Applying Bayesian Networks to model Uncertainty in Project Scheduling

By:

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Declaration:

I certify that this thesis, and the research to which it refers, are the product of my own work, and that any ideas or quotations from the work of other people, published or otherwise, are fully acknowledged in accordance with the standard referencing practices of the discipline.

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Vahid Khodakarami Date

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Abstract

Risk Management has become an important part of Project Management. In spite of numerous advances in the field of *Project Risk Management* (PRM), handling uncertainty in complex projects still remains a challenge. An important component of *Project Risk Management* (PRM) is *risk analysis*, which attempts to measure risk and its impact on different project parameters such as time, cost and quality. By highlighting the trade-off between project parameters, the thesis concentrates on project time management under uncertainty.

The earliest research incorporating uncertainty/risk in projects started in the late 1950's. Since then, several techniques and tools have been introduced, and many of them are widely used and applied throughout different industries. However, they often fail to capture uncertainty properly and produce inaccurate, inconsistent and unreliable results. This is evident from consistent problems of cost and schedule overrun.

The thesis will argue that the simulation-based techniques, as the dominant and state-of-the-art approach for modelling uncertainty in projects, suffers from serious shortcomings. More advanced techniques are required.

Bayesian Networks (BNs), are a powerful technique for decision support under uncertainty that have attracted a lot of attention in different fields. However, applying BNs in project risk management is novel.

The thesis aims to show that BN modelling can improve project risk assessment. A literature review explores the important limitations of the current practice of project scheduling under uncertainty. A new model is proposed which applies BNs for performing the famous *Critical Path Method* (CPM) calculation. The model subsumes the benefits of CPM while adding BN capability to properly capture different aspects of uncertainty in project scheduling.

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1 Introduction

1.1 Motivation

Projects inevitably involve risk and concerns about risk are regular worries of project managers. *Risk Management* has become an important part of Project Management. Although a variety of writers have proposed a range of processes and techniques, *Project Risk Management* (PRM) is rapidly evolving and handling uncertainty in complex projects remains a challenge.

An important component of PRM is *risk analysis.* Also known as *risk quantification,* it attempts to measure risks and their impacts on different project parameters (i.e. time, cost and quality). Traditionally project scheduling under uncertainty has attracted more research and attention in the project management community. In some of the early project management literature, ‘risk analysis’ was equivalent to ‘the analysis of risk on project plan’ (Williams 1995). This thesis concentrates on modelling uncertainty in project time management. However, it explicitly highlights the three dimensional trade-off between project parameters, namely time, cost and quality.

The earliest studies incorporating uncertainty/risk in project scheduling were in the late 1950’s (Malcolm 1959) and (Miller 1962). Since then, a variety of techniques have been introduced, several tools have been developed, and many of them are widely used throughout different industries. However, they often fail to capture uncertainty properly and (or) produce inaccurate, inconsistent and unreliable results.

Project uncertainty has several aspects of which only some can be categorised and treated as risks. Several authors, for example (Ward and Chapman 2003) and (Atkinson et al. 2006), have recently argued that project risk management should be focusing on managing uncertainty and its various sources rather than emphasising a set of possible events that might impair project performance. Most of quantitative techniques in the current practice of project risk management are based on the 'Probability Impact' concept, which suffers from serious shortcomings. More sophisticated efforts and techniques are needed to recognise and manage important sources of uncertainty.

On the other hand *Bayesian Networks* (BNs) as a powerful technique for decision support under uncertainty have attracted a lot of attention in different fields. A BN is a graphical model with a rigorous mathematical engine in the background. It offers a powerful, general and flexible approach for modelling risk and uncertainty. Its capability of modelling causality and also conditional dependency between variables make it perfectly suitable for capturing uncertainty in projects. Yet, BNs are rarely applied in project risk management.

This thesis introduces a novel approach for incorporating uncertainty in project scheduling. The idea is to use BNs to perform the well-known *Critical Path Method* (CPM) calculation. CPM as a simple yet effective scheduling approach provides very useful time related information about projects and their activities. But it is purely deterministic. The proposed approach enriches the benefits of CPM by incorporating uncertainty and adding the strong analytical power of BNs.

1.2 Research Hypothesis and Methodology

The hypothesis of this thesis is that it is possible to use BNs to quantify uncertainty in project scheduling and improve project risk assessment.

The research methodology comprises a literature review to investigate the current state of project scheduling under uncertainty. This determines the need, scope and objectives of the new approach. A literature review follows to investigate the background, theory and applications of BNs. This provides the conceptual and the functional framework for the new approach. The modeling process as the appropriate representation of uncertainty is studied in detail. Two case studies are used to verify the models. The first case study, taken from the literature, verifies the model by comparing its numeric results against the result of a simulation-based model. The second case study is a real construction project that suffered from serious delay. It demonstrates how the model can be applied in a real project to capture different aspects of time related risks.

1.3 Structure of the thesis

An overview of the subsequent chapters is as follows:

Chapter two briefly reviews the project risk management process and explores the currently popular techniques in project scheduling under uncertainty. Chapter three identifies important issues that are missing in the current practice of project risk assessment and reveals the need for more sophisticated techniques to address these issues. A modified version of chapter three is published in (Khodakarami 2005). Chapter four explains BNs and their theoretical and technical framework. Chapter five proposes a new model for incorporating uncertainty in project scheduling by applying BNs on the famous *Critical Path Method* (CPM). An earlier version of this chapter is published in (Khodakarami et al. 2007a) (a copy of this paper is attached in the appendix). Chapter six discusses the various sources of uncertainty in activity duration and proposes a prototype BN model for modelling these sources. A modified version of this chapter is published in (Khodakarami 2007b). Chapter seven evaluates the models by summarising the result of two case studies. Chapter eight concludes the thesis and points the way forward for future research.

2 Current techniques in project scheduling under uncertainty

This chapter explains some important techniques that are applied to handle uncertainty in project scheduling. First a brief overview of the project risk management processes and their components is presented. Then ‘Risk analysis’ as the focus of this thesis is discussed and current techniques are reviewed.

2.1 Project Risk Management Process

‘Risk Management’ has become an important part of ‘Project Management’ and has attracted a wide range of research during the last decade (Williams 1995). Since 1990 various *Risk Management Processes* (RMP) have been proposed. Probably the most popular *Project Risk Management Processes* (PRMP) are chapter 11 of the PMBOK (Project Management Body of Knowledge) guide (PMI 2004), the PRAM (Project Risk Analysis and Management) guide (PRAM 2004) and the RAMP (Risk Analysis and Management for Projects) guide (RAMP 2005). Most organisations adopt one of these guides or use them to develop their own process. This thesis does not intend to explore the detailed differences between different guides since, apart from fundamental differences in assumptions and methodologies (Chapman 2006), they all aim to capture risk and uncertainty in the following three stages:

- *Risk Identification*
- *Risk Analysis*
- *Risk Response*

The *‘Risk identification’* stage attempts to discover the main sources of risk. This stage is also known as *qualitative risk management*. By using various data gathering techniques (e.g. interviewing, brainstorming, Delphi technique, checklists etc.) from all parties involved in the projects, the possible risks that might affect the project are identified.

The usual output of the risk identification stage is a document called the *'Risk Register'*. Many authors have discussed risk registers in their works (Barry 1995). (Williams 1994) states two main roles for a risk register:

- A repository of a corpus of knowledge.
- To initiate the analysis and plans that flow from it.

(Chapman and Ward 2003) consider a risk register as documentation of the sources of the risks, their responses and also risk classification. (Ward 1999) describes the purpose of a risk register 'to help the project team review project risk on a regular basis throughout the project'. (Patterson and Neailey 2002) present a risk register database system to aid managing project risk. Risk registers can be a good management tool during the course of a project. However, it is not possible to identify all risks and capture all aspects of them. There are always unknown (i.e. undiscovered, unattended or immeasurable) risks that often are more important than the identified risks in the risk register. This will be addressed in section 3.3.

The '*Risk analysis*' stage attempts to measure the risk and its impacts on different project outputs (i.e. cost, time, performance). This stage is also known as *quantitative risk management*. The likelihood that each identified risk will occur and also its possible impact on the project is estimated. The combination of the risks, probabilities and their impact create 'probability-impact' (PI) matrices. This matrix can be used to assign ranks to risks and then prioritise them. Most of the available quantitative tools and techniques (simulation based tools) implement the PI values to quantify uncertainty in projects. However, use of PI matrices has some important shortcomings (Chapman 2006), which will be addressed in chapter 3.

The '*Risk response*' stage attempts to formulate management responses to the risk. Also known as 'Risk Mitigation', it uses the results of the analysis stage in order to improve the chance of achieving the project objectives. 'Risk response' is a decision making process. A number of alternative strategies are available when planning risk responses, which can be described under one of the following strategies (Hillson 1999):

- *Avoid* - seeking to eliminate uncertainty by reducing either the probability or the impact to zero.
- *Transfer* – seeking to transfer ownership and/or liability to a third party (i.g. insurance)
- *Mitigate* – seeking to reduce the size of the risk exposure in order to make it more acceptable to the project or organization
- *Accept* – recognizing residual risks and responding either actively by allocating appropriate contingency, or passively doing nothing except monitoring the status of the risk.

There are several other publications with different perceptions of project risk management processes. For example (Al-Bahar and Crandall 1990), the (UK Ministry of Defence 1991), (del CaÃno and de la Cruz 2002), (Wideman 1992), British Standard Institute (BSI 1999), NASA (Rosenberg et al. 1999), the U.S. Department of Defence (Defense Systems Management College 2000), and the (US Dept. of Transportation 2000) suggest the use of processes with different stages or phases. Regardless of which risk management process is adopted for managing risk/uncertainty, 'risk analysis' is always an important component of the process.

2.2 Project Risk Analysis

The term 'Risk Analysis' in this thesis is equivalent to 'Quantitative Risk Analysis' or 'Risk Measurement' as one stage of 'Project Risk Management'. In some of the literature, 'Risk Analysis' is synonymous with 'Risk Management'.

Risk analysis is the most formal aspect of the project risk management process (PRAM 2004), often involving sophisticated techniques and usually requiring computer software. Such techniques can be applied with varying levels of effort depending on the available resources for the analysis and also the required level of detail.

Risk analysis is usually initiated by a qualitative analysis and its results support the decision making process in the Risk Response stage. It is a continuous process that can be started at almost any stage in the life-cycle of a project. However, it is most beneficial to use it in the earlier stages of project (i.e. feasibility study and planning) and iteratively update it at intervals during the implementation phase.

Risk analysis can provide several benefits to the project including:

- Help to justify decisions and enable more efficient and effective management of the risks.
- Formulation of more realistic plans, in terms of both timescales and costs.
- Build-up of statistical information of historical risks that will assist in better modeling of future projects.
- Assistance in evaluation of claims and disputes.

This thesis in particular focuses on quantifying risk/uncertainty involved in project duration. The next section, reviews some of the main approaches and techniques in project scheduling under uncertainty.

2.3 Project Scheduling Under Uncertainty

Project scheduling under uncertainty is the most widely studied area of risk quantification in project management. Producing a reasonable and reliable project schedule is one of the crucial tasks of project managers. Moreover, having a realistic schedule for the project is one of the most cited factors of project success (Fortune and White 2006). Several techniques are proposed for modelling risk and uncertainty in project scheduling. This section reviews a number of notable techniques. CPM and PERT are the classic approaches for project scheduling.

Simulation-based techniques are the state-of-the-art approach that is adopted by many project management software tools and are arguably the best practice available. Alternative approaches including Critical Chain Method and Fuzzy logic are reviewed briefly.

In all techniques it is assumed that the project network is fixed and there is no probabilistic or conditional branching. Projects with decision branches, repetitive process or with alternative ways of approaching activities are not considered in this thesis.

2.3.1 Critical Path Method

'Critical Path Method' (CPM) is the most famous technique in project scheduling. Although CPM does not incorporate uncertainty (being purely deterministic), it is listed here because many of more sophisticated techniques (including the proposed technique in this thesis) are derived from the CPM concept or use CPM calculations for producing their baseline project schedule (Moder 1988).
Developed in 1957 (Kelley 1961), CPM has become the standard technique in project management and most project management tools support CPM. According to (Pollack-Johnson and Liberatore 2005) nearly 70% of project management professionals use CPM. CPM includes the following steps:

- Specifying individual activities using a 'Work Breakdown Structure' (WBS), defining activities' sequences and dependency between them.
- Drawing a network diagram that models the activities and their dependency.
- Estimating duration for each activity (this is a single point estimation as CPM does not take into account any variation in activity's time).
- Identifying the *Critical Path* (i.e. the longest-duration path in the network) by calculating activities time parameters,
- Updating the CPM diagram as the project progresses.

The basic mathematical notation used for CPM calculation is:

$a_j : Activity\ j$

$D_j = Duration\ of\ a_j$

$ES_j = Max[ES_i + D_i \mid i\ one\ of\ the\ predecessor\ activities\ ]$

$EF_j = ES_j + D_j$

$LF_j = Min[LF_k - D_k \mid k\ one\ of\ the\ successor\ activities\ ]$

$LS_j = LF_j - D_j$

$TF_j = ES_j - LS_j = LF_j - EF_j$

Informally, the critical path is determined by performing forward and backward passes through the project network. The forward path computes the earliest start (ES) and the earliest finish (EF) time for each activity. The backward path computes the latest start (LS) and the latest finish (LF) time for each activity. The *Total Float* (TF) for each activity (which is the time that the activity's duration can be increased without increasing the overall project completion time) is the difference in the latest and earliest finish of each activity (Figure 2-1).

A critical activity is one with no float time and should receive special attention (delay in a critical activity will delay the whole project). The critical path then is the path(s) through the network that consists of only critical activities.

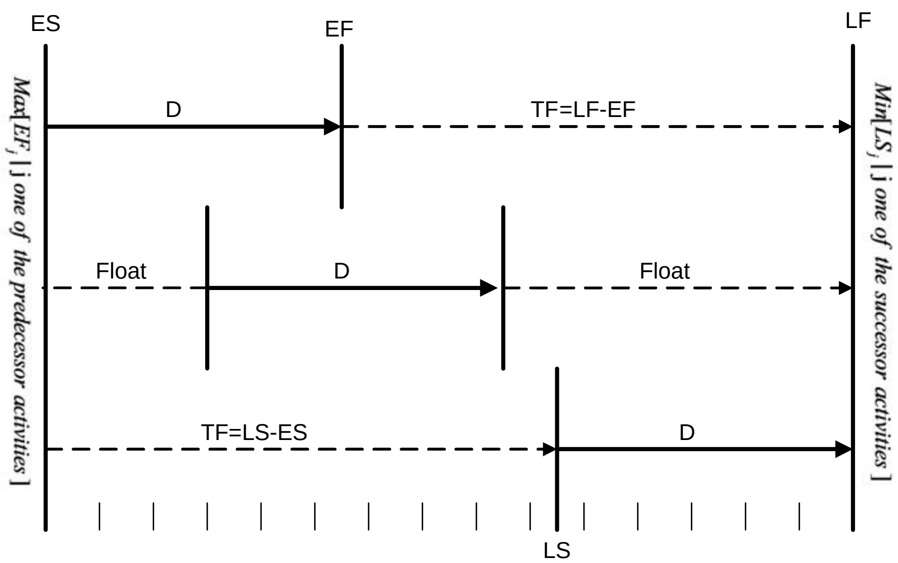


Figure 2-1 : CPM parameters in an activity

Although CPM makes no attempt to handle or quantify uncertainty, it provides very useful information about activities time and the overall project schedule.

2.3.2 PERT

The earliest research incorporating uncertainty/risk in project management started in 1957 with the introduction of PERT (Program Evaluation and Review Technique) [(Malcolm 1959), (Moder 1988), (Miller 1962)]. A distinguishing feature of PERT is its ability to deal with uncertainty in activity duration. For each activity instead of having a single estimate, PERT assumes a Beta probability distribution. Three estimations (optimistic, most likely, and pessimistic times) are used to calculate the expected time and the standard deviation for the activity *j*:

$$\text{Expected Duration:} \quad \mu_j = (Optimistic + 4 \times Most\ Likely + Pessimistic)/6$$
$$\text{Standard Deviation:} \quad \sigma_j = (Pessimistic - Optimistic)/6$$

The expected value of a critical path is calculated using the expected value of each activity. The variance of the critical path (i.e. the variance of project completion time) can be calculated by summing the variances of the activities in the critical path. Given this variance and assuming a normal distribution for the critical path the probability that the project will be completed by a certain date can be calculated.

In the 1960s PERT was a great success and several associated techniques were introduced (Levin and Kirkpatrick 1965) and (Pritsker and Happ 1966) and (Adlakha and Kulkarni 1989). However, in the 1970s later studies raised doubts about the practicality (Sapolsky 1972) as well as theoretical assumptions of PERT (MacCrimmon and Ryavec 1964). The assumption of independence between activities and also the assumption that the duration of all activities have a Beta distribution are not practical. More importantly PERT assumes only one path as the critical path and assumes this path does not change. However, it is quite possible that the critical path that was identified based on the most likely or expected completion time will not necessarily end up being the critical path. In other words PERT ignores other scenarios in which another path takes longer than the identified critical path. This produces unrealistic and overly optimistic estimates for the project duration. By the 1980s the standard PERT was ‘effectively dead as a working concept’ (Webb 1997).

2.3.3 Simulation

Monte Carlo simulation (MCS) was first proposed for project scheduling in the early 1960s (Van Slyke 1963). However, it was not until the 1980s when sufficient computer power became available that simulation became the dominant technique for handling risk and uncertainty in projects (Fishman 1986) and (Ragsdale 1989). In its simplest approach, MCS uses the project activity diagram. The duration of each activity is estimated by shortest, most likely and longest duration and also the shape of the distribution (such as Normal, Beta etc.). Then critical path calculation is performed several times, each time using random values from the activities’ distribution function. A sufficient number of runs provide a probability distribution for the possible results (i.e. time or cost).

More advanced tools, for example PertMaster (Primavera 2008), use simulation not only for handling uncertainty in duration and cost, but also for providing a whole risk analysis process. They can link the ‘project schedule’ to the ‘risk register’ and apply simulation to perform ‘probability impact analyses’.

MCS can also provide a basic sensitivity analysis by measuring the correlation between the duration of a task and the duration of the project. This gives an indication of how much the duration of each task affects completion of other tasks or the entire project. It can also be used for identifying tasks that are most likely to cause delay on the project (i.e. critical tasks) and prioritising them.

Simulation has been adopted as the state-of-the-art technique by several types of project management software tools (Cook 2001). A survey by the Project Management Institute (PMI 1999) showed that nearly 20% of project management software packages support Monte Carlo simulation. Another survey by (Pollack-

Johnson and Liberatore 2003) found that 17% of project mangers used probabilistic analysis and/or simulation within project management software.

However, simulation has its own drawbacks. One serious methodological flaw in traditional MCS of project networks is the assumption of statistical independence for individual activities which share risk factors in common with other activities (van Dorp and Duffey 1999). Most available simulation packages assume that the marginal distributions of uncertainty for individual activities in the project completely define the multivariate distribution for project schedule. It is intuitively obvious that this assumption is highly suspect for many projects which involve multiple activities of a similar type and/or have different activity types, which are influenced by common risk factors. An example would be risk of bad weather for all activities scheduled under the open sky in the same time period. (van Dorp and Duffey 1999) demonstrated that failure to model such types of risk dependence during MCS can result in the underestimation of total uncertainty in project schedule. The most effective way to deal with dependence in a statistic is to use a causal structure to explain it. MCS is not capable of modelling causal structures.

Another weakness of MCS explained in (Williams 2004), is the inability of simulation to capture the actions taken by the managers to recover any slippage in activity/project duration. MCS simply runs through a network assigning values to random variables on each iteration. It ignores the fact that in reality if an activity was running late, management would take actions to affect the activity duration. Uncertainty in an activity is usually the result of a chain of causes (sources) and can be affected by a chain of actions (controls).

Furthermore, MCS is only as good as the information that is fed into it. If the duration distributions of the project activities are incorrect or inadequate, the simulation results are erroneous and invalid. In reality duration of most activities are estimated subjectively. In order to capture all aspects of uncertainty in activity (project) duration various known and unknown sources of risk have to be addressed. This will be discussed more in chapter 3.

2.3.4 Critical Chain Method

In the late 1990's *Critical Chain project management* (CCPM) was developed as an alternative to the classical methods for project planning and control (i.e. CPM). CCPM is an extension of Goldratt's *Theory of Constraints* (TOC) (Goldratt 1997). TOC is a tool for managing repetitive production systems based on the principle that every system has a constraint, and its performance can be improved by improving the performance of the constrained resource.

According to CCPM the duration of most activities are overestimated in order to be almost certain (for example 90%) of completing the task on time. As a result the safety margin allocated to the majority of tasks are more than what is really required. Because the safety margin is internal to the activity, if it is not needed, it is wasted. In order to minimise the effect of Parkinson's Law (i.e. activities expand to fill the allocated time), CCPM uses a 50% confidence interval for estimating duration of each activity. For example, if a typical activity was originally estimated to takes 10 days with 90% confidence interval (i.e. we expect to complete the activity in 10 days about 90 out of 100 attempts), the 50% likelihood estimation would be half that, or 5 days. The safety time associated with each activity (i.e. the difference between 50% likelihood estimation and the original estimation) is made explicit and shifted to the end of the critical chain (longest chain) to form the project buffer. The project buffer is considered as part of the project and is used to protect against uncertainty in contingency conditions.

CCPM generated some controversy in the project management community. CCPM proponents claim it is a revolutionary way of thinking and the most important breakthrough in project management history (Steyn 2001). Others dismissed this and argue that CCPM's uniqueness is in the terminology rather than in its substance (Raz et al. 2003). CCPM suffers from following weaknesses:

- It focuses mainly on the uncertainty inherent in the schedule. Instead of addressing the root cause of duration uncertainty, CCPM accepts it and attempts to overcome it by means of buffer management.

- It is presented as a revolutionary concept that replaces, rather than complements current project management practice. Therefore it is not properly integrated with the accepted body of knowledge and state of the practice (Raz et al. 2003).
- The assumption that all task durations are overestimated by a certain factor is questionable and over-simplistic (Pinto 1999).
- Sound estimation of project and activity duration (and consequently the buffer size) is still essential (Trietsch 2005).

2.3.5 Other techniques

Project risk management in general (and quantifying risk in projects in particular) is an interdisciplinary field with input from various research communities with different perspectives including Management Science, Operations Research, Manufacturing/Construction Engineering and Risk Analysis. The Project scheduling literature is visible among the publications of these communities. However, the proposed models seem to work on some small or specially constructed networks and it is not apparent if any of them are used in practice. Therefore, they are not considered here. (Herroelen and Leus 2005) provides an extensive review of fundamental techniques for project scheduling.

An alternative approach that has interested several researchers in the past two decades [(Liberatore 2002), (Kuchta 2001)] is *Fuzzy* project-scheduling. The fuzzy set scheduling literature recommends the use of *imprecision* rather than uncertainty, *fuzzy numbers* rather than stochastic variables and *membership functions* rather than probability distributions. The output of a fuzzy scheduling will normally be a *fuzzy schedule*, which indicates fuzzy starting and ending times for the activities. This may be as difficult to generate as probability distributions of activity duration and also there is no generally accepted computational approach available. Therefore the fuzzy project-scheduling approaches have been kept in the academic sphere. A summary of most of the published research works in fuzzy project scheduling can be found in (Bonnal et al. 2004).

2.4 Current state of practice in project risk analysis

Quantifying uncertainty in project duration is an important part of project risk analysis and project risk management. In the last 50 years a number of techniques were proposed to model project scheduling. The classic approaches (i.e. CPM and PERT) are not practical any more. The Critical Chain approach is too controversial and is not widely accepted/applied by practitioners. Other techniques (e.g. fuzzy based approaches and analytical approaches) are only applied on small projects and are not generally practical in real projects. MCS remains the best practice in modelling uncertainty in project scheduling. In a survey (Raz and Michael 2001) revealed that there is a relation between use of risk analysis tools and better project management performance. They also found that simulation and probability impact assessment are the most commonly used techniques.

Simulation software products, often known as 'risk analysis packages', represent the core of the project risk quantification process. Several of these packages take a project plan that has been created by one of the popular project management software packages (for example *Microsoft Project*, *Primavera Project Planner* or *Open Plan*) and import the durations and the network. They provide advanced MCS to quantify the cost and schedule uncertainty associated with project plans. The choice of available software packages is wide although some products that emerged during the 1990's have not survived into the new millennium (Webb 2003). '*Pertmaster Project Risk*' by (Primavera 2008), *'@Risk for projects'* by (Palisade 2008),'*Risk+*' by (Deltek 2008) are among the most popular software packages. It must also be said that many of these products were created in the early 1990s and their general operational characteristics have not altered to any great degree since then. When changes have arisen they have tended to integrate with other systems rather than adding any significant capability or methodology (Webb 2003).

More importantly the following questions arise:

- How well can these techniques model uncertainty/risk in projects?

- Do they provide enough information and support for project managers in the decision-making process?
- Are they capable of capturing different aspects of uncertainty?

This chapter summarized the current techniques in project scheduling under uncertainty. The next chapter answers the above questions by discussing some important issues that are missed in the current practice and need to be addressed explicitly.

3 The need for a new approach

Despite the extensive research and availability of several techniques and tools in project risk analysis, the dilemma of quantifying uncertainty in projects is still challenging. As (Chapman 2006) argues, there are serious limitations in 'current practice' in project risk management. This chapter explores some key outstanding issues that need to be addressed in modelling uncertainty in projects.

3.1 Causality in project uncertainty

The current project risk management processes induce a restricted focus on managing project uncertainty. As (Ward and Chapman 2003) argue, this is because the term 'risk' has become associated with 'events' rather than more general sources of significant uncertainty. The definition of 'risk' appears to be the most fundamental point of contention in the project risk management community (Chapman 2006). The discussion about terminology and various definitions of risk is not in the scope of this thesis. However, from a modeling point of view it is important to have a broader perspective concerned with the concept of risk/uncertainty.

Managing uncertainty in projects is not just about managing perceived events (i.e. threats or opportunities) and their implications. It is about identifying and managing different sources of uncertainty which shape the perception of possible threats/ opportunities. For example, uncertainty in duration of a particular activity may arise from a lack of knowledge of what is involved rather than from the uncertain consequences of potential threats or opportunities.

The current widespread use of probability and impact assessment as the core concept in quantifying risk in projects is not appropriate because:

- Risk probability assessment investigates the likelihood that each specific risk will occur (PMI 2004). But occurrence of each risk is conditional on some triggers (sources) and allocating unconditional probability numbers to risk events is not sensible (Fenton and Neil 2005a). For example, if the risk is defined as 'key staff leaves the project team' the possible source might be 'job satisfaction' or 'staff motivation'.
- The impact assessment investigates the potential effect on a project objective such as time or cost (PMI 2004). But this assessment is not complete without considering the possible mitigating responses. For example, the impact of 'key staff leaves the project team' is influenced by the possible responses such as 'recruiting new staff' or 'reallocating the jobs'.

As (Ward and Chapman 2003) explain, the use of 'probability impact' for quantifying risks generates unnecessary uncertainty by over-simplifying estimates of impact and associated probability. They argue that the use of 'probability impact' should be completely killed off (Chapman and Ward 2002).

As (Atkinson et al. 2006) discuss, the deliberations about uncertainty in projects should focus on appreciating the variety of sources of uncertainty requiring management attention. This is well beyond a set of possible events that might impair project performance. This has implications for the development of quantitative approaches to project risk analysis. These approaches need to recognise the full range of sources of significant uncertainty. They also need to be able to model the causal relationship (dependency) between the related variables and the possible control/response mechanism that affecting their influence on the project.

A causal framework for risk can provide an unambiguous and useful description of risk for the purpose of modeling and analysis. For example, a risk may be characterized by a causal chain involving the risk itself (i.e. event or condition) and at least one consequence which characterises the impact (e.g. delay). Additionally there may be one or more *trigger* (source), one or more *control*, and

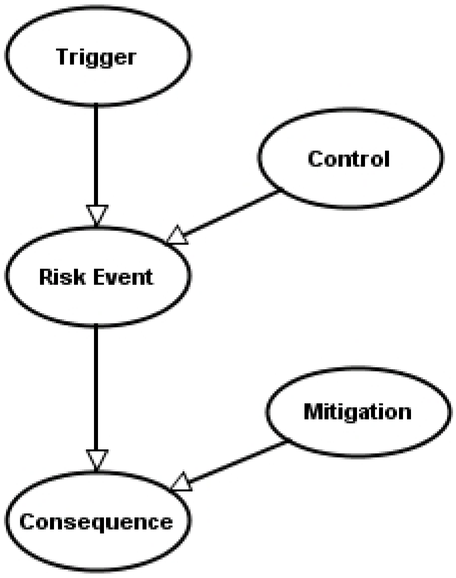


Figure 3-1 : Causal framework of risk

one or more *mitigating* (response) as shown in Figure 3-1 (Fenton and Neil 2005b).

A number of authors, for example (Ackermann et al. 2007), (Eden 2004), (Maytorena-Sanchez et al. 2004) and (Rodrigues and Bowers 1996), suggest applying 'System Dynamics' and 'Cognitive Mapping' technique for modelling such causality in complex projects. Cognitive mapping, also known as 'cause mapping', is a visual representation of subjective data which can demonstrate the causal chain between elements of a project. Figure 3-2 shows an example of a cognitive map that demonstrates the causal relation between, for example, 'use of state of the art technology' and 'potential for schedule delay' in a complex project (Ackermann et al. 2007). It is a useful technique for identifying risks and understanding the complex relationship between them. However, it is purely qualitative and cannot quantify the project uncertainty. A better alternative, which is capable of quantitative modelling, will be introduced and discussed in detail in chapter 4.

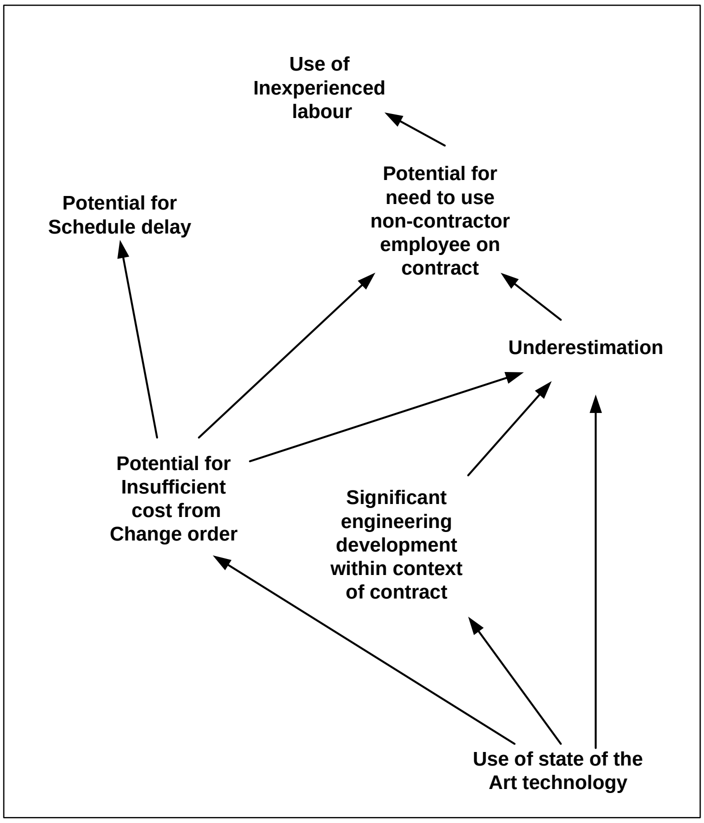


Figure 3-2 : An example of a cognitive map (Ackermann et al. 2007)

3.2 Estimation and Subjectivity

One of the most important as well as challenging aspects of project management (and project risk management) is the estimation of project parameters (i.e. time and cost). The reliability of output of any model depends on the quality of estimations (garbage in garbage out). Usually estimation is made by probabilistic assessment of future conditions. Understanding the nature of probability helps to understand the nature of estimation.

There are two types of probability:

- Frequentist
- Subjective

Frequentist probability (also known as *aleatoric* - alea means dice in Latin) arises from a complete random/uncertain situation (Shafer 1976). Frequentist uncertainty can be estimated by use of historic data. Subjective probability (also known as *epistemic*) on the other hand, is related to a measure in belief in a proposition, or more generally to a lack of complete knowledge (Oakes 1986).

Any estimation is conditionally dependent on some assumptions and conditions even if they are not mentioned explicitly. These assumptions and conditions are major sources of uncertainty and need to be addressed and handled explicitly.
For example, the duration of an activity is uncertain because we are not sure how much effort (resource) is required to complete the activity. Just because we are uncertain about a quantity does not mean that it is random (may take any value in the range by chance).

Frequentist uncertainty can be modeled by classical frequentist methods, for example MCS. The greater challenge is to model subjective uncertainties. Purely subjective probabilities (guestimates) are unreliable and inconsistent and suffer from inaccuracy, which may lead to faulty or biased estimations. More sophisticated methods that support coherent use of subjective probabilities is needed. The Bayesian approach to probability provides a formal framework for such methods. Details of Bayesian probability will be discussed in chapter 4.

3.3 Unknown Risks

One important category of uncertainty in projects is 'Unknown Risks'. These are important sources of uncertainty because their impact on a project may outweigh all other sources of risks.

Although unknown risks are thoroughly acknowledged (perhaps with different names) by several authors, none of the existing approaches for project scheduling is able to model and quantify this type of risk. The conventional 'probability impact' approach at best is only capable of modelling 'known risk'. Most of the current quantitative techniques for risk analysis are event-oriented and more concerned about 'risk of something happening'. They assume that a list of events (conditions) that may take place is known, the impact of each risk on activity duration is also known and even the nature of the response to each risk is roughly known.

Unknown risks are undiscovered (unpredictable), unattended (too much effort is required to clarify them) or immeasurable (their impact is unknown or hard to quantify). An example of unknown risks are *'Internally Generated Risks'* (IGRs) as described in (Barber 2005). IGRs have their origin within the project organisation, arising from rules, policies, structures, actions, decisions, behaviours or culture. They are:

- Common, because organisational issues (e.g. policies, processes, culture etc.) are widespread in most projects.
- Important, because they often influence more that one activity.
- Poorly managed in projects, because they are hardly documented in risk registers and also they are often intangible and hard to quantify.

Current risk analysis approaches are unable to deal with unknown risks. However, unknown risks are not developed totally 'out of the blue' and should be considered in quantitative techniques. (Chapman and Ward 2003) and (Chapman et al. 2006) suggest using a single adjusting factor called *'cube factor'*. Also known as *'KUUUB factor'*, it reflects three subjective scaling factors for:

- *Known Unknowns* are explicit assumptions that matter. These are identified sources of uncertainty that could have uncertain consequences (see risk register as discussed in section 2.1).
- *Unknown unknowns* are implicit assumptions that might have uncertain consequences.
- *Biases* are systematic estimation errors. 'Availability', 'anchoring' and 'selective' are examples of estimating bias. 'Availability' means estimators assess the probability of an event simply by the cases that can be brought to mind. 'Anchoring' refers to human tendency to stay close to the initial estimate. 'Selective' refers to cases when "you see what you want to see", for example when there is an intention to plan the activity time in a deadline or the activity cost in a budget.

Using the adjustment factor approach appears to be a practical method for modeling unknown risks. However, it also involves a great degree of subjectivity.

3.4 The Trade-off between time, cost and performance

By its definition a project has to be completed in a limited time, with a tolerable cost and within some expected level of performance. Hence, time, cost and performance are the main targets of a project and meeting one or some of these targets is the main success criteria (objectives) in most projects.

The concept of success factors in projects has been widely studied (Fortune and White 2006). However, defining the ‘true’ success factor of a project is not easy and it may even change in different phases of a project.

Most projects usually have a pre-defined time (i.e. deadline), cost (i.e. budget) and quality (i.e. requirement and specifications) which are discussed and agreed in the project contract. However, in operation these objectives are variables and also inter-relate with each other. Working towards achieving one is usually detrimental to the other two: "Good! Fast! Cheap! Pick any two" (Kohrs and Welngarten 1986). In fact, balancing these threefold objectives, also known as trade-off analysis, is one of the essential decisions that project managers make.

For example, the minimum possible time to finish an activity can be achieved at a maximum level of effort (assuming the quality is not sacrificed). By extending activity duration, the effort required is usually reduced. The upper time limit for an activity is the point which beyond that further reductions in effort (i.e. cost or resources) is small. Within this time range, the project manager can balance time, effort, and quality to achieve the overall objective of the project.

Depending on the actual constraints (objectives) of the project, this trade-off analysis enables us to minimize the activity (project) duration under budget constraints or minimize the budget that is required to accomplish the project on the scheduled deadline.

The importance of the trade-off problem has long been recognised. A simplified version (i.e. assuming duration and cost are deterministic) of the trade-off problem known as *'Resource Constrained Problem' (*RCP*)*, has attracted a wide range of research in the operations research literature. Several heuristics and approximation methods are proposed (Brucker et al. 1999). They suggest using different continuous functions for approximating the time-cost trade-off. The problem has been solved for relatively small instances when the time-cost relation is approximated by a single scope linear function. But it still remains a challenge for more complex (realistic) functions even with the assumption that duration and cost are deterministic. The formulation of a stochastic time–cost trade-off is even more complex if possible at all (Herroelen and Leus 2005).

In practice, current project scheduling tools require the manual translation of design information (i.e. time and cost) to activities and typically do not provide dynamic links between time estimates and corresponding costs. This can be addressed by defining the conditional dependencies and causal relations between different project objectives.

3.5 Dynamic Learning

Despite the fact that projects are different and usually one-off experiences, the need to learn from one project to the next is clearly of particular importance to managing uncertainty in projects. "As managers, executives, and researchers in project management, we have yet to learn how to learn" (Cooper et al. 2002).

Complex projects usually have a dynamic behavior. This is due to the influence of various known and unknown factors and the management actions taken in response. One of the great challenges is to explore this dynamic behavior, identify the causes of these behaviors, quantify (at least roughly) the scale of them and extract decision-making lessons. This includes both obvious and intuitive lessons and also lessons about complex non-intuitive behaviors of projects. Modelling (and where appropriate quantitative modelling) plays an essential role in deriving these lessons. Causal models can explain project behaviour and enable lessons to be identified and learned (Williams 2003b).

Learning is also useful for capturing the effect of 'Unknown Unknowns'. As addressed in section 3.3 the unknown risks are difficult to quantify. The adjustment factor approach can roughly capture their effect but the estimation of this factor is highly subjective. This estimation can be improved by learning from new information (i.e. evidence) as the project progresses.

At the start of a project there is little evidence about the distribution of unknown factors (unless it is learnt from previous projects). They can be estimated subjectively by a non-informative distribution (e.g. uniform distribution) or by a distribution with a large variance. As the project progresses new information (e.g. actual progress of activities) becomes available. The difference between the actual and estimated duration of an activity can update the belief (i.e. distribution) about unknown factors. Assuming that unknown factors are common throughout the project (for example organisational issues), this learnt distribution of unknown factors now can be used for upcoming activities (phases) of the project as well as future projects with similar conditions. This will improve the duration estimations and in consequence the quality of decision made. Examples of such a learning mechanism will be discussed in chapter 6.

