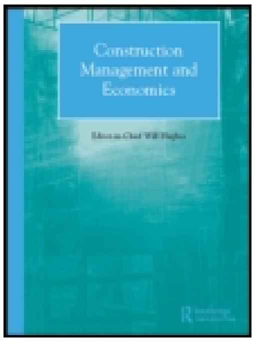

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Modelling standard cost commitment curves for contractors' cash flow forecasting

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Cash flow forecasting and control are essential to the survival of any contractor. The time available for a detailed pre-tender cash flow forecast is often limited. Therefore, contractors require simpler and quicker techniques which would enable them to forecast cash flow with reasonable accuracy. This paper identifies causes behind the inaccuracy of current standard value S-curves (which are often used as an alternative approach for cash flow forecasting) and proposes the use of standard cost commitment models. The process of developing and testing the cost commitment models involved first collecting actual data for 150 completed projects. Several criteria were identified to classify these projects. Tests were conducted to identify which of these criteria affected the shape of the cost commitment curves. Projects were then distributed into different groups and S-curves were fitted into each using the logit transformation technique. Errors incurred when fitting these curves were measured and compared with those associates in fitting individual projects. Results showed that the difference between these errors was not significant. The reliability of selecting the cost commitment curve to model (instead of value curves) was evaluated. Results confirmed the hypothesis that cost commitment models are more accurate and reliable than value models. Finally, the paper outlines some of the practices involved in utilizing the proposed models.

Keywords: S-curves, cost commitment, cash flow forecasting, cost control, ANOVA tests.

Introduction

Insolvency is more likely to occur in the construction industry than most other industries. Figures published by the DTI (1989) show that the construction industry accounts for approximately 17.5% of all cases of bankruptcy and liquidation in the UK. Cash flow forecasting and control are essential for the survival of any contractor. The main input data required to forecast cash flow for individual projects are field costs, clients' payments and the time lag between disbursements and receipts. Considerable effort is required to compile a cash flow plan and forecast the field cost-flow for an individual project. The conventional process of preparation entails the calculation of production quantities for each time interval according to progress schedules and multiplying them by the estimated unit costs. Clients' valuations are derived from the field cost by adding the relevant markups.

The need for cash flow forecasts applies equally to current contracts as to those contracts to be tendered for. Cash flow forecasts are often essential at the bidding stage in order to estimate the financing of the project and its possible influence on the overall liquidity of the company. However, contractors do not usually plan detailed schedules before contracts are awarded because of the cost involved and the short time available. Therefore, contractors require a simple and fast technique which would enable them to forecast cash flow with reasonable accuracy.

Many models have been developed to assist contractors in their pre-tender cash flow forecasts. The majority of these have been based on standard value S-curves, developed using actual past construction projects. However, these have not received general acceptance, since their reliability is in question. Cumulative value curves vary significantly and, unless a detailed calculation is produced, cash flow forecasts are likely to be inaccurate. This paper identifies the causes behind the variability of value curves and proposes the use of standard cost commitment models instead.

Previous work

Wray (1965) outlined the importance of project control and suggested the use of cumulative plots of cost versus

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time, and cumulative value versus time. He argued that the contractor or client should plot their cumulative monthly value or monthly cost and compare it with envelopes of the budgeted S-curves. He concluded that the so called Project Status Reporting System (PSRS) would provide senior managers with a clear, concise picture of the overall financial situation.

Jepson (1969) argued that S-curves representing labour man hours or labour costs can only act as indices for financial control. He claimed that a contractor might, due to a change of method, be losing money while labour costs remain less than forecasted. Moreover, he showed that the net cash flow was unlikely to be a good tool for the control of performance on site because actual values tend to vary widely from forecast ones.

In the early 1970s, with high interest rates and more appreciation of financial management, there was a surge in cash flow forecasting in both contractor and client organizations. Money was invested by construction clients (mainly public authorities) into research and hence more study was dedicated to the client's cash flow forecasting. This was demonstrated by the development of a series of typical value S-curves by many researchers (Hardy, 1970; Bromilow and Henderson, 1974; Balkau, 1975; Bromilow and Henderson, 1977; Drake, 1978; Hudson, 1978; Singh and Woon, 1984; Oliver, 1984; Miskawi, 1989 and Khosrowshahi, 1991). All of these have been obtained by fitting selected functions (mostly polynomial regression) to the available data.

Several models for clients to use were developed using these value curves. Balkau (1975) derived the Bromilow and Henderson S-curve in an empirical formula to allow prediction of the cumulative cash flows. This formula was first used in a capital works programming model (Balkau, 1975) and in a life cycle costing model (Marshall and Tucker, 1974) and later updated (Bromilow and Davies, 1978).

Research into contractors' net cash flow forecasting took advantage of the available value curves. Thus, several models were developed on computers which required the input of value curves (Mackay, 1971; Khong, 1982; Allsop, 1980; etc.). Cash flow and other curves were derived from value curves and time lags. Commercial packages adopted the same approach, some of which had a library of typical S-curves to allow users to select an S-curve that closely represented their projects (cash flow, cash flow manager, etc.).

Accuracy of previous models

The accuracy of cash flow forecasts generated from standard value curves depends on whether the adopted S-curve accurately represents the project to be constructed. Bromilow and Henderson (1977) used four general building projects to develop their value S-curve. Hardy (1970) analysed 25 different types of projects and found that there was no close correlation between the values considered even when separating them into different categories.

