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Agent-based Simulation of Multiple-round Timber Combinatorial Auction

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7 **Abstract:**

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

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

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 issue relates specifically to 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 period has been one of the main problems for the Québec government. The timber lots were previously assigned through licencing. In the new forest regime now in place in Québec, auctions are applied in order to assign 25% of timber lots. This new regime results in more flexible access to timber, and in establishing timber licence prices.

Two main types of auctions for timber allocations exist: 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. In general, 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 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 (i.e., bundle) of items according to their needs. Here, items are not geographically defined forest stands. For example, they can be defined 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 calculates the

highest value of the bundles. Once identified, the winners must agree on a specific time to harvest the stand in which they share access.

A main advantage of combinatorial timber auction over single-unit timber auction is its ability to consider the individual values of the products available in a mixed forest stand. While mixed forest stands can be sold with a single-unit auction, the latter fails to obtain the best combination of values for each single product. Therefore, the combinatorial auction is more complex timber auction process. The objective of this paper is to experimentally compare both types of auction within a controlled environment using simulation.

In this paper, timber combinatorial auction 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., mix 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 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 is limited to four types of products; softwood and hardwood, each with two levels of qualities.

The simulation model contains a framework to follow the dynamics of the auctions systems over the course of several rounds. Agent-based modelling was used to design and implement different agent behaviours. It was used to simulate realistic bidding agents, auctioneer agent, and auction mechanisms, including realistic bidding patterns and the 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 m³ (i.e., revenue of the seller) and bidders' procurement 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 multiple simulations.

The remainder of the paper is organized 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.

2 Theoretical Background

In this section, the theoretical background of the research is presented in three sub-sections: timber auctions, multiple-round auctions, and previous work and contribution of this paper.

2.1 Timber auctions

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. The timber action studies have been focused on comparing open and closed auctions (Mead, 1967; Hansen, 1985; Athey *et al.*, 2011), reserve price (Paarsch, 1997; Elyakime *et al.*, 1994, 1997), collusion (Baldwin *et al.*, 1997), competition and information (Athey and Levin, 2001), and timber resale market (Haile, 2001).

Cramton *et al.* (2006) described a 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, several types of products (e.g., species) are for sale, and bidders can bid on any bundle of them. The bundle of bids that maximizes their combined value defines the winning bids. Combinatorial auctions can be used in many applications. Resource allocation 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). However, in the specific case of timber auctions, combinatorial auctions can have some downsides compared to single-unit actions. Timber combinational auctions may result in the disturbance of remaining resources, the need to spend money on clearing the logged site, and/or the damage of the forest ecosystem.

2.2 Multiple-round auctions and auction simulation

Multiple-round auctions are a series 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 new auctions, sometime after a delay (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 them. 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.

Iterative auction is slightly different from multi-round combinatorial auction. Parkes (2006) explained iterative combinatorial auction as several combinatorial auctions that happen over a period of several rounds. In an iterative combinatorial auction, the bidders can change their bid values according to the past rounds. Therefore, the bidders bid for the bundles they want, and they can always improve their bids in the next rounds. However, in a multi-round combinatorial auction, once bidders submit their bids they cannot change them in next rounds.

Multi-agent simulation is an efficient method to simulate and analyze such auction systems (Vidal, 2007). Multi-agent simulation, or agent-based simulation, models the behaviours and interactions of the actors of a system (e.g., bidders, auctioneer). This simulation approach involves a computerized model of a system that consists of reactive,

intelligent or goal-driven agents that interact with each other and their environment. Such agents manage their actions within the simulated environment. They can even have goal-directed behaviours. In other words, agent-based simulation is a tool to study complex systems that are difficult, if not impossible, to study analytically. For instance, agent-based simulation can be used to investigate winner selection and intelligent bidders' behaviour.

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 published papers regarding combinatorial auction using agent-based systems. For example, Kutanglui and Wu (2001) used combinatorial auction as an autonomous distributed scheduling system. They used iterative bidding process to optimize job shop scheduling problem.

