

The Effects of Using a Bid Generator in Reverse Multi-attribute Auctions

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Abstract

In this paper we analyze the results of a multi-attribute auction experiment conducted via the Imaras electronic auction system. In this experiment the auctioneers were divided into two groups. One of these groups was offered an additive supportive tool that allowed for automatic generation of bids. We examine differences in the performance and the bidding style of the auctioneers from these two groups as well as differences in behavioral factors describing the system evaluation, use and usefulness.

Keywords: multi-attribute auctions, electronic auctions, auction support, multiple criteria decision making.

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1. Introduction

A multi-attribute auction is an economic mechanism which supports exchanges of goods or services defined by multiple attributes. In contrast to the traditional single-attribute auction, in which the sole issue is price, in the multi-attribute auction there are many issues specified by the bid-maker (e.g., product quality, price, terms of payment and terms of delivery). The bids submitted by the bid-takers have to specify the levels of each issue. Auction rules must also define: (1) the protocol (either a one-round or a progressive auction); (2) additional qualification criteria for bids; and (3) the withdrawal policy. Furthermore, one of the most important elements of the auction rules is the winner determination rule (Teich et al. 2004; Bichler and Kalagnanam 2006).

It is relatively easy to select the winning bid in a single-attribute auction, e.g. the bid-taker chooses a bid of the lowest price. Such a selection is not obvious however if multiple issues are taken into consideration. That is because the bid-maker faces a multiple criteria decision problem, the solution of which depends on both intrinsic and subjective structure of preferences and the method used for the preference elicitation and value function construction. In this context, several preference aggregation methods have been proposed (see, e.g., Che 1993; Teich et al. 2001; Padhi and Mohapatra 2010).

Information on a bid-maker's preferences and value (scoring) function can be made public or kept private. In most multi-attribute auction mechanisms the bid-makers are given the bid-taker's value function either explicitly (Bichler 2000; Bellosta et al. 2011) or partially (Beil and Wein 2003; Adomavicius et al. 2012).

When value function is public, the bid-makers know the bid-taker's evaluation of their bids. In such a situation the bidding process is similar to a single attribute auction, however, every bid-maker has to solve a bi-criteria problem: the bid-taker's value function and the bid-maker's value function. When the bid-maker's preferences are not disclosed the problem is complicated because the bid-makers are unable to determine if they are making bids that are better or worse for the bid-taker. In such situations, bid-makers can unintentionally make reverse concessions (i.e., propose bids that are better for them and worse for the bid-taker than their previous bids), win-win concessions (bids that are better for both the bid-taker and the bid-maker) or lose-lose concessions (bids that are worse for both the bid-taker and the bid-maker). The problem of unintentionally made reverse concessions is discussed in negotiation context (Bichler et al. 2003; Filzmoser and Vetschera 2008; Wachowicz and Wu 2010). It results from the different structures of preferences of a buyer and a seller that are not often strictly opposite.

The latter question is not trivial, especially when a seller wants to plan her bidding strategy that includes consecutive concessions for the forthcoming auction rounds. If the auction is conducted via an electronic web-based system, such as those offered by Ariba, IBM (Emptoris) or PerfectCommerce, additional supportive mechanisms may be applied to prevent sellers from making reverse concessions or to suggest the 'optimal' mix resolutions levels within the bid (Beil and Wein 2003). If the buyer's preferences must be kept private, such supportive mechanisms cannot be used. However, other tools that help sellers to identify various bidding possibilities within their own scoring spaces can be implemented. One such tool is a bid generator implemented in the Imaras auction support system (Kersten et al. 2013), which helps bidders to determine various bids of equal value (score) to them. Technically, the generator builds a list of offers that consist of various mixes of issues' options but result in the same or similar value calculated according to the seller's value function. Sellers use the generator to identify

alternative bids, which are indifferent for them but are (typically) of different value for the buyer. By submitting these alternative bids, the sellers may try to assess the buyer's value function and seek win-win bids, e.g., bids that are feasible and require the smallest possible concession.

