequential and simultaneous auctions, Boutilier *et al*. (1999) and Tesauro and Bredlin (2001) investigated bidding strategies that use history (past auctions). Mathematical functions are widely used by different strategies to calculate optimal bid(s) value, or to calculate the amount of bid at every time step for the bidder.

The application of multi-agent technology to simulate and study auction systems is generating increasing interest (Vidal, 2007). Indeed, such a simulation allows researchers to study the interactions among agents and process large amounts of data. Furthermore, multi-agent simulation enables the modeling of bidders' interactions and bidding strategies in complex environments. Mehlenbacher (2007) explain that multi-agent simulation has some advantages, as it does not require simplifying assumptions of mathematical analysis, nor assumptions about Bayesian Nash equilibrium used by econometric methods.

However, although bidding processes have been used in the field of distributed artificial intelligence, such as in the Contract-Net, the design of a simulation system of auctions requires to address and overcome challenges. One of these challenges is the randomness of bidders' preferences (Shoham and Leyton-Brown, 2009 and Vidal, 2007).

In order to analyze different bidding strategies in different applications, several studies use autonomous agents. A software agent is a situated autonomous computer system capable of sensing and reacting to change in its environment without the direct intervention of a user. As a consequence, a software agent has a certain level of control over its actions. A software agent can also exhibit goal-directed behaviour by interacting with other agents or humans (Wooldridge and Jennings, 1994). These agents are autonomous and intelligent software entities that are designed to conduct different task with minimum human supervision. Andreoni and Miller (1995) implemented experiments with artificial adaptive agents systems and investigate learning in auctions. To study the interaction of agents they used genetic algorithm to implement adaptive learning algorithm. However, their method is not compatible with the context of time pressure, as many factors should be considered. They explained that adaptive learning is very hard to investigate in auction. Bapna *et al.* (2003) applied different types of agents to simulate auctions, aiming to maximize both seller and buyer profit. They introduced agents with virtual behavior that can play with real human bidders. They also proposed hybrid bidding strategies, which consist three different bidding strategies.

In an auction, bidders need to consider the other participants when they offer their bids. In contrast, a seller (i.e., the auctioneer) should consider the protocol of the auction, potential buyers, and other competing sellers in order to sell items with highest profit (Park *et al*. 1999). Agents use different models to find their best moves (i.e. equilibrium strategies); one model in game theory is to use a prediction of other bidder's possible moves and payoffs (Kreps, 1990). Other researchers have reported the design of an agent with the ability of predicting opponents, move in the bid, as well as opponents' idea about other participants (Gmytrasiewicz and Durfee, 1995; Vidal and Durfee, 1996). However, when the model is complex and dynamic with a large number of bidders, the behaviour modeling of other agents is impossible. Even if some models exist, using them is difficult and implementation is complex (Park *et al*. 1999).

Cramton (2007) studied the design of auctions and highlighted the reason why auction is appropriate for the allocation of natural resources to individual companies. For instance, the author claimed that the structure of bidder's preferences and the competition level are two examples of settings that determine the best auction format. Simultaneous sealed first-price auction is one of the best options for a weak competition and for bidders with additive values. It is indeed easy to implement. It requires no price discovery. It controls weak competition and bidder collusion (Milgrom 1987). Sealed-bid auction is less disposed to collusion, while in open bidding, bidders use predetermined agreements through their bids. Similarly, sealed-bid auction returns higher revenues when bidders have different preferences (Maskin and Riley 2000; Klemperer 2002).

Athey *et al*. (2011) used some data of timber sales for auction design to compare the results of open and sealed-bid timber auctions. As an observed outcome, small bidders are attracted more to sealed-bid timber auctions, which generate greater revenue for the U.S. in some forests.

In collaboration with the partner of this project, the *Bureau de mise en marché des bois* of the Québec government, a simulation platform was developed and implemented in order to study various configurations of multiple-round sealed-bid timber auctions. This type of auctions consists of a number of auctions announced at predefined time periods and concurrently (i.e., a each time period, a set of timber lots are announced simultaneously). It was selected by the *Bureau de mise en marché des bois* as the Québec timber auction system. The aim of this paper is to present a multi-agent auction simulation model and the results of various experiments, and to analyse these results in order to better understand the impacts of these configurations.

3.3 Multiple-Round Timber Auction Model

The proposed model contains three main components: the seller (i.e., government), the buyers (i.e., mills, entrepreneurs), and the auctioneer (i.e., a governmental agency). The auctioneer manages the publication and general organisation of the auction. The seller wants to sell several items (i.e., timber lots). The auctioneer announces the items periodically in several rounds of auctions. In other words, at each round, there are many items to be sold. At the start of each round, which is decided by the auctioneer, the items for sale in this period are announced. These items have specific characteristics such as their location, their timber volume, and their species and quality, which make them different from each other. Once the auctions are initiated, bidders must decide whether or not they wish to bid on these items, and how much. Because bidders can be located anywhere, transform different types of timber, and supply different forest products markets, they have different valuation and interest on each of the items.

The design of such an auction system includes several decision variables and parameters. First, there is a set of items (*I*) that the auctioneer announces to the bidders. Each item *i* is unique, with a specific set of features. In other words, the potential value of each item is different from the others. In the simulation, these features are randomly assigned to each item. More specifically, it is assumed that each item consists of two species including hardwood and softwood, two different levels of quality for each species, a predefined volume, a ground slope, and a geographic location. In other words, each item to be sold is represented by a volume of hardwood of quality 1, a volume of hardwood of quality 2, a volume of softwood of quality 1, a volume of softwood of quality 2, a location, and a reserve price. Before the auction, the seller can measure the reserve price. It is the lowest price the seller is willing to receive form each lot. However, to calculate this price, many factors should be considered to have an optimal reserve price. Paarsch (1997) describes how the optimal reserve price in timber auctions can be measured from some criteria such as volume of timber by species, upset rate of each species, location, year, and month of the auction. In this simulation, because there is limited information, the reserve price is set according to the location, the volume of hardwood of quality 1, the volume of hardwood of quality 2, the volume of softwood of quality 1, the volume of softwood of quality 2, and the upset rate of each species with different qualities.

Next, the simulation model contains different types of agents. Bidder agents, also called bidders (*j*), participate in the auction and bid for items. Here, three kinds of bidding agents are defined according to their needs for specific types of products. These three types include the paper mill, the lumber mill, and the entrepreneur. Paper mills mostly require softwood; lumber mills mainly need hardwood; and, entrepreneurs are interested in both softwood and hardwood. The parameters of each bidder include the type of bidder as well as its transformation capacity per year (i.e., both paper mills and lumber mills), their supply need per year, their location, their bidding pattern, and their forest products market price. Similarly, in order to study the impacts of various auction configurations, the proposed simulation model includes also several parameters such as the number of bidders, the average lot size, the auction periodicity, and the number of auction per year.

At the start of the auction, the auctioneer calls all of the potential bidders. These bidders may not be interested in all items. Therefore, at each round, several individual items are generated and announced to the bidders. For each individual item auction, each bidder i has an entry cost k_i of gathering information and entering the auction and a private value for the item v_i depending on their valuation of the item. Other factors include distance, supply need, transformation capacity, and the market price that mills can obtain for their products. Concerning entrepreneurs, their capacity is defined as the forecast of their buyers' aggregated demand. Similarly, their need is defined as their capacity minus the volume of their past wins.

After announcing items and receiving bids, the auctioneer chooses the winner that has offered the highest price for each item. Some bidders may win one or more items, while others may obtain none. If the item is not assigned at a specific round, it remains in the set of items to be sold and is announced again during the next round of the auctions until it is sold. The developed model allows bidder agents to update their needs in order to reflect changes in their environment.

3.4 Agents' model

The design of such a simulation platform requires the modelling of the behaviour and interactions of two types of agents, namely the auctioneer and the bidders. In sequential simultaneous timber auctions, bidders face two non-trivial decisions: (1) Which sub-set of items (i.e., timber lots) is more profitable for them to bid on; and (2) How much should they bid for each item. The first question depends on the characteristics of the lot and on the supply needs of the mill. The second depends on their valuation of each lot, as well as on the bidder's bidding pattern. The design of our simulation platform proposes several elements to address these questions. The next section explains the auctioneer's and bidders' decision problems and the processes design to solve and simulate them.

3.4.1 Auctioneer

In a sequential auction, at the start of each round, the auctioneer announces the auction. Once the auction is closed after a specific time period, the auctioneer identifies the winners. The design of a simulated auction system requires the auctioneer to consider the potential issues regarding the auction process and the behaviour of the bidders. One of the key issues in sequential auction is collusion. For a single unit auction, Graham and Marshall (1987) and Mailath and Zemsky (1991) address the collusion problem caused by a group of bidders who cooperatively agree to bid in an auction. Such cooperation usually occurs via meetings outside the auction. By colluding, bidders collaborate to decrease the level of competition to pay less for the auctioned items.

In order to avoid collusion, the *Bureau de mise en marché des bois* proposes in its auction design that an auction is cancelled if it receives 2 bids or less. In this context, the items for sale are simply offered again during the next rounds of auctions. In many cases, such a constraint prevents collusion because the probability of collusion is lower when a bidder wants to have an item at a specific time and the bidder knows there is a chance of cancelling the auction. Therefore, the bidders prefer participating in the action without collusion and winning the auction rather than collaborating with others and losing their winning chance. Similarly, mills belonging to the same corporate group or company are not allowed to bid separately. Another technique to avoid collusion is simply to increase the number of bidders. Because the auctioneer has a limited control over the number of bidders (there is indeed a limited number of forest products companies in the region), bids are allowed from outside of the region.

After selecting items to be auctioned, and for a given number of bidders, the auctioneer identifies the first highest price for each item, as long as the price is higher than the reserve price. Subsequently, the auctioneer announces the winner and the price paid by the winner. Hence, at the end of each period, all bidders know the winner of each item and its price. If an item does not have any winner, the auctioneer offers again that item at the next round of the auction.

3.4.2 Bidders

For each item i, bidder j chooses a value according to its bidding pattern. The value for the item could be either zero (not interested) or a number equal or larger than the reserve price RP_i. It is assumed the bidders know the reserve price of each item. In a single item auction, for each item i, bidder j has a private value $v_{i,j}$ for the item, as defined by equation (1).

$$v_{i,j} \in [RP_i, MP_{i,j}] \tag{1}$$

Equation 1 defines the value interval, where $MP_{i,j}$ shows the maximum price that bidder j is willing to pay for item i. This price reflects the price that the bidder is prepared to pay to have a minimum profit from the item. Obviously the farther the item is from the mill the smaller the maximum price, because of transport costs. According to the characteristics of the item (e.g., overall quality of the forest lot), bidders define their maximum prices. For each item i, V_i and R_i

show respectively the volume and the type of item. Furthermore, the distance of the item i to bidder agent j is shown by $D_{i,j}$. Equation (2) defines the maximum price $MP_{i,j}$.

$$MP_{i,j} = V_i(MRP_i - HC_i - D_{i,j}TC_i - PC_{i,j} - PR_{i,j}) \quad (2)$$

MRP_i is the average revenue of the final product generated from item i. HC_i is the cost of harvesting item i. $D_{i,j}TC_i$ is the total transportation cost. The average processing cost of converting the product i into the final product of bidder j is $PC_{i,j}$. Finally, $PR_{i,j}$ is the minimum profit that the company is willing to gain from the item.

3.4.2.1 Bidders' items selection problem

At each round, bidders are offered many items. They might consequently be interested in more than one item simultaneously. They should therefore decide on which items they want to bid, considering the characteristics of the items, including their species, their size and their quality, as well as the bidders' need and the items' distance to their mills. The distance from an item to the processing facilities must be considered since transportation accounts for a significant share of procurement costs. Bidders must also make sure they have the capacity to process (i.e., harvest and transport) the items they bid on. Furthermore, in practice, bidders might be more interested on larger volume items. In other words, when companies have access to more volume in the same location, they need less coordination with other mills or entrepreneurs, who might be interested in buy undesirable species (in case of mixed species lots). Larger volume items might also involves scale economies with respect to harvest cost. Therefore, bidders must weight these parameters and constraints in order to find the best set of items to bid on. A set of such items is referred to as the solution of items to bid on at each round. This best solution represents the mills or entrepreneurs list of items that are the most profitable to bid on. It is expected that bidders bid according to it. In some cases, bidders may have several possible sets of items to bid on. Bidder agents try to find the best solution in their region. The challenge is to establish the option that yields the most profit for them. Two opposite problems may arise from the bidding process. On the one hand, obtaining more than needed induces unnecessary costs for the bidders, such as inventory related costs. On the other hand, bidders can bid on several items and win nothing because they have poorly estimated their value or bid too low. This decision problem is defined by the following binary integer programing model:

$$\text{maximize:} \quad \sum_{i \in I} \frac{V_i}{D_i} x_i \tag{3}$$

$$\text{subject to:} \quad MP_{i,j}\, x_i \geq RP_i \qquad \forall\, i \tag{4}$$

$$\sum_{i \in I} V_i x_i \leq ND_j \tag{5}$$

$$x_i \in \{0,1\} \qquad \forall\; i \tag{6}$$

In this model, V_i, D_i, and RP_i are respectively the volume of item i, the distance of item i from the mill, and the reserve price of item i. $MP_{i,j}$ is the maximum price that bidder j is willing to pay for item i. The need of bidder j at time t (i.e., the total volume of wood to acquire) is ND_j. Binary decision variable x_i represents whether or not an item is selected.

In this formulation, each bidder assigns a weight to each possible item at each round. The weight is defined as the volume of the item over the distance of the item to the bidder's mill, in order to maximize the volume while minimizing the distance to obtain it. Therefore, the larger the volume and the smaller the distance, the more interesting the item is. Although it is rather simple, this interest indicator provides a good guide for bidders to identify interesting items.

The objective function aims to maximize the total interest of items. The first constraint (4) ensures that the bidder consider only the feasible items, for which the maximum price the bidder is willing to pay is higher than the reserve price of the item. Constraint (5) states that the sum of the selected items is less than its need, in order to avoid bidding on more items than needed. This may include a small buffer to account for lost bids. Equation (6) is the integrity constraint.

3.4.2.2 Approaches for the bidding patterns

In order to design realistic bidding patterns for simulation purposes, we first developed four pure patterns based on fundamental concepts from the literature that we adapted to the specific problem of forest auctions. Then, we compared and analyzed the performance of these four bidding patterns in order to ultimately develop and hybrid pattern capable of modeling a wide range of bidding behaviours. To do so, we assumed that bidders have information concerning past auction outcomes, including winners and winning prices of all items. In other words, we generally assumed that the information known by bidders is limited to private information and public information concerning the results of the previous auctions. The behaviour of bidders during in auctions is called the bidding pattern. Five bidding patterns approaches are presented hereafter, respectively *random bidding*, *fixed behaviour*, *adaptive*, *learning*, and *adaptive learning*.

3.4.2.2.1 Random bidding approach

In the *random bidding* approach, bidders bid randomly a value between a minimum price (or the reserve price) and a maximum price. This approach is the most simple pattern as bidders are inattentive to past auctions or private information and do not follow any particular logic. Equation (7) describes the random bidding approach. In this equation, *r* is a random number between 0 and 1.

$$v_{i,j} = r * \left(MP_{i,j} - RP_{i,j}\right) + RP_{i,j} \tag{7}$$

3.4.2.2.2 Fixed behaviour approach

The second approach is a slight variation of the random bidding approach. Therefore, in the *fixed behaviour* approach, bidders systematically bid according to their risk averseness, as shown in equation (8):

$$v_{i,j} = K * \left(MP_{i,j} - RP_{i,j}\right) + RP_{i,j} \tag{8}$$

Here, k is a constant between 0 and 1, which is decided by the bidder before the auction as a fixed bidding pattern. In other words, if k=1, then the bidder systematically bid her maximum value (i.e., risk averse). On the contrary, if k=0, then the bidder bids her lowest value (i.e., cool-headed).

3.4.2.2.3 Adaptive approach

Bidders using the random bidding and the fixed behaviour approaches are Zero Intelligent (ZI) agents (Mathieu *et al*. 2006). In other words, by using any of the first two approaches, bidders bid ignoring any internal and external information, such as past auctions wins. Although bidders do not know about other bidders' approaches, they can build a strategy line for themselves using private information. Wei *et al*. (2010) suggest a bidding pattern for multi-round auctions that considers the impact of time on the valuation function. Because we assume that bidders have an annual supply target to achieve in order to supply their mill with a specific type of wood, we exploited this idea to develop an approach that adjusts the valuation function according to the time remaining to achieve that target, but also to the remaining supply need of the bidder at the time of the auction. Indeed, the smaller the remaining time a bidder has to achieve her supply target, or the smaller the percentage of her target she achieved with previous auctions, the more concessions she is likely to make (i.e., the more risk averse she becomes). Consequently, we develop the third approach, namely the *adaptive* approach, in which bidders bid according to their perception of the pressure of the remaining time and supply need. In other words, the adaptive approach is designed to keep the bid value low, and to only increase it when the pressure to achieve the supply target is high.

Therefore, we define the influence of the remaining time to achieve the supply target (*t)* and of the remaining supply need to achieve the target (n) as a linear increasing function, defined by equation (9).

$$v_{i,j} = \left(\frac{MP_{i,j} - NP_{i,j}}{2}\right) * tanh\left(\alpha * \frac{f_1(y)}{f_2(d)} * \frac{f_{j3}(n)}{f_{j4}(c)} - 2\right) + \left(\frac{MP_{i,j} + NP_{i,j}}{2}\right) \tag{9}$$

Here, $f_1(y)$ and $f_2(d)$ are functions representing respectively the whole year (or time period over which the bidder must achieve a specific supply target) and the remaining time until the end of the year (or time period). Next, $f_{j3}(n)$ and $f_{j4}(c)$ are functions representing respectively the remaining supply need at the specific time of the auction, and the overall supply target of the bidder. All of these functions are continuously increasing. This valuation reflects a number between the minimum price and the maximum price for an item *i* that a bidder *j* is willing to pay.

This type of behaviour can be interpreted in the system as adaptive to the perceived pressure of time and supply need, with respect to the bidder's supply target. In other words, at the start of the year, bidders offer near minimum price as they have time to achieve their target. However, if their target is high, their perception of the pressure to achieve it may force them to bid higher. As the auction progresses, bidders have less time and therefore have fewer possibility of winning in the next rounds of auctions. Therefore, while they initially accept the risk of losing and decide to bid less, as time passes without winning, they will choose to bid more, with less profit, in an attempt to increase the likelihood of winning a bid. Figure 3–1 shows some examples.

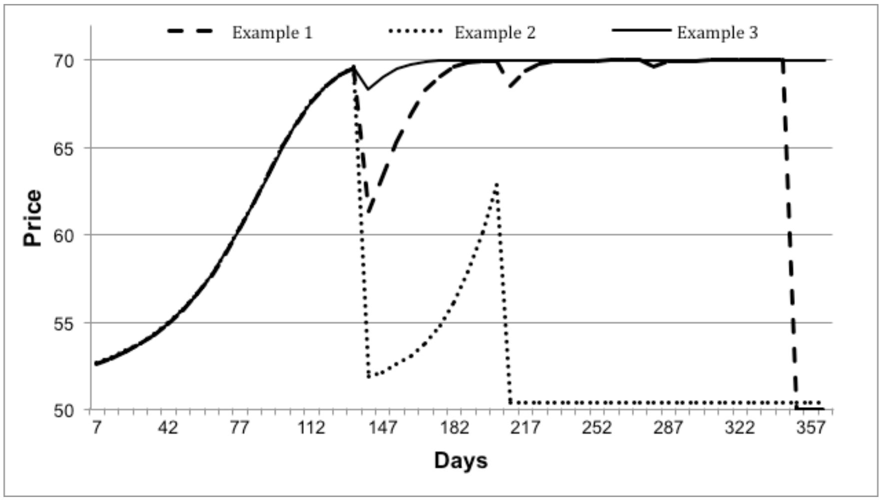


Figure 3–1. Examples of adaptive approach behaviour

In these examples, each point of each line shows a simulated bid at time *t* for an item with minimum and maximum prices of 50 and 70 respectively. At the start of the simulation, the bidder offers near minimum price, as there are still many opportunities to win. As the time progresses, if the bidder does not win, she incrementally bids higher. Drop points represent a specific win. When the bidder wins an item which volume represents a higher portion of her supply target, the drop is larger. When the bidder wins, she starts bidding from drop point, and gradually increases her bid until it reaches her maximum price or she wins again. Similarly, an early win of an item has a larger drop point than a late win of the same item, unless the supply target is achieved by the win. For instance, example 2 shows a bidder that has stopped bidding because she won sufficient bids early on.

3.4.2.2.4 Learning approach

Recently, agent-learning algorithms have reached remarkable outcomes (Vidal, 2007). The purpose of learning in multi-agent systems is to create some agents, which can use previous experience for their future bidding (Mitchell, 1997).

Learning theory leads to many valuable tools (Mathieu *et al*. 2006). These tools help multi-agent researchers to find the achievable equilibrium points of a system. At the design stage of a multi-agent system, designers do not know exactly every condition that agents will encounter during their operations. Therefore, by adding a learning capability to the agents, designers provide their agents with the capacity to adapt their behaviour to situations that happen at run time.

In sequential auctions, learning is a method that helps bidder agents to build their offers according to available information. Learning agents use algorithms to analyze available data to bid more carefully. In order to do this, we propose a learning approach, which aims to estimate the winning value of an item according to specific parameters, using the results from prior auctions, including sale prices, the items' lot sizes, and the winners' location. Using the distance between the winners' mill and the items, the price paid and the characteristics of the items, a learning bidder agent runs a regression model to estimate the likely value of new items to be auctioned. Such an approach allows bidder agents to identify an 'average' winning bidding pattern based on past auctions. At each round, learning agents computes the coefficient of the regression function (10), in which $y_{i,j}$ is the price of item i estimated by bidder j, $d_{i,j}$ is the distance of bidder j to item i, and $x_{1,j}$, $x_{2,j}$, $x_{3,j}$ and $x_{4,j}$ are the volumes of the four species/quality combination considered in this study.

$$v_{i,j} = y_{i,j} = \beta_0 + \beta_1 d_{i,j} + \beta_2 x_{1,i} + \beta_3 x_{2,i} + \beta_4 x_{3,i} + \beta_5 x_{4,i} \tag{10}$$

3.4.2.2.5 Adaptive learning approach

Out of the four bidding patterns presented above, only the last two strategies proposed some sort of bidding behaviour that changes over time according to specific, yet different, information input. The adaptive approach adjusts the valuation function according to bidder's objectives and the time left to achieve it. The learning approach only adjusts the valuation function according to past winning conditions. If these two behaviours seem to follow reasonable bidding rationalities, a rational bidder can adopt any bidding pattern that is between these two. Therefore, we introduced a fifth approach that is a hybrid of both the third (adaptive) and fourth (learning) approaches. More specifically, the valuation function of such a bidder is described by the equation (11).

$$v_{i,j} = \alpha\left(\frac{MP_{i,j} - NP_{i,j}}{2}\right) * tanh\left(\frac{f_1(y)}{f_2(d)} * \frac{f_3(n)}{f_4(c)} - 2\right) + \beta\left(\frac{MP_{i,j} + NP_{i,j}}{2}\right) + (1 - \beta)y_{i,j} \tag{11}$$

In this equation, α and β are coefficients defined within [0;1]. With such a hybridisation mechanism, the pure adaptive and learning bidding patterns can be reproduced. For instance, when $\alpha = \beta = 1$, the bidder behaves like a pure adaptive bidder. When $\alpha = \beta = 0$, the bidder agent behaves like a the pure learning bidder. This mechanism also allows creating bidder agents that equally demonstrate both behaviours simultaneously. In other words, when α = 1 and β = 0, the valuation function of the pure learning agent is adjusted by the pressure of target achievement as with the adaptive behaviour. On the contrary, when α = 0 and β = 1, the hybrid agent behave simply as a risk neutral bidder agent with a fixed behaviour.

3.5 Experiments

Several experiments were carried out in order to validate and analyze different aspects of the proposed model. The first two experiments were designed specifically to validate the programmed behaviors of the bidder agents. In the first experiment, we compared the four pure bidding patterns and analyse the results to make sure that the overall outcome of each strategies was coherent with their design specificities. Similarly, the second experiment was designed to validate the hybrid approach, and to compare, in a competitive setup, different configurations of hybrid bidder agents (from the pure adaptive to learning).

Next, in a third part, we carried out an experiment to better understand the impacts of various auction design parameters on the outcome of the auction. This experiment was specifically designed with randomly generated populations of hybrid bidder agents. A factorial design plan of 81 scenarios was implemented and simulated in order to understand the impacts of specific auction design parameters, including average lot size, periodicity, number of item sold and number of bidders. The results of this experiment were validated separately with experts from the *Bureau de mise en marché des bois* of the Québec government.

3.5.1 Methodology of experiments

The methodology we used to achieve the objectives of the study includes 3 experiments. In the first two experiments, four different scenarios were simulated. Each scenario is a combination of a number of potential bidders and an average lot size. Scenarios with different number of bidders are used to assess the impact of more or less competition on the auctions outcome, while scenarios with different average lot sizes are used to assess the impact of the average item size on supply target achievement. In each scenario of the first experiment, there are an equal number of bidder agents using each type of bidding patterns. In the second experiment, we simulated and compared the same four scenarios with a set of bidder agents containing an equal number of each five configurations of hybrid bidder agent, as described in Table 3–1. Finally, in the third experiment, a factorial design plan was used as the combinations of three levels of average lot size, three levels of periodicity, three levels of number of item sold, and three levels of number of bidders.

Table 3–1. Defining five configurations by assigning different α and β

β \ α	1	0.75	0.5	0.25	0
1	Adaptive approach (1)				
0.75				(4)	
0.5			(3)		
0.25		(2)			
0					Learning Approach (5)

3.5.2 Random parameters and common elements

For all experiments, the locations of bidders' mills and sold items are randomly generated. Transportation costs are calculated based on the Euclidian distance between items and mills. Other random parameters were generated by uniform distribution including lot size; volumes of hardwood and softwood of quality 1 and 2 in each item; process cost at each mills; annual production capacity of each bidder's mill; bidders' initial supply targets; and market price of each wood product made of hardwood and softwood of quality 1 and 2.

Because each bidder is generally interested in only one combination of species/quality, the market price is different for each combination of species/quality and for each bidder. Therefore, the market price is set to be lower for the species/quality the bidder does not want. It is equivalent to the price of the unprocessed wood in the market, plus transportation cost to the mill. Because market price affects the valuation function through equation 2, if an item contains a large volume of uninteresting species/quality, the resulting bid is lower. This assumption is realistic because we consider that in case of a win, the unused species/quality volumes are sold to other mills without any loss.