2.3 Previous work and the contribution of this paper

In order to study the impacts of various configurations of auctions in the Québec timber industry, Farnia *et al.* (2013) used agent-based simulation. In particular, we modelled a multiple-round single-unit first-price sealed-bid timber auction system using different types of bidder agents (i.e., reactive agent, learning agent, adaptive agent). In this simulation model, several auctions are announced simultaneously. Bidders must bid (or ignore) in all auctions simultaneously during that round. The results of this study suggest that adaptive and learning bidding behaviours have the best outcome according to goal achievement and cost minimization, respectively. We also analyzed how the auction outcome is affected by different auction configurations.

Later, Farnia *et al.* (2015) proposed 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 were limited to simulations of one combinatorial auction at a time, in order to study the impacts of various behaviours on the auction outcome. To our knowledge, there is no study of multiple-round timber combinatorial auctions and no study that compares the performance of multiple-round combinatorial auctions and multiple-round single-unit auctions. This paper aims to fill this gap by experimentally comparing multiple-round single-unit and combinatorial auctions in a dynamic environment over one simulated year of timber procurement.

3 Multiple-round Timber Combinatorial Auction Model

The simulation models presented hereafter builds up on the model proposed in Farnia *et al.* (2013) by including all the necessary elements required for the simulation of combinatorial timber auction. This section presents this model.

3.1 Auction context

In practice, an auction involves an auctioneer, a seller, and several bidders, although the seller could take the role of auctioneer. In the Québec timber auction system, the auctioneer, or government agency, announces and controls the auction as well as the attribution process. The seller, the province of Québec, offers timber products to the market. The bidders are the auction participants. For simplification, the proposed simulation model only considers the auctioneer and the bidders. Similarly, we assumed that each forest stand consists of four different classes of quality and species, which are

173 sold as a whole. These classes were developed with the help of the *Bureau de mise en*
174 *marché des bois* of the Québec government. They represent softwood and hardwood,
175 each with two levels of qualities. In the remainder of this paper, these classes are referred
176 to as species or products. Therefore, there are four different types of products, including
177 softwood of quality 1 and 2 (s_1 , s_2), and hardwood of quality 1 and 2 (h_1 , h_2). In order to
178 create a more realistic model, each lot has other specifications that make them different
179 from each other. These specifications include the location of the forest stand and the
180 volume of each species. The location of each forest stand is randomly defined during
181 simulation, while their lot size (i.e., size of forest stand) is defined at the start of the
182 simulation. The volumes by species are randomly defined according to the lot size.

183 There are three types of bidders in this model: softwood mills, hardwood mills, and
184 entrepreneurs. This segmentation is done according to the supply need of the bidders.
185 Softwood mills require softwood, and include lumber mills and paper mills. Hardwood
186 mills are interested in hardwood. Entrepreneurs are interested in both softwood and
187 hardwood products. In our model, it is considered that softwood mills mostly bid for the
188 bundles that include s_1 and s_2 . These bundles are considered as s_1 , s_2 , s_1s_2 , and
189 $s_1s_2h_1h_2$. Large softwood mills might bid for s_1 , s_2 , or any bundle that contains s_1 and
190 s_2 , while small softwood mills might only bid for either s_1 or s_2 . If a softwood mill wins
191 bundle $s_1s_2h_1h_2$, the mill will resell the undesired volumes to other mills. The illustrated
192 example also applies to hardwood mills that may be interested in h_1 , h_2 , h_1h_2 , and
193 $s_1s_2h_1h_2$. The entrepreneurs are also interested in any bundles of s_1 , s_2 , h_1 , and h_2 . In
194 order to simplify the simulation model, and particularly the winner determination process,

as well as to reduce the number of combinations that significantly increase simulation time, entrepreneurs only bid for s_1 , s_2 , s_1s_2 , h_1 , h_2 , h_1h_2 , and $s_1s_2h_1h_2$ 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.

