Revaluation of Bundles by Bidders in Combinatorial Auctions

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Abstract

Current implementations of combinatorial auction mechanisms do not allow bidders to change their valuations of bundles during the course of the auction, forcing them to spend time and money in estimating bundle valuations with accuracy at the very start of the auction. But in the common value model, bidder valuations can change in response to signals from other bidders. Here we propose a multi-round package bidding scheme called RevalBundle which, at the end of each round, provides bidders with information to help them modify and resubmit their valuations. RevalBundle also provides incentives for truthful reporting of valuations by making the final payments of winners independent of their reported valuations. Moreover, the seller’s revenue is higher than that realized by the VCG method. Experiments are reported that clarify the features and properties of the mechanism.

1. Introduction

Over the last decade or so, there has been a huge surge in interest in using auctions to set up new markets, for example, energy, transportation, and pollution permits [12]. The primary benefit of auction is its efficiency when there is a lot of uncertainty among the buyers and the sellers regarding the values of the items [13]. But when items are complementary in nature, it is undesirable to auction them separately. Items 1 and 2 are complementary for a bidder (agent) j if \( U_j \{1\} + U_j \{2\} < U_j \{1, 2\} \) where \( U_j \{S\} \) denotes the increase in utility of bidder j as a result of acquiring the set S of items. In such cases the bidder wants to win both the items and not just one of them. In combinatorial auctions, bidders can bid on bundles (packages) of items which prevent the exposure problem [12]. The exposure problem occurs when bidders end up with an incomplete bundle, i.e. instead of the entire package they want to win; they manage to win only some of the items from that package.

In many real life situations, combinatorial auctions are preferred to separate single item auctions. Consider, for example, allotment of railroads [15], auction of adjacent pieces of real estate [15], allocation of airport takeoff and landing slots [17], bundling of routes for transportation and logistics services [18], FCC spectrum auctions ([8], [14]), and supply chain management [22]. Other applications include travel package planning, where the problem is to allocate airline or railway tickets and hotel accommodation to travelers who have their own preferences with regard to location, cost and hotels [9].

In single-unit combinatorial auctions, there is only one unit of each item. Let \( M = \{1, 2, 3, \ldots, m\} \) be the set of items and \( N = \{1, \ldots, n\} \) the set of bidders. Bidders submit bids on the \((2^m - 1)\) possible non-empty bundles \( S \subseteq M \) of items. Let \( v_i(S) \) be the maximum price bidder i is willing to pay for bundle S. An allocation of items to bidders is described by variables \( x_i(S) \in \{0, 1\} \), where \( x_i(S) = 1 \), if and only if bidder i gets bundle S. An allocation \( \{x_i(S) \mid i \in N, S \subseteq M\} \) is feasible if no item is allocated to more than one bidder.

In the Winner Determination problem (WDP), the task is to allocate the items in such a way that the seller’s revenue is maximized:

\[
\text{Max} \sum_{i \in N, S \subseteq M} v_i(S) x_i(S) \text{ such that } \sum_{i \in N} \sum_{S \subseteq M, j \in S} x_i(S) \leq 1 \text{ for all } j \in M \text{ and } x_i(S) \in \{0,1\}
\]

In this formulation, called the OR formulation of the WDP, a bidder can win more than one bundle. The XOR formulation adds the constraint that a bidder can win at most one bundle. In the common value model, the actual value is the same for everyone but bidders have different private information about that value. A bidder might change
her estimate of the value depending on what signals she gets from other bidders. This is in contrast to the private value model where her value is not affected by other valuations ([12], [13]). However, the current combinatorial auctions do not address this need for change of valuations during the course of the auction and this can discourage bidders from participating in the auction. This issue was pointed out and addressed in RevalSlot [5]. This mechanism ensures that those bidders who can only identify a range, within which their valuations lie, instead of the exact valuations, can participate in the auction. In this scheme, the bidders are initially asked to report their valuations within a range and then an ascending proxy auction is run on the reported values. The results of the ascending proxy auction are communicated back to the bidders so that they can revise their valuations and report the revised valuations within a shorter range. Again, an ascending proxy auction is run on the revised valuations. This continues till a termination condition is reached.

