Risk Simulation Techniques To Aid Project Cost & Time Planning & Management

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Overview

It is essential to address uncertainties associated with individual activity durations and costs at the planning stage of projects in order to establish realistic project budgets and forecasts. If uncertainties are not considered at the planning stage then difficulties (i.e. cost and time overruns) may arise later during the project implementation stage. The repeated trial approach of Monte Carlo simulation, integrated with network logic and critical path analysis, offers an effective and established method for integrating risk assessment into project schedule and cost analysis. Individual activity durations and costs are best input to simulations as probability distributions, or possible ranges that reflect incomplete knowledge, uncertainty or the level of ignorance, rather than as deterministic single-point estimates.

The cost-time simulation techniques proposed here are novel in the way the simulation output, and the intermediate calculations leading to that output, are analysed and presented statistically. Analysis focuses on the downside risk of time and cost overruns and their interactions. Semi-standard deviations of calculated project cost and time probability distributions relative to target values quantify specific downside risks associated with such targets. The proposed techniques can be effectively applied and tailored to small and medium-sized projects using spreadsheets backed by Visual Basic macros without recourse to proprietary project software.

Background to Project Risk Simulation

Probabilistic risk modelling and simulation techniques integrated with deterministic sensitivity analysis are useful and established project planning and management tools[1]. Indeed simulation continues to push back the boundaries of science and business management in many areas[2]. The Monte Carlo simulation method (see note 2 for a basic description and definition) has its roots in the recognition by Daniel Bernouilli more than 250 years ago that repeated trials (Bernouilli Trials) provide a statistical basis with which to quantify events with uncertain outcomes. The theory had to wait for computer technology to advance before the technique was first applied in the mid-twentieth century to aid investment decisions under uncertainty [3]. Its power was then rapidly applied to many diverse fields that required outcomes to be quantified statistically under conditions of uncertainty to aid decision-making[4]. There are many applications for it in the oil & gas industry, where dealing with high cost projects with large and diverse uncertainties is a daily eventuality[5].

The early applications of simulation techniques to project planning and networks highlighted the discrepancies between decisions based upon probabilistic and deterministic analysis[6]. Complications that frequently arise in applying simulation models to analyse complex project networks are:

- the correlations and dependencies between time and cost and the sensitivity of those correlations to work delays, which are often influenced by contractual terms[7]
- High levels of uncertainty, incomplete knowledge and a lack of precedence with which to benchmark the costs and durations of certain activities[8,].
- Inherent uncertainties associated with non-monetary risks (e.g. social, environmental, political and legal impacts), which are fuzzy and not random [9].

It is important to keep in mind that, as with deterministic methods, the probabilistic techniques depend upon well-researched estimates for ranges of component activity costs, times and resource requirements as their basic input data. Failure to use validated input data to define input distributions or over reliance on "*guesstimates*" will lead to unreliable results. "The garbage" appearing to be "well turned out" in the form of computer graphics can exacerbate the classic problem of "garbage in - garbage out". In order to overcome the problems associated with high uncertainty and / or ignorance of risks associated with some component activities models are being developed that extend the probabilistic approach by applying, for example, game theory[10], possibility theory and fuzzy numbers[11], and stochastic budget simulation[12].

Despite risk management being designated as one of the eight core areas of the ***Project Management Body of Knowledge*** (PMBOK)[13], and simulation tools scoring highly in industry surveys as the most suitable tool for project risk management[14] literature reviews and other surveys[15] have found that these tools tend not to be used to their full potential by project managers. The surveys suggest that the application of simulation tools is impeded by low knowledge, skill base, and lack of commitment to training and professional development in many organisations. Nevertheless, successful applications of simulation techniques to real world projects continue to be published[16] , which, together with the emerging ability to build such models rapidly on standard office software packages, suggest that they will become more widely applied in the near future.

Few doubt now that risk simulation techniques are useful, but software availability and transparency may be the drivers that encourage practicing project managers rather than academics to use the techniques more widely. Advances in personal computer processing capacities and versatile, user-friendly spreadsheet software now make it possible for sophisticated simulation models to be built and applied efficiently to a wide range of projects. For a medium sized project (e.g. 20 activities performed in five parallel sequences with complex dependencies) a model simulating costs and time, analysing risks and critical paths can be constructed, run and evaluated, with a little practice in a single working day. The models, results and graphics presented in this article are all built in spreadsheet workbooks (Microsoft Excel) with simulation and analysis manipulated by Visual Basic (VBA) macros.

Project Risk Simulation Models

Risk simulation models are usually built to forecast uncertain outcomes and then to select the most attractive or most-likely range of feasible outcome scenarios from those calculated to inform the decision-making. Forecasting is notoriously difficult and has been compared to driving a car blindfold while taking directions from someone looking out of the rear window[17]. Risk simulation models aid the process by deriving time and cost forecasts from simulation trials that provide insight to project risks by quantifying on a statistically probable basis the chances of the project being completed within budget targets.

In the models presented in this article Monte Carlo simulations are applied to project (CPM or PERT) networks and critical path analysis[18] to output results from a large number of trials. The output is then analysed statistically to predict the most likely duration, completion date and cost for any project activity and the probability of specific targets being achieved. The techniques proposed recognise advantages in tailoring outputs from simulation models to suit specific projects rather than constraining projects into generic project software. These advantages include being able to focus on specific dependencies between activities, costs and time and being able to select for analysis intermediate parameters derived during the simulation (e.g. fluctuating critical paths and floats of key activities) that can reveal specific uncertainties (i.e. risks or opportunities).

Integrating Deterministic and Probabilistic Techniques

Hypothetical projects illustrate the advantages and pitfalls of a probabilistic, project cost-time simulation technique. The techniques integrate deterministic and probabilistic models and run them in sequence and in parallel. Indeed the results of the two complement each other and together they are worth more than either considered in isolation. In this way the same standards of cost-time-resource analysis, network logic, critical path definition, Gantt charts and precedence diagrams are applied prior to applying the simulation analysis. Moreover, the deterministic analytical processes form an integral part of project cost-time simulation and provide sensitivity checks on the output.

Treating a project as a network of activities is crucial to all deterministic and probabilistic techniques as a project is more than just the sum of its individual activities. The length of time taken for one activity may or may not be critical to the project completion time or cost. Some of the crucial questions that the proposed risk simulation techniques set out to answer are:

- What are the risks associated with achieving specific cost and time targets?
- What impact do changes in cost or time of an activity have on the whole project?
- When can the project as a whole be completed?
- Can it be delivered on time and within budget?

If the output is analysed appropriately simulation enhances the quality of answers that can be provided to these questions from deterministic methods used in isolation and therefore improve risk management.

Cost-time Project Simulation Techniques

Following completion of network time analysis, probabilistic methods allocate duration and cost estimates to each activity. The estimates are selected at random for each simulation trial (based on a random number generator) from probability distributions defined for each activity. As iterations (trials) of the simulation are repeated, chance decides the values of the input variables (within the limits of the distributions) that are selected. Different total

project durations and total project costs will almost certainly result from each trial. Computer processing speed is now so rapid that time and cost analysis of a project network can be repeated and recorded many hundreds of times very rapidly.
The technique involves equations formulated to combine logic relationships and sequences (e.g. project networks) with numerical values of input variables (e.g. activity times and costs) evaluated in repeated trials. Input variables are treated either as single number (deterministic) estimates or probability distributions where uncertainty is involved. These variables may behave independently of each other or be related by complex dependencies. Project network and precedence diagrams reveal some dependencies between activities, but others are often more subtle and require careful consideration in defining the calculation algorithms.

Forward and backward passes through the project activity network with deterministic data (e.g. the most likely activity duration times) will establish a critical path or a critical chain of activities[19]. This is essential if the total project duration is to be computed as a key out put parameter, in addition to the sum of all the component activity durations. However, as different times are sampled for each activity in each simulation trial the critical path may change from trial to trial. Simulation algorithms must account for this by performing a forward and backward pass for each trial.

Defining Cost & Time Distributions for Project Network Activities
It is necessary to consider every project network activity and decide how much confidence can be placed on its time and cost estimate. Basic probability distributions are frequently extrapolated from a three-point initial estimate. For example: a low-side estimate (**P10** or ten percent chance of being less than), central tendency estimate (mode or **P50**/median), and a high-side estimate (**P90** or ninety percent chance of being less than). Input estimates are then transformed into probability distributions of a specific mathematical type (e.g. triangular, beta[20], normal, lognormal or uniform) for sampling by the simulation[21]. These transformations are achieved rapidly by spreadsheet macros. It is critical that defined input distribution limits cover the possible range for these uncertain variables. A common failure is to define variables with too narrow a range and for subsequent events (e.g. supplier delays) to breach these limits. The credibility of the results emanating from any simulation depends on the quality of the input data. Where critical knowledge is lacking for estimating the initial value ranges then more complex distributions and mathematics may be required (e.g. trapezoidal distributions and fuzzy mathematics[22]).

