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The highs and lows of unbalanced bidding models

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Abstract

The unbalanced bidding models developed in the first 50 years, since Marvin Gates first invented them in 1956, have suffered from a significant common flaw. Typically designed as linear programming models, with the objective being to maximise the contractor's profits from a project, they have incorporated constraints on the prices for each of the items such that they are each bound by lower and upper limits. The intent of this was to find optimum prices falling somewhere *within* these limits. Instead, the effect of these models has been that all optimal prices (barring only one) are found to lie exactly *on* the extreme edge of these limits. In effect then, these models serve only to decide which items should be assigned their lowest acceptable price, and which items should be assigned their highest acceptable price. Tests done on a series of simulated hypothetical projects, created randomly by way of an automated process, illustrate this effect, which has previously not being observed. This effect is suggested as being undesirable – these pricing boundaries are vague and heuristically difficult to determine and hence relatively 'soft' in nature, rather than being inelastic and hard-and-fast. The risks - that these limits are designed to avoid – are not of the nature that they are incurred (fully) marginally beyond these limits and yet not incurred at all within the limits. Nevertheless, even though these boundaries are only vaguely definable by nature, these models do somehow need to acknowledge that extreme prices are unacceptable and normal ('central') prices are fine. This problem has been solved with the use of component unit pricing (CUP) theory.

Keywords: pricing, optimisation, unbalanced bidding, risk analysis

1. Background

Unbalanced bidding describes the process of contractors deciding unit prices for each of a project's component items, such that these can then form the basis of their contractual agreement with the client. Prior to this, it is typical that the client and the contractor will have provisionally agreed to the overall tender price for the project as a whole (possibly on the basis of a competitive tender) but then the detailed level of the individually priced items become necessary. These are required in order to provide the basis for determining the interim monthly progress payments, the value of variations and of any escalation

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adjustments. The item prices form an essential basis of the contract and yet they are difficult for clients to properly assess (Skitmore and Cattell, 2012).

Contractors can benefit greatly from optimised item prices. Tests done on a hypothetical project showed a contractor enjoying an increase of 150% in profit by way of optimised unbalanced prices, by comparison to the equivalent balanced prices (the latter describing those produced by way of simply applying the same mark-up to the estimated costs of all of a project's items) (Cattell, 2011).

Gates (1956) was the first to identify unbalanced bidding as a strategy. This led to various efforts (Stark, 1968; Ashley and Teicholz, 1977; Teicholz and Ashley, 1978; Green, 1986; Tong & Lu, 1992) to determine a mathematical basis for optimising this, all of which entailed linear programming (LP), except for one that involved quadratic programming (Diekmann, *et al*., 1982). All of these efforts sought to maximise profits and yet recognised that unbalanced bidding is a 'risky' strategy. Cattell *et al.* (2010) identified these risks. The principal mechanism by which to moderate these risks was the universal use of LP constraints on each of the prices, restricting them within defined lower and upper limits. The intent was seemingly that optimum prices would be found that would fall somewhere *within* these limits.

2. What identifies these limits?

None of this research suggested a basis for deciding these limits. It appears that it was intended that subjective human judgement would be sufficient. Presumably, contractors were intended to be adequately able to identify the points at which any single price crossover point would differentiate acceptable pricing from that which is unacceptable. These models do not cater for the combined effect of multiple item prices being at or near these limits and yet, presumably, the risk of many or all prices being 'on the edge' is greater than a scenario where only one price is at or near its limit (at times when the other items are priced more moderately).

3. Unintended consequences

Numerous tests have been made using this LP modelling technique and in all instances, all of the items (barring only one), in each experiment, get priced at their very limit. The models, in effect, only serve to decide which items get priced at their highest extreme limit and which ones get priced at the lowest limit. Furthermore, they serve to consistent identify the one item in each project that gets needed to be priced somewhere within its limits, in order that the summation of the extension of all the item prices exactly equates to that project's overall tender price, which is input into these models as another constraint.

4. Alternative algorithm

The exact same results can be accomplished without the use of linear programming, using a conceptually simpler method that is mathematically less abstract. The objective is to maximise a project's overall expected profit and this comprises contributions from each of the project's constituent items. These contributions have been found (Cattell *et al.*, 2007) to have a linear relationship with the prices of these items, with various slope coefficients (referred to as being their *Beta* coefficient in Cattell *et al.*, 2007). Different items will contribute various proportions towards profits, for every dollar added to their prices. In other words, given a choice of where to allocate or distribute the overall tender price, amongst all of a project's constituent items, some items will deliver more profit when assigned a dollar, than other items. Clearly then, the objective of maximising profit can be translated to identifying those items that will deliver the most profit / dollar of price and these are then assigned their highest possible prices. This can be accomplished by way of assigning the least prices to those items that will contribute the least profit for every dollar of price. This "unbalancing" of the bid will deliver the maximum profit to the exact same extent as by way of using LP, assigning each item with the exact same price as the technique of LP will also identify.