Although RevalSlot addresses the need for change in valuation during the course of the auction, there are certain problems which must be tackled before it can be used as a practical combinatorial auction mechanism. First, RevalSlot requires that the auctioneer declares a slot size at the very beginning of the auction, which can itself be a costly process, as the auctioneer then has to determine a range where the valuations of all the participating bidders can fit in. Second, the mechanism is not suitable for those bidders who have an exact idea of their valuations as they have to continuously submit their fixed valuations in terms of new slot sizes. Third, since the slot size is the same for all the packages, the bidders who want to bid only for the smaller packages have to wait for quite a few rounds before the slot size reduces to a level where they can get meaningful information feedback. Fourth and importantly, the mechanism employs an ascending proxy auction at the end of each revision of valuations. Since, in each round of an ascending proxy auction, a WDP has to be solved and there can be several rounds in an ascending proxy auction, employing an ascending proxy auction at the end of each revision in RevalSlot leads to so many WDP solutions that it makes the mechanism computationally impractical to use. In an iterative combinatorial auction [7], where winners have to be determined after each round, it is not desirable and practical to solve the WDP afresh after each round [20, pp. 362].

In this paper we attempt to address the issue of the change in bidder valuations during the course of the auction while addressing the weaknesses of RevalSlot that we have discussed above. Here we propose a new multi-round auction mechanism called RevalBundle to address the problem of bundle valuation. At the start of the auction, it is expected that the bidders have initial (lower bound) estimates of the bundle values. At the end of each round, bidders get information feedback to help them revise the valuation of the bundles, and resubmit revised valuations for the next round. The final payments made by the winners are computed in a way that encourages bidders to report their valuations truthfully. Therefore, the auctioneer is relieved of the burden of deciding on the slot sizes and the bidders who have an exact idea of their valuations need not recompute their valuations at the end of every round. RevalBundle solves one WDP in each round, so the number of times the WDP is solved is kept under manageable limits. The problem of truthful reporting of valuations that surfaces whenever bidders are asked to report their valuations is handled by separating the payment process from the bidding process. Thus the objectives of this paper are as follows:

- To propose a multi round combinatorial auction mechanism that helps to increase bidder participation; bidders who do not have the exact values of bundles at start can also take part in the auction; and based on signals received during the auction from other bidders, reevaluate the bundles;
- To provide discounts to winning bidders to induce the bidders to report truthful values to the seller; the winning bidders pay the second winning price of the final round thus making the final payment independent of the final valuations of the winning packages;
- To show that the second winning price in our mechanism will be greater than or equal to the revenue from the VCG mechanism, thus increasing the revenue for the seller;
- To report on some experiments conducted on the mechanism under certain assumptions of bidder behaviour; the effect of feedback to bidders in the form of highest valuations vis-à-vis the deadlock levels [1] of the packages has also been studied.

2. Combinatorial Auctions in Literature

Combinatorial auction can be single round, multi-round or continuous. The first price sealed bid combinatorial auction is a single round auction. The payment rule is ‘pay-your-bid’ which forces bidders to guess about the bids of others, leading to inefficient outcomes. The other single round combinatorial auction is the VCG mechanism which integrates Vickrey’s seminal ideas [21] with the Clarke-Groves design ([6], [10]). In this mechanism, bidders report
their valuations to the auctioneer who solves the WDP and allocates the bundles. The winners however, do not pay what they have bid, rather they pay the marginal negative effect that their participation has on the reported values of the other bidders [3]. This encourages the bidders to bid truthfully. However, VCG revenues are sometimes very low, and the mechanism is computationally complex, so it has not been used frequently in practice. Moreover, both the above forms of auction do not allow the bidders to change their valuations.

Multi-round combinatorial auctions allow bidders to raise their bids in each round based on the outcome of the previous rounds. The Simultaneous Multiple Round (SMR) auction [8] has been used by the FCC from 1994 to 2003 to allocate spectrum, and has earned over $40 billion in revenue [14]. The SMR auction, however, does not allow package bidding, so high complementarities create an exposure problem [7]. The FCC has subsequently allowed package bidding in its Auction #31 for the upper 700 MHz band [14]. Laboratory experiments on FCC spectrum auction using simultaneous multi-round auctions with package bidding (SMRPA) have been reported in [8]. Ascending Proxy auctions [3] and the Clock-Proxy auction [2] allow multi-round package bidding using specific rules for fixing minimum prices on items and bundles at the start of each round. All these methods assume that bidder valuations remain the same throughout the course of the auction. In the case of ascending proxy auctions bidders submit their valuations at start to a proxy agent, which bids on their behalf by determining the packages of highest utility [3]. In each round the ask prices of the packages are increased and the proxy agent submits fresh bids on behalf of each bidder until a termination condition is reached. iBundle [16] is an example of such an auction.