3.6 A new approach is needed

Project risk analysis techniques have not been fully matured and there are a number of areas requiring further development. This chapter discussed a number of issues that need to be addressed in order to enhance the effectiveness of project risk analysis in general and project scheduling in particular. The current level of risk analysis is often shallow, largely driven by the capabilities of the available tools and techniques.

Current practice of project scheduling is firmly based on the probability-impact concept which limits its ability to model the actual risk (uncertainty) involved in projects. It suffers from the following limitations:

- It treats risk as external events with known probability, therefore fails to address the causal relation between various sources of uncertainty.
- It assumes the impact is known and definable, therefore fails to address the management actions.
- It is based on the assumption of randomness (i.e. frequentist probability) whereas most project uncertainty is subjective (lack of knowledge).

The aim of this thesis is to develop a new approach for analysing project uncertainty that explicitly addresses the key issues underlying this chapter. The model offers a new methodology for quantifying uncertainty in project scheduling and adds significant capabilities to the project risk analysis.

Nevertheless it must be said that uncertainty and ignorance are inevitable on projects. Therefore the result of the model (in fact any risk analysis model) should not be regarded as a conclusion (i.e. assuming its results are exact). No model can remove or even lessen the uncertainty; therefore the analysis should be seen as giving a deeper insight, not as a method of increasing certainty. It should quantify various sources of uncertainty and explore their effects on project parameters in order to support decision-making and prompt possible responses to risk. In other words, we analyse risk to understand it and make informed decisions. As (Redmill 2002) asserts:

> “It is often claimed that the greatest value of risk analysis lies not in the values derived but in the fact that the process forces us to think deeply about, and therefore better understand, the risks”.

Analysing risk/uncertainty in projects is not just about applying some probability distribution to project parameters and getting probabilistic results. It should capture different aspects of ‘incomplete knowledge’ (Pender 2001), quantify and integrate them and provide better understanding of project risk. This means providing "decision support" and "what-if analysis" capabilities to decision makers. This can be achieved by addressing trade-off analysis, unknown risk and dynamic learning explicitly. More sophisticated techniques are required.

4 Bayesian inference and Bayesian Networks

The primary vehicle that I have adapted for handling uncertainty in project scheduling is *Bayesian Networks* (BNs). This chapter reviews BNs and all the associated theoretical and technical issues related to their development, use and validation. It first outlines a brief overview of the Bayesian approach including its background, Bayes' theorem and Bayesian inference. Then BNs and their features are discussed.

4.1 The Bayesian approach to probability and statistics

In order to understand BNs, it is important to understand the Bayesian approach to uncertainty. This section provides an introduction to the Bayesian approach.

4.1.1 Background

The term 'Bayesian' came into common usage in the 1950s, although the origin of the Bayesian approach goes back to 1763, when Thomas Bayes published his famous paper (Bayes 1763). This contained the first detailed description of a theorem derived from elementary probability theory, which is now associated with his name. During the 19th century, when mathematicians and philosophers continued to debate the meaning of probability, the idea of *'inverse probability'* (i.e. inferring backwards from the data to parameters) was dominant in practical application of statistics (Fienberg 2006).

During the first decades of the twentieth century an alternative approach, later named as *'frequentist'* because of its frequency interpretation of probability, was developed. This was based on Fisher's approach to inference (Fisher 1922), where 'likelihood' was claimed as a distinct form of probability (probability predicts unknown outcomes based on known parameters whereas likelihood estimates unknown parameters based on known outcomes). Later the method of *hypothesis* *testing* and *confidence intervals* revolutionized both the theory and practice of statistics. The frequentist method, which some refer to as 'classical statistics', quickly spread to diverse areas of applications and supplanted the inverse probability in the first half of the twentieth century (Efron 2005).

In the 1950s, there was a renewed interest in foundations and statistical decision theory that led to developments surrounding the role of 'subjective probability' and new statistical tools for scientific inference and decision-making. This was the Neo-Bayesian revival that fused the renewed emphasis on the likelihood principle with Bayes' theorem and subjective probability as the mechanisms for achieving inferential coherence (Fienberg 2006).

In the following decades the applications of Bayesian statistics grew in the number of published papers and users. The modern era of the Bayesian approach began in the late 1980s when the introduction of Monte Carlo Markov Chain (MCMC) methods made Bayesian computations possible for realistic-sized problems. Since then Bayesian methods have spread rapidly into a large variety of application areas.

4.1.2 Bayesian vs. frequentist

Generally, the field of statistics is concerned about inferring the probability of an uncertain event. The difference between classical and Bayesian approach is summarised in Table 4-1.

	Frequentist	**Bayesian**
Variable	Random	Uncertain
Probability	Physical property (objective)	Degree of Belief (Subjective)
Inference	Confidence interval	Bayes' theorem

Table 4-1 : Frequentist vs. Bayesian approach

In the classical approach (i.e. frequentist) parameters (i.e. variables) are random, probability is a physical property (also known as relative frequency or objective) and confidence interval techniques are used to infer something about relative frequencies. In contrast, in the Bayesian approach variables are uncertain, probability is a property of the person who assigns the probability (i.e. subjective probability) and Bayes' Theorem is used to infer unknown probabilities of events from known probabilities of other events.

Both approaches have their own advantages and disadvantages, which have led to an endless debate (Efron 2005) that is beyond the scope of this thesis.

The frequentist approach for measuring uncertainty requires accurate information about many past instances of the event (i.e. repeated trials). The subjective approach is based on some prior body of knowledge and measuring uncertainty is conditional on this prior knowledge.

In reality most uncertain events of interest do not have a lot of historical data associated with them and even where relevant historical data does exist it must still usually be informed by subjective judgements before it can be used for measuring uncertainty. So we cannot rely on the frequentist approach to measure them. The Bayesian approach is the only feasible method for tackling many practical problems. For example, for the 'probability that England win the next world cup', the frequentist approach has no answer but the Bayesian approach can assign a value.

The Bayesian approach can also provide a rational way of revising our beliefs in the light of new information (i.e. evidence).

4.1.3 Bayes' Theorem

Obtained from the elementary axioms of probability, Bayes' theorem expresses the relationship between conditionally dependent variables. Bayes' theorem uses a numerical estimate of the degree of belief in a hypothesis before some evidence has been observed and calculates a numerical estimate of the degree of belief in the hypothesis after the evidence has been observed.

Formally, Bayes' theorem is stated as:

$$P(H/E) = \frac{P(E/H) \cdot P(H)}{P(E)} \qquad \text{where } P(E) \neq 0$$

Equation 4-1

Here:

- *H* represents a *hypothesis* and *E* represents some *evidence*.
- *P(H)* is called the *'prior probability'*. This is our prior belief about the hypothesis before we have observed the evidence. In other words *P(H)* is the uncertainty distribution that represents the state of our knowledge about the hypothesis without observing any evidence. In the absence of empirical data subjective probability can be used for assessing *P(H)*.
- *P(E/H)* is called the *'likelihood function'* . It indicates the probability of observing evidence given the hypothesis.
- *P(H/E)* is called the *'posterior probability'*. This is the description of our state of knowledge about the hypothesis after observing the evidence.
- *P(E)* is called the '*marginal probability'* of *E*. This is the probability of witnessing the new evidence *E* under all possible hypotheses. It can be calculated as:

$$P(E) = P(E/H)P(H) + P(E/\neg H)P(\neg H) \quad (\neg\, H \textit{ is the copmplement of } H)$$

Equation 4-2

In general, given n mutually exclusive and exhaustive hypotheses $H_1, H_2, ..., H_n$ such that $P(H_i) \neq 0$ for all $1 \leq i \leq n$ the full version of Bayes theorem is:

$$P(H_i / E) = \frac{P(E/H_i) \cdot P(H_i)}{\sum_{j=1}^{n} P(E/H_j) \cdot P(H_j)}$$

Equation 4-3

In continuous form, Bayes' theorem is expressed as:

$$f(\theta / X) = \frac{\pi(\theta) \cdot l(X / \theta)}{\int \pi(\theta) \cdot l(X / \theta) d\theta}$$

Equation 4-4

4.1.4 Bayesian Inference

Bayesian inference is based on a conceptually simple collection of ideas. We are uncertain about the quantity of a parameter. We can quantify our uncertainties as subjective probabilities for the parameter (prior probability), and also conditional probabilities for observations we might make given the true value of the parameter (likelihood function). When data arrives, Bayes' theorem tells us how to move from our prior probabilities to the new conditional probabilities for the parameter (posterior distribution) (Goldstein 2006). The following example illustrates how Bayesian inference is performed.

Example 4-1:

A project manager is analysing the cause of delay in a particular task in a project. A part of the task is done by a sub-contractor. The project manager believes, based on the good reputation of the sub-contractor, that there is 95 percent chance of delivering the sub-contract on time. There is an 80 percent chance of a delay in the task if the sub-contractor fails to deliver on time. Even if the sub-contractor delivers on time, there is still a 10 percent chance that the task overruns its schedule (as a result of other internal reasons). If the task is actually late, what is the probability that the sub-contractor had failed to deliver on time?

Before knowing about this particular task, subjective estimation (e.g. sub-contractor's reputation) reflects the prior probability of having the sub-contract delivered on time (SC):

$P(SC) = 0.95$ and hence,
$P(\neg SC) = 0.05$

The likelihood function is the conditional probability of delay in the task given the actual state of sub-contract delivery:

$P(Delay / SC) = 0.1$ and hence,
$P(\neg Delay / SC) = 0.9$
$P(Delay / \neg SC) = 0.8$ and hence,
$P(\neg Delay / \neg SC) = 0.2$

Using Bayes' rule (Equation 4-1) to update the probability, the posterior probability (i.e. the chance of sub-contract being delivered on time given the task is late) is:

$$\mathrm{P(SC/Delay)} = \frac{\mathrm{P(Delay/SC)} \cdot \mathrm{P(SC)}}{\mathrm{P(Delay/SC)} \cdot \mathrm{P(SC)} + \mathrm{P(Delay/\neg SC)} \cdot \mathrm{P(\neg SC)}}$$
$$= \frac{0.1 \times 0.95}{0.1 \times 0.95 + 0.8 \times 0.05} \approx 0.70$$

So the prior probability of 95% is revised to 70% as a result of the evidence of a delay in the task.

Bayesian inference when there are only two variables involved is fairly simple (as shown in the above example). However, it becomes much more complex when several variables with several states are involved and a complex set of conditional dependencies exists between them. BNs are introduced to overcome this problem.

4.2 Bayesian Networks

Bayes' theorem has been used to perform probabilistic inference in the situation where one feature of an entity has a direct influence on another feature of that entity (e.g. delay in sub-contract influences the delay in task in example 4-1). Now consider the situation in which several features are related through inference chains and we are interested in probabilistic inference involving features that are not related via a direct influence. In these situations the conditional probabilities cannot be computed using a simple application of Bayes' theorem. BNs have been developed to address this situation. BNs (also known as Belief Networks, Bayes Nets, Causal Probabilistic Networks, Causal Nets, Graphical Probability

Networks, Probabilistic Cause-Effect Models, and Probabilistic Influence Diagrams) enable us to perform probabilistic inference among several features in an acceptable amount of time.

In addition, the graphical nature of BNs gives us a much better intuitive grasp of the relationships among the features (Neapolitan 2004). This section defines a BN and shows how it can be constructed.

4.2.1 BN definition

A BN consists of a set of *nodes* (representing variables) and a set of *directed edges* (representing causal influences between variables) between variables (Jensen 1996). Each variable has a finite set of mutually exclusive states. The variables together with the edges form a *directed acyclic graph* (DAG) (a directed graph is acyclic if there is no directed path $A_1 \to \cdots \to A_n$ such that $A_1 = A_n$). To each variable 'A' with parents $B_1,...,B_n$, a conditional probability table $P(A / B_1,...,B_n)$ is assigned. If the variable has no parents then the table reduces to the unconditional probabilities $P(A)$ (i.e. prior probability).

One important property of BNs is their ability to represent the joint probability distribution $P(A_1,...,A_n)$ for all the variables $A_1,...,A_n$ in a compact form. This is done by use of the '*chain rule*', which says in a BN the full joint probability distribution is the product of all conditional probabilities specified in the BN (Jensen 1996):

$$P(A_1,...,A_n) = \prod_i P(A_i / A_1,...,A_n)$$

Equation 4-5

The more compact representation of the joint probability makes the probability calculation easier. If we have access to the joint probability distribution, then we can calculate the marginal probability for any variable, $P(A_i)$ (see section 4.1.3

and Equation 4-2), and also the conditional probability of $P(A_j / A_i = a_i)$ (see section 4.1.3 and Equation 4-3).

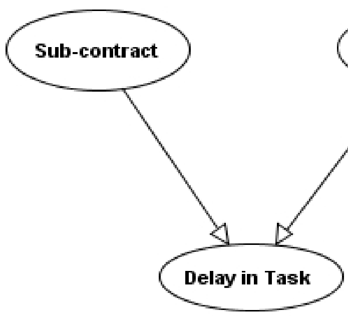
BNs address the problems of storing and representing the joint probability distribution of a large number of random variables and also doing Bayesian inference with these variables.

Example 4-2:

Suppose in addition to the sub-contract delay in example 4-1, the project manager has noticed that the 'staff quality' also has a direct influence on the task's duration and therefore on its delay. Now there are two independent variables that influence another variable. Figure 4-1 shows the BN for this example.

'Sub-contract' and 'Staff Quality' are parents of 'Delay in Task'. The links represent the causal or influential relation between the variables. Each node has a set of possible states (e.g. 'on time' and 'late' for sub-contract node). Attached to each node, there is a *'Node Probability Table'* (NPT). The NPT can be a prior probability (e.g. 'Staff Quality' in Figure 4-1) or a conditional probability given the states of its parents (e.g. 'Delay in Task' in Figure 4-1) . The NPT values can be assessed by prior knowledge (subjective estimation or expert judgment), empirical data, or a combination of both.

On time	0.95
Late	0.05



Good	0.7
Poor	0.3

Sub-contract	On time		Late	
Staff Quality	Good	Poor	Good	Poor
False	0.95	0.7	0.7	0.01
True	0.05	0.3	0.3	0.99

Figure 4-1: BN and NPT for each node for example 4-2

We want to know the probability of a variable given observations on other variables. For example the probability that the task finishes on time without any evidence is $P(Delay\ in\ Task\ is\ true) = 0.855$.

This is called the *marginal distribution*. To see how this can be calculated by Equation 4-2 let us define the following notation:

$$
\begin{array}{lll}
D: \ Delay\ in\ Task & (d_1: \ D\ is\ 'false',\ d_2: D\ is\ 'true') \\
SC: \ Sub\text{-}contract & (sc_1: \ SC\ is\ 'late',\ \mathrm{sc}_2: \ SC\ is\ 'on\ time') \\
SQ: \ Staff\ \ Quality & (sq_1: \ SQ\ is\ 'good',\ \mathrm{sq}_2: \ SQ\ is\ 'poor')
\end{array}
$$

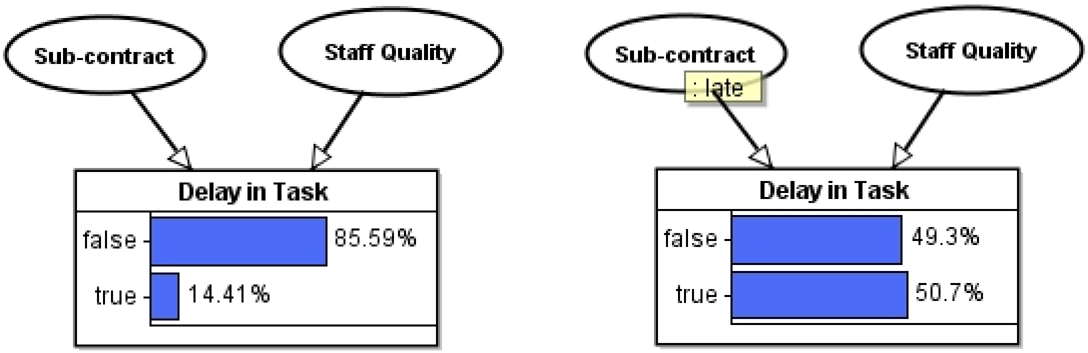
According to the chain rule (Equation 4-5) the joint probability distribution is:

$$P(D,\ SC,\ SQ) = P(D/SC, SQ) \cdot P(SC).P(SQ)$$

The marginal probability distribution for 'Delay in Task' can be calculated using Equation 4-2:

$$
\begin{aligned}
P(D,\ SC) &= \sum_{j=1}^{2} P(D/SC, sq_j) \cdot P(SC).P(sq_j) \\
P(D) &= \sum_{i=1}^{2} \sum_{j=1}^{2} P(D/sc_i, sq_j) \cdot P(sc_i).P(sq_j) \\
P(D = d_1) &= \sum_{i=1}^{2} \sum_{j=1}^{2} P(D/sc_i, sq_j, D = d_1) \cdot P(sc_i).P(sq_j) \\
&= 0.95 \times 0.7 \times 0.95\ +\ 0.7 \times 0.3 \times 0.95\ +\ 0.7 \times 0.7 \times 0.05\ +\ 0.01 \times 0.3 \times 0.05 \\
&= 0.8559
\end{aligned}
$$

Figure 4-2a shows the probability graph for marginal distribution of 'Delay in Task'.



a) $P(Delay\ in\ Task\ is\ true)$ b) $P(Delay\ in\ Task\ is\ true / Sub\text{-}cont.\ is\ late)$

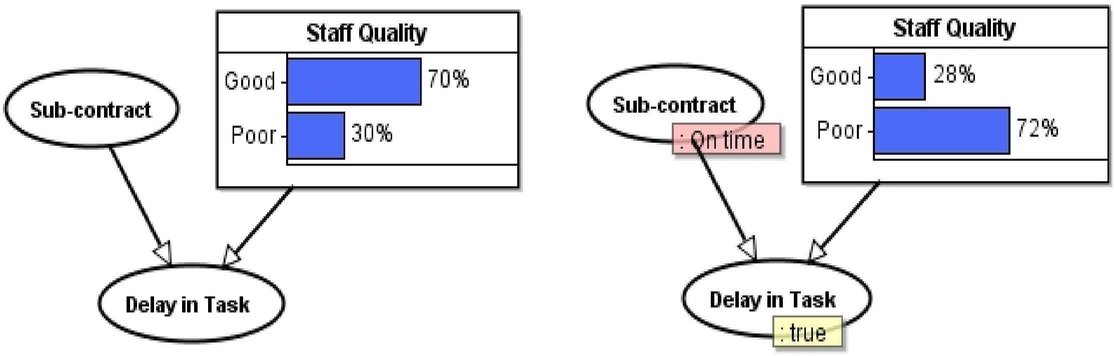
Figure 4-2: Probability of task finishes on time a) with no evidence, b) sub-contract is late

The predictive capability of the model enables us to infer from cause to effect (from parent to child). For example, suppose that we know the sub-contractor has failed to deliver on time. The new information (evidence) is used to update our belief about the probability of finishing the task on time. This is the posterior distribution of 'Delay in Task' and can be calculated as follows:

$$
\begin{aligned}
P(D,\ SC, SQ / sc_2) &= P(D / sc_2, SQ) \cdot P(sc_2).P(SQ) \\
&= \sum_{i=1}^{2} P(D / sc_2, sq_i) \cdot P(sq_i) \\
&= 0.7 \times 0.7 + 0.01 \times 0.3 \\
&= 0.493
\end{aligned}
$$

Figure 4-2b shows the probability graph for the posterior distribution of 'Delay in Task' given the 'Sub-contract' was late.

The diagnostic capability of the model enables us to infer from effect to cause (from child to parent). For example, suppose the 'sub-contract' is delivered on time but there is a delay in the task. We want to update our belief (Figure 4-3a) about the distribution of 'staff quality'. Figure 4-3b shows how new information about 'Sub-contract' and 'Delay in Task' updates the probability graph for 'Staff Quality'. This is the conditional probability and can be calculated by Equation 4-3 as follows:



a) $P(staff\ \ quality\ is\ good) = 0.7$ b) $P(staff\ \ quality\ is\ good) = 0.28$

Figure 4-3: Probability of 'staff quality' a) with no evidence, b) after observing evidences

$$
\begin{aligned}
P(SQ = sq_1 / D = d_2, SC = sc_1) &= \frac{P(D = d_2, SC = sc_1 / SQ = sq_1).P(SQ = sq_1)}{P(SQ)} \\
&= \frac{0.05 \times 0.7}{0.05 \times 0.7 + 0.3 \times 0.3} \\
&= 0.28
\end{aligned}
$$

4.2.2 BN a method of knowledge representation

In addition to the basic property of BN (i.e. use of the chain rule for calculating joint probability table), a BN is a graphical model. The structure of the network is formulated in a graphical communication language. By use of three general connections, which are serial, diverging and converging connections (Figure 4-4), it can capture all the possible ways in which variables can become dependent/independent. The link between two variables can often be interpreted as representations of causal relation between them.

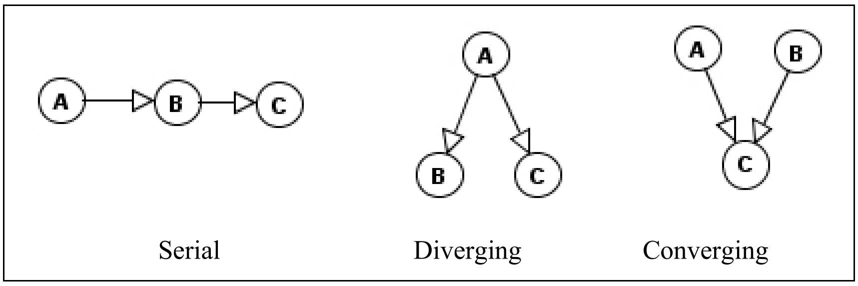


Figure 4-4: Basic causal connections

The graphical language of BNs makes it easier to understand and explain the causality. In this respect, BNs can be used for interpersonal communication. Its graphical specification is easy for humans to read, and it helps focus attention.

In addition to causal knowledge, BNs provide a meaningful way for modeling various type of knowledge such as deterministic, statistical and analogical (Neil et al. 2000). BNs provide a powerful method for knowledge representation, which makes them suitable for a wide range of problems involving uncertainty and probabilistic reasoning.

4.2.3 Constructing a BN

Building a BN for a domain of application involves three main steps:

Step I) Identify the variables that are of importance, along with their possible state values.

Step II) Identify the relationships between the variables and express them in a graphical structure.

Step III) Assess the probabilities required for its quantitative part.

The above three steps are, in principle, performed one after the other. However, building a BN usually requires a careful trade-off between the desire for a large and rich model on the one hand and required effort for construction, maintenance, and probabilistic inference in the network on the other hand. In practice, therefore, building a BN is a creative process that iterates over these steps until a desired network is achieved.

The initial step (identifying variables) is not always straightforward. (Heckerman 1996) suggests the following as a guideline for defining variables:

1) Correctly identify the goals of modeling (e.g. prediction versus explanation versus exploration)
2) Identify many possible observations that may be relevant to the problem

3) Determine what subset of those observations is worthwhile (considering the complexity of the network) to model
4) Organize the observations into variables having mutually exclusive states.

(Jensen 2001) suggests three type of variables when building a BN model:

1) *Hypothesis variables*: these are not observable variables (or only observable at an unacceptable cost). Identifying these variables is the primary task in BN model building.
2) *Information variables*: these variables can be observed (and reveal something about hypothesis variable)
3) *Mediating variables*: these are introduced for a special purpose (for example to simplify the conditional probabilities tables).

During development of a BN, variables (nodes) can be easily added or modified. The graphical nature of BNs allows variables to be conveniently added or removed without significantly affecting the remainder of the network.

After defining the variables, the next step is to construct the graphical part of network. This requires identifying the probabilistic dependency between the represented variables and capturing them in directed arcs. The direction of arcs needs to be defined carefully. (Neil et al. 2000) recommend a category of five types of reasoning between variables, called *idioms* (i.e. definitional/synthesis, cause-consequence, measurement, induction and reconciliation), as a guideline for constructing the network. However, for domain experts who do not have a background of probability theory this might add unnecessary complexity to the modeling process. The simplest way is to take the direction of causality (cause to effects) for direction of the arc between variables. This is merely a guideline principle, therefore the resulting graphical structure has to be reviewed and refined in terms of dependency between variables.

For instance, in example 4-2 the direction of arc is from ‘staff quality’ (i.e. cause) to ‘delay in task’ (i.e. effect).

The last step in building a BN is assessment of probability values and assigning them to the node probability tables (NPT). The NPT represents the strength of the causal dependency between connected nodes. Depending on the type of a node (i.e. discrete or continuous) , the NPT might be a discrete probability table or a continuous probability distribution. In prior nodes (without any parent) the NPT is the prior probability, which can be estimated subjectively or based on empirical data. In nodes with parents, the probability of every state of the node conditional on every instance of its parents is assessed. In example 4-2, the NPT for 'delay in task' contains the probability values for all possible combination of states for all three nodes (see Figure 4-1).

For instance, when the 'Sub-contract' is 'on time' and 'Staff Quality' is good, the probability of 'Delay in Task' is estimated 0.05. This might come from previous data or in most cases from expert opinion. Eliciting these probabilistic values appears to be hard and time-consuming.

The most common sources of information for eliciting numeric probabilities are (statistical) data, literature, and domain experts. In data-rich application domains, statistical data can be used to elicit probabilities. However, in many application domains (including project risk management) there are few or no reliable data available. Therefore the knowledge and experience of experts in the domain of application is the main source of probabilistic information. A number of formal methods (e.g. structured interviews with experts) have been developed for eliciting probabilities (Renooij 2000), (Meyer and Booker 1991) and (van der Gaag *et al.* 1999). However, these techniques tend to be quite time-consuming and given that an expert's time is usually scarce and expensive, they are impractical if not impossible in real-life problems (Druzdzel and van der Gaag 2000). A number of techniques have been developed that reduce the number of probabilities to be assessed. Two such techniques that are used in this thesis will be discussed in section 4.4.1.

In many situations (especially for numeric nodes) the NPT for the child node can be set as a distribution based around a single expression (such as an arithmetic expression or minimum or maximum of the parents).

4.2.4 Inference in Bayesian Networks

Once a BN is constructed, we are able to determine various probabilities of interest from the model. These probabilities are not stored directly in the model, and hence need to be computed. Since a BN involving a set of variables determines a joint probability distribution for the variables, we can (in principle) use the BN to compute any probability of interest. However, exact inference in BNs is known to be NP-hard (Cooper 1990) and (Dagum and Luby 1993). In response, several methods have been developed to improve the efficiency of probabilistic inference in BNs including:

- (Shachter 1988) developed an algorithm that reverses arcs in the network structure until the answer to the given probabilistic query can be read directly from the graph.
- (Pearl 1986) developed a message-passing scheme that updates the probability distributions for each node in a BN in response to observations of one or more variables.
- (Jensen 1996) created an algorithm, called '*Junction Tree',* that first transforms the BN into a tree where each node in the tree corresponds to a subset of variables in the BN. The algorithm then exploits several mathematical properties of this tree to perform probabilistic inference, also called '*propagation*'. The 'Junction Tree' algorithm is the most commonly used technique and is adopted by the state of the art Bayesian technology (AgenaRisk 2007) and (Hugin 2007).

4.2.5 Software Tools for BNs

There are several commercial [(AgenaRisk 2007), (Hugin 2007), (Netica 2007) and (Riscue 2007)] as well as non-commercial [(WinBUGS 2007) and (OpenBayes 2007)] software tools for developing BN models. These tools provide a graphical editor for building the BN and also a runtime module, which takes care of probabilistic calculation and evidence transmission. With such tools it is possible to build a BN and also perform the propagation algorithm in a reasonable amount of time.

In this thesis, I have used the AgenaRisk toolset (AgenaRisk 2007) for building and running all the models described later. Given the close relationship between the RADAR (Risk Assessment and Decision Analysis Research group in Queen Mary University of London) and the Agena company, the choice of AgenaRisk software was inevitable. In contrast to other BN tools, AgenaRisk provides the following features that were especially important for the kind of models developed in this thesis:

- A powerful and highly intuitive user interface
- Capability of linking pre-defined BNs to construct large-scale networks.
- A wide range of built-in statistical distributions and expressions for constructing NPTs.
- Capability of mixing discrete and continuous nodes to model qualitative and quantitative variables in a model (i.e. hybrid model).

The other major benefit of using AgenaRisk was that I was able to influence its development through testing and feedback. This is because AgenaRisk follows an *Agile* development method (Schwaber and Beedle 2002). Agile methodologies are an iterative approach to software development. Each iteration delivers more functionality but also responds to constant customer feedback (Agile Manifesto 2008). The models produced in my study were used to test the functionality of the new versions of the toolkit. Feedback and detected bugs were directly reported to the AgenaRisk development team.

During the course of my studies several such iterations made major enhancements in the AgenaRisk toolkit. A number of these enhancements that are relevant to the type of BN model used in this thesis are explained in section 4.5.

However, there are still limitations in the toolkit (for example efficiency of the inference algorithm and also backward propagation between linked networks) that need to be addressed.

4.3 Applications and Advantages of BNs

BNs offer a powerful, general and flexible approach for modelling risk and uncertainty. The advantages of BNs are now widely recognized and they are being successfully applied in diverse fields. During the last decade, researchers have incorporated BN techniques into easy-to-use toolsets, which in turn have enabled the development of decision support systems in a diverse set of application domains. Since 2000 further technology and tool advancements mean that end-users, rather than just researchers, are now able to develop and deploy their own BN-based solutions. The number of applications of BNs has been increasing year-on-year (Fenton and Neil 2007a).

The first working applications of BNs focused on classical diagnosis in medicine (Horvitz et al. 1989). Companies such as Microsoft and Hewlett-Packard have used BNs for fault diagnosis, and in particular printer fault diagnosis (Breese and Heckerman 1996). A range of BN-based systems is being used to improve decision support and assessing safety in critical systems. These include BN models to predict human errors in complex socio-technical systems (Gregoriades et al. 2003a) and (Gregoriades et al. 2003b), air traffic management (Neil et al. 2003), railway safety assessment (Marsh and Bearfield 2004) and terrorist threat assessment (Laskey and Levitt 2002).

Recently a number of BN models have been developed for quantification of operational risk in investment banking (Ramamurthy et al. 2005) and (Neil et al. 2005). Software quality and fault prediction in software engineering has been another application of BNs (Fenton et al. 2002). In addition, BNs have been used in many other fields such as SPAM filtering, personalization systems, legal reasoning, ecology and security. The online bibliography in (Fenton 2008) provides details of hundreds of references and publications about applications of BNs.

4.4 BNs and project risk management

The key benefits of BNs that make them highly suitable for the project risk analysis domain are:

- They provide a rigorous method to make formal use of subjective information. BNs provide a visual and formal mechanism for recording and testing subjective probabilities. This is a particularly attractive feature in project risk analysis, as in most cases the only practical choice is the use of subjective judgments (see section 3.2).
- They explicitly quantify uncertainty. Their causal framework provides a useful and unambiguous approach for analyzing risk. This is in stark contrast with the probability impact approach (as discussed in section 3.1) where none of the concepts has a clear unambiguous interpretation.
- Parameter learning- the probabilistic inference capability of BNs leads to updating the posterior probability distribution in the light of observed values (i.e. evidence). This specially offers a mechanism for updating the belief about unknown factors, which are very difficult to measure and were assessed subjectively before (see section 3.5).
- Complex sensitivity analysis. BNs are capable of reasoning from effect to cause as well as cause to effect. This can answer a wide range of 'what-if?' questions and offer a complex sensitivity analysis when several variables change simultaneously.
- Make predictions with incomplete data.

BNs provide an ideal approach for modelling uncertainty in projects; however they are rarely used in project risk analysis. The first efforts to apply BNs in project scheduling were conducted by (McCabe 1998) and (Nasir et al. 2003). They developed a BN to model the relationship between major risk variables that affect duration of activities in a construction project. They identified ten risk categories specific to building construction schedules (e.g. environment, geotechnical, owner, labor, design, area, contractor, political, non-labor resources and material). Detailed risk variables (in total 70 risks) in each category were identified. Eight activity groups were identified to represent all types of activities in a construction project (e.g. mobilization/demobilization, foundation/piling, labor intensive, equipment intensive, technical/electrical, roof/external, demolition, and commissioning). In the next step, by reviewing the literature and conducting a comprehensive expert survey, the relationships between different risks and different activity types were identified and subsequently quantified. For each activity group the output of the model suggested a percent increase or decrease from the most likely duration to define the pessimistic and optimistic durations. The most likely duration of activities is assumed to be known and is used as a reference point. The result of the BN model (in the form of upper and lower limits of activities duration) was exported to a MCS model to incorporate the effect of risks on the project schedule.

The BN model provided a very flexible modelling environment. It was validated with historical data from 17 case studies with very good results. However, the model had the following limitations:

- The model was specific to building construction projects; therefore it cannot be applied to other industries and different type of projects.
- The BN model predicted the upper and lower bounds of activity duration as percentage of the most likely duration. It assumes that the most likely duration is already known and takes it as an input to the model.
- The output of the model (the upper and lower limits of activity durations) needs another approach (i.e. MCS) to calculate decision making results such as the expected project duration, the probability of delay/completion etc.
- The upper and lower bounds of activity duration were restricted to a few pre-defined values. For example on the pessimistic side the percent increase of activity duration is limited to 10, 25, 50 and 100%.
- All the risk variables were binary types. Variables with more than two states could not be modelled properly.
- The final BN model was overly complex. The graphical structure was unorganised and difficult to follow and understand.

- Although it provided good predictive results, the most powerful feature of BNs namely diagnostic analysis (e.g. reasoning from effect to cause, learning and 'what if?' type analysis) was not used.

In this thesis I develop a BN model to model and quantify uncertainty in project scheduling. The approach is general enough to be applied to any type of project. Chapter 5 introduces a BN model for project scheduling. This provides detailed information about time parameters of individual activities and also the whole project. Chapter 6 proposes a separate BN model that captures the relationship between risk variables that affect the duration of a general activity in any type of project. The combined BN model takes advantage of all the capabilities of BNs and provides a mechanism for modelling all aspects of uncertainty in project scheduling.

The ultimate aim is to make this sort of analysis available for use by a typical project risk manager. However, there are technical challenges as discussed in the next section.

4.5 Building large-scale BNs for real-sized problems

Despite the many benefits discussed, there are fundamental barriers that dramatically restrict the use of BNs in dealing with large-scale problems (Neil et al. 2000). For domain experts (prospective users) who are neither probability theorists nor mathematicians, the task of constructing the network is not always straightforward and sometimes is a painstaking manual process. The challenge is how the power of BNs can be made easily accessible to practitioners and be practically applied in real-word problems. This section addresses some of these practical issues along with the related emerging research.

4.5.1 Constructing NPT for qualitative nodes

BNs may represent either qualitative or quantitative variables. Qualitative nodes are used to model real-world variables whose values are typically measured on a discrete subjective scale like {low, medium, high}. In most practical cases, eliciting complete sets of probability values for this kind of nodes is not possible or cost-effective. So, a key challenge is how to construct the relevant NPTs using minimal amounts of information (Fenton *et al.* 2007b).

For example, consider the small fragment of BN shown in Figure 4-5.

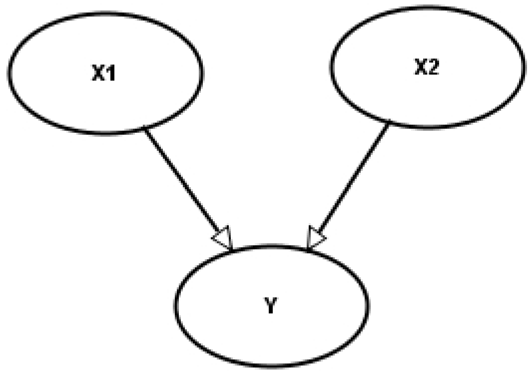


Figure 4-5 : Ranked nodes

Assuming each of the nodes has five states ranging from very low to very high, the NPT for the node Y has 125 states. Although it is not impossible to exhaustively elicit this number of probabilities, experience shows (Fenton et al. 2007b) that all kinds of inconsistencies arise when experts attempt to do so (for example, assigning dissimilar probabilities to similar states). When the number of states rises and/or there are additional parents, exhaustive elicitation (i.e. assessment of probability values for all the possible combination of states) becomes infeasible. In real-world models with typically several dozens of such fragments and extremely limited (if any) statistical data available, exhaustive elicitation is not possible. This problem has been addressed by many authors (Druzdzel and van der Gaag 2000) and (Wellman 1990).

(Fenton et al. 2007b) suggest a solution for this problem by introducing a class of BN nodes, called *ranked nodes,* which provide a semi-automated method for NPT construction. Ranked nodes are discrete variables with an ordinal scale, which are mapped onto a bounded numerical scale. They are defined on an underlying unit interval scale, [0-1], which is discretised to the number of states accordingly. For example, a 5-point scale such as {very low, low, average, high, very high} is associated with a numeric interval such as {[0-0.2), [0.2-0.4), [0.4-0.6), [0.6-0.8), [0.8-1)}. This underlying numeric scale, which is invisible from the user, is used to simplify the task of generating the NPT and therefore constructing and editing BNs. Instead of manual derivation of the NPT for all combinations of states, a simple averaging scheme (e.g. weighted mean, min, max, weighted min and weighted max) can be used to express the 'central tendency' of the child node based on the value of the parent nodes. For example, suppose the BN of Figure 4-5 led to expert elicitation as follows:

• When *X1* and *X2* are both 'very high' the distribution of *Y* is heavily skewed toward 'very high'.
• When *X1* and *X2* are both 'very low' the distribution of *Y* is heavily skewed toward 'very low'.
• When *X1* is 'very low' and *X2* is 'very high' the distribution of *Y* is centred below 'medium'.
• When *X1* is 'very high' and *X2* is 'very low' the distribution of *Y* is centred above 'medium'.

Such assertions suggest intuitively that Y is some kind of weighted average function of X1 and X2. Rather than assessment of probabilities for all the 125 states, the NPT for Y can be simply defined as the weighted average of X1 and X2.

Such a scheme works for many practical situations. Obviously, there is a trade-off between the benefits of a general method (simplicity of ranked nodes) and the cost of developing a bespoke model (exhaustive elicitation of all NPT states). However, ranked nodes provide a practical advantage and have proven to be acceptable to practitioners (Fenton et al. 2007b).

4.5.2 Handling continuous nodes

So far it was assumed that the values that nodes in a BN can take are discrete. But for modeling quantitative variables we need to consider continuous numeric nodes. In theory they could take any number of possible values. However, exact inference in BNs, for example using the 'Junction Tree' algorithm (see section

4.1.4), for continuous variables (with the exception of Gaussian variables) is computationally intractable (Cooper 1990). Hence, most BN tools adopt some sort of numerical approximation for quantifying continuous nodes.

In *static discretisation*, the modeler splits the range of the continuous distribution into a finite set of predefined intervals. The number (length) of intervals affects the accuracy of the result of BN on one hand and the computational complexity of the inference algorithm on the other hand. The higher the number of defined intervals, the more accuracy is achieved, but at a heavy cost of computational complexity and speed. Therefore the number of intervals needs to be set carefully otherwise, it is likely to introduce inaccuracy an error to the model.

Example 4-3:

Figure 4-6 shows the distribution graphs[1] for three nodes with the same distribution, $Normal(\mu = 5, \sigma^2 = 1)$, but with different discretisation levels. Nodes *A*, *B* and *C* respectively have two, three and five equal intervals in the range of *[0-10]*.

