Modeling Cost Escalation in Large Infrastructure Projects

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Abstract: Cost overruns in large infrastructure projects have been commonplace in the past decades. Budgeting for cost escalation is a major issue in the planning phase of these projects. In this paper, we first review various methods of forecasting escalation factor and study the changes in construction costs in the past 25 years by analyzing movements of a cost index. We then introduce a system for modeling the escalation uncertainty in large multiyear construction projects. The system uses a Monte Carlo simulation approach and considers variability of project component durations and the uncertainty of escalation factor during the project lifetime and calculates the distribution for the cost. System application is demonstrated using a numerical example. The system can be used by planners and cost estimators for budgeting the effect of cost escalation in large projects with multiyear schedules.

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Background

In the past several decades, large construction projects have been known for their cost overruns and late completion times (Pickrell 1990; Flyvbjerg et al. 2003). Many factors are responsible for these cost overruns such as underestimation of costs to make the projects more viable, addition of scope during later stages of project planning and even during construction, changed conditions, etc. One of the most important contributing factors to the magnitude of cost overrun in large transportation projects are project delays. Furthermore, the length of project development phase from planning to construction, seems to be a major factor in the extent of cost overrun (Flyvbjerg et al. 2004). The longer, larger projects tend to be more prone to cost overruns.

A new trend has emerged in managing large infrastructure projects in that the owners have started conducting formal probabilistic risk assessment for project budget and schedule. As an example, the Federal Transit Administration has required a risk assessment/mitigation study for any new transit project applying for federal funding. Another example is the cost estimate validation process (CEVP™) (Reilly et al. 2004) which is a risk analysis approach required by the Department of Transportation of the State of Washington. CEVP is basically a probabilistic risk analysis that utilizes Monte Carlo simulation to assess the likelihood of completing a project within a certain budget and schedule. Most of the risk assessments consider the cost and schedule risks separately. Even when the cost and schedule risks are considered in an integrated manner, the escalation factor is assumed to be a fixed value.

A more realistic way to assess cost escalation is to consider the uncertainty in the value of escalation factor. This uncertainty is a major contributor to the overall cost uncertainty and can be modeled using appropriate probabilistic models. In this paper, we first review various methods of forecasting escalation factors and then introduce a system for modeling the escalation uncertainty in large multiyear construction projects. The system uses a Monte Carlo simulation approach and considers variability of project component durations and the uncertainty of escalation factor during the project lifetime and calculates the distribution for the cost.

Cost escalation in construction, as used in the context of this paper, is the increase in the cost of any construction elements of the original contract or base cost of a project due to passage of time. Escalation is caused by many factors such as inflation, market conditions, risk allocation clauses in the contract, interest rate, and taxes (Hanna and Blair 1993). Escalation is a risk that can account for a substantial part of construction cost, especially in long term projects where the variability and uncertainty is greater. In multiproject programs, the effect of escalation can be the prime concern. Therefore there is a need to assess the risk of cost escalation in construction programs.

Methods of Forecasting Escalation Factor

Construction cost indices have been used to measure the cost trends in the construction industry (Wilmot and Cheng 2003). In the United States, there are several indices used for construction projects. The Engineering News Record (ENR)'s cost indices are one of the most important, oldest, and commonly used in the construction industry. ENR started in 1909 with the construction cost index, but it was not established until 1921 (Westney 1997; Grogan 2003). The base year was established as 1913. ENR reports two composite cost indices for representing the cost of construction material and services: construction cost index (CCI) and building cost index (BCI). The main difference between these two indices is that the CCI assumes a much larger portion of labor hours (200 h of common labor) compared to BCI. We are going to concentrate on BCI, because it seems that modern projects with

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their high level of mechanization and equipment use are more likely to correlate with BCI. The BCI is more suitable to model cost of structures while CCI can be used to model projects where the labor cost is a high proportion of the total cost of the project (Capano and Karshenas 2003).

The BCI is computed by combining 66.38 h of skilled labor of bricklayers, carpenters, and structural ironworkers rates, 25 cwt of standard structural steel shapes at the mill price prior to 1996 and the fabricated since 1996, 1.128 t of portland cement, and 1,088 board-ft of 2×4 lumber. The price of this combination was \$100 in 1913.

