How to bid at consumer-oriented reverse e-procurement platforms. A decision model for SME suppliers.

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Introduction

Reverse procurement platforms which enable buyers to place requests for proposal online and then offer suppliers the possibility to bid for contracts have been intensely used in a B2B-context for several years. Since about 2004, such platforms have become available to ordinary consumers and are constantly gaining in popularity. Being primarily a tool to increase competition, these platforms generate significant consumer surplus and exert intense price pressure on the suppliers. As the analysis of data from the painting industry shows, auction prices are almost always far below the industrial average (Klafft and Spiekermann 2006). In most extreme cases, painters agreed to work for as little as € 4 per hour (compared to an average wage for painters of € 12,98 according to Statistisches Bundesamt 2005). This raises the question how potential suppliers – many of whom are small and medium-sized enterprises (SME) or even self-employed persons with little auctioning experience – can exploit the potential benefits of the new platforms without becoming victims of phenomena like the winner's curse. One solution to this problem can be decision support systems which assist the SMEs during the bid preparation phase. The goal of such systems can be described as follows: Maximize the expected contribution to profit of a bid portfolio by taking into consideration the supplier's capacity constraints. In this paper, a decision model will be presented which uses likelihood of success functions derived from empirical data to solve the abovementioned optimisation problem.

Determining likelihood of success functions from empirical data

Empirical data on procurement auctions for three standardised services (sanding and sealing of planks, tiling, painting of ingrain wallpapers, downloaded from the platform www.letsworkit.de) served as an input for the derivation of functional relationships between a bid and its likelihood of success. For each service category, the price distribution of winning bids (normalised on a per m^2 basis) was determined. Figure 1 shows as an example the empirically determined distribution for painting of ingrain wallpapers.

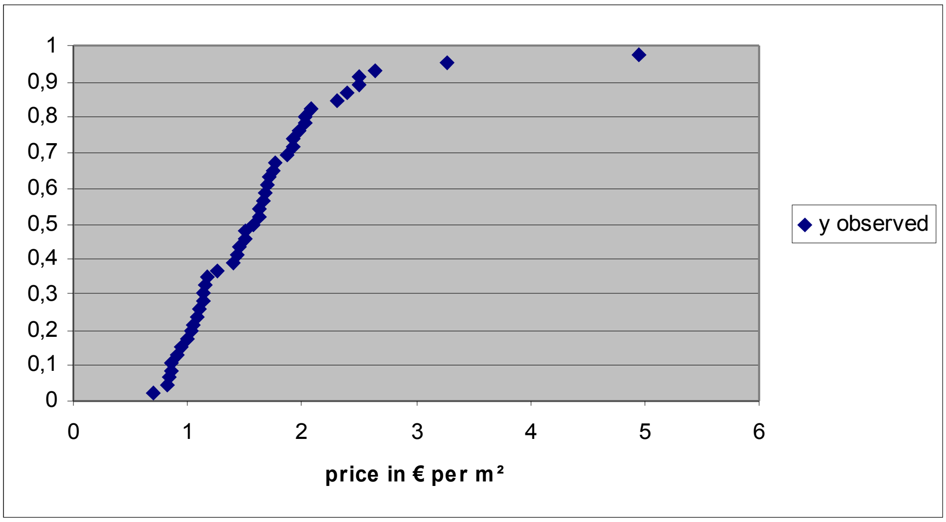

Figure 1: Painting of wallpapers – distribution of winning bid prices in € per m²

All three distributions showed similar distribution patterns which closely resembled the ones observed in biological growth processes (Lopez et al 2004). It was therefore decided to use biological growth functions as candidates for the functional approximation of the winning bid distribution. Candidate functions included

- the Gompertz-function: $F(x) = a + c * e^{-e^{-b*(x-d)}}$
- the von-Bertalanffy function: $F(x) = (a^b - (a^b - c) * e^{-b*d*(x-xo)})^{(1/b)}$
- the logistic function: $F(x) = \dfrac{1}{1 + k \cdot e^{-T \cdot x}}$ and
- the Janoschek-function (Janoschek 1957): $F(x) = 1 - e^{-b \cdot x^C}$

All these functions were fitted to the three observed distributions by performing a least square minimisation (see e.g. Hartung et al. 1995) using Newton's algorithm (see e.g. Rardin 1998). The goodness of fit was then evaluated by calculating the remaining sum of squares due to error (SSE). The results are displayed in Tables 1 to 3.