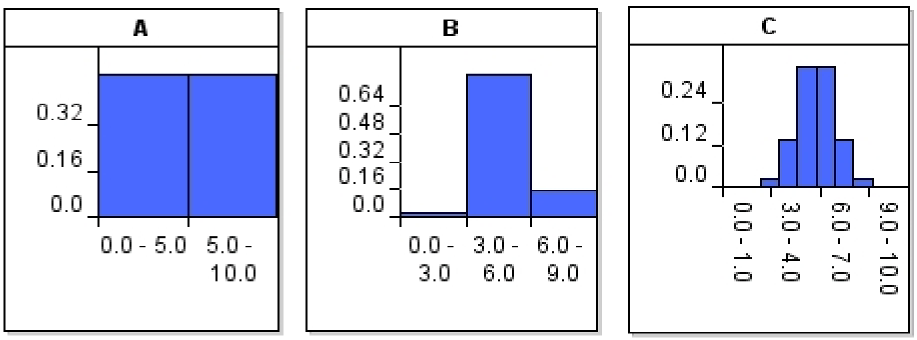


Figure 4-6 : Static discretisation in a continuous node with Normal(5,1)

Various undesirable effects can flow from a poor discretisation:

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[1] In all the distribution graphs presented in this thesis, the vertical axe shows the probability values and the horizontal axe shows the numeric range of the variable.

- The shape of the distribution can be entirely misleading. For example, node *A* looks like a uniform distribution and graph *B* looks non-symmetric in Figure 4-6.
- The distorted distribution reports erroneous mean and variance values. For example, the variance of nodes *A* and *B* are 6.25 and 1.46 respectively.
- Evidence entered into a poor discretisation becomes "spread out" across the whole interval that it belongs to. For example, in node *A* entering a value of 3 means that the [0, 5) range will be selected.
- Extra care is required when arithmetic functions are involved between variables. For example, if two variables are added, the intervals set for the child node should be anticipated properly to contain all possible outcomes from all combinations of sample values from different intervals in the parent nodes.

In order to achieve accurate approximation, it is also important to consider the highest density regions (i.e. where the main body of the probability mass will reside) for each node. The length of intervals needs also to be anticipated carefully. This is cumbersome, error prone and highly inaccurate (Neil et al. 2006).

To get round the problems of static discretisation (Neil et al. 2007) propose an approximate inference algorithm based on a new method of inference called *Dynamic Discretisation* (DD). The approach is a simpler version of (Kozlov and Koller 1997)'s scheme for using an iterative method to partition multivariate continuous functions. Starting at the full range of the variable, it recursively splits the range into two intervals until it converges to an acceptable level of accuracy (can be set by user). The NPTs are regenerated (partially or wholly) and the propagation algorithm is executed in each iteration.

The resulting DD algorithm, implemented in the AgenaRisk software, overcomes the problem of inaccuracy as well as wasted effort over selecting and defining discretisation intervals. The modeller only has to specify the variable's range, for instance [0-10] in the nodes of example 4-3, and the software provides appropriate discretisation as shown in Figure 4-7.

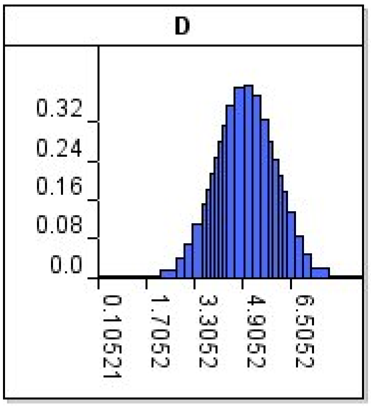


Figure 4-7: Dynamic discretisation in a continuous node with Normal(5,1)

However, in terms of efficiency, using DD increases computational time and also memory significantly. Faster and more efficient propagation algorithms are still required (Neil et al. 2007).

4.5.3 Object Oriented Bayesian Networks

The '*Object Oriented Bayesian Networks'* (OOBN) approach is proposed as a general framework for large-scale knowledge representation using Bayesian Networks (Koller and Pfeffer 1997). The idea is analogous to the Object-oriented programming languages that provide a robust, flexible and efficient framework for constructing computer programs. This section provides an overview of the OOBN framework.

The basic element in OOBN is an object; an entity with identity, state and behavior. Each object is an instance of a *class.* Classes of objects provide the ability to describe a general network that can be used in different instances. In OOBN a class is a BN fragment including three sets of nodes (as shown in Figure 4-8):

- *Input nodes,* (represented by dashed ellipses in Figure 4-8) have no parent in the class. They correspond to the parameter passed from the associated object.

- *Output nodes,* (represented by shaded ellipses in Figure 4-8) can be parents of nodes outside instances of the class.
- *Encapsulated nodes,* (represented by circles in Figure 4-8) can only have parents and children inside the instance class.

An instance of a class (i.e. an object) is linked to the network through *interfaces.* An interface, also called as *reference link*, connects an output node in one object to an input node in other objects (represented by a dashed link in Figure 4-8).

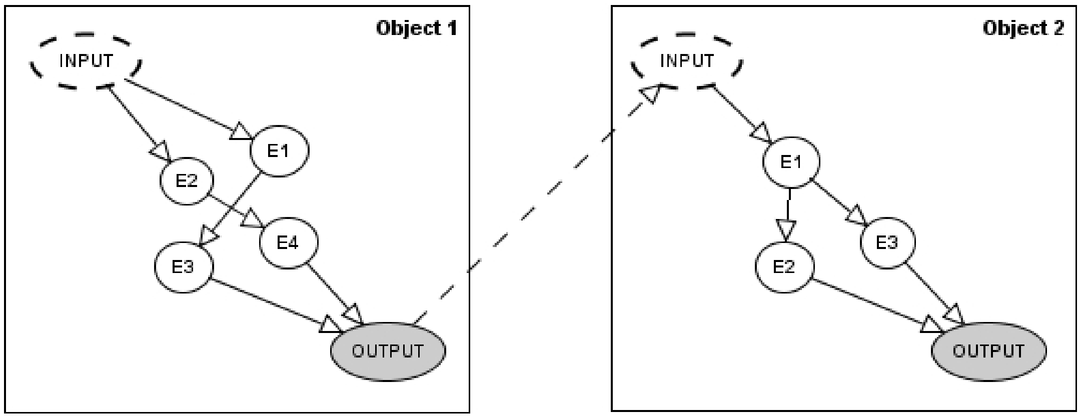


Figure 4-8: Structural representation of BN objects

Classes encapsulate the internal details, which enable them to be used as templates, formed together as a library, and combined into a model as needed. Figure 4-9 shows how Bayesian objects are linked through interfaces to build a large BN.

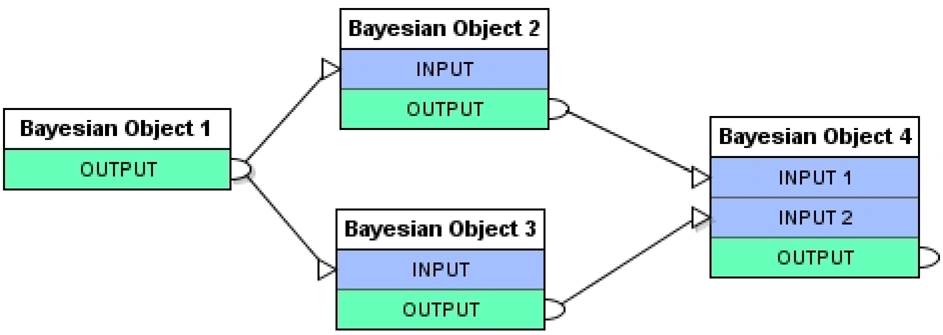


Figure 4-9: A large network can be built by connecting objects

By using OOBNs, complex models can be constructed easily using inter-related objects. Furthermore, OOBN supports an inheritance hierarchy, which means a sub-class can inherit much of its structure from the super-class. This allows the common aspects of related classes to be defined only once.

It is claimed that OOBNs also can speed up the inference process (Koller and Pfeffer 1997). The inference algorithm can be improved significantly by making additional structural information accessible. By encapsulating the internal attributes, probabilistic computation can be localized within the object. Also for objects of the same class (i.e. having the same probabilistic model), the inference calculation can be reused.

However, none of the BN software tools that support OOBN actually implement the inference algorithm in a genuinely Object-oriented manner. For example in Hugin, the OOBN is transformed into a big BN, which is used to construct the junction tree and perform the inference algorithm. (Bangso et al. 2003) proposed a method that keeps the structure of objects and pre-compiles classes locally, then 'plug' in to the junction tree. (Langseth and Bangsø 2001) propose a method for learning parameters in OOBNs. AgenaRisk supports a limited version of OOBNs which performs forward but not backward inference.

4.6 BN vs. alternative reasoning methods

There are a number of alternative methods and technologies for modelling uncertainty, including Dempster-Shafer theory (Dempster 1968) and (Shafer 1976) and Fuzzy causal networks (Zhang et al. 2006) and (Kosko 1986). A comprehensive overview and in-depth comparison of these approaches and the advantages and disadvantages of each method is provided in (Wright and Cai 1994). They concluded that no single formalism for uncertainty is superior to all others and each of them has unique and significant strength as a modelling tool.

In particular Dempster-Shafer (D-S) belief networks has attracted considerable attention for modelling knowledge about propositions in uncertain domains. This section briefly describes the D-S method and compares it against the BN method.

A D-S belief network graphically describes knowledge and the relationships among variables using the so-called theory of *belief function*. The D-S theory is based on two ideas:

- Obtaining degrees of belief for one question from subjective probabilities for a related question.
- Dempster's rule for combining such degrees of belief when they are based on independent items of evidence.

Differences between BN and D-S models exist in the graphical representations, numerical details and methods of performing inference (Cobb and Shenoy 2003).

At the numerical level, a D-S belief network assigns a D-S belief function or *basic probability assignments (bpa's)* to subsets of the variables in the domain, while a BN uses the product of all conditional probabilities to represent the joint probability distribution for all variables (see Equation 4-5).

A D-S belief network is updated by specifying evidence as bpa's, whereas updating of knowledge in a BN is accomplished by using likelihood functions (see section 4.2.1).

The differing numerical representations in BN and D-S belief networks each have relative advantages and weaknesses. BNs are easier to construct in domains where knowledge is causal, whereas D-S belief networks are easier to represent non-causal knowledge.

However, the two types of models are also similar in important aspects and their underlying structures have many similarities. In principal any BN model can be replicated in a D-S belief network model (Zarley et al. 1988). Similarly, any D-S belief network model can be approximated by a corresponding BN model (Shafer 1986).

From a practical point of view, BNs are more attractive than D-S networks because:

- Computationally, D-S belief networks are much more expensive to calculate than BNs. In practice, it is more efficient to transform the D-S network to a BN (Simon and Weber 2006).
- An adequate understanding of the D-S theory requires considerable effort and a strong background in probability theory (Zadeh 1986).
- There is a lack of software tools that implement D-S theory whereas there are several well-developed software tools available for implementing BN (see section 4.2.5).

4.7 Summary

This chapter reviewed the background, theory and the state-of-the-art of BNs. In the reminder of this thesis I shall make full use of BNs for modelling uncertainty in project scheduling.

5 Bayesian Critical Path Method (BCPM)

Chapter 3 argued about the need for a new approach to properly incorporate risk/uncertainty in projects. Chapter 4 introduced BNs and their proven capability of modelling uncertainty. This chapter aims to define a general framework for applying BNs to project scheduling. In particular, a new model is proposed which incorporates CPM calculations in BNs. The model benefits from advantages of both CPM and BNs. Therefore, it has promising capability to handle project uncertainty properly.

After a discussion about motivation of the model, the structure of the model is explained and then a numerical example illustrates the details of the model.

5.1 Incorporating CPM in BNs

CPM (as introduced in section 2.3.1) is a method used and accepted on many major projects in the planning, scheduling, and controlling phases. CPM is an important management tool that produces a 'road map' that shows the relationships between activities and also useful information about time parameters of each activity (e.g. start and finish time). Proper use of CPM scheduling will warn about situations that may lead to time delays. Likewise, CPM provides a good communication device between different parties of a project. As an analytical tool for comparing the approved work plan with actual performance, CPM is also accepted as a valid means of proving liability in courts and other administrative boards of appeal (Baki 1998). In addition to all the above advantages, simplicity and availability of several software tools have made CPM a standard method for project planning and control. Hence, a majority of project managers use CPM (Pollack-Johnson and Liberatore 2005). The main drawback of CPM is its assumption that all parameters (e.g. activities' time and cost) are deterministic. This is an unrealistic assumption that makes CPM results inaccurate and impractical especially in complex and risky projects.

On the other hand, as discussed in Chapter 4, BNs provide a method of handling uncertainty. The aim of this thesis is to develop a general approach that applies BN modelling to incorporate uncertainty in project scheduling and handles the issues identified in chapter 3.

As (Neil et al. 2001) argue, the key to the successful design of BNs is a meaningful decomposition of the problem. A large BN is too complex to be designed and also explained in one stage. Therefore, the approach here is divided into following two steps:

1. I show how CPM is mapped to BNs. This will provide a general framework that can be applied to any project. The rest of this chapter explains this step by introducing the BCPM model. In order to avoid extra complexity, the causal structure of 'duration' is ignored. It is assumed that duration of an activity can be modelled by a single node.
2. I show how the BCPM model can be expanded to capture causal relations and other factors affecting 'Duration'. This will be discussed in Chapter 6.

5.2 Structure of the BCPM model

The building blocks of a CPM network are the project 'activities'. Activities are specified by using a work breakdown structure (WBS). The CPM models activities and their sequential dependencies as a network. There are two types of CPM networks (Figure 5-1):

- Activity On Node (AON)
- Activity On Arc (AOA)

Apart from some variations in terminology, these two approaches are essentially the same. AON, also known as *precedence diagram*, is used in this thesis as it is simpler and also is used by most project management software packages. AON networks can also model different *lead* and *lag* relationship (e.g. start-to-finish, start-to-start and finish-to-finish) between activities. In this thesis only the normal

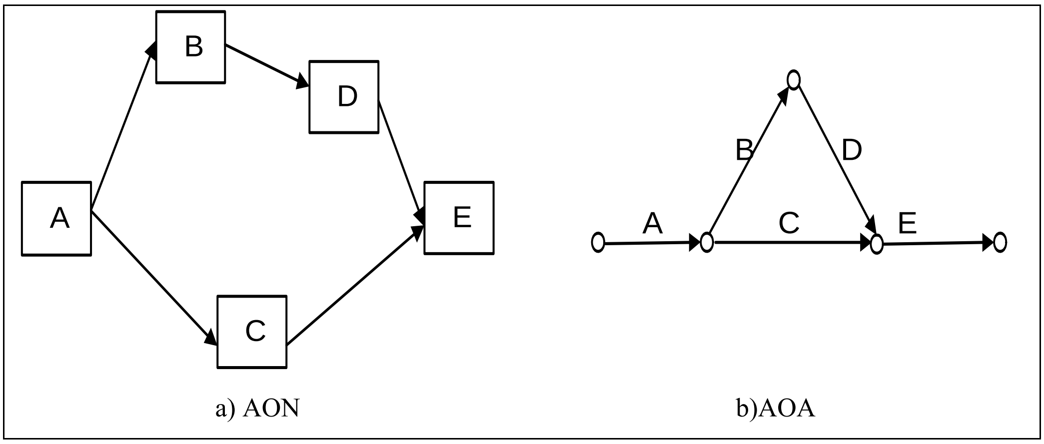


Figure 5-1 : Network representation in CPM

relation of finish-to-start is discussed (i.e. the succeeding activity is started immediately after the preceding activity is finished). However, other types of preceding relationship can be easily modelled by slight changes in the model.

The precedence dependency between activities is modelled by the links between immediate precedence activities. Each activity has five main time parameters: duration, earliest start, earliest finish, latest start and latest finish. These parameters are calculated by forward and backward calculations as explained in section 2.3.1.

The building block of the BCPM model is also 'activity'. Figure 5-2 shows a schematic model of the BN fragment associated with an activity. It shows the relation between the activity parameters and also the relation with the predecessor and successor activities. Each activity in a CPM network is mapped to a set of five nodes in the BN, representing the activity's time parameter as follows:

- The *Duration* node models the uncertainty associated with the activity's duration. This node is the central component of the BCPM approach and will be discussed in detail in chapter 6. In its simplest case, its NPT might be any arbitrary probability distribution (e.g. Triangular, Normal, Beta etc.).
- The *ES* node models the earliest time that an activity may start. The *ES* for an activity is the earliest time that all the predecessor activities are finished. This node is a child of *EF* nodes in all the immediate predecessor

activities. The NPT is an arithmetic expression that takes the maximum value of *EF* from all the immediate predecessor activities.

- The *EF* node models the earliest time that an activity may finish. It is a child node of the *ES* and the *Duration*. The NPT is an arithmetic expression that adds up 'Duration' to *ES*. *EF* is the parent of *ES* node for all successor activities.
- The *LF* node models the latest time that an activity should finish. This is the latest time that all the successor activities should start. This node is a child of *LS* nodes in all the immediate successor activities. The NPT is an arithmetic expression that takes the minimum value of *LS* from all the immediate successor activities.
- The *LS* node models the latest time that an activity should start. It is a child of the *LF* and the *Duration*. The NPT is an arithmetic expression that subtracts *Duration* from *LF*. *LS* is the parent of the *LF* node for all predecessor activities.

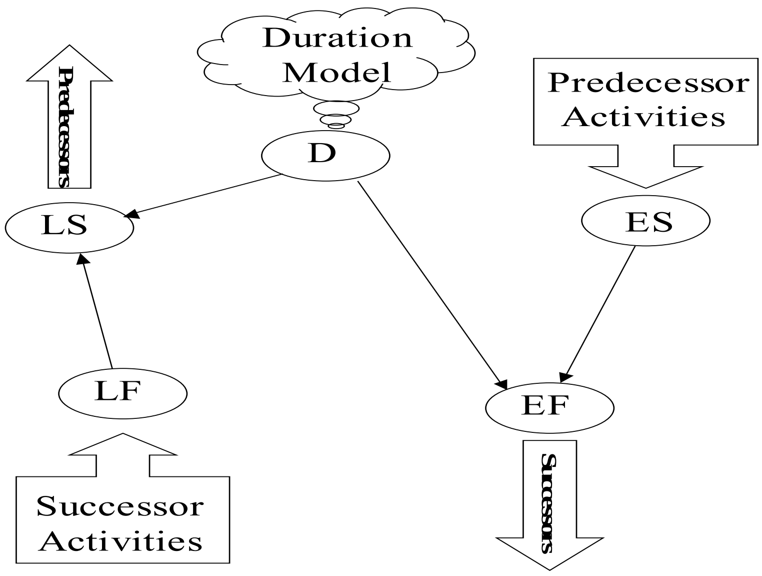


Figure 5-2 : Schematic of BN for an activity

The above five nodes model the CPM parameters for each activity. The next step is to define the links in the network. The precedence dependency between activities and also the forward and backward path in CPM is modelled through the links in the BN:

- The *EF* of each activity is linked to the *ES* of all immediate successor activities. These links model the forward path in CPM calculation.
- The *LS* of each activity is linked to the *LF* of all immediate predecessor activities. These links model the backward path in CPM calculation.

Finally the NPT for the activity's parameter should be set. All nodes are numeric type with continuous intervals. By using the DD technique (see section 4.5.2) the range of variables can be easily set (e.g. [0, ∞]). The NPTs are defined by relevant arithmetic expression to model the CPM calculations (see 2.3.1). For example ES of each node is defined by the maximum of EF of all the predecessor activities. Table 5-1 summarises the properties for all the nodes. The next section illustrates this mapping procedure by means of a simple example.

Node	Type	Intervals	NPT
Duration	Numeric	DD in $[0,\infty]$	$N(\mu,\delta)$
ES	Numeric	DD in $[0,\infty]$	$Max[EF_j \mid \text{j } one\ of\ \ the\ predecessor\ activities\ ]$
EF	Numeric	DD in $[0,\infty]$	$ES + D$
LS	Numeric	DD in $[0,\infty]$	$LF - D$
LF	Numeric	DD in $[0,\infty]$	$Min[LS_j \mid \text{j } one\ of\ \ the\ successor\ activities\ ]$

Table 5-1: Summary of nodes' properties for the BCPM model

5.3 BCPM Example

Consider a small project with five activities *A, B, C, D* and *E*. Activity *A* is the predecessor for both *B* and *C*, also both activities *C* and *D* are predecessors for *E*. The deterministic estimation of duration of activities *A, B, C, D* and *E* is 5, 10, 4, 2 and 5 weeks respectively. Figure 5-3 shows the AON representation of CPM network along with time parameters for each activity. Activities *A, C* and *E* with no float time are critical and the overall project takes 20 weeks (i.e. the earliest finish of activity *E*). In normal CPM calculation it is usually assumed (Ahuja et al. 1994) that the earliest start of the first activity is zero (*ES_A=0*) and the latest finish of the last activity is equal to its earliest finish (*LF_E=20*).

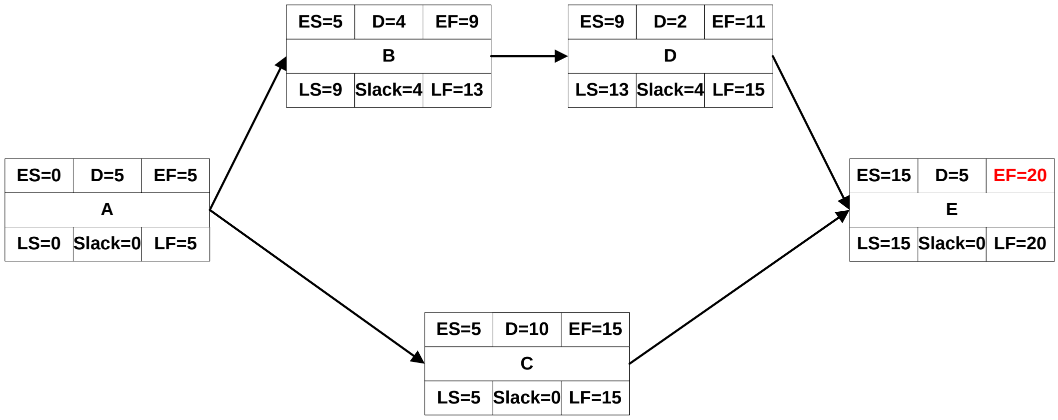


Figure 5-3 : CPM graph for example 5.3

Using the mapping process explained in the previous section, the BCPM network is shown in Figure 5-4.

The forward pass calculation of CPM is done through connecting the *ES* of predecessor activities to the *EF* of their successor activities (light grey nodes in Figure 5-4). The starting activity of the project, *A*, has no predecessor. So *ES_A* (read earliest start of *A*) is the start of the project and is set to zero. *A* is predecessor for *B* and *C* so *EF_A* is linked to the *ES_B* and *ES_C*. Similarly, *EF_B* is linked to the *ES_D*. Activity *E* has two predecessors, so there are two links from both *EF_C* and *EF_D* to the *ES_E*. *EF_E* is the earliest time for project completion time.

The same approach is used for the backward pass calculation of CPM with connecting the *LF* of successor activities to the *LS* of their predecessor activities (dark grey nodes in Figure 5-4). The last activity of the project, *E*, has no successor. So *LF_E* (i.e. project deadline) is set equal to *EF_E* (in this case 20 weeks). Activity *E* is successor of *C* and *D* so *LS_E* is linked to the *LF_C* and *LF_D*. Similarly, *LS_D* is linked to the *LF_B*. Activity *A* has two successors, so there are two links from both *LS_B* and *LS_C* to *LF_A*.

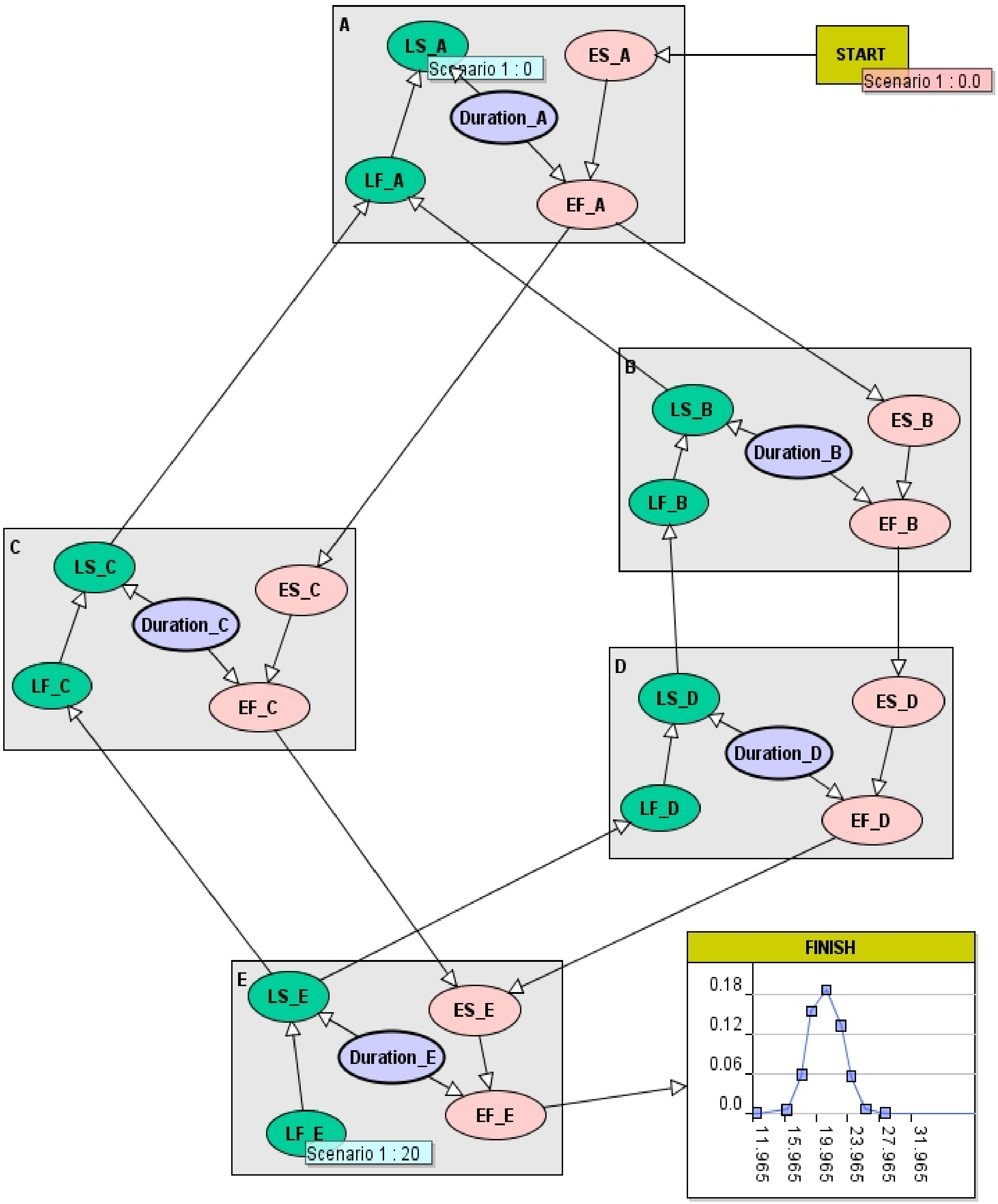


Figure 5-4 : BCPM for example 5.3

For the sake of simplicity it is assumed that all *Duration* nodes are prior nodes (i.e. a node without any parent, see 4.2.1). Their NPT is simply the prior probability that can be modelled by a rational subjective probability distribution with a suitable expected value and shape. It is assumed that the distribution of all activities have a Normal distribution with mean equal to the deterministic estimation of the duration and variance equal to one.

The NPT for all other nodes is defined by an arithmetic expression to reflect the CPM calculations as listed in Table 5-1:

$$ES\_B = EF\_A$$

$$ES\_C = EF\_A$$

$$ES\_D = EF\_B$$

$$ES\_E = Max\ [EF\_C, EF\_D]$$

$$For\ all\ nodes : EF = ES + D$$

$$LF\_D = LS\_E$$

$$LF\_C = LS\_E$$

$$LF\_B = LS\_D$$

$$LF\_A = Min\ [LS\_B, LS - D]$$

$$For\ all\ nodes : LS = LF - D$$

The model successfully incorporates uncertainty into the CPM. Instead of having a single point estimate a probability distribution is calculated for all parameters of each activity (i.e. *ES*, *EF*, *LS* and *LF*). For example, Figure 5-5 shows the probability graph for *ES* and *EF* of activity *C* where the mean of the graphs are equal to the deterministic values in Figure 5-3 (*ES_C=5*, *EF_C=15*). The mean and variance of the project finish time are 20 weeks (equal to the deterministic value) and 4.67 respectively (Figure 5-4).

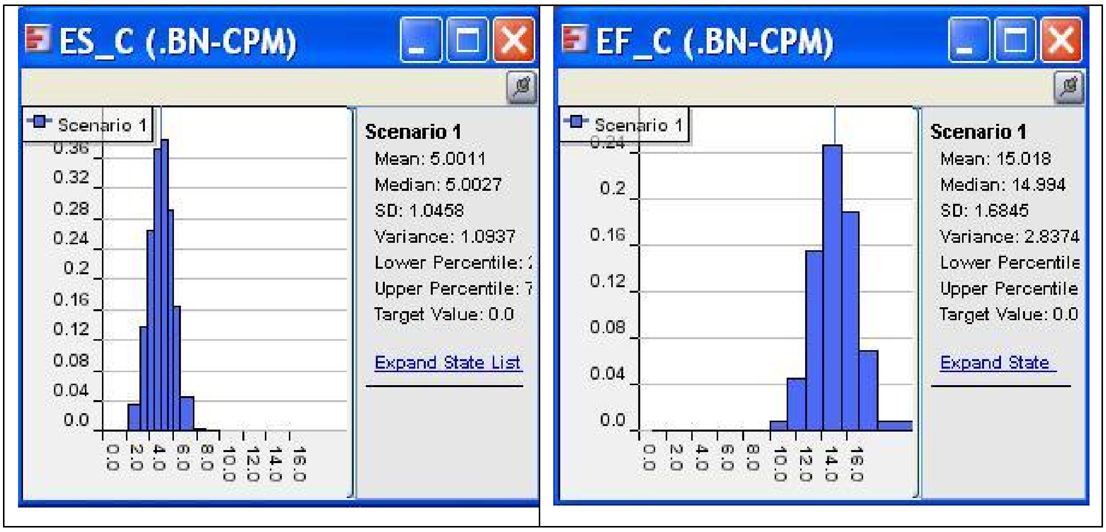


Figure 5-5 : Probability graph for ES and EF of activity 'C'

This example showed how the CPM is mapped into a BN. The model provides probabilistic distributions for the time parameters of all activities as well as the whole project. But more importantly, it can take advantage of all the capabilities of BNs (section 4.3) to capture different aspects of project risk. It offers a robust method for modelling risk in project scheduling which is capable of addressing the limitations of current practice of project scheduling (e.g. MCS based techniques) as defined in Chapter 3 (i.e. causality, subjectivity, trade-off analysis, unknown risks and learning). These capabilities will be added to the model through the ‘Duration’ network, which will be discussed in detail in Chapter 6.

5.4 Criticality

One of the most useful concepts in CPM is criticality. Interest in critical paths and critical activities stems from the need to focus management's attention on the activities that determine the progress of the project. Critical activities require special attention (e.g. effective and efficient execution) because if delayed they will delay the completion of the project.

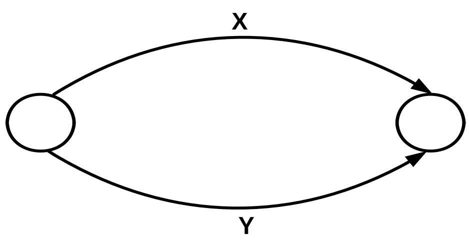
The definitions of *critical path* (CP) and *critical activity* (CA) in the CPM model are straightforward and unambiguous (see section 2.3.1). However, defining (and also measuring) criticality *under uncertainty* is not as simple as it is in the CPM. For example, in the PERT approach the stochastic structure of the model implies that almost any path may be critical with nonzero probability. A path is critical if its duration is longer than that of any other path. *Path criticality index* (PCI) is the probability that the path is of longest duration (Martin 1965).

A more relevant concept is activity criticality as it helps to identify the activities that may cause delay to the project. *Activity criticality index* (ACI) (Elmaghraby 2000) is a possible measure of the criticality of an activity. It is the probability that the activity will fall on a critical path. Theoretically, the determination of the ACI can be achieved through a three step procedure summarized as follows:

(1) determine the criticality indices of all paths;
(2) identify the paths that contain the activity of interest;

(3) compute the activity criticality by summing up the criticality indices of all paths that contain it.

However, the complete enumeration of all paths and the computation of their criticality is very difficult, if possible at all. Furthermore, as (Williams 1992b) argued, the ACI does not give an intuitively helpful metric to management. ACI sometimes remains invariant even when time parameters of activity widely change. For example, consider the simple AOA network shown in Figure 5-6. The network contains two independent activities, X and Y. The possible durations of activities and the associated probabilities are given for two scenarios. Activity Y is identical in both scenarios but activity X is obviously more important in scenario B. It is expected that the criticality of activity of X changes in scenario B. However, according to ACI, in both scenarios activity X is equally critical ($ACI_X = 99\%$).



Scenario A:

	Probability	Duration	ACI
X	50%	1	99%
	50%	2	
Y	99%	0	1%
	1%	1000	

Expected Project Duration: 11.48

Scenario B:

	Probability	Duration	ACI
X	50%	100	99%
	50%	200	
Y	99%	0	1%
	1%	1000	

Expected Project Duration: 158.5

Figure 5-6 : ACI example (Williams 1992b)

To address the above problem, (Williams 1992b) suggested *Significance index* (SI) as an alternative to ACI. SI can be deduced from the total float, the expected duration of activity and the duration of the project:

$$SI = E[\frac{activity\ length}{activity\ length + total\ float} + \frac{total\ project\ duration}{E[total\ project\ duration]}]$$

But SI is extremely difficult to compute and it may also yield counter-intuitive results. For example, consider a network with two serial activities X and Y. Activity X has a duration equal to 100, while activity Y has a duration equal to 10 with probability of 0.5, and a duration equal to 20 with probability of 0.5. It is clear that activity X is more significant (in the sense that the same proportional increase/decrease in the duration has more effect on the project completion). But according to SI both activities are equally significant ($SI_X=SI_Y=1$) because both activities lie on a single path.

(Williams 1992b) also suggested the so called *Cruciality index* (CRI) as a measure of the relative importance of an activity with respect to the project completion time. CRI is defined as the absolute value of the correlation between the activity duration and the total project duration. Although CRI overcomes some of the disadvantages of ACI, it is not only very difficult to compute but can also produce counter-intuitive results. For example, if the duration of an activity is deterministic (or stochastic with very small variance) its cruciality is zero (or close to zero) even if it is always on the critical path.

The BCPM model provides a new interpretation of activity criticality under uncertainty. It can measure the relative importance of an activity without having to measure the criticality of path(s). Similar to standard CPM, the criticality of an activity can be measured by its total float (i.e. the difference between the *Latest Finish* and the *Earliest Finish*). If *TF* is zero (or even worse, negative) the activity is critical as it must be completed (otherwise it causes delay on the project) by a date that is earlier than the current plan shows is possible (i.e. *EF*). If *TF* is small the activity is slightly critical, as it would take a small slippage to make the activity critical. Even activities that have a large amount of float can be critical if their worst-case estimates exceed the calculated float.

In other words, the criticality of each activity can be estimated by comparing the probability distribution of the *LF* with the probability distribution of the *EF* of the activity. This is modeled by introducing the 'Criticality' node in the BCPM model for each activity as shown in Figure 5-7. 'Criticality' is a Boolean node that is 'true' when $LF \leq EF$.

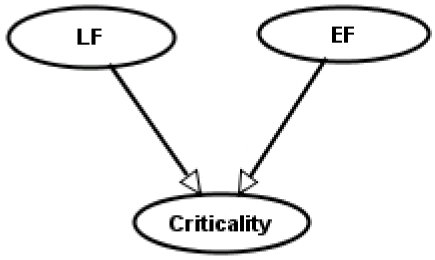


Figure 5-7 : Criticality node compares the *LF* with *EF* of each activity

This offers a simple (it is the natural expansion of the original concept of criticality in the classic CPM) yet more meaningful interpretation of activity criticality than other metrics because:

- Unlike 'ACI', it inquires into activity criticality rather than into whole path criticality. The activity criticality is a more relevant concept than path criticality as it defines the 'troublesome' activities that we wish to manipulate.
- Unlike 'SI', it considers the distribution function of activity duration (*LF* and *EF* are determined by *D*, see Table 5-1). Therefore in similar conditions the larger the activity duration the higher the criticality of the activity.
- Unlike 'CRI', it can measure criticality even for deterministic activities or activities with small variances.
- More importantly (unlike all other metrics), it takes into account the role of project deadline (i.e. *LF* of terminal activity). If the project deadline changes, the *LS* and *LF* of all activities will change (see section 5.2) and

consequently the criticality of activities will change. This is more realistic because when there is a tight deadline on the project, a higher number of activities are expected to be critical (or more critical) but when there is a loose deadline, most activities have extra float time therefore become less critical.

In terms of computation, the criticality of activities in the BCPM model can be easily measured as the distributions of LF and EF for all activities that are already computed. Figure 5-8 shows the BCPM with criticality nodes for the example of section 5.3 when the project deadline is 20 weeks.