Oliver (1984) analysed projects collected from three construction companies. He concluded that, although the number of projects analysed was statistically small, construction projects are individually unique and follow such diverse routes that value curves based on historical data are not capable of providing the accuracy required for individual project control. Drake (1978) collected projects from regional health authorities and further classified them into different cost categories. He fitted an S-curve into each of these categories. Unfortunately, no figures were published of the number of projects analysed or of the level of accuracy of the fitted functions.

Singh and Woon (1984) fitted envelopes of S-curves for high-rise commercial industrial and residential buildings. The envelopes contained half of the values considered in each category. Although they did not quote the number of projects analysed, the graphs plotted through the scatter points show that the sample was small and the values outside the envelopes were not relatively close.

The idiographic approach

The failure of the aforementioned authors to produce typical value curves indicates the shortcomings of nomothetic models – that is, models which aggregate groups of projects in order to develop a single standard curve. This points the way to the introduction of an idiographic approach. The basic principle of this methodology is that value curves are generally unique and should be modelled separately (i.e. a curve should be fitted for each project).

Berny and Howes (1982) modified a nomothetic approach to reflect the specific form of individual projects. By proposing an equation for the general case of an individual project curve, as distinct from the curve of the general (standard) function, they moved from a nomothetic to an idiographic approach.

Kenley and Wilson (1986) applied the idiographic methodology further and used the logit transformation to fit data. They analysed 72 commercial and industrial building projects in two groups of data. They also developed a value S-curve for each individual project and an average one for each of the two groups. The error obtained from the two average curves was much higher than that of the individual fits. This meant that the systematic error involved in the group regression was high and the individual curves took a unique shape.

They concluded by saying that it was their belief that group models are both functionally as well as conceptually in error.

It is important to acknowledge that idiographic models are only useful for analytical purposes. Forecasting requires the use of a standard curve developed out of a group of projects similar to the one to be executed (i.e. nomothetic models). The need for cash flow forecasting (and cost control) and the failure of previous work to prove the feasibility of standard value curves made it necessary to choose another variable that could be modelled more accurately and thus used to calculate the value curve. This is the major objective of this paper.

The process of developing the cost commitment model

In the absence of accurate standard value curves, the contractor should rely on another variable which can be used to derive the value curve and hence the cash flow forecast. The variable was chosen and modelled in the following steps:

(i) The reasons behind the variabilities of actual value curves were identified.
(ii) Another variable which is not affected by the above reasons was selected.
(iii) Different criteria amongst the data to be collected were proposed.
(iv) Actual cost commitment values for 150 construction projects were collected under the proposed criteria.
(v) A simple technique to fit the S-curve nomothetically and idiographically was chosen.
(vi) The fitting technique was used to model a series of S-curves within different groups.
(vii) The accuracy and feasibility of the model was tested.
(viii) The results were then compared with a previous value model (Kenley and Wilson, 1986).

The cause of variability in value curves

The causes of variability in value curves were identified on a logical basis and not a numerical one. Four factors were selected as contributing to the failure of previous research to develop standard value curves; the relative importance of each factor is unknown. The four factors are listed below:

(i) Construction projects are unique and the progress of work varies from one project to another.
(ii) In previous work, the choice of project groupings was poor.
(iii) Unbalancing (front-end loading) and over-measure distort the shape of the value curve. This can be shown by comparing the bills of quantities of several tenders for the same contract (Stark, 1974).
(iv) Errors in estimating affect the shape of the value curve, and lead contractors to submit different tenders for the same project.

Cost commitment curves

After identifying the possible causes of variability in value curves, it is interesting to note that, for the same project and the same schedule of work, two contractors are likely to produce two different value curves. This is due to estimating errors and unbalancing implemented by different contractors. These two factors have no effect on the actual commitment curve of a project. Also, cost commitment curves are not affected considerably by contractual arrangements (e.g. lump-sum contracts). Therefore, if actual cost commitment curves were found to vary significantly, it means that projects are unique and cannot be modelled into groups.

To the authors' knowledge, only two people have attempted to model cost commitment curves for construction projects (Berdicevsky, 1978 and Zoiner, 1974). Berdicevsky selected three university projects of different sizes to examine the feasibility of developing a general formula for public construction. Zoiner selected four typical housing projects of different sizes and rates of progress. They estimated the cost-flow of all these projects by preparing the detailed construction schedules, and compiling and itemizing the relevant construction costs. Prediction curves were obtained using polynomial regression. Peer (1982) derived a common cost function prediction curve from the estimated data of all the aforementioned housing and public projects. He concluded that the accuracy achieved in combining all projects was still within acceptable limits. The number of projects used and the errors caused by estimating and scheduling the activities of the contractors undermines the reliability of the models of Berdicevsky, Zoiner and Peer. The difficulty in obtaining actual data could be the only justification for the attempted estimate.

As outlined before, poor classification of projects could be one of the causes of the failure of previous models. It is important to note that there are two disadvantages when classifying projects in more detail:

(i) The user, before winning the contract, knows little of the detailed activities of the project. Moreover, if these curves are to be used in the corporate financial model (Kaka, 1990), the contractor needs to supply the number of projects he/she expects to win over a year, and, clearly he/she can only do this if the categories are broad (such as commercial buildings) and not too narrow (such as, say four-storey commercial buildings).

(ii) When further classifying the sample of projects to be analysed, the number of projects within these groups will be reduced to levels where the groups will not be statistically representative.