The clock phase of the Clock-Proxy auction addresses the problem of valuation of different bundles to a certain extent. It does set a lower bound on the price of each bundle based on which bidders bid for the subsequent ascending proxy auction. For situations, where the items to be auctioned have high degree of complementarities among them, the setting of lower bounds for the bundles is not much of a help. In such a case, the problem of valuating the different bundles still remains, as the bidders get only one chance of providing the values for each package. PAUSE [11] and AUSM [4] have been proposed to relieve the auctioneer of having to face and solve the winner determination problem. In these auctions, the burden of evaluating a combinatorial bid is transferred to the bidder making the bid. The auctioneer has to only confirm the bid’s validity which is a computationally tractable problem. One other interesting combinatorial auction is the Resource Allocation Design (RAD), which was proposed by Kwasnica et al [14]. Instead of simply increasing the prices, the auction tries to compute a set of appropriate prices compatible with the current provisional allocation by solving a number of linear programs.

In a continuous combinatorial auction, bidders need information feedback after each bid. This issue is addressed in [1] by providing a bidder with the deadness level (DL) and the winning level (WL) on each package of her choice, which helps her to value packages more accurately. The deadness level of a package is the minimum bid that ensures that the bid stays in contention for the winning allocation. The winning level of a package is the minimum bid that will immediately make the bid a part of the winning allocation given the current state of the auction. The method is efficient in the sense that non-competitive bids are eliminated, so no time is wasted on such bids. It makes use of a dynamic programming formulation to solve the WDP in an incremental manner, so it does not scale up well to a large number of items.

None of the above combinatorial auctions that we have discussed address the need for change of valuation. All the auction schemes described above assume that bidders are absolutely sure about the exact valuations of bundles at start, i.e., that bidders are perfectly rational. But in practice, bidders are bounded rational, with limited computing power, and it is difficult for them to value bundles exactly. RevalSlot [5] attempts to enhance bidder participation by designing a scheme which allows a bidder to participate if she can identify a range within which her valuations lie. The scheme during the course of the auction provides information feedback in a manner which helps the bidders to refine their valuations in terms of decreasing range of valuations. However, this price feedback mechanism makes the auction running time prohibitively high because of the number of WDP problems this mechanism has to solve.

3. **RevalBundle: Mechanism for a multi-round combinatorial auction**

*RevalBundle* is a multi-round combinatorial auction where bidders are allowed to report their valuations on individual items or on bundles in every round. Based on the valuations submitted in a round, a WDP is formulated as given in Equation (1) and solved using a standard optimizer package like CPLEX (or some other
approach [19]), and the winning allocation along with the highest valuation of each package is communicated back to the bidders. Bids have an OR structure in the sense that each bidder can have more than one provisionally winning package. After the final round, the payment is so computed that it becomes independent of the winning valuations. The main components of the mechanism are Bidding, Validation, Disclosure of Relevant Information to Bidders, Termination and Payment Determination.

3.1 Bidding

The bidders submit their initial valuations to the auctioneer. This initial valuation is expected to be inexact and likely to undergo an upward revision. It may so happen that a bidder has an exact idea of her valuations before the start of the auction. In such a case, the bidder would continue to submit the same valuations in the subsequent rounds. At the end of each round, there are some provisional winners. The unhappy bidders [16] (bidders who have not won any bundle) may decide to increase their valuations of the bundles of interest and submit their revised valuations to the seller. The bidders who are a part of the winning allocation are expected to continue with the valuations of the previous round. Since the final payment does not depend on the valuations of final winning bids, bidders are expected to report truthful values.

3.2 Validation

Bidders who report 0 as the initial valuation for a bundle cannot report a positive number as the valuation for that bundle in subsequent rounds. A bidder is not allowed to reduce her valuation of any bundle in subsequent rounds. This prevents oscillations in the auction. However, if a bidder decides not to go further on any bundle, it is assumed that she will continue with her previous valuation on the bundle.

3.3 Disclosure of Relevant Information to Bidders

At the end of each round, the auctioneer announces the (provisional) winning allocation and the highest valuations on each bundle. To maintain confidentiality and avoid collusion, bidders are not identified. The disclosed information helps the bidders to zero in on a value for each bundle. In RevalSlot the ask prices of different packages are announced, and since ask prices are always less than or equal to the highest valuations, the possibility of bidders reporting ‘dead’ [1] values is much less in this mechanism as compared to RevalSlot.

3.4 Termination Condition

The auction terminates if in any two subsequent rounds, the reported valuations are identical and the winning allocation remains the same.