A simulation run consists in a 365 time period simulation, in which bidder agents have a unique bidding pattern according to the tested scenario. Each bidder agent is defined by specific public and private parameters including a mill location, a supply target to achieve and a set of cost and revenue functions. In order to obtain a relevant level of statistical significance, each simulation of each experiment was repeated several times. Also, a simple Taboo Search application was programmed in the simulation platform to solve the Bidders' items selection problem described in Section 3.4.2.1. This algorithm was used by all bidder agents in every simulation.

Next, in order to analyse the influence of specific design parameters, the average sale price per m^3 and the average target achievement of each simulation runs were measured. In the context of public land, the designer of the auction process is interested in both aspects of the auction outcome. More specifically, the average target achievement is a criterion that measures how much bidders are able to fulfill their needs. In other words, it measures the impact of the auction process on the sustainability of mills' economic activities. Target achievement of a bidder is defined as the volumes of all items won by the bidder during the entire simulation over its supply target. Next, the average sale price represents public economical gain from the auction process. In other words, although the auction process must be designed to generate a large economical gain in the interest of the public, it cannot do so at the expense of local economic sustainability.

3.5.3 Synthesis of the experiments

As summarized in Table 3–2, the first part of the experiments focused on the validation of the agents' behaviours. A total of 280 simulation runs were carried out. The second part studies the impacts of various auction design parameters on the outcome of the auction. 1900 simulation runs were carried out and analyzed. The next section presents and discusses the results.

Table 3–2. Experimental design specificities

	# of scenarios	# of repetitions	# of simulation
Part 1: Behaviour validation experiments			
1	2 parameters, 4 scenarios	Each scenario was repeated 50 times	200
	• number of bidders	2 levels (100 and 200)	
	• average lot size	2 levels (10,000 m^3 and 20,000 m^3).	
2	2 parameters, 4 scenarios	Each scenario was repeated 20 times	80
	• number of bidders	2 levels (100 and 200)	
	• average lot size	2 levels (10,000 m^3 and 20,000 m^3).	
Part 2: Auction design experiments			
3	4 parameters, 81 scenarios	Each scenario was repeated 20 times	1620
	• auction periodicity	3 levels (7 days, 15 days and 30 days)	
	• average lot size	3 levels (10.000 m^3, 15.000 m^3 and 20.000 m^3),	
	• number of items sold	3 levels (100, 250 and 500),	
	• number of bidders	3 levels (100, 150 and 200),	

3.6 Results and discussion

This section presents and discusses each experiment. Although more experiments were carried out during the development phases of the simulation platform, only the results of the mentioned experiments are analyzed in this paper.

3.6.1 Experiment 1

In this experiment, the average price is first considered to compare the four bidding patterns. Figure 3–2 shows the average sale price per m^3 of the four approaches in all tested scenarios.

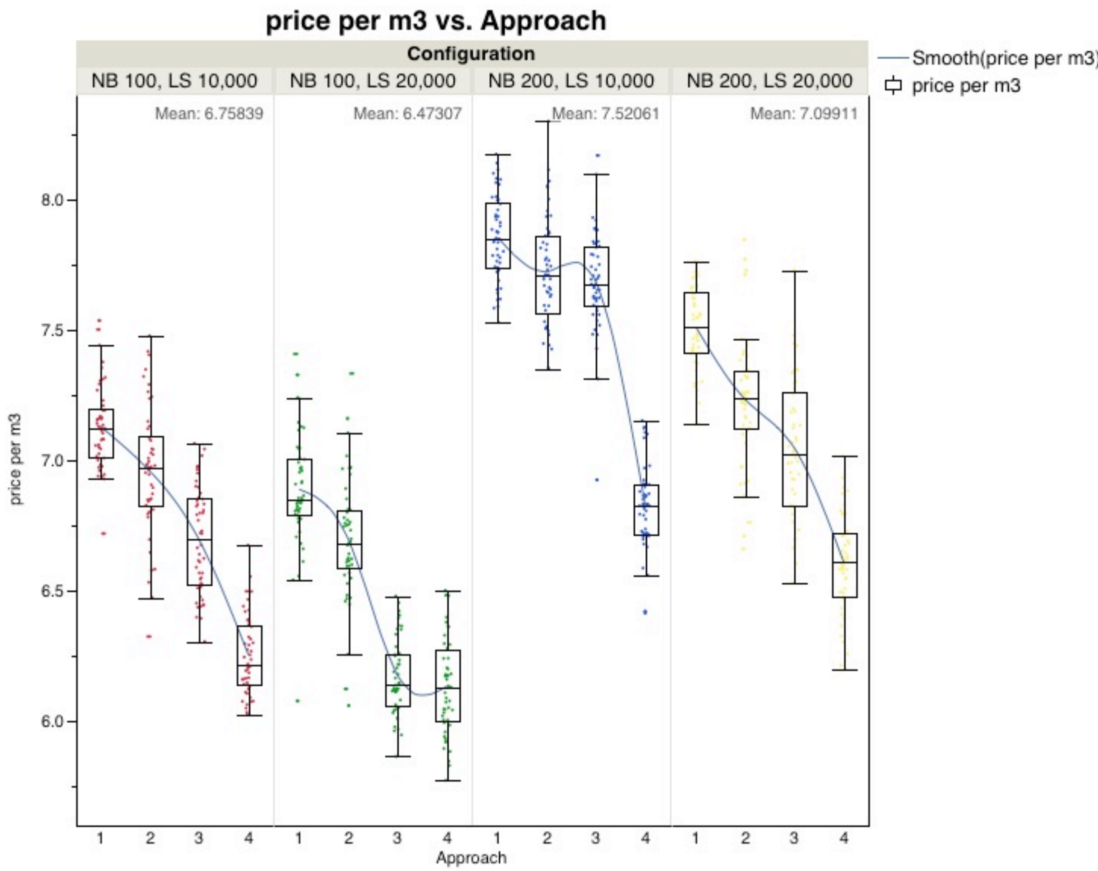


Figure 3–2. Average sale price per m3 of four approaches in different setup configuration

First, we can observe that bidders with strategies 1 and 2 pay, on average, more than the last two strategies, which is consistent with the development objectives. Indeed, a bidder using pattern 3 (i.e., the adaptive approach) bids systematically low, unless it is under pressure of achieving its supply target. Similarly, a bidder using the fourth pattern only bids what is likely necessary to win, and not more. This pattern is also more adapted than the third to achieve lower buying prices. Indeed, as seen in Figure 3–2, bidders using approach 3 pay a higher price than the bidders using approach 4, except in the situation where the competition is lower and the lots are larger (NB 100, LS 20.000). In this specific case, when an adaptive bidder wins an item, because the large volume of the item represents a larger portion of its supply target, its next bid will be lower than if the item represented a smaller portion of its need. Therefore, based on the price paid per m^3, the learning approach is better than all other approaches in almost every configuration. However, the price in the adaptive approach is almost equivalent to the price in the learning approach when the competition is low and the lots are bigger. This validates what we intended to program. Similarly, comparing the first scenario with the second, and the third scenario with the fourth, we can also observe that price paid seems to be less when items are bigger. This result, to be confirmed by the fourth experiments, is a first indicator on how to design the auction in order to maximize revenue from the seller point of view. The second aspect that we analyzed in these experiments is the average target achievement as seen in Figure 3-3.

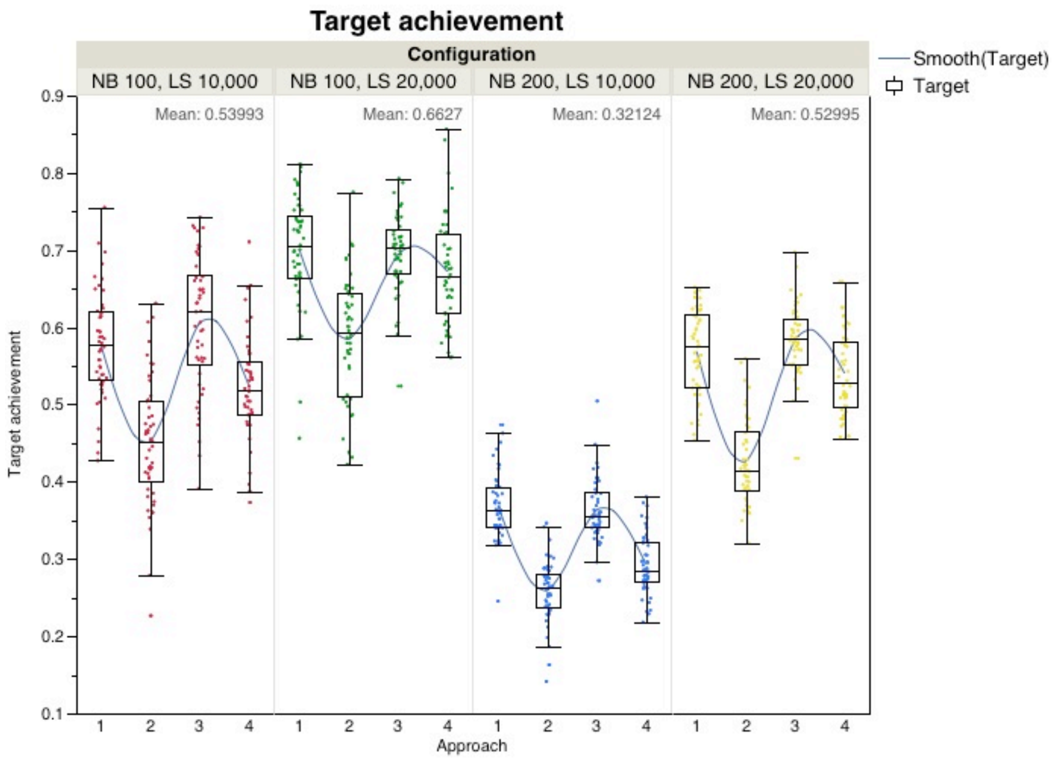


Figure 3–3. Average target achievement of four approaches in different setup configurations

Here, the average target achievement displays a similar general trend in all scenarios. Bidders using approach 2 have the lowest average target achievement. This is caused by the inability of their pattern to adapt the bid to win an item (not even by generating randomly a high bid like approach 1). Also, approaches 1 and 3 are able to generate a better target achievement than the other approaches. Although the target achievement of approach 1 and approach 3 are equivalent, it seems that bidders using approach 1 are only able to obtain a good target achievement by sometime generating higher winning bids. Therefore, they do so at the expense of their average paid price, which is much higher than bidders using approach 3 (see Figure 3–2). On the same token, bidders using the adaptive approach 3 are able to achieve lower paid price because they only increase their bids when needed (pressure to achieve the target). These bidders also outperform the bidders using the learning approach 4, because their bidding patterns controls the bid so as to improve target achievement, while the learning approach is insensitive to target achievement. These results, again, validate what we intended to program. .

In general, as shown in Figure 3–2 and Figure 3-3, bidders using approaches 1 and 2 tend to pay higher for the items in comparison to bidders using approaches 3 and 4. This occurs also while they do not necessarily achieve a better target achievement compared to bidders using approaches 3 and 4. As a result, the learning approach bidders pay less for the item, while the adaptive approach bidders have a better target achievement. Therefore, according to their objective, bidders should use any combination of these two approaches. This is why, in the remaining experiments, approaches 1 and 2 were abandoned, as they do not try to achieve any particular objective.

3.6.2 Experiment 2

In order to better understand the impacts of combining the adaptive and the learning bidding patterns, we carried out another experiment dedicated to validating this type of hybrid bidder agents. In order to see how this approach performs, we considered and compared 5 combinations of the adaptive and learning approaches, with different α and β as explained in Table 3–2. Note that the pure adaptive and learning approaches were included in this experiment. As studied in experiment 1, we compared the average price per m^3 and the average target achievement. As shown in Figure 3–4 and Figure 3-5, there are no absolute best hybrid bidder agents. However, the performance of the approaches is different in each of the four simulated scenarios. For instance, target achievement (Figure 3–4) seems generally more correlated to the scenario, than to the type of hybrid combination. However, in more competitive scenarios, the more adaptive the bidder agent is, the (slightly) better its target achievement. In less competitive scenarios, this advantage of the adaptive behaviour seems to fade, especially with respect to the learning bidder agents, which actually perform well, which is rather different from the results of the first experiment. This can be explained by the nature of the competitive game. In other words, the auctions simulated in the second experiment are more competitive than the auctions in the first. Indeed, in the second experiment, all bidder agents present some more or less pronounced capacity to adapt to achieve their supply target objective. However, this was not the case in experiment 1, in which bidder agents using approach 1 and 2 were incapable of adapting to the situation. Therefore, these agents were more prone to loose against more intelligent agents. Consequently, pure adaptive agents were not necessarily better than the hybrid agents from that perspective.

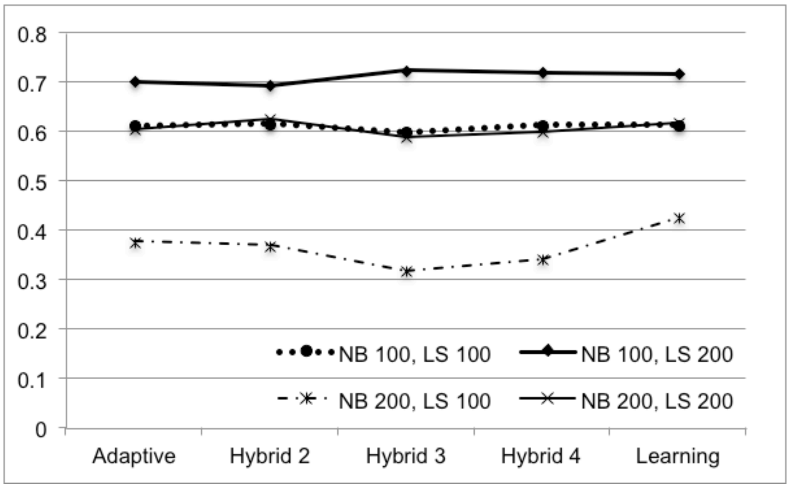


Figure 3–4: Average target achievement of five approaches in different setup configurations

Concerning the average sale price (Figure 3-5), several observations can be made. First, because an adaptive agent under pressure can offer bids that are higher than necessary to win an item, it is coherent to observe a poor performance of these agents to achieve a good sale price in a competitive game (BN 200, LS 10.000). However, when the game is less competitive (NB 100, LS 20.000), then adaptive agents actually perform well because they are designed to keep their bid as low as possible when not under pressure. This general result can be observed with hybrid agents as well. However, we can noticed that because hybrid 2, 3 and 4 are respectively defined with an incremental decrease of α from equation (11), and therefore an incremental decrease of the influence of the adaptive behaviour, it is coherent to observe a performance of these agents that becomes also incrementally further to the performance of the pure adaptive behaviour. In other words, the less a hybrid agent is influenced by the adaptive behaviour, the less sensitive to competition it is to achieving good sale prices. This also confirms the findings of the first experiment, which, compared to the learning approach, the adaptive approach has a stronger negative impact on the sale price, than it has a positive impact on target achievement.

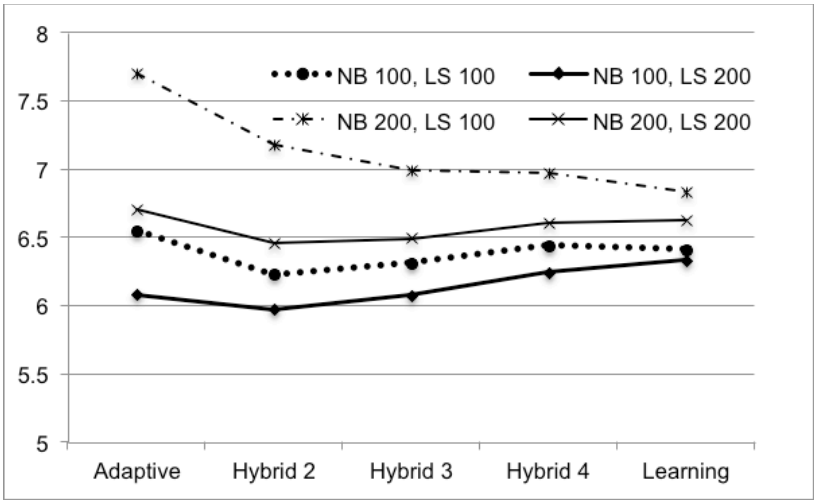


Figure 3–5. Average sale price of five approaches in different setup configuration

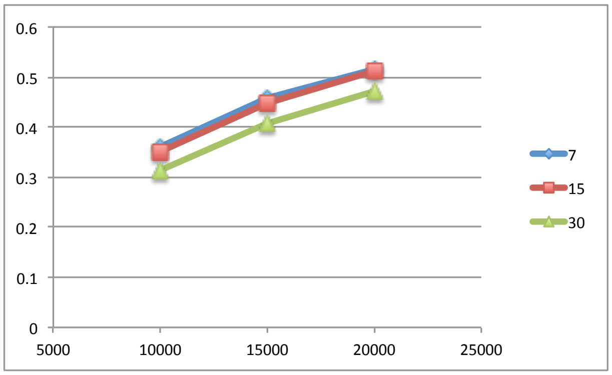
As expected, the observed performance of the different types of hybrid agent is generally correlated to how much of the pure behaviours they are made of. However, it seems that the influence of the adaptive behaviour is more significant than the influence of the learning behaviour, although they all display an almost equally good performance with respect to target achievement. Therefore we can safely assume that the generation of a population of randomly generated hybrid agents is representative of a population of rational bidders driven by any combination of both objectives.

3.6.3 Experiments 3

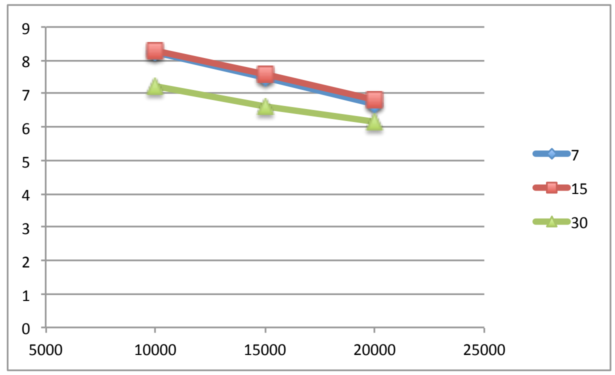
As discussed earlier, experiment 3 aims to better understand the influence of several auction design parameters on the outcome of the auction. In order to design such an auction, the designer needs to define the number of auctions per year, the average lot size of the items for sale, the periodicity of the auction, and, as far as possible, influence the number of bidders by, for instance, selecting lots' location in a strategic manner. These are referred to as the independent variable. From the seller's point of view, these design parameters should be defined in a way to maximize the revenue. However, because the seller is also the Québec government, it must make sure forest companies can operate at sufficient capacity to cover their fixed cost of operation by allowing them to be supplied with large enough quantity of timber. Therefore, as discussed previously, both the average price and the target achievement must be studied. These are referred to as the dependant variables.

As explained in the methodological section, experiment 3 is an extensive simulation of 81 different scenarios defined as the combination of various levels of number of bidders, item lot size, periodicity, and number of items sold as presented in Table 3–2. Using the data generated by the experiments, we carried out several analyses. First, an analysis of variance presented in the annexe (Table 3–3 and Table 3–4) validates statistically the results generated by the simulation model. For simplification purpose, this analysis only studies the influences of all combinations of just any two independent variables on both dependant variables. Both ANOVA studies present a R-square above .95, which indicates a high significant level of statistical confidence. Next, in order to better understand the combined influence of any two independent variables on the outcome of the auction, we systematically computed the average target achievement and sale price for the combination of all levels of all pairs of two design parameters.

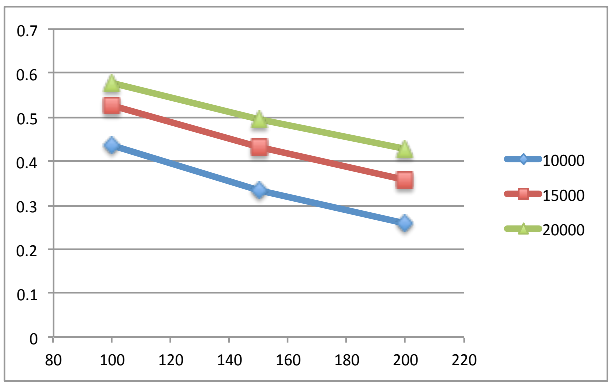
First, from a general standpoint, all results show systematic opposite effects of all design parameters on both outcomes. For instance, lot size affects positively target achievement and negatively sale price (Figure 3–6). More specifically, when item size gets larger, the sale price per m^3 decreases from \$9 to, sometime, \$4.5, which is rather considerable. This can be explained by the difference in the quantity of bidders interested in bidding. Indeed, large size items are not necessarily interesting to bidders with remaining supply needs smaller than the lot size. In other words, if items lot size are small, then the number of potential bidders for this item increases, which increases competition. Consequently, more participation in the auction causes more demand, which in turn affects the sale price. This result presents a limit of the model to be improved, as it is counter-intuitive for the experts who validated the model. Indeed, in this model, we consider a fix harvesting cost per m^3, although in reality, a scale economy can be gained from harvesting larger items (e.g., less low bed transportation are needed to move harvesting equipment). Therefore, if a scale economy can be gained from larger items, then bidders might be willing to pay more to win these items. Although this shortcoming limits our ability to investigate properly the impact of item size, it does not affect the remaining of the study insofar as the lot sizes of each simulation configuration are within a limited range. In other words, within each round of auctions, because the lot sizes are similar, no scale economy is significantly higher for some items. Therefore, these items are less interesting from that perceptive. However, if both small and large items are simultaneously sold within one round of auctions, then a fix cost of harvesting should be considered.



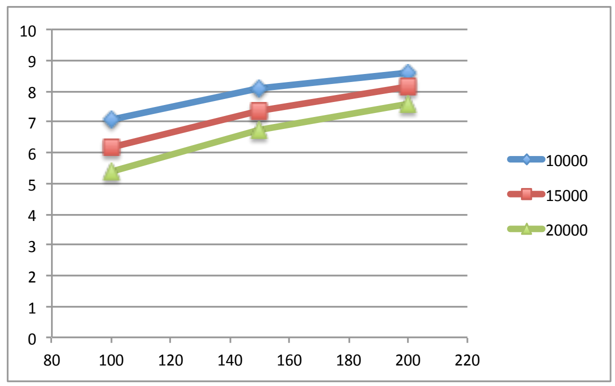
a). Target achievement: combined effects of periodicity and lot size



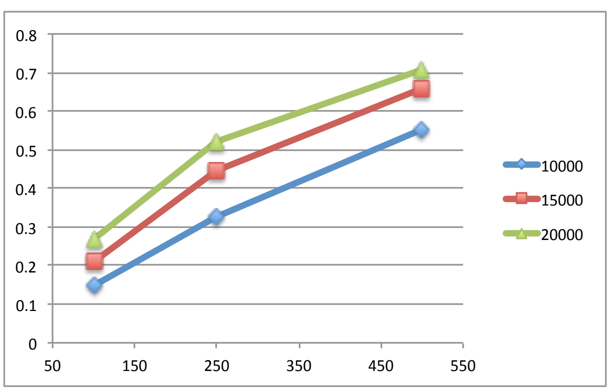
b). Price per m^3: combined effects of periodicity and lot size



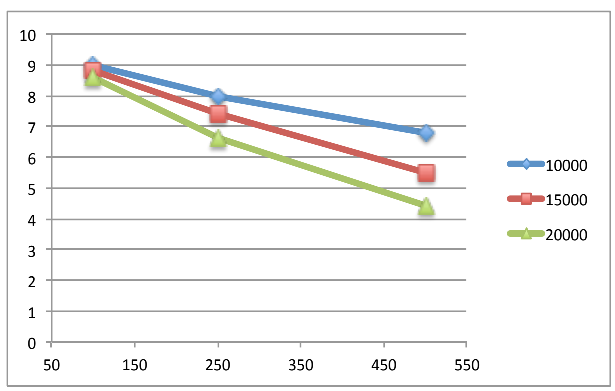
c). Target achievement: combined effects of number of bidders and lot size



d). Price per m^3: combined effects of number of bidders and lot size



e). Target achievement: combined effects of number of auctions and lot size



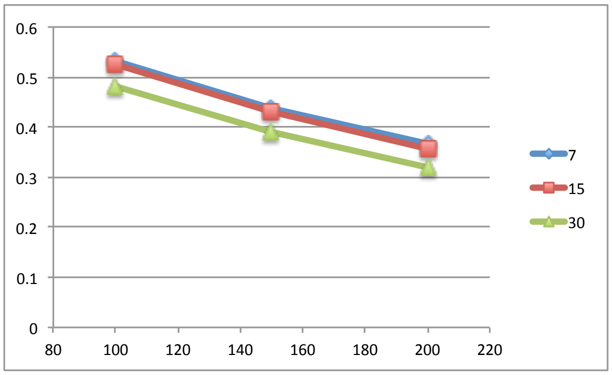
f). Price per m^3: combined effects of number of auctions and lot size

Figure 3–6. Comparative analysis of target achievement and sale price (Part 1)

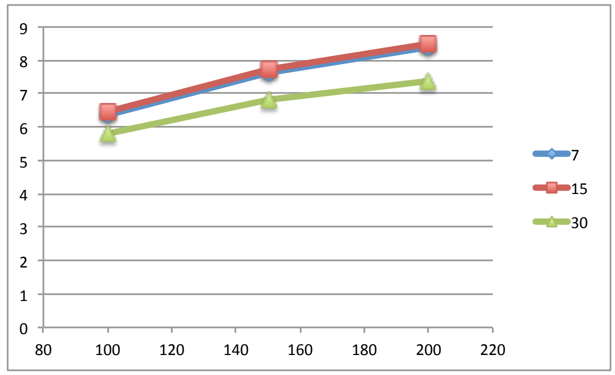
Along the same line, if lot size has a rather clear general influence on both outcomes, this influence is mitigated to different extents by the other design parameters. For instance, periodicity (i.e., the delay between two rounds of auctions) has a rather limited influence for values below 15 days. Indeed, as verified in the statistical analysis, there is no significant statistical difference between the simulation results with a periodicity of 7 days and a periodicity of 15 (Figure 3–6, a., b. and Figure 3-7, a., b., c., d.). However, a periodicity of 30 days between two rounds of auctions tends to decrease both target achievement and sale price. Therefore, shorter periodicities tend to be generally more beneficial than longer ones. This influence can be explained as follows. When periodicity increases, while the total number of auctions remains unchanged, the number of items for sale increases at each round. In other words, there are fewer rounds of auctions, but more auctions at each round. Consequently, the influence of periodicity on sale price target achievement can be explained by the fact that bidders can achieve lesser price if they can bid simultaneously on more items (i.e., more supply quantities per round).