On these bases, four general criteria were proposed for the classification of the collected projects. The effect of these criteria on the shape of the S-curve was unknown and would be determined using statistical tests. It could always be argued that further classification of projects may yield more accurate models. However, this would have increased the complexity of the data collection process. Furthermore, it would have compromised a central objective of these models, the simplicity and speed of their use. The proposed criteria could easily be identified for any project using existing information systems. These criteria are as follows:

(i) Type of project – this is divided into the following ten sub-divisions:
  - (a) Private commercial buildings – new
  - (b) Private industrial buildings – new
  - (c) Private commercial buildings – refurbishment
  - (d) Private industrial buildings – refurbishment
  - (e) Public buildings – new
  - (f) Public buildings – refurbishment
  - (g) Housing – refurbishment
  - (h) Civil roads
  - (i) Civil other
  - (j) Small

(ii) Size of contracts. These were classified according to duration; there are three sub-divisions:
  - (a) From zero to six months (0–6)
  - (b) From seven to twelve months (7–12)
  - (c) From thirteen and above (13–36)

(iii) Company – each company is analysed separately.

(iv) Type of contract – there are three sub-divisions:
  - (a) Traditional contractor (trad)
  - (b) Design-and-build contractor (d&b)
  - (c) Management contractor (man)

The logit transformation

In order to model different groupings and individual actual cost curves, a simple and reliable method of S-curve fitting is needed. Investigations have shown that specific transformations of sigmoid (S) curves can produce linear functions. The parameters of the sigmoid function are provided by the parameters of the linear equation, which in turn are found through linear regression. The equation of the curve of best fit for data which approximates to one of the S-curve functions, can be found by linear regression of suitably transformed data and then substitution of the linear parameters into the S-curve function.

The selection of an appropriate S-curve function was examined by Ashton (1972), who outlined four of the best known S-curves and their transformations (the integrated normal curve, the logistic curve, the sine curve and the urbans' curve). Ashton found the above curves to be very similar in shape, with most variation found at the extremes. He concluded that the selection of an appropriate S-curve was more a matter of application than anything else.

Kenley and Wilson (1986) showed that value curves, cash in and cash out curves approximate the S-curves listed above and hence used the logit transformation successfully. The actual cost commitment model developed in this paper also adopted the logit model as it is the simplest of the transformation techniques and most easily allows the change to double transformation necessary in the model analysis.

The linear equation is found by a logit transformation of both the independent and dependent variables:

$$\mathrm{Logit} = \mathrm{Ln}\,\frac{Z}{1-Z}$$

where Z is the variable to be transformed and Logit is the transformation.

The logistic equation for cost commitment flows can be expressed as:

$$\mathrm{Ln}\,\frac{c}{1-c} = \alpha + \beta \cdot \mathrm{Ln}\{t/(1-t)\}$$

where (c) is the actual cost (dependent variable) in a particular time (t) (the independent variable). α and β are constants.

It can also be expressed as:

$$c = \frac{F}{1+F} \quad \text{where } F = e^{\alpha}\left(\frac{t}{1-t}\right)^{\beta}$$

The cost commitment model given above uses scales from 0.0 to 1.0 where the ratio (on the abscissa or ordinate) 1.0 is equivalent to 100%. As percentage scales are to be used with convention, the equations should be expressed as follows:

$$c = \frac{100 \times F}{1+F} \quad \text{where } F = e^{\alpha}\left(\frac{t}{100-t}\right)^{\beta} \qquad (1)$$

The practical application of the logit transformation model implies that construction project cost flow curves approximate the S-curve yielded by Equation 1. This being so, a transformation of the data should approximate to a line described by Equation 2 and with parameters α and β.

$$Y = \alpha + \beta X \tag{2}$$

where $Y = \mathrm{Ln}\,\frac{c}{100-c}$ and $X = \mathrm{Ln}\,\frac{t}{100-t}$

In order to transform data for a particular project, X and Y must be calculated for each value of t and c respectively. Deriving the constants α and β is thus a simple linear regression of the transformed data. For further details see Kenley and Wilson (1986).

The industrial data

The data required for the model were the monthly actual cost commitment for individual contracts. Several companies were approached for the provision of the data during industrial interviews. Five British companies showed a special interest in the work and were ready to provide the data.

Table 1 presents the types of companies providing the data, with the number of contracts provided by each. The term 'large' was used to describe companies which had a contracting annual turnover greater than £150 million, while 'medium' denotes turnover between £10 and £150 million.

The last column in Table 1 indicates the number of projects used in the analysis. Projects that were either too short (i.e. below 3 months) or those that were irregular, in that they were stopped for considerable length of time and restarted, were not used in the analysis. Those projects were considered irregular and thus, would influence the accuracy of the proposed models. The number of projects used to develop the models was sufficient and thus exclusions could be made without the need to resort to the normalization of uncharacteristic gaps. Company C provided the data from their computerized database. The data involved all contracts completed and current since 1987. The figures for the current contracts included an up-to-date actual cost-flow plus the monthly cost predictions for the months up to the expected completion date. Taking into account the reliability of the model in analysing actual cost values and the fact that many current contracts were due to be completed in one or two months, it was decided to reject contracts less than 80% completed. This was thought to have a negligible effect on the reliability of the model since the last 10% of the individual contracts are excluded anyway when fitting the S-curve.