How the simulation model mathematically defines and samples individual activity variables as probability distributions (e.g. triangular, lognormal, beta, etc.) can lead to significant variations in the cost-time outputs calculated for the project as a whole. Deciding on which distribution type a variable should conform to can be difficult and will to some extent depend upon the risk ranking and assessment methodology adopted[23]. Many fundamental attributes are normally distributed (e.g. equipment life), but derived attributes that result from the multiplication of constituent attributes (e.g. cost of items with multiple components) tend to be lognormally distributed. Triangular and Beta distributions approximate a range of distribution types, including those that are negatively or positively skewed, with the Beta distributions giving more weight to the central tendency estimate.

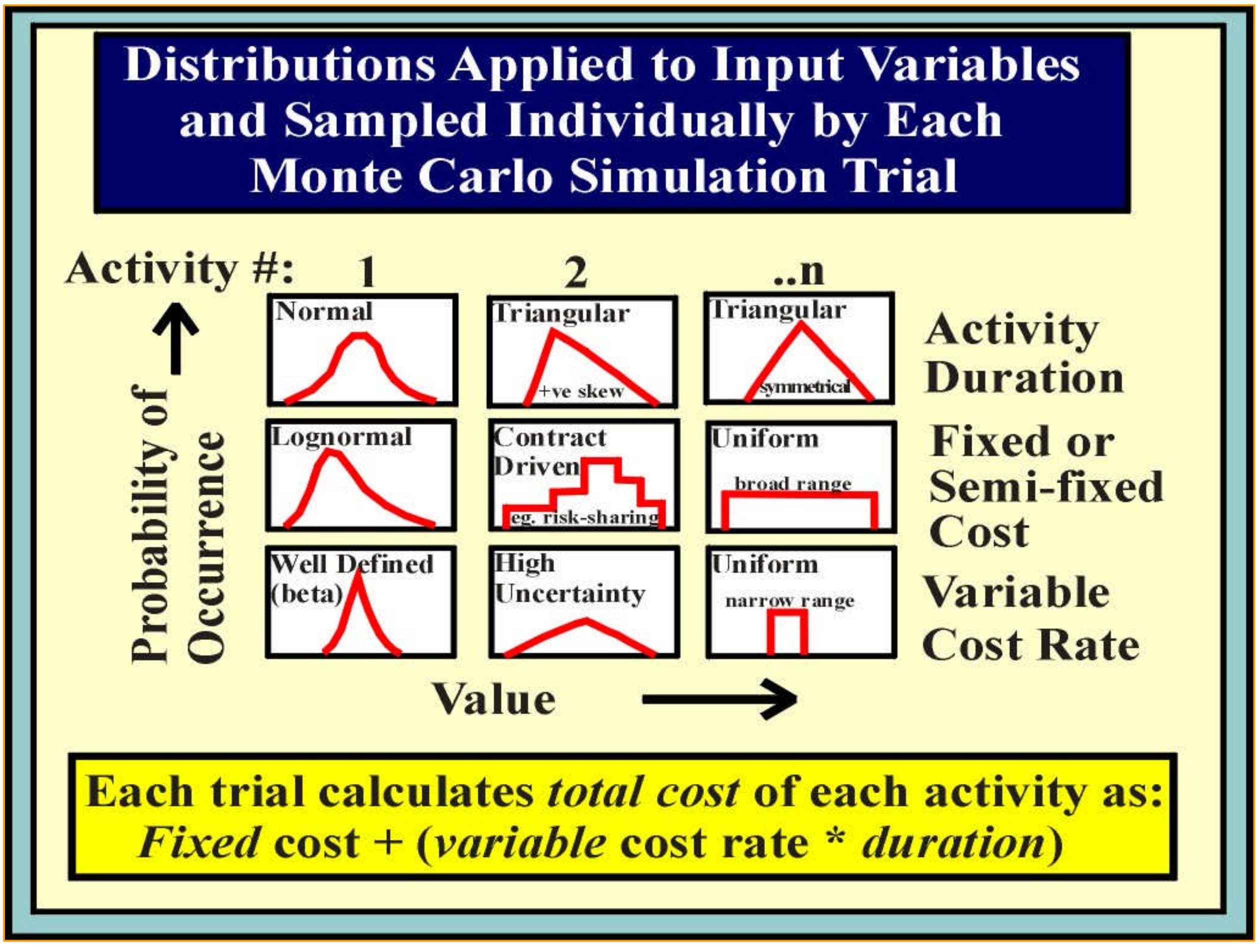


Figure 1: Multi-input distribution diagram

Component costs in a volatile market are often best described by a uniform distribution with a wide range where no one value has a greater probability of occurrence than another within the defined range. Many types of cost in more stable market settings are realistically defined by normal or lognormal distributions with large or small standard deviations depending upon the uncertainties.

In addition to mathematically defined distributions specific activity variable distributions may be defined by real historical data. These empirically defined distributions may or may not be similar to the mathematical distributions. Of course historical performance of similar activities in recently completed projects is no guarantee that such activities can be performed to such specifications in the future. Planners should therefore view historical data critically and consider extending the upper and lower limits of distributions to recognise other outcomes that could possibly occur in the future. In many cases activity cost distributions are constrained by commercial contractual terms. Some examples are fixed price contracts, gain-share and profit share alliance contracts[24], where contractors assume significant risks of cost and time over-runs in exchange for a share in any cost savings made relative to a target budget. Simulation algorithms must appropriately sample contractually defined and historically derived distributions. It is a useful check to study the values of specific activity variables sampled by the simulation trials to check for credibility.

Provisional Assessment of Simulation Output

Comparing simulation output frequency distributions for total project cost and time with the most likely deterministic calculations is a useful credibility check that the simulation is functioning correctly. The shape of the output variable frequency distributions can reveal whether they are well enough defined for meaningful statistical analysis. Calculating a standard deviation of a key output metric as the simulation trials build up helps to identify when statistical stability is reached and the number of trials that must be exceeded to achieve this. It is prudent to run the simulation for several hundred trials beyond initial stability.

Impact of Defining Activity Variable Distributions in Different Ways

A relatively simple 12-activity project with two parallel paths evaluates the impact of invoking different mathematical distribution options to define the individual project activity cost-time variable distributions for sampling by the simulation trials. Three-point input estimates for each of three activity attributes (duration, fixed cost and variable cost rate) were systematically sampled in different simulations by four different mathematical distributions (i.e., triangular, uniform, normal and lognormal) in various combinations and with various dependencies.

The deterministic calculation for the example indicates most likely total project duration of 45 days (sum of all activity durations of 65 days) and a total project cost of £650,000. The simulation results for full project duration are illustrated in Figure 2 as cumulative probability distributions.

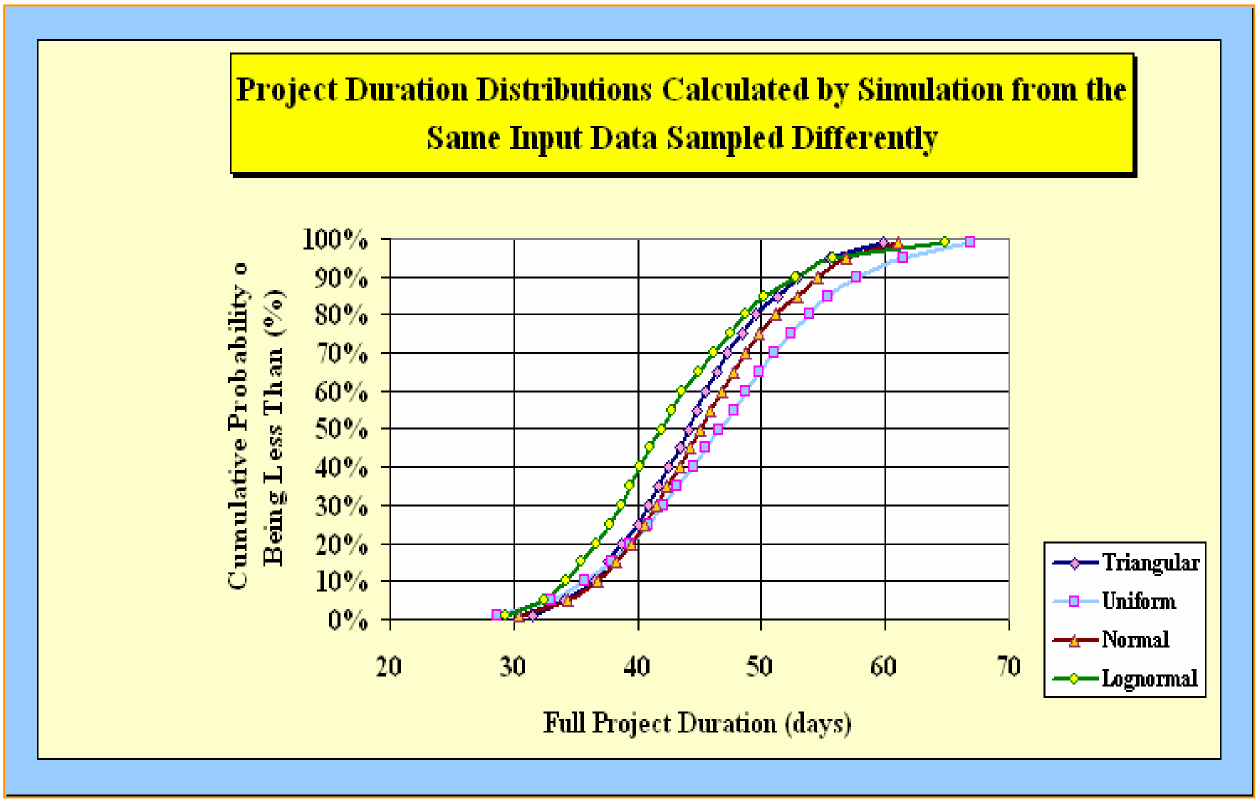


Figure 2: Cumulative probability distributions are the most common method used to statistically display and compare distribution ranges.