3.2 Simulation procedure

The general simulation procedure is as follows: 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. In order to do that, bidder agents have specific behaviours detailed in Farnia *et al.* (2013) and outlined in Section 3.3. In

brief, bidder agents have a random behaviour that is between a pure adaptive behaviour (i.e., capable of adapting the value of their bid according to their goal achievement level and the time left to achieve it) and pure learning behaviour (i.e., capable of adjusting the value of their bid according to the market value inferred through past auction outcomes).

After receiving the bids, the auctioneer chooses the winners according to a winner determination algorithm, which is detailed in Appendix 1. 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 remaining rounds of auction.

3.3 Bidder agent behaviour

In order to have realistic simulation, the bidding behaviour 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 behaviour: a learning behaviour and an adaptive behaviour. Similarly to Farnia *et al.* (2013), we compare the adaptive learning behaviour with other realistic approaches. On the one hand, the learning behaviour considers the history (i.e., past rounds of the auction) to define a bidding function, the aim of avoiding over-bidding (i.e., bidding over market value). This behaviour was deemed the most profitable for the bidder. On the other hand, the adaptive behaviour considers the bidder's current needs and the time left to fulfill the remaining needs. This bidding behaviour was the most capable of fulfilling supply needs. Bidders value each bundle of products in the lot for sale. The sets and indexes to calculate the value of each bundle are indicated in Table 1.

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

246

247

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

248

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

maximize:

$$\sum_S \frac{V_S}{D_{j,S}} x_S \quad (2)$$

subject to:

$$MP_{j,S} x_S > RP_S \quad \forall S \quad (3)$$

$$\sum_S V_S x_S < ND_{j,S} \quad (4)$$

$$x_S = \{0,1\} \quad \forall S \quad (5)$$

253 In this mathematical programming, bidder j assigns a weight to each desirable bundle in
 254 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). 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.

Next, the valuation function of the bidders' bidding approach is described in Equation (6), as suggested in Farnia *et al.* (2013), and adapted to consider bundles instead of lots.

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

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 procurement volume (i.e., a year), and $f_2(d)$ is the duration of the time remaining 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 volume remaining at any specific moment in the simulation to achieve the target procurement 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). These two elements of the equation aim to create a behaviour that increases the bid value when the bidder's procurement target achievement is low and when the time remaining to achieve it is short. In other words, it aims to emulate the procurement managers' reaction to stress with respect to how far it is to its objectives. α aims to create a different level of resistance to stress.

275 $y_{i,S}$ is the learning part of the adaptive learning behaviour. For example, if S consists of
 276 species $s1$ and $s2$, $y_{i,S}$ for these species is calculated according to Equation (7). We
 277 estimate the coefficients of this equation using a regression analysis on the history of the
 278 auction. More details can be found in Farnia *et al.* (2013). At each round, the bidders
 279 consider the winning history and extract the information including the location of the
 280 winner and the winning price of each bundle. As each bundle is considered separately,
 281 there are less data available to compute Equation 7 than when species are considered.
 282 This may affect the capacity of the learning part to anticipate a valid bidding price.
 283 Eventually, when not enough data is available, bidders estimate the bidding price of a
 284 bundle according to the price history of a single species. More specifically, bidders
 285 estimate the coefficients $(\beta_0, \beta_1, \beta_2 \dots)$ of the regression function at each round and for
 286 each bundle, adding the most recent information about the winning bids. Next, once the
 287 coefficients are estimated, and using the information of the current auction, the bidder
 288 anticipates the value $y_{j,s1s2}$ of the bundle, with $x_{j,s1}$ and $x_{j,s2}$ being the volume of $s1$ and
 289 the volume of $s2$ in bundle $s1s2$, respectively, using Equation (7). Next, the offer of
 290 bidder $v_{j,s1,s2}$ is calculated with Equation (6).

$$291 \quad y_{j,s1s2} = \beta_0 + \beta_1 D_{j,s1s2} + \beta_2 x_{j,s1} + \beta_3 x_{j,s2} \quad (7)$$

292 In Equation (6), α and γ are defined as coefficients that vary within the interval $[0;1]$. In
 293 this model bidders behave according to their specific values of α and γ that are given to
 294 them during the setup phase of the simulation. The valuation function is purely adaptive
 295 if $\alpha = \gamma = 1$. When $\alpha = \gamma = 0$, the valuation function is strictly based on learning.