Several contracts involved small payments of a month or two after the end of the cumulative cost-flow. These payments were caused by slight repairs or clearing may arise during the maintenance period which may require the attendance of the contractor. These payments were not included in the curve fitting analysis as they did not represent direct construction cost. The contracts were classified according to the criteria specified before. The number of contracts in each category provided by each company is shown in Tables 2 and 3. The provided cost figures included all direct cost and site overheads. The cost also included the design cost for design-and-build contracts.

All of the above projects were constructed between 1986 and 1989. The data were provided with the commencing dates, and were adjusted for inflation. The general cost indices were used to adjust the monthly cost.

The base figure of 100% was taken to be the practical completion on site; the equivalent figure for time was taken to be the time at which 100% cost was committed

Table 1 Types of companies providing the data

Company name	Size of type of company	No of projects Provided	Used
A	Construction division in a large construction company	60	57
B	Construction division in a large construction company	50	47
C	Medium building contracting company	38	20
D	Medium building contracting company	24	24
E	Medium road contractor	11	2
		Total	150

by the contractor. The origin was taken to be the commencement of work on site, a convenient and easily identified point.

Measuring the accuracy of fit

In order to draw comparisons between this and other models, it was necessary to measure the accuracy of the fit. The measure chosen, put forward as a risk index by Jepson (1969) and abbreviated to 'SDY' by Berney and Howes (1982), is the standard deviation about the estimate of Y. This measure was also used by Kenley and Wilson (1986) in their idiographic value model. SDY adopts the common measure of dispersion.

$$\mathrm{SDY} = \sqrt{\{\Sigma(\mathrm{Y}-\mathrm{YE})^2/\mathrm{N}\}}$$

Where: Y is the actual value at any accounting period
YE is the estimated (or fitted) value
N is the number of observation (accounting periods)

This measure permits models to be compared. The model with the lowest SDY value has the best fit and is therefore the most desirable.

Exclusion of data at the extremes

The nature of the logit transformation is such that as the data approaches either 0% or 100%, then the logit will approach − or + infinity respectively. One of the limitations of linear regression is that extreme values dominate the analysis, to the extent that α and β values can be unduly influenced by a small number of extreme values rather than by the bulk of the data. Within cash flow analysis, the extreme data points are arguably the least significant (due to the small amounts of monies involved) but they can be the most dominant in the regression analysis. A simple method for countering the problem is to exclude the data points outside an acceptable range from the analysis.

Kenley and Wilson (1986) performed a systematic trial-and-error process to locate the optimum exclusion range in their value curves. Results showed that approximately 10% exclusion of both ends would yield the lowest mean SDY value. It was decided to adopt the same exclusion range for the analysis of the cost commitment model.

Analysis and results

The procedure of building and testing the model involved first fitting an S-curve through each individual contract. Values of α and β were calculated and the SDY measure was used to determine the accuracy of the individual fits. These values are shown in the box plot (Fig. 1). The box plot is a non-parametric test (available on statgraf – see Hoaglin *et al.*, 1983; Velleman and Hoaglin, 1981) which can be used to compare visually two or more groups and identify possible out-liers. The

Table 2 Grouping the data into size and type of contract

	According to type of contract				According to size (months)		
Company	Traditional	Design and build	Demolition and build	Management	(0–6)	(7–12)	(13–36)
A	55	2	0	0	11	33	13
B	37	7	0	3	7	28	12
C	8	10	0	2	0	11	9
D	18	4	2	0	2	11	11
E	2	0	0	0	0	2	0

Table 3 Grouping the data into types of projects

	Private buildings				Public					
	Commercial		Industrial		Buildings		Housing	Civil		
Company small	new	refurb	new	refurb	new	refurb	refurb	roads	other	
A	15	15	5	3	0	0	11	0	4	4
B	19	7	9	4	3	1	1	1	2	0
C	11	3	5	0	0	1	0	0	0	0
D	12	1	5	1	1	3	1	0	0	0
E	0	0	0	0	0	0	0	2	0	0

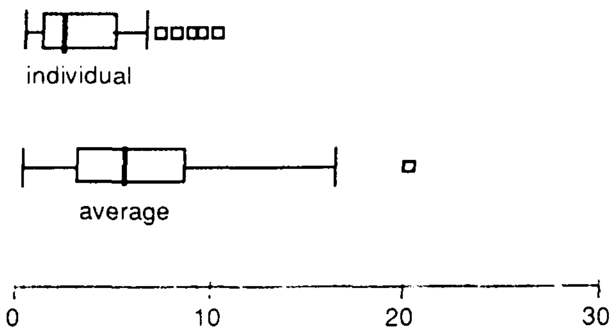

Figure 1 Boxplot of individual and average errors (SDY)

actual α, β and SDY values are listed with the actual cost commitment values in (Kaka, 1990).