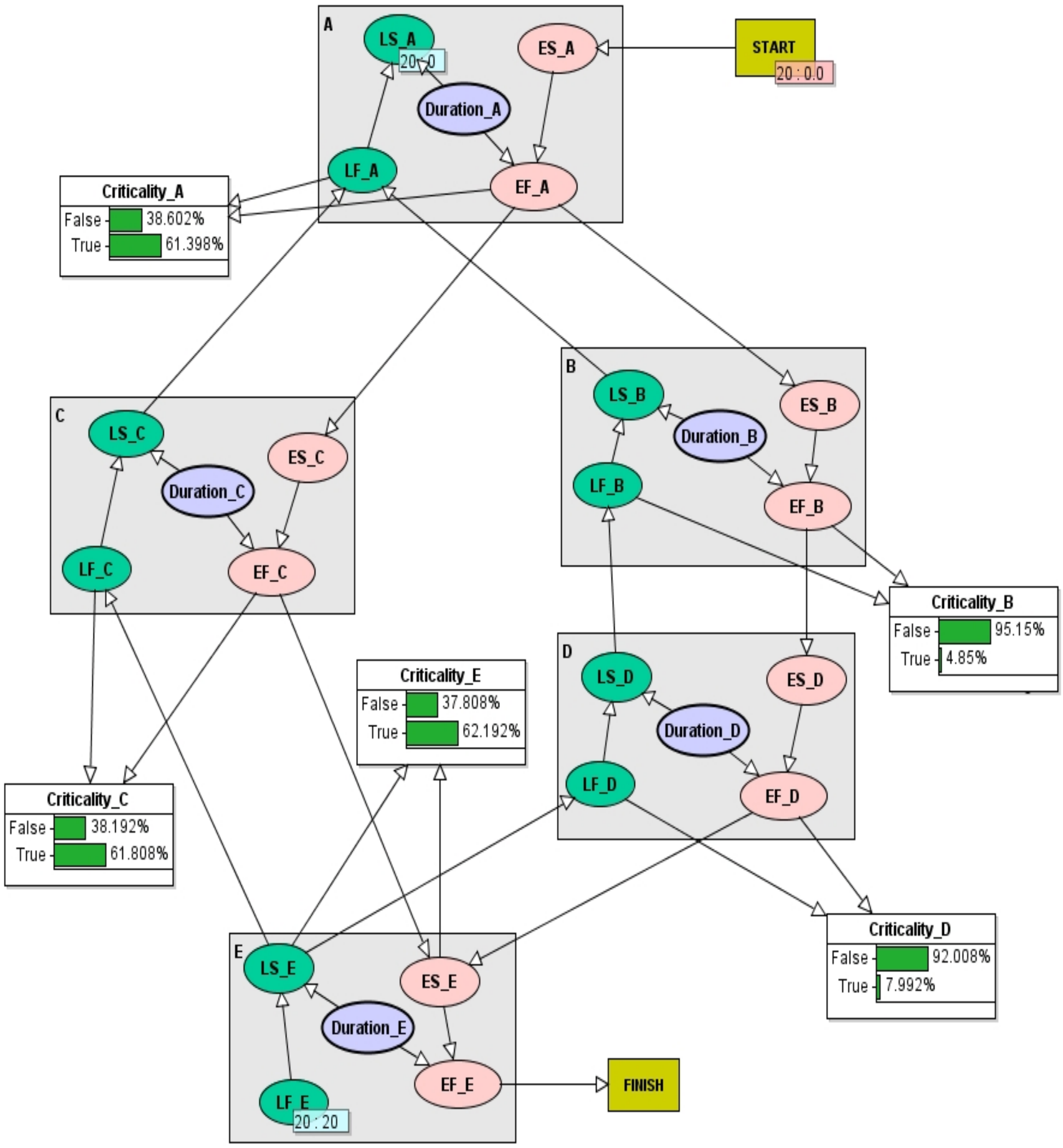


Figure 5-8 : Example 5.3 with criticality

Table 5-2 summarizes the ACI, CRI and the BCPM criticality for each activity. It also compares the result of the activities' criticality in three different scenarios (i.e. loose deadline, normal deadline and tight deadline). For example, the criticality of activity *E* (i.e. the most critical activity) changes from 62.19% to 74.8% and 42.8% when the project deadline changes from 20 to 17 and 23 weeks respectively.

	ACI	CRI	BCPM Critically		
			LF=20	LF=17	LF=23
A	100	58.21	61.4	71.3	51
B	4.28	0.05	4.85	8.5	1.05
C	98.69	55.57	61.8	74.1	42
D	4.28	0.04	7.99	12.9	1.69
E	100	58.27	62.19	74.8	42.8

Table 5-2 : Summary of criticality indices for example 5.3

5.5 The Object Oriented framework

As was seen in example 5.3, even for a small CPM network the corresponding BN is reasonably large and complex (compare Figure 5-3 and Figure 5-4). In real projects with several activities, constructing the BN requires significant effort, which is not effective especially for users with little experience in BNs (see Section 4.5). However, the structure of the model is highly repetitive and perfectly suits the Object Oriented framework. As defined in section 4.5.3, a Bayesian object is a fragment of BN that encapsulates the internal nodes and is linked to other objects through interfaces.

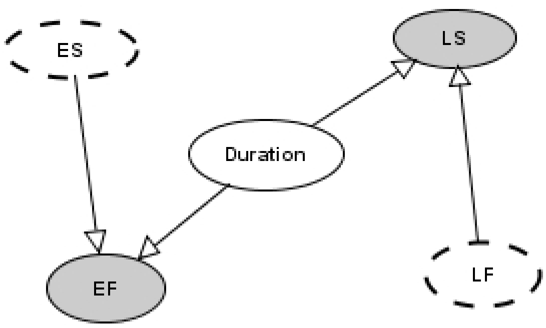


Figure 5-9 : Activity object

Figure 5-9 shows an instance of the 'activity' object. It contains the five time parameters of an activity. 'ES' and 'LF' are input nodes (shown by dashed ellipse) that take their value from other objects. 'EF' and 'LS' are output nodes (shown by shaded ellipse) that send their value to other objects. In this example, 'Duration' is a private (encapsulated) node. Once this object is constructed, it can be saved as a class and used as a library as required. This makes the model construction much easier.

For instance in example 5.3, instead of constructing the whole network node by node, for each activity an instance of the activity class is added to the network. Then the inference links are used to connect related nodes as explained in section 5.2. Figure 5-10 shows the resulting network, which is very similar to an ordinary AON representation of CPM network (Figure 5-3).

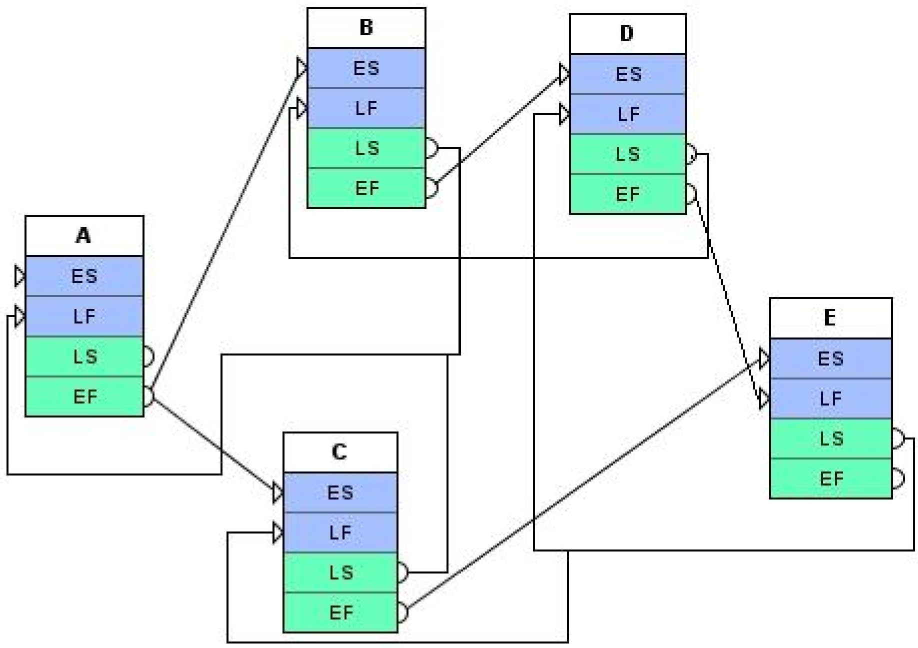


Figure 5-10 : Bayesian network for example 5.3 using object oriented framework

5.6 Elaborating the duration node

The essential component of the BCPM model is the 'Duration' node associated to each activity on the network. So far the 'duration' was assumed to be a prior node. But in reality the duration of an activity is affected by several known and unknown factors. The real power of the BCPM model is its capability to model these factors and their influence on the duration of activities (and consequently the duration of project).

This elaboration can be done in a separate BN model (a separate class in object oriented framework), which is attached to the ‘Duration’ node of ‘Activity’ in the ‘BCPM’ model as shown in Figure 5-11.

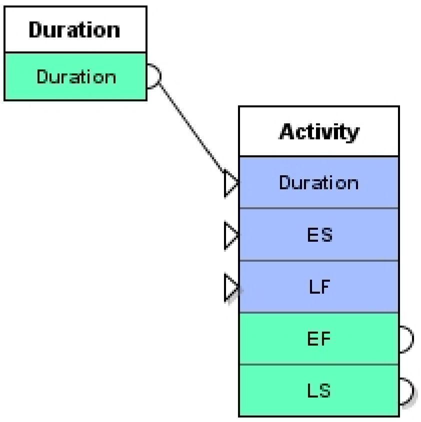


Figure 5-11 : Duration object is linked to Activity object

The next chapter describes a BN model for ‘Duration’ of a prototype activity. Coupled with the BCPM model described in this chapter, it provides a sophisticated method for incorporating uncertainty in project scheduling.

6 Duration Model

Chapter 3 discussed the issues that need to be considered in project risk analysis. This chapter introduces a BN model for addressing these issues. A BN model for duration of a prototype activity is proposed. This is a general model to demonstrate how different types of uncertainty can be modelled in a project activity. At the same time it is so flexible that it can be easily modified to model any specific situation to whatever level of detail is required. In conjunction with the BCPM model of Chapter 5 it provides an effective and flexible approach for modelling uncertainty in project scheduling.

6.1 Prototype Activity

The BCPM model introduced in chapter 5 is a general model applicable to any type of project. To keep the generality of the model, this chapter introduces a BN model for a *prototype activity*.

(Klein et al. 1994) introduced the idea of prototype activity. In many cases large projects can be regarded as a set of activities which are sufficiently similar to each other. A prototype activity might be considered as the representative of a group of activities under consideration. It encompasses properties of the range of activities. In practice, use of prototype activities can reduce the perceived costs of risk analysis in terms of time, effort and money (Klein et al. 1994). The actual project activities then can be regarded as variations of the prototype activity.

It is also possible to select a range of prototype activities with different structures to model a diverse range of circumstances in a complex project. Furthermore, they may have a life beyond the project in which they were invoked. A library of such prototype models, once created and structured, can form the basis for analysis of activities in other similar projects.

The ‘Duration’ model in this chapter is intentionally designed to be very general to model a universal activity. The key idea here is to show the modelling process and also the underlying logic of the model. In practice the network can be modified to capture the appropriate level of detail. If an activity is regarded as less important, its ‘Duration’ network may be reduced to a single node (as in the example of section 5.3). If the activity is more risky and more sophisticated analysis is required, its ‘Duration’ network can be expanded to model more detail. It is also possible to use alternative logic to construct a model with alternative structure.

Figure 6-1 shows the overall network proposed here for modelling different sources of uncertainty in duration of a prototype activity. The logic and structure of each of the model components is explained in the following sections.

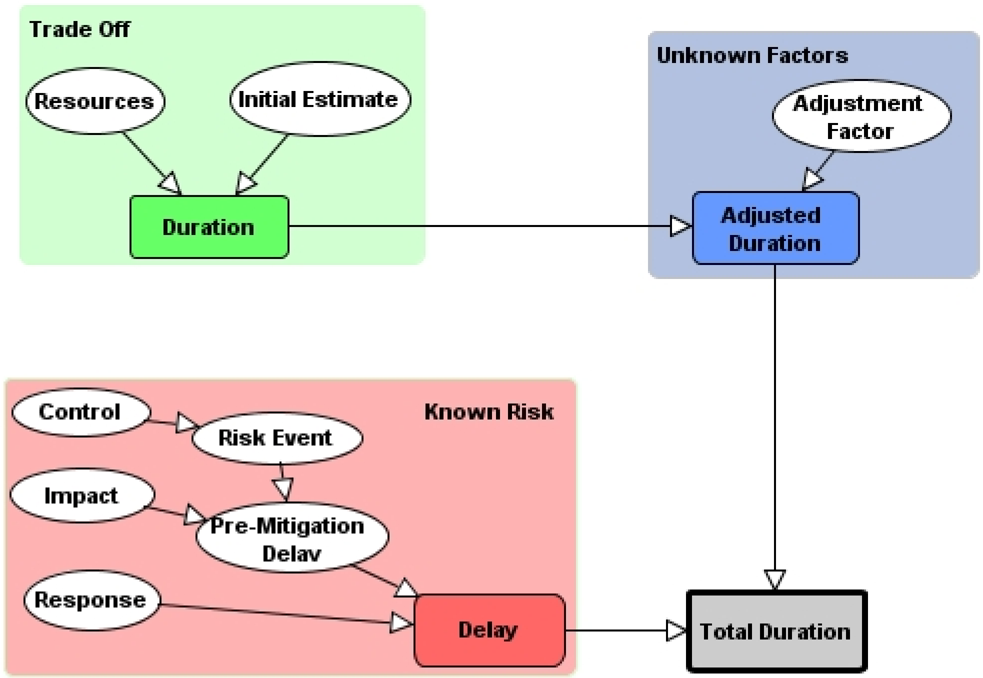


Figure 6-1 : BN for duration of prototype activity

6.2 Sources of uncertainty in activity duration

Distinction between different sources of uncertainty in duration of project activities will help to construct a framework for the BN model of activity duration. The foundations and different aspects of uncertainty is widely studied in the risk management literature (Helton and Burmaster 1996). A number of authors argue that there are different types of uncertainty (i.e. *variability* and *ignorance*) that are philosophically very different, hence should be kept separate in risk analysis modeling (Vose 2000) and (Ferson and Ginzburg 1996). Another argument suggests that there is only one kind of uncertainty stemming from our lack of knowledge (Zio and Apostolakis 1996), (Winkler 1996) and (O'Hagan and Oakley 2004). In other words the distinction between uncertainties are merely for our convenience in investigating complex phenomena and is not meant to imply that these are fundamentally different kinds of uncertainty. The latter view is adopted here to help constructing the BN model for activity duration. The distinction between different sources of uncertainty in this chapter is not used for basic philosophical reasons. It should be thought of in terms of a separation that can deal with the uncertainties more easily and effectively.

As (Winkler 1996) explains, the distinction between different sources of uncertainty helps in the following practical aspects of modeling and obtaining information:

1. How to structure an overall model.
2. How to identify, assess, and combine available information (e.g. hard data, expert judgment, and any other sources of information), and how to come up with probabilities to represent uncertainties.
3. Whether to gather more information, and if so, what type of information.
4. How to use sensitivity analysis effectively in the modeling process.

The above issues are considered in designing the duration network. The following sections of this chapter explain how different sources of uncertainty are modelled separately in the BN.

6.3 Variability and trade-off

Concern about potential variability in relation to duration, cost or quality is an obvious aspect of uncertainty in a particular planned activity. An activity, no matter how well defined, generally involves some uncertainty associated with the various performance criteria. This uncertainty may be termed the variability of the activity. The variability of activity is transferable between its parameters. All three dimensions of a project are variable and interact with each other. How long an activity may take depends directly on how much money is spent and/or what level of quality is achieved.

In other words, there is a trade-off between the uncertainty associated with the duration and the uncertainty associated with the cost. For example, if asked to estimate the probability of delay in a particular activity of a project, a manager may respond by contending that such probability can be reduced to virtually zero if there is no limitation on spending money on the activity. The activity duration can be viewed as a function of resource availability. Moreover, different resource combinations have their own costs. For example, using more productive equipment or hiring more workers may save time, but the project's direct cost could increase.

In order to model the uncertainty associated with the activity duration we need to consider the uncertainty associated with other aspects of activity such as cost and the quality of execution. However, quantifying this trade-off (variability) is problematic. In specific cases it might be possible to define a precise mathematical relationship between activity characteristics. However, such a relationship could be complex, intractable or even unidentifiable. Thus, in practice, approximate relationships are likely to be the most suitable for practical analysis.

Nevertheless, the capability of BNs in quantifying conditional dependency between variables provides a simple yet reasonable way for modelling the variability of activity parameters. For example, Figure 6-2 shows an effective representation of the trade-off between the duration of an activity and the level of required/available resources. The properties of the nodes are summarised in Table 6-1.

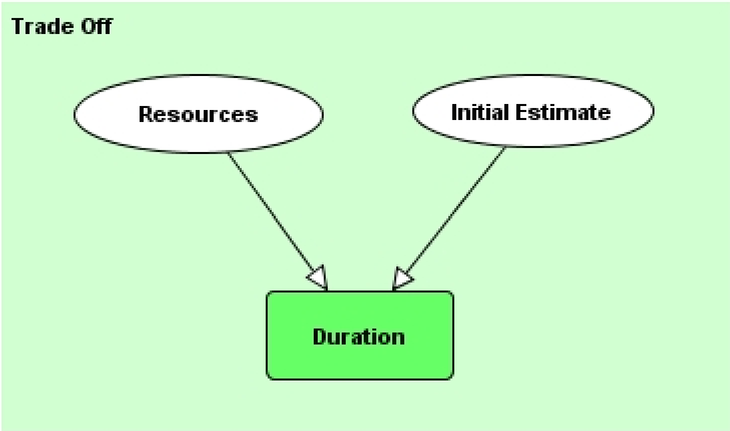


Figure 6-2 : Trade off sub-network

The idea here is that the most likely value of the activity's duration can be estimated by minimal information (i.e. subjective or based on historic data). This is not the mean (or average) value of the activity distribution, but it is the time that the estimator believes that the activity takes assuming the 'normal' conditions are applied. Its estimation should be well within the capabilities of any experienced planner. This is modelled by the 'Initial Estimate' node in Figure 6-2.

The 'Duration' is modelled by a Triangular distribution. This is, as (Aven and Kvaloy 2002) suggest, a reasonable distribution because it focuses on a so-called 'observable quantity' (i.e. expressing states of the 'world'). It is also suitable from a practical point of view as it is much easier to estimate minimum, maximum and most likely values for duration rather than estimating mean, variance or other statistical parameters (Williams 1992a). However, estimating the upper bound of the duration is not easy and is usually underestimated. (Flybjerg 2006) explains this by psychological and political reasons. Psychological explanations account in terms of optimism bias; that is, most people judge future events in a more positive light than is warranted by actual experience. Political explanations, on the other hand, explain inaccuracy in terms of strategic misrepresentation. In order to increase the chance of winning the bid, forecasters and managers deliberately and strategically overestimate benefits and underestimate time (or costs). In the BN model (Figure 6-2) the lower and upper bond of duration is conditionally dependent to the 'real' conditions of activity. This 'real' condition is characterized by the trade-off relation between activity's parameters.

Node	Type	States	NPT
Initial Estimate	Continuous Interval	Simulation (0, ∞)	Single point estimation
Resources	Ranked	Very Low, …, Very High	Discrete probability distribution
Duration	Continuous Interval	Simulation (0, ∞)	Partition Expression (see Table 6-2)

Table 6-1 : Nodes' properties for trade-off sub-network

The 'Resources' node (in Figure 6-2) represents the level of available/required resources that directly influence the activity duration. For simplicity I use a 'Ranked' node (see section 4.5.1) with five states: {very low, low, medium, high, very high}. The lower the quality of resources (for example less money) the longer the task takes and vice versa (assuming the output quality is fixed).

The 'Duration' node (in Figure 6-2) models the variability (trade-off) by combining 'Initial Estimate' and 'Resources'. 'Duration' is a continuous interval node with a triangular distribution. Its NPT is a 'partitioned expression' which means the probability distribution function varies depending on the state of the 'Resource' node as shown in Table 6-2. The upper, lower and medium values of the distribution can be defined appropriately.

Resources	Expression
Very Low	$Triangular(1.4\times IE,\ 1.8\times IE,\ 2.5\times IE)$
Low	$Triangular(1\times IE,\ 1.3\times IE,\ 1.5\times IE)$
Medium	$Triangular(0.9\times IE,\ 1\times IE,\ 1.2\times IE)$
High	$Triangular(0.8\times IE,\ 0.9\times IE,\ 1\times IE)$
Very High	$Triangular(0.7\times IE,\ 0.75\times IE,\ 0.9\times IE)$

Table 6-2 : summary of NPT for 'Duration'

For example, in one extreme scenario (i.e. the most economical performance) when level of 'Resources' is 'very low' the associated distribution for 'Duration' is defined as: $Triangular(1.4\times IE,\ 1.8\times IE,\ 2.5\times IE)$ ('IE' abbreviates the 'Initial Estimate'). The interpretation of this scenario is that if the level of available resources is ‘very low’ the duration of activity dramatically increases compared to what was initially estimated (‘Initial Estimate’ assumes normal condition). For instance, if the activity was initially estimated to take 10 weeks and the level of resources is ‘very low’ the distribution of the duration of activity is Triangular(14,18,25).

In another extreme scenario (i.e. fastest performance) when level of ‘Resources’ is ‘very high’ the associated distribution for the ‘Duration’ is defined as: $Triangular(0.7 \times IE,\ 0.75 \times IE,\ 0.9 \times IE)$. This can be interpreted as accelerating the activity by 25%.

In normal conditions (i.e. when level of resources is ‘medium’), the distribution of ‘Duration’ is defined as $Triangular(0.9 \times IE,\ 1 \times IE,\ 1.2 \times IE)$ in which the most likely value is the same as the ‘Initial Estimate’. The lower and upper value of the distribution (i.e. representing the variability of the duration) are set as -10% and +20% of the ‘Initial Estimate’ respectively.

Despite the simple structure of the network, it approximates the trade-off relation between duration and resources in an effective and practical manner. Its underling logic is that the duration of an activity is usually estimated based on framing assumptions regarding available/required resources. On the other hand, these framing assumptions are themselves subject to uncertainty resulting from lack of clarity, data and structure. Because project parameters are interrelated, duration variability arises from variability in other parameters. In other words the duration estimation would be much easier and more accurate if all the affecting parameters (i.e. resources) could be clearly evaluated.

‘Initial Estimate’ is estimated with minimal information assuming that the level of resources is normal compared to similar projects and environments. But in reality, by its nature, the level of resources involves uncertainty and may vary from activity to activity or even during the course of an activity. In the BN model the prior distribution (section 4.2.1) of ‘Resources’ represents the variability of resources.

As an example, for the BN shown in Figure 6-2 the prior distribution of 'Resources' is set as 0.05, 0.1, 0.55, 0.2, 0.1 for Very low, low, medium, high, very high respectively. It is interpreted as follows: although it is more likely (i.e. 55%) that the level of 'Resources' would be 'medium', there is a slight chance (i.e. 5%) that 'Resources' happens to be 'very low'. This consequently will reflect on the 'Duration' distribution through conditional dependency defined in the 'Duration' NPT (it is assumed that the quality of execution is fixed).

Figure 6-3 shows how the variability in level of resources affects the variability in distribution of 'Duration'. It shows two scenarios both with 'Initial Estimate' of 10 weeks. In the first scenario where the 'Resources' is known to be medium, the distribution of 'Duration' has mean value of 10.5 and the 90% confidence interval is spread between 9.5 and 11.2. In the second scenario there is no hard evidence about the level of resources (we don't know exactly what is the level of resource so we use the prior distribution of 'Resources'), the mean of 'Duration' is still 10.5 but the 90% confidence interval is now spread between 8.3 and 12.7.

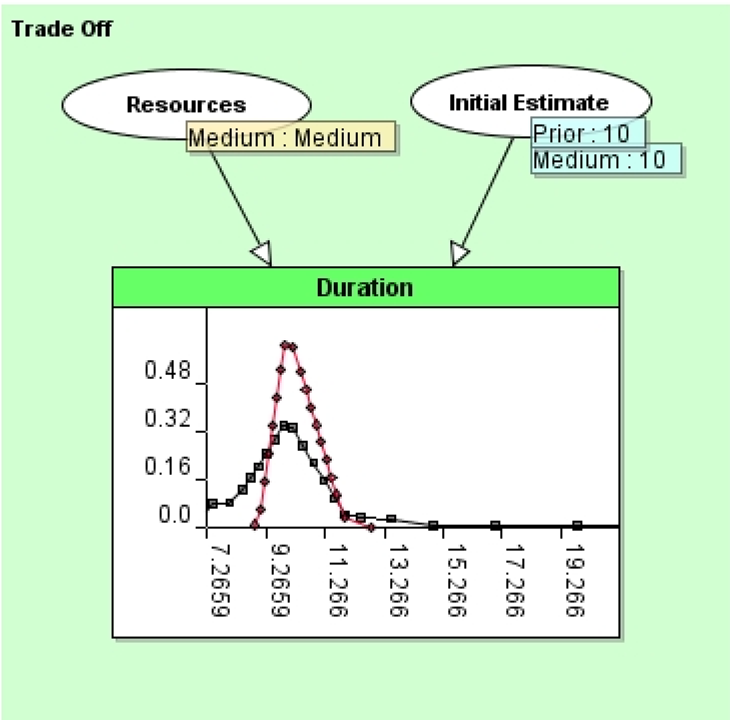


Figure 6-3 : Variation in duration

The network can model the trade-off analysis in both directions:

1) Estimating the 'Duration' based on available 'Resources':

If the level of available resources are restricted (for example limited budget or lack of experienced people) what is the effect on the activity duration? In other words what is the effect of 'Resources' on the distribution of 'Duration'?

Figure 6-4 shows this type of trade-off in different scenarios. While the 'Initial Estimate' in all scenarios is 10, changing the level of available 'Resources' will change the central value as well as dispersion of distribution of 'Duration'. The estimation of 'Duration' is directly affected by the available level of 'resources'. For example, when 'Resources' is known to be 'low', 'Duration' has the mean value of 12.6 (e.g. 26% more than the 'Initial Estimate') in the range of 11.2 and 14. In contrast, when 'Resources' is known to be 'high', 'Duration' has the mean value of 7.8 (e.g. 22% less than the 'Initial Estimate') in the range of 7.3 and 8.4.

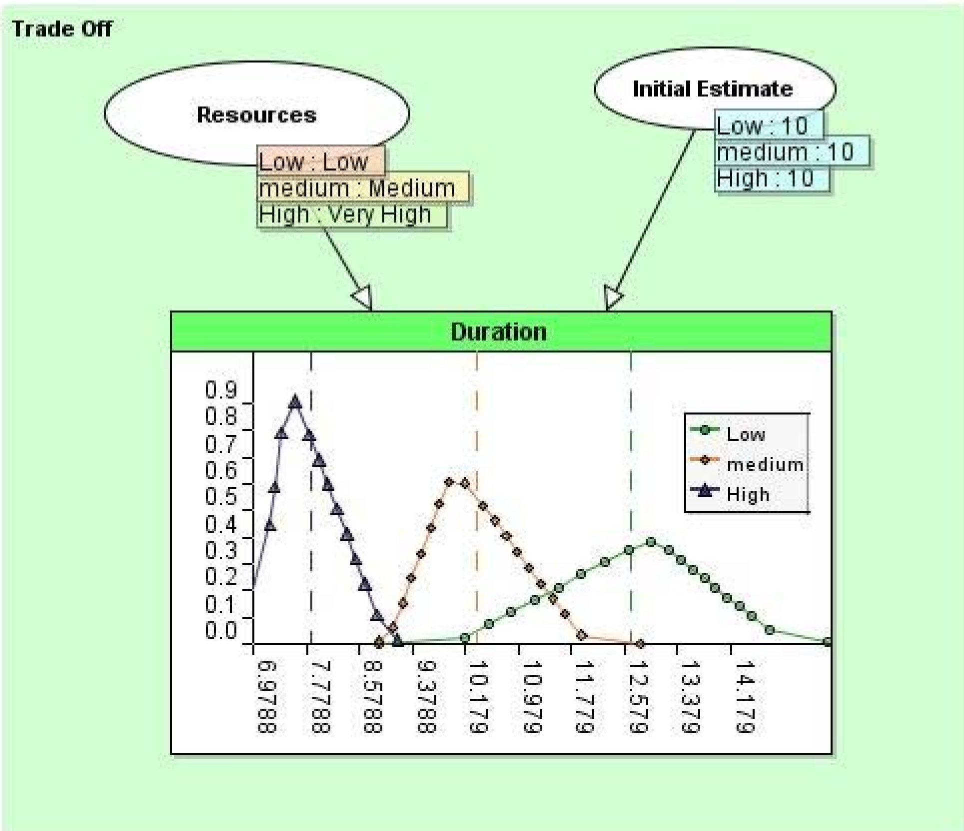


Figure 6-4 : Duration changes when the level of resources changes

2) Estimating the level of required 'Resources' based on constraint on 'Duration'

If there is a deadline on the activity what is the level of required resources? In other words, if we want to finish the activity by a given time how much resource should be allocated to the activity?

This type of trade-off can be easily analysed by backward propagation in the BN as shown in Figure 6-5. The 'Initial Estimate' was 10 weeks but it is required to finish the activity in 8 weeks. The backward propagation updates the distribution of 'Resources'. It is clearly skewed toward 'very high' compared with the prior distribution as shown in Figure 6-5.

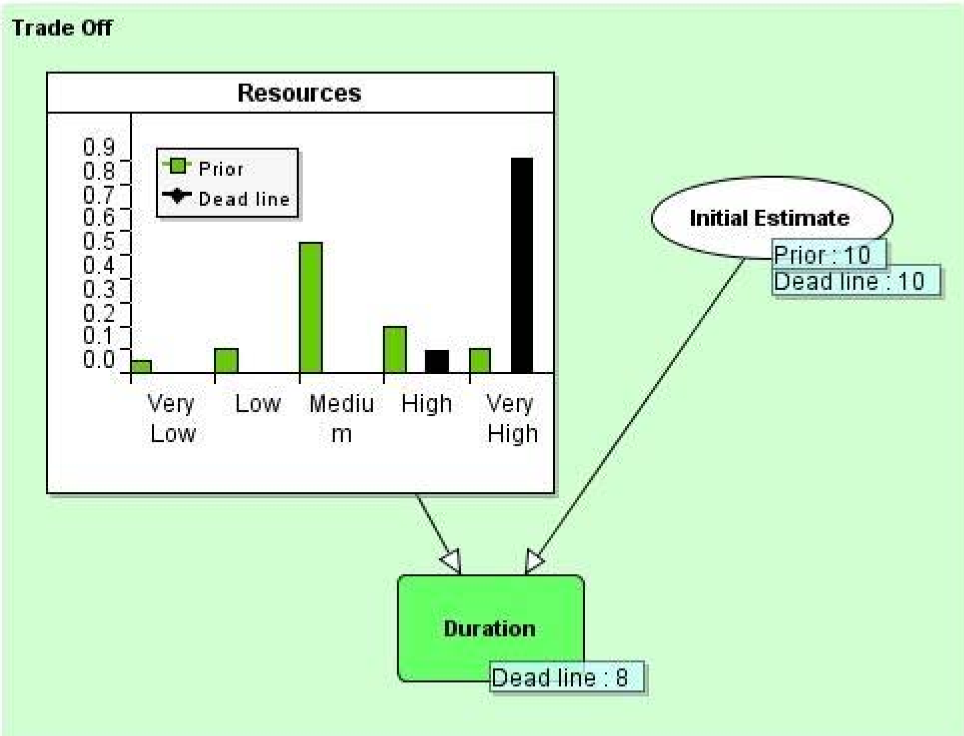


Figure 6-5 : Prior vs. required resources

6.4 Known Risk

Another important source of uncertainty is 'known risk'. This type of uncertainty/risk underlies established PRM and has been thoroughly acknowledged by almost all authors albeit perhaps with different terminology. 'Known Risk' is also referred to as: foreseen uncertainty, foreseen risk, external risk and risk event. The concept of 'known risk' is based on a fundamental assumption that a list of events (conditions) that may take place is known, their impact on activity duration (i.e. delay) is also known and even the nature of the 'solution space' is roughly known.

(Kendrick 2003) defines all the significant listed project risks (i.e. the risk register) as known risks which are either under control or not. For known risks, at least in theory, it is possible to plan a control or response, but for unknown risks specific planning is not of much use. Two basic options are available in managing known risk: dealing with causes and dealing with effects (Figure 6-6).

Known controllable risks, such as use of a new technology, are at least partially under control and the project team may be able to modify the project plans to avoid or minimise the probability of occurrence of risk. For known uncontrollable risks, such as bad weather or loss of key project staff, there is no control on the source of the risk. For these problems, the project team has to deal with the effects after the risk occurs.

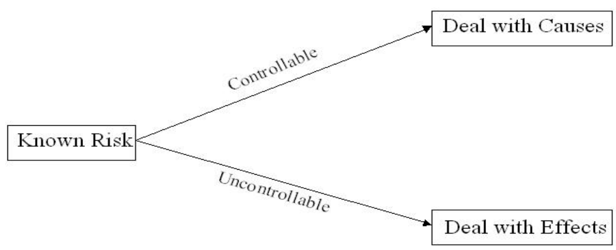


Figure 6-6 : Controllable and Uncontrollable known risks

The above concept is applied to design the BN sub-network shown in Figure 6-7. It presents a clear causal structure that 'tells the whole story'. The properties of nodes is summarised in Table 6-3.

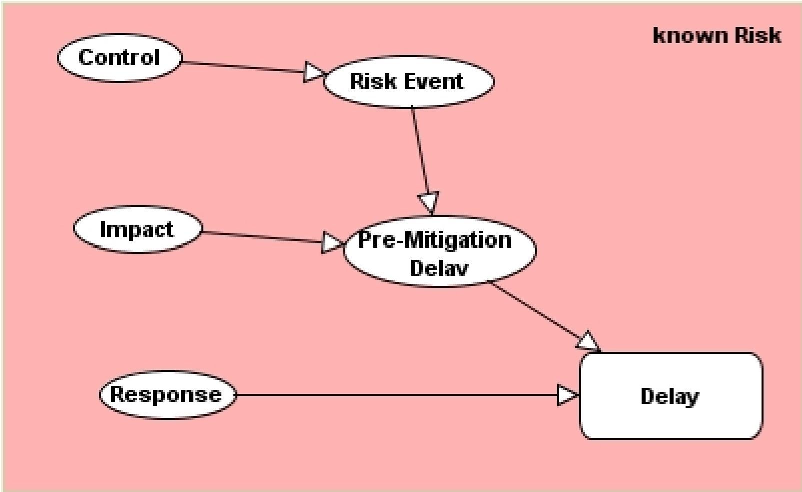


Figure 6-7 : Known risk sub-network

'Risk Event' is a 'Boolean' node with two possible states of Happen/Not Happen. The probability of each state is conditionally dependent to the state of the 'Control' node. 'Control' models the 'proactive' actions that are predicted to prevent or reduce the probability of the occurrence of risk. 'Control' is a labelled node with the number of states equal to the number of possible options that may control the risk. An obvious option is 'no control' or 'ignorance' which models the reactive strategy for dealing with risk.

Node	Type	States	NPT
Control	Labelled	Option1, Option 2,	Manual
Risk Event	Labelled	Happen/Not Happen	Manual
Impact	Ranked	Very Low, …, Very High	Manual
Pre-Mitigation Delay	Continuous Interval	Simulation (0,1)	TNormal(Impact, 0.01, 0, 1)
Response	Labelled	Option1, Option 2,	Manual
Delay	Continuous Interval	Simulation (0,1)	(see Table 6-5)

Table 6-3 : Nodes' properties for known risk sub-network

For example, suppose a risk event is defined as 'Key staff leave the project team'. Suppose the prior probability that the risk happens (i.e. a key staff actually leaves the project) is estimated as 10%. The possible options for controlling this risk might be 'offering better salary package' or 'improving staff motivation'. This might reduce the probability of occurrence of the risk to 0.05. The conditional probability table for this known risk is shown in (Table 6-4).

Risk Event	Control	
	no control	better salary
key staff leave	0.1	0.05
all key staff stay	0.9	0.95

Table 6-4 : Risk occurrence is dependent on 'Control'

(Figure 6-8) shows how the effect of 'Control' on 'Risk Event' is modelled in the BN. For example, if there is 'no control' the probability of occurrence of risk is estimated to be 60% (see 'Happen' bar in the probability graph of 'Risk Event' in Figure 6-8), while an appropriate control (e.g. paying more salary) may reduce the probability of occurrence of risk to 20%.

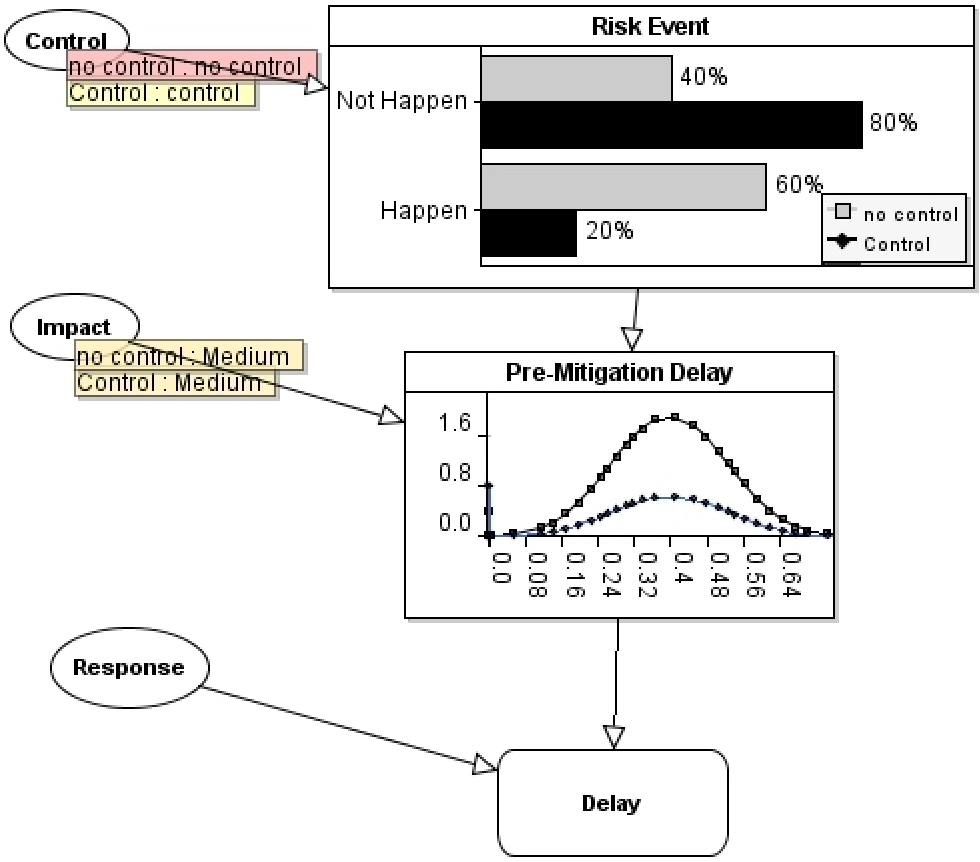


Figure 6-8 : Control affects 'Risk Event' and 'Delay'

The ‘Impact’ is a ranked node (see section 4.5.1) that models the significance of the outcome delay. One of the benefits of this model is that the impact has a probability distribution. This is more realistic than the conventional ‘Probability Impact’ approach (as argued in section 3.1).

The ‘Pre-Mitigation Delay’ node combines the probability of ‘Risk Event’ with its ‘Impact’ to calculate the outcome delay. For reason of modelling simplicity, the delay is defined as a percentage of the duration of activity. It is also assumed that the maximum delay is not more than 100% of the activity duration. Hence, both the ‘Pre-Mitigation Delay’ and ‘Delay’ are continuous interval in the range of (0 1). Using ‘Ranked’ type (as explained in section 4.5.1) simplifies the task of generating the NPT. Furthermore, a simple averaging scheme (such as weighted mean, min, max, weighted min and weighted max) can be used to express the ‘central tendency’ of the child node based on the value of casual parent nodes. This feature is used in defining the NPT for ‘Pre-Mitigation Delay’ node. It has a TNormal (i.e. truncated normal) distribution in the range of (0,1), the mean value is a function of ‘Impact’ (e.g. *Impact-0.1*) and variance of 0.01.