There are other construction indexes. These include (Westney 1997):

1. Building indexes. At least 15 major indexes are compiled in the United States covering from one to seventeen types of buildings in from 1 to over 200 different locations.
2. Means construction cost index. This index is designed to reflect the overall building industry escalation.

Forecasting methods used to produce numerical estimates of escalation, escalation factor, or cost escalation range from the relatively simple to complex and sophisticated techniques. It is important to note that forecasting techniques are used to forecast one of three periods: (1) short term (next 3 months); (2) medium term (4 months–2 years); and (3) long term (more than 2 years). Estimating the increase in price over the long term is almost impossible because of the many uncertainties beyond the control of all parties (Westney 1997). The same is true of long-term construction projects with multiyear schedules and start dates in the future. Despite this difficulty, the owners of large long-term projects need to come up with the estimated cost of these projects. The more prudent way to approach these problems is to calculate a range of possible costs rather than a single figure. Forecasting methods for escalation factors can be grouped into two major categories: (1) quantitative methods and (2) qualitative methods (Makridakis et al. 1998).

Quantitative Methods

Quantitative methods are used when sufficient quantitative information is available. Most of the forecasting techniques for escalation, escalation factor, and cost escalation are quantitative methods. According to Makridakis et al. (1998), quantitative methods work under three conditions:

1. Historical information is available;
2. This information can be quantified in the form of numerical data; and
3. There is an assumption of continuity.

The last condition implies that some of the past pattern will continue into the future. This is an underlying premise of all the quantitative and many qualitative forecasting methods. Quantitative methods can be divided into two major categories: statistical and causal methods. Statistical methods utilize time-series analysis and curve fitting methods to forecast the variable in the future (Hanna and Blair 1993). On the other hand, causal methods are developed assuming that the variable to be forecasted presents an explanatory or causal relationship with one or more independent variables (Hanna and Blair 1993; Makridakis et al. 1998). Statistical or time-series techniques require a substantial amount of historical data and basically work under an assumption of continuity. Therefore, they have the disadvantage of not being able to forecast a shift in trend (Hanna and Blair 1993).

Often, the forecasting system based on statistical methods functions as a black box. This means that they do not allow much understanding of the data because there is no explicit model. This system uses the pattern in the historical data to extrapolate that pattern into the future, but it makes no attempt to discover the factors affecting the behavior. Makridakis et al. (1998) suggest that there are two main reasons to utilize a system as a black box. First, the system may not be understood, and even if it were understood it might be extremely complex to assess the relationships that govern its behavior. Second, the main objective of the system is not to know how it occurs but to forecast what will occur.

Simple Average and Exponential Smoothing

Examples of statistical methods consist of simple average and exponential smoothing. The method of simple average is basically to take average of all observed data as the forecast. The simple average is suitable for data that fluctuate around a constant or have a slowly changing level and do not have a trend or seasonal effects. The fundamental principle of the exponential smoothing is that the values of the variable in the latest periods have more impact on the forecast and therefore should be given more weight (Kress 1985). This method implies that as historical data get older, their weight will decrease exponentially. Usually, it is a poor model for medium or long term forecast. Forecasts can be thrown into great error because of large random fluctuation in recent periods.

Box–Jenkins Approach

Other more complicated statistical forecasting methods are sometimes used also, but rarely in construction. For example, methods based on auto regressive integrated moving average (ARIMA) models are available, however their use has been limited (Kress 1985). The time series analysis, forecasting, and control with the ARIMA model has come to be known as Box–Jenkins methodology. Despite Box–Jenkins promising results and power, forecasters and decision makers seldom use this method because it is complicated. It is best suited to short-term forecast, such as: daily, weekly, or monthly and it requires a large amount of data.

Causal Methods

Unlike statistical methods, the basic principle of causal methods is that changes in the value of a particular variable are closely related with the changes in some other variables. Consequently, if sufficient accurate information is available on the future of the other variable(s), it can be used to predict the future value of the variable to be forecast (Kress 1985). Sullivan and Claycombe (1977) have pointed out that causal models are frequently used in econometrics and have been found to give excellent results for forecast periods ranging from 3 months to 2 years. In causal methods, the variable whose values determine the outcome of the system is called explanatory variable. Explanatory variables are also called independent variables and regressors.