The motivation for this study was to determine if a decision support tool such as the Imaras bid generator affects the bidding process and its results. In this paper we present results of the auction experiment in which the Imaras system was used. We discuss differences between behaviour, performance and system use of two groups of bidders: (1) bidders who could access the generator; and (2) bidders who could not access the generator. The paper consists of four more sections. Section 2 briefly describes the Imaras system and the experiment. Section 3 compares two auction types, those with the generator and those without. Bidders' assessment of the system and the bidding process is discussed in Section 4 and the conclusions are given in Section 5.

2. Imaras – the system and the experiment

The Imaras system uses an iterative reverse auction algorithm which allows bid-takers to keep their preferences secret (Kersten and Wu 2012). The system has been used both in lab and online experiments. The participants are students of different degree programs and different universities. For the purpose of online experiments several process rules were adopted - they maintained the auction and allowed those students who began late to bid.

2.1 Imaras auctions

The Imaras auction process is of a fixed length and is divided into rounds. The round time can be fixed or flexible. In the latter case, the round time depends on bidders' actions, e.g., a new round begins after a fixed time, which follows the second bidder's bid in the round. This allows the auction to continue. Bidders are informed via email if the round deadline is set. When a round deadline is reached the system moves to the next round. After each round, a set of limits (constrains) is defined and shown to bidders to direct them to submit bids that will be better for the buyer. Bidders can submit single or multiple bids during the round and can also see the current best bid for a buyer.

For this experiment, bidders could submit multiple bids. There are also different options for information disclosure; for example, either all bids are shown or only the winning bid is shown or no bid is shown.

In the case of flexible round time, the auction terminates when either its deadline is reached or the best possible bid has been submitted.

The Imaras bidding page is shown in Fig. 1. Section A contains general information about the auction with the navigation bar on the left-hand side of the screen. Sections B and C show tabular and graphical presentations of the bidding history. Section D shows a bidding construction tool, which is a series (3 in the figure) of drop down lists from which the bid-maker can select one of the acceptable alternatives. The bid generator is shown in Section E. In Fig. 1 only the input box (highlighted) in which the bid-maker enters the desired scoring value is shown. Before this box there is information about the maximum value that can be entered; the value shown is repeated below, i.e., (maximum 75).

The bid obtained through the drop-down lists (D) or the generator (E) is shown in Section F. Below is a button to submit the bid.

The scoring function is defined on all alternatives in the decision space. A seller and a buyer have a rating value associated with each option available on each attribute. The scoring function (rating) for each alternative (a combination of options selected for each attribute) is defined as a sum of ratings of options, according to the principles of simple additive weighting (SAW) method (Keeney and Raiffa 1993). The scoring function is quasi-linear and it is standardized to interval [0, 100].

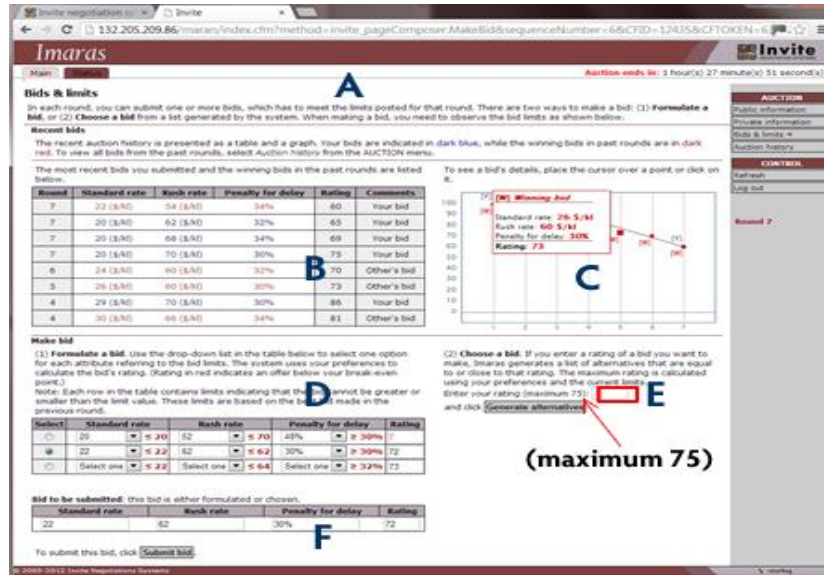


Fig. 1. Screenshot of Imaras bidding page: general information (A), tabular bidding history (B), graphical bidding history (C), bid construction (D), bid generation (E), and bid submission (F).