3.5 Payment Determination

After the auction terminates, the second highest revenue is determined by solving another WDP, this time with an additional constraint which ensures that the winning combination is not selected. The discount is calculated by subtracting the second highest revenue from the optimal revenue. It is then shared among the winning bidders in proportion to the valuations they have provided in the final round for the winning bundles. For example, let us consider that at the end of the auction there are two winners, b1 and b2 and the optimal revenue and the second highest revenue are $V^*$ and $V_2^*$ respectively. In this case, bidders b1 and b2 together get a discount of $(V^* - V_2^*)$ to be proportionately distributed among them. Now, let us assume that the final valuations for the winning packages submitted by bidders b1 and b2 are $v_1^*$ and $v_2^*$ respectively, i.e. $V^* = v_1^* + v_2^*$. Then the final payments, $P_1$ and $P_2$ are calculated using the formula

$$P_1 = v_1 - \frac{v_1}{v_1 + v_2} \times (V^* - V_2^*)$$

$$P_2 = v_2 - \frac{v_2}{v_1 + v_2} \times (V^* - V_2^*)$$

4. Theoretical Results

The revenue from RevalBundle is greater than or equal to the revenue from the VCG mechanism.

**Proof:** Let $V'$ denote the optimal revenue and $V_2^*$ denote the second highest revenue. Then, we can calculate the total discount as $D = V' - V_2^*$. Let bidder $i$ win a package $S$ with the valuation $v_i$. Then discount given to bidder $i$ for the package $S$ is $d_i = (v_i / V') \times D$. Note that since we have used OR formulation, a bidder can win more than one package. In the case of the VCG mechanism, the discount for bidder $i$ is calculated as $d_{i(VCG)} = V' - V_{i(i)}^*$, where $V_{i(i)}^*$ is the optimal revenue in the absence of bidder $i$. Under all circumstances, $V_2^* \geq V_{i(i)}^*$. So $D \leq d_{i(VCG)}$, and since $(v_i / V')$ is always $\leq 1$, $d_i \leq d_{i(VCG)}$. Hence, the discount in RevalBundle will always be less than or equal to the discount given in VCG auction. □
## 5. The RevalBundle Algorithm

**Step 1:** Ask the bidders to submit their initial valuations for the packages they are interested in.

**Step 2:** Validate the reported valuations according to the following rules

- Any bidder who bids 0 for a bundle cannot report a positive value as her valuation for the same bundle in any subsequent round.
- A bidder’s valuation of a bundle should not decrease from one round to the next.

**Step 3:** If each single valuation reported in the current round is exactly equal to the corresponding valuation reported in the previous round then go to Step 8.

**Step 4:** Solve the Winner Determination Problem on the reported values.

**Step 5:** Determine the maximum valuation for each package.

**Step 6:** Announce the provisional winning allocation and the maximum valuations of each package.

**Step 7:** Ask the unhappy bidders to revise and resubmit their valuations. Go to Step 2.

**Step 8:** Find the current revenue \( (V^*) \), and the winning combination.

**Step 9:** Calculate the second highest revenue \( (V^*_2) \) by solving another WDP, this time with an additional constraint which ensures that the winning combination is not selected.

**Step 10:** Determine the discount to be given to the winning bidders as \( D = V^* - V^*_2 \).

**Step 11:** Calculate the payment for each winning bidder \( i \), as \( v_i - \frac{v_i}{V^*} \times (V^* - V^*_2) \).

**Step 12:** Terminate the auction.

## 6. Worked Out Example

Consider a combinatorial auction of 3 items (A, B and C) and 3 bidders (1, 2 and 3). We assume certain behaviour for the bidders in this example. The initial valuations of the bidders are given in the first row (round 1) of Table 1. Every bidder will have a budget limit beyond which she would not increase her valuations. These budget limits are private to the bidders and are not divulged to the seller. In this example, we assume that the valuations provided by a
bidder on different bundles indicate the order of preference of the bundles for the bidder, and hence a bidder may distribute her total budget limit amongst her preferred set of bundles.