Regression

Regression methods are any modeling of a forecast variable Y as a function of a set of explanatory variables X_1–X_k. The regression method's accuracy depends upon a consistent relationship with the independent variable(s). In regression methods, an accurate estimate of the independent variable(s) is crucial. Multiple regression methods very often require a large amount of data.

Neural Networks

Neural networks are part of the causal or explanatory methods. Neural networks are fundamentally based on simple mathematical models of the way the human brain is believed to work (Makridakis et al. 1998). They are distinguished for providing a nonlinear forecasting method when they are applied to time series. The use of neural networks for modeling cost escalation in construction has been limited. Hanna and Chao (1994) presented a neural network model as an alternative approach to forecast cost escalation in construction. Williams (1994) developed two neural models to forecast the change in ENR construction cost index. The first model was developed to forecast the change of the construction cost index 1 month in the future. The second model was developed to forecast the change of the construction cost index 6 months in the future. The models employed several variables as inputs in an attempt to capture the major factors that causes variation in construction prices. The initial analysis of the data collected suggested that the most important determinant of the construction cost index was its recent performance. Williams (1994) concluded that the neural networks models produced poor predictions of the changes in the construction cost index. One of the most important difficulties of neural network models was the selection of the right inputs.

Qualitative Methods

Qualitative forecasting methods, in contrast with quantitative methods, do not require data in the same way. The inputs required depend on the specific method and are in essence the product of judgment and accumulated knowledge (Blair et al. 1993; Hanna and Blair 1993; and Makridakis et al. 1998). They can be used separately but are more often used in conjunction with quantitative methods.

Qualitative methods are also called subjective methods (Blair et al. 1993) and judgmental methods (Kress 1985). Blair et al. (1993) recommend the use of qualitative methods in long term forecast (forecast of duration over 2 years) because statistical methods, in general, are not suitable for it; as mentioned earlier, statistical methods cannot predict a shift in the trend. Although forecaster's intuition may frequently prove to be more reliable than any mathematical method (Chatfield 1975), it would be difficult to calculate a confidence level for the forecast. Subjective and intuitive estimates are widely used in construction estimating, especially when there is insufficient historical data.

Surveys

Surveys of expectation is one method of forecasting escalation. Surveys have proved to be less expensive, very accessible, and perform as well as many economic models. Several surveys of expected escalation are available today. Two of the most easily accessible and longest-standing surveys are the Livingston survey of professional economists and the Michigan survey of households. These are not aimed at construction costs but the methodology can be tailored for construction industry. One can conduct a survey of expectation of construction professionals to forecast escalation in this industry. Because the survey information is virtually costless, a cost–benefit analysis suggests that many firms might agree to use surveys to assess the future cost of escalation (Thomas and Grant 2000).

Use of BCI in Escalation Estimating

In most long-term projects, the owner accounts for escalation by incorporating its perceived effect in the project budget. In high inflationary times, one solution to mitigate the reflect of cost escalation is the use of escalation clauses in the contract. Escalation clauses are needed to prevent severe financial overrun by the contractor and to reduce the amount of contingency in the contractor's bid.

A common method of considering the effect of escalation is to assume a deterministic escalation factor (such as 3%/year) and apply that to the base cost of the project at the midyear of construction. As an example, if a project is scheduled to start in 2006 and end in 2008, its midyear of construction is calculated as 2007. So if the estimate is prepared in 2005, the escalated budget will be the cost in 2005 escalated to the cost in 2007, i.e., the base cost will be multiplied by $1.03^2 = 1.0609$.

We propose to use the ENR's BCI as a measure of construction cost escalation. This is already a commonly used index and the industry is familiar with it. Further, the index has been reported in a consistent manner for the past 80 years and is reported for 20 major United States cities so that the effect of project location can be considered. The drawbacks in using the index is that it is not affected by crew productivity and does not explicitly consider the cost of equipment or management. Furthermore, if the project cost cannot be reasonably represented with the cost of cement, steel, and lumber, then the BCI may not be the best indicator of price variations. Despite these shortcomings, this index remains one of the best known and the most used indices in the industry today. Fig. 1 shows variations of BCI in the past 25 years.