The part of the page which bidders use to formulate and generate bids is shown in Fig. 2. Fig. 1 shows the situation when the generator is available but not used. Fig. 2, Section E, shows the result of the generator usage. The bid-maker entered a value of 48 (maximum was 50) and Imaras displayed seven alternatives in the table. Note, that only three alternatives yield value of 48, one alternative yields a value of 49 and three alternatives a value of 47. This is because the generator searches seven alternatives yielding the required value and if there are fewer, then it selects alternatives with value as closed to the required one as possible.

Make bid

(1) **Formulate a bid.** Use the drop-down list in the table below to select one option for each attribute referring to the bid limits. The system uses your preferences to calculate the bid's rating. (Rating in red indicates an offer below your break-even point.)
 Note: Each row in the table contains limits indicating that the bid cannot be greater or smaller than the limit value. These limits are based on the best bid made in the previous round.

Select	Standard rate	Rush rate	Penalty for delay	Rating
<input type="radio"/>	Select one ▼ ≤ 20	Select one ▼ ≤ 70	Select one ▼ ≥ 30%	50
<input type="radio"/>	Select one ▼ ≤ 22	Select one ▼ ≤ 62	Select one ▼ ≥ 30%	49
<input type="radio"/>	Select one ▼ ≤ 22	Select one ▼ ≤ 64	Select one ▼ ≥ 32%	48

(2) **Choose a bid.** If you enter a rating of a bid you want to make, Imaras generates a list of alternatives that are equal to or close to that rating. The maximum rating is calculated using your preferences and the current limits.
 Enter your rating (maximum 50):
 and click **Generate alternatives**

If you choose one bid from the list below, then it will also be shown in the bid table on the left-hand side so that you can submit it.

Select	Standard rate	Rush rate	Penalty for delay	Rating
<input type="radio"/>	22	62	30%	49
<input type="radio"/>	22	64	32%	48
<input type="radio"/>	22	61	30%	48
<input checked="" type="radio"/>	20	68	30%	48
<input type="radio"/>	20	66	30%	47
<input type="radio"/>	20	70	32%	47
<input type="radio"/>	22	60	30%	47

Bid to be submitted: this bid is either formulated or chosen.

Standard rate	Rush rate	Penalty for delay	Rating
20	68	30%	48

To submit this bid, click **Submit bid**.

Fig. 2. Screenshot detail: bid construction (D), bid generation (E), and bid submission (F).

The bid-maker selected the fourth alternative from the top of the table (indicated in column Select), which then is shown in Section F so that it can be submitted.

2.2 Experiment design

An online auction experiment was conducted with 76 students from a university in Poland in the fall of 2012. All participants were divided into 24 auction instances with three sellers in each and one instance with four sellers. Thirteen auction instances were set up with the generator in the system and twelve without.

Four participants did not make any bids, therefore the number of sellers in four instances was lower. These instances were removed from further analysis, leaving 21 instances with three active sellers.

Table 1. Participants' demographics.

Generator was:	Available	Not available
No. of students – sellers	40	36
<i>Demographics (%)</i>		
Age group		
– 25 and younger	78	67
– 26-30	20	18
– 31 and older	2	15
Gender (female)	63	44
Experience with system (no)	100	100
Experience with task (no)	77	72
<i>Expectations</i>		
Task difficulty (scale 1-7)	4.5	4.4
Aspiration level rating	63.7	64.0
Reservation level rating	43.2	41.0

2.3 Business case

A procurement case was used in the experiment. This case involves a milk producing company (buyer) which requires a logistics provider (seller) to sign a contract for transportation services. The company approached several providers and invited them to participate in an auction. The transportation service contract contains three attributes, the values of which need to be established: standard rate of transportation, rush rate for unexpected delivery, and penalty for non-delivery or delivery of spoiled goods. Although all three attributes are expressed in monetary terms, they cannot be added up because they are in non-linear relationship for both the buyer and the sellers. Furthermore the preferences for each of the attributes differ among the sellers (for detailed description see Kersten, Vahidov et al. 2013).