3.4 Winner determination

This section introduces the winner determination algorithm for the simulated combinatorial auction. As previously explained in Section 3.1, different kind of bidders are interested in different combinations of products. The winner determination algorithm is presented in Appendix 1. The algorithm shows the winner determination procedure that is triggered within the simulation to determine the solution of each auction. The outcome of this 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 require more advanced algorithms.

4 Results and Discussion

Using this simulation model, we carried out a simulation experiment described in the next section. Then, using the results of this experiment, four specific analyses are presented in the following sections. First, we examine the outcomes of the combinatorial auction simulation in terms of average unit selling price for the seller (Analysis 1) and in terms of procurement target achievement for the bidders (Analysis 2). For a bidder, Procurement target achievement is the ratio of the total volume won in all rounds over its total need for the entire horizon. Then, we compare these results with those obtained with single-unit auctions as presented in Farnia *et al.* (2013) (Analysis 3 and 4).

4.1 Simulation experiment description

In order to study these elements, we carried out a large simulation experiment with the simulation model introduced in the previous section. More specifically, the experiment proposes a series of sensitivity analysis of the impacts of several parameters on the average unit price (\$/m³) and procurement target achievement (%) of the combinatorial auction. The parameters that can be changed in the model are as follows:

- the number of auctions per year (i.e., number of lots for sale);
- the auction periodicity (i.e., the number of days between two rounds of auction);
- the lot size (i.e., the total volume of timber for sale in a lot); and
- the number of bidders (i.e., total number of potential bidders).

In order to assess the impacts of these parameters on the average unit price and procurement target achievement, three levels (low, medium and high) are defined for each parameter. With the help of our research partners, the *Bureau de mise en marché des bois* of the Québec government, we proposed different values for these levels in order to explore realistic conditions for the specific case of Québec. Therefore, 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 m³. Finally, the number of bidders is set to 100, 150, and 200. The number of bidders represents the total number of companies that could participate in an auction. However, for any specific auction, the number of companies that actually bid is far smaller (from two to eight) because they are geographically far from the stand, or are simply not interested in bidding according to their needs. When the number of bidders in simulation model set to 100, 150, and 200, the actual number of bidders for each auction is 2-4, 4-6, 6-8 respectively. All 3⁴

(81) configurations of these parameter levels were tested. For each configuration, the experiments are repeated 25 times for a total of 2,025 experiments.

In this study, within each simulation, lot size is the same for all lots in all auctions. 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, which could lead to scale economies. This remains for future work to address.

4.2 Analysis 1 – Average unit price

Table 2 shows the analysis of variance for the average unit price (i.e., dependent variable) resulting from the combinatorial auctions. In order to simplify the analysis, these studies only analyze the effects of each parameter (i.e., independent variable) and all combinations of any two of them. 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 combined effect of the number of auctions and lot size.

Figure 1 illustrates the effects of each parameter. As shown, when the number of auctions increases, the average unit price decreases due to more supply on the market (i.e., all things being equal, when more supplies are available, the price drops). The average unit price also diminishes when the lots get larger, again because of more supply. When the number of bidders increases, so too does the price. The slope of increasing price is higher between 100 to 150 compare to 150 to 200. The reason is that in the lower range of the number of bidders in the market, the price is more sensitive to competitiveness. Where as

when there are more potential bidders the price tends to move towards its market value. Along this line, the price also decreases when the number of auctions increases, even if lot size changes. However, the price is lower when the lot size gets larger. The reason for this result is that both the number of auctions and the lot size significantly increase supply. That is one side of argument. Other side – larger the lot size, there are economies of scale in harvesting operations, so bidders may be willing to pay high prices compared to smaller lots. However we did not consider this element in our model. This can be considered in future studies. Therefore, the combination of these two parameters affects the average unit price. These intuitive results tend to validate the simulation model.