Along the same line, and from a general standpoint, the number of auctions affects positively target achievement, and negatively sale price. Furthermore, it has a mitigating effect on both the lot size and the number of bidders. More specifically, as the number of auctions decreases, the influence of lot size (Figure 3–6, f.) and the influence of the number of bidders (Figure 3-7, f.) on sale price are reduced as well. For the same reason, this can be explained by the fact that reduced supply leads to a higher number of interested bidders, even if the items' lot size is large or the number of potential bidders is low. This result is interesting because it shows that higher competition, in other words, a higher number of interested bidders, with respect to a certain level of supply, leads to a market price that better represents the limit of forest companies to purchase items.

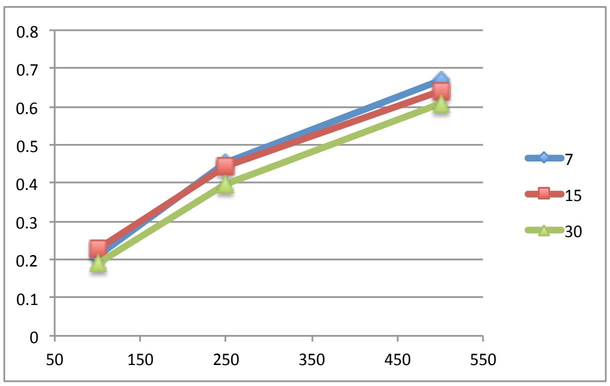
Differently, and as expected, the number of bidders has a positive impact on sale price, but a negative impact on target achievement, whatever the context (Figure 3–6, c., d. and Figure 3-7, a., b., e., and f.). This result can be explained as follow. As competition and demand increase, the number of bids received during each auction is similarly increased, which results in a higher probability of receiving high value bids. Along the same line, increased competition also reduces the probability of each forest company to win, and therefore reduces their ability to achieving their target.



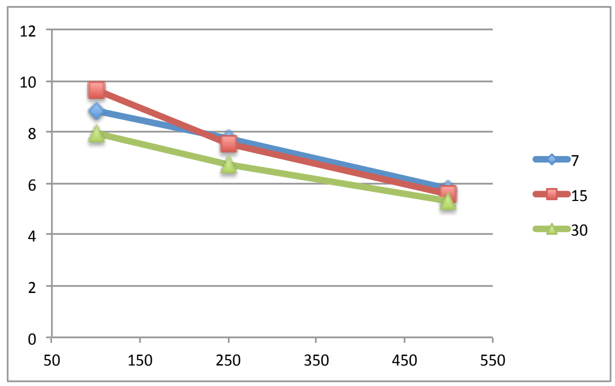
a). Target achievement: combined effects of periodicity and number of bidders



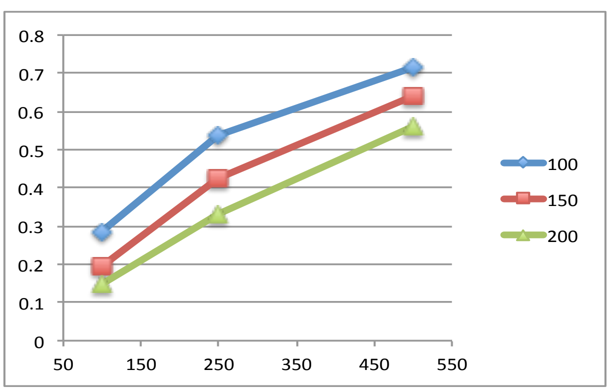
b). Price per m^3: combined effects of periodicity and number of bidders



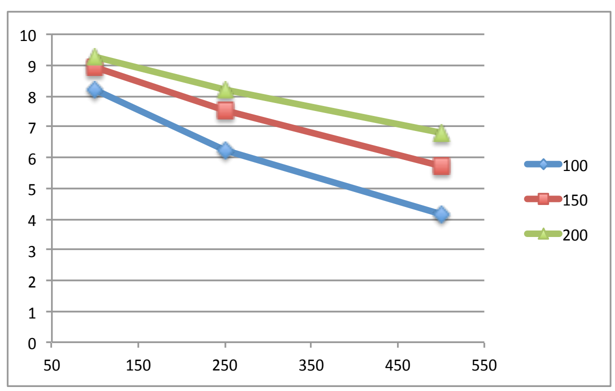
c). Target achievement: combined effects of periodicity and number of auctions



d). Price per m^3: combined effects of periodicity and number of auctions



e). Target achievement: combined effects of number of bidders and numbers of auctions



f). Price per m^3: combined effects of number of bidders and numbers of auctions

Figure 3–7: Comparative analysis of target achievement and sale price (Part 2)

Finally, we also studied the correlation between the target achievement and the sale price (results not presented). As it can easily be observed in Figure 3–6 and Figure 3-7, this correlation is negative, which tends to show that both objectives cannot be achieved simultaneously. In other words, it seems that the government that owns the forest has a dilemma as it can either maximize its revenue, or support the industry by allowing companies to better achieve their supply target, but not both.

3.7 Conclusion

This paper first proposed theoretical bidding patterns for the design of automated software agents in the context of natural resource auctions. These bidding patterns were then implemented into a multi-agent simulation platform, which was used in various simulation contexts in order to validate these models, as well as to better understand the impact of various auctions design parameters on the auction performance. This performance was measured through two main indicators illustrating, on the one hand, the forest companies' ability to achieve their supply needs (i.e., target achievement), and, on the other hand, the government's ability to generate revenue from the forest sales (i.e., sales price per m^3).

The analysis of the results first shows that the adaptive and learning bidding patterns have the best results and achieve their design objectives. They can thus be used as general guidelines in designing a company's bidding pattern. Next, concerning the design of the auction process, the results tend to indicate that the government (i.e., the forest owner) cannot simultaneously achieve high revenue while providing an effective supply channel to forest companies. It is therefore necessary to find a compromise in order to maintain forest companies' activities, and generate descent revenue for the public. The results also demonstrate the intuitive impact of the number of potential bidders on the revenue generated. It also shows that target achievement is improved by the sales of larger forest lots, while it decreases the average sales price.

3.8 Acknowledgement

This work was funded by the FOR@C Research Consortium, and the NSERC. The authors would also like to acknowledge the contribution of the experts at the *Bureau de mise en marché des bois*, of the Québec government for their advices, explanations and validation of the models.

3.9 Annexes

Table 3–3. Analysis of variance of Price per m3

Number of observations = 1620 *R-squared = 0.9687*
Root MSE = .320843 *Adjusted R-squared = 0.9681*

Source	***Partial SS***	***DF***	***MS***	***F***	***Prob > F***
Model	5061.57087	32	158.17409	1536.56	0.0000
Lot size	503.714321	2	251.85716	2446.63	0.0000
Periodicity	262.610509	2	131.305255	1275.55	0.0000
Lot size # Periodicity	13.0142071	4	3.25355179	31.61	0.0000
Number of Bidders	999.679136	2	499.839568	4855.62	0.0000
Lot size # Number of Bidders	21.4218789	4	5.35546972	52.02	0.0000
Number of Auction	2855.00328	2	1427.50164	13867.27	0.0000
Lot size # Number of Auction	172.841574	4	43.2103934	419.76	0.0000
Periodicity # Number of Bidders	12.7947761	4	3.19869404	31.07	0.0000
Periodicity # Number of Auction	103.995341	4	25.9988354	252.56	0.0000
Number of Bidders # Number of Auction	116.495846	4	29.1239614	282.92	0.0000
Residual	163.366382	1587	10294038		
Total	5224.93725	1619	3.22726204		

Table 3–4. Analysis of variance of Target Achievement

Number of observations = 1620 *R-squared = 0.9844*
Root MSE = .025587 *Adjusted R-squared = 0.9841*

Source	***Partial SS***	***DF***	***MS***	***F***	***Prob > F***
Model	65.6814675	32	2.05254586	3135.01	0.0000
Lot size	6.8359268	2	3.4179634	5220.52	0.0000
Periodicity	.710617117	2	.355308558	542.69	0.0000
Lot size # Periodicity	.003363833	4	.000840958	1.28	0.2739
Number of Bidders	7.43414058	2	3.71707029	5677.37	0.0000
Lot size # Number of Bidders	.039392754	4	.009848189	15.04	0.0000
Number of Auction	49.977939	2	24.9889695	38167.57	0.0000
Lot size # Number of Auction	.293985382	4	.073496345	112.26	0.0000
Periodicity # Number of Bidders	.001303433	4	.000325858	0.50	0.7374
Periodicity # Number of Auction	.13328915	4	.033322288	50.90	0.0000
Number of Bidders # Number of Auction	.251509432	4	.062877358	96.04	0.0000
Residual	1.0390365	1587	.000654717		
Total	66.720504	1619	.041210935		

3.10 References:

Airiau, S., Sen, S., 2003. Strategic bidding for multiple units in simultaneous and sequential auctions. Group Decision and Negotiation, 12(5), 397-413.

Andreoni, J., Miller, J., 1995. Auctions with artificial adaptive agents. Games and Economic Behavior, 10(1), 39-64.

Anthony, P., Jennings, N. R., 2002. Evolving bidding strategies for multiple auctions. In: Proceedings of the 15th European Conference on Artificial Intelligence, 178-182.

Ashenfelter, O. 1989. How auctions work for wine and art. Journal of Economic Perspectives 3:33-36.

Athey, S., Levin, J., 2001. Competition and information in us forest service timber auctions. Journal of Political Economy, 109(2), 375-417.

Athey, S., Levin, J., Seira, E., 2011. Comparing open and sealed bid auctions: evidence from timber auctions. The Quarterly Journal of Economics, 126(1), 207-257.

Baldwin, L. H., Marshall, R. C., Richard, J. F., 1997. Bidder collusion at forest service timber sales. Journal of Political Economy, 105(4), 657-699.

Bapna, R., Goes, P., Gupta, A., 2003. Replicating online Yankee auctions to analyze auctioneers' and bidders' strategies. Information Systems Research, 14(3), 244-268.

Binmore, K., & Klemperer, P., 2002. The biggest auction ever: the sale of the British 3G telecom licences. The Economic Journal, 112(478), C74-C96.

Boutilier, C., Dean, T., Hanks, S., 1999. Decision-theoretic planning: structural assumptions and computational leverage. Journal of Artificial Intelligence Research, 11, 1-94.

Cliff, D., Bruten, J., 1997. Minimal-Intelligence agents for bargaining behaviors in market-based environments. Hewlett-Packard Labs., Technical Report, HPL 97-91.

Cramton, P., 2007. How best to auction oil rights. In: Humphreys, M., Sachs, J. D., Stiglitz, J. E., (eds.). Escaping the resource curse. New York: Columbia University Press, 5, 114-151.

Elyakime, B., Laffont, J. J., Loisel, P., Vuong, Q., 1994. First-price sealed-bid auctions with secret reservation prices. Annales d'Economie et de Statistique, 115-141.

Elyakime, B., Laffont, J. J., Loisel, P., Vuong, Q., 1997. Auctioning and bargaining: an econometric study of timber auctions with secret reservation prices. Journal of Business & Economic Statistics, 15(2), 209-220.

Ganuza, J.J., 2004. Ignorance promotes competition: an auction model with endogenous private valuations. The Rand Journal of Economics, 35(3), 583-598.

Gerber, A., Klusch, M., 2002. Agent-based integrated services for timber production and sales. IEEE Intelligent Systems, 17(1), 33-39.

Gerding, E. H., Dash, R. K., Byde, A., Jennings, N. R., 2008. Optimal strategies for simultaneous vickrey auctions with perfect substitutes. Journal of Artificial Intelligence Research (JAIR), 32, 939-982.

Gmytrasiewicz, P. J., Durfee, E. H., 1995. A rigorous, operational formalization of recursive modeling. In Proceedings of the First International Conference on Multi-Agent Systems, 125-132.

Gode, D. K., Sunder, S., 1993. Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. Journal of political economy, 101(1), 119-137.

Graham, D. A., Marshall, R. C., 1987. Collusive bidder behavior at single-object second-price and English auctions. The Journal of Political Economy, 95(6), 1217-1239.

Greenwald, A., Boyan, J., 2005. Bidding algorithms for simultaneous auctions: A case study. Journal of Autonomous Agents and Multiagent Systems, 10(1), 67-89.

Grossklags, J., Schmidt, C., Siegel, J., 2000. Dumb software agents on experimental electronic markets. In: Informatiktage 2000, G. fur Informatik e.V.,Ed. Leinfelden-Echterdinge, Germany: Konradin Verlag.

Haile, P., 2001. Auctions with resale markets: an application to us forest service timber sales. American Economic Review, 91, 399-427.

Hansen, R., 1985. Empirical testing of auction theory. American Economic Review, 75, 156-159.

Kagel, J.H., 1995. Auctions: a survey of experimental research. In: Kagel, J.H., Roth, A.E., (Eds.). Handbook of Experimental Economics, Princeton University Press, Princeton.

Karuga, G., Nair, S., Tripathi, A. K., 2005. Sizing of lots in identical-item sequential online auctions. Working Paper, University of Connecticut.

Klemperer, P., 2002. What Really Matters in Auction Design. Journal of Economic Perspectives, 16(1), 169 – 189.

Kreps, D. M., 1990. Game theory and economic modeling. New York: Oxford University Press.

Lange, A., J. List and M. Price 2011. Auctions with Resale when Private Values Are Uncertain: Theory and Empirical Evidence. International Journal of Industrial Organization, 29, 54-64.

Lu, J., Perrigne, I., 2008. Estimating risk aversion from ascending and sealed-bid auctions: the case of timber auction data. Journal of Applied Econometrics, 21, 1221-1247.

Mailath, G., Zemsky, P., 1991. Collusion in second price auctions with heterogeneous bidders. Games and Economic Behavior, 3, 467-486.

Maskin, E., J. Riley, 2000. Asymmetric Auctions. Review of Economic Studies, 67, 439 – 454.

Mathieu, P., Beaufils, B., Brandouy, O., 2006. Artificial economics, agent-based methods in finance, game theory and their applications. Berlin: Springer.

McAfee, R.P., McMillan, J., 1987. Auctions and Bidding. Journal of Economic Literature, 25, 699-738.

Mead, W. J., 1967. Natural resource disposition policy: oral auctions vs. sealed bids. Natural Resource Journal, 7, 194-224.

Mehlenbacher, A., 2007. Multiagent system platform for auction experiments. University of Victoria, Economics Department Discussion Paper, DDP0706.

Menezes, F.M., 1993, Sequential actions with delay costs, a two-period model. Economics Letters, 42.

Milgrom, P., 1989. Auctions and bidding: a primer. Journal of Economic Perspectives, 3, 3-22.

Pinker, E., Seidmann, A., Vakrat, Y., 2000. Using transaction data for the design of sequential, multi-unit, online auctions. Working Paper CIS-00-3, Simon School, University of Rochester.

Mitchell, T. M., 1997. Machine learning. Boston: McGraw Hill.

Paarsch, H., 1991. Empirical models of auctions and an application to British Columbia timber sales. University of British Columbia mimeograph.

Paarsch, H., 1997. Deriving an estimate of the optimal reserve price: An application to British Columbian timber sales". Journal of Econometrics 78, 333–357.

Park, S., Durfee, E.H., Birmingham, W.P., 1999. An adaptive agent bidding strategy based on stochastic modeling. Agents, 147-153.

Shehory, O., 2002. Optimal bidding in multiple concurrent auctions. International Journal of Cooperative Information Systems, 11, 315-327.

Shoham, Y., Leyton-Brown, K., 2009. Multiagent systems: algorithmic, game-theoretic, and logical foundations. Cambridge University Press.

Tesauro, G., Bredlin, J. L., 2001. Strategic sequential bidding in auctions using dynamic programming. In Proceedings of the First International Conference on Autonomous Agents, Bologna.

Vidal, J. M., 2007. Fundamentals of multiagent systems with NetLogo examples.

Vidal, J. M., Durfee, E. H., 1996. The impact of nested agent models in an information economy. In: Proceedings of the Second International Conference on Multi-Agent Systems, 377-384.

Weber, R.J., 1983. Multiple-object auctions. In: Wiggans, R., Shubik, M., Stark, R.M., (eds.). Auctions, bidding, and contracting: uses and theory. New York: New York University Press, 165-191.

Wei, Z., Shu-juan, J., Juan, Z., Yong-quan, L., 2010. Simulation and strategy analysis for multi-round auction. In: 2010 IEEE International Conference on Educational and Information Technology (ICEIT), 2, V2-4.

Yue, C., Mabu, S., Yu, D., Wang, Y., Hirasawa, K., 2010. A bidding strategy of multiple round auctions based on Genetic Network Programming. In: 2010 IEEE Congress on Evolutionary Computation (CEC), 1-8.

Zeithammer, R., 2004. An equilibrium model of a dynamic auction marketplace. Working Paper, University of Chicago.

CHAPTER 4 : ARTICLE 2 : AGENT-BASED SIMULATION OF MULTI-ROUND TIMBER COMBINATORIAL AUCTION

Abstract:

This paper presents a simulation-based analysis of a multiple-round timber combinatorial auction in the timber industry. Currently, most timber auctions are single unit auctions (i.e., each forest stand is sold separately). However, other types of auctions could be applied in order to take advantage of the various needs of the bidders with respect to species, volumes and quality. This study aims to analyze the use of combinatorial auction to this specific context using a simulation approach. Various number of auctions per year, periodicity, lot size, and number of bidders are considered as parameters to setup the different market configurations. The outcomes of both combinatorial auction and single unit auction are compared with respect to different setup configurations. In particular, this analysis shows that combinatorial auction can bring more profit for both seller and buyer when the market is less competitive.

Keywords: Timber auction, combinatorial auction, learning strategy, multi-agent simulation

4.1 Introduction

Several problems plagued the timber market in Québec in recent years: decrease in forest activities, drop in lumber sales, and constrained access to wood supplies. One of the issues relates specifically to the long-term exclusive timber licences: the wood supplies of a timber licence may not always match the company's needs at a specific time. Consequently, allocating timber access to suitable companies for a defined time period has been one of the main problems for the Québec government. In the new forest regime now in place in Québec, auctions are applied in order to assign 25% of the timber lots that were previously assigned through licencing. This new regime results in a more flexible access to timber, as well as a price index that will be used to establish timber licence prices.

There exist two main types of auctions for timber allocations: single-unit auctions and combinatorial auctions. On the one hand, in a single-unit auction, the seller aims to sell the whole lot to one bidder. Currently, most timber auctions use the single-unit method because of its ease of implementation. When the winner of each lot is announced, the winner has a specific time period to access the lot according to its need. The Québec government uses single-unit auctions to allocate timber access to buyers who are willing to pay more for entire lots.

On the other hand, timber combinatorial auctions may have some advantages over single-unit auctions. These more complex auctions allow bidders to bid on any combination (bundle) of items according to their needs. Here, items are not geographically defined forest stands. They can be defined, for example, as specific volumes (lots) of a specific mix of species and quality within a given stand. Therefore, mixed forest stands can be sold to potential users. In order to identify the winners, the auctioneer must compute the highest value of the bundles. Once identified, the winners must agree on a specific time to harvest the stand in which they share the access.

In this paper, timber combinatorial auctions are studied as an interaction procedure between an auctioneering agent and several bidding agents to assign timber quantities. The auctioneer, i.e. government agents, announces several different lots with defined types of products (i.e., mixed of species and quality) to the market on a regular basis through combinatorial auctions. The bidders (i.e., forest companies and entrepreneur agents) offer sealed bids for any bundle of products of the lots that are announced at each round. The bidders are not allowed to change their offers after submitting their bids. As mentioned above, the auctioneer chooses the winners according to the highest value of the bundles, and the bidders must agree on a specific time to harvest the stand. In order to study these interactions and this type of procedure, a simulation model was developed.

The simulation model needs a framework to follow the dynamics of the auctions systems over the course of several rounds. Agent-based modeling was used to design and implement different agent behaviours. In other words, it was used to simulate realistic bidding agents, auctioneer agent, and auction mechanisms, including realistic bidding patterns and auctioneer's winner determination process.

This paper, which extends Farnia *et al*. (2013), explores how the outcomes of combinatorial auctions in terms of selling price per m^3 (revenue of the seller) and bidders' target achievement can change in different setup configurations. In addition, the study compares the revenue stream of the seller and the target achievement of the bidders of combinatorial auctions and single-unit auctions using several simulations.

The remainder of the paper is organised as follows. In Section 2, the theoretical background is presented in details. The research objective is described in Section 3. In Section 4, the simulated multi-period timber combinatorial auction model is described. Results and discussions including four different experiments are presented in Section 5. Finally, Section 6 concludes the paper and presents a brief overview of future research.

4.2 Theoretical background and research objectives

Limited natural resources such as oil, mineral rights, radio spectrum, and timber have been studied regarding policies and mechanisms used to allocate and value them. Timber allocation and pricing is of specific interest in Québec, as well as in several jurisdictions in the world. Many auction models have been used to solve timber allocation problems, (Mead, 1967; Hansen, 1985; Paarsch, 1991; Elyakime *et al*., 1994, 1997; Baldwin *et al.*, 1997; Athey and Levin, 2001; Haile, 2001; Athey *et al.*, 2011). These studies are mostly related to the areas of competition and information, comparing open and closed auctions, collusion, and reserve price. Others, described below, are more specifically related to our study in multiple-round combinatorial timber auction.

Farnia *et al.* (2013) studied multiple-round single-unit timber auctions using simulation. The authors studied the effects of several bidding patterns on the auction outcome. Their results suggests that the adaptive and learning bidding patterns have the best outcome. They also analyzed how this outcome is affected by different setup configurations.

Cramton *et al.* (2006) described a timber combinatorial auction model as a method of assigning products to buyers. However they did not compare the single unit auction with combinatorial auction. In a timber combinatorial auction, there are several types of products (e.g., species) for sale, and bidders can bid on any bundle of these products. The bundle of bids that maximizes their combined value defines the winning bids. Combinatorial auctions can be used in many applications. Resource allocation is a type of problem that can be solved through combinatorial auction, e.g., allocating airport landing time periods to airlines (i.e. Rassenti *et al*., 1982; Ghassemi Tari and Alaei, 2013; Wang and Dargahi, 2013). Combinatorial auctions are also useful for scheduling problems of loading cranes in maritime terminals (i.e. Brewer, 1999; De Vries and Vohra, 2003; Cramton *et al.*, 2006; Jung and Kim, 2006).

Multiple-round auctions are a series of any type of auctions that are announced sequentially. At each round, one or many auctions are announced simultaneously. Once a round is completed and the winners identified, the auctioneer announces (potentially after a delay) new auctions (Grossklags *et al*., 2000). In the case of a multiple-round combinatorial auction, each auction includes several types of products and bidders bid sequentially on any bundle of products. This type of auction is used in Lau *et al.* (2007) in order to solve a large-scale scheduling problem. In their model, to schedule jobs to the bidders, each job agent submits a determined list of jobs using multiple-round combinatorial auction. Along the same line, Kwon *et al.* (2005) proposed a multiple-round combinatorial auction for truckload procurement that can be beneficial for both carriers and shippers by assigning better service allocations.

Multi-agent simulation is an efficient method to simulate and analyze auction systems (Vidal, 2007). It allows investigating the complex interactions among different kinds of agents and can handle different types of large-scale data, a common occurrence in combinatorial auctions. Moreover, investigating bidder's behavior and winner selection can be performed as modeling the multi-agent simulation platform. One of the challenges in designing and simulating auction systems is the randomness of the parameters of the simulated auction model (Shoham and Leyton-Brown, 2009). We are aware of few papers that have been published regarding combinatorial auction using agent-based systems. For example, Kutanglui and Wu (2001) used combinatorial auction as an autonomous distributed scheduling system.

Finally, Farnia *et al.* (2015) presents a time-based timber combinatorial auction. To the basic timber criteria (i.e., quality and species), the authors add a timetable as a criterion in order to address harvest operations coordination directly in the winner determination process. However, experiments are limited to simulations of one combinatorial auction at a time, in order to study the impacts of various behaviors on the auction outcome. To our knowledge, there is no study of multiple-round timber combinatorial auctions. Also, as the literature reviewed, there are not any studies about the efficiency comparison of multiple-round combinatorial auctions and multiple–round single unit auctions. This paper aims to fill this gap.

4.3 Research objectives

In this paper, several configurations of multiple-round combinatorial auctions are studied using agent-based simulation. The basic simulation model consists in several sets of combinatorial auctions that are announced sequentially in multiple rounds. Within each round, each set of auctions is announced simultaneously. In this paper, the first goal is to investigate the effect of several configurations of the basic model on the outcome of the combinatorial auctions, i.e. price per m^3, and on the achievement level of the purchase volume target of the bidders. Furthermore, the goal of this study is to analyze the difference between multiple-round combinatorial auctions and multiple- round single-unit auctions in several configurations of the basic combinatorial auction model.

4.4 Multiple-round timber combinatorial auction

The proposed simulation model involves three components: an auctioneer, a seller, and bidders. The auctioneer, or government agency, manages the announcement and controls the auction as well as the Attribution process. The seller, the State in our case, offers timber products to the market. The bidders are the auction participants.

In this model, combinatorial auctions are used to sell forest stands. We assumed that each forest stand consists of four different species. The species are divided into softwood and hardwood, each with two levels of qualities. Therefore there are four different types of products, including softwood of quality one (s1), softwood of quality two (s2), hardwood of quality one (h1), and hardwood of quality two (h2). In order to make the model more realistic, each lot has other specifications that make them different from each other. These specifications include the location of the forest stand and the volume of each species. The location of each forest stand is randomly defined during simulation, while their lot size (i.e., size of forest stand) is defined at the start of the simulation. The volumes by species are randomly defined according to the lot size.

There are three types of bidders in this model: softwood mills, hardwood mills, and entrepreneurs. This segmentation is done according to the supply need of the bidders. Softwood mills require softwood, and include lumber mills and paper mills. Hardwood mills are interested in hardwoods. Entrepreneurs are interested in both softwood and hardwood products. In our model, it is considered that softwood mills mostly bid for the bundles that include s1 and s2, where s1 is softwood with quality 1 and s2 is softwood with quality 2. These bundles are considered as s1, s2, s1s2, and s1s2h1h2. Large softwood mills might bid for s1, s2, or any bundle that contains s1 and s2, while small softwood mills might bid only for either s1 or s2. If a softwood mill wins bundle s1s2h1h2, the mill resale the undesired volumes to other mills. The illustrated example also applies for hardwood mills that may be interested in h1, h2, h1h2, and s1s2h1h2. The entrepreneurs are also interested in any bundles of s1, s2, h1, and h2. In order to simplify the simulation model, and particularly the winner determination process, as well as to reduce the number of combinations that significantly increases running time, entrepreneurs only bid for s1, s2, s1s2, h1, h2, h1h2, and s1s2h1h2 bundles.