Modeling of Escalation Factor

The escalation factor is the rate of change of the BCI from year to year and can be calculated from the following equation:

$$\Delta_i = [(I_i/I_{i-1}) - 1] \times 100\% \tag{1}$$

where Δ_i=percent of change of period i; I_i=index of period i; and I_{i-1}=index of the previous period $(i-1)$. A positive value of Δ_i is an indication of increase in cost. In contrast, if the value of Δ_i is negative, that is because period i has experienced a deflation. Δ_i is then the escalation factor that we are trying to model. The average value of Δ for the period 1980–2004 is computed as 3.13%/year using the following equation:

$$r = \left[\left(\frac{I_e}{I_b} \right)^{1/n} - 1 \right] \times 100\% \tag{2}$$

where r=average rate of change; I_e and I_b=index values in the ending period; and the beginning period, respectively; and n=number of periods between e and b.

Historical Trend in BCI Values

According to ENR's BCI, from December 1980 to December 2004, the cost of construction has increased 115.98% in the United States (Fig. 1). In Fig. 1, we notice that early in the 1980s was a period of high inflation for the construction industry in the United States. During 1979–1983, the cumulative percent of change for the United States was 26.03% with an average of 5.96%/year. Then there was a relatively long period of low inflation in the United States. The cumulative percent of change for BCI during 1983–2001 was 48.67% with an average rate of 2.23%/year. In the period 2001–2004, the cumulative percent of change for the United States was 15.26% with an average of 4.85%/year. For the United States, the BCI, on average, has increased by 3.13%/year with a standard deviation of 2.42%.

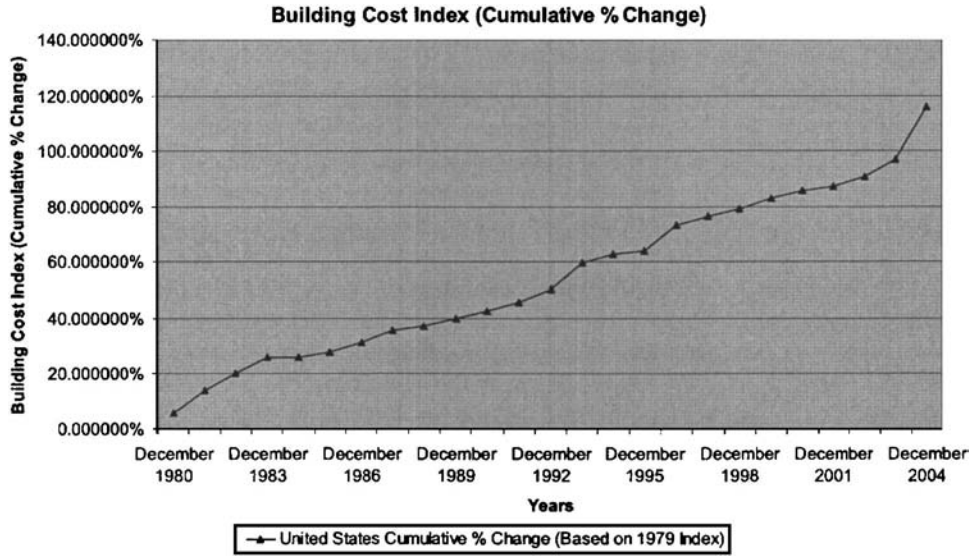

Fig. 1. BCI variations during 1980–2004

Modeling Uncertainty in Value of Escalation Factor

In order to model the uncertainty in the value of the index, we propose to use a normal distribution to represent the escalation factor. Modeling the escalation factor as a random variable will allow the realization of the range of escalation costs that can affect the project; however it seems logical that while values of escalation factors may change randomly, they do not do so independently. It seems that the value of the escalation factor in a year would be somehow related to the value of the factor in the immediately preceding year(s). In order to examine this hypothesis, we have plotted the value of the index for each period against the value of the index for the immediately preceding period. Fig. 2 shows that there is a strong correlation between these pairs (correlation coefficient=0.9828).

