Integrating Risk into Project Control using Bayesian Networks

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Abstract

Projects are, by definition, risky and uncertain ventures. Therefore, the performance and risk of major projects should be carefully controlled in order to increase their probability of success. Quantitative project control techniques assist project managers in detecting problems, thus responding to them early on, by comparing the baseline plan with the project progress. However, project risk and uncertainty are rarely considered by these techniques. This paper proposes a project control framework that integrates the project uncertainty and associated risk factors into project control. Our framework is based on Earned Value Management (EVM), which is an effective and widely used quantitative project control technique. The framework uses hybrid Bayesian Networks (BNs) to enhance EVM with the ability to compute the uncertainty associated with its parameters and risk factors. The framework can be applied to projects from different domains, and we illustrate its use with a simple example and a case study of a construction project.

Keywords: Project management, Project control, Risk analysis, Bayesian Networks, Earned Value Management

1. **Introduction**

Projects are key elements to implement the strategy of most organisations. Despite extensive research in project management, many projects fail to meet their schedule and cost objectives, with poor estimation being the largest contributor to these failures (Price Waterhouse Cooper, 2012). Quantitative project control techniques provide project managers with a greater understanding of the project performance often in multiple success criteria (Hazir, 2015). This enables them to respond to potential problems in earlier stages, which can increase the probability of success. Quantitative project control techniques typically monitor the project's progress, and compare it to the baseline plan to assess any deviations (W. H. Lipke, 2003; PMI, 2011). These techniques can provide an accurate assessment of the performance when the baseline plan and project progress can be precisely estimated. However, there is a great deal of uncertainty involved with both of these elements (Atkinson et al., 2006; Hall, 2012). Firstly, projects are subject to risk which may affect the baseline plan. Both the plan and project performance assessments may need to be adjusted when risk factors realise. Secondly, completion rate of activities needs to be determined in order to assess project progress. However, it is often difficult to give a precise estimate of completion rate especially for unique and complicated activities.

In this paper, we propose a novel project control framework that uses Bayesian Networks (BNs) to incorporate uncertainty and risk factors associated with the success measures of a project into project control. Our framework computes these factors when estimating project control metrics. It enables project managers to assess their confidence on these metrics, and to make 'what-if' analysis for different risk scenarios. The proposed model is based on a widely accepted project control approach called Earned Value Management (EVM) (PMI, 2011). This paper enhances the EVM approach, and extends the previous modelling work in this area (Khodakarami & Abdi, 2014b), by providing a comprehensive and widely applicable project control framework that enables EVM to take uncertainty and risk factors into account in project control, and expects minimal technical requirements regarding uncertainty modelling from project managers. We also present an associated Python script for the proposed framework, i.e. PRObabilistic Project COntrol Tool (PROPCOT, 2020), to enable a wider use of the tool. The parameters for PROPCOT can be defined in a spreadsheet for ease of use and then PROPCOT can automatically populate the proposed BN framework based on these parameters.

In the remainder of this paper, Section 2 introduces the EVM project control approach and reviews previous attempts to incorporate uncertainty into this approach. Section 3 gives a recap of BNs and reviews its previous uses in project management and control. Section 4 describes the proposed Bayesian EVM framework and illustrates its use with a simple project example, and Section 5 applies the proposed approach to a case study of a construction project. Finally, Section 6 presents our conclusions and discusses the possible future steps.

2. Project Control

Many frameworks are available for measuring project success as its definition is not straightforward (Atkinson, 1999; Ika, 2009; Jugdev & Moller, 2006). A useful framework must take three basic constraints of projects into consideration. These are the time constraint, budget constraint, and completion of work adhering to a baseline plan with technical specifications. EVM is a widely used project control approach, recommended by the Project Management Institute (PMI, 2013) as it is able to monitor a project in terms of these three elements. It has been used in different domains including defence (E. H. Kim et al., 2003), construction (Fleming & Koppelman, 1997), and software (Boehm, 2003) industries.

EVM compares the value of the work completed in the project with the baseline plan and actual expenditures. The parameters of EVM can be used to make predictions about completion time and budget of the project. Calculations regarding EVM are simple and have been implemented in many project management software packages. EVM uses three parameters as inputs and calculates several performance indices to estimate project progress in terms of time, cost and work plans. The input parameters for EVM calculations are as follows:

- *Planned Value (PV)* is the estimated total value of the project in the project plan.
- *Earned Value (EV_t)* is the planned value of the completed work at the time of project control *t*, and it is calculated by multiplying the total PV of the project by the percentage of completion of the project at *t* (PC_t).

$$EV_t = PV \times PC_t$$

- *Actual Cost (AC_t): AC_t* is the resources spent for the completed work up to *t*.