The next step was to distribute the contracts amongst the proposed criteria and hence identify which of these affected the shape of the S-curve. A method was required to determine whether the shapes of individual curves in different groups belonged to the same group. Values of α and β were used to regenerate the individual contracts into 12 time intervals. Cost values were extracted from the individual fits in three stages: the first, second and third quarters, as shown in Fig. 2. Each

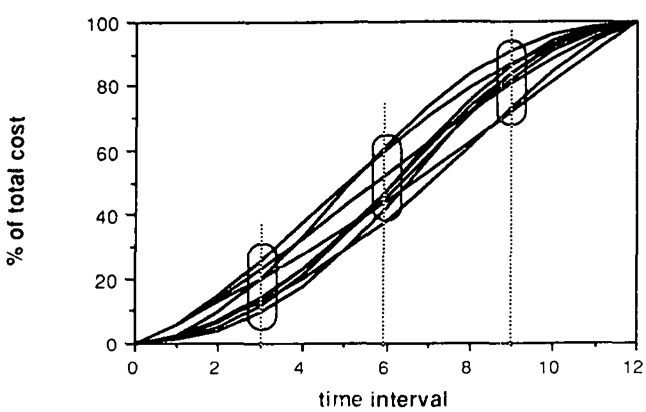

Figure 2 Extracting values from data sample

criterion was analysed separately and the individual projects were distributed into the relevant groups. Three sets of cost values were extracted for each group and were compared with those of the other groups.

The technique used in the comparisons was the One Way Analysis of Variance (One Way ANOVA). The ANOVA test is able to confirm whether one of the groups differs from the rest. The most important assumption in conducting the ANOVA is that the samples are randomly selected. Therefore, contractors were requested to select the projects randomly and then classify them.

In order to assimilate the variability of the S-curves within different groups, the effect of the other criteria had to be eliminated. This was achieved by eliminating groups either with small numbers of projects or with projects of a particular specification to establish the homogeneous distribution of other criteria. For example, when analysing whether different companies had different cost commitment curves, Company E was excluded from the test, due to the type of work it performed (road works only). If Company E was included in this test, any difference achieved within the groups cannot be attributed solely to different companies.

The test was conducted three times for each criterion and the whole process was repeated four times for the proposed criteria. The Open Access spread sheet was used to perform the tests, and the F ratios achieved are listed in Table 4. The value of F has to exceed the F limit in order to confirm that groups are different.

The ANOVA identified two criteria that affected the shape of the S-curves: the size of the project (duration) and the type of the contract. The next step of the analysis established new groups according to the type of contract and duration of projects. Seven groups were collected and an average curve was fitted into each. Values of α and β for the seven groups are listed in Table 5.

In order to determine the level of systematic error involved in modelling the average curves, SDY was measured for each average curve and the individual fits which belong to that group. The box plot (Fig. 1) shows that the systematic error varies widely from 0.2 to 15.8. However, the bulk of the data lies within the range of 3.2 to 8.4 with a median 5.5. The random error (SDY of each individual fit) is shown to be within the range 0.5 to 6.5. It can be concluded then that the systematic error is higher than the random error. This coincides with

Table 4 Results of the ANOVA tests

	F values (at 1st, 2nd, 3rd quarter)			F limits (confidence of interval)	
Test	1	2	3	5%	1%
A	1.11	0.14	0.94	2.76	4.13
B	42.39	40.34	17.51	3.13	4.92
C	18.22	22.74	16.32	3.17	5.01
D	1.17	1.14	0.89	2.48	3.56

Table 5 α and β values for the effective groups

Effective groups	α	β
(traditional) (0–6)	1.151	1.388
(traditional) (7–12)	0.213	1.223
(traditional) (13–36)	−0.243	1.303
(d&b) (7–12)	0.407	0.926
(d&b) (13–36)	−0.029	1.034
(Man) (7–12)	−0.948	1.696
(Man) (13–36)	−1.372	1.328

Kenley and Wilson's results which showed even higher values of SDYs for the average curves.

A visual test was implemented to evaluate the effect of the selected criteria on the shape of the S-curves. The average curves for the seven groups were plotted together on 12 time intervals (0 and 12 correspond to 0% and 100% respectively) and inspected for difference in profiles (Fig. 3). In addition, the variability of the individual fits for each group were examined by plotting randomly selected projects (Fig. 4). The shapes of these individual fits were compared with the corresponding average curves. The objective of the test was to evaluate the range of variability within each group and determine the degree of randomness of these shapes within the range.

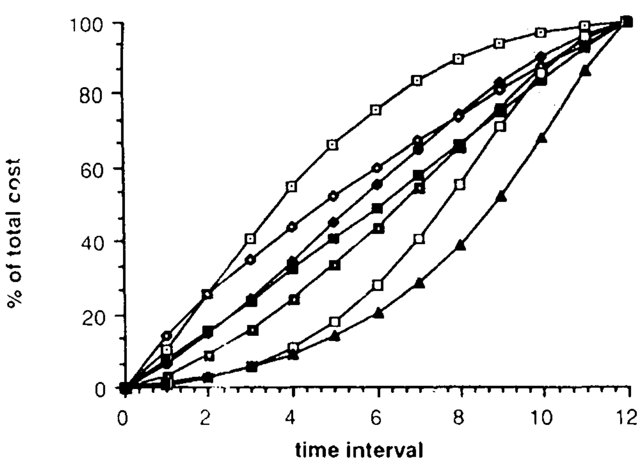

Figure 3 Average cost flow curves for the groups. □ = trad (0–6); ◆ = trad (7–12); ■ = trad (13–36); ◇ = d&b (7–12); ■ = d&b (13–36); □ = man (7–12); ▲ = man (13–36)

Figure 3 shows that the effect of project size (duration) on the shape of the S-curve is significant. The smaller the size of the project, the more convex is the shape of the curve. For projects with 13–36 months' duration, the shape is concave. The results were sent back to contractors who provided the data to obtain practical explanations. They suggested that the cost build-up at the start in smaller projects tends to be higher, as contractors are expected to complete the job in a short period, and work is often started with all resources on site.