Use of Normal Distribution in Modeling Escalation

Based on the above, the following is proposed for modeling the escalation factor. First, we define the mean (μ) and the standard deviation (σ) of the normal distribution for the escalation rate. The normal distribution was shown to effect escalation cost variability in a realistic manner (Touran et al. 1994). Parameters of the distribution can be estimated by analyzing escalation rates for the past few years reported by various sources, such as: Engineering News Record and R. S. Means, although in this paper we have used the rate of change of the BCI. For example, we have calculated monthly changes in the value of BCI using Eq. (1) for the period January 2000–December 2004 (60 data points). A chi-square test of goodness of fit showed that normal distribution with mean 0.28% and standard deviation 0.51% (monthly) is an ac-

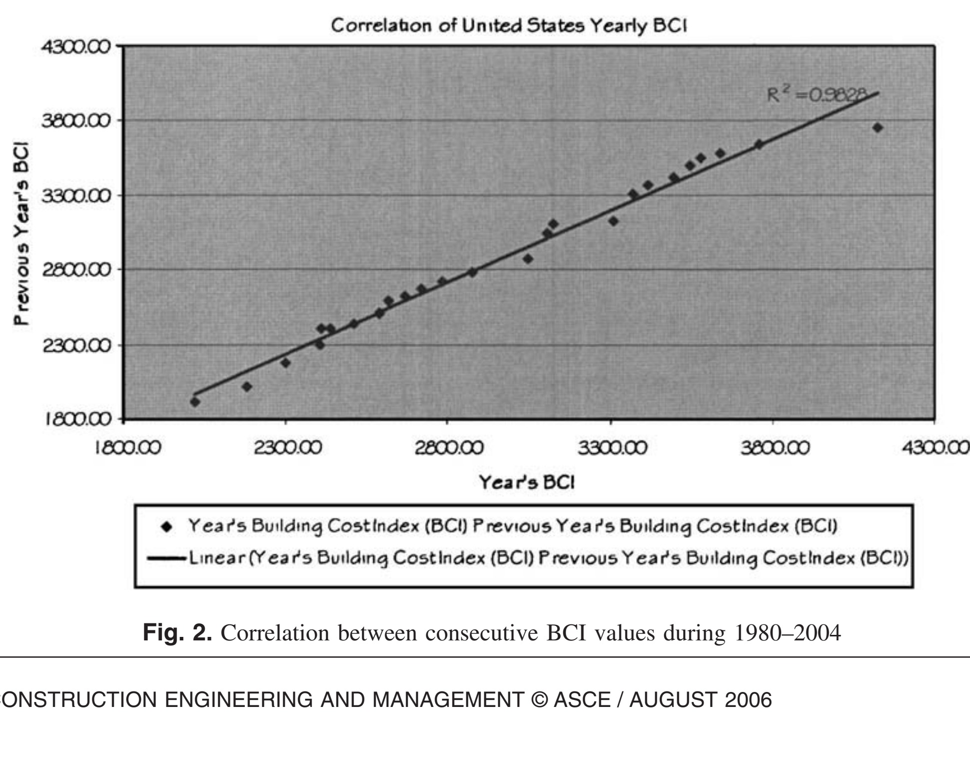

Fig. 2. Correlation between consecutive BCI values during 1980–2004

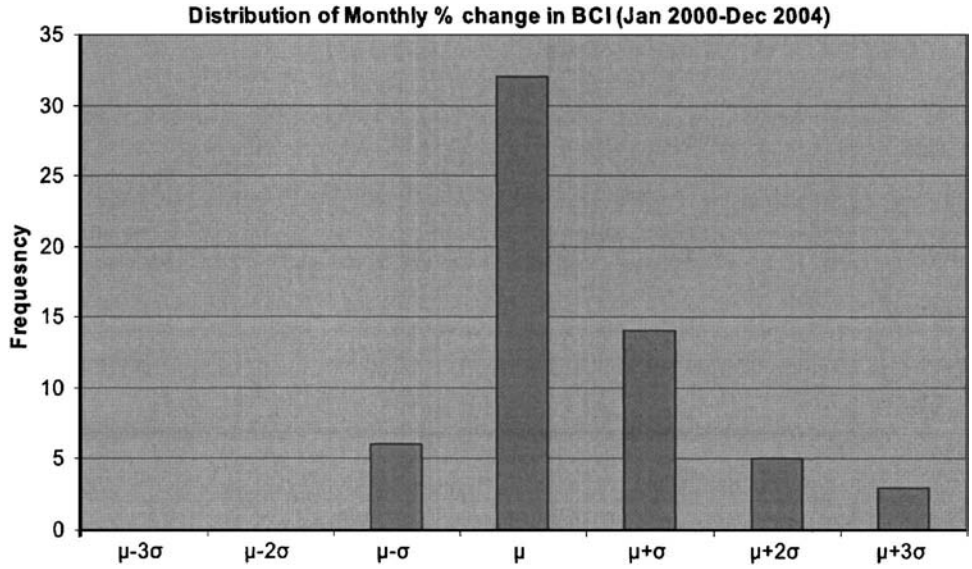

Fig. 3. Distribution of monthly changes in BCI for period (January 2000–December 2004)