PV, EV_t and AC_t are measured in the same unit. Typically, they are measured by using the budgeted cost or effort estimate of the project activities. Using these three main parameters, EVM calculates absolute and relative time and cost performance indicators for the project. The time performance indicators of EVM are as follows:

- *Schedule Performance Index* at *t (SPI_t)* is the ratio of EV_t to the cumulative planned value of the project until *t*, i.e. PV_t.

$$SPI_t = EV_t / PV_t$$

- *Schedule Variance* at *t (SV_t)* is the difference between EV_t and PV_t.

$$SV_t = EV_t - PV_t$$

Similarly, cost performance indicators are as follows:

- *Cost Performance Index* at *t (CPI_t)* is the ratio of EV_t to AC_t.

$$CPI_t = EV_t / AC_t$$

- *Cost Variance (CV_t)* is the difference between EV_t and AC_t.

$$CV_t = EV_t - AC_t$$

EVM metrics can also be used to predict the total cost and duration of the project at the completion. *Estimate at Completion (EAC)* predicts the cost of the whole project at the completion date. It is calculated by the ratio of the total *PV* of project to the project CPI_t.

$$EAC = \frac{PV}{CPI_t}$$

Time Estimate at Completion (TEAC) predicts the duration of the whole project at the completion data, and it is calculated by the ratio of the initial estimation for the project duration (*PD)* to project SPI_t.

$$TEAC = \frac{PD}{SPI_t}$$

Table 1 shows a simple project example that consists of four activities to demonstrate the use of EVM. This example is a student project that is planned to be completed in 6 months. The project activities are reviewing the relevant studies, developing a quantitative model, conducting simulated experiments on the model and analysing their results. Table 1 shows *PV* of these activities in each month.

Table 1 Student Project Activities (hours)

Activities	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**TOTAL**
Literature review	75	100	75				250
Modelling		30	45	75			150
Experiments				162	18		180
Analysis				8	32	40	80
PROJECT							580 hours

Suppose the student is now in the end of 4th month of the project and would like to assess the project progress in terms of time and effort spent. *PV* of the modelling, literature review, experiment and analysis activities are respectively 250, 150, 162 and 8 hours for the end of 4th month. The student also needs to assess the *PC* and the *AC* for each activity. The student estimates that she completed 80% of the literature review, 70% of the modelling, 40% of the experiments and 30% of the analysis, and she spent 230, 100, 35 and 30 hours for these activities respectively. The *EV*, *SPI*, *CPI*, *EAC* and *TEAC* are calculated from these values as shown above. Table 2 shows the EVM calculations for this project, and Figure 1 shows a graphical illustration of EVM measures. *EV* and *AC* values stop at the time of project control that is the end of April whereas *PV* values are calculated for the whole duration of the project. The EVM results show that the project is progressing delayed but slightly under the planned effort as SPI is less than 1 and CPI is greater than 1. This can also be seen from the difference between PV and EV, and AC and EV in the end of April in Figure 1. EAC for the project is 650 hours of work, and about 2.5 months of delay is expected.

Table 2 Traditional EVM for Student Project Example

Project Definition			Project Progress			Metrics		Predictions	
Work Package	**PV_{Total} (hours)**	**PV_{April} (hours)**	**PC %**	**AC (hours)**	**EV (hours)**	**SPI**	**CPI**	**TEAC (months)**	**EAC (hours)**
Lit. Review	250	250	80%	230	200	0.80	0.87		
Modelling	150	150	70%	100	105	0.70	1.05		
Experiments	180	162	40%	35	72	0.44	2.06		
Analysis	80	8	30%	30	24	3.00	0.80		
PROJECT	**660**	**570**	**60%**	**395**	**401**	**0.70**	**1.02**	**~ 8.5**	**650**