Table 1: Goodness of fit - Sanding and sealing of planks (n = 25 observations)

Approximation function:	Gompertz	Bertalanffy	logistic	Janoschek
SSE:	0,023	0,021	0,056	0,059

Table 2: Goodness of fit -Tiling (n = 60 observations)

Approximation function:	Gompertz	Bertalanffy	logistic	Janoschek
SSE:	0,107	0,099	0,203	0,272

Table 3: Goodness of fit - Painting of ingrain wallpapers (n = 45 observations)

Approximation function:	Gompertz	Bertalanffy	logistic	Janoschek
SSE:	0,036	0,036	0,050	0,041

The results show that von-Bertalanffy-functions are best suited for modelling the distribution of winning bids at consumer-oriented reverse procurement auctions. The likelihood that a bid with a given price x_B per unit will be rejected in such an auction can therefore be modelled as:

$$F_1(x_B) = (a^b - (a^b - c) * e^{-b*d*(x_B - x_o)})^{(1/b)} \qquad (1)$$

with a = 1, $x_0 = 0$, $x_B > 0$ and b,c, and d positive values to be determined through least square fitting or an alternative fitting method. In the three cases under analysis here, the optimal values for b,c and d were the following:

Table 4: Optimisation results for the von-Bertalanffy approximation

Optimization results:	parameter b	parameter c	parameter d
Painting	0,03101	0,69012	57,36920
Tiling	0,13429	0,00000	1,43405
Sanding and Sealing	0,04656	0,00000	6,81197

The resulting von-Bertalanffy-functions provide a good fit in the sanding and the painting case, and an acceptable fit in the tiling case, as can be seen in figures 2 to 4.

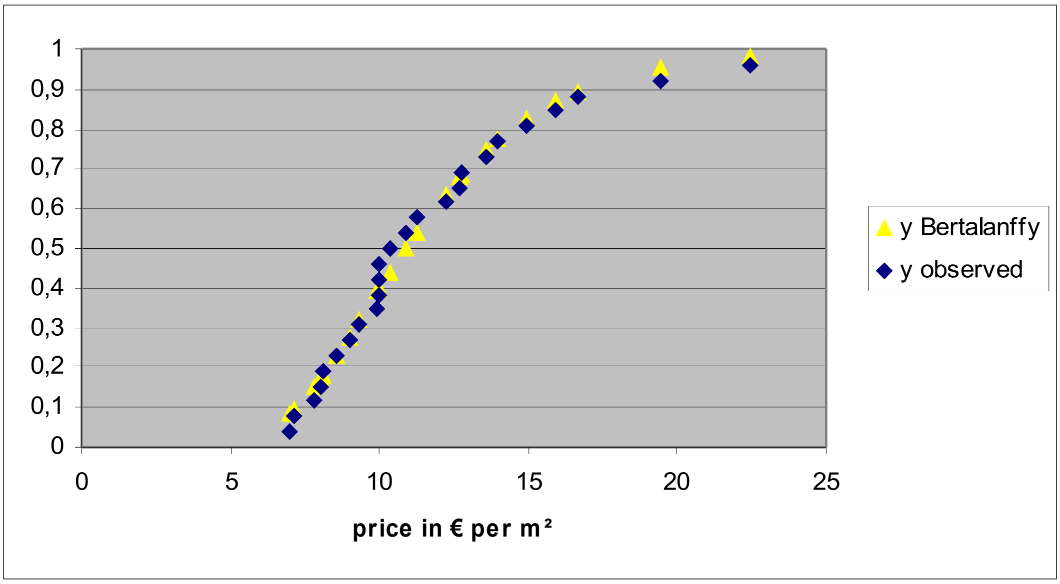

Figure 2: Sanding and sealing of planks – a von-Bertalanffy approximation of the winning bid distribution