ceptable fit for the data (p value larger than 5%) (Fig. 3). For every iteration of the simulation, a random value for inflation is generated for the first period. In the subsequent periods, the generated values for the previous period will serve as the mean of the normal distribution used to model the inflation rate assuming the same standard deviation. This is done to give a higher weight to the value of escalation in the period immediately before the period of interest (Touran et al. 1994; Clark 2001). The proposed approach is more or less similar to the method of *simple average* described earlier but does incorporate the random variability of the escalation factor. Estimation of μ and σ for the normal distribution may be based on any number of years. As an example, if the project is going to start in 2005, it may make sense to use the data from the most recent trend (since 2001) in calculating distribution parameters. On the other hand, if the project has a duration of several years (such as some multistage transit projects), then it may be prudent to use a longer time series for the basis of parameter estimation.

Computer System for Risk Assessment

The computer system developed is based on the approach described above for modeling the escalation factor. The computer model developed consists of two modules or phases: (1) precedence relationships and (2) escalation cost modeling. In the first module, the duration of each project and their precedence relationships are defined. As a result of this phase, we will be able to obtain the start and finish period for each project and the total duration of the construction program.

In the second module, the escalation rate of the construction program and the base cost of each project are defined. As a result we will be able to obtain the escalated cost of each project and the construction program in general. For a simple and more flexible approach these two modules were implemented on Microsoft Excel. For simulation modeling we utilize @Risk (Palisade Corp. 2004).

Module 1—Precedence Relationships

The developed system can be used for risk assessment of large multiyear construction programs, otherwise the effect of escalation may not be significant. The candidates specifically were large transit programs consisting of several projects. In the precedence module the main objective is to obtain the variability of start and finish periods for each project. This can be caused by the variation in the completion of the preceding projects or by variation in each project's duration (Shi et al. 2001) In this phase the spreadsheet computes the program duration and the critical path of the construction program and the start and finish period of each project.

The duration of a project is subject to uncertainty. In order to incorporate the variability of the project duration to the model, we have modeled the duration of each project as a random variable from a normal distribution. This is consistent with the PERT approach where total project duration (which consists of the sum of activity durations along critical path) is normal according to the central limit theorem (CLT) (see Walpole et al. 2002). First, we define for each project i the mean (μ), and the standard deviation (σ) of the normal distribution. Then, we compute the duration of the project as a random variable. Fig. 4 shows a template created in Excel that allows the user to input project data and then calculate the Program duration.

In large construction programs most of the projects normally have a precedence relationship with other projects. In order to incorporate the precedence relationship in the model, first the user must define the precedence relationships among projects. These relationships can take the form of finish-to-start, start-to-start, finish-to-finish, and start-to-finish. Each precedence path will be calculated according to their relationship type. Based on this input the start and finish period (the month in which the start and finish for each project is scheduled) for each project is computed. These start and finish times are random in nature, although the user has the option to assume deterministic durations for each project and calculate fixed values for start and finish of each project. Alternatively, start and finish of each project can be directly entered using the information available from the construction program master schedule.

CAPITAL PROJECT NAME: *Numerical Example*

Period: Month

ID	Projects	Project Duration: Mean (Month)	Standard Deviation (Month)	Random Variable (Month)	Total Duration (Month)	Predecessor: Predecessor ID	Relationship Type	Lag	Path Duration (Month)	Start Period (Month)	End Period (Month)
1	Project 1	14	1.4	14	14				0	0	14
									0		
									0		
									0		
									0		
2	Project 2	12	1.2	12	12				0	0	12
									0		
									0		
									0		
									0		
3	Project 3	25	2.5	25	25	1	FS	0	14	14	39
									0		
									0		
									0		
									0		
4	Project 4	16	1.6	16	16	1	FF	4	2	2	18
									0		
									0		
									0		
									0		
5	Project 5	20	2	20	20	1	FS	0	14	14	34
						2	FS	0	12		
									0		
									0		
									0		

Fig. 4. Input form for precedence links

Module 2–Escalation Cost Modeling

In the escalation cost modeling module the main objective is to model the uncertainty of escalation for each project and ultimately for the whole construction Program. This phase is defined in three steps: (1) define the base cost or current budget of each project; (2) define the parameters of the escalation rate; and (3) simulate the escalated project cost. Fig. 5 shows the input screen for this module.