4.3 Analysis 2 – Procurement target achievement

We analyzed the effect of the same parameters (i.e., number of auctions, periodicity, lot size, and number of bidders) on the average target achievement of the bidders. Table 3 shows the analysis of the variance of the parameters on the target achievement. As 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.

To illustrate the analysis of variance, Figure 2 shows the effects of single parameters. Both the number of auctions and the 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 there are more timber through the auction system, thus bidders can win more timber supply to fulfill their needs. Similarly, when the 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 choose from at each round. Consequently, bidders tend to bid only on the amount they need as defined by Equation (2) to (5). Hence, they may lose opportunities by not participating in other auctions. Therefore, bidders tend to win lower volumes when there are more auctions in one round. Again, these results are intuitive and tend to validate the model. The next sections delve further into the comparison of combinatorial and single-unit timber auctions.

4.4 Analysis 3 – Average unit price comparison

In this section, we use the results of the simulation carried out with the combinatorial model, and compare them with the results of the single-unit auction from Farnia *et al.* (2013) with respect to the average unit price by calculating the relative gain of using combinatorial auctions expressed as a percentage of the average unit price of the single-unit auction (Equation 8):

$$Relative\ gainP = 100 \times \left(\frac{Average\ unit\ price\ (combinatorial\ auction)}{Average\ unit\ price\ (single-unit\ auction)} - 1 \right) \quad (8)$$

In order to perform this analysis, we again consider the number of auctions, periodicity, lot size, and the number of bidders. Figure 3 displays the impact of these parameters.

First, the combinatorial auction is preferable to the single-unit auction when the number of auctions increases. Although the number of auctions has a negative impact on the average unit price in the combinatorial auction, the combinatorial auction tends to dampen this effect compared to the single-unit auction. In other words, the ability of the combinatorial auction to obtain the maximum value from the products present on a stand allows the seller to minimize this negative impact. Similarly, the combinatorial auction is preferable to the single-unit auction when there are fewer bidders. Again, fewer bidders

406 leads to decreased competition and, therefore, smaller revenue (i.e., average unit price).
 407 For the same reason, the combinatorial auction is able to obtain higher revenue than the
 408 single-unit auction. This impact is again similar to large lot sizes, which increase the offer.
 409 Together, these results tend to show that the relative gain of combinatorial auction
 410 increases when market conditions are not favourable for the seller (i.e., low competition).
 411 Furthermore, this phenomenon is exacerbated when the difference between potential
 412 supply and demand is larger. For example, when there are 250 auctions and 150 bidders
 413 in the market, the difference between the outcomes of both types of auctions is not
 414 significant.

415 Concerning the impact of periodicity of the auction (i.e., number of days between two
 416 rounds of auction), the higher the delay between two rounds, the more favourable the
 417 combinatorial auction. This can be explained using the same logic. When the delay is
 418 large (30 days), there are more items for sale at each round (the total number of auctions
 419 and bidders remaining the same). This creates a situation of low competition that tends to
 420 favour combinatorial auction. However, for a periodicity of 7 or 15 days, there are fewer
 421 items for sale leading to a higher competition, which favour the single-unit auction.

422 **4.5 Analysis 4 – Procurement target achievement comparison**

423 In this section, we compare combinatorial and single-unit auctions with respect to target
 424 achievement. To do so, we similarly calculate the relative gain from using the
 425 combinatorial auction expressed as a percentage of the target achievement of the single-
 426 unit auction (Equation 9).

$$427 \quad \text{Relative gain TA} = 100 \times \left(\frac{\text{Target achievement (combinatorial auction)}}{\text{Target achievement (single-unit auction)}} - 1 \right) \quad (9)$$

Figure 4 presents the impact of each parameter on the procurement target achievement.