Uniform sampling in contrast to triangular, normal or lognormal sampling maximises the degree of uncertainty applied to the input data. Input sampling mechanisms can lead to simulation calculated project duration and cost varying by as much as 10%. Variations of such magnitude could influence project decisions.

Dealing with Dependencies among Project Activity Variables

Project network diagrams establish dependencies between activities that influence the calculation of the full project duration time where there is more than one path of parallel activities. In addition to sequence dependencies among activities there are often other dependencies between time and cost that may vary from activity to activity within a specific project. Figure 3 illustrates graphically the nature of some such dependencies.

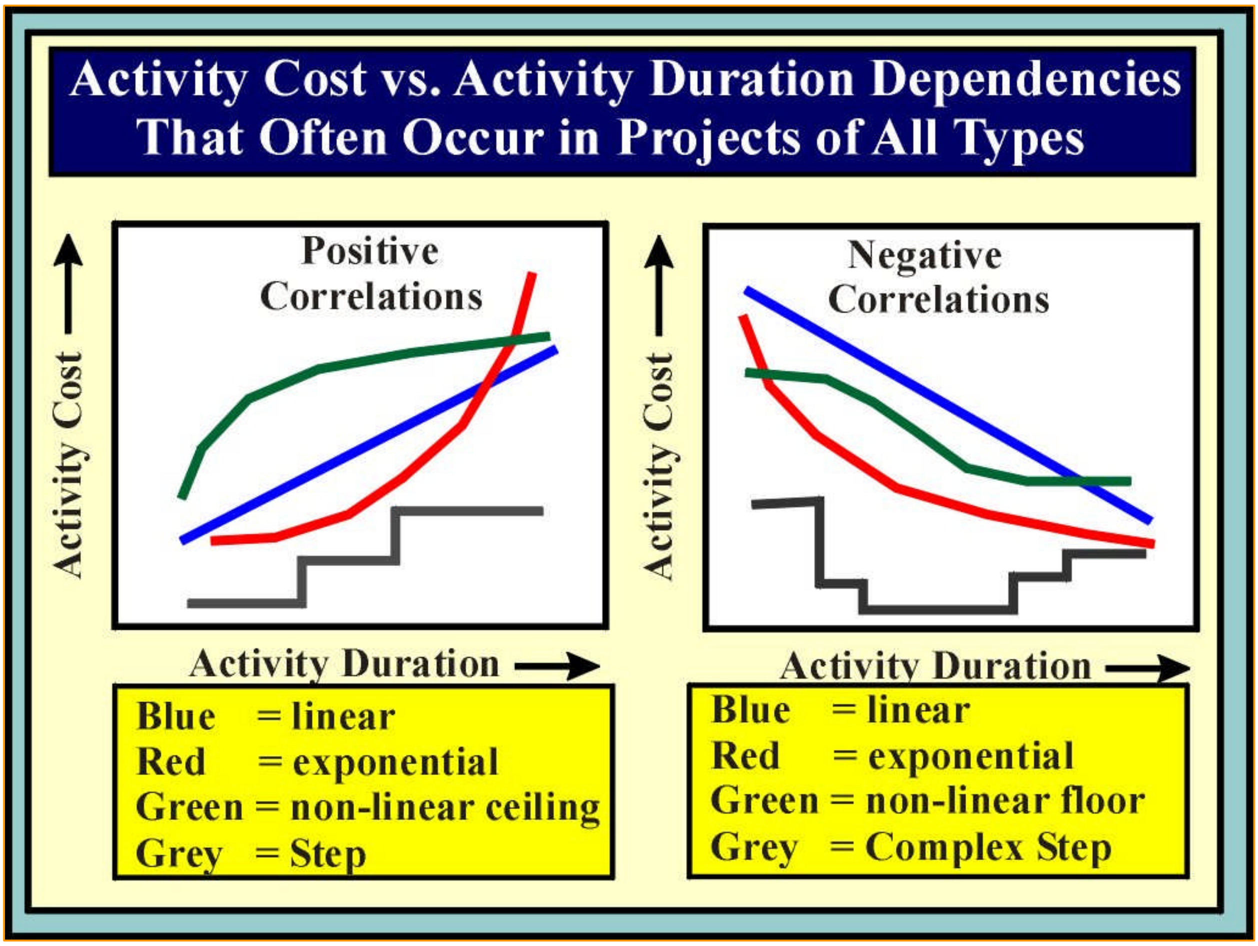


Figure 3: Cost – time attributes of project activities can be totally independent, but frequently exhibit dependencies that can range from curvilinear correlations to complex, contract-driven discontinuous steps.

Correlations between variables define positive or negative, linear or non-linear, progressive or discontinuous (e.g. step-like) dependencies. Each activity should be assessed to establish whether dependency exists between its cost and time attributes. If dependencies are ignored then a simulation is free to select a sample independently from each cost and time distribution. The selected cost-time combination may then be unrealistic for that activity. In dependent cases one random number is used to select an activity time and the same random number is used to either select a cost value from a dependency relationship or the cost distribution.

Dependencies can sometimes be subtle and /or complex. It then helps to establish the cause of each dependency and to evaluate how it might influence a specific activity. One complexity is that the cost of a single project activity can be made up of several independent and dependent costs. Dividing activity costs into "***fixed cost***" and "***variable cost rate***" components simplifies cost - time relationships in the models presented here. ***Fixed costs*** by nature are those that involve single payments regardless of how long an activity takes to complete. The term "***semi-fixed***" is often more appropriate as many so called "fixed" costs have time-related penalty or reduction factors associated with them. The distribution ranges of semi-fixed costs due to uncertainties in their estimates can differ from cost values determined by time related dependencies.

Variable costs are clearly time dependent (e.g. day rate contracts). For easy manipulation in a cost-time simulation variable costs can be expressed as rates (e.g. cost/day). ***Overheads*** usually involve both fixed and variable components despite the over simplification made in many projects of allocating overheads as a fixed percentage[25]. Having defined cost distributions in the model, total cost for an activity is then calculated in each trial as: semi-fixed cost plus variable cost rate multiplied by activity duration.

Time dependencies of the two components of each activity cost are defined separately. It is possible to have a positive dependency between fixed cost and activity time and a negative dependency between variable cost rate and activity time. Contrasting dependencies are not unreasonable. For instance, variable cost rates may have to be higher to finish an activity in a shorter time (more manpower or equipment needed) and fixed costs may end up lower due to lower material & support costs.

Cost-time dependencies are often contractually driven and can be complex (Figure 3), such as step relationships determined by contract penalty, bonus or gain-share clauses. Simulation cost-time algorithms need to take such relationships into account if they have material impact on the total cost of an activity and / or the full project. It is generally not realistic in cost-time simulations to assume that activity cost and time distributions are independent and can be simply sampled by unrelated random numbers.

Impact of Applying Different Cost-time Dependencies

The 12-activity project with two parallel paths evaluates the impact of different time-cost dependencies. Figure 4 shows full project time and cost cumulative probability distributions calculated by five simulation runs, using the same input data and triangular distribution sampling with different linear cost-time dependencies.