The type of contract affected the S-profile considerably. Traditional contracts take the usual S-shape especially in medium to large contracts. Design-and-build contracts were shown to have a significant build-up at the start of the project, due to the cost of the design process and professional fees at the start of the project. Management contracts have a considerably slow start for few months, due to the planning involved in the selection of subcontractors which occurs at the start of the project. Moreover, the premium cost which is usually incurred by the traditional contractor at the start is often carried over to subcontractors in management contracts. After the initial phase, management contracts accelerate with significantly high growth. When the planning phase is over, and all activities have been distributed to subcontractors, the job has to progress rapidly, especially as most of these contracts tend to be located in busy areas with restricted spaces, and fast progress is essential. The aforementioned curves seem to occupy a wide range of area within the graph (Fig. 3) and include various shapes of curves. This is a strong support to the data sample and the process used to identify the effective criteria.

A similar test was carried out to compare empirically the variability of individual profiles within each group with the variability between the average curves themselves. Values of SDY were estimated between the average curves and compared with those between average and individual fits. Results (Table 6) showed that values of SDY between the average curves are significantly higher. This coincided with the visual test and supported the reliability of the analysis and models. Finally, values were extracted from Table 6 in order to distinguish between the extent of the influence of project duration versus contract type (Table 7). The average values for the SDYs incurred due to the difference in the type of contract is shown to be greater than that due to the duration. However, the difference, in addition to being small, is created by the fact that differences between durations of projects are gradual rather than immediately such as in the case of different types of contracts. Therefore, it can be concluded that both of the proposed criteria should be equally accounted for when selecting a standard S-curve.

Comparison of the cost commitment model with a previous value model

In order to support the hypothesis that standard cost commitment models are more accurate than value models, a comparison was needed to evaluate the

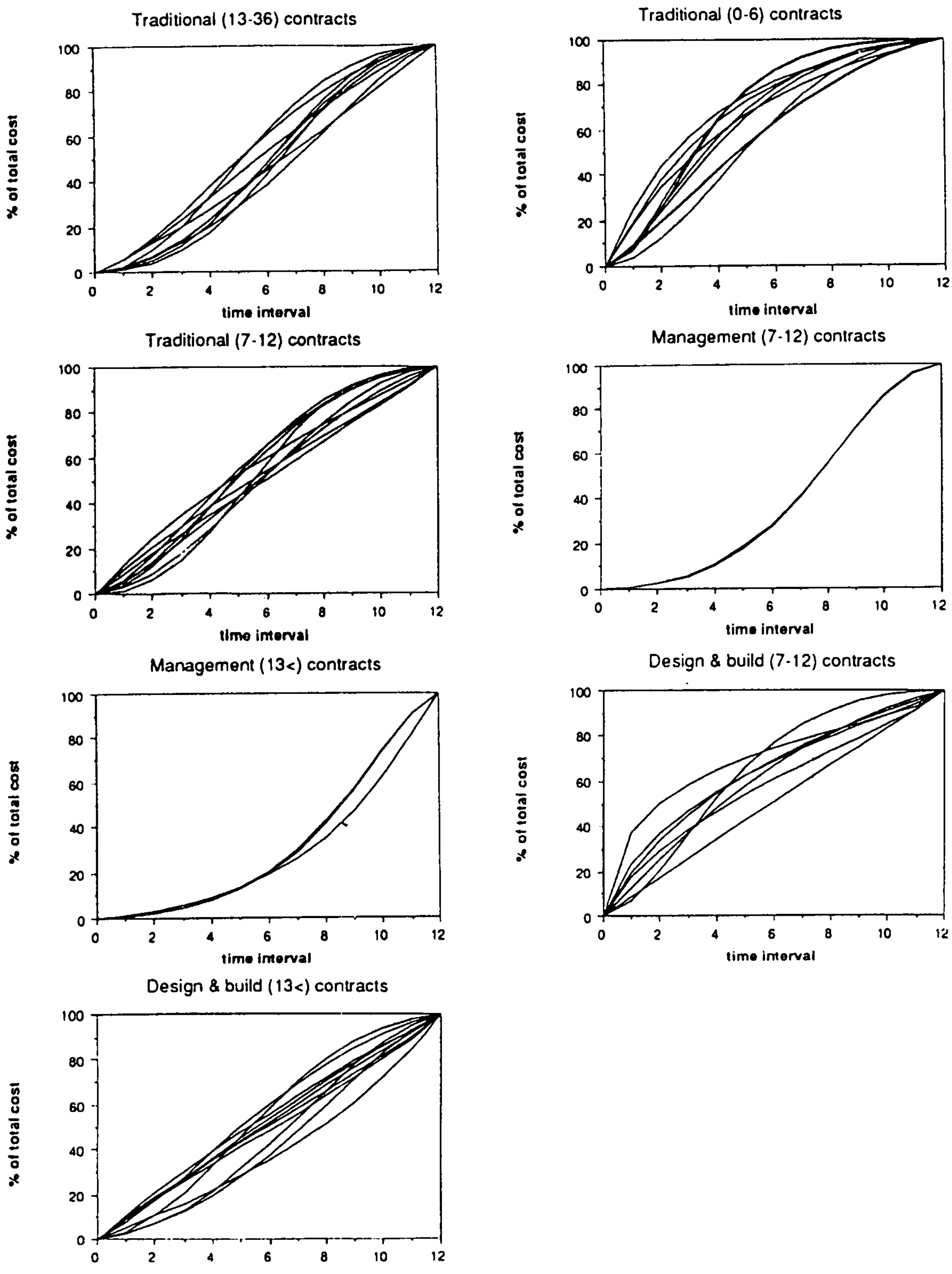

Figure 4 Graphs showing variations within separate groups

Table 6 SDY values measuring the difference between the standard average cost curves