In this example, Agent 1 prefers bundle ABC over bundle AB, bundle BC over bundle AC and so on as indicated by her initial valuations. Agent 1 is not interested in item C, and hence reports a valuation of 0 for that bundle. The auction starts with the auctioneer solving the WDP on the values provided by the bidders in round 1. The valuations of each bidder and the announced results are shown in Table 1. The figures marked with a ‘*’ indicate that the corresponding package is a part of the (provisional) winning combination, and the figures in bold indicate the highest valuation for every bundle in a particular round. At the end of round 1, Bidder 2 is the unhappy bidder and she is expected to report a valuation more than the highest valuations of bundles she is interested in subject to her budget constraint. The mechanism assumes that valuations for happy bidders (bidders who have provisionally won a bundle) will remain same in the next round. For this example, we assume that an unhappy bidder would report 30 more than the highest valuation in the previous round for her (most) preferred bundle if the new valuation does not exceed the budget limit. Thus bidder 2 reports 140 in round 2 preferred bundle if the new valuation does not exceed the budget limit. So agent 1 reports 160 for the same package is a part of the (provisional) winning combination, and the figures in bold indicate the highest valuation for every bundle in a particular round. At the end of round 1, Bidder 2 is the unhappy bidder and she is expected to report a valuation more than the highest valuations of bundles she is interested in subject to her budget constraint. The mechanism assumes that valuations for happy bidders (bidders who have provisionally won a bundle) will remain same in the next round. For this example, we assume that an unhappy bidder would report 30 more than the highest valuation in the previous round for her (most) preferred bundle if the new valuation does not exceed the budget limit. Thus bidder 2 reports 140 in round 2 for ABC, her most preferred bundle and becomes the provisional winner. In round 3, bidder 2 again becomes unhappy and hence reports 200 for the same package ABC in round 4 since highest price for the package is 170 in the previous round. In round 5, both agent 1 and agent 3 become unhappy. Agent 1 can not increase her valuation on her most preferred package ABC since its budget limit is exceeded. So agent 1 reports 160 for her next preferred bundle AB in round 6. Agent 3 behaves in a similar way, and the auction continues. At the end of round 12, Bidder 2 is unhappy again. But she is unable to increase her valuations as it would exceed her budget limit for all the bundles of her interest. So, in the next round, the same valuations are repeated, the allocation remains identical, and the auction terminates with agent 1 and agent 3 becoming the winners with winning valuation being equal to 258. To determine the payments, a WDP is formulated with the added constraint that prevents [1, AB] [3, C] from getting selected. This gives [2, B] [2, AC] as the second price winners, the second price being 250 in this case. Thus, the bidders 1 and 3 get a discount of 8 (= 258 – 250). We then calculate the payments by dividing the discount among the two bidders, according to the final round valuation of the winning bundles: Payment for Bidder 1 = [190 – (190/258)*8] = 184.11 and payment for Bidder 2 = [68 – (68/258)*8] = 65.89.

7. Experimental Results

We have implemented the mechanism to test the working of the proposed auction. Our results show the expected trends. The implementation was done in C++ which used CPLEX 10.2 routine CPXmipopt to solve all WDP formulations. We have generated data sets using the Combinatorial Auction Test Suite (CATS 2.0, [15]). We have carried out our experiments on multiple data sets. We present below representative trends from one of the sets generated from the ‘regions’ problem domain. This particular set consists of 15 items, 50 bidders and in total 4000 bid valuations; these valuations were divided among 50 bidders with 80 for each bidder. The valuations generated by CATS were between 141 and 1168942. We assumed a predefined bid increment of 25000. In effect this meant that all valuations below the bid increment were ignored.

Before running RevalBundle on the bids, we preprocessed the bid valuations to ensure there were no entries on the same package from the same bidder. When such a case occurred we removed the lower bid valuation and kept the higher value. In the runs, we have assumed a budget limit for each bidder which was taken as the amount that was generated for each package from CATS suite. We took two different levels of input. First, we took input level of 0.3, i.e. in effect all the bidders initially reported their valuations as 30% of the final valuations and slowly revised them if required. Next we carried out our experiment on an input level of 0.7, i.e. in effect all the bidders initially reported their valuations as 70% of the final valuations.

One desirable feature of RevalBundle is that it allows bidders to learn from the valuations of others, and participate even if the initial valuation is low. We have tried to determine the effectiveness of the mechanism by measuring the following parameters: Revenue, Valuation of Winning Bundles (Price discovery), Efficiency, and Total gain of Winning Bidders.