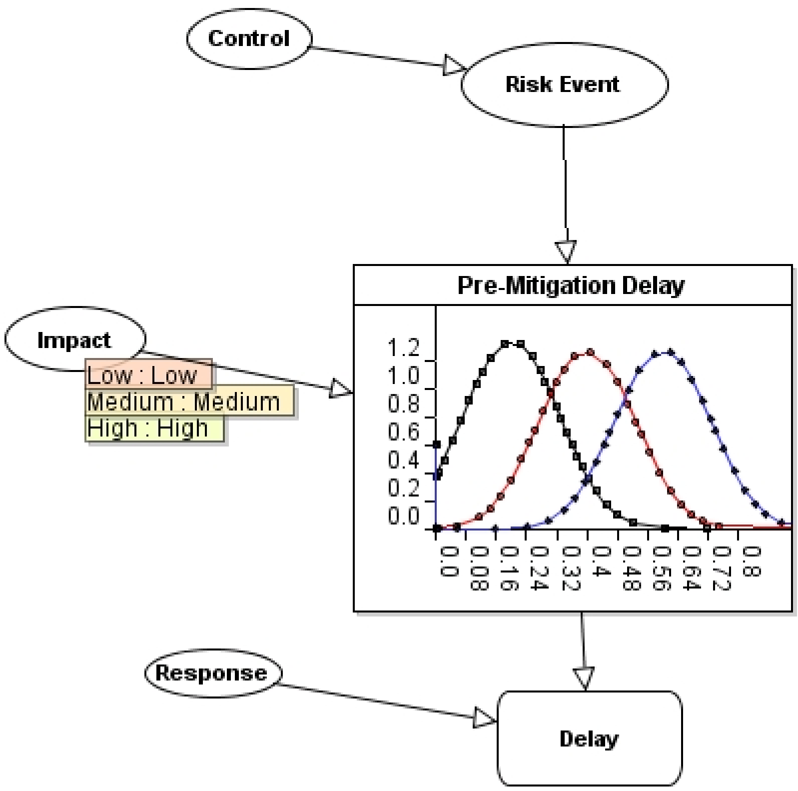


Figure 6-9 : Impact affects Pre-Mitigation Delay

Figure 6-9 shows how the level of impact changes the probability distribution of 'Pre-Mitigation delay'.

The 'Response' node models the management reaction to the occurred risk. It is a labelled node with the number of states equal to the number of possible options that may be taken as a response to the risk. It has the same structure and logic as 'Control' node. The difference is in the concept that control deals with cause of risk whereas 'Response' deals with consequence of risk.

In other words control usually takes place before a risk event happens while response is the reaction of a project team to the risk after it has happened. For instance, suppose a risk event is defined as 'Key staff leaves the project team'. The possible options for responding to this risk might be 'hiring new staff' or 'reallocating the job to existing staff' or 'doing nothing'. Each of these options may change (hopefully reduce) the final delay.

Similar to 'Pre-mitigation delay', the 'Delay' is defined as a percentage of the activity duration with the maximum of 100%. Hence, the 'Delay' node is a continuous interval in the range of (0 1). Its NPT is partitioned expression which is defined based on the state of the 'Response' node. For each state an appropriate factor is multiplied to the value of the 'Pre-Mitigation Delay'. (Figure 6-10) shows how different responses change the probability of 'Delay'.

Table 6-5 summarises the NPT for the 'Delay' node in the 'Key staff leaves the project team' example, assuming that 'hiring new staff' and 'reallocating the job to existing staff' will reduce the delay by 60% and 30% respectively.

State of 'Response'	NPT expression for 'Delay'
Doing nothing	1*(Pre-Mitigation)
Hiring new staff	0.4*(Pre-Mitigation)
Reallocating the job	0.7*(Pre-Mitigation)

Table 6-5 : NPT for 'delay'

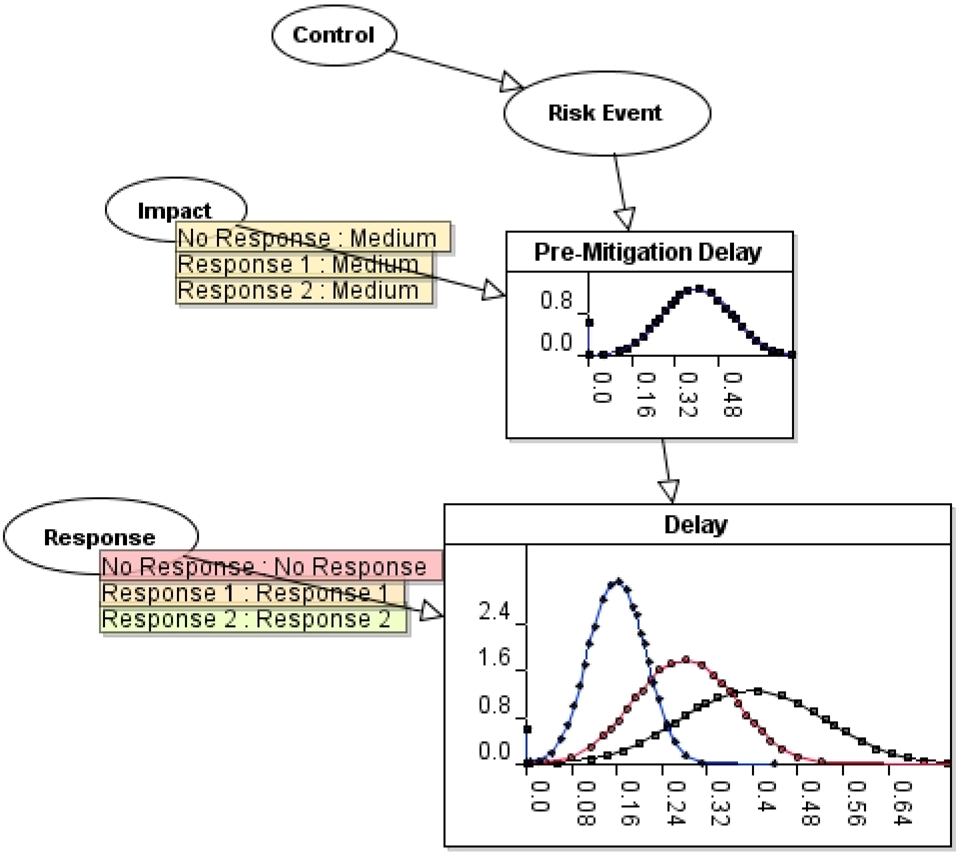


Figure 6-10 : Response affects Delay

6.5 Unknown Factors

Another major type of uncertainty is 'Unknown Factors'. This is also referred to as 'unknown unknown' (Chapman and Ward 2003), 'unk-unk' (Wideman 1992) and 'unforeseen risk' (Loch et al. 2006). Unknown factors often appear to be even more significant than 'variation' and 'known risk'.

> "It is often said that the real risks in any projects are the ones that you fail to identify" (Ward 1999).

(Kendrick 2003) declares that unlike known risks for which it is possible to plan a control or response for them (at least in theory), for unknown risks specific planning is not of much use.

"Unknown unknowns make people uncomfortable because existing decision tools do not address them" (De Meyer et al. 2002).

A key example of unknown factors are organizational factors such as rules, policies, processes, standards, structure, culture, management etc. (Ward 2005) explains how *organisation structure, co-ordination and control systems, communications and information systems, knowledge management,* and *support for organisation learning* affect the quality and scope of project management undertaken. Such factors define the basic resources that project management must work with, and they set the tone for how project management will be able (or allowed) to operate. Sometimes shortcomings in organisational capabilities are not evident until systematic attempts to identify and manage uncertainty are made (Atkinson et al. 2006).

(Mosleh et al. 1997) suggest using an adjusting factor for modelling the influence of organizational factors in probabilistic safety analysis. (Chapman and Ward 2003) and (Chapman et al. 2006) introduced F^3 factor (*cube factor*) which is an adjusting factor combined by three scaling factors: F_k for known unknowns, F_u for unknown unknowns and F_b for bias.

The concept of an adjustment factor is employed for modelling unknown factors in the BN model as shown in Figure 6-11.

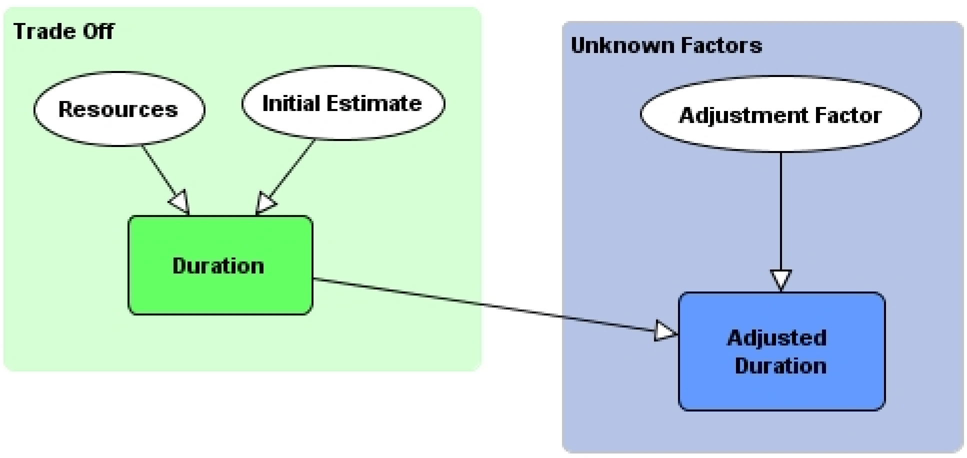


Figure 6-11 : Unknown sub-network

Node	Type	States	NPT
Adjustment Factor	Continuous Interval	Simulation (0,10)	Truncated Normal
Adjusted Duration	Continuous Interval	Simulation (0,∞)	Duration * Adj. Factor

Table 6-6 : Summary of nodes' properties in Figure 6-11

Any aspect of uncertainty which is left out in the variability/trade-off part (section 6.3) and the known risk part (section 6.4) is addressed in the 'Adjustment Factor' node. Table 6-6 summarises the properties of the nodes.

In order to quantify the influence of unknown factors on activity duration, it is necessary to estimate the value of the 'adjustment factor'. However, it will itself be uncertain in size. The 'Adjustment Factor' node is a continuous interval in the range of (0,10) (assuming that the maximum effect of it is tenfold). It is in the region of one if a negligible adjustment is involved. A factor less than one will signify a downward adjustment to the duration (to adjust overestimation), while a factor more than one signifies an upward adjustment (to adjust underestimation). The prior distribution for 'Adjustment factors' reflects the analyser's assessment of unknown factors.

A rational subjective probability distribution with suitable expected value and non-zero spread, as (Chapman et al. 2006) suggest, can quantify the adjustment factor. For illustration, Figure 6-12 shows the probability graph for 'Adjustment Factor', where the prior distribution is set as TNormal(0.7, 0.3, 0.5, 10). The mean, 10% and 90% percentile value of the distribution are 1.01, 0.59 and 1.53 respectively. The interpretation is that the average adjustment is around one (i.e. the mean of distribution), however it is possible that, say in the worst-case scenario, a 53% increase (the upper interval of the distribution is 1.53) or, say in the best-case scenario, a 41% decrease (the lower bond of distribution is 0.59) is implemented on the duration of activity.

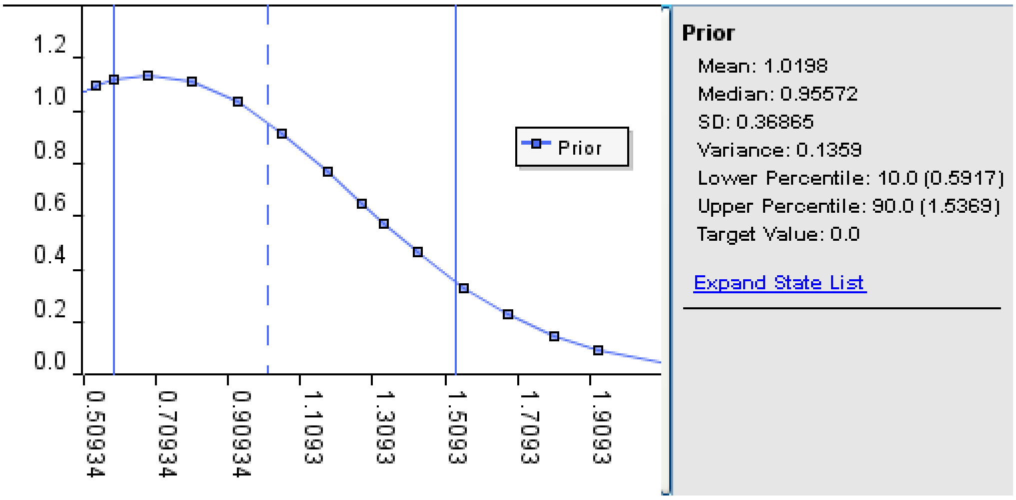


Figure 6-12 : Prior distribution for Adjustment Factor

'Adjusted Duration' is then calculated by multiplying 'Adjustment Factors' by 'Duration'. It is a continuous interval node in the range of (0, ∞). Figure 6-13 shows the distribution of 'Adjusted Duration' after applying the 'Adjustment Factor' on the 'Duration'. It is assumed that the 'Initial Estimate' is 10 weeks, the 'Resources' is medium and the distribution of 'Adjustment Factor' is similar to Figure 6-12.

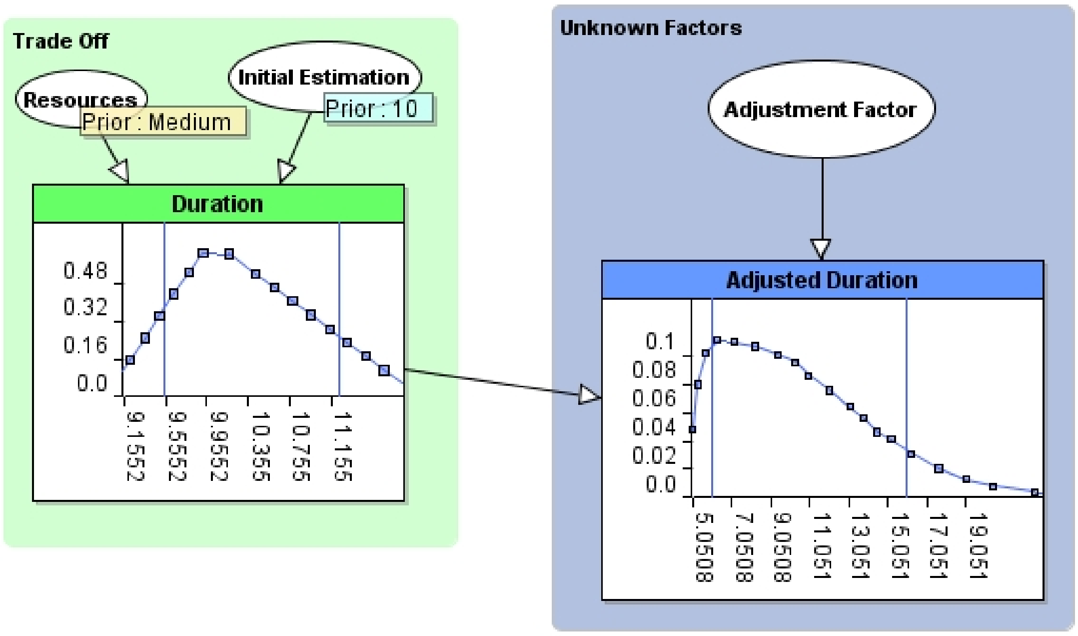


Figure 6-13 : Adjusted duration

The distribution of 'Duration' (i.e. before adjustment) has mean, 10% and 90% percentiles equal to 10.33, 9.53 and 11.23 respectively. Whereas the distribution of 'Adjusted Duration' has mean, 10% and 90% percentile equal to 10.55, 6.08 and 15.88 respectively. Note that the distribution of 'Adjusted Duration' is much wider than distribution of 'Duration'. This is because the prior distribution of 'Adjustment Factor' is wide (Figure 6-12).

Choosing an appropriate 'Adjustment Factor' is important in the process of estimating the duration of activity even though its estimation is highly subjective. At the same time, unknown unknowns are not always caused by spectacular out-of-the-blue events. They usually arise from the unanticipated interaction of many events, each of which might, in principle, be foreseeable. Dealing with unknown uncertainty requires a greater emphasis on learning. The challenge in managing unknown uncertainty is to find the balance between planning and learning. Learning permits adapting to unknown uncertainty (De Meyer et al. 2002). For example, organizational factors act as common causes of delay in many activities. All project activities take place in a wider organisation context and how the organisation operates will have a major impact on what can be achieved.

One of the great advantages of Bayesian Networks as discussed in section 4.2 is their capability of parameter learning. This can be achieved by updating the posterior probability distribution in the light of new evidence (observed values). The prior distribution of 'Adjustment Factor' might seem worryingly subjective. However, this can be updated when for example the first phase or predecessor activity of a project is completed and its actual duration is identified. This new information is propagated through the network and updates the distribution of 'Adjustment Factor'. This updated distribution is believed to be a better estimation of 'Adjustment Factor' and can be used in later phases or successor activities.

To illustrate this crucial concept, Figure 6-14 shows the posterior distribution for the 'Adjustment Factor' after entering new evidence in 'Adjusted Duration'. Suppose the 'Initial Estimate' was 10 weeks and the 'Resources' was known to be medium. The prior distribution of 'Adjustment Factor' was similar to Figure 6-12.

Now suppose that this activity is finished and the actual duration is known. Figure 6-14 shows the result of two scenarios. In the scenario called 'ahead' the activity was actually finished in 8 weeks (sooner than the initial estimation of 10 weeks). The expected value of the updated distribution of 'Adjustment Factors' is 0.77 (the probability graph is skewed to the left). In the scenario called 'late' the activity was actually finished in 12 weeks (later than the initial estimation of 10 weeks). The expected value of the updated distribution of 'Adjustment Factors' is 1.16 (the probability graph is skewed to the right). Also the spread of the updated distributions is much less than the spread of the prior distribution (the posterior distributions have sharp graphs whereas the prior distribution has a flat graph in Figure 6-14).

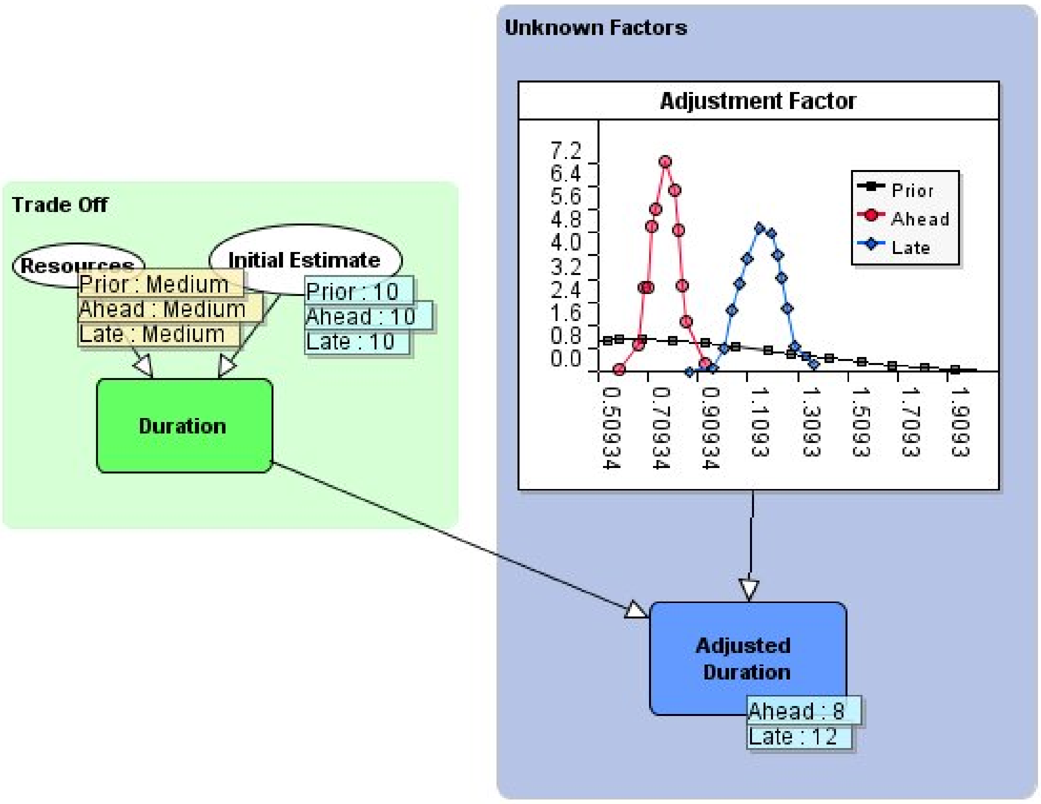


Figure 6-14 : Distribution of 'Adjustment Factor' is learnt

This updated distribution is a better estimation of 'Adjustment Factor' because it is learnt from hard evidence (observed information). Assuming that unknown risks are common between activities, this learnt distribution can be used in estimation of duration of successor activities.

For example, suppose the activity shown in Figure 6-14 is the predecessor of a similar activity (i.e. common unknown factors) which was initially estimated to take 20 weeks with medium level of resources. Knowing that the predecessor activity was actually late, Figure 6-15 shows how the learnt distribution of 'Adjusted Factor' (i.e. the 'late' scenario in Figure 6-14), is used (dashed ellipses in Figure 6-15) to update the distribution of 'Adjustment factor' and consequently the estimation of 'Adjusted Duration' for the successor activity. Note that in the prior scenario the 'Adjustment Duration' has a wide distribution with mean, 10% and 90% percentiles equal to 21.1, 12.5 and 31.9 respectively. However, the updated distribution has a much narrower distribution with mean, 10% and 90% percentiles equal to 23.99, 21.27 and 26.85 respectively.

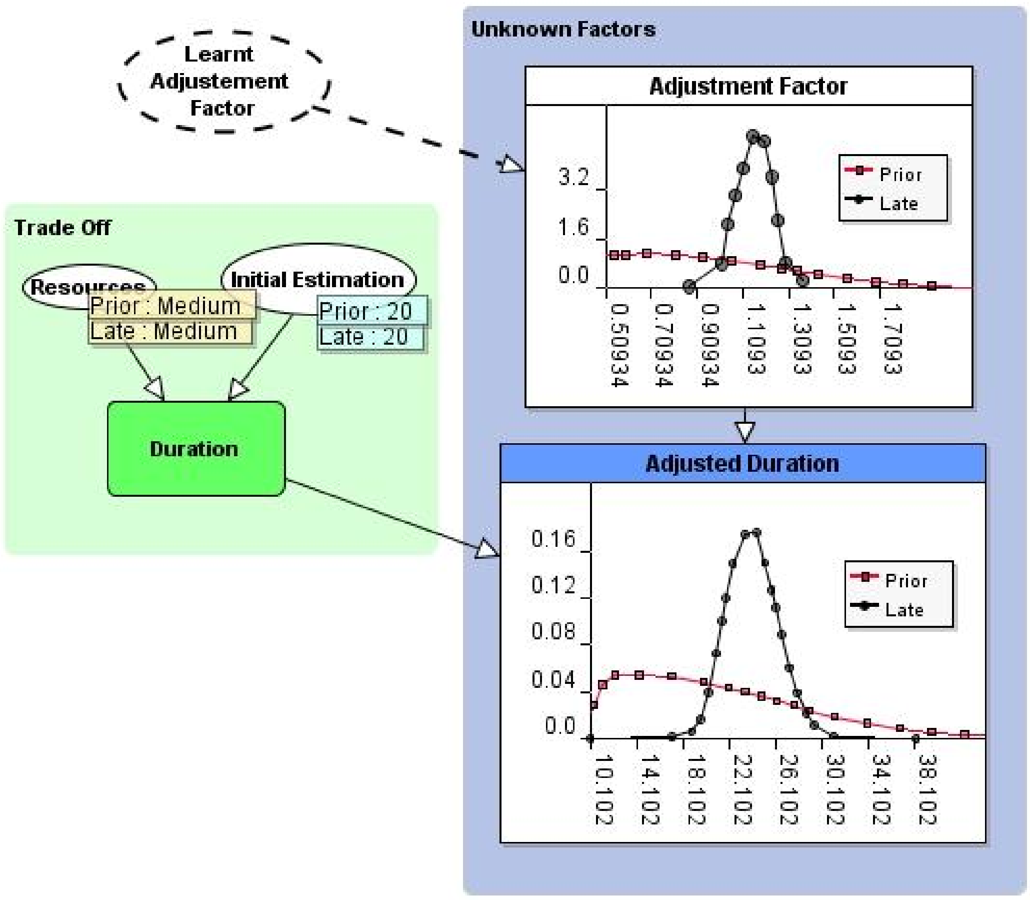


Figure 6-15 : Learnt distribution is used to estimate the duration of a successor activity

6.6 Total Duration

By connecting the three above sub-networks together, the 'Duration' model now is capable of capturing different aspects of uncertainty in duration of a general project activity as was explained in section 6.1. Figure 6-16 shows the cumulative distribution for the total duration of a task in three scenarios.

In the baseline scenario, the only available information (evidence) is that the 'Initial Estimate' is 10 weeks. There is no evidence regarding level of available resources, unknown factors and possible known risks. Using the prior distributions the model generates the distribution for 'Total Duration' which has a mean of 12 weeks, and the 80% upper percentile is 15.5 weeks.

The second scenario ('low' in Figure 6-16) estimates the worse case scenario (although the model can estimate even worse conditions). The 'Initial Estimate' is still 10 weeks but available 'Resources' is thought to be in the 'low' level, unknown factor has negative impact on duration and there is a high chance that some external event happens. In this scenario the mean value for the generated distribution for 'Total Duration' is 19.5 weeks and the 80% upper percentile is 23.7 weeks.

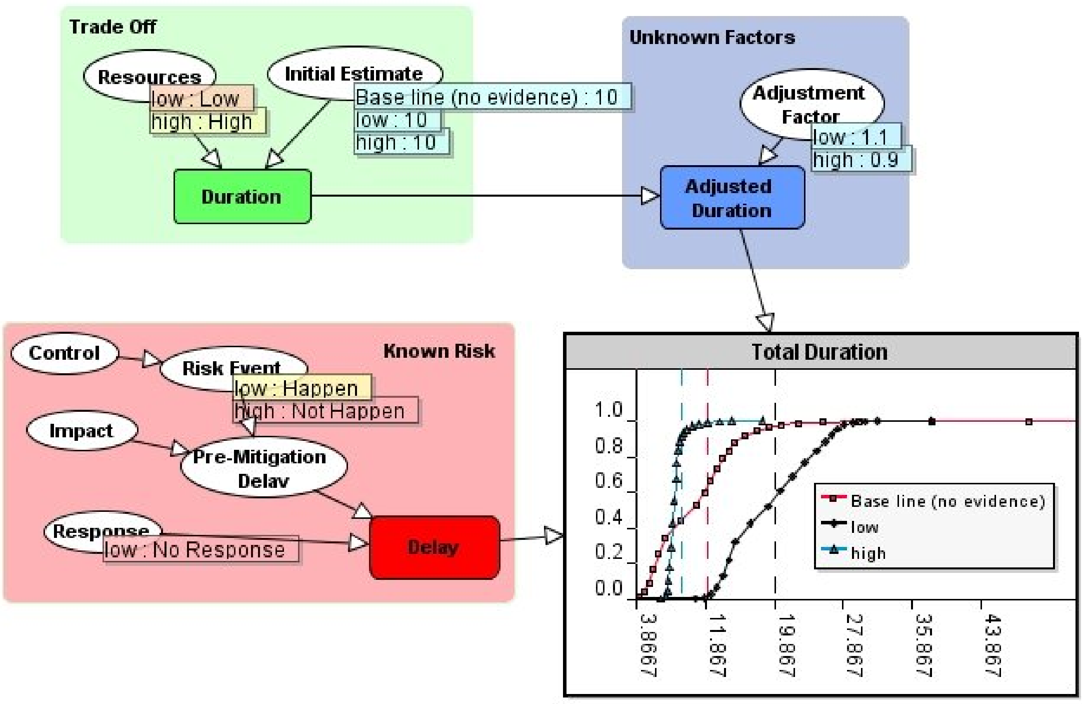


Figure 6-16 : Total Duration in different Scenarios

The third scenario ('high' in Figure 6-16) estimates the best-case scenario (although the model can estimate even better conditions). 'Initial Estimate' is still 10 weeks but available 'Resources' is thought to be in the 'high' level, unknown factor has positive impact on duration and there is a no chance that some external event happens. In this scenario the mean value for the generated distribution for 'Total Duration' is 7 weeks and the 80% upper percentile is 10 weeks.

This simple yet powerful network informs us about the source of the uncertainty a project may face and the conditional nature of the estimation of activity duration. It enables us to manage and plan responses to specific or general sources of uncertainty. It explicitly deals with all the objectives that were addressed in Chapter 3 including: handling sources of uncertainty, handling trade-off analysis, adjusting subjective estimates, quantifying common causal risks, sensitivity analysis and dynamic learning. It also follows (Chapman and Ward 2000) suggestion that:

> "Estimation should be so easy to use that the usual resistance to appropriate quantification based on lack of data and lack of comfort with subjective probabilities is overcome".

6.7 Practical Implementation

The BN models introduced in Chapter 5 and 6 apply the best tool for modelling uncertainty (BNs) to the most common approach of project planning (CPM). They offer a rigorous method for incorporating uncertainty in project scheduling. The presented approach can be applied to any project at any required level of detail.

The method has two main components:

- BCPM network
- Duration network

The first step is to build the BCPM model (i.e. the scheduling engine of the method, which calculates the probabilistic start and finish time for all the project activities). It starts with specifying individual activities, their sequence and the precedence dependency between them. Similar to classic CPM, a work breakdown structure (WBS) can be used to develop the list of activities. Using the procedure describe in section 5.2, the project network is transformed to a BN.

The next step is to elaborate the BCPM model using the 'Duration' network as explained in this chapter. This will capture different sources of uncertainty, their causal relationship and their influence on the duration of activities. The 'Duration' networks will be attached to the BCPM network to construct an integrated BN model.

The integrated BN model provides a rigorous quantitative technique that enables us to do advanced assessments in the risk analysis (see 2.2) stage of the Risk Management Process (RMP). Nevertheless, applying such advanced analyses requires adopting a formal RMP (see section 2.1). Depending on what RMP is adopted in the project organisation, there are other stages prior to the risk analysis stage, for example, *define, focus* and *identification* stages in the PRAM guide (PRAM 2004). There are also other stages that follow the risk analysis stage, for example, *planning* and *management* stages in the PRAM guide (PRAM 2004). Decisions about which RMP is appropriate and what are the other required stages is not discussed in this thesis. The BCPM model is general and flexible enough to be employed in any RMP.

The BCPM model not only incorporates uncertainty in the CPM approach but also takes full advantage of BN capabilities in addressing the shortcoming of current practice of project scheduling under uncertainty (i.e. MCS based approach). By using the forward propagation capability of BNs, it can quantify possible sources of uncertainty and estimate their impact on the project duration (i.e. predictive). By using the backward propagation capability of BNs, it provides the analysis of various time-cost combinations and also updates our knowledge about unknown risks by dynamic learning of adjustment factors (i.e. diagnostic).

Several considerations (i.e. trade-off between richness and efficiency of the model) may underlie the decision about what level of detail is appropriate. On the one hand developing the project network at too high level of detail will obscure important issues that should be addressed. On the other hand developing the project network in great detail may be too complex, requiring too much information (and effort) that is not cost-effective.

Nevertheless, what makes the BCPM model unique and powerful is its capability to model the project at any required level of detail (available information). If an activity is regarded as less important (i.e. no detailed analysis is required) its duration can be modelled (with minimum level of information and effort) by a single node with an appropriate probability distribution (e.g. as in the example of section 5.3). For those activities that require detailed analysis, the 'Duration' node can be elaborated (e.g. the 'Duration' network in section 6.6) to provide better insights about sources of uncertainty and possible decision alternatives.

7 Evaluation and Case Studies

The aim of this chapter is to evaluate the proposed models. Section 7.1 discusses the general difficulty of empirical evaluation in project risk management and defines criteria for evaluating the models. Section 7.2 and 7.3 describe the application of the proposed BN models on two projects. The first project is taken from the literature and the second project is a real case study.

7.1 The challenge of evaluating project risk analysis methods

The traditional criteria for validity and reliability (i.e. rooted from the positivist perspective) is based on empirical data such as evidence, objectivity, truth, deduction, reason, fact and mathematical data (Golafshani 2003). Usually in quantitative research study samples are needed to gather the relevant information and statistics may be used to evaluate the results.

However, in the field of project risk management there is no such empirical data available and it is very hard to conduct any empirical studies in which the effectiveness of the model in producing acceptable results is evaluated. In a study to find which methods of project risk analysis were most useful in practice, (Galway 2004) revealed a striking deficiency in the literature cited on the use of the risk analysis techniques. There are few or no sets of case studies that empirically evaluate project risk analysis and illustrate when the methods worked or failed. The reasons behind this lack of empirical data in project management include (Galway 2004):

- Details of business projects and management methodologies and data are often considered proprietary. The experience of what works and what does not in project management is often considered to be a key competitive advantage.

- Many high-technology areas and public sector projects may impose levels of classification that effectively prohibits access to their details.
- Managers are often reluctant to submit to any quantitative risk analysis as it may reveal poor performance or analysis or both.
- An effective review of a project requires extra resources, which in many cases are not available.

The lack of available data and case studies make it almost impossible to do any experiments for validation purpose. Therefore, many researchers have developed their own concepts of validity (Golafshani 2003). In order to evaluate the proposed BN models and validate their results two criteria are considered, namely *accuracy* and *informativeness*.

'Accuracy' concerns the closeness between the result of the model and the reality. It is clearly an important determinant of the model trustworthiness. To assess the accuracy of the CPM calculation in the BCPM model, a case study taken from literature is used to compare the result of the model against the result of the MCS approach. Section 7.2 explains this case study.

On the other hand, accuracy cannot be emphasized too strongly because the model is used to predict the future or currently unknown events or states of the project. Accuracy alone is not sufficient for a model to be trustworthy. The model is not 'truth', and it is never possible to say for sure that the model is perfect (Kaplan and Burmaster 2006). Moreover, the evolution of projects as they face challenges and are modified means that a risk analysis cannot be evaluated just by accuracy. For example, an early project schedule may be perfectly competent, but a change in requirements or a mid-course modification in technology would make the original schedule "inaccurate".

Therefore 'informativeness' is defined as the second criterion for evaluating the model, which means the model is informative and constructive in a sense that it can help us structure our knowledge about the project. In other words, the second criterion is the analytical capabilities of the model and demonstrating how it can:

- Help the analyst to structure thinking.
- Provide richer insights about decision alternatives.
- Provide a better picture of different parameters affecting the project.
- Provide a better understanding of the project and improve communication between different parties.
- Makes estimation easier and more systematic.
- Clarify what estimates measure and what they do not measure

Section 7.3 uses a case study taken from a real construction project to demonstrate the informativeness of the BCPM and the 'Duration' network.

7.2 Aircraft Development Example

This example aims to test the accuracy of the BCPM model. The key hypothesis is that the predicted distribution for the project duration in the BCPM model is consistent with the established state-of-the-art scheduling methods (i.e. MCS). This will show the correctness of the critical path calculation (section 5.2) of the BCPM model.

This example has been used in a number of studies (Bowers 1994) and (Williams 2004). The basis of the project network is actual data from the UK Ministry of Defence (MoD). However the data are illustrative.

Figure 7-1 shows a simplified CPM graph describing the development of a military aircraft. It shows parallel streams of activities for developing the airframe, engine and avionics, as well as their assemblage. Note that D/b is an abbreviation for 'Development bath', or test aircraft, a key element in the development programme.

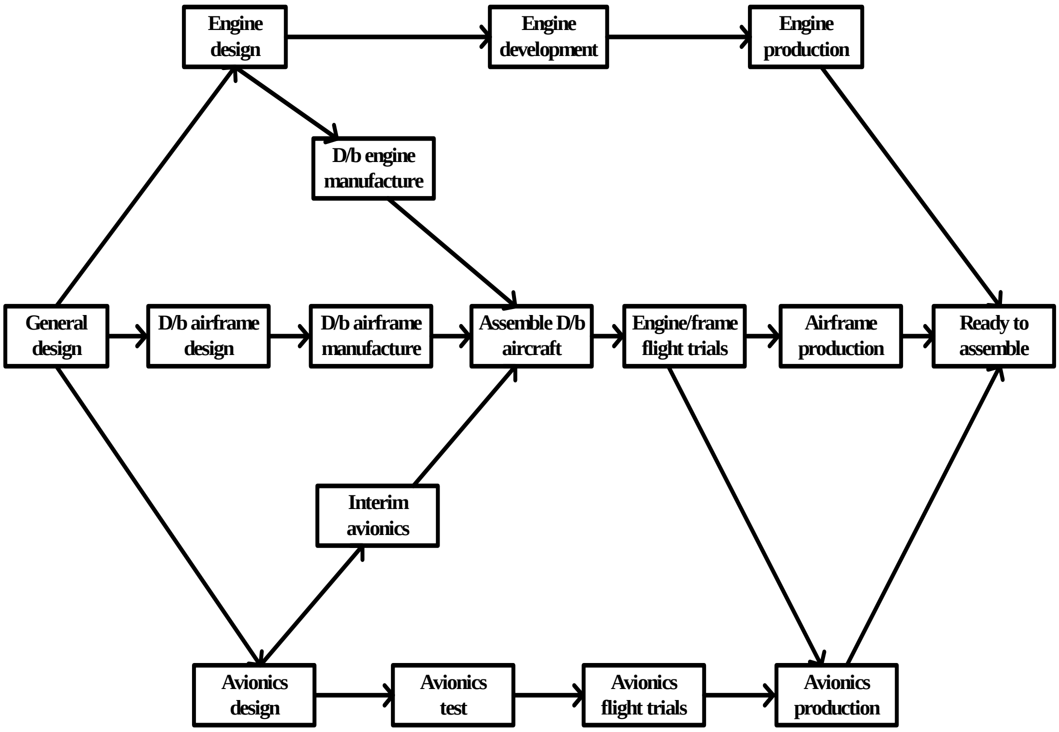


Figure 7-1 : CPM network for aircraft development example

Table 5-1 summarises the probability distribution for the duration of activities.

Activity	Distribution	Triangular Distribution			Data
		Min	Mode	Max	
General design	Triangular	4	10	21	Bowers
Engine design	Triangular	21	32	55	Bowers
Avionics design	Triangular	1	7	19	Bowers
D/b airframe design	Triangular	6	15	32	Bowers
D/b engine manufacture	Triangular	7	9	11	Bowers
Interim avionics	Triangular	7	14	27	Bowers
D/b airframe manufacture	Triangular	8	11	17	Bowers
Assemble D/b aircraft	Triangular	3	5	10	Bowers
Engine development	Triangular	20	23	40	Williams
Engine production	Triangular	12	13	14	Williams
Avionics test	Gamma	mean 10 mode 5			Williams
Avionics flight trials	Discrete	Relative probability 1:2:1:1 of 4, 5, 6, 24			Williams
Engine/frame flight trials	Discrete	Relative probability 1:2:2:1:0.5 of 5, 6, 7, 8, 13			Williams
Airframe production	Triangular	12	14	18	Williams
Avionics production	Triangular	14	16	24	Williams

Table 7-1 : Data for aircraft development example

As declared in the table, information for some activities are taken from (Bowers 1994). Other activities which are not explained in (Bowers 1994) are illustrative and taken from (Williams 2004). The time-unit throughout is months.

7.2.1 Simulation result

The probability distribution of the duration of the project using PertMaster software (Primavera 2008) is shown in Figure 7-2.

The mean duration for the project is found to be 90.5 months, and the 90% upper percentile (i.e. the time by which you would be 90% sure that the project will finish) is 103 months.