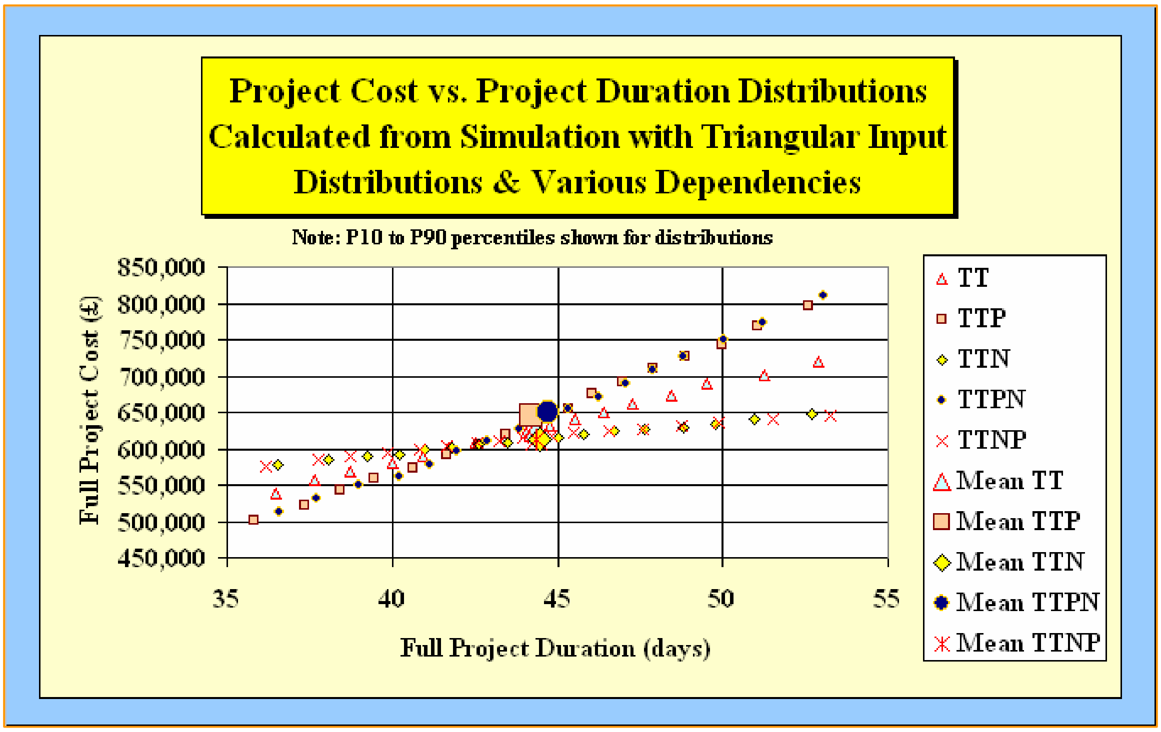


Figure 4: Project cost and duration relationships resulting from a range of linear cost-time dependencies. Distribution symbols are: TTP refers to positive dependencies; TTN refers to negative dependencies; TTPN refers to positive time-fixed cost and negative time-variable cost rate dependencies; TTNP refers to negative time-fixed cost and positive time-variable cost rate dependencies.

The simulation with no cost-time dependencies (TT) calculates full project cost distributions that bisect those for simulations with linear positive (TTP) and negative (TTN) cost-time dependencies. The positive and negative dependencies calculate cost distributions with a wider and narrower range of values, respectively. The means of the five calculated full cost distributions show more than 6% variation (TTPN the highest; TTN the lowest). Distributions TTP and TTPN have the largest standard deviations signifying more uncertainty than the other distributions.

Calculated Project Cost - Time Displays

The relationship between total project duration and full project cost is the primary objective of a cost-time simulation. Figure 5 plots calculated cost versus time for the 12-activity project example used above. It includes simulation trial points and distribution statistics to define an envelope of possible outcomes and provide a useful visual display of range and uncertainty.

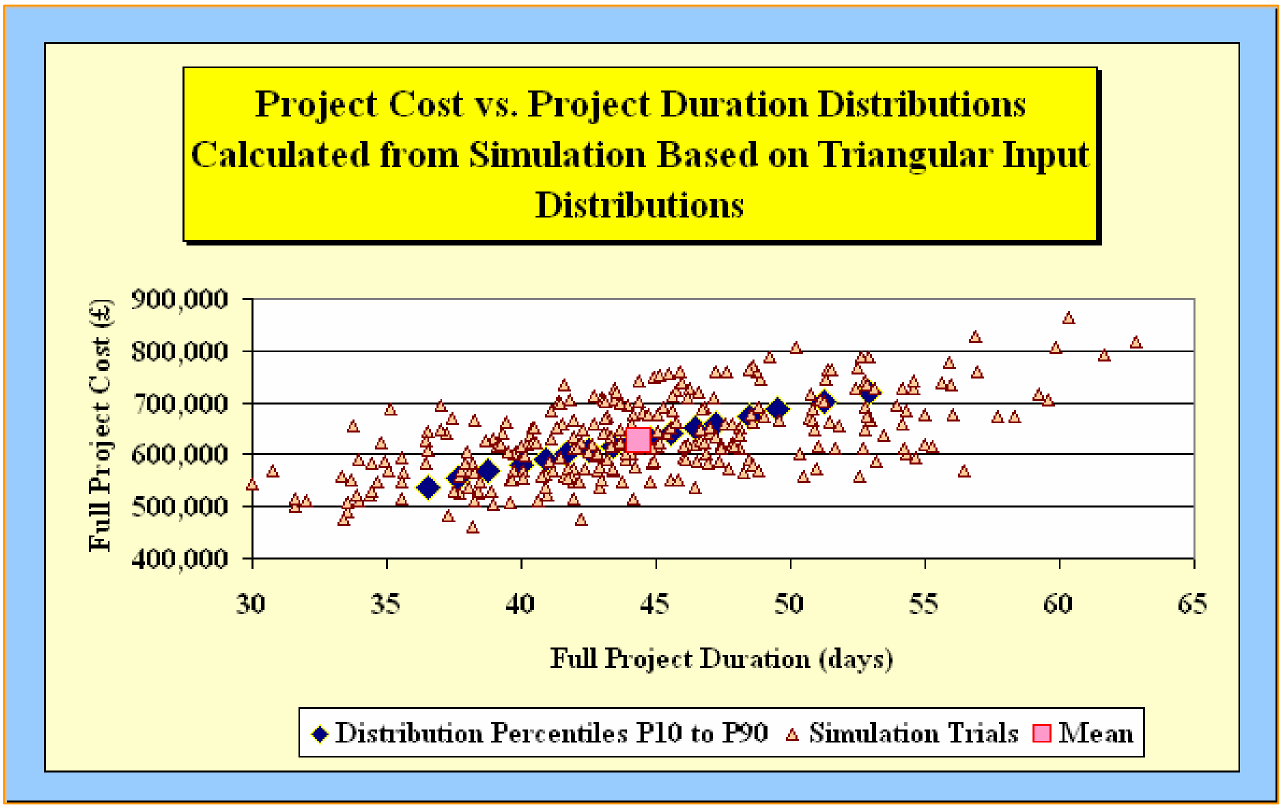


Figure 5: Full project cost and duration data displayed as individual simulation trial results and statistically in terms of percentiles and arithmetic mean of the full distributions of calculated data.

Risk, Opportunity & Performance with Respect to Specified Targets

Cost-time simulations have the valuable ability of quantifying uncertainty and risk. Uncertainty in a symmetrical distribution is quantified by the standard deviation. Standard deviations become less meaningful for skewed distributions (e.g. costs for some projects). Measuring, monitoring and mitigating risks (i.e. negative or downside uncertainties) is often more critical in cost-time simulation than quantifying opportunities (i.e. positive or upside uncertainties). Measuring project performance against cost and time targets (e.g. budgets or contract specifications) and quantifying the risks of exceeding those targets is a key project management task aided by cost-time simulation

Semi-standard Deviation as a Measure of Risk

A simple way to quantify risk is to record the percentage of simulation trials that exceed a specified target. However, a percentage says little about the magnitude by which that target might be exceeded. A ***semi-standard deviation*** (SSD)[26], measuring the mean squared deviation of a distribution occurring above a target value, measures the magnitude of risk associated with exceeding that target value and is calculated in the same units as the distribution itself.