In order to make the case easy to understand, the quasi-linear scoring function was interpreted as profit. In the case, the function was not given explicitly; instead a spreadsheet-like profit calculator was inserted.

3. Results

The overall results are discussed in Section 3.1, followed by a discussion of the generator usage in section 3.2. Section 3.3 compares bids made with and without the generator

3.1 General results

Overall results from the experiment are shown in Table 2.

Eleven sellers (31%) did not use the generator despite the fact that this tool was available. There were two winners (18%) in this group. In comparison, ten bidders out of 25 (i.e., 40%), used the generator and won the auction. The small dataset does not allow to test the significance of this difference. However, the fact that the relative number of auction winners is higher when bidders use the generator than when they do not use it is interesting and should be verified with a larger dataset. We may hypothesise, however, that the generator increases bidders' effectiveness.

To test the effect the generator use on outcomes we grouped sellers who did not use the generator together regardless of the availability of this tool. Table 2 shows that there were no significant differences in general results between the sellers who used the generator and sellers who did not, with the exception of the average number of bids. The sellers who used the generator submitted significantly more bids ($p = 0.037$) than the sellers who did not use generator (9.8 vs. 6.7). There were no significant differences in outcome variables between the winners who used and those who did not use the generator.

Table 2. Overall results.

	Generator was:	
	Available	Not available
No. of instances	12	9
Avg. no. of rounds	5.8	5.7
	Used at least once	Not used
No. (%) of sellers	25 (69)	11 (31) 27 (100)
– No. (%) of winners	10 (83)	2 (17) 9 (100)
Avg. no. of bids / bidder	9.8	6.7^
– Submitted by winners	13.1	8.3
Avg. no. of single seller's bids per round	1.9	1.6

– Submitted by winners	2.2	1.7
Avg. seller's profit	11.5	15.6
Avg. buyer's profit	66.7	55.3
No. (%) of Pareto-optimal agreements	4 (40)	1 (9)
No. (%) of non Pareto-optimal agreements	6 (60)	10 (91)
– % of dominating alternatives	0.1	4.0

Significance compared to sellers who used generator: $\hat{p} \leq 0.05$

Interestingly, the winning sellers who used the generator achieved lower profit than those who did not (11.5 vs. 15.6). The auctions in which the winning sellers used the generator resulted in a higher profit for the buyer than the auctions in which the winners either did not or could not use the generator (66.7 vs. 55.3). These results may be due to the larger number of bids made when the generator was used (see Table 2), the ease in bid formulation and the use of profit value in bid construction.

The number of winning bids which are Pareto-optimal is higher when the generator was used by winners than when it was not used (40% vs. 9%).

3.2 Generator use

In order to gain insight into the way the generator was used and into the effects of using it, we first compared bids made with and without the generator in those auctions, in which the generator was available. Bid generator is a tool, which makes bidding easier. Instead of deciding one every attribute value and checking its impact on profit the tool allows to generate seven alternative bids for the same or very close profit value. It is not only easier to formulate a bid but it also facilitates control of the profit value, which is the key measure for the sellers.

When a tool is very easy to use and it provides its user with some additional value, the possibility to generate several alternatives yielding the same profit, then such a tool may be overused with negative consequences. Consider the following situation. One seller submits a bid from among bids yielding the same profit value (called here equal bids), which yields the highest profit for the buyer. This seller reasons that in such a way she may achieve high profit herself and win because her bid also yields high profit for the buyer. If other bidders act similarly, then the admissible bidding set (set from which bids can be selected) may contract very quickly. It is thus possible that the generator's unintended consequence is such contraction of the admissible bidding set that there are only few admissible bids towards the end of the auction. This situation could explain why profit was lower when the tool was used than when it was not used.