Here, contrary to the previous section, the gain concerns the bidders. However, the combinatorial auction is preferable in similar market conditions (i.e., low competition); in other words, when the number of auctions is high and the number of bidders is low. For the same reason, the combinatorial auction is also favourable when the lot size is larger, and when there are more items in the market. However, concerning the impact of periodicity (delay between two rounds of auction), the effect is different. In other words, although the combinatorial auction remains favourable over the single-unit auction, a long delay (30 days) between two rounds of auctions tends to diminish the benefit of the combinatorial auction with respect to target achievement. This can be explained differently. Bidder agents are programmed in order to find a compromise between learning market value, and adapting to achieve their procurement target. To adapt, bidders adjust the value of their bid at each round of auction (first two elements of Equation (6)). If there are fewer rounds because periodicity is high, then bidders have fewer opportunities to adapt their bids and win. This phenomenon seems to be slightly exacerbated with the combinatorial auction compared to the single-unit auction.

4.6 Discussion

Our results show that the design auction parameters that affect the average unit price of combinatorial auction are the number of auctions, the number of bidders and lot size. These parameters qualitatively affect the single-unit in a similar manner. However, the combinatorial auction average unit price is higher in low-competitive market conditions.

450 The number of auctions, the number of bidders, periodicity, and lot size also affects the
451 bidders' procurement target achievement. Similar to the average unit price, the target
452 achievement with the combinatorial auction is higher in low-competitive market
453 conditions. This can be explained by the fact that when there are more auctions or fewer
454 bidders, bidders can bid on a variety of bundles directly related to their needs, without
455 impeding the other bidders to do the same. In other words, in combinatorial auctions,
456 bidders can fulfill their needs with a combination of auctions, while in single-unit
457 auctions they bid on fewer auctions and may win species they do not necessarily need. In
458 single-unit auctions, the resale of these species is managed privately and not controlled
459 by the auction itself. This process was not simulated in this platform.

460 However, when analyzed in greater detail, these results show that the combinatorial and
461 single-unit auctions have their different domains of predilection. For example, the
462 combinatorial auction seems to be better suited for market conditions with low
463 competition (e.g., fewer bidders, more auctions), which is generally the case in the
464 Québec timber auction due to the geographical distance of the lots. Because the
465 combinatorial auction allows more companies to simultaneously access timber by bidding
466 on just the products they need, while allowing the seller to get the maximum value from a
467 forest stand, it seems better suited for the Québec timber procurement context than the
468 single-unit auction. Of course, more work is required to validate this finding. For instance,
469 the scale economies associated with large lot sizes was not modelled in this study. It is
470 not clear whether this could affect the result. Along this line, the coordination of harvest
471 operations when there are several winners for one forest stand may also affect the overall
472 results by increasing total cost of ownership, which is not taken into account here.

Similarly, the complexity of the implementation of combinatorial auction may lead to unknown outcomes worth investigating. For example, in some provinces of Canada, there are overlapping tenures (where different species are allocated to different companies), and this system has many problems related to enforcement of harvesting and management regulations.

5 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 tested in various setup configurations to analyze the impacts of different configurations. Two main indicators were used to measure the performance of the model. The average unit price (\$/m³) evaluates the seller's ability to generate revenue. Next, procurement target achievement evaluates the bidder's capability to fulfill their needs from auctions. We also analyzed these indicators in order to compare the combinatorial and single-unit auctions.

The results shown in the previous sections present several interesting features. First, the auction design parameters affects the impacts of both the combinatorial and single-unit auctions for the seller and the bidders in a similar manner. Second, when the number of bidders increases, so does competition, which in turn increases the average unit price and decreases the bidder's ability to achieve their procurement target.