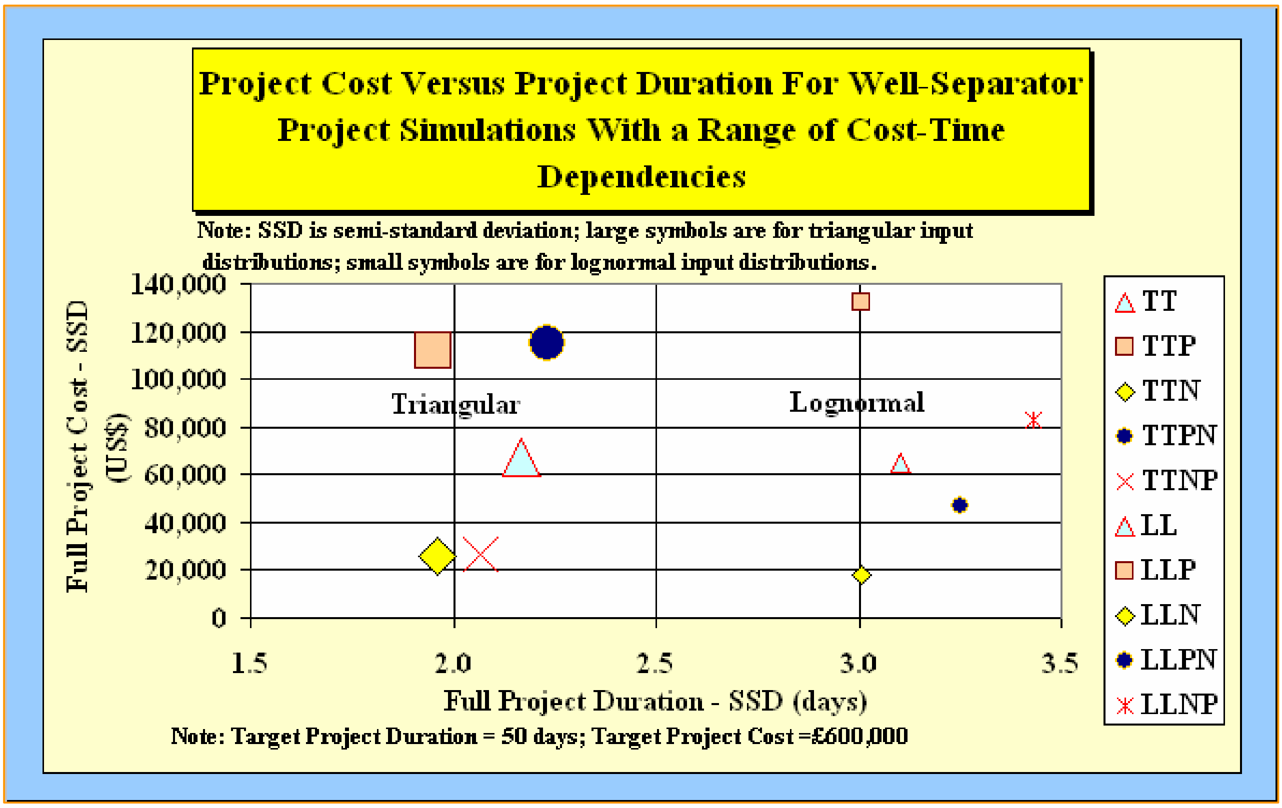


Figure 6: Semi-standard deviation (SSD) measures the mean squared deviation of distribution values that fall above specified targets for project duration and cost. It is a useful way of quantifying levels of risk associated with cost or duration aspects of a project.

Figure 6 plots SSD for project cost (relative to a target cost of £600,000) versus project duration (relative to a target project duration of 50 days) for the 12-activity project example. Simulation cases for triangular and lognormal sampling of the same input data with a range of cost-time dependencies are represented in this graph. In terms of SSD the lognormal sampling of input distributions results in a 50% higher risk of project duration exceeding the target than for the triangular input distributions. This is consistent with lognormal distributions being positively skewed and the project duration calculation being based on addition of component activity durations along the critical path.

In contrast the project cost SSD risks in Figure 6 are comparable for the two distribution types where no cost-time dependencies exist. The higher SSD risk for the positive time-cost dependencies (i.e. TTP and LLP) and lower risks for the negative time-cost dependencies (i.e. TTN and LLN) are consistent with the differences in Figure 4. It is also worth noting that the SSD cost difference between cases TTN and TTP is less than the difference between cases LLN and LLP, which is consistent with the different nature of the input distributions.

Evaluating SSD for a range of potential project cost and duration targets can a useful process in actual setting meaningful and achievable project budget targets. Such SSD relationships can help a project manager to focus on meaningful targets and to monitor them on an ongoing basis throughout the life of the project. SSD values can suggest realistic safety time buffers to be incorporated as contingencies into the final project schedule and to quantify the risks of exceeding such targets.

In practice it is unlikely that actual events during the implementation of any project will follow exactly the forecasts made by the risk simulation models. However, attempts to quantify the range of possible outcomes and risks associated with them is a significant advance on the deterministic alternative of evaluating a most likely case and running high and low sensitivity cases for which no probabilities of occurrence are established. On the other hand deterministic sensitivity cases can complement, and serve as a check on, the ranges of the probability distributions output by the risk simulations.

Cost-time simulation assigns probabilities of occurrence to possible project outcomes and quantifies the risks of exceeding specific budget targets. Using cost-time simulation in planning and ongoing monitoring of projects leads to more consistent decisions and better awareness of the magnitude of the risks involved.

Defining & Using Project Logic to Evaluate Simulation Trials - A Hypothetical Project Simulation Case Study

A hypothetical project to plan, build and commission a manufacturing factory with three separate product processes is analysed as an example. It consists of 20 activities networked with 5 parallel paths. The example illustrates a cost-time simulation with relatively complex interactions performed using spreadsheets. The project used for the example could alternatively have involved corporate or non-construction themes, e.g. introducing a change initiative or developing a new IT system, which are also best planned and implemented using project techniques[27]. The cost-time simulation techniques developed here are generic to projects undertaken in a wide range of industrial and corporate environments.

Hypothetical Manufacturing Factory		Estimated Time to Complete			Estimated Fixed Cost to Complete			Estimated Variable Cost Rate		
Activity Number	Activity Description	Fast (P10)	Most Likely (P50)	Slow (P90)	Low (P10)	Most Likely (P50)	High (P90)	Low (P10)	Most Likely (P50)	High (P90)
20 Activities ; 5 parallel paths			Days			£000			£ 000	
1	Market Survey	60	90	120	20	30	40	0.30	0.50	0.75
2	Short-list Potential Products	15	30	45	5	10	15	1.25	1.50	1.75
3	Feasibility Study	60	90	120	20	30	40	0.30	0.50	0.80
4	Select Product Mix	15	30	45	5	10	15	1.25	1.50	1.75
5	Short-list Potential Locations	15	30	45	5	10	15	1.25	1.50	1.75
6	Negotiate with Land-owners	40	60	80	5	10	15	1.25	1.50	1.75
7	Obtain Planning Permissions	60	90	120	10	15	20	1.25	1.50	1.75
8	Finalize Site Selection	15	30	45	5	10	15	1.25	1.50	1.75
9	Detailed Design/Process Eng.	60	90	120	30	50	70	2.00	2.50	3.00
10	Contract & Build Factory	150	180	240	200	250	300	1.00	1.25	1.50
11	Install Product Line X	40	50	60	75	100	120	1.25	1.50	1.75
12	Install Product Line Y	30	45	60	50	75	100	1.25	1.50	1.75
13	Install Product Line Z	20	30	40	40	50	60	1.25	1.50	1.75
14	Construct Admin. Facilities	80	90	100	75	100	125	0.75	1.00	1.25
15	Recruit Operating Staff	20	30	40	15	20	25	0.75	1.00	1.25
16	Develop Marketing Plan	20	30	45	20	30	40	0.50	1.00	1.50
17	Install Safety & Control Systems	60	90	120	30	50	70	0.50	0.75	1.00
18	Train Staff	30	40	50	15	20	25	0.25	0.50	0.75
19	Setup Distribution Systems	30	50	70	5	10	15	0.25	0.50	0.75
20	Test & Commence Production	15	25	40	15	20	30	1.50	2.00	2.50
			Days			£ 000			£ 000	
Totals		835	1200	1605	645	900	1155			

Table 1: Three-point input data for hypothetical project to plan, construct and commission a manufacturing factory to define symmetrical input case. Input distributions are defined for 3 variables: time, fixed cost, and variable cost rate, associated with each of the twenty component activities. The model assumes no cost-time dependencies.

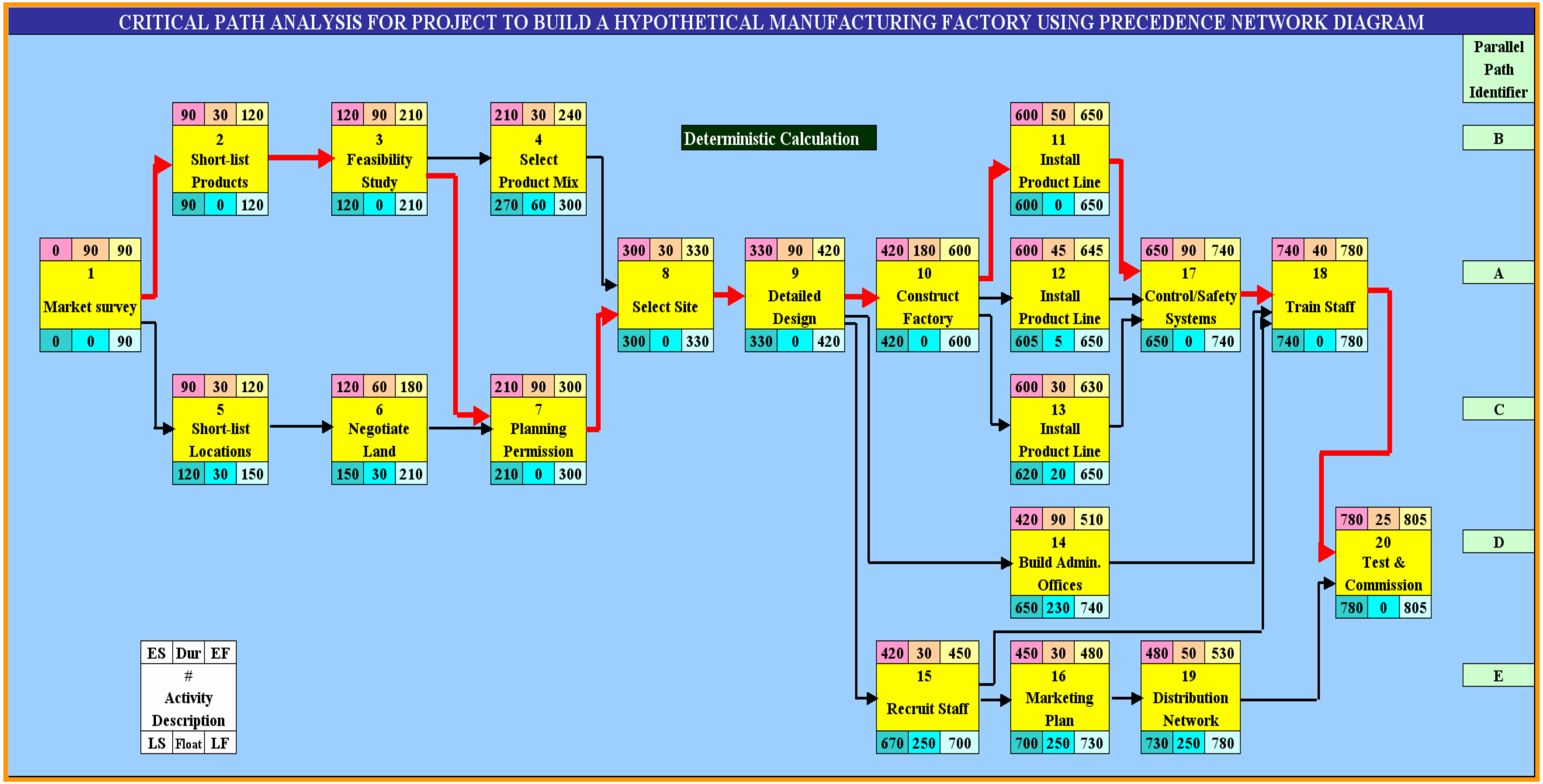
Table 1 lists the 20 project activities and the their three-point estimates for activity duration, fixed cost and variable cost rate that form the input for the cost-time simulation. Duration times are in days and the costs are quoted in thousands of pounds. The input data define ***symmetrical*** distributions. In addition to the input distributions another prerequisite for the simulation is the project network logic, i.e. which activities must be completed before others may begin and which activities can be performed at the same time on parallel paths. Each simulation trial then performs forward and backward passes and establishes critical paths. This logic can be listed and input into the model in the form of a simple table such as that shown in Table 2. It is not essential for the simulation algorithms that activities converging into subsequent activities have to be numbered sequentially. However, it can help the analyst of tabulated data if, where possible, there is a systematic scheme to the activity numbering system and labels are used to distinguish parallel paths.