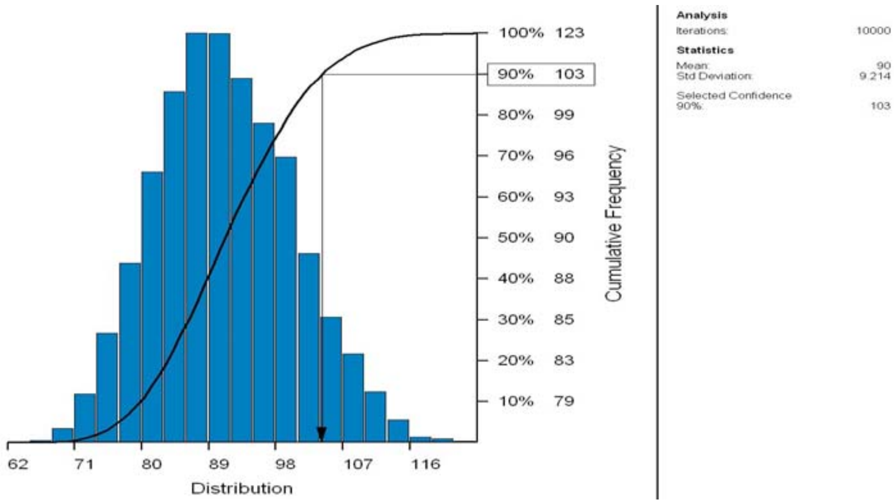


Figure 7-2 : Simulation result for the distribution of project duration.

7.2.2 BCPM model

Figure 7-3 shows the BCPM model for the aircraft development example. The result of the probability distribution of project duration is shown in Figure 7-4. The mean duration for the project is estimated as 91.4 months, and the 90% upper percentile is 101.4 months.

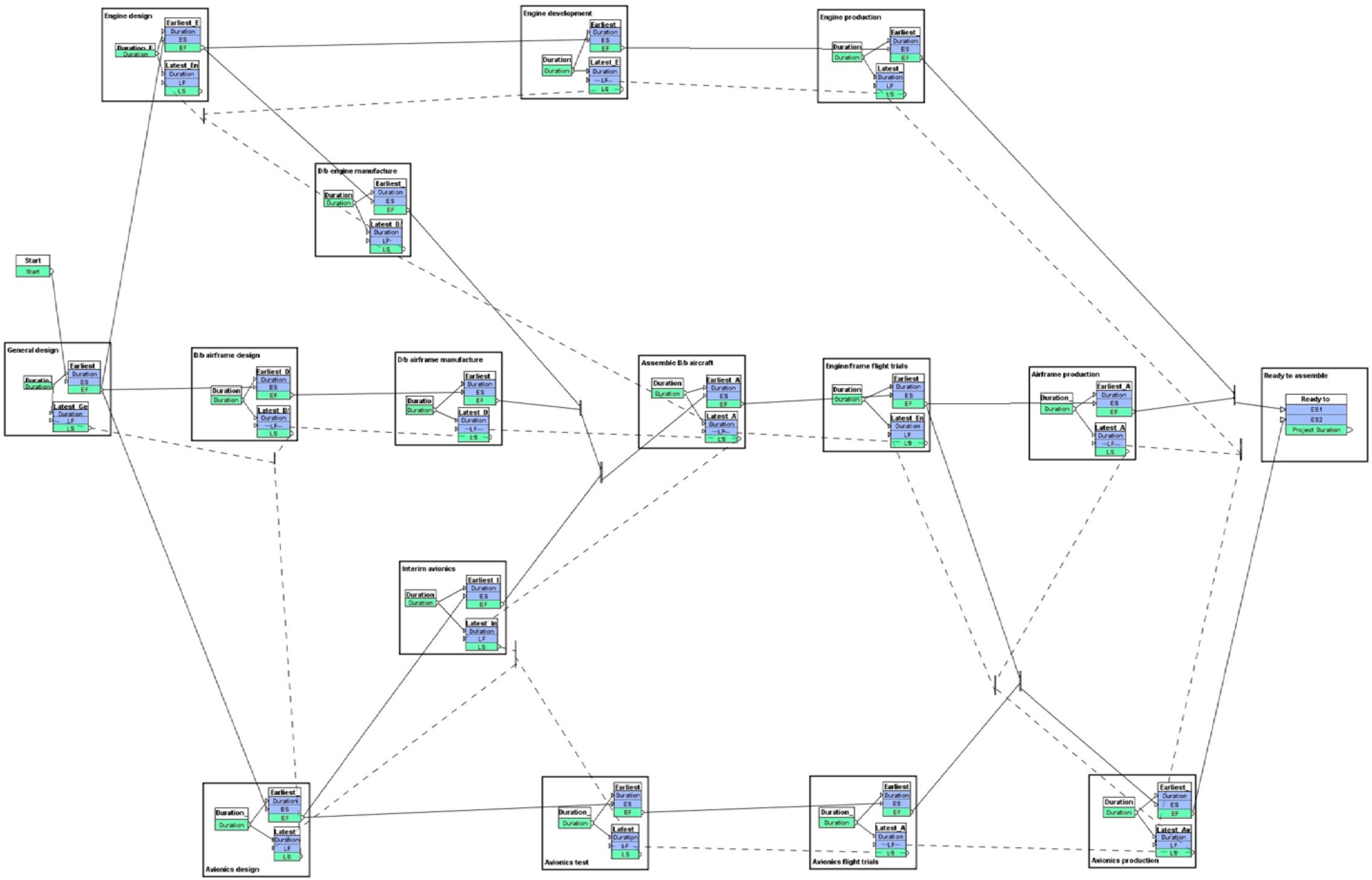


Figure 7-3 : BCPM model for the aircraft development example

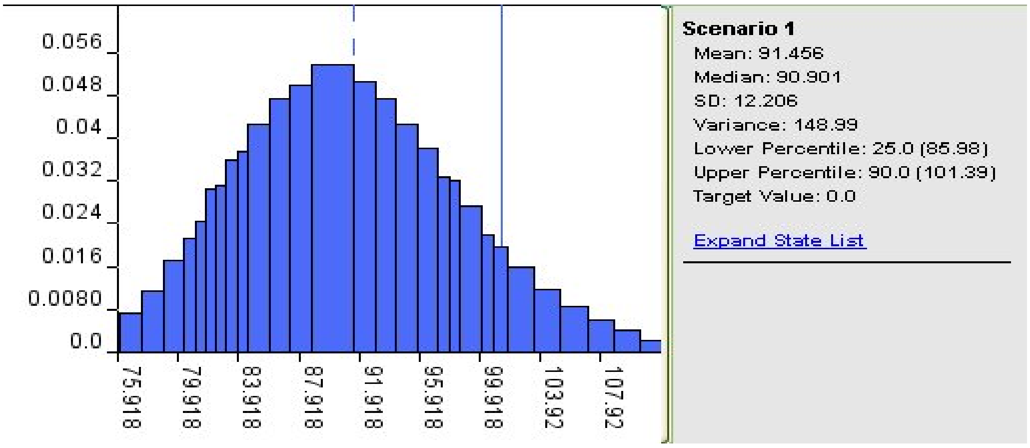


Figure 7-4 : probability distribution graph by Bayesian Network

As is summarised in (Table 7-2) the probability distribution of project duration calculated by the BCPM model is very similar to the one calculated by the MCS model. This shows that the primary target prediction of the BCPM model is consistent with the established MCS results. In other words, the BCPM model accurately performs the critical path calculations.

Method	Mean	SD	Median	Percentile				
				10%	30%	50%	70%	90%
Simulation	90.5	9.2	91	79	85	90	96	103
Bayesian Network	91.4	12.2	90.9	81	87	91	95	101.4

Table 7-2 : Comparisons between BN and simulation

7.3 Health & Fitness project

This project was a major construction/refurbishment project including design and construction of a new Health and Fitness club and bar facilities in Queen Mary University of London (it is abbreviated to H&F project). The site of the project is the old student union building. The following parties were involved in the project:

- *Owner:* Queen Mary University of London (QMUL).
- *Client:* Student Union in QMUL.
- *Designer:* A private company responsible for engineering and architectural design.
- *Consultant:* A private company responsible for auditing, budgeting and surveyor.
- *Contractor:* A private company responsible for project execution.
- *Project manager:* A private company responsible for managing the project.
- *Project office:* Administrative office in QMUL responsible for governing the project (and all other projects owned by QMUL) and coordinating between different involving parties.

The information used in this case study was provided by the *Project Office* (PO) in QMUL. My formal request for accessing the information of the H&F project, was approved and supported by the head of PO. No formal Risk Management Process (RMP) was implemented in the project. As a result, there was little formal documentation and the data acquisition was difficult.

In a period of two months (from January to March 2008) several data gathering sessions were held in the PO. The data acquisition process included:

- Unstructured interviews: I was introduced to two of the senior project managers in the PO that were involved in the H&F project. In five interview sessions, qualitative information about schedule risk (e.g. different sources of risks and their impact on project) was gathered. I also

- Reviewing the project documents: Detailed and quantitative information (e.g. project network, milestones) was extracted from the project plan, proposed and approved schedules, progress reports, risk register and minutes of meetings.

Background and summary of the project:

The project was proposed and approved in 2005. The initiating and planning phases of the project started in 2006. The construction budget was £2.7m and the whole project cost was estimated at around £4m. The execution phase of the project was divided into the following two phases:

I) Enabling work
   i. Demolishing the existing facilities
   ii. Relocating the prayer room

II) Main Scheme.

Through a tendering process the contractor was appointed (apparently based on the lowest price proposal) and the contractual completion date was set as 27th August 2007. The project schedule was produced based on this completion date. Figure 7-5 shows the high level plan for the project.

Phase (I) started on 22nd Jan 2007 and was planned to take 8 weeks. The same contractor was appointed for phase (II). The main scheme started on 26th March and was originally planned for 22 weeks.

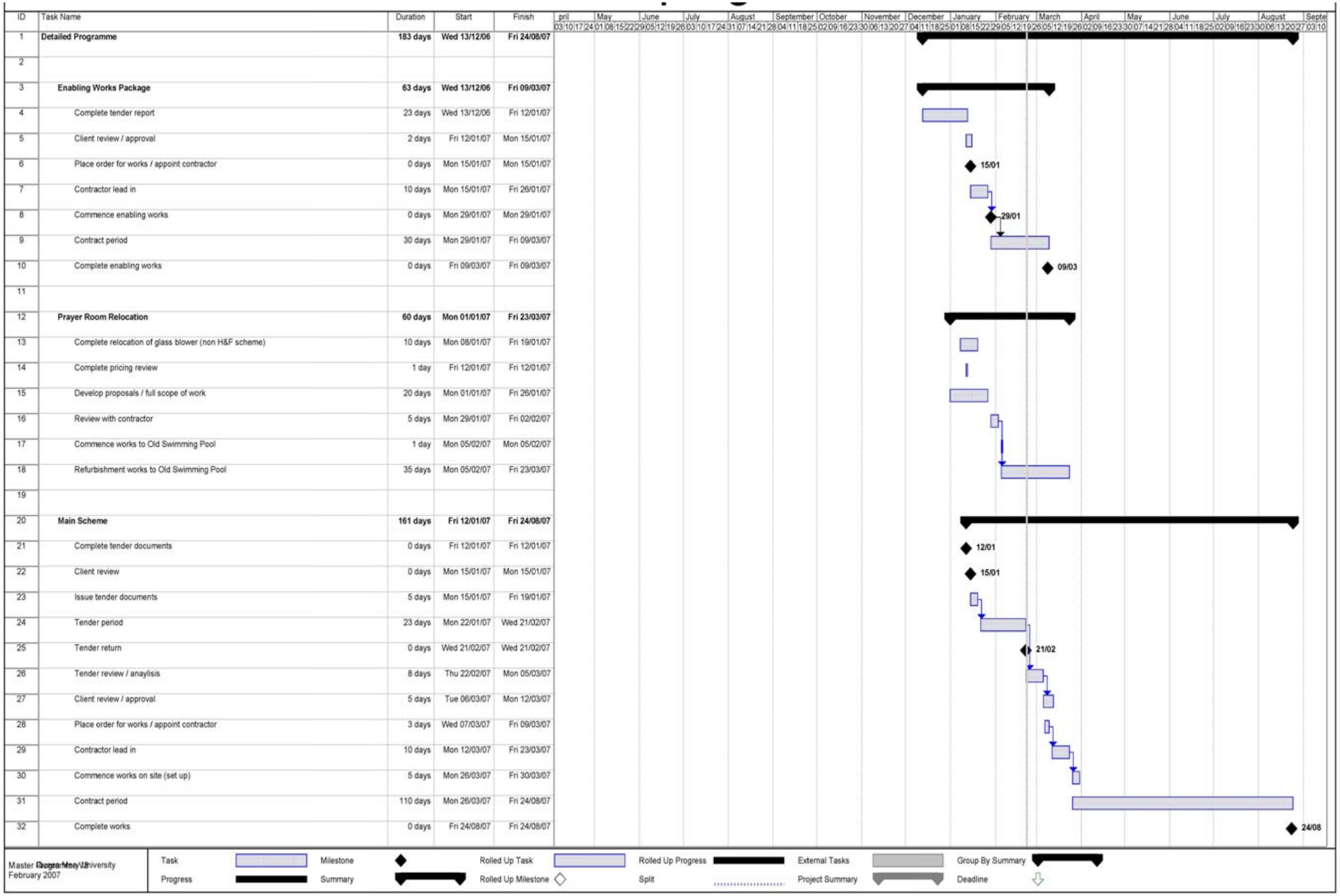


Figure 7-5 : High level schedule for the H&F project

As part of the owner's requirement a risk register was developed (see Figure 7-6). In total 24 risks were identified including: 7 duration related, 5 cost related, 4 health and safety and 8 general/requirement risks. The risk register was based on an industry's template and had no actual effect in the project scheduling process.

It is notable that even the very definition of risk items was confusing. It is not clear what is the source and what is the consequence of risk. Some risk items are very specific and some are very general. For instance, 'Indicative scheme cost Exceeds budget' and 'Delay in receipt of contractor's construction phase plan' are both items on the risk register. The latter is a specific source of time risk while the former is a general consequence of cost risk. Other examples of unclear risk items are 'completion of prayer room' and 'anticipating the completion date' which seem to be goals or deadlines rather than risks.

The scoring scheme, based on the 'Probability Impact' concept, was as inaccurate as the risk definition. For each identified risk, a score (1, 2, 3, 4) was assigned to the probability, mitigation probability and cost impact (see Figure 7-6). The total score of each risk was calculated by adding these scores. The scoring system was not sensible because:

- The basis of assessing the scores was purely subjective (guess).
- The definition of scores was ambiguous. For example 'Mitigation Probability' had 4 states: possible, maybe possible, unlikely and highly unlikely taking the score of 1, 2, 3 and 4 respectively. This was very confusing or at least unclear.
- The method of calculating the final score (simply adding the scores for probability, mitigation and impact) was questionable.
- It was just useful for prioritising the risks but it failed to quantify the possible impact of the risks on the project in a meaningful way.

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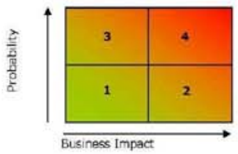

Type / Probability
Low Risk = 1
Low - Medium Risk = 2
Medium Risk = 3
High Risk = 4

Mitigation Probability
Possible = 1
Maybe possible = 2
Unlikely = 3
Highly Unlikely = 4

Cost Impact
Low Cost = 1 (£0 - £5,000)
Medium Cost = 2 (£5000 - £25,000)
High Cost = 3 (£25,000 - £100,000)
Very High Cost = 4 (£100,000

Final Risk Score
Medium Risk = 4-6
Very High Risk = 10 - 12

Item	Raised by	Risk Identified	Type / Probability (4,3,2,1)	Mitigation	Mitigation Probability (4,3,2,1)	Cost Impact (4.3.2.1)	Final Score	Update (Summarised)	Primary Action	Secondary Action	Status
1	BS	Indicative scheme cost exceeds budget.	4	Identify base line cost and Value Engineer as necessary	3	3	10	Current cost report indicates projected expenditure above budget.	BS	HLM	Open
2	MTT	Incoming electrical supply is inadequate to meet new requirements		Early survey of existing services and assessment of alternative energy usage			0	Confirmation provided that incoming supplies are adequate	MTT	HLM	Closed
3	QMUL	Operational requirements for new facility are not fully identified		Early involvement and consultation with user groups	1	2	3	Design signed off in full agreement with users and consultees.	QMUL	HLM	Closed
4	QMUL	Space for prayer room is not identified		Investigate alternative solutions and identify agreed scheme.			0	Old swimming pool agreed as location	QMUL	HLM	Closed
5	QMUL	Extent of works required to provide alternative prayer room results in delay to completion.	4	Assessment of works to be carried out. Suitable procurement selection	2	3	9	New multi faith facility completed.	HLM	QMUL	Closed
6	QMUL	Capacity of bar does not meet requirements		Analysis of potential accommodation levels with consideration given to future extension	1	2	3	Design demonstrates capacity levels are achieved.	QMUL	HLM	Closed
7	HLM	Asbestos within existing building		Carry out surveys and include any removal within construction programme			0	Works related to asbestos now complete	QMUL	BS	Closed
8	MTT	Unable to re-use existing services	1	Surveys to be undertaken in conjunction with new proposals	2	3	6	Services now stripped out and works progressing.	MTT	HLM	Closed
9	QMUL	Loss of revenue as a result of closure during construction	4	Carry out works during low season and consider phased programme to minimise any loss	3	3	10	Delay to the construction programme will result in further loss of income. Mitigation measures to be considered.	HLM	QMUL	Open
10	QMUL	Delay to overall project programme caused by failure to approve scheme	1	Regular stages of sign off throughout project. Early engagement with users / occupiers.	1	3	5	Design has been fully signed off and is being constructed on site.	HLM	QMUL	Closed
11	HLM	Building levels result in poor access for disabled users	1	Site survey to be undertaken, use of vertical transportation as necessary.	1	3	5	Designs produced which allow for disabled access.	HLM	QMUL	Open
12	QMUL	Overrun of construction period results in further loss of income	4	Tender documentation to be of sufficient detail. Selection of contractors with suitable experience.	4	3	11	Contractor reports further delays to the project. Grounds for further slippage not yet identified.	BS	HLM	Open
13	QMUL	Benefits and progress of scheme fail to be communicated to users	4	Ensure communications strategy is established to keep relevant parties informed of scheme progress and opening.	1	2	7	Dealy to scheme completion will need to be communicated to users.	QMUL	HLM	Open
14	HLM	Fire Escape Strategy precludes beneficial use of available space		Consultation with fire officers			0	Consultation to be held during design development.	HLM	QMUL	Closed
15	QMUL	Noise during construction period proves disruptive to college activities	2	Consider restrictive times for noisy working. Phasing of construction activities.	2	2	6	To be monitored as the scheme progresses.	QMUL	BS	Open
16	MTT	Adaptation of existing services results in 'down time' for other areas of the college.	2	Survey of existing services. Phasing of any re-connections.	2	2	6	Electrical shutdown programmed for w/e of 20/7/07.	MTT	QMUL	Open
17	QMUL	Planning approval is not obtained for works.		Early consultation with local planning authority.	1	2	3	Planning approval obtained.	HLM	HLM	Closed
18	QMUL	Delay to main scheme completion as a result of delay in relocating of prayer room	2	Ensure works are progressed expediently in line with main scheme requirements.	2	3	7	Multi faith facility now complete.	HLM	QMUL	Closed
19	QMUL	Client changes to layout impact on project timelines and cost.	2	Change control process to be implemented with approvals obtained as appropriate.	1	3	6	No further changes requested to date.	QMUL	HLM	Open
20	HLM	Co-ordination of design activities to ensure fast track project approach can be delivered.	3	Early co-ordination with all consultants. Ensure construction details are developed during tender stage ready for start on site.	2	1	6	Construction details being developed	HLM	DT	Open
21	HLM	Poor control of quality on site.	2	Regular site visits and checks to ensure compliance with specification.	2	1	5	To be carried out once works start on site	HLM	DT	Open
22	QMUL	Contractor claiming costs for variations.	3	Ensure variations kept to a minimum	2	3	8	Contractor has claimed costs for variations and out of hours working.	HLM	DT	Open
23	QMUL	Risk to safety of staff and students during construction phase.	2	Ensure site is well enclosed with suitable signage.	2	2	6	Contractor to implement	Contr.		Open
24	BS	Delay in receipt of contractors construction phase plan.		Early draft of plan to be provided following appointment	2	2	4	Construction phase plan received and approved.	BS	Contr.	Closed

Figure 7-6 : Risk register for the H&F project

What actually happened in the project was very far from what was planned and the project's risk analysis approach proved to be useless. In the 'Enabling Work' phase, relocating the prayer room was much more demanding than anticipated. As a result it finished 4 weeks later than the planned date (58% delay) and consequently the main scheme was delayed. However, the target completion date remained fixed as the end of August.

In June 2007 it was reported that the project was 4 weeks behind the agreed schedule. The progress was very slow and the schedule risk was getting worse. The contractor reported a number of reasons for the delay such as 'asbestos works in the existing ceiling' and 'underground drainage layout' (unanticipated work). The consultant did not agree with the reasons (i.e. start of dispute between contractor and consultant).

It was obvious that the completion date was not going to be met. The delay expanded in July and August to 6 and 9 weeks respectively. In August (the original completion date) the new completion date was set as the end of October. At this time the dispute between the contractor and the consultant increased. Each party blamed the other for the delay and the project faced ever-increasing problems. The contractor requested a time extension to cover the overrun, which was rejected by the consultant.

To make the situation worse, further problems happened and consequently the project faced further delays. In October the contractor changed its site management team completely. Also sub-contractors failed to deliver on time. A new completion date was proposed as the end of November. In November the new completion date was estimated as the middle of December. In December the project was 14 weeks behind. Surprisingly enough as time was passing instead of getting closer to the completion date, it was actually getting later. The project was terribly behind its schedule and mitigation was on the basis of the damages (e.g. cost overrun, continuing noise and disturbance on the site) limitation.

In December 2007 (i.e. five months after the original contractual finish date), still there was not any clear idea how long the remaining activities were going to take and when the project would be finished.

In the next few months the dispute between the contractor and the consultant got worse. The contractor claimed a number of new (proposed) dates for the project completion but none of them was achieved. The project eventually completed at the end of May 2008 with some 40 weeks delay.

Although there was a complete project plan along with a risk register, the project was far behind its planned time and budget. How useful were the project plan and the risk register? What went terribly wrong that caused this 160% schedule slippage (and probably the same extent over budget)? The next section describes how the BN approach of Chapter 6 could address these questions.

7.3.1 BN model for the H&F project

Before discussing the developed BN model for the H&F project, it is necessary to clarify the scope of the model. There were several aspects of the project (e.g. project finance, project organization, bidding and contracts, judgement over claims, and risk ownership) that were not addressed here. The reason was because in the process of data gathering, I realized that the required information about some of the sensitive aspects of the project (such as finance and governing the project) was either unavailable or inaccessible (see section 7.1 for reasons for reluctance to reveal the data). Nevertheless, the accessible data was sufficient for the purpose of this case study (i.e. demonstrating the applicability and usefulness of the BCPM model). As was mentioned in section 6.1, if more detailed analysis is required (assuming the information is available), the BCPM model is capable of capturing any required level of detail. The BN introduced in this section is a simplified high-level model of the project from the owner's (Queen Mary University of London) point of view. It aims to show how the BCPM model could incorporate the uncertainty and risk affecting the project duration in a sensible, robust and yet simple manner.

Identifying sources of uncertainty:

Through several interviews with the key members of the project team (senior project managers in the project office in QMUL and also the external project manager), examining the project's documents as well as reviewing relevant literature in the construction industry, for example (Mbachu and Vinasithamby 2005), (Winch and Kelsey 2005) and (Chapman 2001), the following problems were highlighted as the main causes of delays in the H & F project:

Unrealistic project deadline:

The idea was to launch the facilities at the start of the academic year (September 2007). In order to mitigate possible delays, a 6 weeks contingency was included. The planned deadline of 24th August 2007 was very tight and unrealistic. In fact all other contractors who responded to the tendering invitation had estimated the duration much longer than 22 weeks (the average of all the proposed periods for the contract period was 26 weeks). The project had a fixed-price contract and the 'Liquidated and Ascertained Damages' (LAD) was agreed as £5000 per week (i.e. penalty for every week delay from the contractual completion date due to contractor's fault). However 'Extension of time' (EOT) claims (i.e. contractors often challenge the enforceability of LAD) are very difficult (Williams 2003c) and also they are a reactive mechanism to transfer the liability of the delay risk to the contractor not to prevent or manage it. The sensible approach would be to either correct the time constraint to be more realistic and achievable or properly manage the affecting resources (see section 6.3) in a way to meet the tight time constraint. The H & F project had a fixed-price contract and the main resources were supplied by contractor and consultant.

Contractor:

'Bid to win' is a common strategy in bidding a construction project (Williams 2003c). The contractors' survival depends on winning new contracts. In the highly competitive market an increasingly important element in winning a bid is to accept tight time-constraint contracts. However, the ability to deliver the project on time (i.e. contractual time) is a matter of experience, productivity and efficiency. The contractor's quality in areas such as management, planning, control, pricing and finance, resources (funding, personnel and equipment), and handling subcontracts has a direct effect on the project duration. Apparently the appointment of the contractor was based on lowest-price proposal. Nevertheless the inefficiency and poor quality of the contractor was a major cause of delay in the H & F project (for example, lack of experience in estimating the required effort and generating a realistic detailed plan, inability in handling sub-contracts, changing the site management team).

Consultant:

A private company won separate contracts for design, quantitative survey and project auditing. Its responsibilities included a wide range of areas such as providing prompt and complete design (i.e. plan, architecture, mechanical and electrical), supplying required and accurate information, resolving technical issues promptly, auditing and monitoring the project progress, communicating with the contractor and reporting to the project office. Although the main delay occurred in the construction phase, the quality of design played an important rule and had a direct effect on the construction period. On a few occasions during the main scheme lack of detailed and finalised design caused significant delay on the project. For example, the lighting and electrical design was not available at the required time causing significant delay on installing the lighting and electrical system. Another example was a complete change in the design of the air conditioning system that introduced several technical problems and significant delay. A crucial source of delay in the H & F project was related to the quality of the consultant.

Known risk:

There were a number of time-related risk items which were identified in the risk register. These were foreseeable external event/conditions that could impact on project duration. For these risks, it is often possible to predict appropriate control mechanisms (to prevent the risk) or response mechanisms (to reduce the outcome delay). For example, 'noise and access problem' was predictable because the project's site was located in the middle of an academic department. To reduce the noise disturbance, delay in some activities (e.g. demolition) was predictable. A possible response would have been to introduce overtime shifts (i.e. before/after normal office hours or weekends) to perform these noisy activities.

Unknown risk:

These are all other unidentified/unrecognised sources of delay. For example, organizational factors turned out to be very important in the H & F project because several parties (e.g. client, designer, contractor, consultant and project office) were involved. These include aspects such as coordination, communication, supervision, clear roles and responsibility and decision-making, which are common throughout all activities. They are especially important when the project starts to go off track (early signals of delay). How the different project parties respond and cooperate with each other to put the project back on track is very crucial. It appeared that the H&F project suffered from a number of organizational problems such as unclear definition of roles and responsibilities and also ineffective communication between different parties. Rather than coordinating with each other to find solutions for the project problems, the parties involved (i.e. contractor and consultant) blamed each other and refused to take responsibility.

Constructing the BN:

After gathering the information and identifying the above sources of delay, the next step was to construct the BN model of the project. As explained in section 6.7, the model has two main components: Duration and BCPM.

The Duration model captures sources of uncertainty on activities duration. A customized version of the BN model introduced in section 6.6 was built to model the above sources of delay in the H & F project. As shown in Figure 7-7, a minor modification was made in 'Resources' section. Two new ranked nodes (as defined in section 4.5.1) were introduced to model the quality of 'Contractor' and 'Consultant' as main drivers of the resource quality. The level of Resources then was defined as the minimum of the quality of 'contractor' and 'consultant'. This reflects the conservative assumption that the level of resource is high if only both of contractor and consultant have high quality.

The rest of the network has the same logic and structure as the BN for duration of prototype activity explained in section 6.6.

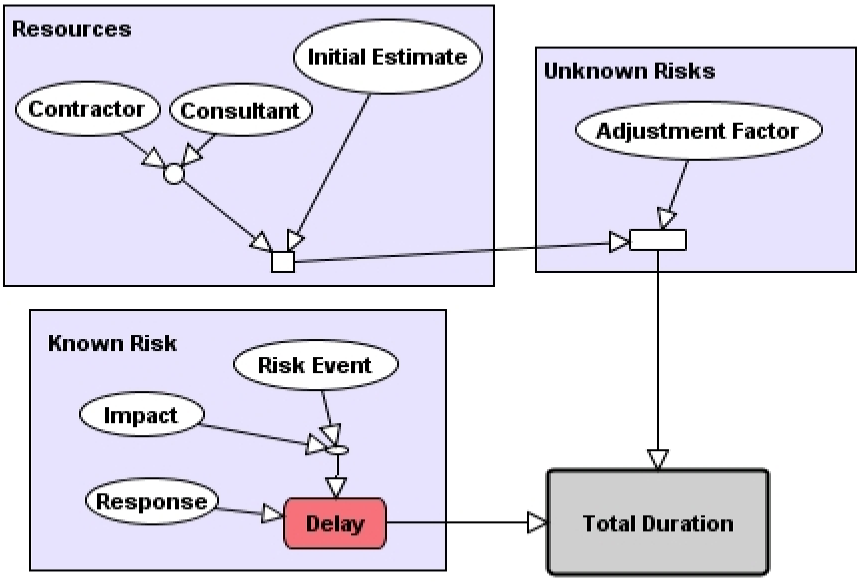

Figure 7-7 : Customised version of activity network for H&F project

The BCPM part of H&F project model was built based on the high level project plan (Figure 7-5) as shown in Figure 7-8. It models the three main phases of the project (i.e. demolition, prayer room and main scheme). Each phase has a set of 4 nodes (i.e. ES, EF, LS, LF) to calculate the CPM time parameters as discussed in section 5.2.

The ‘Demolition’ phase was less complex so it has a more simplified duration model. It only contains ‘known risk’ to model possible identified risks such as ‘finding asbestos’ (see Figure 7-8).

The prior probabilities for the BN nodes were assessed. This assessment was based on relevant information (when data was available) or explicit assumptions/subjective belief (when data was not available/accessible).

The ‘Initial estimate’ for ‘demolition’ and ‘prayer room’ was set 6 and 7 weeks respectively, equal to their duration in the original project plan (Figure 7-5). But the duration of ‘main scheme’ in the original plan (22 weeks) appeared to be too optimistic. Therefore, the ‘Initial Estimate’ for the ‘main scheme’ was set to 26 weeks, equal to the average of durations proposed by four different contractors (i.e. 22, 26, 31, 25 weeks) who had participated in the tendering.

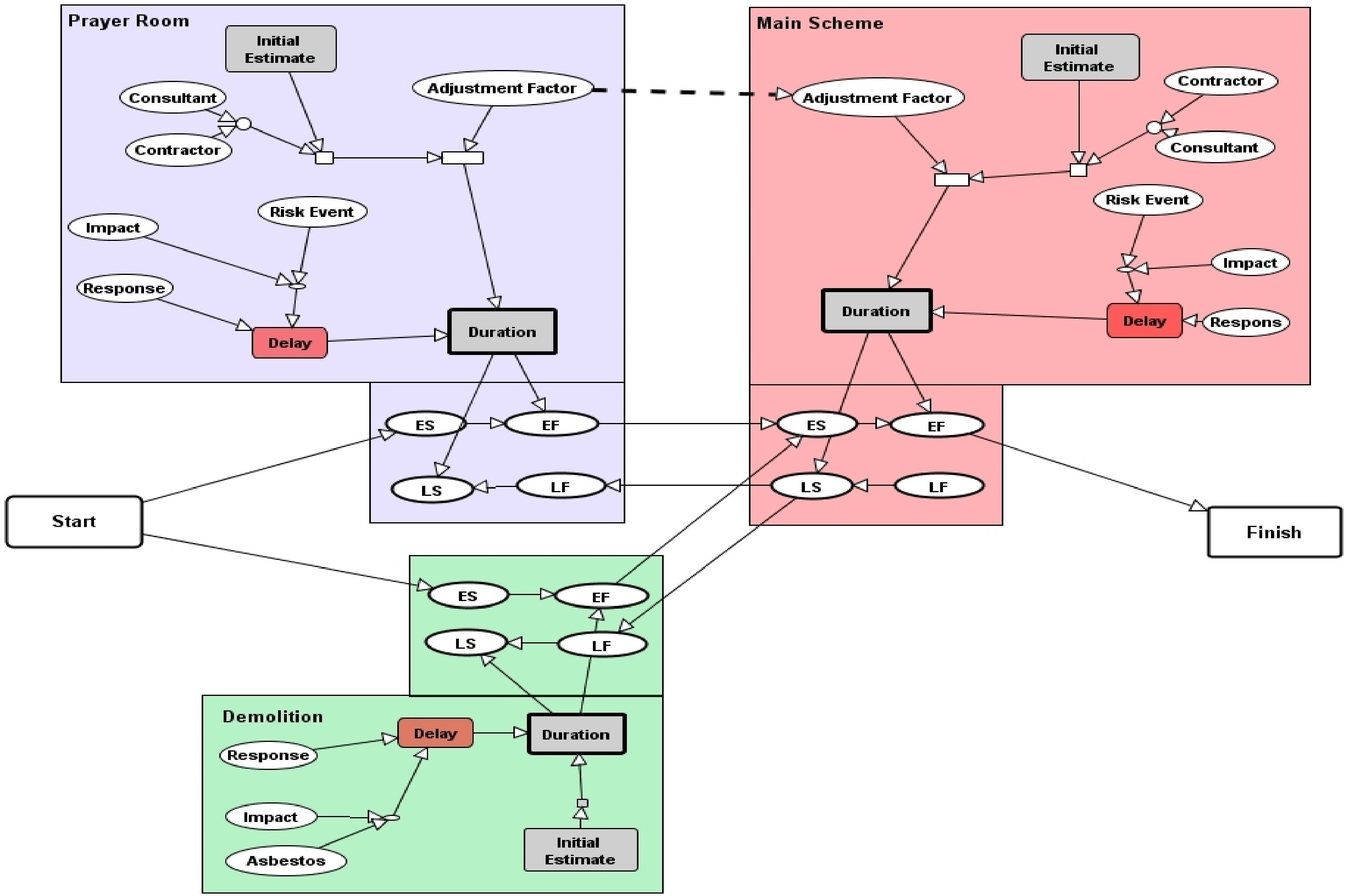

Figure 7-8 : BCPM model for the H & F project

The prior probabilities for quality of ‘Contractor’ (and ‘Consultant’) were set as 0.05, 0.25, 0.55, 0.1 and 0.05 for very low, low, medium, high and very high respectively. In the absence of previous data or formal evaluation, this simply reflects the assumption that the quality of the contractor (consultant) is more likely to be at medium level.

The prior distribution for the ‘Adjusted Factor’ was set as TNormal(0.7, 0.3, 0.5, 10). This appears a rational estimation because with mean, 10% and 90% percentile values equal to 1.01, 0.7 and 1.53 respectively, it reflects the assumption that although the average adjustment is negligible, it is possible that the initial estimation is 30% (i.e. $0.7 \times IE$) overestimated or 53% (i.e. $1.53 \times IE$) underestimated.

As explained in section 6.4, the ‘Adjustment Factor’ can be learnt as more information becomes available. The learning is made by the dashed link from the ‘Adjustment Factor’ in the ‘Prayer Room’ phase to the ‘Adjustment Factor’ in the ‘Main Scheme’ phase.

7.3.2 Results and analysis

The model is capable of different types of analysis depending on how much data is available. The first analysis is the baseline estimation for the project duration. This is the initial prediction of the project completion with minimal information using prior probabilities (as explained before) without considering the occurrence of ‘known risk’ (i.e. no information is available about known risks).

Figure 7-9 shows the result of the cumulative distribution for the main scheme phase and the probability distribution for the overall project duration. For the main scheme phase the mean is 32.3 weeks, the 80% percentile is 42 weeks and there is only 40% chance that the phase finishes in 22 weeks (the contractual deadline). For the overall project duration, the mean and 80% percentile are 41.6 and 53.5 weeks respectively. This initial prediction of the model is very powerful. Because even at the early stages of the project with the minimum available data, it reveals that the original project schedule was unrealistic and the

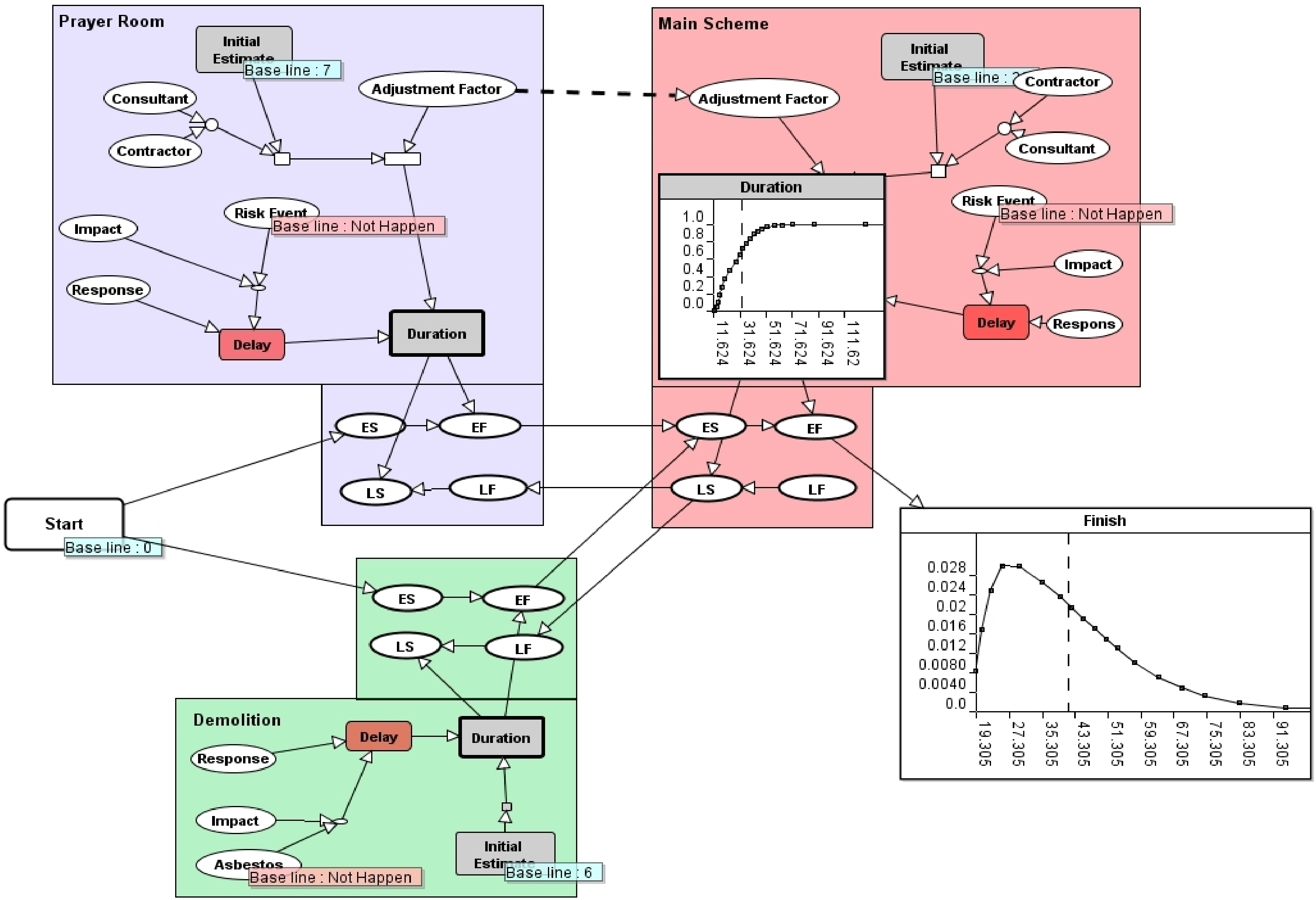

Figure 7-9 : Cumulative and probability distribution in baseline scenario

chance that the project would be finished on the contractual deadline was only 40%.