The algorithm to implement this strategy is as follows:

- sort the items in descending order of their *Beta* coefficient

- assign all the items their lowest acceptable price

- calculate the summation of the extension of all these prices

- calculate the difference (*'Delta'*) between the tender price and this summation

- if *Delta* is less than 0, then report an error (flagging the need to make these minimum prices even lower) and terminate

- as long as *Delta* is more than 0, then starting at the top and looping down through all the items in their sorted sequence, price each item with its highest acceptable price, adjusting *Delta* by way of…

  $Delta$ -= Q_n * $(P^{max}_n – P^{min}_n)$

  where Q_n = BQ quantity for item n

  P^{max}_n = maximum acceptable price for item n

  P^{min}_n = minimum acceptable price for item n

- if this loop has reached the last item, then report an error (flagging the need to make these maximum prices even higher) and terminate

- else, P_{n-1} += $Delta / Q_n$ which will serve to finish off from identifying all of the optimum prices (as defined for the purposes of the LP models that have previously been advocated).

This algorithm should be computationally more efficient than using LP but more importantly (because LP will be very fast, anyway) it is an easier algorithm to understand and to implement. This algorithm bears a strong resemblance to that advocated by Teicholz and Ashley (1978).

For the purposes of this research, this alternative algorithm is important because it provides proof of the cause of the outcome that all of the 'optimum' item prices (barring only one) will be prices that sit at the very edge of their acceptable pricing limits. In effect, all that the LP approach is shown to accomplish is to split the items into two sets: those to be allocated their maximum prices and those to be given their minimum prices, with one item remaining to serve to satisfy the finer details of the tender price constraint.

The problems are, principally, two-fold, as follows:

(1) that the risks from pricing have been found (Cattell *et al.*, 2010) to not transcend from being non-existent within some range to suddenly being excessive outside of some sharp boundary; and

(2) that contractors are, furthermore, believed to be incapable of being precise with being able to recognise and thus set any such boundaries.

However, the precision of these limits is proven to be highly significant to the outcome of the use of these models. There is a 50% chance that any adjustment to any single limit will lead to a different solution (as regards offering a list of optimal prices): with each item adopting exactly either its lower or upper limit in each case.

Nevertheless, there is little basis for contractors to decide these limits and at best they can only do this with a fairly considerable degree of *vagueness*, rather than with any confidence of absolute *sharpness*.

5. Solution

Inuiguchi and Ramik (2000) suggest that Fuzzy Mathematical Programming and, more particularly, that Fuzzy LP is better suited to this nature of problem. Fuzzy LP provides a basis to recognise that, depending on the degree of confidence being sought in the outcome, the solution varies, taking account of the inherent imperfections in the precision to which each aspect of the input can be expressed, whether this is ambiguous in nature (being of either one value or another), or is vague (being, to some degree, fuzzy / blurred or not 'sharp' by nature).

The alternative, more typical approach to such challenges lies with stochastic modelling, such as by way of making use of Monte Carlo simulation. Stochastic models recognise the inherent uncertainty and inconsistency of financial data (amongst other areas of application).

Besides the inherent indefinite nature of the data involved, the other issue lies with recognising that risks increase *gradually* as prices become more extreme. They typically do not transcend from a state where the risks are non-existent to becoming entirely unacceptable, at any price point that is only marginally different. In mathematical terms, this is referred to as the transition from membership to non-membership of the feasible region. Furthermore, CUP Theory (Cattell, 2011) has shown that this rate of transition (from low-risk prices to high-risk prices) is different for different items and should be capable of being determined. Thus, if a contractor is wishing to reduce their risk, they will find that changing to more moderate pricing for some items will yield more of a change to their risk than with other items. With this in mind, clearly any optimisation of this domain should seek to recognise these differences between items and not treat them all as having the same nature of risk profile. Changes to more moderate pricing with some items can be more effective as regards lowing risk whilst preserving profitability, relative to other items.

CUP Theory is, therefore, based on recognition that the problem with item pricing has not one, but two objectives. The one objective (that has been catered for by way of the abovementioned traditional approach using LP) is to seek the maximisation of the contractor's profit. However, this approach fails to recognise the significance of a second objective: to also minimise the contractor's risk. LP models are limited by catering for only one objective. However, Pareto optimisation facilitates that LP models can be manipulated so as to satisfy two or more objectives – even though the underlying mathematical mechanism (for instance, solved by way of the Simplex Algorithm) is restricted to having only one expressed objective function. Pareto optimisation caters for situations where the multi-objective aspect of a problem is nontrivial, i.e. where satisfying one objective distracts from - or competes with - satisfying another of the objectives. When objectives conflict, there are potentially an infinite number of optimal solutions and the chosen solution will depend on some degree of preference being given to one of the objectives at the expense of the others. This implies some degree of weighting having to be applied to each of the objectives.

In the case of item pricing, a model can be structured so as to have the single objective of maximising the contractor's utility (as with CUP Theory), with utility being expressed as a function of both profit and risk.

6. Conclusion

This paper has provided proof that the popular structure of unbalanced bidding models, in which LP is used to maximise the profit and in which the problem of risk is catered for solely by way of item price limit constraints, delivers an unexpected and unwelcome solution. Rather than avoiding extreme pricing, these models instead serve to induce such pricing: pricing every item at the extreme edge of what is considered acceptable, even when the extent of these edges is difficult to determine.

Whilst almost all unbalanced bidding models have had this form, future models will benefit from a different approach – one that caters for the inherent uncertainties and also that caters for recognition that the risks climb as prices become more extreme and don't simply switch over to becoming simply unacceptable at some magical single point of transition.

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