Hypothetical Manufacturing Factory		Parallel Paths				
Activity Number	Activity Description	Numbered Activities that Must be Completed Before Named Activity Can Commence				
20 Activities.	5 parallel paths:	A	B	C	D	E
1	Market Survey					
2	Short-list Potential Products	1				
3	Feasilibility Study		2			
4	Select Product Mix		3			
5	Short-list Potential Locations	1				
6	Negotiate with Land-owners			5		
7	Obtain Planning Permissions		3	6		
8	Finalize Site Selection		4	7		
9	Detailed Design/Process Eng.	8				
10	Contract & Build Factory	9				
11	Install Product Line X	10				
12	Install Product Line Y	10				
13	Install Product Line Z	10				
14	Construct Admin. Facilities	9				
15	Recruit Operating Staff	9				
16	Develop Marketing Plan					15
17	Install Safety & Control Systems	11	12	13		
18	Train Staff	17			14	15
19	Setup Distribution Systems					16
20	Test & Commence Production	18				19

Table 2:   Network logic for hypothetical manufacturing factory project. The inter-dependencies among project activities in essential input to the simulation model in order to enable it to accurately calculate full project duration where there is more than one path of activities.

It is a visual asset to establish the project network logic diagrammatically, but this is not essential for the simulation process. Precedence network diagrams are easy to construct in spreadsheet workbooks and ideal to link into the deterministic and simulation calculations for project duration to ensure that the network logic is correctly configured. The more parallel paths that exist the more important the network diagrams become in verifying the logic. A precedence diagram for the hypothetical manufacturing factory project is illustrated in Figure 7.

Figure 7: Activity network for hypothetical manufacturing factory project expressed in precedence diagram format. This diagram represents the most likely deterministic case (Table 1) with the critical path of activities linked by red arrows. The simulation model can be linked to this diagram to enable the results of iterations of the model to be displayed and analysed.



It is useful to have two copies of the precedence diagram – one linked to the deterministic model (to check the network logic) and the other linked to the simulation model. When evaluating the simulation one trial at a time for a few trials (to verify the network logic) the linked precedence diagram can be reviewed after each trial to check the values selected from the activity distributions. This provides insight into how critical paths may fluctuate with varying input values. It also provides a further check that the simulation model is sampling the input distributions and combining the selected values with the network logic and other dependencies in the manner intended.

Table 2 and Figure 7 show that although the project has relatively few component activities the logic is complex, with five parallel paths and several converging and diverging paths. The critical path into activity numbers 17 and 18, for example, each depend upon 3 converging activities. The critical paths leading forward from activity numbers 9 and 10 both depend upon 3 diverging pathways.

In addition to the symmetrical input case a ***skewed*** case formed input for a second simulation of the project to illustrate the modelling power of the technique. The skewed case involves the same P10 and P50 values as the symmetrical case (Table 3) but higher P90 values for the three variables. The two simulations used triangular sample distributions and no time-cost dependencies.

Hypothetical Manufacturing Factory		High Case Estimates For Skewed Input Distributions		
Activity Number	Activity Description	P90 Time Estimate	P90 Fixed Cost Estimate	P90 Variable Cost Rate Estimate
20 Activities ; 5 parallel paths		Days	US$ 000	US$ 000/day
1	Market Survey	150	60	1.00
2	Short-list Potential Products	60	25	2.00
3	Feasilibility Study	150	60	1.00
4	Select Product Mix	60	25	2.00
5	Short-list Potential Locations	60	25	2.00
6	Negotiate with Land-owners	100	25	2.00
7	Obtain Planning Permissions	150	30	2.00
8	Finalize Site Selection	60	25	2.00
9	Detailed Design/Process Eng.	150	100	3.50
10	Contract & Build Factory	300	400	1.75
11	Install Product Line X	80	175	2.00
12	Install Product Line Y	90	150	2.00
13	Install Product Line Z	60	75	2.00
14	Construct Admin. Facilities	120	175	1.50
15	Recruit Operating Staff	60	40	1.50
16	Develop Marketing Plan	75	60	2.00
17	Install Safety & Control Systems	180	90	1.25
18	Train Staff	75	40	1.00
19	Setup Distribution Systems	90	25	1.00
20	Test & Commence Production	60	40	3.00
Totals		2130	1645	

Table 3 Input data for skewed high (P90) case distributions

Summary results are illustrated in Figures 8, 9 and 10. Not surprisingly the skewed case distribution shows a much greater range and higher statistical mean of 979 days than the symmetrical case distribution with mean project duration of 831 days. The flatter cumulative probability curve for the skewed case is a qualitative indication of the higher levels of uncertainty associated with that case.