The main power of the model emerges in handling various ‘What if?’ type analysis. It enables us to study different scenarios and quantify them based on available information or underlying assumptions. To illustrate this type of analysis, Figure 7-10 shows the probability distribution graph for the duration of main scheme phase and the cumulative distribution for the project duration in three different scenarios:

In the first scenario (called ‘Known Risk’ in Figure 7-10), I was interested in modelling the effect of occurrence of (identified) risks on the project completion. For instance, one of the identified risks in the risk register (Figure 7-6) was ‘finding asbestos within existing building’. If this occurs, it requires extra health and safety considerations that probably would interrupt the project. For simplicity, I assumed that the impact of this risk is medium. The new information/assumption was fed to the model (i.e. entering evidence in the relevant nodes) and propagated through the network. Table 7-3 summarises the parameters of the outcome distribution for the project duration and also the main scheme phase. The mean and 80% percentile for the project duration distribution has changed to 53.5 (was 42 in the base-line scenario) and 68 (was 53.5 in the base-line scenario) weeks respectively. Although the influence of possible control or responses on this risk are not modelled here, it could be easily modelled if the detailed analysis is required. For example, carrying out surveys to spot the existence of asbestos before commencing the work and then out-sourcing the asbestos removal to specialist sub-contractors to save the time are possible control and responses relevant to this risk.

In the second scenario (called ‘Adjustment’ in Figure 7-10), I assumed, based on apparent organisational issues in the project (such as unclear definition of roles and responsibilities and ineffective communication), that the adjustment factor is greater than one. For example, by entering 1.2 as evidence in the ‘Adjustment Factor’ node and propagating through the network, the new estimation for the probability distribution of the project duration is achieved as summarised in

Table 7-3. The mean and 80% percentile has changed to 48.2 and 52.6 weeks respectively.

The third scenario (called 'Worst case' in Figure 7-10) is a combination of the previous two scenarios. Here, I assumed that not only external risks might happen (e.g. finding asbestos) but also the value of adjustment factor is known to be greater than one (e.g. 1.2). After entering evidence in the relevant nodes and propagating through the network, the new estimation for the probability distribution of the project duration is achieved (Table 7-3). The mean and 80% percentile value for the project duration has changed to 67 and 85 weeks respectively. This scenario reflects the real circumstances of the H&F project. What actually happened during the construction of project was a combination of external risks (such as finding asbestos) and internally generated risk (i.e. unknown risks such as organisational issues).

It is notable that the probability of achieving the contractual deadline (i.e. 30 weeks) in the worst case scenario (i.e. similar to real condition of the project) was less than 5%. In others words without significant changes (i.e. managing sources of uncertainty as explained before) it was extremely unlikely to deliver the project on time.

Scenario	Main Scheme Duration			Project Duration		
	Mean	SD	80%	Mean	SD	80%
Base-line	32.37	14.8	42	41.6	18	53.5
Known Risk	37.4	18.2	54.2	48.1	24.6	68
Adjustment	37.9	9	42	48.2	9.7	52.6
Worst Case	53.2	14.4	68.3	67	18.2	85

Table 7-3 : Summary of probability distribution of Figure 7-10

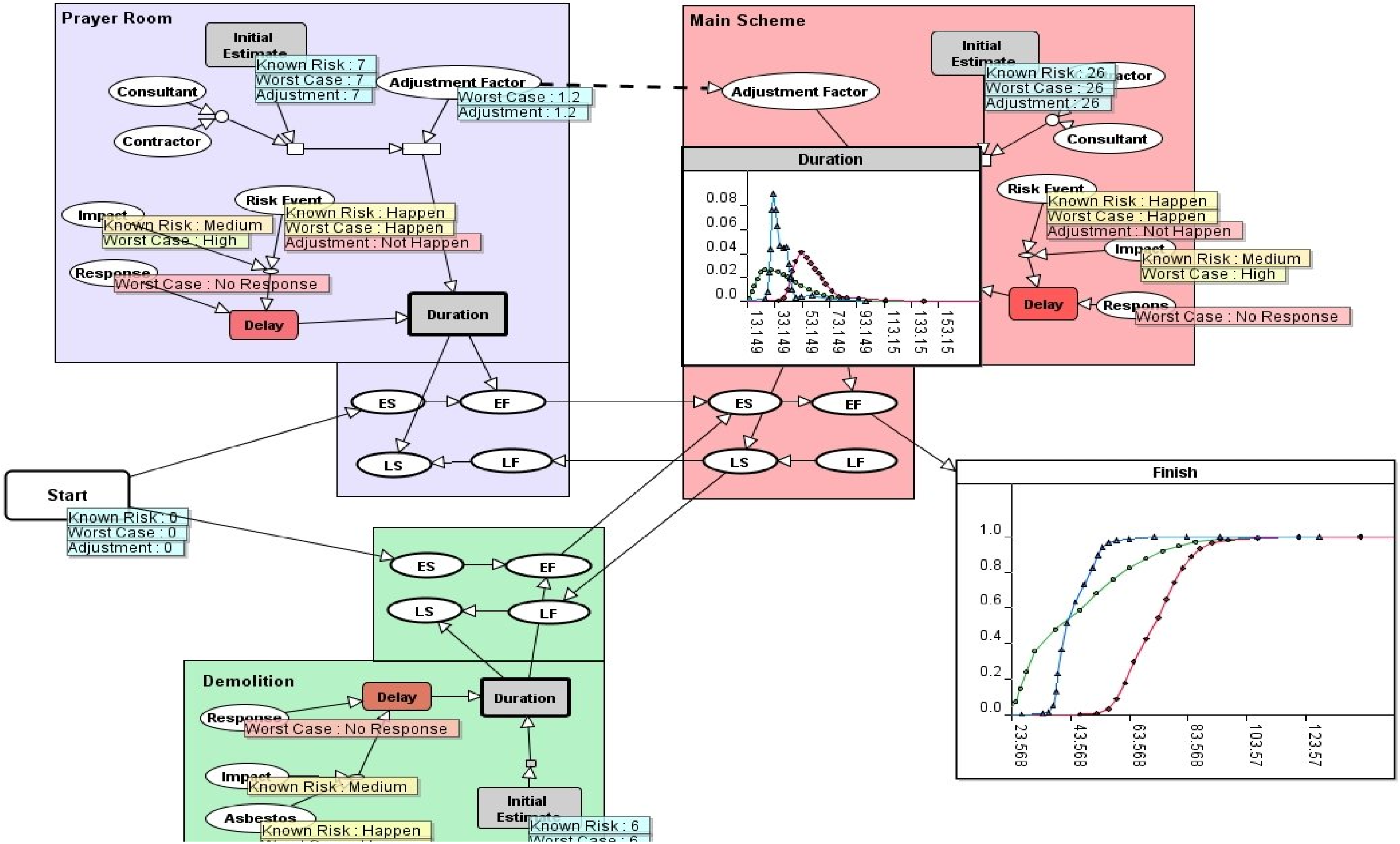

Figure 7-10 : Probability distribution for the project duration in different scenarios

The trade-off relationship between duration and resources can be analysed using diagnostic capability of the BNs (i.e. backward propagation). This is another type of 'what if?' analysis that answers questions about the cause node based on evidence entered in the child node. In the next scenario (called 'Deadline' in Figure 7-11), I was interested to know what level of contractor's quality is required in order to meet the contractual deadline. Figure 7-11 shows the probability graph for 'Contractor' node when 22 is entered as evidence in the 'Duration' node and assuming all other nodes are the same as the base-line scenario (Figure 7-9). Note that the probability for the 'Contractor' is clearly skewed towards 'Very high' and 'High'. In other words a contractor with medium level of quality would not be able to deliver the phase on time (i.e. what actually happened in the project).

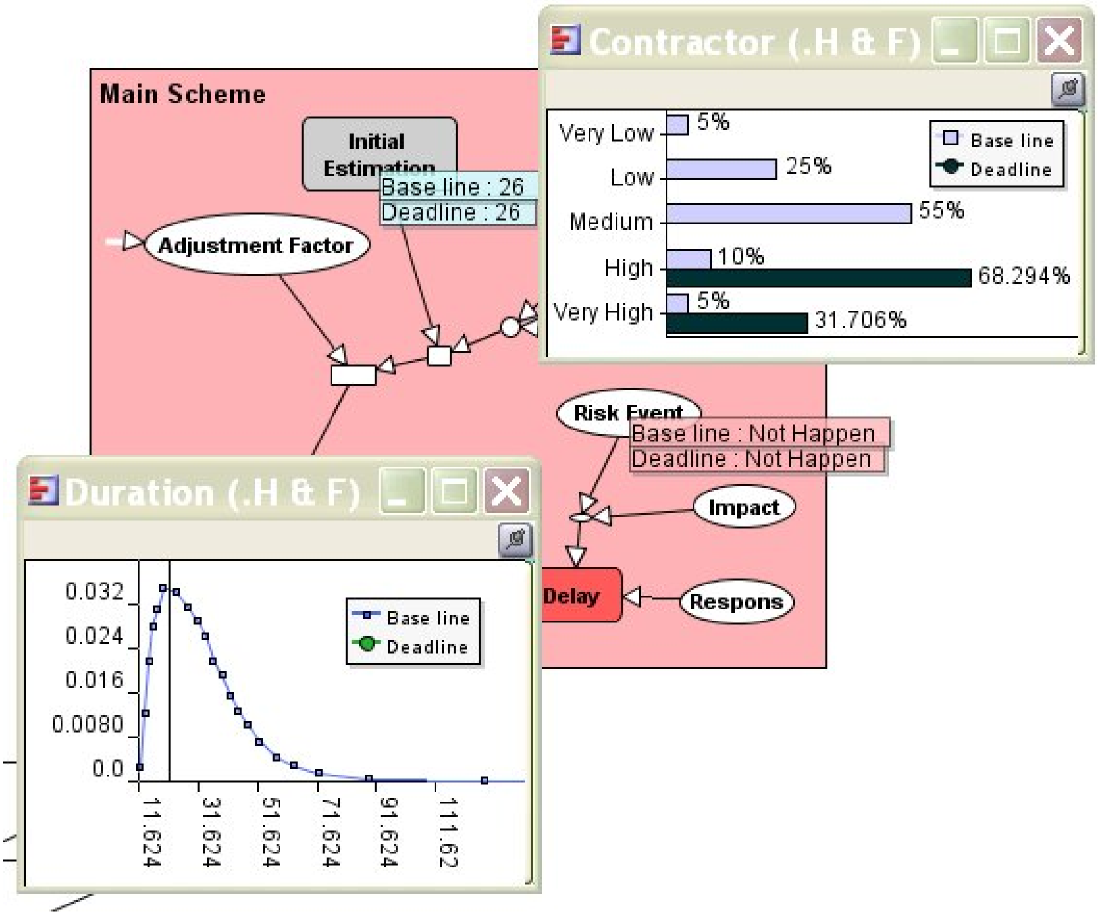

Figure 7-11 : Required level of contractor's quality changes when there is deadline

Another distinctive feature of the model is its ability to learn and update its parameters as more information becomes available. As explained in section 6.5 measuring unknown risks is highly subjective, and therefore requires more emphasis on learning. Having more information about delay in an earlier phase of the project can update our belief about unknown uncertainty (i.e. adjustment factor) and consequently duration of the following phases.

It the base line scenario in Figure 7-9 a truncated Normal distribution in the range of (0.7,10) with an expected value around one seemed reasonable to estimate ‘Adjustment Factor’ (i.e. prior distribution in section 4.1.3). This prior estimation in-turn was used to estimate the duration of each of the three phases in the project. When the ‘Prayer Room’ phase finished, its actual duration was entered as evidence (i.e. observed information) to update the distribution of ‘Adjustment Factor’ (i.e. posterior distribution in section 4.1.3). This is shown in Figure 7-12 where the actual duration of prayer room was 13 weeks (its initial estimate was 7 weeks). The 6 weeks delay in this phase was caused by a combination of known risks (e.g. technical problems in installing the drainage system) and unknown risks (e.g. organizational factors). The drainage system problem caused a 2 weeks delay. Thus the remaining 4 weeks delay was caused by unknown risks. By entering this observed information in the relevant nodes and propagating through the network, the posterior (learnt) distribution of ‘Adjustment Factor’ (i.e. distribution of ‘Adjustment Factor’ given that the initial estimation and the actual duration were 7 and 13 weeks respectively) was achieved (Figure 7-12). The mean and 80% percentile of the updated distribution is 1.19 (was 1.02 in prior distribution) and 1.66 (was 1.24 in prior distribution) respectively (Table 7-4).

Scenario	Adjustment Factor			Main Scheme Duration		
	Mean	SD	80%	Mean	SD	80%
Base Line	1.02	0.37	1.24	32.3	14.8	42
Learning	1.19	0.26	1.66	38.1	12.7	54.2

Table 7-4 : Summary of probability distribution in Figure 7-12

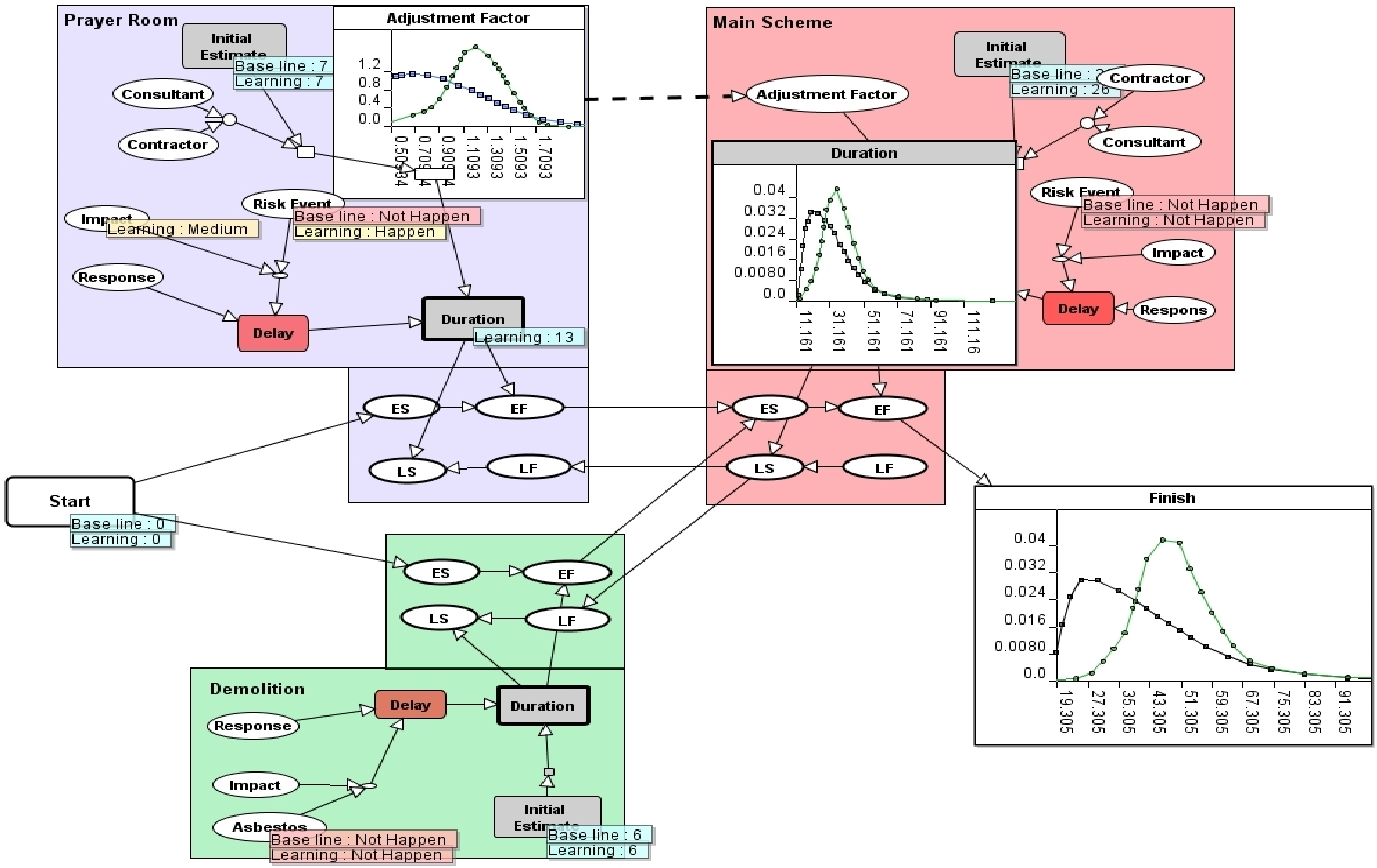

Figure 7-12 : Learning adjustment factor

Now, assuming unknown risks are common causes of delay throughout the project, this updated distribution of 'Adjustment Factor' from the 'Prayer Room' phase was fed (dashed link in Figure 7-12) to the 'Adjustment Factor' of the 'Main Scheme' phase. Consequently the distribution of 'Duration' in the 'Main Scheme' phase and also the distribution of project duration were updated. Note that the learnt distributions in Figure 7-12 are much sharper (having less spread) than the prior distributions and their expected values are shifted toward right. Table 7-4 summarises the distribution of 'Adjustment Factor' and 'Duration' in the 'Main Scheme' with and without learning. For example, the expected value of 'Duration' in the baseline scenario was 32.3 weeks, which was updated to 38.1 weeks after observing new information about actual duration of the 'Prayer Room' phase.

The above scenarios are examples of the analytical capability of the BN model. It was shown that:

- The model provides a rigorous framework for quantifying the project uncertainty using subjective information, framing assumptions and available data.
- Even with the minimal available data (i.e. prior knowledge), the model can reasonably estimate the probability distribution of the project duration and also duration of individual phases.
- The model is capable of powerful sensitivity analysis and 'what if?' type analysis for modelling the trade-off between resources and duration.
- The model can update our prior knowledge in the light of new information as the project progresses (i.e. learning capability).

Furthermore, the model is capable of more detailed analysis if required, albeit only if detailed data is available (hence they are not covered in this case study). For example, the 'contractor' and/or 'consultant' nodes can be expanded in order to capture more details. Another example is capturing possible responses to 'known risks' in order to update the schedule accordingly.

As argued in chapter 3, this model aims to analyse uncertainty in project schedule in order to help make informed and appropriate decisions. We do not expect that such an analysis solves or reduces the uncertainty or guarantees that unforeseen uncertainty will not happen and the project will meet its deadline. However, we can expect the analysis to give a deeper insight to the problem, capture causal relationships between variables and quantify them in a rigorous manner. The BN model proposed in this thesis is capable of these objectives as illustrated in the H&F project.

8 Conclusion

This thesis has focused on the quantification of uncertainty in project duration. More specifically, it has proposed a new approach based on BNs to incorporate uncertainty in project scheduling. A summary of the thesis is presented in section 8.1. The limitation of the model is discussed in section 8.2. The way forward and possible directions for the future research are outlined in section 8.3.

8.1 Summary

Risk quantification is an important part of project risk management (PRM) alongside risk identification and risk response. It aims to measure the risks and their consequences on the three project parameters: time, cost and performance. A reasonable measurement of risk supports the risk response and can improve the decision making significantly. This thesis focused on quantification of risk associated with project duration.

It was argued that the current practice in modelling risk in project time management has serious limitations that need to be addressed.

Firstly, the current practice of project scheduling is firmly rooted in a 'Probability Impact' paradigm. This implies an inadequate interpretation of risk (i.e. external event) which limits the ability to model the project risk effectively. Instead of modelling risks as (external) events that might affect a project, we should focus on sources of uncertainty and quantify their effect on the project outcome (e.g. duration). In order to measure (and then manage) uncertainty effectively, we should be able to capture causal relationship between different sources of uncertainty.

Secondly, most of the uncertainty involved in projects is subjective (i.e. ignorance) rather than frequentist (i.e. randomness). Project parameters are uncertain because of lack of complete knowledge (information) about the project not because of random variation. The estimation of subjective uncertainty is a great challenge. The classical frequentist methods (e.g. Monte Carlo Simulation methods) generally require assuming randomness in uncertainty which might not be true. Usually subjective estimation is conditionally dependent on some assumptions and conditions. More sophisticated methods are needed to explicitly model (quantify) these conditional dependencies (i.e. sources of uncertainty) and also support coherent use of subjective probabilities.

It was discussed that BNs are a powerful technique for decision support and offer a general and flexible approach for modelling risk and uncertainty. The key capabilities of BNs that make them particularly suitable for modelling uncertainty project is that they can:

- Model causality and explicitly quantify uncertainty
- Provide rigorous method to make formal and coherent use of subjective information
- Make prediction with incomplete data
- Update the probability of unknown variables using observed information in other variables (i.e. parameter learning)
- Support probabilistic inference from cause to effect as well as from effect to cause (i.e. sensitivity analysis)

However, BNs are rarely applied in project risk management. This thesis aimed to provide a general approach for modelling uncertainty in project scheduling using BNs. The analytical hypothesis was that it is possible to improve project risk assessment and quantify uncertainty in project scheduling more effectively by using BNs.

Applications of BN in project management was first suggested by (McCabe 1998) and (Nasir et al. 2003). They developed a BN to model the relationship between major risk variables and major types of activities in a building construction project. The model used the most likely value of activity duration as a reference point (i.e. input to the model) and suggested percent increase/decrease from it to define the optimistic/pessimistic duration of the activity. The result of the BN model was then exported to a MCS model to generate the probabilistic project schedule. Although the model provided good predictive results for upper and lower limits of activities duration, the estimation of most likely values was not addressed. Other limitations of the model included: most powerful feature of BNs namely diagnostic analysis (e.g. reasoning from effect to cause) was not used, it was specific to construction projects and not applicable to other industries and different type of projects, another MCS model was needed to translate the result of the model to actual project schedule.

This thesis applied BNs to provide a general (i.e. applicable to any type of project) and complete (i.e. MCS is not required for probabilistic scheduling) method for incorporating uncertainty in project scheduling. The method consists of two components:

- The BCPM network that performs the well-known Critical Path Method to calculate the probabilistic schedule of the project.
- The Duration network that captures different sources of uncertainty affecting duration of activities.

The proposed method subsumes the benefits of CPM while taking full advantage of BN capabilities. This enables the model to address important aspects of project risk analysis, including:

- It provides a causal framework for modelling different source of uncertainty in estimation of activity/project duration.
- It provides an effective approach for modelling trade-off relation between project parameters by capturing conditional dependency between them.
- It provide a coherent use of subjective probabilities for modelling unknown risks (i.e. adjustment factor).
- It can learn (update) the probability of unknown risks using new information (observed data) about the actual project progress.

Two case studies were used to evaluate the models. The first case study, taken from the literature, showed the accuracy of the scheduling part of the model (i.e. BCPM) by comparing its results against the results of simulation models. The second case study was a real construction project that suffered from serious delay. It demonstrated the applicability of the 'Duration' model in capturing different aspects of schedule related risks in a real project.

The models proposed in this thesis can help us move to a new generation of project risk assessment tools that are better informed by available knowledge and data and hence, more valid and useful.

8.2 Model Limitations

The advanced capabilities of the BCPM model make it far superior than the state-of-the-art scheduling technique (MCS based techniques). However, the BCPM is not a panacea. It is far more complex than MCS, requiring more time and effort, special software and trained individuals.

The degree of model complexity employed in analysis is a key aspect of *Risk Management Process* (RMP) (Chapman and Ward 2003). Efficient application of the BCPM model requires a well-established RMP especially in identifying different sources of uncertainty and also in the data acquisition process. In this thesis it was assumed that an appropriate RMP is in place and the organisation is mature enough to understand the costs and benefits of applying such a sophisticated quantitative approach.

The computational complexity of performing inference for a realistic size BN is another issue of concern. For large size BNs, especially when nodes with continuous type are involved, exact inference is infeasible. As briefly presented in section 4.2.4 and 4.5, there have been a number of developments that allow reasonably complex BNs with continuous nodes to be computed accurately and efficiently. However, when the model involves hundreds, as opposed to dozens of, nodes (as would be the case for a large project with hundreds of activities), the inference algorithm do not scale well (either in speed or memory requirement). This becomes the main drawback of the BCPM model for large size projects. So, whereas in terms of analytical power and capability of handling uncertainty in scheduling, the BCPM model is superior to MCS-based methods, in terms of computational efficiency, the MCS approach is faster. For example, running the BCPM model for the 'Aircraft development example' (section 7.2) takes 58 seconds on an average computer, while the simulation based model takes less than 10 seconds on the same computer.

The BCPM model proposed in this thesis is a prototype model of a novel approach in project scheduling. It was shown to be effective and scalable to a real project. However, more research and development is required in order to make the approach applicable and available for genuinely large-scale projects. There is considerable research into developing faster and more efficient approaches to propagation (Neil et al. 2007). Coupled with the availability of improved hardware it should only be a matter of time before it is possible to handle the computational complexity of the resulting very large BNs. It is worth remembering that in the 1980's when MCS was first introduced for project scheduling, it suffered the same efficiency limitation.

8.3 The way forward

The conceptual framework for applications of BNs in project scheduling needs further developments in order to make it fully applicable to very large size projects. There are several potential extensions to the ideas presented in this thesis. Future research could proceed along several different fronts:

- Regarding the computational complexity, more research is required to develop faster and more efficient inference algorithms. Speeding up inference in BNs has been and still remains an active research area.
- Developing software tools that support genuine application of OOBN concepts can address many of the practicality issues of the model. Such an OOBN toolkit should support the inheritance hierarchy, which means a sub-class can inherit much of its structure from the super-class. This

will simplify the construction of the BCPM model. The OOBN toolkit might also improve the efficiency of the BCPM by localizing the probabilistic inference within the objects. More research is required to develop algorithms (and implement them in software toolkits) that support complete Bayesian inference (i.e. forward and backward propagation) between all related objects.

- Regarding the structure of the networks:
    - The argument presented for developing the 'Duration' network could be extended to further components, or different ones. For example, the effect of 'quality of execution' might be added to expand the trade-off analysis in estimating activity duration. It would also be feasible to use a different argument (i.e. based on different assumptions and logic) to develop a different structure for the 'Duration' network.
    - The BCPM model can be refined to model projects with special structure networks such as conditional branching or special precedence dependency between activities (i.e. start to finish, start to start, finish to start and finish to finish). For example, additional nodes might be introduced to define the relation between time parameters of related activities (e.g. EF and ES).

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10 Appendix

Khodakarami, V., Fenton, N., Neil, M. *"Project Scheduling: Improved Approach to Incorporate Uncertainty Using Bayesian Networks."* Project Management Journal, 38(2): 39-49.

Project Scheduling: Improved Approach to Incorporate Uncertainty Using Bayesian Networks

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ABSTRACT

Project scheduling inevitably involves uncertainty. The basic inputs (i.e., time, cost, and resources for each activity) are not deterministic and are affected by various sources of uncertainty. Moreover, there is a causal relationship between these uncertainty sources and project parameters; this causality is not modeled in current state-of-the-art project planning techniques (such as simulation techniques). This paper introduces an approach, using Bayesian network modeling, that addresses both uncertainty and causality in project scheduling. Bayesian networks have been widely used in a range of decision-support applications, but the application to project management is novel. The model presented empowers the traditional critical path method (CPM) to handle uncertainty and also provides explanatory analysis to elicit, represent, and manage different sources of uncertainty in project planning.

Keywords: project scheduling; uncertainty; Bayesian networks; critical path method; CPM

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Introduction

Project scheduling is difficult because it inevitably involves uncertainty. Uncertainty in real-world projects arises from the following characteristics:

- *Uniqueness* (no similar experience)
- *Variability* (trade-off between performance measures like time, cost, and quality)
- *Ambiguity* (lack of clarity, lack of data, lack of structure, and bias in estimates).

Many different techniques and tools have been developed to support better project scheduling, and these tools are used seriously by a large majority of project managers (Fox & Spence, 1998; Pollack-Johnson, 1998). Yet, quantifying uncertainty is rarely prominent in these approaches.

This paper focuses especially on the problem of handling uncertainty in project scheduling. The next section elaborates on the nature of uncertainty in project scheduling and summarizes the current state of the art. The proposed approach is to adapt one of the best-used scheduling techniques, critical path method (CPM) (Kelly, 1961), and incorporate it into an explicit uncertainty model (using Bayesian networks). The paper summarizes the basic CPM methodology and notation, presents a brief introduction to Bayesian networks, and describes how the CPM approach can be incorporated (using a simple illustrative example). Also discussed is a mechanism to implement the model in real-world projects, and suggestions on how to move forward and possible future modifications are presented.

The Nature of Uncertainty in Project Scheduling

A Guide to the Project Management Body of Knowledge (PMBOK® Guide)—Third edition (PMI, 2004) identifies risk management as a key area of project management:

> "Project risk management includes the processes concerned with conducting risk management planning, identification, analysis, response, and monitoring and control on a project."

Central to risk management is the issue of handling *uncertainty.* Ward and Chapman (2003) argued that current project risk management processes induce a restricted focus on managing project uncertainty. They believe it is because the term "risk" has become associated with "events" rather than more general sources of significant uncertainty.

In different project management processes there are different aspects of uncertainty. The focus of this paper is on uncertainty in project scheduling. The most obvious area of uncertainty here is in estimating duration for a particular activity. Difficulty in this estimation can arise from a lack of knowledge of what is involved as well as from the uncertain consequences of potential threats or opportunities. This uncertainty arises from one or more of the following:

- Level of available and required resources
- Trade-off between resources and time
- Possible occurrence of uncertain events (i.e., risks)
- Causal factors and interdependencies including common casual factors that affect more than one activity (such as organizational issues)
- Lack of previous experience and use of subjective rather than objective data
- Incomplete or imprecise data or lack of data at all
- Uncertainty about the basis of subjective estimation (i.e., bias in estimation).

The best-known technique to support project scheduling is CPM. This technique, which is adapted by the most widely used project management software tools, is purely deterministic. It makes no attempt to handle or quantify uncertainty. However, a number of techniques, such as program evaluation and review technique (PERT), critical chain scheduling (CCS) and Monte Carlo simulation (MCS), do try to handle uncertainty, as follows:

- PERT (Malcom, Roseboom, Clark, & Fazer, 1959; Miller, 1962; Moder, 1988) incorporates uncertainty in a restricted sense by using a probability distribution for each task. Instead of having a single deterministic value, three different estimates (pessimistic, optimistic, and most likely) are approximated. Then the "critical path" and the start and finish date are calculated by the use of distributions' means and applying probability rules. Results in PERT are more realistic than CPM, but PERT does not address explicitly any of the sources of uncertainty previously listed.
- Critical chain (CC) scheduling is based on Goldratt's theory of constraints (Goldratt, 1997). For minimizing the impact of Parkinson's Law (jobs expand to fill the allocated time), CC uses a 50% confidence interval for each task in project scheduling. The safety time (remaining 50%) associated with each task is shifted to the end of the critical chain (longest chain) to form the project buffer. Although it is claimed that the CC approach is the most important breakthrough in project management history, its oversimplicity is a concern for many companies that do not understand both the strength and weakness of CC and apply it regardless of their particular and unique circumstances (Pinto, 1999). The assumption that all task durations are overestimated by a certain factor is questionable. The main issue is: How does the project manager determine the safety time? (Raz, Barnes, & Dvir, 2003). CC relies on a fixed, right-skewed probability for activities, which may be inappropriate (Herroelen & Leus, 2001), and a sound estimation of project and activity duration (and consequently the buffer size) is still essential (Trietsch, 2005).
- Monte Carlo simulation (MCS) was first proposed for project scheduling in the early 1960s (Van Slyke, 1963) and implemented in the 1980s (Fishman, 1986). In the 1990s, because of improvements in computer technology, MCS rapidly became the dominant technique for handling uncertainty in project scheduling (Cook, 2001). A survey by the Project Management Institute (PMI, 1999) showed that nearly 20% of project management software packages support MCS. For example, PertMaster (PertMaster, 2006) accepts scheduling data from tools like MS-Project and Primavera and incorporates MCS to provide project risk analysis in time and cost. However, the Monte Carlo approach has attracted some criticism. Van Dorp and Duffey (1999) explained the weakness of Monte Carlo simulation in assuming statistical independence of activity duration in a project network. Moreover, being event-oriented (assuming project risks as "independent events"), MCS and the tools that implement it do not identify the sources of uncertainty.

As argued by Ward and Chapman (2003), managing uncertainty in projects is not just about managing perceived threats, opportunities, and their implication. A proper uncertainty management provides for identifying various sources of uncertainty, understanding the origins of them, and then managing them to deal with desirable or undesirable implications.

Capturing uncertainty in projects "needs to go beyond variability and available data. It needs to address ambiguity and incorporate structure and knowledge" (Chapman & Ward, 2000). In order to measure and analyze uncertainty properly, we need to model relations between trigger (source), and risk and impacts (consequences). Because projects are usually one-off experiences, their uncertainty is *epistemic* (i.e., related to a lack of complete knowledge) rather than *aleatoric* (i.e., related to randomness). The duration of a task is uncertain because there is no similar experience before, so data is incomplete and suffers from imprecision and inaccuracy. The estimation of this sort of uncertainty is mostly subjective and based on estimator judgment. Any estimation is conditionally dependent on some assumptions and conditions—even if they are not mentioned explicitly. These assumptions and conditions are major sources of uncertainty and need to be addressed and handled explicitly.

The most well-established approach to handling uncertainty in these circumstances is the Bayesian approach (Efron, 2004; Goldstein, 2006). Where complex causal relationships are involved, the Bayesian approach is extended by using Bayesian networks. The challenge is to incorporate the CPM approach into Bayesian networks.

CPM Methodology and Notation

CPM (Moder, 1988) is a deterministic technique that, by use of a network of dependencies between tasks and given deterministic values for task durations, calculates the longest path in the network called the "critical path." The length of the "critical path" is the earliest time for project completion. The critical path can be identified by determining the following parameters for each activity:

D—duration
ES—earliest start time
EF—earliest finish time
LS—latest start time
LF—latest finish time.

The earliest start and finish times of each activity are determined by working forward through the network and determining the earliest time at which an activity can start and finish, considering its predecessor activities. For each activity j:

$ES_j = \text{Max} [ES_i + D_i;$ over predecessor activities $i]$
$EF_j = ES_j + D_j$

The latest start and finish times are the latest times that an activity can start and finish without delaying the project and are found by working backward through the network. For each activity i:

$LF_i = \text{Min} [LF_j - D_j;$ over successor activities $j]$
$LS_i = LF_i - D_i$

The activity's "total float" (TF) (i.e., the amount that the activity's duration can be increased without increasing the overall project completion time) is the difference in the latest and earliest finish times of each activity. A critical activity is one with no TF and should receive special attention (delay in a critical activity will delay the entire project). The critical path then is the path(s) through the network whose activities have minimal TF.

The CPM approach is very simple and provides very useful and fundamental information about a project and its activities' schedule. However, because of its single-point estimate assumption, it is too simplistic to be used in complex projects. The challenge is to incorporate the inevitable uncertainty.

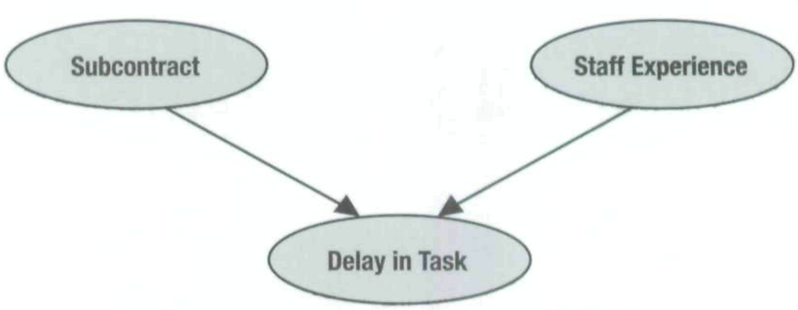
Proposed BN Solution

Bayesian Networks (BNs) are recognized as a mature formalism for handling causality and uncertainty (Heckerman, Mamdani, & Wellman, 1995). This section provides a brief overview of BNs and describes a new approach for scheduling project activities in which CPM parameters (i.e., ES, EF, LS, and LF) are determined in a BN.

Bayesian Networks: An Overview

Bayesian networks (also known as belief networks, causal probabilistic networks, causal nets, graphical probability networks, probabilistic cause-effect models, and probabilistic influence diagrams) provide decision support for a wide range of problems involving uncertainty and probabilistic reasoning. Examples of real-world applications can be found in Heckerman et al. (1995), Fenton, Krause, and Neil (2002), and Neil, Fenton, Forey, and Harris (2001). A BN is a directed graph, together with an associated set of probability tables. The graph consists of nodes and arcs. Figure 1 shows a simple BN that models the cause of delay in a particular task in a project. The nodes represent uncertain variables, which may or may not be observable. Each node has a set of states (e.g. "on time" and "late" for "Subcontract" node). The arcs represent causal or influential relationships between variables. (e.g., "subcontract" and "staff experience" may cause a "delay in task"). There is a probability table for each node, providing the probabilities of each state of the variable. For variables without parents (called "prior" nodes), the table just contains the marginal probabilities (e.g., for the subcontract" node P(on-time)=0.95 and P(late)=0.05). This is also called "prior distribution" that represents the prior belief (state of knowledge) about the variable. For each variable with parents, the probability table has conditional probabilities for each combination of the parents' states (see, for example, the probability table for a "delay in task"

On Time	0.95
Late	0.05



High	0.7
Low	0.3

Subcontract		On Time		Late	
Staff Experience		High	Low	High	Low
Delay	Yes	0.95	0.7	0.7	0.01
	No	0.05	0.3	0.3	0.99

Figure 1: A Bayesian network contains nodes, arcs and probability table

in Figure 1). This is also called the "likelihood function" that represents the likelihood of a state of a variable given a particular state of its parent.

The main use of BNs is in situations that require statistical inference. In addition to statements about the probabilities of events, users have some *evidence* (i.e., some variable states or events that have actually been observed), and can infer the probabilities of other variables, which have not as yet been observed. These observed values represent a posterior probability, and by applying Bayesean rules in each affected node, users can influence other BN nodes via propagation, modifying the probability distributions. For example, the probability that the task finishes on time, with no observation, is 0.855 (see Figure 2a). However if we know that the subcontractor failed to deliver on time, this probability updates to 0.49 (see Figure 2b).

The key benefits of BNs that make them highly suitable for the project planning domain are that they:

- Explicitly quantify uncertainty and model the causal relation between variables
- Enable reasoning from effect to cause as well as from cause to effect (propagation is both "forward" and "backward")
- Make it possible to overturn previous beliefs in the light of new data
- Make predictions with incomplete data
- Combine subjective and objective data
- Enable users to arrive at decisions that are based on visible auditable reasoning.