The parameters of bidder agents include the type of bidder, its location, its capacity per year (which defines their total need), supply needs for each species per year, and their own market prices (i.e., the selling price of their own products). In this simulation model, we also define several parameters that define the configuration of the auctions and the auction environment. These parameters include: number of auctions per year, auction periodicity, number of bidders and lot size. Other parameters of the model are either random within a realistic range, or fixed.

The general simulation procedure is the following. The products of several forest stands are sold over the simulation horizon (one year) via combinatorial auctions. The products of each stand are sold simultaneously during one single combinatorial auction. In other words, each stand is sold individually with one combinatorial auction, which is announced and processed individually. At the start of the simulation, the auctioneer announces several combinatorial auctions simultaneously. So each combinatorial auction concerns one specific forest stand, and bidders bid on any bundle of that stand. The auctioneer announces the available products specifying the volume of each species and the location of the corresponding stand. In order to simplify the simulation of the auction, the reserve price of each bundle is also announced, although in the case study on which we base our simulation this information remains private. For each auction, the bidders bid on any combination of products composing the stand. After receiving the bids, the auctioneer chooses the winners according to a winner determination algorithm, which is explained in section 4.2. Because the auction is combinatorial, each stand may be assigned to one or more bidders. After announcing the winners, the bidders must coordinate harvest operations.

The supply needs of the winners are updated according to the product allocation, which affects their behaviour in the remaining rounds of auction. Therefore, bidder agents must be able to adapt their bidding behaviour over the course of multiple-round auctions. This adaptive learning bidding approach is presented in section 4.4.1.

4.4.1 Bidding approach

In order to have realistic simulation, the bidding pattern inspired by Farnia *et al.* (2013) uses an adaptive learning approach in the context of a single unit auction. This approach combines two types of behavior: a learning behavior and an adaptive behavior. Similarly to Farnia *et al.* (2013), we compare the adaptive learning behavior with other realistic approaches. On the one hand, the learning behavior considers the history (i.e., past rounds of the auction) to define a bidding function, which aim is to avoid over-bidding. This behavior was deemed the most profitable for the bidder. On the other hand, the adaptive behavior considers the bidder's current needs and the time left to fulfill the remaining needs. This bidding behavior was the most capable of fulfilling supply needs. As mentioned in section 3, the bidders must value each bundle of products in the lot under consideration. The sets and indexes to calculate the value of each bundle are indicated in Table 4–1.

Table 4–1: Sets and indexes of the model

j	bidders
$i \in G$	set of lots
$S \subseteq G$	bundles of lots
$MP_{j,S}$	maximum price of bidder j for bundle S
$NP_{j,S}$	minimum price of bidder j for bundle S
RP_S	reserve price of bundle S
V_S	volume of bundle S
MRP_S	average revenue of the final products made from S; includes the revenue of the direct resale of undesired species.
HC_S	harvest cost of bundle S
$D_{j,S}$	distance of the bundle *S* to bidder *j*
TC_S	transportation cost of bundle S
$PC_{j,S}$	average processing cost of converting the bundle *S* into the final product of bidder *j*
$PR_{j,S}$	minimum profit that bidder j is willing to gain from bundle S
$ND_{j,S}$	need of bidder *j* at time *t* for bundle *S*

The bidders need to calculate their maximum and minimum values for each bundle. The minimum value of bidder *j* for bundle S is considered to be equal to the reserve price of bundle S. The reserve price of bundle S is equal to the sum of the reserve prices of the species including in that bundle. The maximum value of bidder *j* for bundle S is shown in equation (1).

$$MP_{j,S} = V_S(MRP_S - HC_S - D_{j,S}TC_S - PC_{j,S} - PR_{j,S}) \qquad (1)$$

As described in Farnia *et al.* (2013) the bidders may face several combinatorial auctions at each round of the auction. Therefore the bidders should consider a decision method to decide on which auction to participate. The decision problem is described as the following binary integer programming.

maximize:

$$\sum_{S} \frac{V_S}{D_{j,S}}\, x_S \qquad (2)$$

subject to:

$$MP_{j,S}\, x_S \geq RP_S \qquad \forall\, S \qquad (3)$$

$$\sum_{S} V_S x_S \leq ND_{j,S} \qquad (4)$$

$$x_S \in \{0,1\} \qquad \forall\ S \qquad (5)$$

In this mathematical programming, bidder j assigns a weight to each desirable bundle at each round. In order to maximize the volume while minimizing the distance to obtain the bundle, the bidder defines a weight as the volume of the bundle over the distance of the bundle to the bidder's mill (equation 2). The first constraint (3) confirms that the bidder considers only the feasible bundles (the maximum price of the bidder is higher than the reserved price of the bundle). In order to avoid bidding on more items than needed, constraint (4) ensures that the sum of the selected bundles is less than the bidder's need, which also considers a small buffer to account for lost bids. Equation (5) shows the binary constraint.

The valuation function of the bidders' bidding approach is described in equation (6), as suggested in Farnia *et al.* (2013).

$$v_{j,S} = \alpha\left(\frac{MP_{j,S} - NP_{j,S}}{2}\right) * tanh\left(\frac{f_1(y)}{f_2(d)} * \frac{f_{j3}(n)}{f_{j4}(c)} - 2\right) + \beta\left(\frac{MP_{j,S} + NP_{j,S}}{2}\right) + (1 - \beta) y_{j,S} \qquad (6)$$

In this equation, $v_{j,S}$ is the valuation function of bidder j for bundle S, $f_1(y)$ is the total duration of the procurement process to achieve a target supply volume (i.e. a year), $f_2(d)$ is the duration of the remaining time at any specific moment in the simulation to achieve that target. Next, $f_{j4}(c)$ and $f_{j3}(n)$ are respectively the target supply volume of bidder j, and the remaining volume at any specific moment in the simulation to achieve the target supply volume. The first two elements of equation (6) represent the adaptive part of the valuation function. The target supply volume of a bidder is a global target (for all species).

$y_{i,S}$ is the learning part of the adaptive learning behaviour. For example, if S consists of species s1 and s2, $y_{i,S}$ for these species is shown in equation (7). We estimate the coefficients of this equation using a regression on the history of the auction. More details can be found in Farnia *et al* (2013). At each round, the bidders consider the winning history and extract the information including the location of the winner and the winning price for each bundle. As each bundle is considered separately, there are less and less data available to compute equation 7. This may affect the capacity of the learning part to anticipate a valid bidding price. Eventually, when not enough data is available, the bidders estimate the bidding price of a bundle according to the price history of single species.

More specifically, the bidders estimate the coefficients (β_0, β_1, β_2…) of the regression function at each round and for each bundle, adding the most recent information about the winning bids. Next, once the coefficients are estimated, and using the information of the current auction, the bidder anticipates the value $y_{j,s1s2}$ of the bundle, with $x_{j,s1}$ and $x_{j,s2}$ being the volume of s1 and the volume of s2 in bundle s1s2, respectively, using equation (7). Next, the offer of bidder $v_{j,s1,s2}$ is calculated with equation (6).

$$y_{j,s1s2} = \beta_0 + \beta_1 D_{j,s1s2} + \beta_2 x_{j,s1} + \beta_3 x_{j,s2} \qquad (7)$$

In Equation (6), α and β are defined as coefficients that vary within the interval [0;1]. In this model the bidders randomly behave according to the different values of α and β. The valuation function is purely adaptive if $\alpha = \beta = 1$. When $\alpha = \beta = 0$, the valuation function is strictly based on learning.

4.4.2 Winner determination

This section describes the winner determination algorithm for the simulated combinatorial auction. As previously explained in Section 3, softwood mills are interested in softwoods (*s1* and *s2*). According to their size and their supply needs, the mills are interested in *s1*, *s2*, *s1s2*, and *s1s2h1h2* (i.e. whole forest stand) bundles. For example if the mill is smaller, it will make an offer for only *s1* or *s2*, while a larger mill, or one needing more supplies, will also make an offer for *s1s2*. Mills which do not wish to collaborate with others at the time of harvest, will also make an offer for *s1s2h1h2*. That way, if they win the bundle, they will control harvest operation planning. Similarly, hardwood mills make offers for *h1*, *h2*, *h1h2*, and *s1s2h1h2* bundles. Entrepreneurs can also make offers for these bundles, as their mission is to sell timbers to all kinds of mills. The following algorithm shows the winner determination procedure that is triggered within the simulation to determine the solution of each auction.

Let

J be number of bidders;
$v_{j,s1}$ *be bidder j's* value of s1;
$v_{j,s2}$ *be bidder j's* value of s2;
$v_{j,h1}$ *be bidder j's* value of h1;
$v_{j,h2}$ *be bidder j's* value of h2;
$v_{j,s1s2}$ *be bidder j's* value of s1s2;
$v_{j,h1h2}$ *be bidder j's* value of h1h2;
$v_{j,s1s2h1h2}$ *be bidder j's* value of s1s2h1h2;
w_{s1} *be the winner of s1;*
w_{s2} *be the winner of s2;*
w_{h1} *be the winner of h1;*
w_{h2} *be the winner of h2;*

[
$v_{s1}=v_{s2}=v_{h1}=v_{h2}=v_{s1s2}=v_{h1h2}=0$

for $j=1$ to J do
$v_{s1} = max\ (v_{s1},\ v_{j,s1})$
$v_{s2} = max\ (v_{s2},\ v_{j,s2})$
$v_{h1} = max\ (v_{h1},\ v_{j,h1})$
$v_{h2} = max\ (v_{h2},\ v_{j,h2})$
$v_{s1,s2} = max\ (v_{s1,s2},\ v_{j,s1,s2})$
$v_{h1,h2} = max\ (v_{h1,h2},\ v_{j,h1,h2})$
$v_{s1s2h1,h2} = max\ (v_{s1s2h1,h2}\ ,\ v_{j,s1s2h1h2})$
end for

If $v_{s1} + v_{s2} > v_{s1s2}$ **then**
w_{s1} = j | $v_{s1}=v_{j,s1}$ *and* $j \in [1,J]$
w_{s2} = j | $v_{s2}=v_{j,s2}$ *and* $j \in [1,J]$
$v_{s1s2} = v_{s1} + v_{s2}$
else
$w_{s1} = w_{s2}$ = j | $v_{s1s2} = v_{j,s1s2}$ *and* $j \in [1,J]$
end if

If $v_{h1} + v_{h2} > v_{h1h2}$ **then**

w_{h1} = j | v_{h1}=$v_{j,h1}$ *and j* ∈ [1,J]
w_{h2} = j | v_{h2}=$v_{j,h2}$ *and j* ∈ [1,J]
$v_{h1h2} = v_{h1} + v_{h2}$
else
$w_{h1} = w_{h2}$ = j | $v_{h1h2} = v_{j,h1h2}$ *and j* ∈ [1,J]
end if

If $v_{s1s2} + v_{h1h2} < v_{s1s2h1h2}$ **then**
$w_{s1} = w_{s2} = w_{h1} = w_{h2}$ = j | $v_{s1s2h1h2} = v_{j,s1s2h1h2}$ *and j* ∈ [1,J]
end if
]

The outcome of this simple procedure selects w_{s1}, w_{s2}, w_{h1} *and* w_{h2}, which are the winners of species s1, s2, h1, and h2 respectively. The winners of each species can be similar or different. This procedure only aims to identify the highest value of a fix and small number of combinations. In reality, the number of combinations can be much higher and required more advanced algorithms.

4.5 Results and discussion

Four experiments using the simulated model are presented in this section. We will first examine the outcomes of the simulation in terms of price per m^3 for the seller and then in terms of target achievement for the bidders. In both cases we will first present the results for combinatorial auctions in various settings. They are then compared with those obtained with single-unit auctions.

In this study, the first objective is to evaluate how combinatorial auctions can benefit the seller in different setup configurations (Experiment 1). Next, target achievement is analyzed in order to know how much the buyer can fulfill its needs through the combinatorial auction (Experiment 2). We then aim at comparing the revenue (i.e., price per m^3) generated in both the combinatorial and single-unit auctions (Experiment 3). Finally, the fourth objective is the compare the ability of companies to achieve their target supply needs with both combinatorial and single-unit auctions (Experiment 4).

4.5.1 Experiment 1 – Price per m^3 in combinatorial auctions

This part of the experiments describes a sensitivity analysis of the impacts of several parameters on the price per m^3 of the combinatorial auction. The parameters that can be changed in the model are the number of auctions per year, the auction periodicity, the lot size, and the number of bidders. In order to assess the impacts of these parameters on the revenue, three levels (low, medium and high) are defined for each parameter. The levels for the number of auctions per year are 100, 250, and 400. The periodicity levels are defined as 7, 15 and 30 days. The three lot sizes are 10,000 15,000 and 20,000 m^3. Finally, the number of bidders is set to 100, 150, and 200. These values are inspired by actual data from timber auctions in Quebec. In this study, within each simulation, lot size is the same for all lots. Therefore, there is no possible scale economy to be gained from large lots. This limitation does not affect the general results, although it limits our ability to properly evaluate the impacts of simultaneous auctions with variable lot sizes.

All 3^4 (81) configurations of these parameter levels were tested. For each configuration, the experiments are repeated 25 times for a total of 2,025 experiments. Table 4–2 shows the analysis of variance for the price per m^3 resulting from the combinatorial auctions. In order to simplify the analysis, these studies only analyze the effects of each parameter and all combinations of any two independent variables. The ANOVA studies show a R^2 above 0.80, which indicates a reasonable level of statistical certainty. The results show that the only significant parameters are the number of auctions, the lot size, the number of bidders, and the combination of number of auctions and lot size.

Figure 4–1 shows the effects of each parameter. As it is shown, when the number of auctions increases, the price per m^3 decreases due to more supply on the market. The price per m^3 diminishes when the lots get larger, again because of more supply. When number of bidders increases, the price per m^3 goes up.

Table 4–2: Analysis of variance for price per[3] from the combinatorial auctions

Number of observations =	*2025*	*R^2 =0.800016*		
Root MSE =	*0.104238*	*Adjusted R^2 =0.796803*		
Source	***Partial SS***	***MS***	***F***	***Prob > F***
Model	*86.5861*	*2.70582*	*249.0248*	***<.0001***
Number of Auctions	*0.327819*	*0.16391*	*15.0851*	***<.0001***
Periodicity	*0.016152*	*0.008076*	*0.7432*	*0.4757*
Lot Size	*0.168619*	*0.084309*	*7.7593*	***0.0004***
Number of Bidders	*10.991764*	*5.495882*	*505.8035*	***<.0001***
Number of Auctions # Periodicity	*0.021667*	*0.005417*	*0.4985*	*0.7369*
Number of Auctions # Lot Size	*0.114439*	*0.02861*	*2.633*	***0.0327***
Number of Auctions # Number of Bidders	*0.014781*	*0.003695*	*0.3401*	*0.851*
Periodicity # Lot Size	*0.011365*	*0.002841*	*0.2615*	*0.9027*
Periodicity # Number of Bidders	*0.046794*	*0.011698*	*1.0766*	*0.3664*
Lot Size # Number of Bidders	*0.044701*	*0.011175*	*1.0285*	*0.3911*
Residual	*21.64437*	*0.01087*		
Total	*108.23046*			

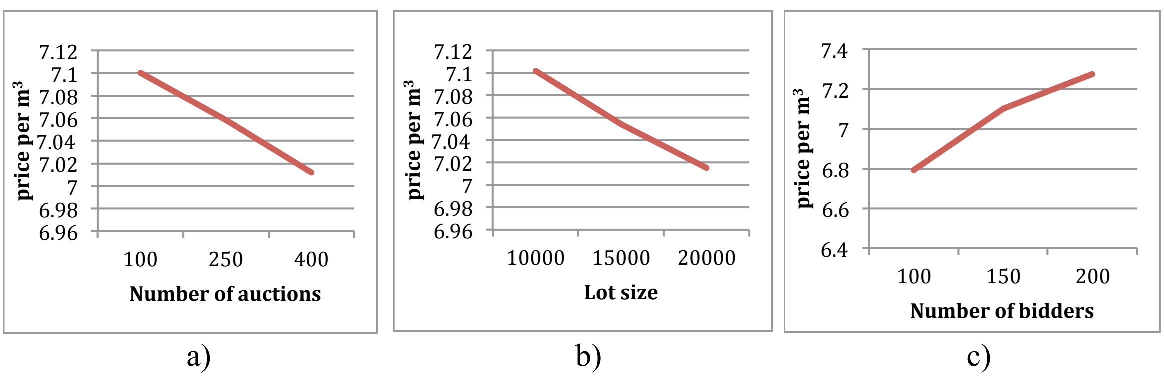


Figure 4–1: Price per m^3 from the combinatorial auctions; (a) impact of the number of auctions; (b) impact of the lot size; (c) impact of the number of bidders.

Figure 4–2 describes how a pair of independent variables affects the outcome of the auction. In particular, this figure shows that when the number of auctions increases, the price per m^3 decreases, even if lot size changes, but the price is lower when lot size gets larger. The reason for this result is that both number of auctions and lot size significantly increase supply. Therefore, the combination of these two parameters affects the price per m^3.

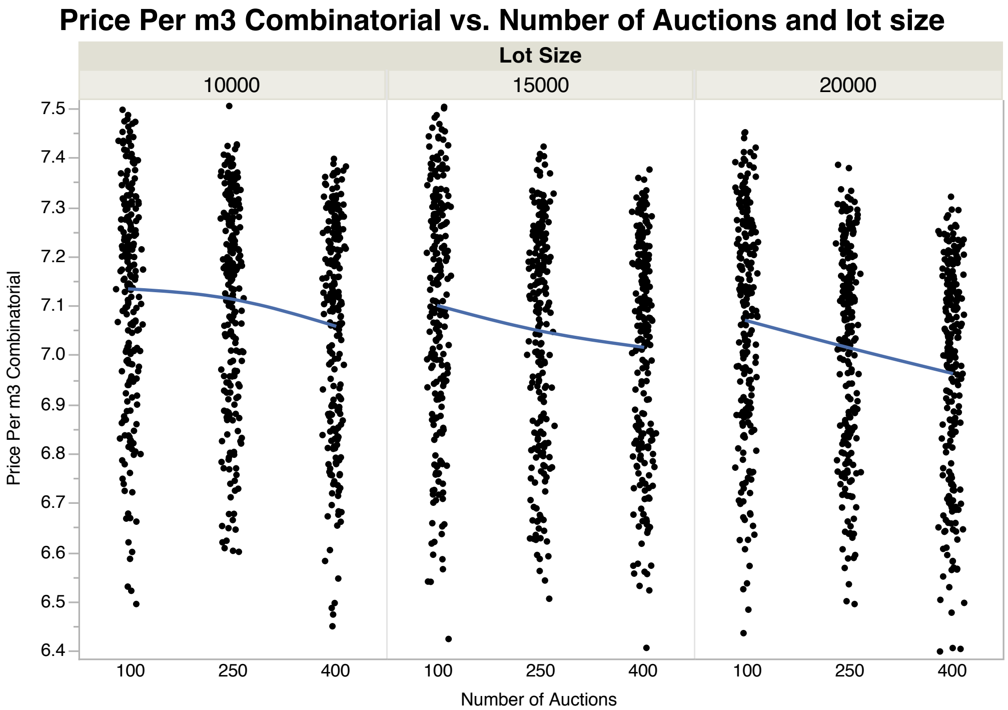


Figure 4–2: Comparative analysis of the price per m^3 from the combinatorial auctions: combined effect of number of auctions and lot size

4.5.2 Experiment 2 – Target achievement of bidders in combinatorial auctions

Target achievement is a dependent variable that represents the ability of the bidders to achieve their target supply volume. This experiment investigates the impacts of a combinatorial auction on this variable. Again, we analyzed the effect of the same parameters (number of auctions, periodicity, lot size, and number of bidders) on the target achievement of the bidders. Table 4–3 shows the analysis of variance of the parameters on the target achievement. As it is shown in this table, the parameters contribute to explaining more than 98% of the variance of the target achievement. All the analyzed parameters have a significant effect.

Table 4–3: Analysis of variance for the target achievement of bidders with combinatorial auctions

Number of observations =	*2025*	*R^2 =0.984379*			
Root MSE =	*0.022816*	*Adjusted R^2 =0.984128*			
Source	***Partial SS***	***DF***	***MS***	***F***	***Prob > F***
Model	*65.345546*	*32*	*2.04205*	*3922.827*	***<.0001***
Number of Auctions	*6.8862696*	*2*	*3.443135*	*6614.349*	***<.0001***
Periodicity	*0.0279949*	*2*	*0.013997*	*26.8894*	***<.0001***
Lot Size	*1.0181216*	*2*	*0.509061*	*977.9187*	***<.0001***
Number of Bidders	*0.053689*	*2*	*0.026844*	*51.5689*	***<.0001***
Number of Auctions # Periodicity	*0.2343491*	*4*	*0.058587*	*112.5476*	***<.0001***
Number of Auctions # Lot Size	*2.2101542*	*4*	*0.552539*	*1061.441*	***<.0001***
Number of Auctions # Number of Bidders	*2.9138346*	*4*	*0.728459*	*1399.388*	***<.0001***
Periodicity # Lot Size	*0.036632*	*4*	*0.009158*	*17.5927*	***<.0001***
Periodicity # Number of Bidders	*0.0523244*	*4*	*0.013081*	*25.1291*	***<.0001***
Lot Size # Number of Bidders	*0.8238443*	*4*	*0.205961*	*395.6564*	***<.0001***
Residual	*1.036946*	*1992*	*0.00052*		
Total	*66.382493*	*2024*			

To illustrate the analysis of variance, Figure 4–3 shows the effects of single parameters. Number of auctions and lot size show a positive impact, while periodicity and number of bidders have a negative impact on the target achievement. The reasons for the positive impact is that there is more timbers through the auction system, therefore, the bidders can win more wood supply to fulfill their needs. Similarly, when number of bidders rises, the auction becomes more competitive and the chance of winning drops. When periodicity is higher, there are more auctions at each round. Therefore, the bidders have more auctions to decide at each round. The bidders tend to bid only on the amount they need, since they think they may win; hence, they might loose some opportunities by not participating in other auctions. Therefore, it is probable that bidders win lower volumes when there are more auctions in one round.

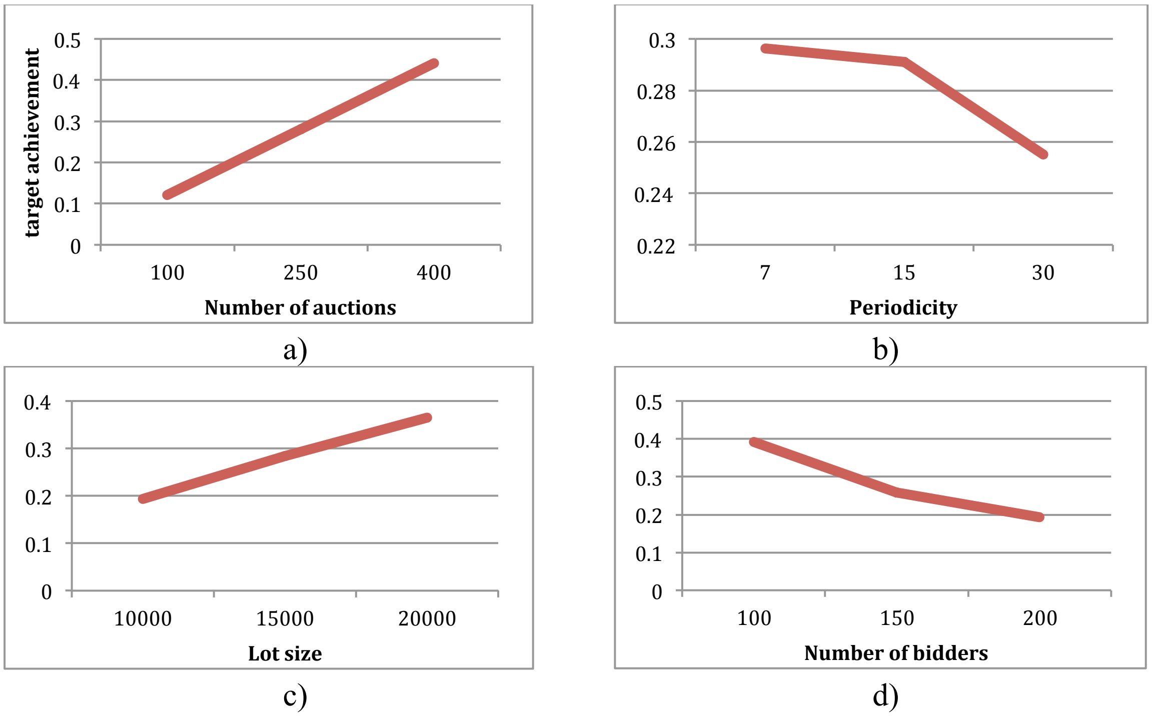


Figure 4–3: analysis of the target achievement of bidders from combinatorial auctions: (a) effect of the number of auctions; (b) effect of periodicity; (c) effect of lot size; (d) effect of the number of bidders

Figure 4–4 shows the comparative analysis of target achievement. As shown, any combination of two parameters has a significant effect on target achievement of combinatorial auction.

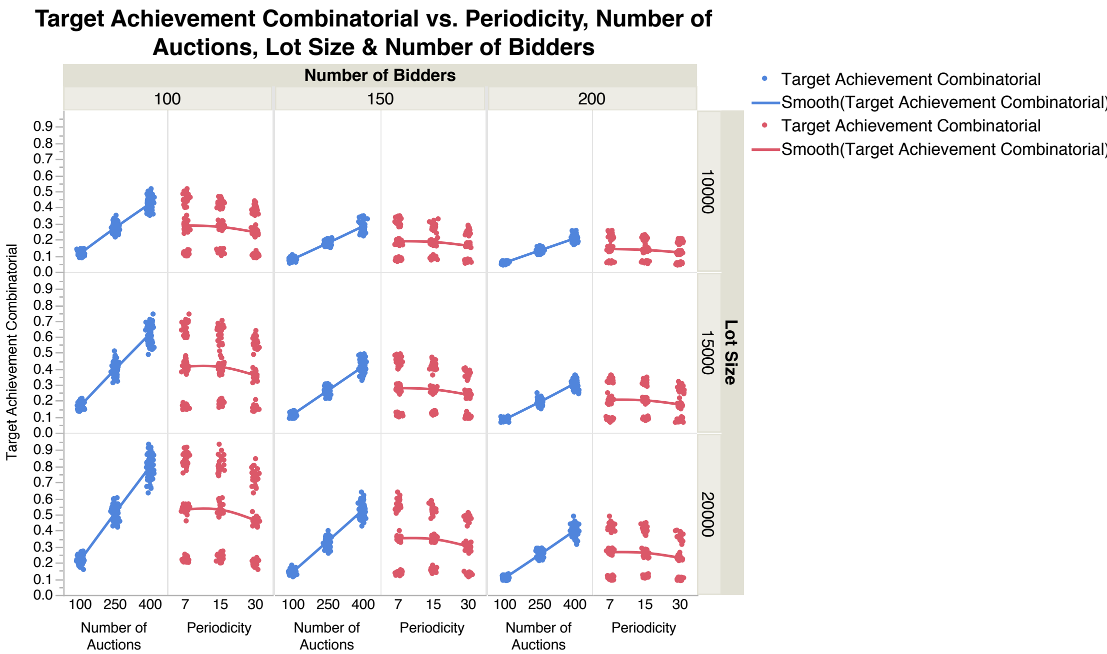


Figure 4–4: Comparative analysis of the target achievement of bidders from combinatorial auctions: combined effects of each two parameter.