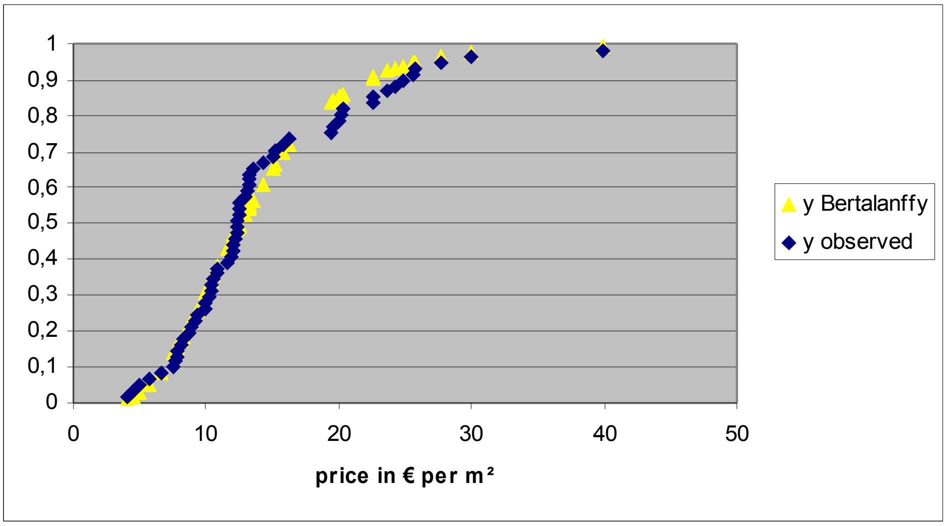

Figure 3: Tiling (excluding material costs) – a von-Bertalanffy approximation of the winning bid distribution

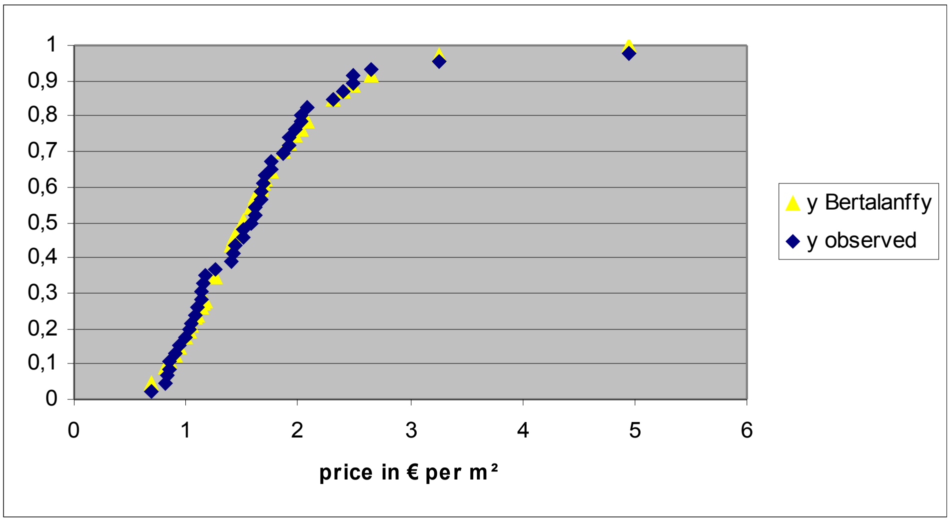

Figure 4: Painting of ingrain wallpapers – a von-Bertalanffy approximation of the winning bid distribution

Approximation formula (1) applies to the whole set of auctions within a service category regardless of the starting price stated by the buyer. Furthermore, this formula does not take into consideration bids which may have already been placed in an ongoing auction. In reality, the starting price or the current best bid constitute a maximum price per unit x_{max} which cannot be exceeded in a specific auction. In order to take this into consideration, formula (1) has to be readjusted as follows:

$$F_2(x_B, x_{max}) = \frac{F_1(x_B)}{F_1(x_{max})},\ 0 < x < x_{max} \qquad (2)$$

In the following paragraph, F_2 will be used as an input for an optimisation model which aims at maximising a supplier's contribution to profit by optimising bids within a given auction portfolio.