BNs, as a tool for decision support, have been deployed in domains ranging from medicine to politics. BNs potentially address many of the "uncertainty" issues previously discussed. In particular, incorporating CPM-style scheduling into a BN framework makes it possible to properly handle uncertainty in project scheduling.

There are numerous commercial tools that enable users to build BN models and run the propagation calculations. With such tools it is possible to perform fast propagation in large BNs (with hundreds of nodes). In this paper, AgenaRisk (2006) was used, since it can model continuous variables (as opposed to just discrete).

BN for Activity Duration

Figure 3 shows a prototype BN that the authors have built to model uncertainty sources and their affects on duration of a particular activity. The model contains variables that capture the uncertain nature of activity duration. "Initial duration estimation" is the first estimation of the activity's duration; it is estimated based on historical data, previous experience, or simply expert judgment. "Resources" incorporate any affecting factor that can increase or decrease the activity duration. It is a ranked node, which for simplicity here is restricted to three levels: low, average, and high. The level of resources can be inferred from so-called "indicator" nodes. Hence, the causal link is from the "resources" directly to observable indicator values like the "cost," the experience of available "people" and the level of available "technology." There are many alternative indicators. An important and novel aspect of this approach is to allow the model to be adapted to use whichever indicators are available.

The power of this model is better understood by showing the results of running it under various scenarios. It is possible to enter observations anywhere in the model to perform not just predictions but also many types of trade-off and explanatory analysis. So, for example, observations for the initial duration estimation and resources can be entered and the model will show the distributions for duration. Figure 4 shows how the distribution of the activity duration in which the initial estimation is five days changes when the level of its available resources goes from low to high. (All the subsequent figures are outputs from the AgenaRisk software.)

Another possible analysis in this model is the trade-off analysis between duration and resources when there is a time constraint for activity duration and it is interesting to know about the level of required resource. For example, consider an activity in which the initial duration is estimated as five days but must be finished in three days. Figure 5 shows the probability distribution of required resources to meet this duration constraint. Note how it is skewed toward high.

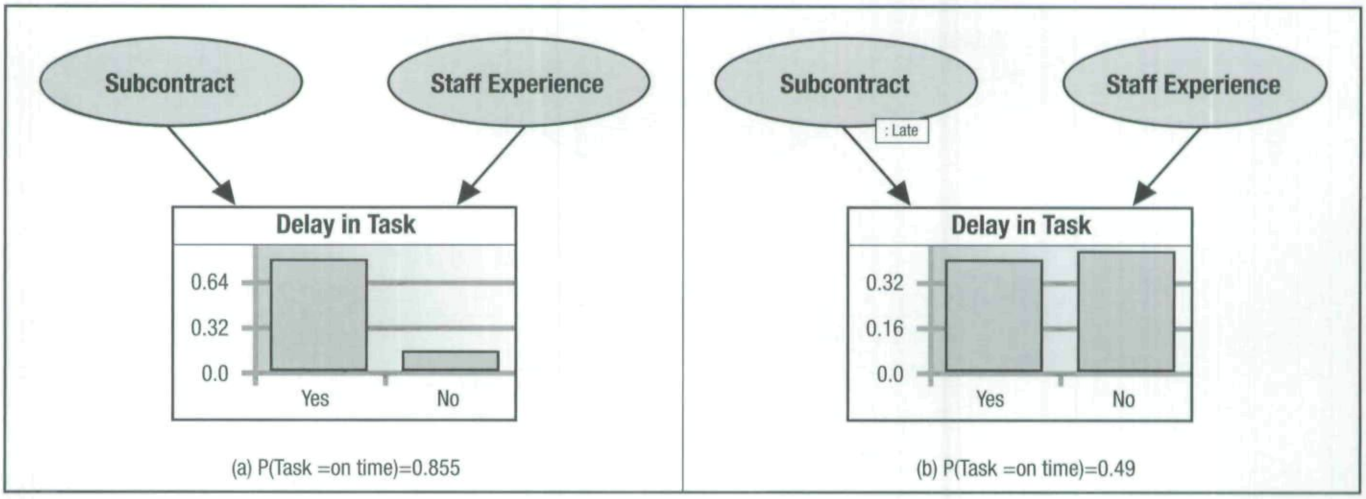


Figure 2: New evidence updates the probability

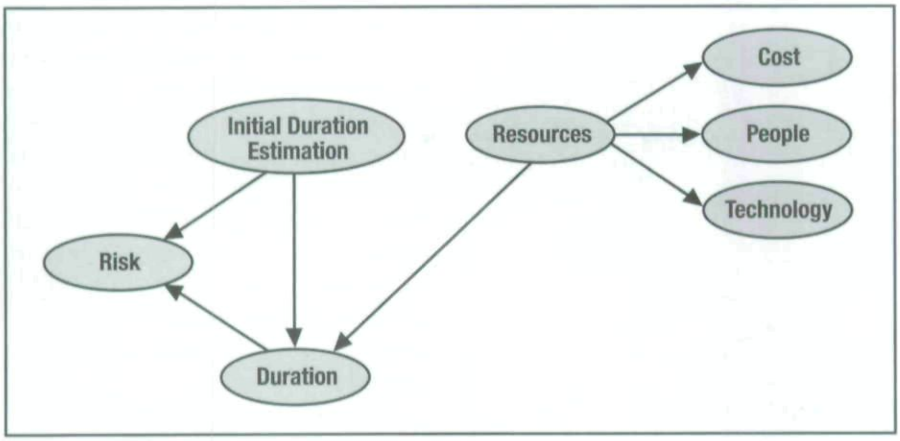


Figure 3: Bayesian network for activity duration

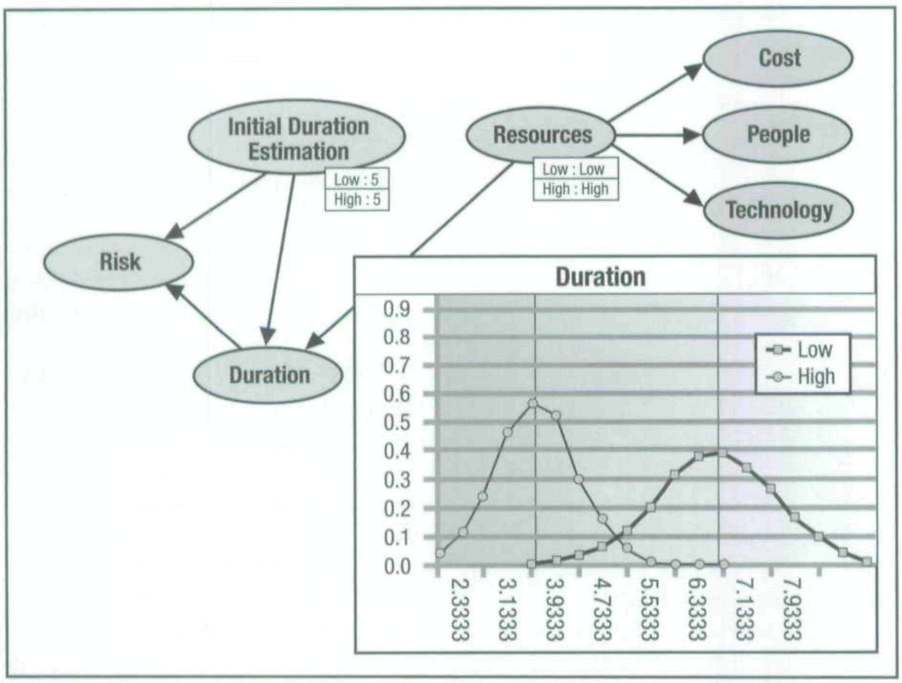


Figure 4: Probability distribution for "duration" (days) changes when the level of "resources" changes

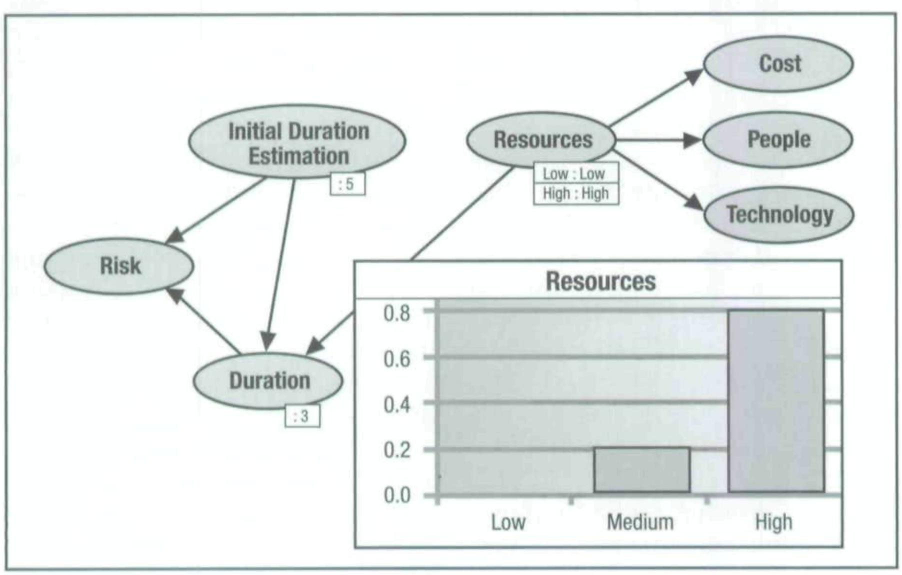


Figure 5: Level of required "Resources" when there is a constraint on "Duration"

Mapping CPM to BN

The main components of CPM networks are *activities*. Activities are linked together to represent dependencies. In order to map a CPM network to a BN, it is necessary to first map a single activity. Each of the activity parameters are represented as a variable (node) in the BN.

Figure 6 shows a schematic model of the BN fragment associated with an activity. It clearly shows the relation between the activity parameters and also the relation with predecessor and successor activities.

The next step is to define the connecting link between dependent activities. The forward pass in CPM is mapped as a link between the EF of each activity to the ES of the successor activities. The backward-pass in CPM is mapped as a link between the LS of each activity to the LF of the predecessor activities.

Example

The following illustrates this mapping process. The example is deliberately very simple to avoid extra complexity in the BN. How the approach can be used in real-size projects is discussed later in the paper.

Consider a small project with five activities—A, B, C, D, and E. The activity on arc (AOA) network of the project is shown in Figure 7.

The results of the CPM calculation are summarized in Table 1. Activities A, C, and E with TF=0 are critical and the overall project takes 20 days (i.e., earliest finish of activity E).

Figure 8 shows the full BN representation of the previous example. Each activity has five associated nodes. Forward pass calculation of CPM is done through the connection between the ES and EF. Activity A, the first activity of the project, has no predecessor, so its ES is set to zero. Activity A is predecessor for activities B and C so the EF of activity A is linked to the ES of activities B and C. The EF of activity B is linked to the ES of its successor, activity D. And finally, the EF of activities C and D are connected to the ES of activity E. In fact, the ES of activity E is the maximum of the EF of activities C

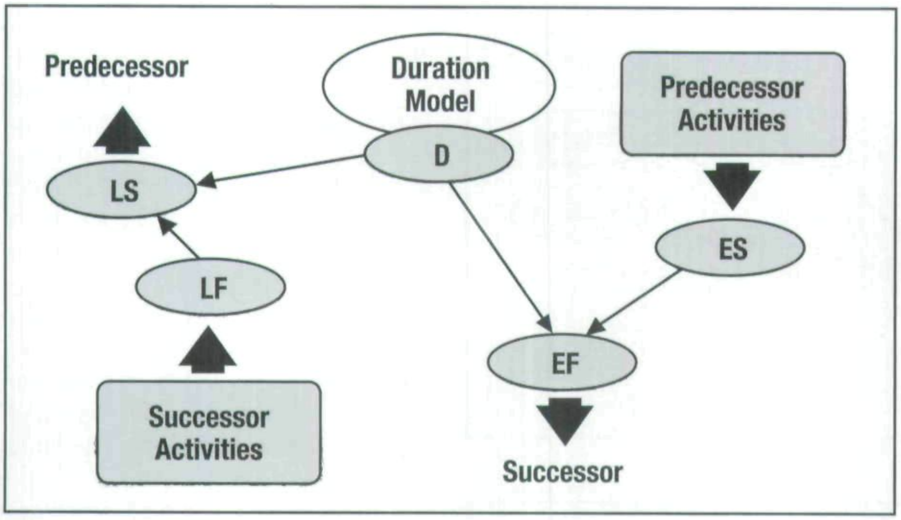


Figure 6: Schematic of BN for an activity

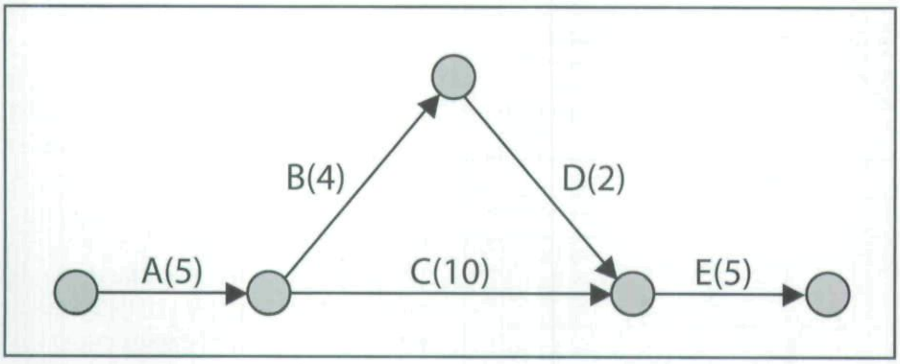


Figure 7: CPM network

one scenario is to see how changing the resource level affects the project completion time.

Figure 10 compares the distributions for project completion time as the level of people's experience changes. When people's experience changes from low to high, the mean of finishing time changes from 22.7 days to 19.5 days and the 90% confidence interval changes from 26.3 days to 22.9 days.

Another useful analysis is when there is a constraint on the project completion time and we want to know how many resources are needed. Figure 11 illustrates this trade-off between project time and required resources. If the project needs to be completed in 18 days (instead of the baseline 20 days) then the resource required for activity A most likely must be high; if the project completion is set to 22, the resource level for activity A moves significantly in the direction of low.

The next scenario investigates the impact of risk in activity A on the project completion time as it is shown in Figure 12. When there is a risk in activity A, the mean of distribution for the project completion time changes from 19.9 days to 22.6 days and the 90% confidence interval changes from 22.5 days to 25.3 days.

One important advantage of BNs is their potential for parameter learning, which is shown in the next scenario. Imagine activity A actually finishes in seven days, even though it was originally estimated as five days. Because activity A has taken more time than was expected, the level of resources has probably not been sufficient.

By entering this observation the model gives the resource probability for activity A as illustrated in Figure 13. This can update the analyst's belief about the actual level of available resources.

Assuming both activities A and E use the same resources (e.g., people), the updated knowledge about the level of available resources from activity A (which is finished) can be entered as evidence in the resources

and D. The EF of activity E is the earliest time for project completion time.

The same approach is used for backward CPM calculations connecting the LF and LS. Activity E is the last activity of the project and has no successor, so its LF is set to EF. Activity E is successor of activities C and D so the LS of activity E is linked to the LF of activities C and D. The LS of activity D is linked to the LF of its predecessor activity B. And finally, the LS of activities B and C are linked to the LF of activity A. The LF of activity A is the minimum of the LS of activities B and C.

For simplicity in this example, it is assumed that activities A and E are more risky and need more detailed analysis. For all other activities the uncertainty about duration is expressed simply by a normal distribution.

Results

This section explores different scenarios of the BN model in Figure 8. The main objective is to predict the project completion time (i.e., the earliest finish of E) in such a way that it fully characterizes uncertainty.

Suppose the initial estimation of activities' duration is the same as in Table 1. Suppose the resource level for activities A and E is medium. If the earliest start of activity A is set to zero, the distribution for project completion is shown in Figure 9a. The distribution's mean is 20 days as was expected from the CPM analysis. However, unlike CPM, the prediction is not a single point and its variance is 4. Figure 9b illustrates the cumulative distribution of finishing time, which shows the probability of completing the project before a given time. For example, with a probability of 90% the project will finish in 22 days.

In addition to this baseline scenario, by entering various evidence (observations) to the model, it is possible to analyze the project schedule from different aspects. For example,

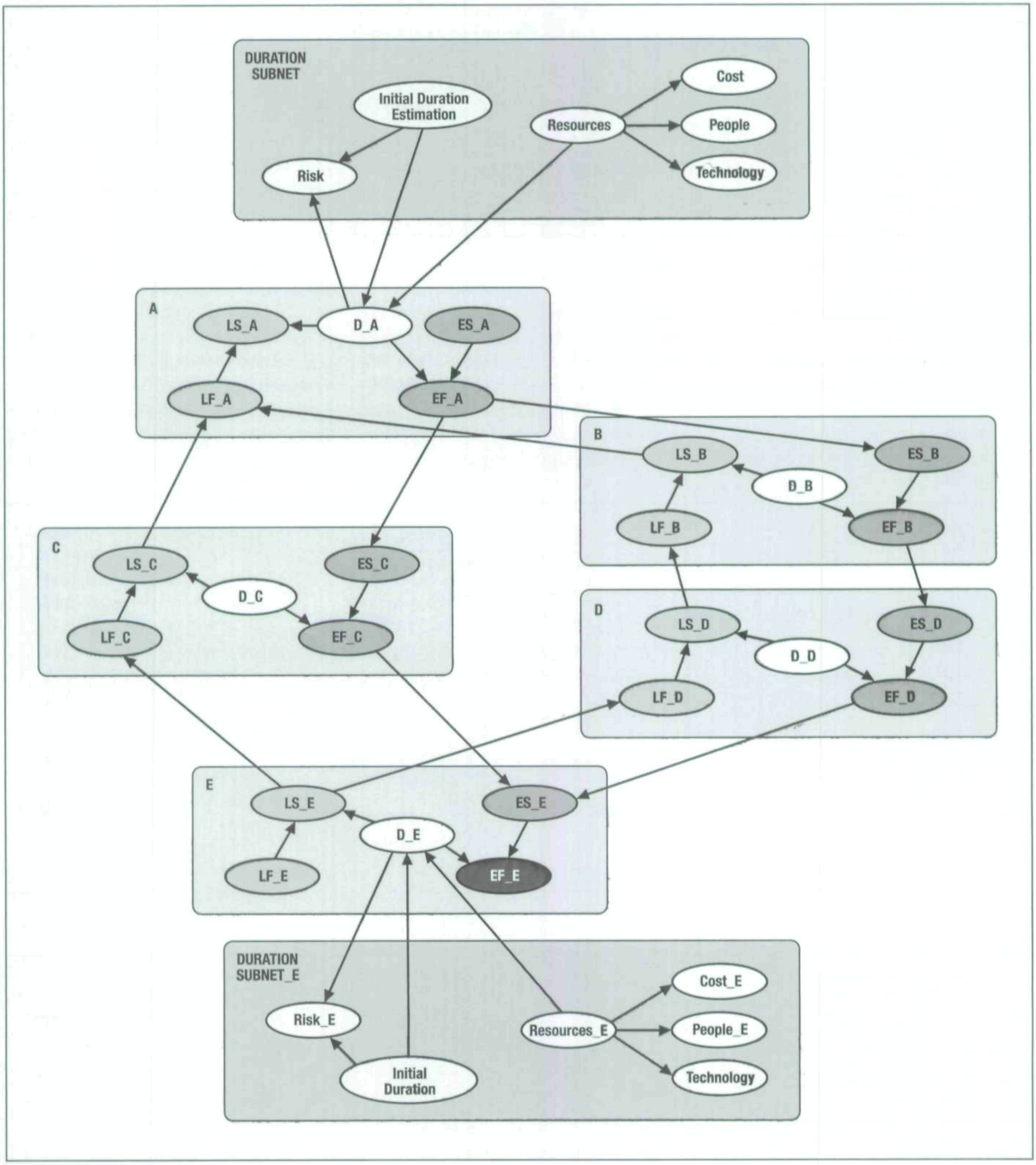


Figure 8: Overview of BN for example (1)

for activity E (which is not started yet) and consequently updates the project completion time. Figure 14 shows the distributions of completion time when the level of available resource of activity E is learned from the actual duration of activity A.

Another application of parameter learning in these models is the ability to incorporate and learn about bias in estimation. So, if there are several observations in which actual task completion times are underestimated, the model learns that this may be due to bias rather than unforeseen risks, and this information will inform subsequent predictions. Work on this type of application (called dynamic learning), is still in progress and can be a possible way of extending the BN version of CPM.

Activity	D	ES	EF	LS	LF	TF
A	5	0	5	0	5	0
B	4	5	9	9	13	4
C	10	5	15	5	15	0
D	2	9	11	13	15	4
E	5	15	20	15	20	0

Table 1: Activities' time (days) and summary of CPM calculations

Object-Oriented Bayesian Network (OOBN)

It is clear from Figure 8 that even simple CPM networks lead to fairly large BNs. In real-sized projects with several activities, constructing the network needs a huge effort, which is not effective especially for users without much experience in BNs. However, this complexity can be handled using the so-called object-oriented Bayesian network (OOBN) approach (Koller & Pfeffer, 1997). This approach, analogous to the object-oriented programming languages, supports a natural framework for abstraction and refinement, which allows complex domains to be described in terms of interrelated objects.

The basic element in OOBN is an object; an entity with an identity, state, and behavior. An object has a set of attributes each of which is an object. Each object is assigned to a class. Classes provide the ability to describe a general, reusable network that can be used in different instances. A class in OOBN is a BN fragment.

The proposed model has a highly repetitive structure and fits the object-oriented framework perfectly. The internal parts of the activity subnet (see Figure 6) are encapsulated within the activity class as shown in Figure 15.

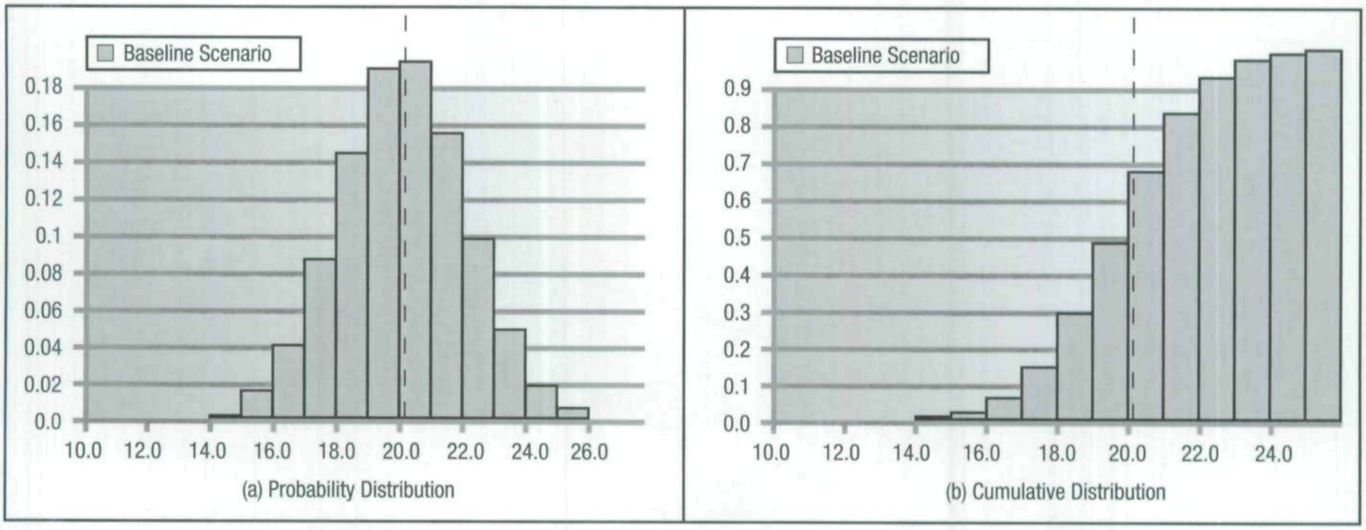


Figure 9: Distribution of project completion (days) for main scenario in example (1)

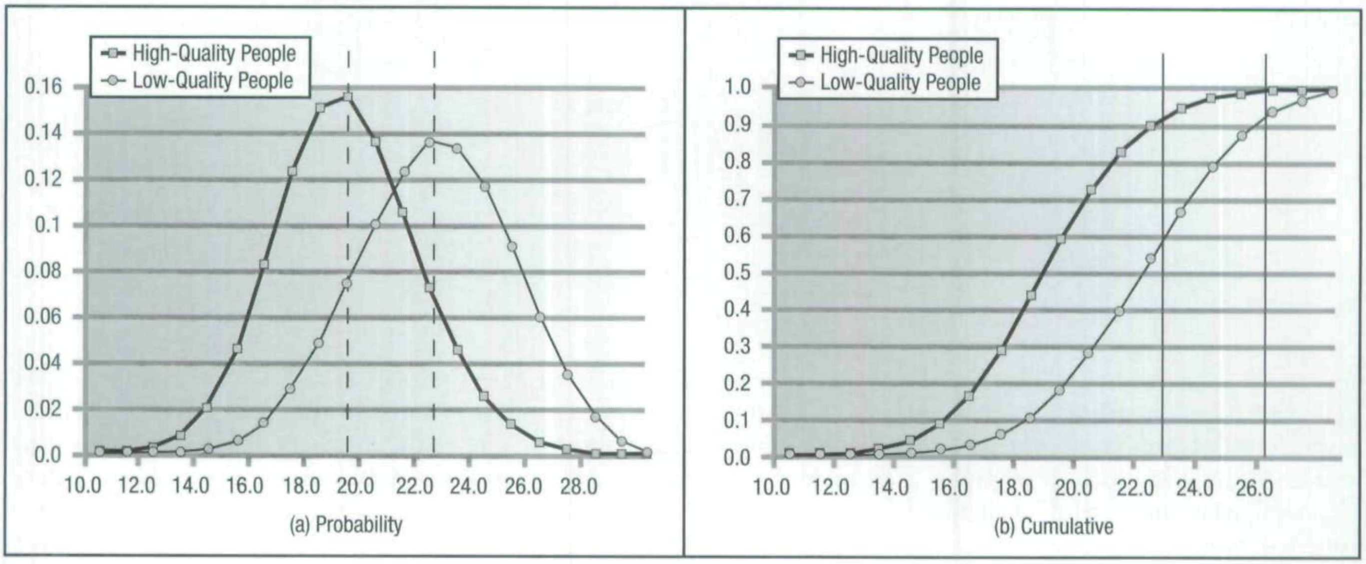


Figure 10: Change in project time distribution (days) when level of people's experience changes

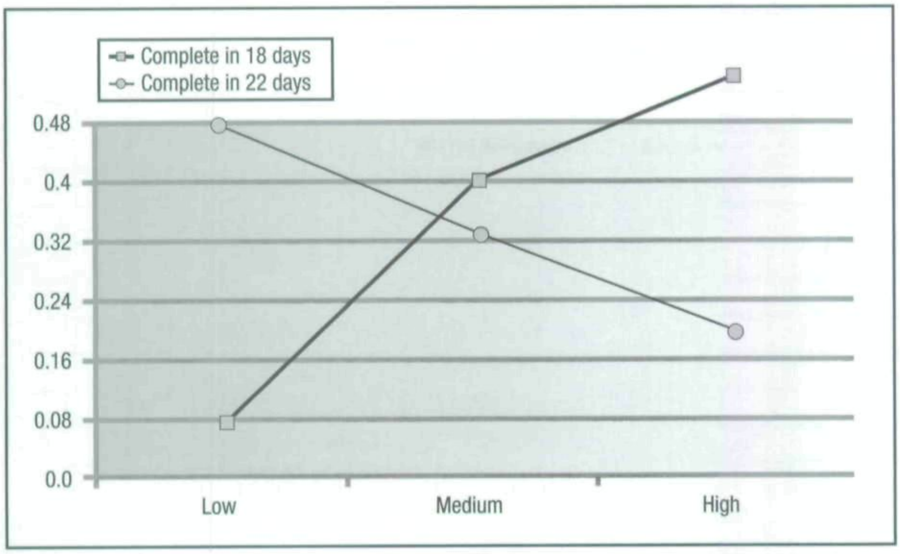


Figure 11: Probability of required resource changes when the time constraint changes

Classes can be used as libraries and combined into a model as needed. By connecting interrelated objects, complex networks with several dozen nodes can be constructed easily. Figure 16 shows the OOBN model for the example previously presented.

The OOBN approach can also significantly improve the performance of inference in the model. Although a full discussion of the OOBN approach to this particular problem is beyond the scope of this paper, the key point to note is that there is an existing mechanism (and implementation of it) that enables the proposed solution to be genuinely "scaled-up" to real-world projects. Moreover, research is emerging to develop the new generation of BNs tools and algorithms that support OOBN concept both in constructing large-scale models and also in propagation aspects.

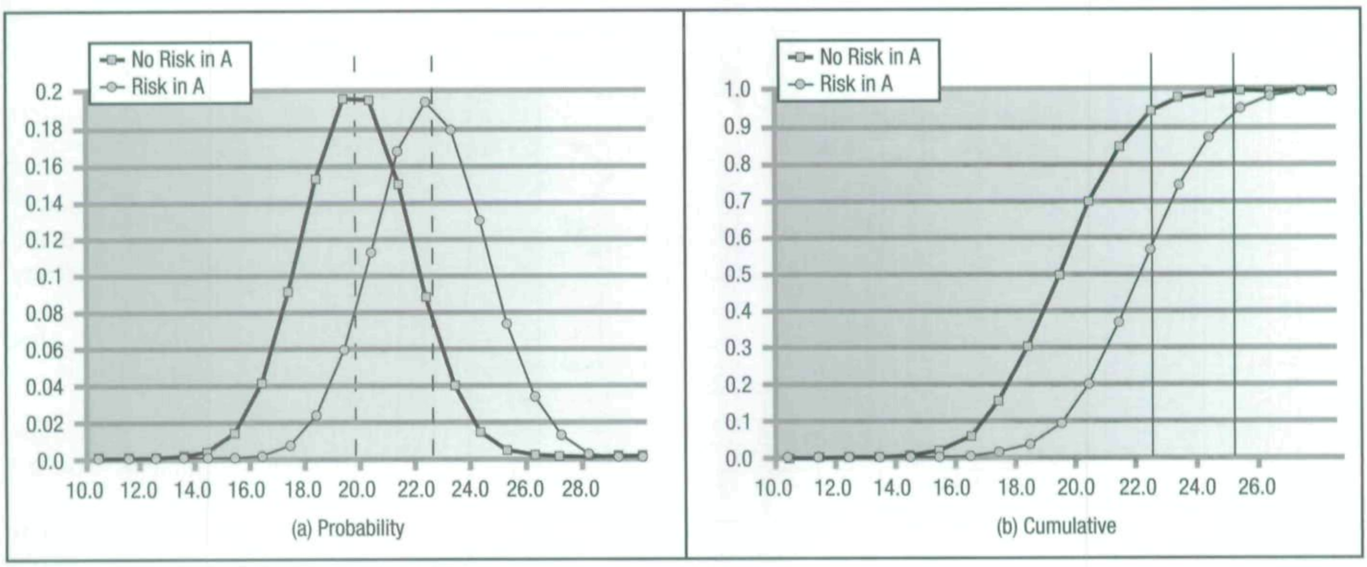


Figure 12: The impact of occurring risk in activity A on the project completion time

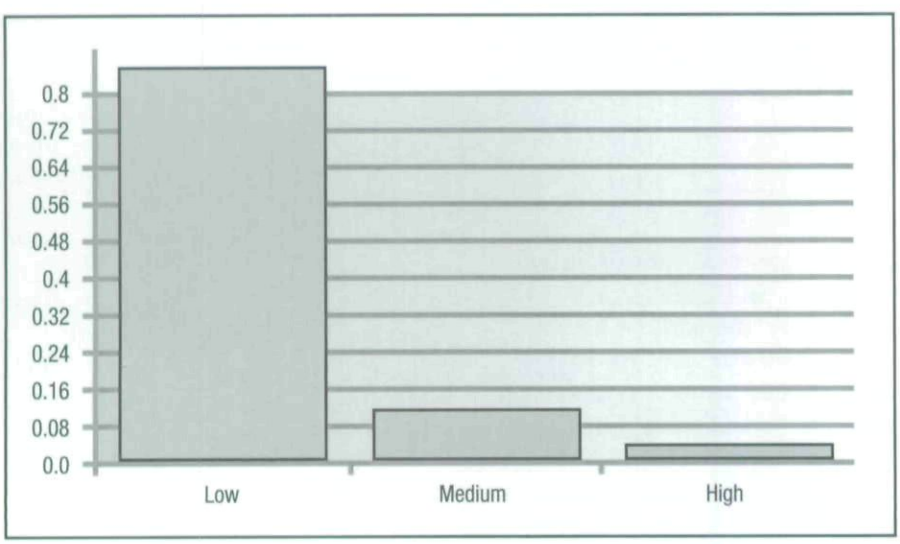


Figure 13: Learnt probability distribution "resource" when the actual duration is seven days

Conclusions and How to Move Forward

Handling risk and uncertainty is increasingly seen as a crucial component of project management and planning. One classic problem is how to incorporate uncertainty in project scheduling. Despite the availability of different approaches and tools, the dilemma is still challenging. Most current techniques for handling risk and uncertainty in project scheduling (simulation-based techniques) are often

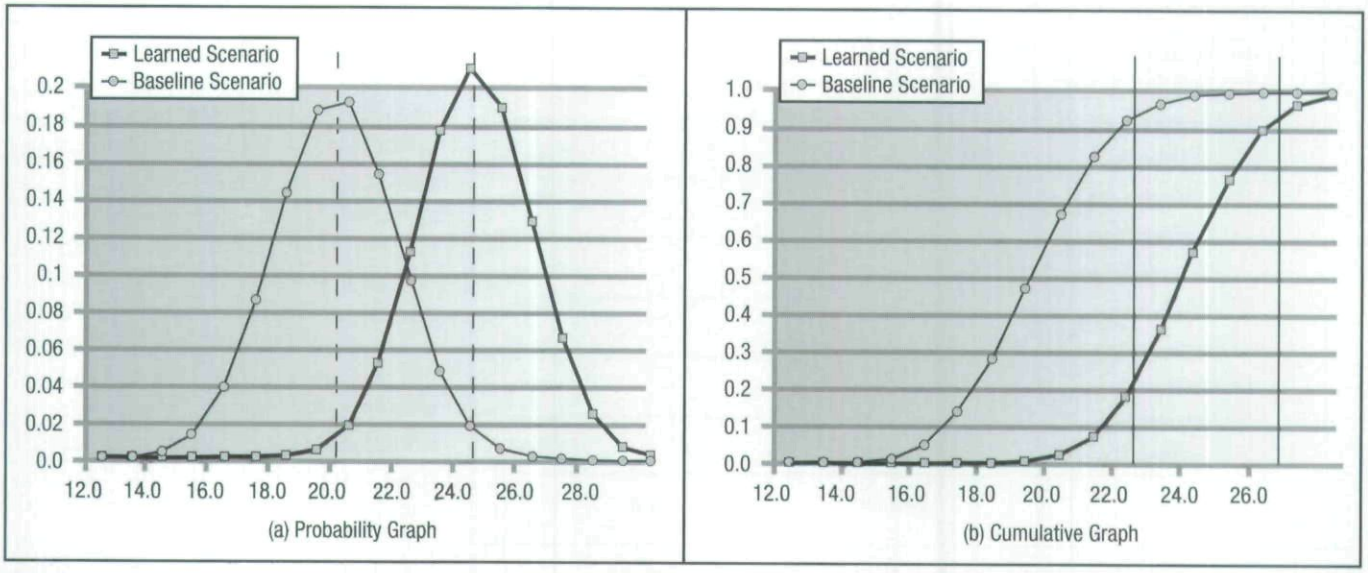


Figure 14: completion time (days) based on learned parameters compare with baseline scenario

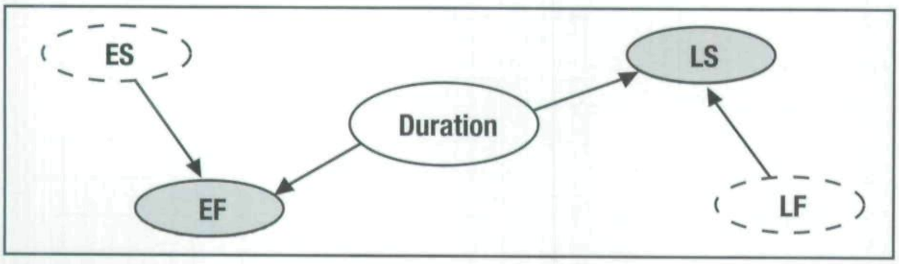


Figure 15: Activity class encapsulates internal parts of network

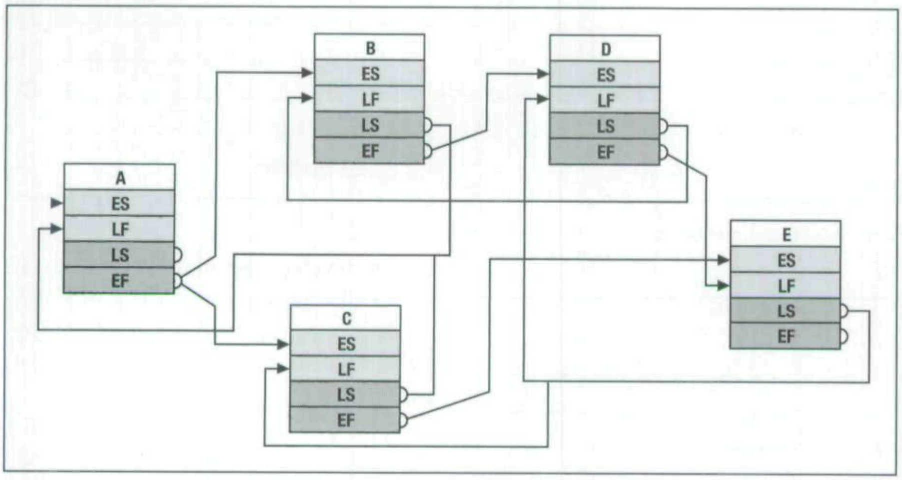


Figure 15: OO model for the presented example

event-oriented and try to model the impact of possible "threats" on project performance. They ignore the source of uncertainty and the causal relations between project parameters. More advanced techniques are required to capture different aspects of uncertainty in projects.

This paper has proposed a new approach that makes it possible to incorporate risk, uncertainty, and causality in project scheduling. Specifically, the authors have shown how a Bayesian network model can be generated from a project's CPM network. Part of this process is automatic and part involves identifying specific risks (which may be common to many activities) and resource indicators. The approach brings the full weight and power of BN analysis to bear on the problem of project scheduling. This makes it possible to:

- Capture different sources of uncertainty and use them to inform project scheduling
- Express uncertainty about completion time for each activity and the whole project with full probability distributions
- Model the trade-off between time and resources in project activities
- Use "what-if?" analysis
- Learn from data so that predictions become more relevant and accurate.

The application of the approach was explained by use of a simple example. In order to upscale this to real projects with many activities the approach must be extended to use the so-called object-oriented BNs. There is ongoing work to accommodate such object-oriented modeling so that building a BN version of a CPM is just as simple as building a basic CPM model.

Other extensions to the work described here include:

- Incorporating additional uncertainty sources in the duration network
- Handling dynamic parameter learning as more information becomes available when the project progresses
- Handling common causal risks that affect more than one activity
- Handling management action when the project is behind its plan.

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