4.5.3 Experiment 3 – Price per m^3 – comparison between combinatorial and single-unit auctions

In this section, we compare the combinatorial auction and the single-unit auction and analyse specifically the impact on revenue (i.e., price per m^3) using different setup configurations. We define this impact as the gain of using combinatorial auctions expressed as a percentage of the average price per m^3 of single unit auction ((price per m^3 of combinatorial auction / price per m^3 of single unit auction - 1) * 100). In order to perform a sensitivity analysis, we again consider the number of auctions, periodicity, lot size, and the number of bidders. Figure 4–5 displays the impact of these parameters.

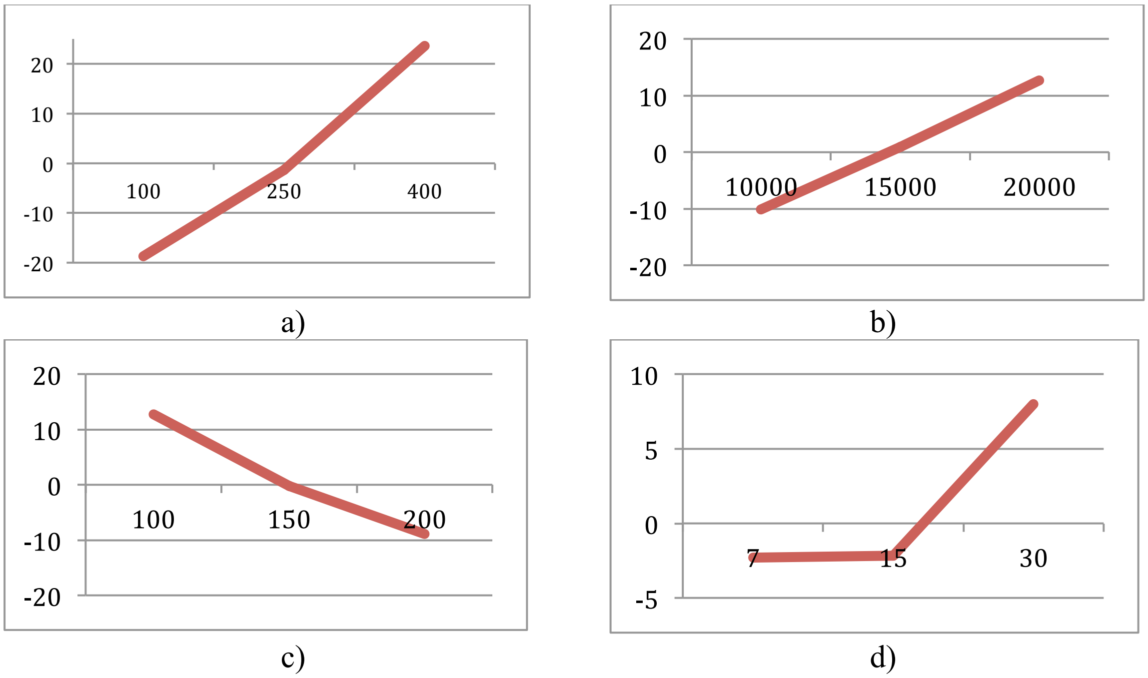
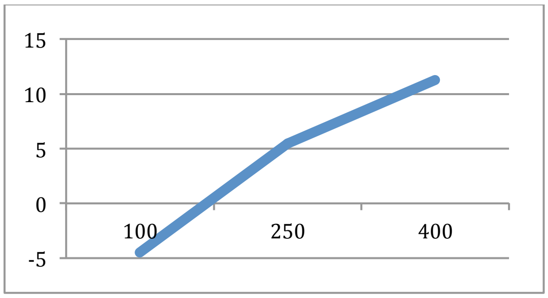


Figure 4–5: percentage change (combinatorial auction over single-unit auction) in price per m^3 as a function of (a) the number of auctions (b) lot size (c) the number of bidders, and (d) periodicity

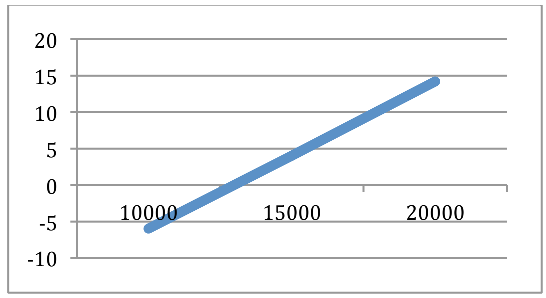
First, the gain increases as the number of auctions rises. In other words, the combinatorial auction is preferable to the single-unit auction as the number of auctions increases. Similarly, the combinatorial auction is preferable to single-unit auction, when there are fewer bidders. The results show that the difference between combinatorial auction and single-unit auction is higher, when the number of auctions and the number of bidders are in non-equivalent market situation. In other words, when there is a considerable difference between potential supply and potential demand, the difference between two auctions is higher. For example, when there are 250 auctions and 150 bidders in the market there is not considerable difference between the outcomes of two types of auctions. The comparative analysis of these parameters is detailed in experiment 4 along with comparative analysis of the effects of the parameters on target achievement.

4.5.4 Experiment 4 – Target achievement of bidders – comparison between combinatorial and single-unit auctions

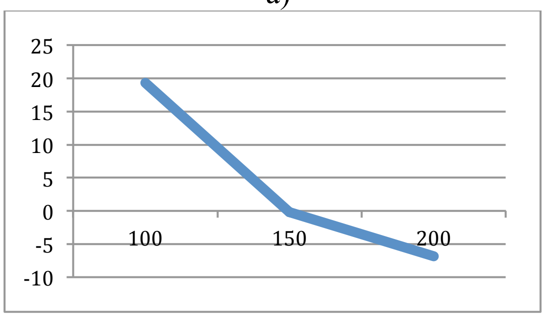
The impact on the target achievement of bidders between combinatorial and single-unit auctions is measured as the target achievement increase from using combinatorial auction expressed as a percentage of the target achievement of single unit auction ((target achievement of combinatorial auction / target achievement of single unit auction -1) * 100). Figure 4–6 presents the impact of each parameter on target achievement.



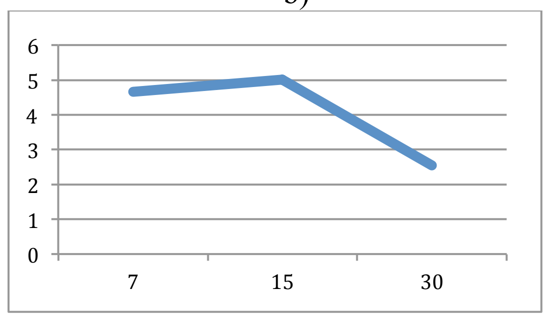
a)



b)



c)



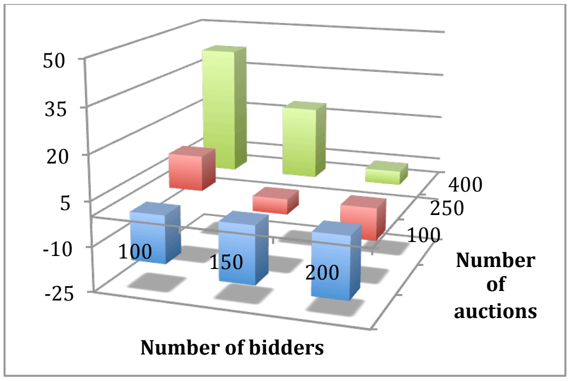
d)

Figure 4–6: percentage change (combinatorial auction over single-unit auction) in target achievement as a function of (a) the number of auctions (b) lot size (c) the number of bidders, and (d) periodicity

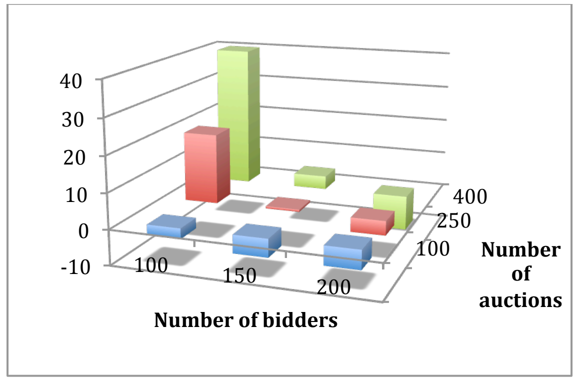
The combinatorial auction is preferable to single-unit auction when the number of auctions is high and the number of bidders is low. Therefore, the combinatorial auction is better than single-unit auction for bidders, when the market is less competitive. Similarly, bidders will prefer combinatorial auction when lot size is larger, or there are more items in the market.

Figure 4–7 presents the comparative analysis of the impact on sale price and target achievement with any two combinations of auction design parameters (i.e., the number of bidders and the number of auctions, the number of bidders and lot size, the number of bidders and periodicity, the number of auctions and lot size, the number of auctions and periodicity, and lot size and periodicity). The results show that the impact on sale price increases when there are more auctions, while lots are large and there are fewer bidders. Figure 4–7 illustrates that the auctioneer can obtain higher price through combinatorial auction, when the market is less competitive (i.e., more demand and less supply). As it is shown, the combinatorial auction is better (in terms of both sale price and target achievement) in situations when there are more auctions, few rounds of auction (higher periodicity), lager lots, and fewer bidders.

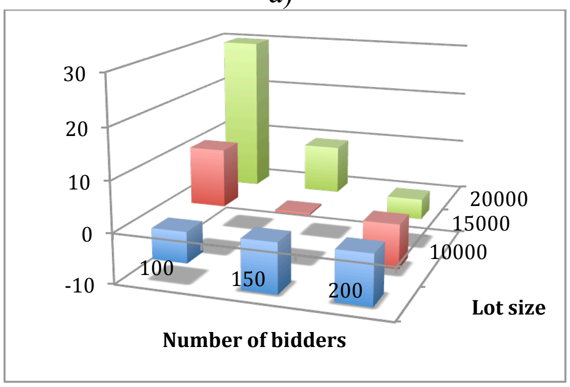
Comparing the comparative analysis of any two combinations of parameters between the sale price and the target achievement (e.g. figure 7(a) and figure 7(b)), it can easily be observed in Figure 7 that this correlation is positive, which tends to show that both objectives can be achieved simultaneously. For example, figure 7(a) and figure 7(b) present that combinatorial auction is preferable over single-unit auction when the combination of “the number of bidders” and “the number of auctions” are 100 and 250, 100 and 400, and 150 and 400 auctions per year.



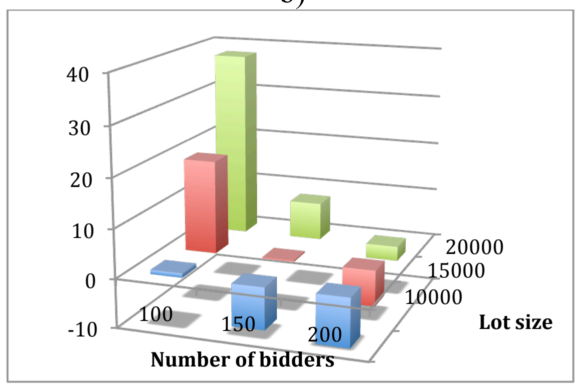
a)



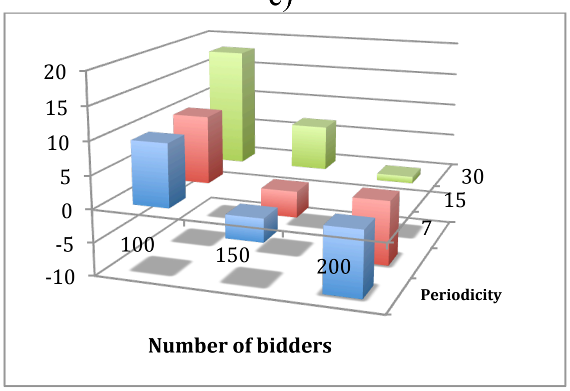
b)



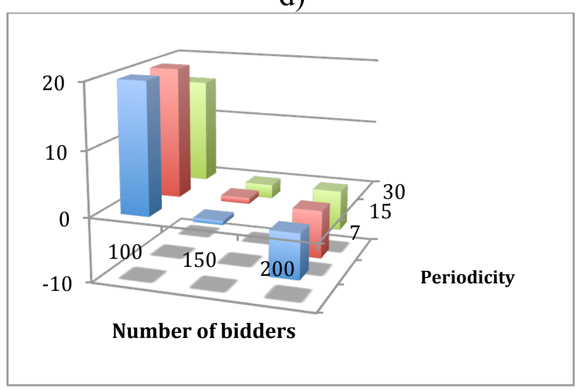
c)



d)

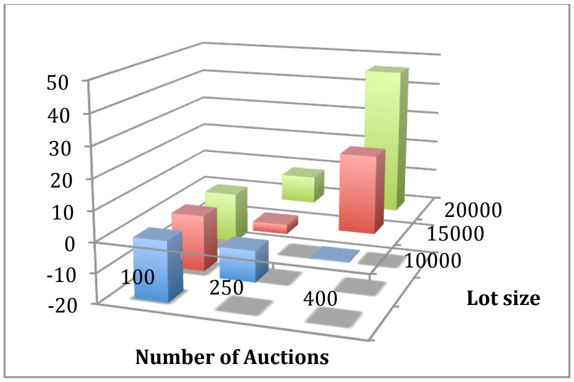


e)

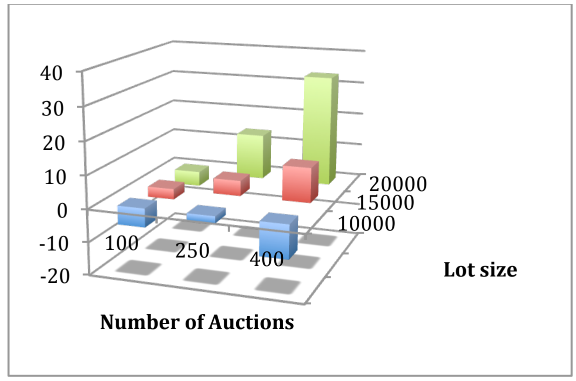


f)

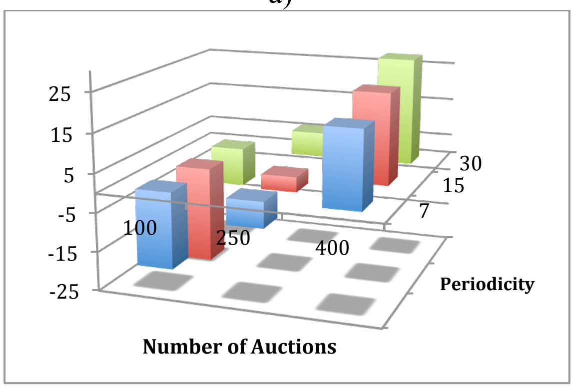
Figure 4–7(part 1): Comparative analysis of the impacts on sale price and target achievement (Part 1). (a) Price per m^3: combined effects of number of bidders and number of auctions. (b) Target achievement: combined effects of number of bidders and number of auctions. (c) Price per m^3: combined effects of number of bidders and lot size. (d) Target achievement: combined effects of number of bidders and lot size. (e) Price per m^3: combined effects of number of bidders and periodicity. (f) Target achievement: combined effects of number of bidders and periodicity.



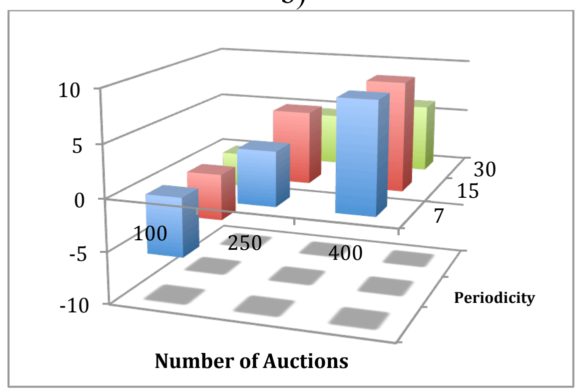
a)



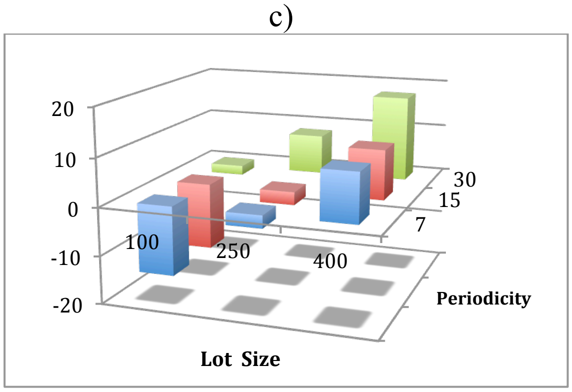
b)



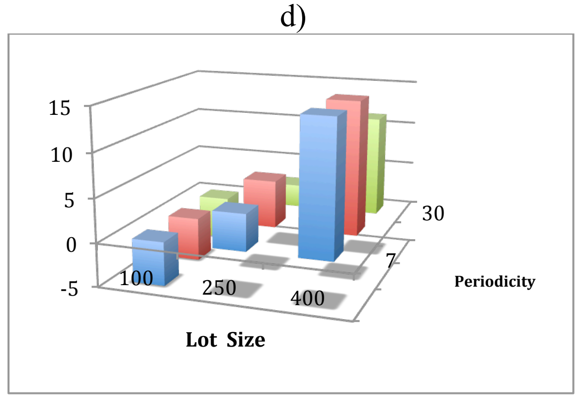
c)



d)



e)



f)

Figure 4-7 (part 2): Comparative analysis of the impact on sale price and target achievement (Part 2). (a) Price per m3: combined effects of number of auctions and lot size. (b) Target achievement: combined effects of number of auctions and lot size. (c) Price per m3: combined effects of number of auctions and periodicity. (d) Target achievement: combined effects of number of auctions and periodicity. (e) Price per m3: combined effects of lot size and periodicity. (f) Target achievement: combined effects of lot size and periodicity.

4.6 Conclusion and future studies

This paper presents a study of a multiple-round timber combinatorial auction using a multi-agent simulation platform. The performance of the auction was experimented in various setup configurations, to confirm that the simulated model provides realistic outcomes. Two main indicators were proposed in order to measure the performance of the model. Sale price per m^3 evaluates the auctioneer capability to gain generate revenue from the auctions. Target achievement evaluates the bidder capability to fulfill their needs from auctions. We also analyzed the indicators for validating the performance of combinatorial auction, and the performance of the comparison of combinatorial auction with single-unit auction.

Our results show that the design auction parameters that effect on the sale price of combinatorial auction are the number of auctions, the number of bidders and lot size. In combinatorial auction price per m^3 is higher when the market is less competitive. The bidders' target achievement also can be effected by the number of auctions, the number of bidders, periodicity, and lot size and combined effects of each two parameter.

The sensitivity analysis of the auctions comparisons also illustrates that the combinatorial auction is preferable over single-unit auction in less competitive situations. The reason is that in combinatorial auction when there are more auctions and fewer bidders, the bidders can bid on variety of bundles of the species, which are related to their needs, without bidding on the species that they don't need. In other words, in combinatorial auction the bidders can fulfill their needs with a combination of auctions, while in single unit auction they must bid on fewer auctions and win species that they don't necessarily need.

Both objectives of timer auction (sale price and target achievement) can be achieved simultaneously following the results of the comparative analysis of any two combinations of parameters. That means the combinatorial auction is better than single unit auction in terms of both objectives when there are more auctions, few rounds of auction (higher periodicity), larger lots, and fewer bidders.

4.7 Acknowledgements:

The FOR@C Research Consortium, and the NSERC funded this work. The contribution of the experts at the *Bureau de mise en marché des bois*, of the Québec government is also acknowledged for their advices, explanations and validation of the models.

4.8 References:

Athey, S., Levin, J., 2001. Competition and information in us forest service timber auctions. Journal of Political Economy, 109(2), 375-417.

Athey, S., Levin, J., Seira, E., 2011. Comparing open and sealed bid auctions: evidence from timber auctions. The Quarterly Journal of Economics, 126(1), 207-257.

Baldwin, L. H., Marshall, R. C., Richard, J. F., 1997. Bidder collusion at forest service timber sales. Journal of Political Economy, 105(4), 657-699.

Brewer, P. J. (1999). Decentralized computation procurement and computational robustness in a smart market. *Economic Theory*, *13*(1), 41-92.

Cramton, P., Shoham, Y., and Steinberg, R., editors, 2006. Combinatorial Auctions. MIT Press.

De Vries, S., & Vohra, R. V. (2003). Combinatorial auctions: A survey. *INFORMS Journal on computing*, *15*(3), 284-309.

Elyakime, B., Laffont, J. J., Loisel, P., Vuong, Q., 1997. Auctioning and bargaining: an econometric study of timber auctions with secret reservation prices. Journal of Business & Economic Statistics, 15(2), 209-220.

Farnia. F., J.M. Frayret, L. LeBel, C. Beaudry, 2013 “Multiple-Round Timber Auction Design and Simulation”, International Journal of production economics, 146(1), 129-141.

Farnia. F., J.M. Frayret, C. Beaudry, L. LeBel, 2015 “Time-Based Combinatorial Auction for Timber Allocation and Delivery Coordination”, Forest Policy and Economics, 50(1), pp 143-152.

Ghassemi Tari, F., Alaei, R., 2013. "Scheduling TV commercials using genetic algorithms", International Journal of Production Research, 51(16), 4921-4929.

Grossklags, J., Schmidt, C., Siegel, J., 2000. Dumb software agents on experimental electronic markets. In: Informatiktage 2000, G. fur Informatik e.V.,Ed. Leinfelden-Echterdinge, Germany: Konradin Verlag.

Haile, P., 2001. Auctions with resale markets: an application to us forest service timber sales. American Economic Review, 91, 399-427.

Hansen, R., 1985. Empirical testing of auction theory. American Economic Review, 75, 156-159.

Jung, S. H., & Kim, K. H., 2006. Load scheduling for multiple quay cranes in port container terminals. Journal of Intelligent manufacturing, 17(4), 479-492.

Kutanoglu, E., & Wu, S. D. (1999). On combinatorial auction and Lagrangean relaxation for distributed resource scheduling. *IIE transactions*, *31*(9), 813-826.

Kwon, R. H., Lee, C. G., & Ma, Z. (2005). An integrated combinatorial auction mechanism for truckload transportation procurement. *University of Toronto, http://www. mie. utoronto. ca/labs/ilr/MultiRound. pdf, Working Paper*.

Lau, H. C., Cheng, S. F., Leong, T. Y., Park, J. H., & Zhao, Z., 2007. Multi-period combinatorial auction mechanism for distributed resource allocation and scheduling. In Proceedings of the 2007 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (pp. 407-411). IEEE Computer Society.

Mead, W. J., 1967. Natural resource disposition policy: oral auctions vs. sealed bids. Natural Resource Journal, 7, 194-224.

Paarsch, H., 1991. Empirical models of auctions and an application to British Columbia timber sales. University of British Columbia mimeograph.

Rassenti, S.J., Smith, V.L., Bulfin, R.L., 1982. A Combinatorial Auction Mechanism for Airport Time Slot Allocation. The Bell Journal of Economics, 13(2), 402-417.

Shoham, Y., Leyton-Brown, K., 2009. Multiagent systems: algorithmic, game-theoretic, and logical foundations. Cambridge University Press.

Vidal, J. M., 2007. Fundamentals of multiagent systems with NetLogo examples.

Wang, C., Dargahi, F., 2013. Service customization under capacity constraints: An auction-based model, Journal of Intelligent Manufacturing, 24(5), 1033-1045.

CHAPTER 5 : ARTICLE 3 : TIME-BASED COMBINATORIAL AUCTION FOR TIMBER ALLOCATION AND DELIVERY COORDINATION

Abstract:

The timber auction system currently used in the province of Québec, Canada, is a single unit auction, in which timber users bid on entire forest stands located within a specific area. In this procurement system, timber users (i.e., winners) are responsible for harvesting the entire stands and for reselling undesirable timber species to others. In order to improve the limits of this system, this paper proposes a sustainable auction system, referred to as time-based timber combinatorial auction. In this approach, time is not part of the definition of the goods for sale. It is used to valuate the good for sale with respect to their expected delivery period. Therefore, this system aims to simultaneously allocate multiple goods, or products in mixed forest stand, to multiple winners, and address the coordination of timber deliveries to their winners. The proposed timber combinatorial auction provides an open access allocation of timber, based on its intrinsic economic value, while allowing the Ministry of natural resources to exercise high standard for environmentally friendly forest operations. From a logistic point of view, a sensitive analysis is conducted in order to compare the proposed time-based combinatorial auction with a combinatorial auction with no delivery coordination. Both models are compared according to bidders' and seller's time flexibility. Experimental results illustrate the impact (i.e., cost) of delivery coordination on total revenue due to loss of value when time preference is not fully satisfied. This cost evaluation can then be used as an upper bound of the cost of coordination, when delivery coordination must be manually negotiated among multi-stakeholder.

Keywords: combinatorial auction, timber auction, coordination, wood freshness, winner determination problem.

5.1 Introduction

Former Québec forest regime, which was based on an exclusive long-term licencing system, was unable to establish a fair price for timber transactions, and therefore a sustainable economic system. Consequently, under the pressure of international trade agreements, the Québec government, along with other provinces in Canada (Niquidet and van Kooten, 2006), decided to make a portion of the annual timber supply (25%) available to anyone through an auction system. With timber available through auctions, buyers can access a larger timber supply according to the value of their own forest products market. In such a context, designing an efficient auction system while preserving a certain level of guaranteed supplies for Québec companies can become a complex task. Different goals are pursued such as offering a certain level of stability to traditional users, offering opportunities to new entrepreneurs and assuring a fair financial return for the public asset. In order to do that, the government currently uses an auction system in which entire forest stands are sold to a single winner. The advantage of this type of auction is that it is rather simple to implement. Bidders can assess the volume of each species available in each stand for sale and evaluate their worth, whether the stumpage sale is lump-sum sale (i.e., one price for the entire stand) or a scale sale (i.e., a unit price -per foot, board measure (fbm), cord, post, etc.- for each species of extracted wood). Furthermore, the seller is not involved in a complex winner determination problem.