Maximising the Contribution to Profit

Knowledge about the relationship between a bid and the corresponding likelihood of rejection enables suppliers to maximise the expected contribution to profit of an auction portfolio. This chapter presents an optimisation model for this task, based upon the following modelling assumptions:

- During the auction process, the only information visible at the platform is the starting price or, if bidding has already begun, the current best bid. The precise bid history is kept secret until the auction ends.
- Due to typically low contract volumes (usually € 1000 or less) and long auction durations (from several days to weeks), suppliers do not monitor the auction actively but let bidding agents work for them. Bidding agents outbid all competitors until the predefined minimum bid is reached.
- The supplier is operating under capacity constraints. Exceeding the available capacity for a given resource results in penalties.
- Additionally, there are also absolute capacity limits which must not be exceeded under any circumstances.

Introducing the supplier's variable costs (per unit) as x_{var}, the expected contribution to profit E_{CTP} for a minimum bid x_B submitted to the bidding agent can then be calculated as

$$E_{CTP}(x_B, x_{\max}) = (x_B - x_{\text{var}}) \cdot (1 - F_2(x_B, x_{\max})) + \int_{x_B}^{x_{\max}} 1 - F_2(x, x_{\max}) dx \quad (3).$$

Let's now consider a risk-neutral supplier with limited production capacities who wants to maximize the contribution to profit of a portfolio comprising i reverse auctions. We introduce

- Participation variables $P_i \in \{0,1\}$, one for each auction i;
- Decision variables $x_{B,i}$ denoting the minimum bid to be entered into the bidding agent for auction i ($x_{var,i} < x_{B,i} < x_{max,i}$);
- Expected contributions to profit per unit $E_{CTP,i}(x_{B,i}, x_{max,i})$;
- Contract sizes $A_i > 0$;
- Fixed transaction costs for bid submission $T_i > 0$;
- Variables $c_{i,j}$ denoting the consumption of resource j for one unit of contract i;
- Capacity constraints $C_j > 0$ which, if violated, lead to fixed penalties $S_j > 0$, and
- Absolute capacity constraints $C_{j,max} \geq C_j$ which must not be exceeded under any circumstances.

Using these variables, the optimisation problem to be solved by the supplier can be described as follows:

$$\max\left(\sum_i \left[E_{CTP.i}\left(x_{B,i}, x_{\max,i}\right) \cdot A_i \cdot P_i - T_i \cdot P_i\right] - \sum_j \left[\left\langle \sum_i \left[c_{i,j} \cdot A_i \cdot \left(1 - F_2\left(x_{B,i}, x_{\max,i}\right)\right) \cdot P_i\right] - C_j \right\rangle^0 \cdot S_j \right] \right)$$

so that $\sum_i c_{i,j} \cdot A_i \cdot P_i \leq C_{j,\max} \forall j$. (4)

The optimisation model in (4) is only exemplary and can be easily adopted to match the specific needs of a particular supplier. It is, for example, possible to model any polynomial penalty function by adding additional Macauley bracket terms, and the supplier's risk preferences might be taken into consideration by weighing the penalty terms with a risk preference factor.

Conclusion, Limitations and Outlook

Optimisation models like the one presented here enable SME suppliers to manage their bid portfolios more systematically and efficiently. They prevent suppliers from placing "ruinous" bids by pursuing the overall goal of CTP maximisation without being misled by any psychological factors. As a result, bidding at consumer-oriented procurement platforms will become more predictable and less risky. If such optimisation tools are integrated into bidding agents, auction platform providers can offer an additional service to the suppliers: the real-time optimisation of bid-portfolios. As the use of agents significantly reduces transaction costs, permanent monitoring of a set of auctions becomes feasible. Therefore, CTP optimisation calculations can be constantly updated according to the latest bid developments, thus significantly improving the quality of bidding decisions. However, the applicability of the model presented in this paper is still somewhat limited:

- So far, the model is only suitable for auctions dealing with standardised and homogeneous services and
- the model does not take into consideration additional information emerging during the auction, such as the number of participating bidders (which most auction portals display at the respective website).

Future work will concentrate on the elimination of these shortcomings, before a prototype of an enhanced bidding agent with an integrated optimisation tool can be developed and tested. Another issue which needs to be addressed is how the widespread use of optimisation agents may influence bidding habits and the resulting auction prices – as this might induce a change in the observed price distribution functions. It will therefore be essential to monitor price distributions very closely after the enhanced bidding agents have been deployed.

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