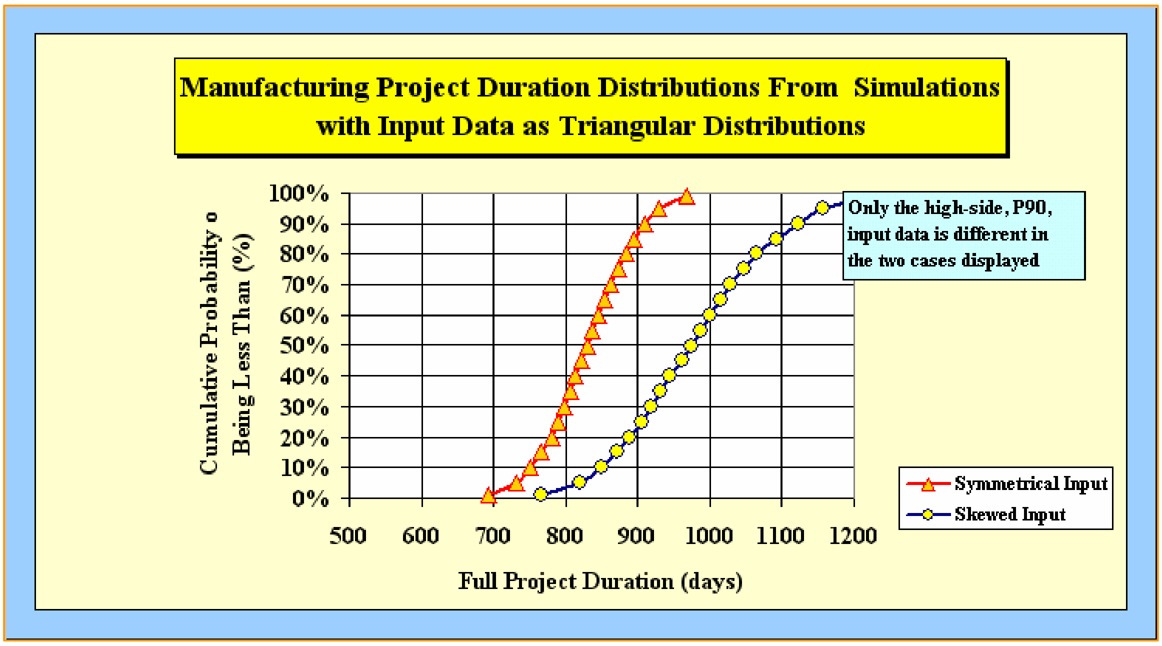
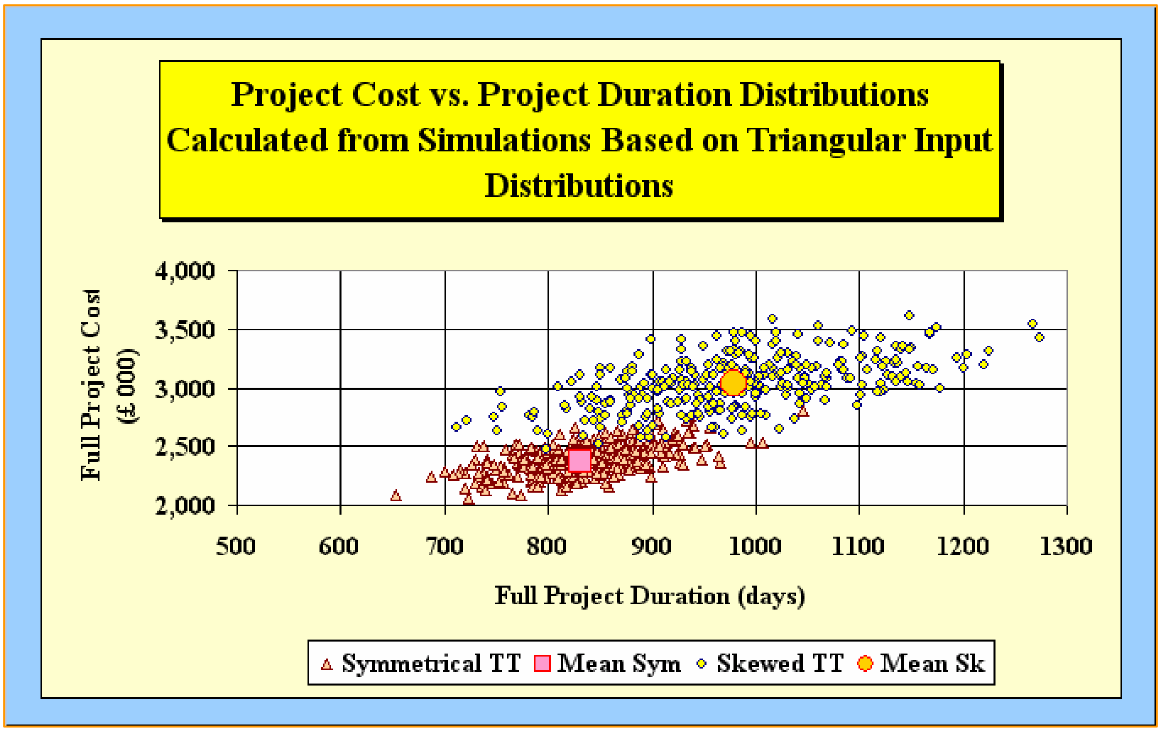
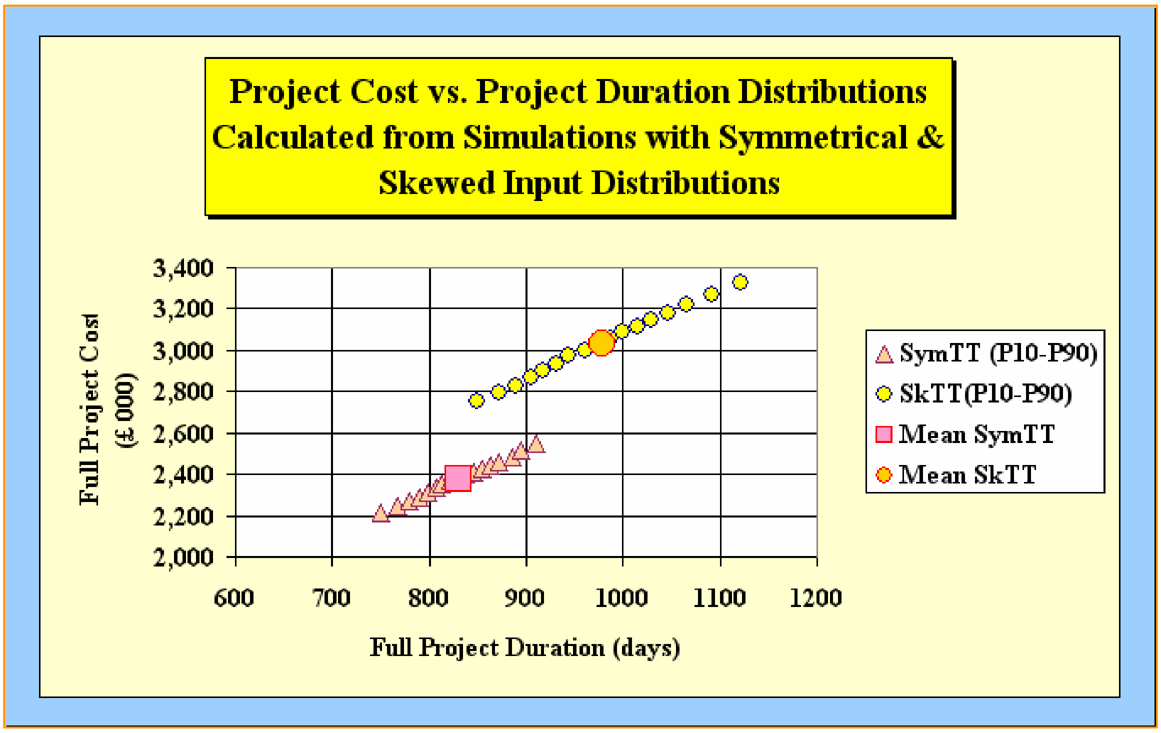


Figure 8: Cumulative probability distributions for calculated project duration from simulations run using the symmetrical and skewed input data for the hypothetical manufacturing factory project.

Project cost versus project duration relationships reveal the greater spread of data points for the skewed input case. P10 to P90 percentiles plus mean (Figure 9) clearly define and distinguish the two simulation cases.





Figures 9a & 9b: Calculated project cost and duration data displayed as individual simulation trial results (Figure 9a) and statistically in terms of percentiles and arithmetic means (figure 9b) of the full distributions of calculated data from the symmetrical and skewed input data for the hypothetical manufacturing factory project.

The semi-standard deviation (SSD) analysis of the calculated simulation distributions quantifies the higher risk of exceeding a range of specified project cost targets for the skewed input case (Figure 10). Such risk plots are also useful for comparing different plans for the same project and for monitoring ongoing project performance.

The value of cost-time simulation models goes far beyond the calculation of full project cost and duration. There are a number of intermediate calculations that are involved in the simulation that are also worthy of analysis. The statistical means of the duration and cost distributions associated with specific activities as sampled by the simulation can provide more detailed insight concerning activities that need further planning and definition in order to reduce critical path times and costs. If input cost data is based upon ballpark estimates (e.g. quoted to greater than + or – 25%) it will certainly result in higher risk / greater range sample distributions than for data based upon definitive estimates (e.g. quoted to approximately + or – 5%). Detailed analysis of specific activities may indicate where more precise estimates are critical for project viability and with which activities most of the risk is associated.