Timber procurement planning in public land and in a multi-firm setting involves many issues that must be considered simultaneously. First, the sharing of the available volumes among forest companies must consider the specific needs of each forest companies, the scheduling and coordination of harvest and delivery activities, wood freshness, as well as the transaction prices for procurement services. When an auction process is introduced in such a context, as it is being introduced in the province of Québec, timber procurement becomes more complicated, which, in turn, forces forest companies to adapt to the new procurement environment.

In the context of public land, timber procurement planning is generally a multi-firm decision problem, which requires the coordination of several companies. Coordination is defined as the management of interdependencies among distinct activities (Malone and Crowston, 1994). In the context of supply chain management, because companies are self-interested, the coordination of their activities with others is essential to improve supply chain efficiency. In the context of timber procurement in public land, such coordination involves several aspects to address, including (1) input-output coordination in time (i.e., what and when), since the forest companies that are responsible for forest operations, harvest entire mixed forest area and deliver uninteresting species/qualities to other companies; (2) quantity availability (i.e., how much), which is a global constraint for all potential timber user; (3) self-interested forest companies (i.e., simultaneous competition and cooperation), which implies that they are responsible for managing their own procurement process, for competing with others, as well as for cooperating with others to coordinate their operations.

In a multi-firm context, timber procurement planners face several challenges. As mentioned above, one of these challenges is associated with the coordination of the distribution of volumes among buyers. The allocation agreement between them should consequently consider the transaction prices (i.e., stumpage sale prices), the timing of the procurement activities, and the wood freshness. Therefore, the coordination of forest operations and the scheduling of deliveries are crucial activities, because timber deterioration and wood freshness influence timber value. In other words, timber procurement planners must coordinate their operations with other companies, which are also involved in planning their own procurement and for meeting their own objectives.

Timber procurement planning and coordination involves a multitude of internal and external factors. In a mixed forest public land environment, forest companies may supply each other through their forest operations. In order to address part of this problem, Beaudoin *et al*. (2010) propose a timber procurement planning model in a two-firm environment based on a negotiation process. However, in the context of n forest companies (n>2), the coordination problem is more challenging and the negotiation process is more complicated. When many potential buyers are involved, auction is an efficient and practical process to allocate goods to buyers according to market value. It has therefore been used for centuries (Marty and Préget, 2010), and generally in its simplest form (i.e., first-price sealed-bid auction, Brown, 2012), for the allocation of pure or mixed species forest stands to forest product companies. Although such market mechanisms, when used in conjunction with government control mechanisms, are instrumental to the creation of a sustainable forest management approach (Kant, 2010), these rather simple applications of the single unit first-price auction cannot directly address the multi-firm coordination problem of forest operations. In Québec, this coordination problem is left to forest companies, which are ultimately responsible for managing their own forest operations within a specific period of time (from months to years) and for reselling undesirable species/qualities to other companies or users. Because mixed species forest stands can be considered as not just one but several goods for sale (i.e., combinations of species/quality), combinatorial timber auction can solve simultaneously the allocation of available wood to potential users and the coordination of harvest and delivery operations.

In combinatorial auctions, a variety of different goods are available in the market. Combinatorial auctions are particularly appropriate when bidders' valuation process depends on the set of goods they wish to purchase. In this paper, we propose a novel application of the combinatorial auction in order to simultaneously allocate the available volumes of mixed species stands to multiple users, and to coordinate timber deliveries and, indirectly, forest operations. To achieve these goals, the proposed combinatorial auction model first allows bidders to bid not only on entire stands (as in traditional first-price auction systems), but also on any combination of species/quality present in these stands. This type of auction helps bidders to directly meet their needs by bidding on the portions of the stands that matches their requirements. This auction system would also stop "bid skewing" behaviours, as described by Athey and Levin (2001), that occurs when bidders take advantage of estimation error of volume availability (made by the seller) in order to create winning bids that generate lower post-harvest cost.

Next, the proposed combinatorial auction system allows bidders to express different values for these combinations of species/quality according to their delivery period. In other words, timber is sold delivered to the mill, which requires the seller to coordinate in time the deliveries of multiple species/quality combinations to multiple buyers. This paper thus proposes a novel Winner Determination Problem (WDP) model capable of simultaneously allocating timber to mills and coordinating their deliveries to multiple buyers. This auction model is more complicated to implement and operate for both the auctioneer and the buyers. However, it is also interesting for smaller forest product companies that want to participate in the auction, but have little bargaining power to coordinate the delivery of their portion of the stand with larger companies. This may, in turn, encourage participation in the auction.

The paper is organized as follows. Section 2 explains the theoretical background of the related auction model. The time-based combinatorial auction model is introduced in Section 3. In Section 4, the winner determination problem model of the proposed auction system is discussed along with its solution limitations. The experiments including the comparison of time-based combinatorial auction and regular combinatorial auction are presented in Section 5. Section 6 presents and analyzes the results of the comparison of the two auction models, including the sensitive analysis of different factors. Finally, Section 7 concludes and discusses the limitation of the time-based combinatorial auction.

5.2 Theoretical background

Allocating and valuing natural resources such as timber stumpage, oil, mineral rights, and bandwidth spectrum are fundamental problems in the modern economy. Many types of auction models have been used to solve timber allocation problems and to ensure an accurate market price (Mead (1967), Hansen (1985), Paarsch (1991), Elyakime *et al*. (1994, 1997), Baldwin *et al.* (1997), Haile (2001), Athey *et al.* (2011)). Farnia *et al*. (2013) simulated and designed an approach for multiple-round timber Auction. Different bidding strategies were simulated and compared in various auction setup configurations. The authors suggest specific parameter configurations in order to maximize the seller's revenue, including the number of auctions per year, the lot size, as well as the auction periodicity. However, like the auction model used in practice, these contributions generally consider single unit (i.e., entire forest stand) auctions for timber allocation, rather than combinatorial auctions, in which each species of a single forest stand can be sold separately.

In a combinatorial auction, as described by Cramton *et al*. (2006), several items are for sale, and bidders can make offers on any sub-set of these items. The winners are the combination of offers that maximize the combined value of these offers. In order to solve these problems, Sakurai *et al.,* (2000) present an algorithm to determine the winners in complex auction setups, such as Internet auction. Bai and Zhang, (2005) consider the reserve price in the context of multi-unit combinatorial auction and presented a new algorithm to solve the WDP. Some researchers consider other attributes as well and propose a solution to combine these attributes with existing WDP models (Cantillon and Pesendorfer, 2007).

In the basic combinatorial auction models, the items for sale are single units that can only be sold entirely. However, items can also be multiple indistinguishable units, which can be sold to multiple bidders. This auction model is referred to as the multi-unit combinatorial auction (MUCA). Similarly, Rabotyagov *et al*. (2013) present a multi-unit market mechanism for forest services. The results showed that fewer bids are more likely to result in higher sale price.

Resource allocation in time and scheduling problems are another type of applications of combinatorial auctions. Several studies have been conducted on this topic in the literature. For instance, Rassenti *et al*. (1982) proposed a combinatorial auction approach to allocate airport landing time slots to competing airlines. Along the same line, Ghassemi Tari and Alaei (2013) proposed a combinatorial auction system for allocating and scheduling TV commercials. Similarly, Wang and Dargahi (2013) propose another approach of combinatorial auction application to constrained manufacturing capacity allocation in the context of mass customization.

Combinatorial auctions are also used in many decentralized and agent-based scheduling problems (De Vries and Vohra, 2003; Cramton *et al.*, 2006; Brewer, 1999). Wellman *et al.* (2001) developed a distributed bidding protocol based on combinatorial and ascending auctions to propose a solution to a complex scheduling problem. Similarly, Jung and Kim (2006) investigated the load-scheduling problem of several cranes in maritime container terminals. In the same vein, Lau *et al.* (2007) proposed a multi-period combinatorial auction for solving a large-scale scheduling problem, in which each agent offers a determined list of jobs. Wang *et al*. (2009) present a formulation of the WDP in the context of an auction-based scheduling problem, in which time is not discretized. Instead, bids for the processing of a set of jobs are formalized using a requirement-based bidding language, which allow software agents to model specific scheduling constraints. A depth-first branch and bound search is used to solve the WDP. Similarly, Kutanglui and Wu (2001) provide an autonomous distributed scheduling system based combinatorial auction. Other applications propose iterative combinatorial auction mechanisms in the context of agent-based scheduling. Iterative combinatorial mechanism is used when bidders cannot decide on their valuations (Parkes and Ungar, 2000; Parkes, 2001), which is not the case in this paper. In these contributions, time is generally directly part of the definition of some constraints in the winner determination problem, if not directly part of the good for sale definition.

The next section compares more specifically time modeling in some of these contributions and the approach presented in this paper.

There are also other auction models, beside combinatorial auctions, which consider multiple attributes (Bichler, et al., 1999; Suyama and Yokoo, 2005) and scoring functions (Müller, et al., 2007; Asker and Cantillon, 2008). For example, Müller, et al. (2007) compared combinatorial scoring auctions with combinatorial price-only auctions (i.e., regular combinatorial auction). These kinds of auctions also measure quality in addition to the bidders' valuations. In these types of auction, the seller calculates the final valuation of the products regardless of the initial valuations of participants. In other words, the calculation of the bids depends on the scores that are measured by the use of a rule or function. These scores are not necessarily equal to bidders' valuations. In this paper, although the auctioneer does not use scoring rules, bidders are allowed to express several valuations of any sub-set of items based on the delivery period.

5.3 Time-based combinatorial auction

This section presents an extension of the classical combinatorial auction model, which aims at simultaneously allocating each individual timber product in a mix species forest stand, and coordinating harvest operations with the winning bidders preferences. The characteristics of the model are explained, including the general model description, the bid structure, as well as the winner determination problem formulation.

5.3.1 Auction system description

The proposed auction model is a seal-bid combinatorial auction. It is an extension of the auction model used by the *Bureau de mise en marché des bois* of the Québec government, which only sells entire forest stands of various sizes. In this model, we make a number of assumptions.

First, the forest stands for sale are mixed, which implies that they contain different species and quality of timber. This assumption is particularly true in Canadian natural boreal forest. Second, there are several kinds of bidders. It assumed that bidders could be loggers and entrepreneurs, who do not directly transform timber as they only harvest and resale timber to different customers. Bidders can also be small or large forest product companies from different sectors (e.g., sawing, pulp and paper, cabinet, wood floor, furniture, engineered wood product) that transform timber of various types into different products.

The practical consequence of such a diverse market is that each bidder may be interested in only part of a stand instead of the entire stand. Our combinatorial model therefore allows bidders to bid not only on entire forest stands, but also on any subset of products (i.e., mix of species and quality) of these stands. Consequently, because each product is sold individually, a combinatorial auction model allows the auctioneer to allocate separately each product in order to maximize revenue. However, bidders cannot bid on part of a product (i.e., a portion of the available volume of a product). Their bids must cover all or nothing of the products available for sale in the stand. For instance, a bidder may want to make an offer for all the available volume of all quality levels of a specific species. In practice, this is not a problem for bidders as volumes available are smaller than their transformation capacity. Furthermore, logs can be stored for a while, before they deteriorate. Consequently, the implementation of such an auction model could lead to many winners with complementary bids in each stand for sale.

This straightforward application of combinatorial auction already allows the auctioneer to gain control of all aspects of the sales (i.e., timber allocation). Indeed, in the auction model currently used in Québec, timber in mixed stands is allocated to winners through lump-sum sales of the entire volume of all the products available in the stand. Winners hence control the resale of undesirable products to other companies or users. In the combinatorial auction, however, the complete control of the sales also comes with the responsibility for managing forest operations and the delivery of each product to their winner. This could eventually lead to timber deterioration problems if stands are harvested too early with respect to their delivery date. Consequently, the auctioneer must guarantee an acceptable level of freshness and manage harvest and delivery operations so as to ensure that freshness meets expected level.

In order to address this issue, our timber combinatorial auction model proposes to further sub-divide the notion of combinations of product in order to add the notion of delivery time preference. In other words, bidders simultaneously bid on both combinations of products and preferred (i.e., latest) delivery period. This implies that, for any bidder, each possible combination of products can be valued differently according to the preferred delivery period. This model is referred to as a time-based combinatorial auction model.

As mentioned above, time dependent combinatorial auction is not new. However, time in the present problem does not have the same conceptual meaning as in other combinatorial auction applications of scheduling and resources allocation in time. For instance, in the application of combinatorial auction to allocate airport landing time slots of Rassenti *et al*. (1982), time compatibility is managed directly with distinct slot definitions (i.e, good for sale) and bid contingency rules. In other words, as illustrated in Figure 5–1, all time slots are distinct goods, defined as time period usage of specific resources that are sold separately. This is not the case in our problem because the available timber is sold once. In other words, in our problem, time is only a dimension of good valuation as timber deteriorates with time. Time is therefore a characteristic of the transaction, not an attribute of the good for sale (or the good itself), as presented in Figure 5–1. In Figure 5–1, the seller does not allow the bidder to offer a value for a good for every period of time, while in Figure 5–2, the bidders can make an offer for each good and each period of time.

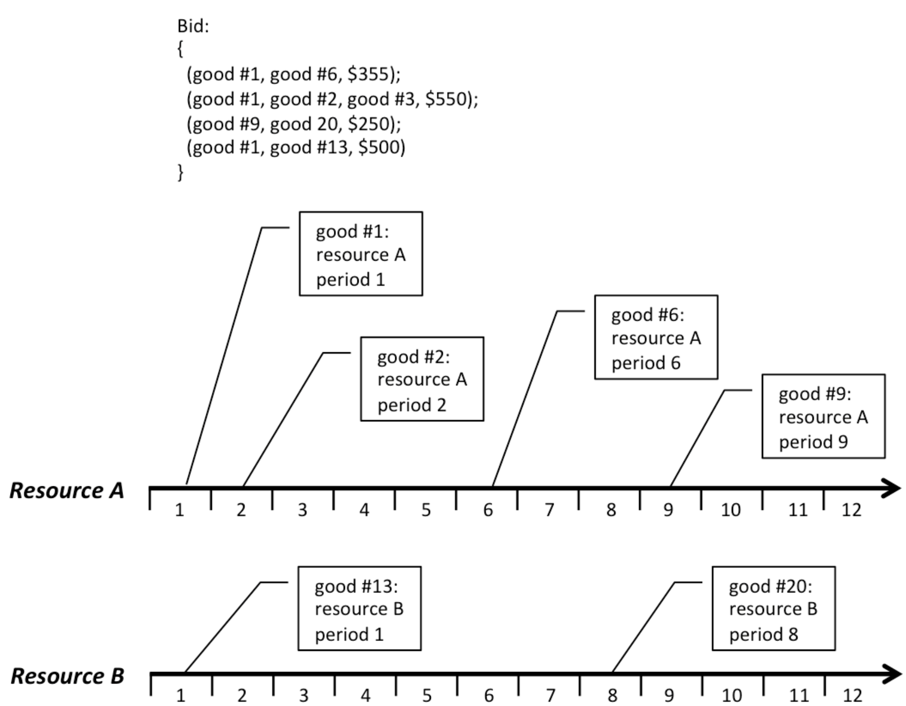


Figure 5–1. Time-based good and bid definition

The application of combinatorial auction for the allocation and scheduling of TV commercials of Ghassemi Tari and Alaei (2013) modeled the time for each specific commercial break as a bulk product for sale. Only the upper bound of the available amount of time is thus a relevant constraint for the auctioneer. This is conceptually equivalent to the multi-unit auction introduced earlier. Once again, this is not the case in the timber allocation problem because time is not the product for sale. In the timber allocation problem, the combination of winning offers must satisfy a time constraint within which all products must be delivered in order to achieve a certain level of freshness. Indeed, in existing timber auction models, such as single unit and combinatorial auctions, there are unaddressed issues concerning timber freshness. For example, in single unit auction, because the entire lot is assigned to one bidder, the bidder must sell (in the context of mixed forest lots) the species/qualities he does not want. Because this may take time, the wood may not be fresh and may lose its quality at the time of processing. Similarly, in combinatorial auction, after winners have been announced, they must somehow agree on the specific time of harvesting of the lot. However, they may not need the items at the same time, and some of them may wish to keep their share in inventory until they need them. This coordination issue may also affect quality as harvested timber losses its freshness as time passes.

In the proposed model, because bidders announce their time preference with respect to timber delivery, the winner determination problem can directly tackle this coordination issue, and shorten the time between mixed species stand harvesting and timber processing in the mill. Therefore, although bidders may behave irrationally, they must address the need to express their delivery time preferences in the proposed bid structure. The next section describes the proposed bid structure.

5.3.2 Bids structure

Bids are structured as sets of triplets (product combination; period; value), as exemplified in Figure 5–2 and Figure 5–3. In other words, each bid represents a set of valuation for each possible combination of products and delivery period (many of them being possibly void). In this example in Figure 5–2, the bidder valuation of products $A \cup B$ is, respectively, 7, 8 and 6 for period 1,2 and 3. This bid also expresses the willingness of the bidder to buy only A for a value of 3 and a delivery in period 3, and product B for a value of 4 and a delivery in period 1. Among the 5 distinct offers contained in this bid, only one can win the auction. Therefore the bidder totally present five distinct offers which includes three offers for products $A \cup B$ in different periods, one offer for product A at period 3, and one offer for product B at period 1. These offers can be seen at the matrix in Figure 5–3 as non-zero elements. In this bid structure, note that the proposed timber values include all harvest and delivery costs.

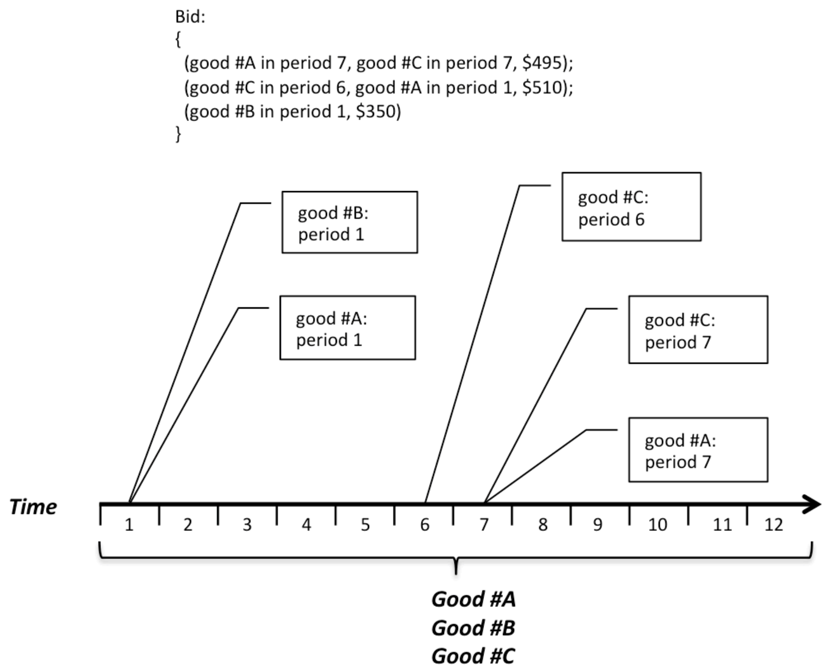
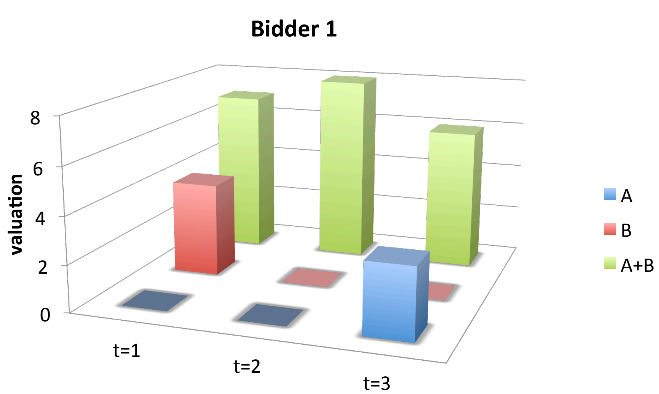


Figure 5–2: Time-dependant valuation of goods



$$
\begin{array}{cccc}
A & B & A \cup B & \\
\left[\begin{array}{ccc} 0 & 4 & 7 \\ 0 & 0 & 8 \\ 3 & 0 & 6 \end{array}\right] & & & \begin{array}{l} t=1 \\ t=2 \\ t=3 \end{array}
\end{array}
$$

Figure 5–3: Bid structure

Although this bid structure is more complex to manage for potential buyers, its complexity mainly depends upon the time granularity imposed by the auctioneer. Because this auction process is linked to the annual procurement planning of forest product companies (see Beaudoin *et al.*, 2007, for a description of this planning problem), it is however unnecessary to have a time-granularity that is smaller than a month. Consequently, because forest product manufacturing plants require specific mix of species and quality, forest engineers and procurement planners only need to focus on the valuation of these combinations with respect to the delivery period. Furthermore, because the Québec timber licencing system requires licensees to send annual procurement plan to the Québec government, it is natural for licensed forest product companies (which potentially represent most bidders) to use a similar time discretization in the auction system, for the purpose of integrating both business processes.

The auctioneer also has the option to use larger time periods, such as the season (3-month period length). This option allows the auctioneer greater time flexibility to plan for harvest and delivery operations, and potentially increase revenue but it is less accurate for buying companies, which are used to monthly plans. This time sensitivity is specifically studied in the experiments section.

Finally, because products are sold separately, the auctioneer (i.e., the Ministry of natural resources) has the opportunity to control specific aspects of the auction to improve fairness. For instance, large forest product companies are generally interested in a few products. During a combinatorial auction of several products from the same area, these large companies might make a global offer to make sure they obtain the products they need, while controlling both the delivery and the resale of the uninteresting products (which is also true for a simple auction). This type of behaviour would limit the ability of smaller timber users to take part in the auction, which would then be dominated by larger companies. Limiting the capacity to make offers only to specific products according to the need of the plants would therefore allow smaller timber users to participate in the auction and have a better control over timber deliveries. The next section describes the corresponding winner determination problem model (i.e., WDP).

5.4 Winner Determination Problem

The process of finding the winners in single unit auctions is straightforward. When the auction is combinatorial, however, a mathematical model must be designed and solved in order to find the combination of offers that maximizes revenue. As mentioned earlier, determining the winners in timber combinatorial auction requires addressing the problem of timber deterioration in time. Because wood tends to deteriorate (e.g., discoloration, decay) once trees are felled, it is necessary to deliver and process them within a reasonable amount of time, before it deteriorates. In this paper, the period length during which all deliveries must be made is referred to the delivery horizon. Therefore, the design of the winner determination problem must address specifically this type of constraints.

In general, the modeling of a winner determination problem depends directly on the auction design, the configuration of the products for sale, as well as on other specific constraints. Because our auction system has a time dependent bid structure, the WDP must include specific constraints to tackle the coordination of deliveries as well as the management of timber deterioration. The next section introduces the proposed mathematical model.

5.4.1 Mathematical model:

The mathematical model presented below is an extension of the WDP for regular combinatorial auctions (Shoham and Leyton-Brown, 2009). We first present the definition of indexes, sets, parameters, and variables. Then, the objective function and the constraints are presented.

Indexes and sets:

$i \in N$	set of bidders
$j \in G$	set of products
$S \subseteq G$	set of bundles of products (power set of products)
$t \in T$	set of time periods
$dt \in T$	set of dates of time periods

Parameters:

$V_i(s,t)$	bidder i's valuation of bundle s at time t
$Q(s)$	volume of bundle s
$Q(j)$	volume of products j
K	length of the delivery horizon (maximum allowable duration between all winning deliveries)

Variables:

$x_{s,i,t}$ Boolean variables, indicating whether bundle *s* is allocated to bidder *i* at time *t*

Objective function:

Maximize

$$\sum_{i \in N} \sum_{s \in S} \sum_{t \in T} V_i(s,t) x_{s,i,t} \pm \varepsilon \sum_{j} Q(j) \ \ x_{s,i,t} \tag{1}$$

s.t.

$$\sum_{s \in S_j} \sum_{i \in N} \sum_{t \in T} x_{s,i,t} \leq 1 \quad \forall j \in G \tag{2}$$

$$\sum_{s \subseteq S} \sum_{t \in T} x_{s,i,t} \leq 1 \quad \forall i \in N \tag{3}$$

$$\sum_{s \in S} (2 * dt_1 - K) x_{s,i_1,t_1} + \sum_{s \in S} (dt_1 - dt_2) x_{s,i_2,t_2} \leq 2 * dt_1 \ \ \forall (i_1, t_1), (i_2, t_2) \tag{4}$$

$$x_{s,i,t} \in \{0,1\} \quad \forall \ \ s \in S, i \in N, t \in T \tag{5}$$

In this integer programming formulation, the objective function (Equation 1) states that the seller aims to maximize the sum of the agents' announced valuations of the combination of products and time period (i.e., maximize revenue). The ε term is introduced in order to avoid multiple solutions for winning determination problem. Therefore, by adding ε and multiplying it by the volume, the solution of the winner determination problem is a bundle that maximizes both value and the sold volume.

Equation (2) states that bidders cannot win bundles of products that have similar products in common (i.e., no overlapping bundles are allocated to the winners). Equation (3) states that no bidder can take more than one bundle at any given valuation (i.e., one bundle at a given time period). Next, Equation (4) deals with time management and prevents delivery preferences of winners to be spread over more than K time periods, which is the length of the delivery horizon.

This constraint is explained in the next section. Finally, Equation (5) ensures that all winners receive a complete subset of products, not a portion of these subsets.

5.4.2 Timber freshness and delivery coordination

As mentioned in the previous section, Equation (4) deals with delivery coordination and timber freshness at the same time. This constraint specifically limits the period of time during which timber delivery to winners can occur. To do so, we define *K* as the maximum allowed duration (i.e., defined as a number of time period) during which all timber transportation to winners can be planned. The larger this duration, the more flexibility the auctioneer has to plan deliveries, and consequently to plan harvest operations. Figure 5–4 presents an example of how time is managed. In this example, we assume that all bundles are mutually distinct and any combination of them can be sold. In the bid received, 5 offers (numbered 1 to 5) are represented in the figure. These offers are made for specific delivery during periods 1, 3, 5, 7 and 9 respectively. In this example, the length of the delivery horizon is 5 periods. Consequently, there are only 3 combinations of offers during which delivery can be made within 5 periods: ({offer #1; offer #2; offer #3}; total value=31), ({offer #2; offer #3; offer #4}; total value=32) and ({offer #3; offer #4; offer #5}; total value=28). Consequently, the winning combination of offers is the second one, with a total value of 32.