The frequency of the generator use and the contraction of the number of equal bids are given in Table 3. First we divided the action process into the following four periods: (1) from the first round up to 25% of rounds; (2) from 25% to 50%; (3) from 51% to 75% rounds (inclusive); and (4) from 76% up to the last round of the auction. We excluded two auctions from this analysis because they have fewer than four rounds.

The difference in the proportion of usage of the generator between the four periods was not significant when all four periods were compared jointly ($\chi^2(3, N = 273) = 5.956, p = 0.113$). The pattern of the generator usage indicates that initially its frequency increases but then it drops down in the last period (76-100%). These changes are, however, not significant with the exception of the difference in use in the first and third period; in the latter the generator was

used significantly more often than in the former ($\chi^2(3, N = 136) = 5.802, p = 0.016$).

Table 3. The impact of the generator use on the equal bids space.

	0 – 25%	25 – 50%	50 – 75%	75 – 100%
<i>Bids made with generator</i>				
No. (%) of bids	29 (33[^])	31 (38)	26 (54)	23 (41)
Avg. no. of equal bids	18.2	11.0	2.5	1.6
<i>Bids made without generator</i>				
No. (%) of bids	59 (67)	50 (62)	22 (46)	33 (59)
Avg. no. of equal bids	19.5	12.1	6.1[^]	6.6[*]

Significance of bids made with and without generator: [^] $p \leq 0.05$, ^{*} $p \leq 0.01$.

Table 3 also shows that the average number of equal alternatives (i.e., alternatives with the same rating) for the seller who used the generator to make a bid did not significantly differ from the case when the generator was used neither in the first period ($p = 0.776$) nor in the second period of auctions ($p = 0.665$). In the third period, the average number of available alternatives when generator was used was significantly lower ($p = 0.023$) than the number of alternatives available when it was not used (2.5 vs. 6.1). In the last period of auctions the average number of admissible equal bids was also significantly lower ($p < 0.001$) for bids made with the generator than for bids made without it (1.6 vs. 6.6).

The difference in the number of equal bids suggests that generator usage impacts the size of the set of admissible bids. This size is determined by the winning bid; after every round the set of admissible bids is contracted: all alternatives which are worse for the buyer than the winning bid are dropped. To determine if the generator affects contraction of the admissible set we selected the winning bids. Because we considered only the winning bids, the small number of observations did not allow us to use four periods, instead we divided the process into two periods (1) from the second round to the middle and (2) from the middle to the end.

Table 4. The impact of generator use on the bidding space.

	Second round to middle	Middle to end
<i>Winning bids made with generator</i>		
No. (%) of winning bids	9 (45)	8 (33)
Avg. no. of alternatives	847	86[#]
<i>Winning bids made without generator</i>		
No. (%) of winning bids	11 (55)	16 (67)
Avg. no. of alternatives	1285	610^{+^}

Significance of bids made with and without generator: [^] $p \leq 0.05$.

Significance of bids made in the first or second half of auctions: ⁺ $p \leq 0.05$, [#] $p \leq 0.01$.

The frequency of the generator use to make winning bids and the contraction of the admissible bidding set are given in Table 4. There were 3374 admissible alternatives at the begging of each auction. In the first half of the auctions, average size of the set did not significantly differ regardless of whether or not the winning bid in the previous round was made with or without the generator (847 vs. 1285). The reason why these numbers are not significant is due to the outliers.

In the second half of the auctions in which the generator was used to make winning bids the admissible sets were contracted to 86 alternatives ($p = 0.010$), when winning bids made without generator the sets were contracted to 610 alternatives ($p = 0.046$). This difference is significant ($p = 0.011$). This may be the reason for the reduction of the winning sellers' profit: towards the end of the auctions, in which the generator was used, sellers had very few alternatives to choose from.