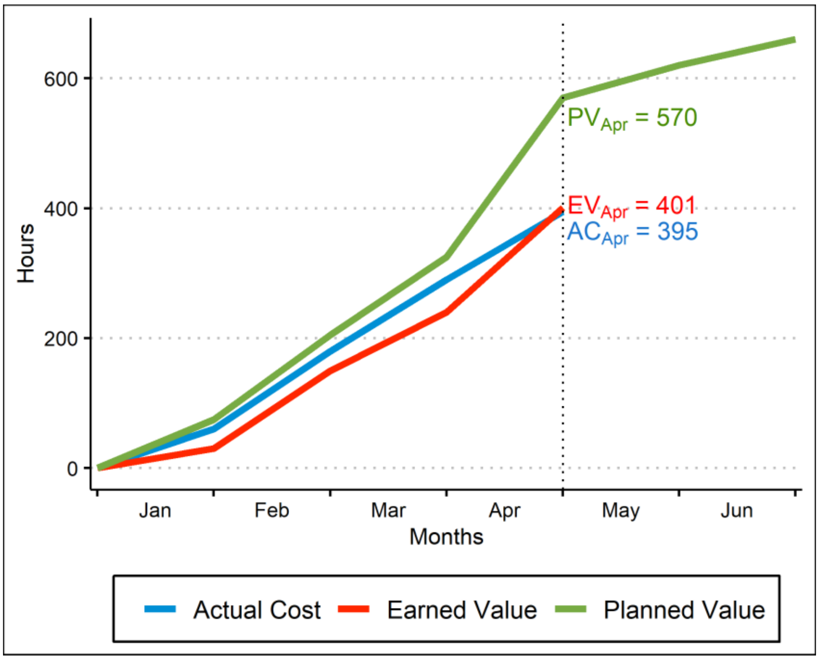

Figure 1 Project Example EVM for April

Since the schedule performance of EVM is measured by comparing the budgeted cost of completed work and the planned work, schedule performance indicators normalise as the activity is close to completion, regardless of the delays. In order to overcome this limitation Lipke (2003) proposes Earned Schedule Management (ESM). ESM calculates the schedule performance based on earned schedule (*ES*), which is the duration for the project when the initial *PV* should have been the equal to the EV_t at project control moment *t*. In order to calculate the *ES* at *t*, i.e. ES_t, we need to find the time increment t' where the earned value of the project EV_t is greater than or equal to the $PV_{t'}$, and is less than $PV_{t'+1}$ as follows:

$$ES_t = t' + \frac{EV_t - PV_{t'}}{PV_{t'+1} - PV_{t'}}$$

where $EV_t \geq PV_{t'}$ and $EV_t < PV_{t'+1}$.

Absolute and relative schedule performance indicators for ESM are calculated as follows:

$$SPI_t = \frac{ES_t}{t}$$

$$SV_t = ES_t - t$$

In the student project example, *ES* is 3.31 for the end of 4^{th} month. *SPI* and *TEAC* based on *ES* are 0.83 and 7.25 months respectively.

In order EVM and ESM to work accurately, a project manager needs to know *PV* and PC_t precisely, but both factors are uncertain by nature. The completion percentage of most activities can be precisely known only when they have not yet started or been fully completed. Otherwise, it is often not possible for project managers to determine, for example, the difference between whether an activity is 35% or 40% complete. PV of activities represent the baseline plan which is subject to many risk and opportunity factors that can adjust PV when they realise (Akintoye & MacLeod, 1997; Lukas, 2012; Tesch et al., 2007). Traditional EVM and ESM disregard the uncertainty regarding these factors.

Several previous studies tried to incorporate uncertainty in EVM and ESM, mostly for predicting project completion time and cost based on these methods. Lipke et al. (2009) used log-normal distribution to define confidence intervals of performance indices. Similarly, Caron et al. (2013) modelled the indices with log-normal distribution and used Bayesian model and Gibbs sampling method to update the model with new observed data. Pajares & Lopez-Paredes (2011) used Monte Carlo simulation to calculate probability distribution of project completion time and project cost to implement uncertainty into EVM. Naeni et al. (2011) developed an EVM method with fuzzy logic to estimate cost and schedule under uncertainty. In the fuzzy EVM method planned values of activities are defined as ordinal variables such as ‘low’, ‘moderate’ and ‘high’, and then converted into fuzzy numbers for calculations. Narbaev & De Marco (2014) proposed a new cost estimate at completion method based on Gompertz Growth Model, which is mainly used to model growth in animals and plants. Colin & Vanhoucke (2014) designed a statistical process control approach that analyses the probability of project falling behind the schedule. This approach defines tolerance limits for EVM/ESM parameters. Batselier & Vanhoucke (2017) developed an Exponential Smoothing-based Method (XSM). This method uses EVM parameters in exponential smoothing formulas. Khesal et al. (2019) attempted to overcome shortcomings of EVM regarding cost, quality, risk, and schedule control by using linear and Taguchi-based quality methods. The study integrated new variables such as "quality earned value", "quality actual cost", and "quality performance index" to the core structure of EVM to include quality and risk management into estimations. Kim and Pinto (2019) attempted to integrate uncertainty into EVM by considering possible trajectories of the CPT parameters. Their study focussed only on CPI and cost overrun probabilities and assigned a probability distribution to only EAC. Acebes et al. (2014) used Monte Carlo simulation in their study to explain time and cost variances in projects. They defined parameters like completion percentage, cost at completion, and time of the cost to run simulations. As a result, they calculated probability distributions and confidence intervals for cost and schedule. In a similar study, Acebes et al. (2015) proposed to use earned value instead of project completion percentage parameter.