**Revenue:** Figures 1 and 2 show how the revenue changes with the progress of the auction for input level 0.3 and 0.7 respectively. For input level of 0.3, the seller’s revenue slowly increases from a low level ultimately attaining a constant value. This is what we expect. The bidders learn more from the valuation of each other in the beginning of the auction which gradually reaches a saturation point as the auction progresses. In case of input level 0.7, the valuations are quite close to final valuations and it is reflected in the way the revenue very quickly reaches a constant value.
Valuation of the Final Winning Bundles: We have plotted the valuations of the final winning bundles with both the input levels. This gives us an idea of how RevalBundle helps in the price discovery of the individual bundles during the course of the auction. We have plotted a few of the winning bundles to give an idea of the trend of the price discovery. As stated earlier, we had 15 items in this particular data set; we denote them as \{A, B, C, D, E, F, G, H, I, J, K, L, M, N, and O\}.

With input level of 0.3, there were 11 bundles in the winning allocation, and we have plotted 3 of those bundles, B1 (HI), B2 (ABEF), and B3 (J). In the case of input level 0.7, there were 9 bundles in the winning allocation, and we have plotted two of them, B1 (CEF), and B2 (ABDG). Figure 3 shows the change in valuations of the winning bundles for input level 0.3 and Figure 4 shows the change in valuations of the winning bundles for input level 0.7. In Figure 3, the valuations show a much sharper rise as the initial start from a much lower level, whereas for input level 0.7, the change in valuations is much less sharp, which is what is expected.

Efficiency: We have also measured the efficiency of the auction and its variation. We define efficiency as the ratio of the second highest revenue to the optimal revenue \(\frac{V_2}{V^*}\). We have plotted the efficiency for both input levels 0.3 and 0.7 as shown in Figures 5 and 6 on the next page. The figures show that the efficiency fluctuates rapidly during the initial stages and then stabilizes at the end of the auction, as losing bidders slowly increase their valuations in order to win their packages of interest consequently increasing \(V_2^*\). Thus, efficiency increases as long as the losing bidders can increase their valuations while staying within their budget limits.

Total Gain of the Winning Bidders: We also show the change in total gain with the progress of the auction. A bidder’s gain is defined as the difference between her reported valuation and her final payment. The total gain is the summation of this over all winning bidders. Our payment method ensures that the total gain equals the discount offered. The efficiency that we have measured is validated by the trend shown by the total gain of the winning bidders in Figures 7 and 8. Fig 7 and Fig 8 corresponds to input levels 0.3 and 0.7 respectively.
If we observe the seller’s revenue with the progress of the auction (Figures 1 and 2), we can see that after a certain stage the revenue attains a constant value and this continues for a number of rounds, before the auction terminates. This is observed in both the levels of input.

As RevalBundle terminates only when the valuations reported in two consecutive rounds are similar, we can infer that towards the end, for a number of rounds, the valuations reported by the unhappy bidders are not sufficient to dislodge the winners from the winning coalition. Therefore, it follows that the information feedback, viz. the highest valuation on each bundle is not helpful enough for the bidders and may result in ‘dead’ values. We studied the change in revenue with the progress of the auction by giving the bidders the information on the deadness levels of different bundles.

To test this, we have used the method of dynamic programming to solve the WDP. We run the program on the same set of data which we used for feedback on highest valuations. Instead of revising the valuations by adding the predefined increment \( \epsilon \) to the highest valuation, we revised the valuations by adding the predefined increment \( \epsilon \) to the deadness levels of the packages in this case. We have plotted the revenue for this and the results are shown in Figures 9 and 10. The figures clearly show that the auction terminated much earlier (within round 8) as this feedback mechanism ensures that no bids are wasted. However, providing the deadness level as the feedback does not result in any change in the seller’s revenue.

8. Concluding Discussion

The new combinatorial auction mechanism RevalBundle addresses the problem of valuation in a common value model. It allows bidders to participate in the auction without having to determine the precise valuation of each bundle, thus increasing bidder participation. We have made the final payments independent of the winning bids, thus inducing the bidders to bid truthfully.

A few questions remain to be addressed:

- Our experiments indicate only preliminary findings. We need to experiment under different bidding behaviours of the agents. We need to validate the mechanism under real life settings by conducting experiments using human participants.
We also need to analyze the effect of second price payment in combinatorial auctions. Under common value model in combinatorial auctions, an ideal payment mechanism enforcing truthful bidding has not been reported yet.

We studied the performance of the auction with different information feedback, viz. highest valuations and the deadness levels. However, we plan to look further at the information feedback of the mechanism, i.e. what information the mechanism provides to the bidders at the end of each round of the auction to ensure that the bidders are able to provide their valuations more meaningfully.

Incremental solution to WDP needs to be examined in details. In any multi-round auction, the efficiency of the scheme depends on how quick a WDP can be solved, and in this context, incremental WDP plays a significant role.

9. References