	trad 0–6	trad 7–12	trad 13–36	d+b 7–12	d+b 13–36	man 7–12	man 13–36
trad 0–6	0						
trad 7–12	14.19						
trad 13–36	21.90	7.71					
d+b 7–12	10.79	6.33	12.96				
d+b 13–36	18.25	4.87	4.97	8.42			
man 7–12	31.65	17.50	9.86	22.44	14.22		
man 13–36	38.75	24.93	17.69	28.56	20.53	10.31	0

accuracy of both models. Limited difference in the accuracy would demonstrate that construction projects are unique, and thus contractors must conduct detailed estimates of the cost and schedule of work in order to forecast cash flow. While an improved accuracy would reveal that the two causes for the variability of value curves (outlined earlier) have significant influence, and thus contractors should alternatively use the proposed cost commitment models.

The idiographic value model developed by Kenley and Wilson (1986) was chosen for comparison, since it is the most comprehensive. The data used for their value curve analysis included two samples. The first sample involved 32 medium- to large-scale commercial and industrial projects provided by a construction company. The second sample comprised data for projects provided by a quantity-surveying firm. This sample included 40 projects and covered a wide range of contractors, using different contractual arrangements. The two samples contained projects constructed in Australia during the period between the late 1960s to the late 1970s. Kenley compared the two samples to determine whether the different sorts of categories in the second sample affected the accuracy of the fitted curves. The comparison was only conducted on the individual curves, and results showed that no difference can be identified between the two samples.

One of the major steps used to formulate the cost commitment model was the identification of the effective criteria in order to reduce the variability of the individual fits within a classified group. Thus, an evaluation of the variability between the individual value curves was required. Fortunately, the SDY measures for the average curve and the corresponding individual curves were available for the two samples. A comparative test was conducted on a sample containing one group of projects and another containing different sorts of groups. No difference between the SDY measures would emphasise that value curves are variable and unique even when classifying them into specific groups. A non-parametric test (the box plot test) was used for its ability to compare and identify different types of data. Results of the test are shown in Fig. 5. The median of sample 1 is significantly smaller than that of sample 2 (6.8 as opposed to 12.5). The bulk of the data is shown in the box range of the plot. Sample 1 varies from approximately 4.7 to 11.5. While sample 2 varies from approximately 8.5 to 15.5. Moreover, the first sample has a left bias distribution while the second has an almost uniform distribution. The above findings confirm that the two samples are different and the sample with one type of group (sample 1) has smaller variability of the project S-curves.

The above test confirmed that a better value model could be achieved by classifying the data into different groups. A further test was required to compare the performance of the cost commitment model with the value model. The same test was used to compare sample 1 of the value model with the SDY values of the average cost commitment model. Figure 5 shows the plots of the two groups of data. The median of the cost commitment group is smaller than that of the value model (approximately 5.5 to 6.8). The bulk of the data for the cost model lies within the approximate range of 3.1 to 8.2, while the range for the value model lies approximately within 4.8 to 11.5. These results confirm that the variability (also systematic error) achieved in the cost commitment model is smaller than that in the value model. This supports the methodology formed at the start of the work that the actual cost commitment flow can be modelled more accurately than the actual value flow.

Table 7 Distinguishing between the extent of the influence of project duration versus contract type

SDY values measuring the difference between the standard average cost curves		Average
Difference due to different durations	14.19, 21.90, 7.71, 8.42, 10.31	12.51
Difference due to different types of contracts	6.33, 17.50, 4.97, 17.69, 22.44, 20.53	14.91

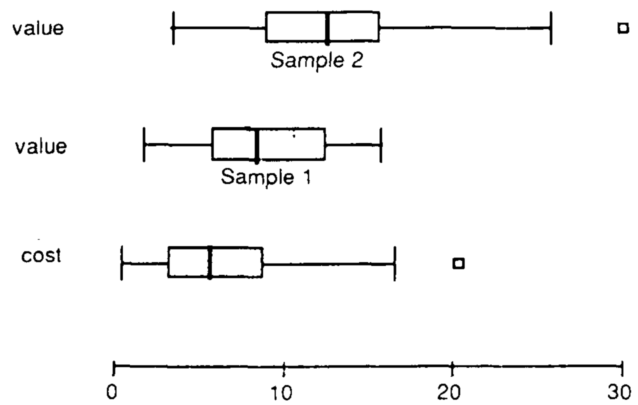

Figure 5 Box plot test, comparing SDY for two samples of value curves with the cost commitment model

It is important to realize that the tails associated in the box plot cannot be taken as a significant factor in the comparison of the two groups. The tails extend to the extreme datum point in the group which is within the outliers cut-off. The tail extends in the cost and value models to 15.5 and 14.5 respectively. The small number of data (32 compared to 150 projects) in the value model could be the reason behind the slightly shorter length of tail. With greater sample of data, higher extreme SDY values are expected. And since the out-lying cut off in the case of value models is greater, a longer tail is likely to be achieved.