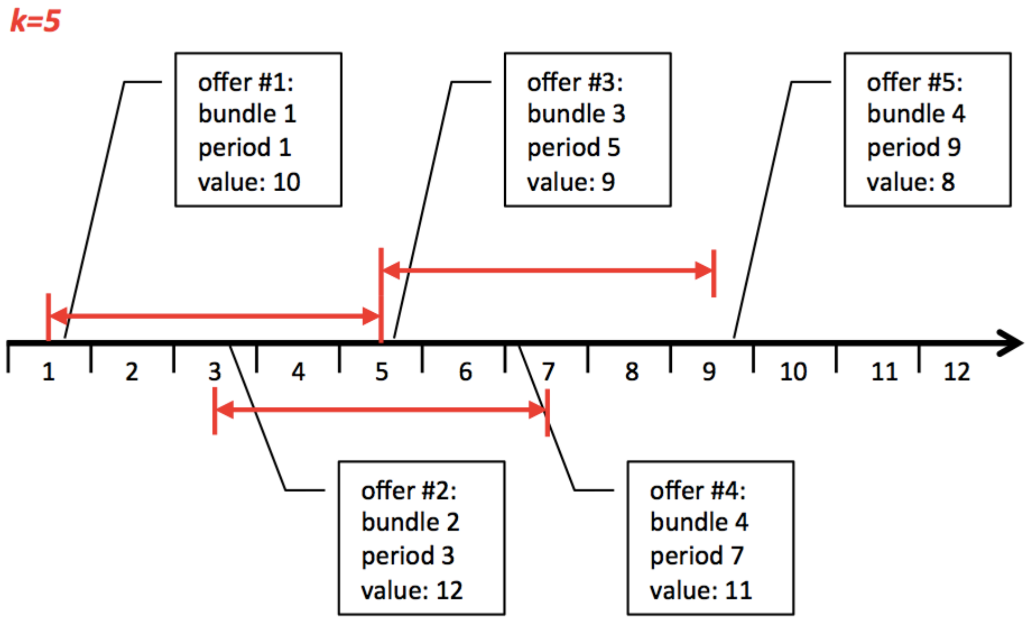


Figure 5–4. Time management example

The length of the delivery horizon can be managed according to the auctioneer's level of flexibility. The smaller the length of the delivery horizon, the fresher is the timber; however, in this case the auctioneer has less flexibility, which can lead to smaller revenue, as studied in the next section. In contrast, the larger the length of the delivery horizon, the more flexibility the auctioneer has to coordinate harvest operations and deliveries. On the other hand, the longer the delivery horizon, the bigger is the risk of timber deterioration.

Granted in practice there is not a large amount of bids that must be processed by the auctioneer (i.e., the duration of the WDP computation is not an issue), the only unknown factor in this winner determination problem, as mentioned earlier, is the effect of the length the delivery horizon on revenue. In the next section, we therefore propose a series of experiments to specifically analyze this aspect.

5.5 Methodology of experiments

In order to evaluate the performance gap between the proposed time-based combinatorial auction and the combinatorial auction without time-management (in this case, we assume that the seller must manage, in conjunction with the winners, the coordination of harvest operations and delivery after the auction), we designed a series of experiments, which is described hereafter.

5.5.1 Bidders' behaviour

In order to simulate different auctions with a diverse population of bidders, which characteristics are similar in both types of auctions, we first introduce a typical bidder behavior that is defined in terms of time preference and time flexibility, followed by the time dependent valuation function used for the experiments.

Time preference and flexibility

A bidder's time preference reflects the month (i.e., time period) during which he or she wants to receive the timber. In addition, a bidder's time flexibility represents how much he or she is flexible with respect to its delivery time preference. For instance, some bidders may be willing to receive their timber at specific periods of time (e.g., April or May), while others may not have very specific time preferences (i.e., any month of the year).

Time valuation function

According to the concepts of time preference and flexibility introduced previously, the time valuation function is defined by equation (6). This function is based on a normal distribution function, where μ represents the bidders' time preference and σ^2, or variance, presents the bidders' time flexibility. *MAXV* is the maximum value that the bidder is willing to pay at its preferred time.

$$Tvalue(t) = MAXV * e^{-\frac{(t-\mu)^2}{2\sigma^2}} \qquad (6)$$

Figure 5–5 presents different examples of time valuation functions for a time preference at month 6 (i.e., $\mu = 6$) and three time flexibilities (i.e., σ^2=1.5, 4 and 7). In this example, the value of *MAXV* is 100. Consequently, the value of the time valuation function equals 100 at time $t = \mu = 6$ for three instances of σ^2.

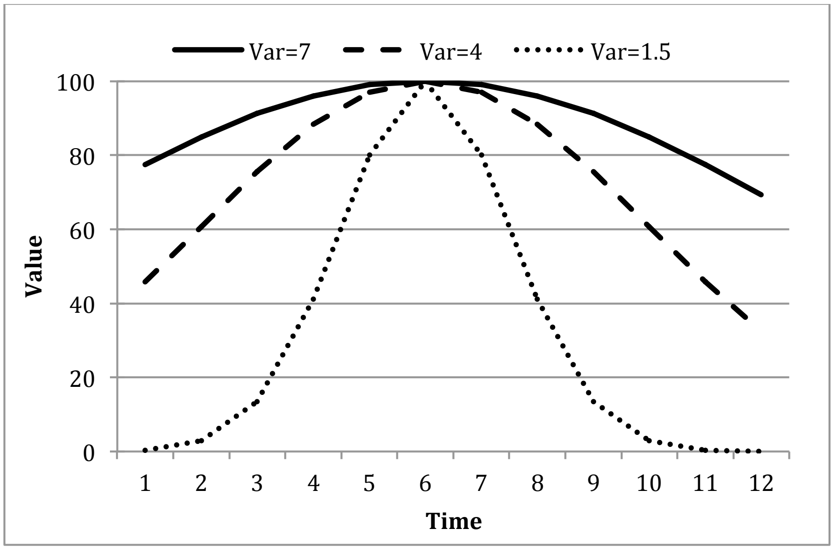


Figure 5–5. Examples of different time value function

As shown in Figure 5–5, for σ^2 = 7, the bidder is the most flexible because its valuations of month 4, 5, 6, 7 and 8 are almost similar. In other words, this means that this particular bidder's delivery time window is 5-months long, with only a slight loss in value at the beginning and the end of that window. For σ^2 = 4, the bidder has a smaller preferred delivery time window of months 5, 6 and 7. Indeed for months 4 and 8, the loss in value is much larger than the previous bidder's profile. This preference is even smaller for σ^2 = 1.5 which corresponds to a delivery time window of basically month 6, with a very large loss in value for the other time periods. Consequently, with a random generation of σ^2 and μ, it is possible to control the generation of very different types of populations of bidders whose preferences can vary greatly.

5.6 Experiments

In the proposed experiments, the seller wants to sell the content of one forest stand, which contains 4 different products that can be sold either as separate items, or as any combination of products. For each individual experiment, 10 bidders were used. Bidders are randomly created with different time preferences, while bidders' time flexibility is controlled for comparison purpose. Note that situations with less than 10 bidders were not studied here. It is possible however, in the case of a low number of bidders, to have no solution for a given level of flexibility (i.e., K). In such situations, we simply assume that the auctioneer can increase K incrementally, until a solution is found. In the extreme case of incompatible bidders' time preferences, the auctioneer can set K to 11 and the model will automatically find a solution, because it is equivalent to the basic combinatorial model. Furthermore, this particular issue is currently part of an agent-based simulation study that deals with the practical and dynamic implementation of this time-based combinatorial auction model.

Furthermore, the general time horizon is 12 periods of one month during which product delivery can be planned. Along the same line, the seller's time flexibility is controlled by the value of K. Several values of K and σ^2 were also tested. Sets (7) to (10) present the values of K, μ, σ^2, and T that were used in the experiments.

$$K = \{0, 1, 2 \dots 11\} \tag{7}$$

$$\mu = \{1, 2, 3 \dots 12\} \tag{8}$$

$$\sigma^2 = \{1.5, 4, 7\} \tag{9}$$

$$T = \{1, 2, 3 \dots 12\} \tag{10}$$

In order to generate several instances of data to be tested and compared with respect to the two auction models, four products were defined with random volumes, standard valuations, and reserve prices. All combinations of these products were also created. To do so, the volume, standard valuation and reserve price of each combination was calculated based on the sum of the volumes, standard valuations and reserve prices of the products specifically included in the combination. Then, 10 bidders were created for each instance. The maximum value that a bidder is willing to pay (i.e., MAXV) was randomly calculated based on the standard valuation of the combination, for each bidder and each combination. For each bidder, μ is created randomly. For each series of experiments, and as mentioned earlier, σ^2 is the same for all bidders, since these experiments aim at evaluating the effect of σ^2 on revenue. Also all values of K between 0 and 11 were systematically tested. Finally, for the time-based combinatorial auction, the specific valuation of each bidder, each combination and each period were calculated using Equation (6). For comparison purposes, in the combinatorial auction with no time management, the valuation of each combination of products was set to the value *MAXV*. In order to improve the significance level of our results, each set of experiments was repeated 30 times, for a total of 1080 optimization results.

5.7 Results and discussion

Using the sets of data defined in the previous section, the model was tested with CPLEX. The average computation time was 3 minutes and 20 seconds. The performance gap between the time-based combinatorial auction and the combinatorial auction with no time management are shown in Figure 5–6.

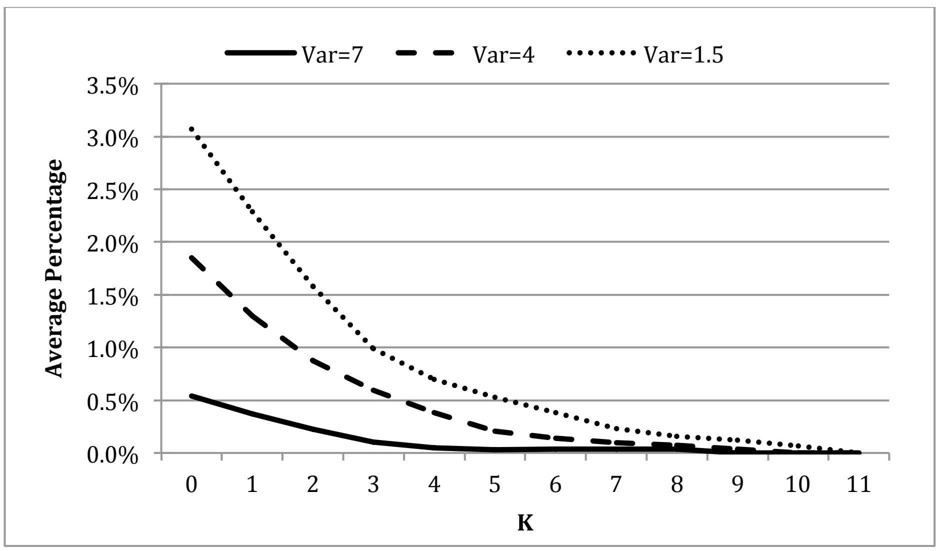


Figure 5–6. Average loss of revenue (in percent of average revenue of combinatorial auction without time management)

As expected, the time-based combinatorial auction leads systematically to a slight loss of revenue, due to the decreasing valuation function used to calculate the offers' value. This loss of revenue represents the maximum value the seller can invest in the coordination of harvest and delivery operations after the auction, in conjunction with the winners. In other words, if the value of this loss of revenue is higher than the cost of managing the coordination of deliveries, then the simple combinatorial auction with no time management is better for the seller. This cost can vary greatly according the number of winners and their willingness to find a compromise.

Furthermore, in practice, the value of a forest stand is directly proportional to the volume of timber available. On the one hand, one can expect this loss of revenue to be higher for a larger stand. On the other hand, forest product companies might be more flexible with delivery time as forest stands for sale get larger, because they represent a more significant portion of the supply. Furthermore, although the seller might experience a larger loss of revenue for larger forest stands, he can also expect scale economies with respect to harvest operations. This loss of revenue must therefore be compared to actual coordination cost and to the impact of scale economies with harvest operations.

Similarly, this loss of revenue is also a function of bidders' time flexibility as presented in Equation (6). This aspect is specifically shown in Figure 5–6. The first observation is that as K increases, the loss of revenue decreases as well, which is perfectly normal (when $K = 11$, time is basically ignored, which is equivalent to the combinatorial auction with no time management). When $K = 0$, in other words when all products are delivered during the same preferred time period, then the average loss of revenue is between 0.5% and 3%, according to the bidders' time flexibility.

The second observation is that when bidders' flexibility is low (i.e., high drop of value when moving away from the preferred period), in other words when σ^2 is small, then the loss of revenue increases up to 3% on average. On the contrary, when bidders have no time preference, then the time-based combinatorial auction is, again, equivalent to the combinatorial auction with no time management).

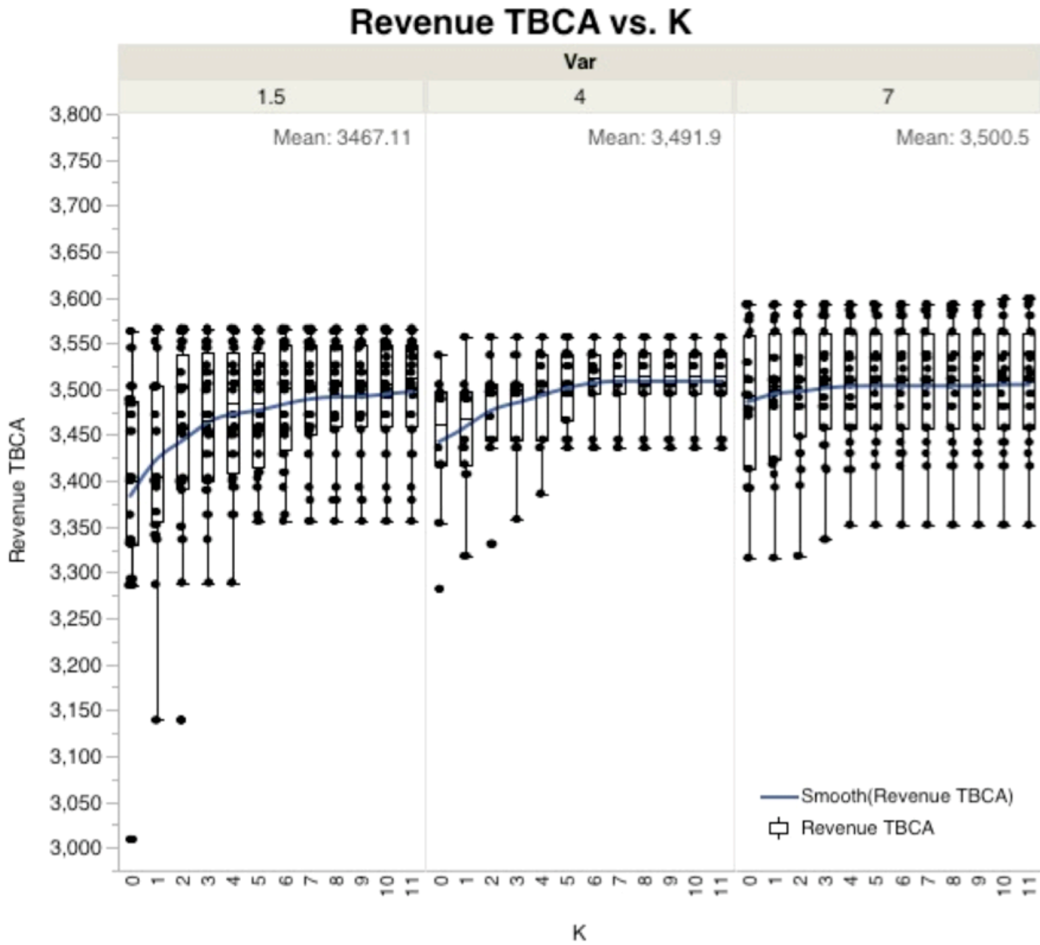


Figure 5–7. Revenue for time-based combinatorial auction (TBCA) for different Ks and Variances

Figure 5–7 shows the revenue generated from time-based combinatorial auction. These results show that when the bidders have more flexibility (i.e., high Variance -σ^2), the average revenue generated almost not affected by K. Therefore, the seller can set the value of *K* in order to facilitate harvest operations coordination with other harvest sites. On the other hand, the lower the flexibility of the bidders (i.e., low Variance σ^2), the bigger is the impact of *K* on the revenue. It also has an impact of revenue variability which increases as bidders flexibility increase. Consequently, there is an element of risk associated with lower bidder flexibility that requires a special attention from the seller. In other words, the seller must adapt the structure of the auction

As a consequence, the profitability of this time-based combinatorial auction is mainly a function of (1) forest stand size and how bidders value larger forest stands; (2) bidders' time preference; and (3) the level of flexibility required by the seller to deliver all products to their winners. Because this latter can be changed by the seller/auctioneer in order to adjust to bidders' time preference, as well as the harvest season, which affects timber deterioration, the time-based combinatorial auction is generally relevant for the auctioneer.

5.8 Conclusion:

This paper proposes a sustainable time-based timber combinatorial auction, which aims to simultaneously allocate multiple products in mixed forest stand to multiple winners, and address the coordination of timber deliveries to their winners. The proposed timber combinatorial auction is economically sustainable. First, all products are sold individually and allocated according to their economic value, with respect to each potential user’s market. In other words, a small timber user in a high value market has more control over procurement operations and timber availability if needed. On the contrary to a pure licensed system, in which procurement volumes cannot be easily adjusted, a combinatorial timber auction give a fair chance to participate to every potential timber user. In a combinatorial auction, and for the same reasons, it is more difficult for large forest product companies to gain complete control over timber availability. Finally, because the seller becomes responsible for managing forest operations, the combinatorial auction allows the Ministry of natural resources to exercise high standards for environmentally friendly forest operations as well.

From a logistic point of view, in contrast to other time-based auction systems, time is not part of the product for sale. It is only used as variable of the valuation of the products for sale. Consequently, although this auction system is more complicated for the bidders than the current first-price sealed bid auction, it has many advantages for both the auctioneer and the bidders. First, time-based combinatorial auction can directly address the coordination of delivery of all products between winners, in order to improve the level of timber freshness. When multiple products must be delivered to multiple winners, the coordination of harvest operations and delivery must be carried out. By directly addressing this issue, the time-based combinatorial auction has the potential to simplify complex post-auction negotiations between the winners and the seller.

Therefore, by carefully setting up the allowed level of flexibility required to coordinate delivery with both, the bidders' expectation and the need for timber freshness, the auctioneer can reduce the cost of planning harvest operations and delivery.

In order to further validate this auction model, future research projects include the implementation of this auction model into a multiple-round auction simulation. Such a project would allow us to evaluate dynamically, and with realistic cost functions, both the level of revenue generated for the auctioneer, but also the logistic usefulness of the auction for the bidder with respect to the coordination of their procurement throughout the year. In this simulation model, all associated costs, such as harvest cost and coordination cost can be measured. The behaviour of the bidders can also be simulated according to bidders' greed and impatience.

5.9 Acknowledgement:

This work was funded by the FOR@C Research Consortium, and the NSERC. The authors would also like to acknowledge the contribution of the experts at the *Bureau de mise en marché des bois*, of the Québec government for their advice, explanations and validation of the models.

5.10 References:

Asker, J., & Cantillon, E. (2008). Properties of scoring auctions. RAND J. Econ., 39(1), 69–85. DOI: 10.1111/j.1756-2171.2008.00004.x.

Athey, S., & Levin, J. (2001). Information and competition in US forest service timber auctions. J. Polit. Economy. 109 (2), 375–417. DOI:10.1086/319558.

Athey, S., Levin, J., & Seira, E. (2011). Comparing open and sealed bid auctions: evidence from timber auctions. Quart. J. Econ., 126 (1), 207–257. DOI: 10.1093/qje/qjq001.

Bai, H., & Zhang, Z. (2005). A winner determination algorithm for multi-unit combinatorial auctions with reserve prices. Proc. 2005 Int. Conf. on Active Media Technology, Takamatsu, Japan, pp. 239–243.

Baldwin, L. H., Marshall, R. C., & Richard, J. F. (1997). Bidder collusion at forest service timber sales. J. Polit. Economy, 105 (4), 657–699. DOI: 10.1086/262089.

Beaudoin, D., Frayret, J. M., & Lebel, L. (2010). Negotiation-based distributed wood procurement planning within a multi-firm environment. Forest Policy Econ., 12(2), 79–93. DOI: 10.1016/j.forpol.2009.07.007.

Beaudoin, D., Lebel, L., & Frayret, J. M. (2007). Tactical supply chain planning in the forest products industry through optimization and scenario-based analysis. Can. J. Forest Res., 37(1), pp 128–140. DOI:10.1139/X06-223.

Bichler, M., Kaukal, M., & Segev, A. (1999). Multi-attribute auctions for electronic procurement. Proc. first IBM IAC workshop on Internet based negotiation technologies, pp. 18–19.

Brewer, P. J. (1999). Decentralized computation procurement and computational robustness in a smart market. Econ. Theory, *13(*1), 41–92. DOI: 10.1007/s001990050242.

Brown, R. N., Kilgore, M. A., Blinn, C. R., & Coggins, J. S. (2012). State Timber Sale Programs, Policies, and Procedures: A National Assessment. Forestry, 110(5), 239–248. DOI: 10.5849/jof.10-079.

Cantillon, E., & Pesendorfer, M. (2007). Combination bidding in multi-unit auctions. CEPR, No. 6083. DOI: 10.2139/ssrn.958730.

Cramton, P., Shoham, Y., & Steinberg, R. (2006). Combinatorial Auctions. MIT Press.

De Vries, S., & Vohra, R. V. (2003). Combinatorial auctions: A survey. INFORMS J. Comput., 15(3), 284–309. doi:10.1287/ijoc.15.3.284.16077.

Elyakime, B., Laffont, J. J., Loisel, P., & Vuong, Q. (1994). First-price sealed-bid auctions with secret reservation prices. Ann. Econ. Statist. , 34, 115–141.

Elyakime, B., Laffont, J. J., Loisel, P., & Vuong, Q. (1997). Auctioning and bargaining: an econometric study of timber auctions with secret reservation prices. J. Bus. Econ. Stat., 15 (2), 209–220. DOI:10.2307/1392306.

Farnia, F., Frayret, J. M., Lebel, L., & Beaudry, C. (2013). Multiple-Round Timber Auction Design and Simulation. Int. J. Product. Econ., 146(1), 129–141. DOI: 10.1016/j.ijpe.2013.06.012.

Ghassemi Tari, F., & Alaei, R. (2013). Scheduling TV commercials using genetic algorithms, Int. J. Prod. Res., 51(16), 4921–4929. DOI: 10.1080/00207543.2013.778431.

Haile, P. (2001). Auctions with resale markets: an application to us forest service timber sales. Amer. Econ. Rev., 91(3), 399–427. DOI: 10.1257/aer.91.3.399.

Hansen, R. (1985). Empirical testing of auction theory. Amer. Econ. Rev., 75, 156–159.

Jung, S. H., & Kim, K. H. (2006). Load scheduling for multiple quay cranes in port container terminals. J. Intell. Manuf., 17(4), 479–492. DOI: 10.1007/s10845-005-0020-y.

Kant, S. (2010). Market, timber pricing, and forest management. Forest. Chron., 86(5), 580–588. DOI: 10.5558/tfc86580-5.

Kutanoglu, E., & Wu, S. D. (1999). On combinatorial auction and Lagrangean relaxation for distributed resource scheduling. *IIE Trans., 31*(9), 813–826. DOI: 10.1023/A:1007666414678.

Lau, H. C., Cheng, S. F., Leong, T. Y., Park, J. H., & Zhao, Z. (2007). Multi-period combinatorial auction mechanism for distributed resource allocation and scheduling. IAT-07. 407–41.

Malone, T. W., & Crowston, K. (1994). The interdisciplinary study of coordination. ACM Comput. Surv., 26 (1), 87–109. DOI: 10.1109/IAT.2007.72.

Marty, G., & Préget, R. (2010). A socio-economic analysis of French public timber sales. J. Sustainable For., 29(1), 15–49. DOI: 10.1080/10549810903463395.

Mead, W. J. (1967). Natural Resource Disposal Policy - Oral Auction versus Sealed Bids. NAT. RES. J.7(2), 194–224.

Mueller, R., Perea, A., & Wolf, S. (2007). Combinatorial scoring auctions. Meteor research memorandum, University of Maastricht, RM07020.

Niquidet, K., & van Kooten, G.C. (2006). Transaction Evidence Appraisal: Competition in British Columbia's Stumpage Markets. Forest Sci., 52(4), 15–49.

Paarsch, H. (1991). Empirical Models of Auctions and an Application to British Columbia Timber Sales. UBC, Vancouver.

Parkes, D. C., & Ungar, L. H. (2000). Iterative combinatorial auctions: Theory and practice. Proc. Conf. AAAI Artif. Intell., 74–81.

Parkes, D. (2001). Iterative combinatorial auctions: Achieving economic and computational efficiency. Doctoral dissertation, University of Pennsylvania.

Rabotyagov, S. S., Tóth, S. F., & Ettl, G. J. (2013). Testing the Design Variables of ECOSEL: A Market Mechanism for Forest Ecosystem Services. Forest Sci., 59(3), 303–321. DOI: 10.5849/forsci.11-110.

Rassenti, S. J., Smith, V. L., & Bulfin, R. L. (1982). A Combinatorial Auction Mechanism for Airport Time Slot Allocation. Bell J. Econ., 13(2), 402–417. DOI: 10.2307/3003463.

Sakurai, Y., Yokoo, M., & Kamei, K. (2000). An efficient approximate algorithm for winner determination in combinatorial auctions. EC, 30–37. DOI: 10.1145/352871.352875.

Shoham, Y., & Leyton-Brown, K. (2009). Multiagent systems: algorithmic, game- theoretic, and logical foundations. CUP, Cambridge.

Suyama, T., & Yokoo, M. (2005). Strategy/false-name proof protocols for combinatorial multi-attribute procurement auction. Auton. Agent Multi Agent Syst., 11(1), 7–21. DOI: 10.1109/AAMAS.2004.255.

Vidal, J. M. (2007). Fundamentals of Multiagent Systems with NetLogo Examples. Unpublished.

Wang, C., Ghenniwa, H. H., & Shen, W. (2009). Constraint-based winner determination for auction-based scheduling. T-SMCA, 39(3), 609–618. DOI:10.1109/TSMCA.2009.2013194.

Wang, C., & Dargahi, F. (2013). Service customization under capacity constraints: An auction-based model, J. Intell. Manuf., 24(5), 1033–1045. DOI: 10.1007/s10845-012-0689-7.

Wellman, M. P., Walsh, W. E., Wurman, P. R., & MacKie-Mason, J. K. (2001). Auction protocols for decentralized scheduling. Game Econ. Behav., 35(1), 271–303. DOI: 10.1006/game.2000.0822.