Caron et al. (2013) draws an analogy between using project performance indices of EVM and "*driving a car while looking just in the rear-view mirror*". They argue that it is not realistic to assume future events will be similar to the past events in an area with high risks and uncertainty like project management. For more accurate estimations, risk factors that affected the past events and those might affect the future ones should be taken into consideration. Our proposed framework complements previous studies by incorporating the uncertainty and risk factors associated with specific project activities in project control and using a unified framework that calculates the project performance metrics based on these uncertainties and risk factors. In the following section, we give an overview of BNs, which is the probabilistic modelling technology that we use for our framework, and in Section 4 we describe the proposed Bayesian EVM framework.

3. Bayesian Networks

Bayesian networks (BNs) are probabilistic graphical models that are composed of a graphical structure and a set of parameters (Pearl, 1988). The graphical structure is a directed acyclic graph (DAG) with nodes representing variables and directed edges between the nodes representing causal and probabilistic relations between those variables. When two nodes A and B are directly connected, i.e. $A \rightarrow B$, A and B are respectively the parent and child of each other. Each node has associated parameters that represent its conditional probability distribution (CPD) with its parents. These CPDs are often represented in a tabular structure for discrete nodes. Other representations include tree-structured (Boutilier et al., 2013) and rule-based CPDs (Poole & Zhang, 2003).

Projects are done to create unique products and services, thus if relevant data is available it is often scarce. This limits the use of purely data-driven learning algorithms in project management as scarce data must be supported with expert knowledge. Moreover, they involve uncertainty that must be considered in planning, execution and control stages. BNs offer a suitable modelling approach for project management due to their ability to incorporate expert knowledge for probabilistic reasoning. The graphical structure of a BN is suitable for modelling causal relations and therefore offer a suitable medium for using expert knowledge. Efficient algorithms are available for computing discrete BNs (Lauritzen & Spiegelhalter, 1988) and hybrid BNs that contain both discrete and continuous variables (Neil et al., 2007; Salmerón et al., 2018). Different types of probabilistic reasoning can be done with BNs including predictive and diagnostic inference and 'explaining away'. Hence, once a BN is built it can be used to make predictions, diagnosis or 'what-if' types of scenario analysis. As a result, BNs have been used in a wide variety of domains for decision analysis and risk assessment problems including medicine (Yet et al., 2014), reliability (Mahadevan et al., 2001), sports (Constantinou et al., 2012, 2013) and legal domains (Fenton et al., 2013, 2014).

Despite these advantages, the use of BNs in the project management domain has been relatively limited. They have been mainly used in the software project management domain due to proximity of this domain to computer scientists. Moreover, BNs have not been widely used for project control despite the need for incorporating uncertainty and probabilistic analysis in this problem (see Yet (2017) for a review of BNs in project management). Fan & Yu (2004) developed a BN that estimates project risks at different stages of software projects. Fenton et al. (2004) designed a BN structure that considers the trade-off between quality, time, and cost in order to select which software project to invest. Project managers can use this structure as a decision support system. Jenzarli (1997) modelled the uncertainties in project schedule by transforming Program Evaluation and Review Technique (PERT) networks to hybrid BNs. Since computation of hybrid BNs are challenging, (E. N. Cinicioglu & Shenoy, 2006; E. Cinicioglu & Shenoy, 2009) offered two methods that respectively use mixture of Gaussians and truncated exponentials to compute PERT BNs. Khodakarami et al. (2007) used dynamic discretization algorithm to solve a similar BN that models project schedule uncertainties based on the critical path method. These models are not designed to be used as a general project control tool as they do not give any insight about project cost. De Melo & Sanchez (2008) developed a discrete BN that estimates delays in software maintenance projects. Luu et al. (2009) also developed a discrete BN model for the same purpose. These BNs do not model parameter uncertainty and cannot take dynamic changes into consideration. Fineman et al. (2009) developed a BN that models the trade-off between quality, time, and cost for projects. Lee et al. (2009) aimed to estimate the budget, time, and missing requirement risks with a BN they designed for shipbuilding projects. Hu et al. (2013) developed a BN for software project risks which is based on data and then updated with expert opinion. Khodakarami & Abdi