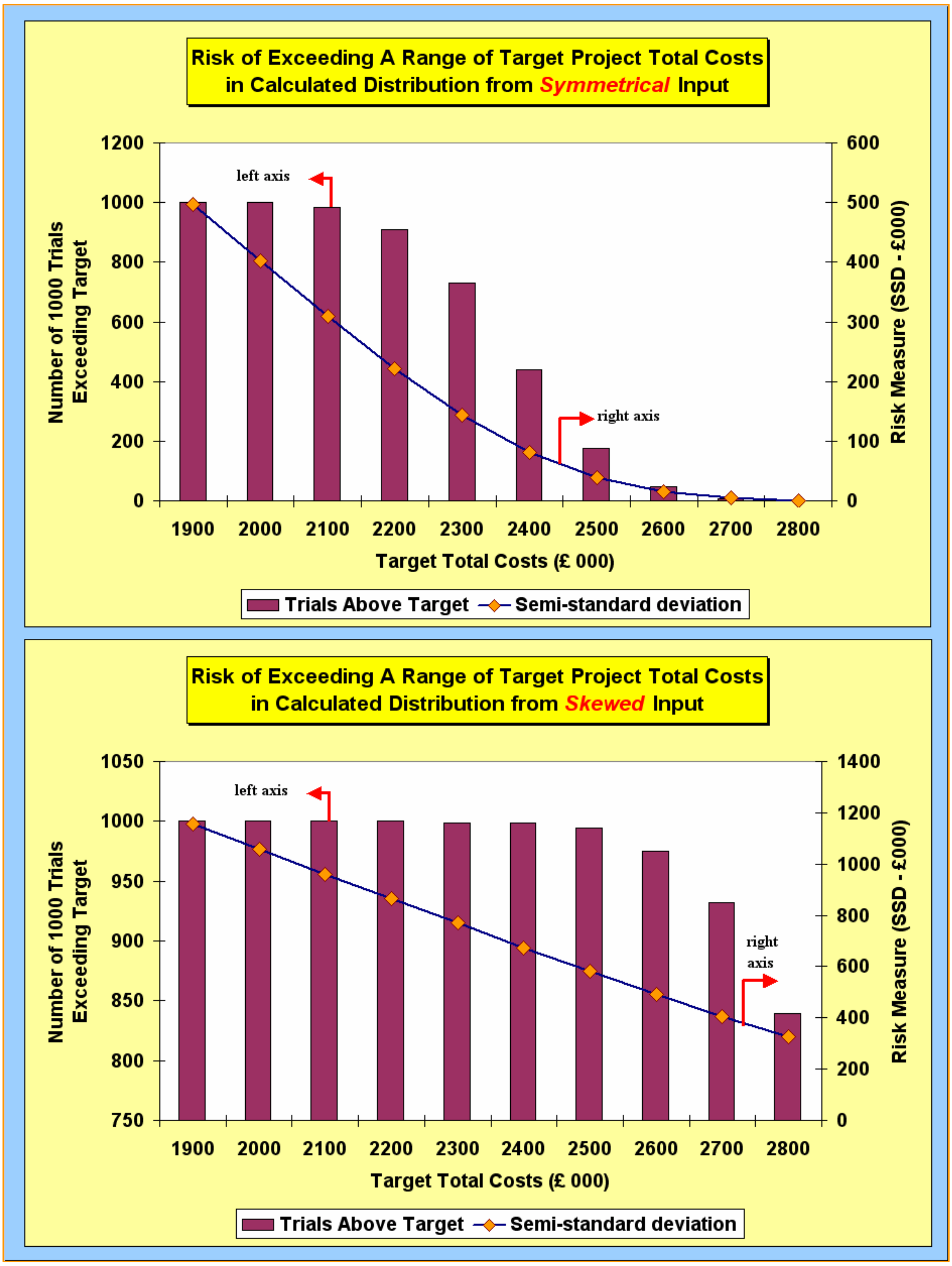


Figure 10: Semi-standard deviation (SSD) provides a comparable measure of risk magnitude associated with project costs for the symmetrical (upper graph) and skewed (lower graph) input cases with respect to a range of project cost targets for the hypothetical manufacturing factory project.

Other relevant intermediate calculations are the critical path fluctuations of activities feeding into convergent points in the project network from trial to trial. The critical path is the sequence of dependent events that prevent a project from being completed in a shorter time interval based upon the allocated resources. The critical path therefore represents a significant project constraint that should be fully analysed and tested. Analysis of the simulation results can help the project manager manipulate or exploit the critical path constraints to minimise risk associated with the main project targets. Actions may involve re-allocation of resources to critical activities or establishing appropriate time buffers[28] to protect key project pathways or groups of activities.

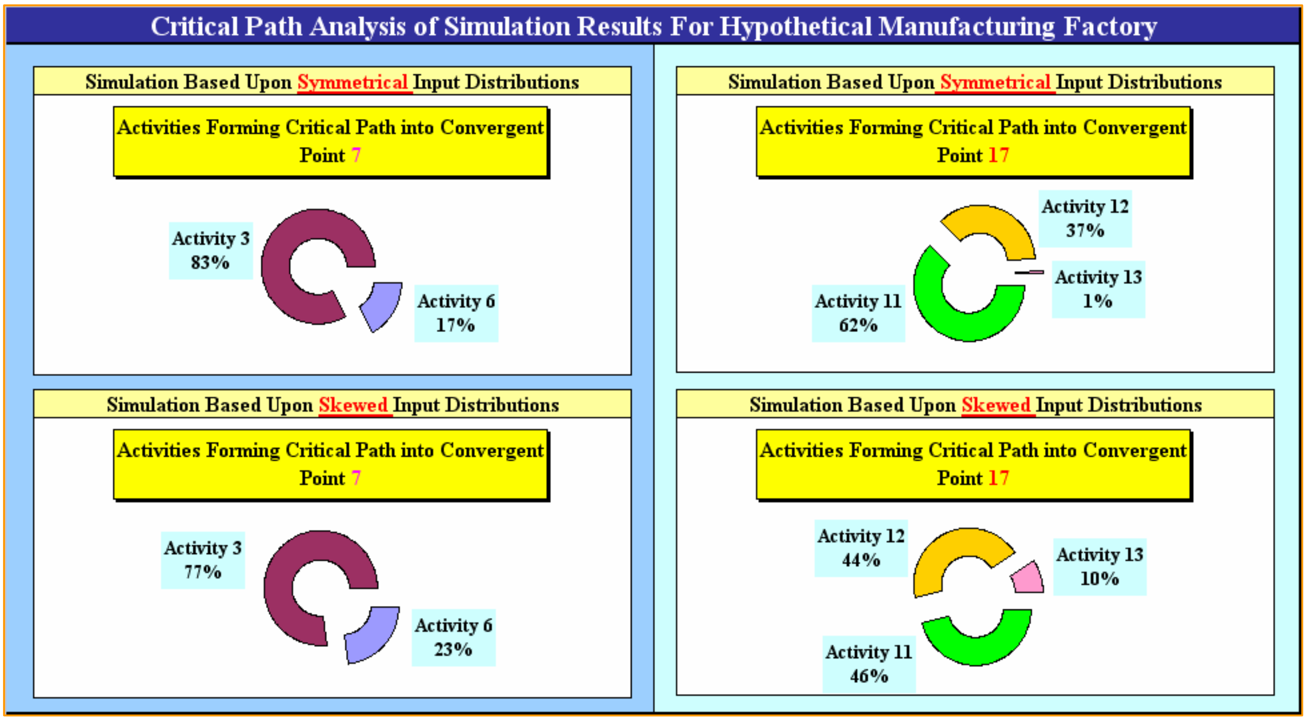


Figure 11: Intermediate calculations for simulation models can be used to identify through which activity the critical path passes for each trial of the model. This data can be analysed statistically to identify dominant critical paths, which can be useful in project management decisions such as resource allocation issues.

Critical path analysis of simulation results is best focused on key project activities (e.g. convergent points) with the analysis expressed as percentages. Figure 11 shows analyses for two convergent points in the symmetrical and skewed simulation cases of the hypothetical manufacturing project. The left-hand pie charts indicate that the critical path is much more likely to pass through activity 3 than activity 6 for both cases. It makes sense therefore to focus resources on activity 6, which is most likely to influence the critical path. The right-hand pie charts show that activity

11 (parallel path B - see Figure 7) forms the critical path in 62% of the simulation trials for the symmetrical input case. For the skewed input distributions activities 11 and 12 each represent the critical path converging into event 17 in about equal measure (i.e. 46% and 44%, respectively). Activity 13 almost never represents the critical path into activity 17 for the symmetrical case and does so for only 10% of the iterations for the skewed case. Clearly effort and resources should be focused on both activities 11 and 12 in terms of ensuring project targets are met. Such information cannot be obtained from deterministic analyses or many proprietary simulation models that focus only on the primary project cost duration calculations.

Another intermediate calculation worthy of further analysis for each simulation trial is the ***float*** associated with key project activities. The percentage of occurrences where float is greater than zero (i.e. not a critical path activity) and the average magnitude of the float time for those non-critical cases can help in resource allocation and planning decisions. This information can also contribute to decisions establishing the magnitude of any safety buffers (i.e., contingency time) that may be required for specific project paths.

Conclusions

- Risk simulation techniques complement the deterministic techniques of network and critical path analysis enabling rigorous models of project plans to be constructed, risks quantified and targets tested with sensitivities prior to the plan being rolled out.
- The choice of probability distribution functions selected to sample project activity input ranges and cost-time dependencies for each activity require careful consideration when building risk simulation models for projects. Input distribution and dependency definition can each account for variations in simulation results of up to about 10% of the calculated mean values from the same three-point estimates for the individual project activity cost-time variables.
- The risk simulation techniques proposed have primary objectives to forecast and display statistical analysis of the ***full project*** time and cost relationships. However, they also aim, as a secondary objective, to focus on the contributions of specific project activities and critical paths to provide detailed insight to interactions that might occur within the project network.
- Semi-standard deviation is a key statistical measurement applied to calculated cost-time variable distributions output by the proposed risk simulation techniques. This statistic quantifies the risk of exceeding

project cost and time targets. It focuses on risk rather than uncertainty and is expressed in the same units as the distribution being analysed.

- Workbook spreadsheets and their built-in statistical functions manipulated by user defined Visual Basic (VBA) macros provide a flexible software tool for building and evaluating risk simulation models customised to specific small to medium sized projects. The wide availability of such software at desktop PC level should ultimately encourage more practicing project managers to adopt spreadsheet based risk simulation techniques such as those described here.

This report expands upon work published by David Wood in the Oil & Gas Journal and Risk Management: An International Journal in 2001

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David Wood has produced a number of similar detailed reports covering a range of themes relevant to the oil and gas industry, e.g. project planning simulation, strategic portfolio modelling, risk and economics analysis, oil and gas asset valuation.

Notes

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