CHAPTER 6 : GENERAL DISCUSSION AND CONCLUSION

This thesis consists of three journal articles dealing with simulation and design of timber auction systems. In this chapter, the relation between the contributions of three papers is presented and discussed. The conclusion of the thesis is also presented. Furthermore, the implementation methods of these papers in the industry are discussed.

6.1 Multiple-round single unit timber auctions

First, the results obtained from our first paper showed that the adaptive and learning bidding patterns have the best results in terms of their design objectives compare to other bidding patterns. Based on the comparison of price paid per m^3 of all bidding approaches, the learning approach is better than all other approaches in almost every configuration. However, the price in the adaptive approach is almost equivalent to the price in the learning approach when the competition is low and the lots are bigger. This validates what we intended to program. Similarly, price paid seems to be less when items are bigger. This result is a first indicator on how to design the auction in order to maximize revenue from the seller point of view. The results combined with comparing target achievement shows learning approach bidders pay less for the item, while the adaptive approach bidders have a better target achievement. Therefore, according to their objective, bidders should use any combination of these two approaches. This is why, in the remaining experiments, fixed behaviour and random approaches were abandoned, as they do not try to achieve any particular objective.

Second, comparing hybrid bidder agents (adaptive learning agents), the less a hybrid agent is influenced by the adaptive behaviour, the less sensitive to competition it is to achieving good sale prices. This also confirms the findings of the first experiment, which, compared to the learning approach, found that the adaptive approach has a stronger negative impact on the sale price, than it has a positive impact on target achievement. As expected, the observed performance of the different types of hybrid agent is generally correlated to how much of the pure behaviours they are made of. However, it seems that the influence of the adaptive behaviour is more significant than the influence of the learning behaviour, although they all display an almost equally good performance with respect to target achievement. Therefore we can safely assume that the generation of a population of randomly generated hybrid agents is representative of a population of rational bidders driven by any combination of both objectives.

The influence of several auction design parameters on the outcome of the auction (price and target achievement) is also tested. All results show systematic opposite effects of all design parameters on both outcomes. For instance, lot size affects positively target achievement and negatively sale price. More specifically, when item size gets larger, the sale price per m^3 decreases. Smaller lots attract more bidders, which causes more demand, which in turn increases the sale price.

Similarly, periodicity has a rather limited influence on value below 15 days. However, shorter periodicities tend to be generally more beneficial than longer ones. This influence can be explained as follows. When periodicity increases, while the total number of auctions remains unchanged, the number of items for sale increases at each round. In other words, there are fewer rounds of auctions, but more auctions at each round. Consequently, the influence of periodicity on sale price target achievement can be explained by the fact that bidders can achieve lesser price if they can bid simultaneously on more items (i.e., more supply quantities per round).

Along the same line, the number of auctions affects positively target achievement, and negatively sale price. As the number of auctions decreases, the influence of lot size and the influence of the number of bidders on sale price are reduced as well. This can be explained by the fact that reduced supply leads to a higher number of interested bidders, even if the items' lot size is large or the number of potential bidders is low. This result shows that higher competition with respect to a certain level of supply, leads to a market price that better represents the limit of forest companies to purchase items.

In contrast, the number of bidders has a positive impact on sale price, but a negative impact on target achievement. This result can be explained as follow. As competition and demand increase, the number of bids received during each auction increase, which results in a higher probability of receiving high value bids. Along the same line, increased competition also reduces the probability of each forest company to win, and therefore reduces their ability to achieving their target.

Finally, the correlation between target achievement and sale price is negative, which tends to show that both objectives cannot be achieved simultaneously. In other words, it seems that the government that owns the forest has a dilemma as it can either maximize its revenue, or support the industry by allowing companies to better achieve their supply target. Using the presented simulation model, the government can optimize its revenue while considering the target achievement of the companies.

The presented model in the first paper does not allow the bidders to bid on a part of the lot. Indeed, some mills or entrepreneurs do not need entire lots, but only some of their products. Therefore combinatorial auction can be investigated which allows the bidders to bid on any subset of the lot.

6.2 Multiple-round combinatorial timber auctions

Analysing the effects of each parameter shows that when the number of auction increases, the price per m^3 decreases due to more supply in the market. The price per m^3 drops when the lots get larger, again because of more supply. By demand increase (number of bidders), the price per m^3 increases as well. The results show when the number of auctions increases, the price per m^3 increases, even if lot size changes, but the price is lower when lot size gets larger. The reason for this result is that both number of auctions and lot size are significantly increase the supply of the market. Therefore, the combination of these two parameters affects the price per m^3 of the market. Therefore, price per m^3 is higher in combinatorial auction when there are fewer supplies and more bidders.

Along the same line, the auctions comparison illustrates that the combinatorial auction is preferable in competitive situations. Combinatorial auction is better when there are fewer auctions while the lots are small and there are few bidders. The auctioneer can sell the products with higher price through combinatorial auction, when the market is competitive (more demand and less supply).

From the bidders point of view, number of auctions and lot size carry positive impact, while periodicity and number of bidders have negative impact on the target achievement. The reasons for positive impact is more supplies through auction system, therefore, the bidders can win more wood supply to fulfill their needs. Similarly, when number of bidders rises, the auction becomes more competitive and the chance of winning drops. When periodicity is higher, the bidders meet more auctions to bid on at same round. Therefore, they have more options (auctions) to decide. The bidders tend to bid only on the amount they need, since they think they may win; hence, they might lose some opportunities by not participating in other auctions. Therefore, it is probable that bidders win lower volumes when there are more auctions at one round. The bidders prefer combinatorial auction, when the market is competitive. On the other hand, the target achievement of combinatorial auction is higher than target achievement of combinatorial auction in competitive auction market. The combinatorial auction is much better than single-unit in situations when there are few auctions, few rounds of auction (higher periodicity), and more bidders.

Although combinatorial auction has some advantages over single-unit auction, it may be difficult for the bidders to arrange for the harvest operations and products delivery, since the winners are chosen only according to what products they want, not when they want the products. The bidders may also not agree on the harvest operation, which induces the low wood quality due to the time difference between the harvesting and processing the wood in the mill. To address this issue, this paper proposes time-based combinatorial auction as a follow up research project. Time-based combinatorial auction aims to allocate multiple products to multiple winners, while consider the coordination of timber deliveries to the winners.

6.3 Time-based combinatorial timber auctions

First, the time-based combinatorial auction leads systematically to a slight loss of revenue, due to the decreasing valuation function used to calculate the offer's value as it moves away from the preferred harvest period. This loss of revenue represents the maximum value that the seller invests in the coordination of harvest and delivery operations after the auction, in conjunction with the winners. In other words, if the value of this loss of revenue is higher than the cost of managing the coordination of deliveries, then the simple combinatorial auction with no time management is better for the seller. This cost can vary greatly according the number of winners and their willingness to find a compromise.

Second, it shows when bidders' flexibility is low (i.e., high drop of value when moving away from the preferred period), then the loss of revenue increases to 3% on average. On the contrary, when bidders have no time preference, then the time-based combinatorial auction is equivalent to the combinatorial auction with no time management.

Finally, the results of the revenue generated from time-based combinatorial auction show that when the bidders have more flexibility, the average revenue generated almost not affected by K (is the length of the delivery horizon). Therefore, the seller can set the value of K in order to facilitate harvest operations coordination with other harvest sites. On the other hand, the lower the flexibility of the bidders, the bigger is the impact of K on the revenue. It also has an impact of revenue variability which increases as bidders flexibility increase. Consequently, there is an element of risk associated with lower bidder flexibility that requires a special attention from the seller.

As a consequence, the profitability of the time-based combinatorial auction is mainly a function of the bidders' time preference and the level of flexibility required by the seller to deliver all products to their winners.

6.4 Industrial impact of scientific contributions

The simulation model and the analysis provided in the first part of this project could help the Ministry of Forests, Wildlife and Parks (MFFP) to configure the proposed auction system. Also, the combinatorial auction is capable of analyzing advanced form of wood auction including allocating wood in mixed forest. As the Quebec government and timber users may face some difficulties in combinatorial auction, a new method of auction (time-based combinatorial auction) is proposed to the government.

This thesis proposes many contributions to the multiple-round single-unit timber auction for the government and forest companies, which had not yet been studied before. There are contributions for both sellers and buyers.

- The bidders learn how to bid in existing auction system using adaptive and agent-learning methods.
- The approach presents a mathematical linear programing model to bidders to select the best set of items to bid on at each round of auction.

- The government (seller) can maximize its revenue using the outcome of the research, which studies parameter configuration of the auction.

This thesis also provides other solutions to the government by proposing a design and simulation of "multiple-round timber combinatorial auction". It provides contributions for the seller as follows.

- The study presents the market conditions and auction parameters in which the auction can generate more revenue for the government.
- It can guide the government whether combinatorial auction can generate more revenue for the government comparing to single unit auction in any specific market situation. The market conditions for which combinatorial auctions can outperform compared to single-unit auction are presented.

This thesis also proposes "time-based timber combinatorial auction" which is a solution to overcome coordination of forest activities among winners. The "time-based timber combinatorial auction" model brings the following contributions for the seller.

- This auction model includes time, which is used to valuate the good for sale with respect to expected delivery period in combinatorial auction. This system allocates multiple goods in mixed forest stand, to multiple winners, and to address the coordination of timber deliveries to winners while considering the freshness of wood.
- The winner determination problem of time-base combinatorial auction is presented for the auctioneers who want to use this auction in their model.
- The model contributes on delivery coordination while it may impact total revenue due to loss of value when time preference is not fully satisfied.

The Quebec government is interested in this research project, as their current system needs to be evaluated in different setup configurations and different market conditions. The results of this thesis can also help the bidders, which are mills and entrepreneurs, in order to determine how to bid using intelligent methods. The second results of this project conduct combinatorial auction, which is opened to bidders who are interested in a portion of a lot. Although the combinatorial auction has some advantages that increases bidders' interests to participate, it needs collaboration among winners in a lot. Therefore we propose and analyze time-base combinatorial auction to the government as an alternative. This model can be investigated to be implemented when the government is not willing to deal with collaboration of the winners while consider wood freshness.

6.5 Conclusion

In the first contribution, the multiple-round single-unit timber auction is simulated. The results indicate that the adaptive and learning bidding patterns have better results compared to the other approaches. These patterns can be applied in designing a company's bidding pattern. Then, the results show that the government cannot simultaneously achieve high revenue while providing an effective supply channel to forest companies. This fact is considered in the design of the auction process to find out an arrangement in order to generate acceptable revenue while keeping forest companies' activities. Further, the results also indicate that the number of potential bidder and number of auctions per year significantly impacts the revenue generated. Finally, paper one demonstrates that by offering larger forest lots leads to higher target achievement of companies, and lower average sales price.

In the second paper, multiple-round combinatorial auctions was designed and simulated. The results indicate that in multi-round auctions with longer time horizon (more rounds) combinatorial auctions perform better than single-unit auctions in sale price and target achievement. Next, our results demonstrate that when the market is more competitive, the selling price per m^3 is higher in combinatorial auction. Then, the results of the auctions comparisons illustrate that the combinatorial auction should be favored by government in competitive situations. On the other hand, the target achievement of the companies in combinatorial auction is higher in less competitive market.

Finally, in the third paper a time-base combinatorial timber auction is proposed. This paper describes how this model is economically sustainable. It describes how all types of products can be sold separately while allocated according to their economic value, while considering each type of timber users, and delivered to users at the time that they need the products. Hence, this auction system has many advantages for both the auctioneer and the bidders, despite of the difficulty of the auction compared to the current first-price sealed bid auction. To increase the level of timber freshness, time-based combinatorial auction directly considers the coordination of harvest operations and delivery of multiple products between multiple winners. Ability to coordinate while assigning the products, can simplify complex post-auction negotiations between the winners and the seller. Therefore, when the allowed level of flexibility required, it is carefully choose to coordinate delivery with the bidders' expectation, the auctioneer can reduce the cost of planning harvest operations and delivery.

6.6 Future work

Future work can be done in several directions as following. The agent-based simulation of the time-based combinatorial auction that was presented in the third paper could be implemented. Similar studies can be done in order to compare the outcomes of time-based combinatorial auction and regular combinatorial auction. Next, in this simulation model, all associated costs; such as harvest cost and coordination cost can be measured. Following, the time-based combinatorial auction can be applied and tested in similar other markets such as allocation of scarce natural resources.

BIBLIOGRAPHY

Airiau, S., Sen, S., 2003. Strategic bidding for multiple units in simultaneous and sequential auctions. Group Decision and Negotiation, 12(5), 397-413.

Andreoni, J., Miller, J., 1995. Auctions with artificial adaptive agents. Games and Economic Behavior, 10(1), 39-64.

Anthony, P., Jennings, N. R., 2002. Evolving bidding strategies for multiple auctions. In: Proceedings of the 15th European Conference on Artificial Intelligence, 178-182.

Ashenfelter, O. 1989. How auctions work for wine and art. Journal of Economic Perspectives 3:33-36.

Asker, J., & Cantillon, E. (2008). Properties of scoring auctions. RAND J. Econ., 39(1), 69–85. DOI: 10.1111/j.1756-2171.2008.00004.x.

Athey, S., & Levin, J. (2001). Information and competition in US forest service timber auctions. J. Polit. Economy. 109 (2), 375–417. DOI:10.1086/319558.

Athey, S., Levin, J., & Seira, E. (2011). Comparing open and sealed bid auctions: evidence from timber auctions. Quart. J. Econ., 126 (1), 207–257. DOI: 10.1093/qje/qjq001.

Athey, S., Levin, J., 2001. Competition and information in us forest service timber auctions. Journal of Political Economy, 109(2), 375-417.

Bai, H., & Zhang, Z. (2005). A winner determination algorithm for multi-unit combinatorial auctions with reserve prices. Proc. 2005 Int. Conf. on Active Media Technology, Takamatsu, Japan, pp. 239–243.

Baldwin, L. H., Marshall, R. C., & Richard, J. F. (1997). Bidder collusion at forest service timber sales. J. Polit. Economy, 105 (4), 657–699. DOI: 10.1086/262089.

Bapna, R., Goes, P., Gupta, A., 2003. Replicating online Yankee auctions to analyze auctioneers' and bidders' strategies. Information Systems Research, 14(3), 244-268.

Beaudoin, D., Frayret, J. M., & Lebel, L. (2010). Negotiation-based distributed wood procurement planning within a multi-firm environment. Forest Policy Econ., 12(2), 79–93. DOI: 10.1016/j.forpol.2009.07.007.

Beaudoin, D., Lebel, L., & Frayret, J. M. (2007). Tactical supply chain planning in the forest products industry through optimization and scenario-based analysis. Can. J. Forest Res., 37(1), pp 128–140. DOI:10.1139/X06-223.

Bichler, M., Kaukal, M., & Segev, A. (1999). Multi-attribute auctions for electronic procurement. Proc. first IBM IAC workshop on Internet based negotiation technologies, pp. 18–19.

Binmore, K., & Klemperer, P., 2002. The biggest auction ever: the sale of the British 3G telecom licences. The Economic Journal, 112(478), C74-C96.

Boutilier, C., Dean, T., Hanks, S., 1999. Decision-theoretic planning: structural assumptions and computational leverage. Journal of Artificial Intelligence Research, 11, 1-94.

Brewer, P. J. (1999). Decentralized computation procurement and computational robustness in a smart market. Econ. Theory, *13(*1), 41–92. DOI: 10.1007/s001990050242.

Brown, R. N., Kilgore, M. A., Blinn, C. R., & Coggins, J. S. (2012). State Timber Sale Programs, Policies, and Procedures: A National Assessment. Forestry, 110(5), 239–248. DOI: 10.5849/jof.10-079.

Cantillon, E., & Pesendorfer, M. (2007). Combination bidding in multi-unit auctions. CEPR, No. 6083. DOI: 10.2139/ssrn.958730.

Cliff, D., Bruten, J., 1997. Minimal-Intelligence agents for bargaining behaviors in market-based environments. Hewlett-Packard Labs., Technical Report, HPL 97-91.

Cramton, P., 2007. How best to auction oil rights. In: Humphreys, M., Sachs, J. D., Stiglitz, J. E., (eds.). Escaping the resource curse. New York: Columbia University Press, 5, 114-151.

Cramton, P., Shoham, Y., & Steinberg, R. (2006). Combinatorial Auctions. MIT Press.

De Vries, S., & Vohra, R. V. (2003). Combinatorial auctions: A survey. INFORMS J. Comput., 15(3), 284–309. doi:10.1287/ijoc.15.3.284.16077.

Elyakime, B., Laffont, J. J., Loisel, P., Vuong, Q., 1994. First-price sealed-bid auctions with secret reservation prices. Annales d'Economie et de Statistique, 115-141.

Elyakime, B., Laffont, J. J., Loisel, P., Vuong, Q., 1997. Auctioning and bargaining: an econometric study of timber auctions with secret reservation prices. Journal of Business & Economic Statistics, 15(2), 209-220.

Farnia. F., J.M. Frayret, C. Beaudry, L. LeBel, 2014 "Time-Based Combinatorial Auction for Timber Allocation and Delivery Coordination" submitted to Forest Policy and Economics

Farnia. F., J.M. Frayret, L. LeBel, C. Beaudry, 2013 "Multiple-Round Timber Auction Design and Simulation", International Journal of production economics, 146(1), 129-141.

Ganuza, J.J., 2004. Ignorance promotes competition: an auction model with endogenous private valuations. The Rand Journal of Economics, 35(3), 583-598.

Gerber, A., Klusch, M., 2002. Agent-based integrated services for timber production and sales. IEEE Intelligent Systems, 17(1), 33-39.

Gerding, E. H., Dash, R. K., Byde, A., Jennings, N. R., 2008. Optimal strategies for simultaneous vickrey auctions with perfect substitutes. Journal of Artificial Intelligence Research (JAIR), 32, 939-982.

Ghassemi Tari, F., Alaei, R., 2013. "Scheduling TV commercials using genetic algorithms", International Journal of Production Research, 51(16), 4921-4929.

Gmytrasiewicz, P. J., Durfee, E. H., 1995. A rigorous, operational formalization of recursive modeling. In Proceedings of the First International Conference on Multi-Agent Systems, 125-132.

Gode, D. K., Sunder, S., 1993. Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. Journal of political economy, 101(1), 119-137.

Graham, D. A., Marshall, R. C., 1987. Collusive bidder behavior at single-object second-price and English auctions. The Journal of Political Economy, 95(6), 1217-1239.

Greenwald, A., Boyan, J., 2005. Bidding algorithms for simultaneous auctions: A case study. Journal of Autonomous Agents and Multiagent Systems, 10(1), 67-89.

Grossklags, J., Schmidt, C., Siegel, J., 2000. Dumb software agents on experimental electronic markets. In: Informatiktage 2000, G. fur Informatik e.V.,Ed. Leinfelden-Echterdinge, Germany: Konradin Verlag.

Haile, P., 2001. Auctions with resale markets: an application to us forest service timber sales. American Economic Review, 91, 399-427.

Hansen, R. (1985). Empirical testing of auction theory. Amer. Econ. Rev., 75, 156–159.

Jung, S. H., & Kim, K. H., 2006. Load scheduling for multiple quay cranes in port container terminals. Journal of Intelligent manufacturing, 17(4), 479-492.

Kagel, J.H., 1995. Auctions: a survey of experimental research. In: Kagel, J.H., Roth, A.E., (Eds.). Handbook of Experimental Economics, Princeton University Press, Princeton.

Kant, S. (2010). Market, timber pricing, and forest management. Forest. Chron., 86(5), 580–588. DOI: 10.5558/tfc86580-5.

Karuga, G., Nair, S., Tripathi, A. K., 2005. Sizing of lots in identical-item sequential online auctions. Working Paper, University of Connecticut.

Klemperer, P., 2002. What Really Matters in Auction Design. Journal of Economic Perspectives, 16(1), 169 - 189.

Kreps, D. M., 1990. Game theory and economic modeling. New York: Oxford University Press.

Kutanoglu, E., & Wu, S. D. (1999). On combinatorial auction and Lagrangean relaxation for distributed resource scheduling. *IIE transactions*, *31*(9), 813-826.

Kwon, R. H., Lee, C. G., & Ma, Z. (2005). An integrated combinatorial auction mechanism for truckload transportation procurement. *University of Toronto, http://www. mie. utoronto. ca/labs/ilr/MultiRound. pdf, Working Paper*.

Lange, A., J. List and M. Price 2011. Auctions with Resale when Private Values Are Uncertain: Theory and Empirical Evidence. International Journal of Industrial Organization, 29, 54-64.

Lau, H. C., Cheng, S. F., Leong, T. Y., Park, J. H., & Zhao, Z., 2007. Multi-period combinatorial auction mechanism for distributed resource allocation and scheduling. In Proceedings of the 2007 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (pp. 407-411). IEEE Computer Society.

Lu, J., Perrigne, I., 2008. Estimating risk aversion from ascending and sealed-bid auctions: the case of timber auction data. Journal of Applied Econometrics, 21, 1221-1247.

Mailath, G., Zemsky, P., 1991. Collusion in second price auctions with heterogeneous bidders. Games and Economic Behavior, 3, 467-486.

Malone, T. W., & Crowston, K. (1994). The interdisciplinary study of coordination. ACM Comput. Surv., 26 (1), 87–109. DOI: 10.1109/IAT.2007.72.

Marty, G., & Préget, R. (2010). A socio-economic analysis of French public timber sales. J. Sustainable For., 29(1), 15–49. DOI: 10.1080/10549810903463395.

Maskin, E., J. Riley, 2000. Asymmetric Auctions. Review of Economic Studies, 67, 439 – 454.

Mathieu, P., Beaufils, B., Brandouy, O., 2006. Artificial economics, agent-based methods in finance, game theory and their applications. Berlin: Springer.

McAfee, R.P., McMillan, J., 1987. Auctions and Bidding. Journal of Economic Literature, 25, 699-738.

Mead, W. J., 1967. Natural resource disposition policy: oral auctions vs. sealed bids. Natural Resource Journal, 7, 194-224.

Mehlenbacher, A., 2007. Multiagent system platform for auction experiments. University of Victoria, Economics Department Discussion Paper, DDP0706.

Menezes, F.M., 1993, Sequential actions with delay costs, a two-period model. Economics Letters, 42.

Milgrom, P., 1989. Auctions and bidding: a primer. Journal of Economic Perspectives, 3, 3-22.

Mitchell, T. M., 1997. Machine learning. Boston: McGraw Hill.

Mueller, R., Perea, A., & Wolf, S. (2007). Combinatorial scoring auctions. Meteor research memorandum, University of Maastricht, RM07020.

Niquidet, K., & van Kooten, G.C. (2006). Transaction Evidence Appraisal: Competition in British Columbia's Stumpage Markets. Forest Sci., 52(4), 15–49.

Paarsch, H. (1991). Empirical Models of Auctions and an Application to British Columbia Timber Sales. UBC, Vancouver.

Paarsch, H., 1997. Deriving an estimate of the optimal reserve price: An application to British Columbian timber sales". Journal of Econometrics 78, 333–357.

Park, S., Durfee, E.H., Birmingham, W.P., 1999. An adaptive agent bidding strategy based on stochastic modeling. Agents, 147-153.

Parkes, D. (2001). Iterative combinatorial auctions: Achieving economic and computational efficiency. Doctoral dissertation, University of Pennsylvania.

Parkes, D. C., & Ungar, L. H. (2000). Iterative combinatorial auctions: Theory and practice. Proc. Conf. AAAI Artif. Intell., 74–81.

Pinker, E., Seidmann, A., Vakrat, Y., 2000. Using transaction data for the design of sequential, multi-unit, online auctions. Working Paper CIS-00-3, Simon School, University of Rochester.

Rabotyagov, S. S., Tóth, S. F., & Ettl, G. J. (2013). Testing the Design Variables of ECOSEL: A Market Mechanism for Forest Ecosystem Services. Forest Sci., 59(3), 303–321. DOI: 10.5849/forsci.11-110.

Rassenti, S.J., Smith, V.L., Bulfin, R.L., 1982. A Combinatorial Auction Mechanism for Airport Time Slot Allocation. The Bell Journal of Economics, 13(2), 402-417.

Sakurai, Y., Yokoo, M., & Kamei, K. (2000). An efficient approximate algorithm for winner determination in combinatorial auctions. EC, 30–37. DOI: 10.1145/352871.352875.

Shehory, O., 2002. Optimal bidding in multiple concurrent auctions. International Journal of Cooperative Information Systems, 11, 315-327.

Shoham, Y., & Leyton-Brown, K. (2009). Multiagent systems: algorithmic, game- theoretic, and logical foundations. CUP, Cambridge.

Suyama, T., & Yokoo, M. (2005). Strategy/false-name proof protocols for combinatorial multi-attribute procurement auction. Auton. Agent Multi Agent Syst., 11(1), 7–21. DOI: 10.1109/AAMAS.2004.255.

Tesauro, G., Bredlin, J. L., 2001. Strategic sequential bidding in auctions using dynamic programming. In Proceedings of the First International Conference on Autonomous Agents, Bologna.

Vidal, J. M. (2007). Fundamentals of Multiagent Systems with NetLogo Examples. Unpublished.

Vidal, J. M., Durfee, E. H., 1996. The impact of nested agent models in an information economy. In: Proceedings of the Second International Conference on Multi-Agent Systems, 377-384.

Wang, C., Dargahi, F., 2013. Service customization under capacity constraints: An auction-based model, Journal of Intelligent Manufacturing, 24(5), 1033-1045.

Wang, C., Ghenniwa, H. H., & Shen, W. (2009). Constraint-based winner determination for auction-based scheduling. T-SMCA, 39(3), 609–618. DOI:10.1109/TSMCA.2009.2013194.

Weber, R.J., 1983. Multiple-object auctions. In: Wiggans, R., Shubik, M., Stark, R.M., (eds.). Auctions, bidding, and contracting: uses and theory. New York: New York University Press, 165-191.

Wei, Z., Shu-juan, J., Juan, Z., Yong-quan, L., 2010. Simulation and strategy analysis for multi-round auction. In: 2010 IEEE International Conference on Educational and Information Technology (ICEIT), 2, V2-4.

Wellman, M. P., Walsh, W. E., Wurman, P. R., & MacKie-Mason, J. K. (2001). Auction protocols for decentralized scheduling. Game Econ. Behav., 35(1), 271–303. DOI: 10.1006/game.2000.0822.

Yue, C., Mabu, S., Yu, D., Wang, Y., Hirasawa, K., 2010. A bidding strategy of multiple round auctions based on Genetic Network Programming. In: 2010 IEEE Congress on Evolutionary Computation (CEC), 1-8.

Zeithammer, R., 2004. An equilibrium model of a dynamic auction marketplace. Working Paper, University of Chicago.