Step 1: Define Base Cost of Each Project

At this stage the user has to input the base cost for each project. The base cost is the cost estimate for each project expressed in current period dollars.

Step 2: Define Escalation Rate

The user has to select the mean (μ) and standard deviation (σ) of the escalation rate. The process of generating random numbers to represent escalation rates in consecutive periods (months or years) was described earlier in this paper. For the first period, an escalation rate e_1 is generated by sampling a normal distribution with parameters μ and σ, i.e., $N(\mu,\sigma)$. For each subsequent period a random number is generated using $N(x,\sigma)$ to represent e_2, e_3, etc. It should be noted that the model is not limited to using normal distributions. If the user believes that another distribution would yield more reasonable results, he can easily change the distribution type, because @Risk supports a whole range of statistical distributions. Alternatively, the user can run

CAPITAL PROJECT NAME: *Numerical Example*

Monthly Inflation Rate	
Mean	0.002870899
Standard Deviation	0.00175

Month	1	2	3	4	5	6	7	8	9	10	11	12
Inflation Rate	0.0000	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029

No.	Project	Base Cost (Current Budget)	Project Start Period (Month)	Project Duration (Month)	Escalation Factor: 1	2	3	4	5	6	7	8	9	10	11	12
1	Project 1	$25,000,000.00	0	14	1.0000	1.0029	1.0058	1.0086	1.0115	1.0144	1.0173	1.0203	1.0232	1.0261	1.0291	1.0320
2	Project 2	$21,000,000.00	0	12	1.0000	1.0029	1.0058	1.0086	1.0115	1.0144	1.0173	1.0203	1.0232	1.0261	1.0291	1.0320
3	Project 3	$156,000,000.00	14	25	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	Project 4	$34,000,000.00	2	16	0.0000	0.0000	1.0058	1.0086	1.0115	1.0144	1.0173	1.0203	1.0232	1.0261	1.0291	1.0320
5	Project 5	$116,000,000.00	14	20	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
6	Project 6		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
7	Project 7		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
8	Project 8		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
9	Project 9		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	Project 10		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
11	Project 11		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
12	Project 12		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
13	Project 13		0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Fig. 5. Input form for escalation cost modeling

the model with various reasonable distributions and then compare the cumulative distribution functions (CDFs) (possibly picking the worst case depending on the situation).

Step 3: Simulate Escalated Cost

Using the values of e_i, escalation rate for the midpoint of each period is calculated by taking an average of escalation rates at the beginning and end of each period, i.e., $e_{\mathrm{im}}=(e_i+e_{i+1})/2$ (Touran and Lopez 2005). The escalation factor E_n for any period n in the future is

$$E_n = (1 + e_{m1}) \times (1 + e_{m2}) \times (1 + e_{m3}) \times \cdots \times (1 + e_{mn}) \quad (3)$$

For any project j with duration D_j, a start period s, and a finish period f, an average escalation factor is calculated as

$$E_j = (E_{s+1} + E_{s+2} + E_{s+3} + \cdots + E_f)/D_j \quad (4)$$

It should be noted that if the cost histogram of each project is available (such as the distribution of costs available from *schedule of values*), then the user can calculate escalation by applying escalation factor for each period by the estimated cost for that period. In such case, no averaging of the escalation factor would be necessary. With the average escalation factor E_j and the base cost BC_j of project j, one can compute the escalated project cost EC_j

$$\mathrm{EC}_j = E_j \times \mathrm{BC}_j \quad (5)$$

From here the total program cost can be calculated by summing up individual escalated project costs. The developed system uses @Risk software to run the simulation. All the steps described in the two phases explained above will be repeated for a number of iterations or realizations. The number of iterations depends on the confidence intervals desired for the results. Each iteration produces a single value for total escalated Program cost. These values can then be organized into a histogram of total escalated Program cost. Using this histogram, a probability density function (PDF) and a cumulative distribution function (CDF) for total escalated Program cost is compiled. These distributions can then be used to assess the effect of escalation on the construction Program.