3.3 Bids made with and without the generator

The generator was used by the sellers wanted to select a bid out of several alternatives with the same or very close rating. One question is whether the selected bid was on average better for the buyer when the generator was used than when it was not used. To measure how good the choice of the alternative was for a buyer we used a normalized distance $D(a)$ in the buyer's rating between the submitted bid and the best alternative for a buyer that has the same rating for a seller:

$$D(a) = \frac{R^{max}(a) - R(a)}{R^{max}(a) - R^{min}(a)}$$

where $R(a)$ is the buyer's rating of the alternative a , $R^{max}(a)$ and $R^{min}(a)$ are ratings of, respectively, the best and the worst available alternative for the buyer with the same rating for the seller.

The distance is equal to 0 for the best bid for the buyer and 1 for the worst alternative. This distance was calculated only when more than one alternative with the same rating for the seller was available.

To compare the distribution of bids by their rating for the buyer, we grouped bids into four groups based on the distance to the best alternative for the buyer $D(a)$. The first group includes bids with the distance value from 0.75 to 1 (the worst alternatives), the second group includes bids with the distance value from 0.5 to 0.75, etc. The four categories, the best and worst alternatives, and a bid made in the category [0.25; 0.5) are shown in Fig. 3.

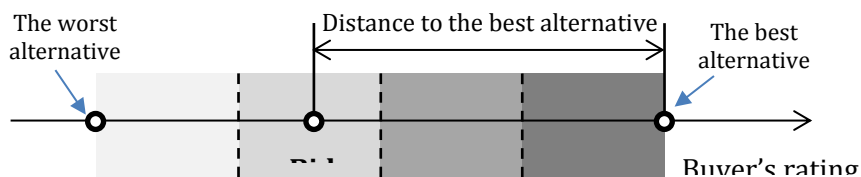


Fig. 3. Selection of the best bid for a buyer.

The average distance to the best bid when the generator was not available was not significantly

different ($p = 0.659$) from the case when the generator was available (0.60 vs. 0.62) (see Table 3). In auctions when the generator was available the average distance to the best bid was significantly lower ($p = 0.003$) for bids made with the generator than for bids made without the generator (0.51 vs. 0.66).

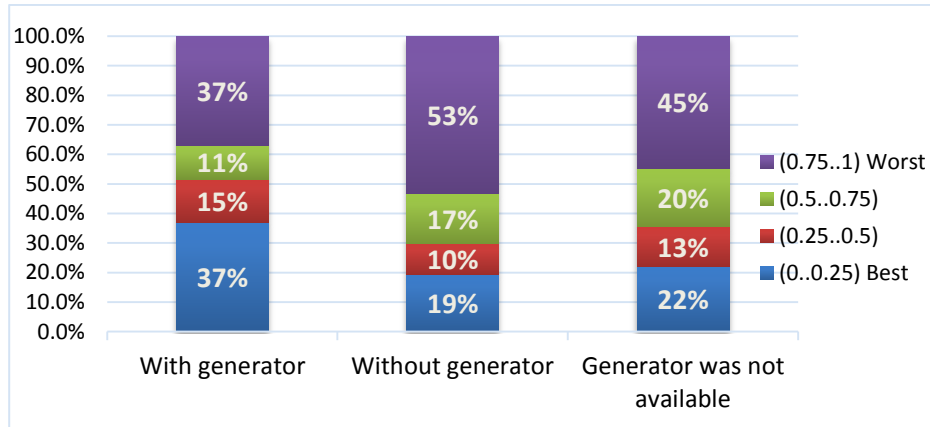


Fig. 4. Selection of the best bid for a buyer.

This result is interesting, but we do not know the reasons underlying it. Note, that the bidders with the generator do not know anything more about the buyer's preferences than the bidders who did not use the generator. The difference between these two groups of bidders is that using the generator makes it easier to obtain several alternative bids with the same rating. Also the generator makes bid formulation easier and this may be the reason why bid-makers, who used it, submitted more bids than those who did not use it. The final result was not beneficial to the latter bid-makers. Although the use of the generator led to bids yielding higher score for the buyer and not worse for the seller, the winners who used it made more bids than winners who did not use it. Therefore the former's profit was lower than the latter's (see Table 2).