Practical application of the models

Cost commitment models can be used for two important applications: project cost control, and cash flow forecasting. In order to control (and measure) the performance of any project, the contractor has to estimate the monthly cost of that particular project and then compare it with the actual ones. The traditional practice of conducting the estimate entails formulating the contract schedule (plan) and calculating the cost of executing each item in the contract. This is usually a tedious task and often subject to errors. Standard cost commitment models are developed using actual data from previous projects. The fact that they are easier to use and free from estimating errors, amke their use desirable. However, as shown in the analysis, they contain random and systematic errors as a result of the modelling. To the authors' knowledge, there has not been any work which involved measuring the corresponding SDY values for estimated and actual cost commitment curves of significant number of projects. Therefore, a conclusion cannot be put forward here on the feasibility of using these curves for cost control.

The use of standard cost commitment models for cash flow forecasting is much more appropriate, especially at the tendering stage. The contractor at this stage has very limited time to formulate a reliable schedule plan and hence most contractors do not forecast the cash flow for their individual projects, until they actually have won them. It is essential to realize that cash flow forecasting and planning at the tendering stage is very important for the contractor in order to estimate the cost of financing the project, the overdraft limit that he/she may apply for and the various strategic actions (markup, front-end loading, creditors' time delays, etc.) that may be taken to overcome possible difficulties.

Standard S-curves are commonly known to be one of the best and easiest alternatives for a comprehensive and detailed estimate. It was confirmed in this paper, that standard cost commitment models are more accurate to use than the traditional value models. Contractors with more than one contract in progress can be more confident when using these curves, as random errors are consolidated by the plus, minus combinations.

The first step in the cash flow forecasting process, is to select an appropriate standard cost commitment curve. The size and type of contract to be executed (or tendered for) are the main criteria for the selection. Values of α and β are used (Table 5), with the estimated cost and duration of the project, to derive the monthly cost commitment values. These values can then be used to calculate the monthly valuations (what the client owes) of the project. Delays in payments to clients, suppliers, labour and subcontractors are then used to obtain the cash-in and cash-out of the project. The net cash flow is the product of subtracting the cash-out from the cash-in values. Full description of such a model can be seen in (Kaka and Price, 1991).

Contractors may use the models developed in this paper or actually develop their own using the same technique outlined. The process which was used to develop these models is confirmed to be reliable as shown in the various verification tests.

Conclusions

A cost commitment model has been developed and successfuly tested. Four main causes that contributed to the variability and failure of previous value curves forecasting models were identified. Two of those could be eliminated by using the actual cost commitment model instead. The actual monthly cost commitment values of 150 construction projects from five construction companies were used in the analysis. Projects were classified according to four different strategic criteria. A method was developed to identify which of the criteria affected the S-shape. Two categories were identified and 148 projects were distributed within seven groups. Seven average curves were developed for the seven groups using the logit transformation of the groups data. The average curves were plotted together for comparison and were shown to cover a wide area and various profiles. Results were sent back to the five companies for practical interpretations. Comments confirmed that the modelled profiles were closely related to the characteristics of these contracts.

Ascertaining the degree of accuracy produced by the model was a major part of the work. The variability of the individual fits within a group were evaluated using the SDY measures to find the difference between the average and the individual fits. The bulk of the SDY measures ranged from 3.2 to 8.4 with a median of approximately 5.5. The difference between the groups was evaluated using the SDY measures between the average fits. The results confirmed that the difference between the groups is generally higher from the variability between individual projects within the groups. This was further supported by a visual test showing randomly selected individual fits within the separate groups. The profiles of the envelopes were closely related to the average curves.

Results of the cost commitment model were compared with a previous value model. Although the effect of the groupings on the variability of the value curves was shown to be significant, the variability in the value curves was determined to be within the wide range of 4.8 to 11.6, with a median of 6.8. This confirmed that better results were achieved in the cost commitment model.

In addition to evaluating the model with respect to accuracy, there was a need to test it in relation to the concept of the regression analysis. The idiographic argument of the high systematic error involved in the group regression was tested in the cost commitment model. The variability between individual fits within each group (systematic error) was compared with the random error involved when fitting the individual curves. Results confirmed that the random error is restricted in SDY values ranging from 1.8 to 3.75 with a median of 2.75. This was smaller than the systematic error which was still relatively high. However, the visual test – used to plot randomly selected individual fit within different groups – showed that these fits had various random profiles within relatively thin envelopes. This randomness reduced the actual systematic error to a value below the SDY measures. Moreover, the degree of the systematic error involved in the analysis is closely related to the application of the model. In the case of using the S-curve for projects' cost control, the systematic error measured by the SDY values could be of significance. In the case of higher systematic error, the difference between the average curve and the individual project can be hardly attributed to a uniform random error.

In cash flow forecasting, the systematic and random errors involved in the cost commitment forecast will be consolidated and reduced in the final single net cash flow curve (Kaka and Price, 1991). The errors will consolidate further when formulating the total company net cash flow. The contractor usually executes several projects at the same time (the number varies considerably according to the size of the firm). Thus, when combining many cost commitment curves together in a particular group, the average curve would be an excellent approximation of the sum. Therefore, as far as the corporate financial model (Kaka, 1990) is concerned, the cost commitment model developed produces reasonable results. The systematic error only occurs when the group of projects used to derive the average curve include further strategic sub-categories. However, this is unlikely to happen since the groupings were established according to the outlined technique which was evaluated for reliability.

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