Numerical Example

The numerical example presented is a hypothetical construction Program that consists of five projects. Durations and interproject relationships are given in Fig. 4. Because every project duration is modeled as a normal random variable, each project duration is identified with a mean and standard deviation. If the durations are fixed, then standard deviations are entered as zero. The mean duration of the total Program is calculated as 39 months. Base cost of each project in current dollars is given in Fig. 5. The Program's total cost in current dollars is estimated as $352 million. The period used for analysis is month. For the inflation rate we utilize a mean (μ) of 0.287%/month (3.50%/year) a standard deviation (σ) of 0.175%. In Fig. 5, each row belongs to a project and the escalation factors for the periods when a project is active is calculated. For other periods, the escalation factor is defaulted to zero. We simulate the scenario for 5000 iterations. Alternatively, we could have analyzed the monthly escalation rates for the period 2001–2005 (this is the period of the latest trend where there has been increased levels of escalation) from ENR building cost index data and calculated the mean and standard deviation directly from data.

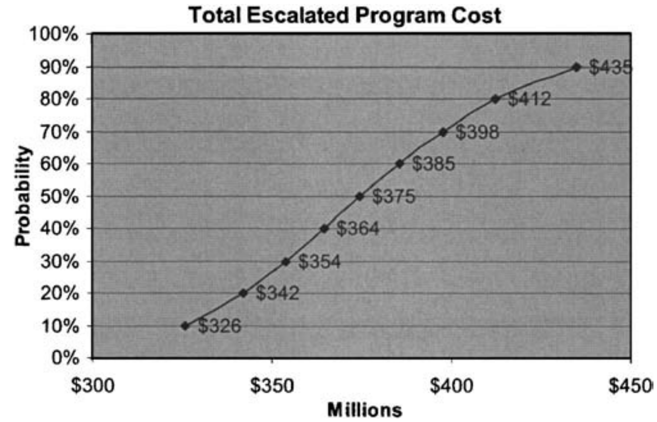

Fig. 6. Cumulative distribution function of total escalated program cost

The results of the simulation are presented in Fig. 6. The expected value of the escalated budget is simulated as $378 million, 7.4% above the unescalated budget of $352 million. The budget allocated to the project would depend on the level of confidence that the owner would like to have against the effects of escalation. For example, if the owner uses 80% as a desired confidence level, the escalated cost will be $412 million (Fig. 6). Such a budget ($60 million above the base cost in current dollars) allows a contingency of 17.05% above the total base cost of the Program. This means that there is an 80% chance that the escalated cost of the Program will be lower than $412 million. It should be noted that this contingency is required to cope with escalation. For other risk factors (technical, environmental, and other) separate contingency should be considered.

The model shows the possibility that the project cost may be lower than the original current dollar estimate. This is due to the fact that month-to-month variations in price index can be negative. Indeed, in the past 60 months (January 2000–December 2004), during 20 months, the BCI for average United States prices have been negative (although we are witnessing inflationary pressures in 2004–2005). A more conservative approach would be to use a truncated distribution for the value of inflation that discards all negative values during simulation. That approach might be justifiable if the time unit is larger than 1 month, for example for quarterly or half-yearly analysis. During these longer periods, the BCI has consistently shown upward trend (Fig. 1). The conclusion is that the system is sufficiently flexible for the user to change assumptions in a reasonable way based on available information and objectives of the exercise.

Conclusion

In this paper the importance of cost escalation in large long-term construction projects is examined. Various methods of forecasting escalation rate are reviewed and an approach is proposed that explicitly considers the random variations in the escalation rate. A computer model has been designed to incorporate the effect of cost escalation on large construction programs consisting of several projects spanning over a period of several years. This computer model takes into consideration the uncertainty and variability of both schedule (delays) and escalation factor in an integrated probabilistic approach. The modeling of cost escalation factor is done by considering its variability and its correlation with subsequent periods. The proposed model provides a powerful tool to assess the impact of this factor.

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