(2014b) used BNs to estimate project cost with its causes. Perkusich et al. (2015) aimed to determine problems in software development process using BNs. Sanchez et al. (2020) used BNs for to improve project management maturity by estimating and reducing cost overrun risks. Yet et al. (2016) developed a BN model that estimates the project return and analyses the associated risk. This model can be used for project selection, and it can take causal factors and parameter uncertainty into account for this task. Yet et al. (2020) expanded this BN model and applied it to evaluate real agricultural development projects under socio-political and environmental risks. However, both of these studies were not aimed for project control as they do not estimate potential variations in project schedule.

This paper builds on and addresses the gaps of the hybrid BN model proposed by Khodakarami & Abdi (2014a), and transforms it into a widely applicable project control framework. Their model estimates the EVM parameters and the probability distributions of *CPI* and *EAC* under risk scenarios. They present the BN structure by using a specific example where risk factors are modelled as naive BNs connected to *PV* and *AC* parameters for each activity, and *PC* and *EV* parameters are modelled as single variables representing the whole project. However, replicating or adapting this BN model to a different project is not trivial. Issues including how to define a unified *PC* variable from multiple *PC* distributions, or how to model a partially completed *PV* variable were not addressed. These issues can be challenging especially to experts who are not familiar with BNs. This paper extends their model into a generalized probabilistic project control framework. The proposed framework offers repeatable and reusable BN fragments for modelling risk factors, activities and their relations to the project progress. Therefore, the framework can be applied to different projects by duplicating these fragments and defining their parameters according to project activities. The user does not need to consider, or manually amend, the structure or relations between activity and project progress fragments. Modelling of *PC*s and *PV*s of incomplete activities are taken into account in these fragments. Moreover, we also present the PROPCOT Python script for the proposed framework that collects the inputs regarding the project control task from a spreadsheet and does not require extensive technical knowledge regarding BNs and can be adapted to different projects with reasonable effort (see Section 5). In the following section, we present our BN framework for incorporating uncertainty and risk factors into project control.

4. Proposed Bayesian Framework

Our framework models EVM or ESM of a project by using a hybrid BN that contains both discrete and continuous variables. This enables to incorporate the uncertainty regarding planned values or completion rates of each activity and risk factors associated with these activities into project control. Several efficient algorithms are available for computing such hybrid BNs including Markov Chain Monte Carlo (MCMC) sampling or Dynamic Discretization (DD) (Neil et al., 2007; Salmerón et al., 2018), and these are readily implemented in several commercial (AgenaRisk, 2015) or open-source software (Salvatier et al., 2016). The PROPCOT script is based on PyMC (Salvatier et al., 2016).

The BN structure is based on the well-established principles of EVM and ESM. Figure 2 shows an overview of the proposed BN framework where each node represents a BN fragment. The framework is composed of three types of BN fragments. The 'Risk Factors' fragment is a discrete BN that models the relations between the risk factors. The 'Activity *i* Progress' fragments model the progress by using *PV*, *EV* and *AC* regarding each project activity *i*. Each activity progress fragment has the same BN structure, but their parameters are different due to different PV and completion rates of activities. The 'Project Progress' fragment models the overall project performance metrics and predictions regarding completion time and budget of the project. In the remainder of this section, the structure and parameters of each of these fragments are described.

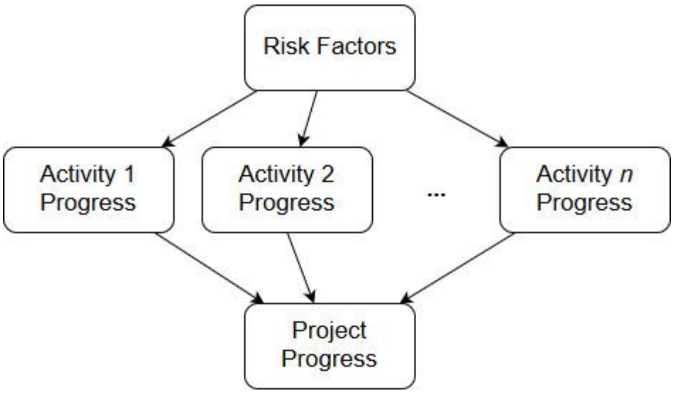

Figure 2 Model Overview

4.1 Risk Factors

Figure 3 shows an example of a 'Risk Factors' fragment where RF_i represents the risk factor i. Risk factors are typically binary variables that represent the realisation of the risk factor or ordinal variables with ranked states, such as 'low', 'medium' and 'high', that represent the degree of the risk factor. Risk factors may adjust the planned values of certain activities when they realise.