The distribution of bids made with or without the generator in the four groups is shown in Fig. 4. This distribution is significantly different ($\chi^2(3, N = 243) = 11.908, p = 0.008$) when the generator was available. Significantly more bids in the "best for the buyer" group were made using the generator than when it was available but not used (37% vs. 19%). Significantly fewer bids were made in the "worst for the buyer" category with generator than without (37% vs. 53%). We can conclude that when using the generator the bidders selected better bids out of alternatives with the same rating for them than when they did not use it.

The distributions of bids made without the generator was not significantly different ($\chi^2(3, N = 381) = 5.113, p = 0.497$) between the situation when it was available and when it was not available. Similarly, the distribution of bids when the generator was available and when it was not available was not significantly different ($\chi^2(3, N = 406) = 2.267, p = 0.519$). These results indicate that when the generator was used, then the bids were better for the buyer than when it was available but not used. If however, the generator was not available, then the bids were not worse for a buyer than in the case when it was available but not used.

4. Behavioural aspects of bidding with and without the generator

After the experiment, the sellers were asked to fill out a questionnaire. We compared responses given by the sellers in two treatments. The results are shown in Table 5. Answers were coded

between -3 (strongly disagree or not satisfied) and 3 (strongly agree or satisfied).

Table 5. Post-auction evaluation of bidders' self-performance and the auction system.

	Generator was available			Generator was not available		
	Overall	Winners	Non-winners	Overall	Winners	Non-winners
Satisfaction with an outcome achieved	-2.08	-0.43	-2.76⁺	-1.61	-0.43	-2.36⁺
Satisfaction with negotiators own performance	-0.79	0.29	-1.24	0.61[^]	0.71	0.55[^]
Satisfaction with experience gained	1.25	1.14	1.29	1.22	1.43	1.09
Satisfaction with personal achievement	-0.33	0.00	-0.47	0.22	0.14	0.27
The system was helpful in achieving my objectives	0.21	0.71	0.00	0.00	0.71	-0.45
The system was helpful in improving my performance	0.38	0.57	0.29	0.61	0.86	0.45
The system was helpful in reaching an outcome faster	0.54	0.71	0.47	0.33	0.71	0.09
The system was helpful in managing the process	0.79	0.43	0.94	0.33	0.29	0.36

Significance compared to negotiations with generator: [^] $p < 0.05$,

Significance compared to the winners: ⁺ $p < 0.05$

We found no significant difference in responses given in the two treatments with the exception of satisfaction with own performance. The sellers were significantly less satisfied ($p = 0.021$) with their own performance when the generator was available, than when it was not available. There were no significant difference ($p = 0.698$) in the responses to this question between the winners in two treatments. Non-winners were significantly less satisfied ($p = 0.014$) with their own performance when the generator was available than when it was not available.

A possible interpretation of the higher satisfaction with own performance for non-winners when the generator was not available is the difference in complexity of the bidding process with and without it. When the process was easier (with the generator), the sellers were more disappointed not to win an auction. When it was harder to bid (with no generator), then they appreciated their performance higher.

In both treatments the winners were significantly more satisfied with the outcome than non-winners ($p = 0.021$, when the generator was available; $p = 0.015$, when it was not available). This is not surprising.

5. Discussion

The alternative bids generator was designed to provide bid-makers with a support tool that makes the bidding process easier and more efficient. Another purpose of this tool was to help

bid-makers to be able to generate alternatives based on their score (profit in our experiment). The results from our experiment are mixed. The tool had no positive effect on the final result. The average profit of the winning sellers' who used the generator was 26% lower than the average profit of the sellers who did not use it (see Table 2). This may be one reason for the generator users to be less satisfied with their performance, than winners who did not use the generator. On the other hand, however, the generator had a positive effect on the average buyers profit because it was higher by 21% than the average buyers profit when the generator was not used.