There are some limitations of the study that should be considered. Although the combinatorial auction seems interesting, the Québec ministry of natural resources must assess the current competitive state of the timber market in order to know whether the combinatorial auction approach is a relevant solution. Furthermore, one of the downsides

of combinatorial auctions concerns the possibility of leftover products in a lot, which will be addressed in future work. For instance, leftover products could be considered in the winner determination problem. In other words, the winner determination problem could consider the highest combination of bids that includes a minimum percentage of the total volume of the lot. Similarly, future work must take various lot sizes into account and include all associated costs, such as harvest and coordination costs. Furthermore, one of the limitations of the study is that the timber lots consist of four species. The study can be investigated to see what are the consequences of auctioning the lots with more than four different species in timber combinatorial auctions. The other limitation of our work is that the advantages of our approach in terms of increased revenues and accomplished targets to either party of an auction is not weighed against the costs of logging equipment deployment and damage to any remaining trees. This issue can be addressed in future studies.

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Table 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 from the final products of all species of bundle S
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 cost of processing 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

570

571 Table 2: Analysis of variance for price from the combinatorial auctions

Number of observations = 2025

 $R^2 = 0.8$

Root MSE = 0.10

Adjusted $R^2 = 0.80$

Source	Partial SS	MS	F	Prob > F
<i>Model</i>	86.59	2.7	249.0	<.0001
Number of Auctions	0.33	0.16	15.09	<.0001
<i>Periodicity</i>	0.02	0.01	0.74	0.48
Lot Size	0.17	0.08	7.76	0.00
Number of Bidders	10.99	5.50	505.80	<.0001
<i>Number of Auctions # Periodicity</i>	0.02	0.01	0.50	0.74
Number of Auctions # Lot Size	0.11	0.03	2.63	0.03
<i>Number of Auctions # Number of Bidders</i>	0.01	0.00	0.34	0.85
<i>Periodicity # Lot Size</i>	0.01	0.00	0.26	0.90
<i>Periodicity # Number of Bidders</i>	0.05	0.01	1.08	0.37
<i>Lot Size # Number of Bidders</i>	0.04	0.01	1.03	0.39
<i>Residual</i>	21.64	0.01		
<i>Total</i>	108.2			

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594

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Appendix 1

This appendix presents the winner determination procedure.

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**

$$v_{s1} = \max (v_{s1}, v_{j,s1})$$

$$v_{s2} = \max (v_{s2}, v_{j,s2})$$

```

631       $v_{hl} = \max (v_{hl}, v_{j,hl})$ 
632       $v_{h2} = \max (v_{h2}, v_{j,h2})$ 
633       $v_{sl,s2} = \max (v_{sl,s2}, v_{j,sl,s2})$ 
634       $v_{hl,h2} = \max (v_{hl,h2}, v_{j,hl,h2})$ 
635       $v_{sls2hl,h2} = \max (v_{sls2hl,h2}, v_{j,sls2hl,h2})$ 
636  end for
637
638  If  $v_{sl} + v_{s2} > v_{sls2}$  then
639       $w_{sl} = j \mid v_{sl}=v_{j,sl} \text{ and } j \in [1,J]$ 
640       $w_{s2} = j \mid v_{s2}=v_{j,s2} \text{ and } j \in [1,J]$ 
641       $v_{sls2} = v_{sl} + v_{s2}$ 
642  else
643       $w_{sl} = w_{s2} = j \mid v_{sls2} = v_{j,sls2} \text{ and } j \in [1,J]$ 
644  end if
645
646  If  $v_{hl} + v_{h2} > v_{hlh2}$  then
647       $w_{hl} = j \mid v_{hl}=v_{j,hl} \text{ and } j \in [1,J]$ 
648       $w_{h2} = j \mid v_{h2}=v_{j,h2} \text{ and } j \in [1,J]$ 
649       $v_{hlh2} = v_{hl} + v_{h2}$ 
650  else
651       $w_{hl} = w_{h2} = j \mid v_{hlh2} = v_{j,hlh2} \text{ and } j \in [1,J]$ 
652  end if
653

```

```
654      If  $v_{s1s2} + v_{h1h2} < v_{s1s2h1h2}$  then  
655           $w_{s1} = w_{s2} = w_{h1} = w_{h2} = j \mid v_{s1s2h1h2} = v_{j,s1s2h1h2}$  and  $j \in [1,J]$   
656      end if  
657  ]  
  
658
```

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