These results suggest that market-makers and bid-takers should include such a tool in multi-attribute auctions but bid-makers should refrain from using it. This conclusion is only tentative and it must be verified.

We think that the generator may be useful for the buyers, but the implications of its usage need to be clearly explained. One reason is that the use of the bid generator has a positive impact on auction efficiency; 40% of the winning bids are Pareto-optimal as opposed to 9% when it was not used. This is also reflected in the fact that the winning bids which were not Pareto-optimal are closer to the efficient frontier when the generator was used; on average 0.1% of alternatives dominate the winning bid as opposed to 4.0% when the generator was not used.

One of the possible reasons why the generator did not have a positive impact on the final results is that bid-makers used this tool often in the first half of the auction but much less so in the second half, and virtually not at all in the last two rounds (see Figure 4). We found that when the bids were made with the generator, then they were better for the buyer than the bids yielding the same profit for the sellers, who did not use it. This suggests that the generator helps bid-makers to select, from among bids of equal profit, the bid that is better for the buyer. This feature could lead to the sellers achieving higher profit when they use the generator than when they do not use it, except for the fact that the generator users make more bids. The overall result is that they make bigger concessions than those who do not use the generator.

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References

- Adomavicius, G., A. Gupta and P. Sanyal (2012). "Effect of Information Feedback on the Outcomes and Dynamics of Multisourcing Multiattribute Procurement Auctions." Journal of Management Information Systems **28**(4): 199-230.
- Beil, D. R. and L. M. Wein (2003). "An Inverse-optimization-based Auction Mechanism to Support a Multiattribute RFQ Process." Management Science **49**(11): 1529-1545.
- Bellosta, M. J., S. Kornman and D. Vanderpooten (2011). "Preference-based English Reverse Auctions." Artificial Intelligence **175**(7): 1449-1467.
- Bichler, M. (2000). "An Experimental Analysis of Multi-attribute Auctions." Decision Support Systems **29**(3): 249-268.
- Bichler, M. and J. R. Kalagnanam (2006). "Software Frameworks for Advanced Procurement Auction Markets." Communications of the ACM **49**(12): 104-108.

- Bichler, M., G. Kersten and S. Strecker (2003). "Towards a Structured Design of Electronic Negotiations." Group Decision and Negotiation **12**(4): 311-335.
- Che, Y. K. (1993). "Design Competition through Multidimensional Auctions." The RAND Journal of Economics **24**(4): 668-680.
- Filzmoser, M. and R. Vetschera (2008). "A classification of bargaining steps and their impact on negotiation outcomes." Group Decision and Negotiation **17**(5): 421-443.
- Keeney, R. L. and H. Raiffa (1993). Decisions with multiple objectives: preferences and value trade-offs, Cambridge University Press.
- Kersten, G. E., R. Vahidov and D. Gimon (2013). "Concession Patterns in Multi-attribute Auctions and Multi-bilateral Negotiations: Theory and Experiments." Electronic Commerce Research and Applications: (in print).
- Kersten, G. E. and S. Wu (2012). Multi-attribute auctioning method and system. Patent pending. <http://www.google.com/patents/US20120246020>. US.
- Padhi, S. S. and P. K. Mohapatra (2010). "Centralized bid evaluation for awarding of construction projects—A case of India government." International Journal of Project Management **28**(3): 275-284.
- Teich, J., H. Wallenius, J. Wallenius, et al. (2001). "Designing Electronic Auctions: An Internet-Based Hybrid Procedure Combining Aspects of Negotiations and Auctions." Journal of Electronic Commerce Research **1**: 301-314.
- Teich, J. E., H. Wallenius, J. Wallenius, et al. (2004). "Emerging Multiple Issue E-auctions." European Journal of Operational Research **159**(1): 1-16.
- Wachowicz, T. and S. Wu (2010). Negotiators' Strategies and Their Concessions. Proceedings of The Conference on Group Decision and Negotiation. G. J. de Vreede, The Center for Collaboration Science, University of Nebraska at Omaha: 254-259.