4.2 Activity *i* Progress

Figure 3 shows a BN fragment for modelling activity progress using the EVM approach. The probability distributions of the planned value and percentage of completion of activity i at time t, i.e. APV_i and $apc_{i,t}$ respectively, need to be defined in the BN fragment. We define APV_i is by a mixture distribution that is conditioned on the associated risk factors. For example, Table 3 shows a case where two risk factors RF_1 and RF_2 affect APV_i, and its probability distribution is defined by a mixture of Normal and Triangular. The probability distribution of $apc_{i,t}$ represents the project managers' assessment regarding activity completion. Since it is often difficult for project managers to estimate an accurate single value for completion percentage, we define it by using a probability distribution bounded between 0 and 1 in our framework. For example, a Uniform (0.6, 0.8) distribution can be used if the project manager thinks the completion percentage of the activity is between 60% and 80%. The actual cost of activity *i* at time *t* $aac_{i,t}$ is an observed value as the project manager can track resources spent for the activity.

Table 3 Parameters of PV_i

	RF_1 = *True*, RF_2 = *True*	RF_1 = *False*, RF_2 = *True*	RF_1 = *True*, RF_2 = *False*	RF_1 = *False*, RF_2 = *False*
APV_i	Normal(20,3)	Normal(13,2)	Triangular(10,13,14)	Normal(10,1)

The rest of the variables in the 'Activity *i* Progress fragment' are defined by functions conditioned on their parents. The earned value of activity *i* at time *t* $aev_{i,t}$ is defined by the planned value of *i* APV_i and percentage of completion of *i* at *t* $apc_{i,t}$ as follows:

$$aev_{i,t} = APV_i \times apc_{i,t}$$

$apv_{i,t}$ represents the work that is expected to be completed until *t* in the project plan:

$$APV_i = \sum_t apv_{i,t}$$

The SPI_t, CPI_t, SV_t and CV_t performance indices of specific activities can be calculated as described in Section 2 in our framework.

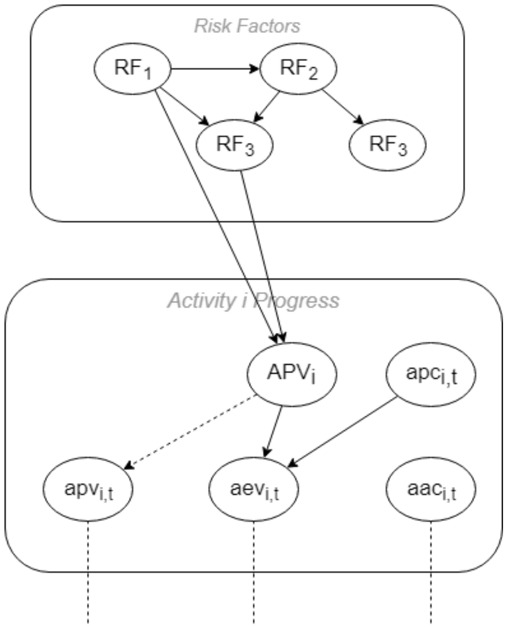

Figure 3 Risk Factors and EVM Activity Progress Fragments

ESM can also be adopted in our framework. Figure 4 shows the BN fragment for modelling activity progress in ESM. Since $aev_{i,t}$ and $apv_{i,t}$ are probability distributions in our framework, we use their expected values to calculate the earned schedule of activity i at t $aes_{i,t}$,

$$aes_{i,t} = t' + \frac{aev_{i,t} - apv_{i,t'}}{apv_{i,t'+1} - apv_{i,t'}}$$

where t' is the time increment where the expected value of $aev_{i,t}$ is greater than or equal to the expected planned value at t', and is less than the expected planned value at t'+1, i.e.

$$E(aev_{i,t}) \geq E(apv_{i,t'})$$

$$E(aev_{i,t}) < E(apv_{i,t'+1})$$

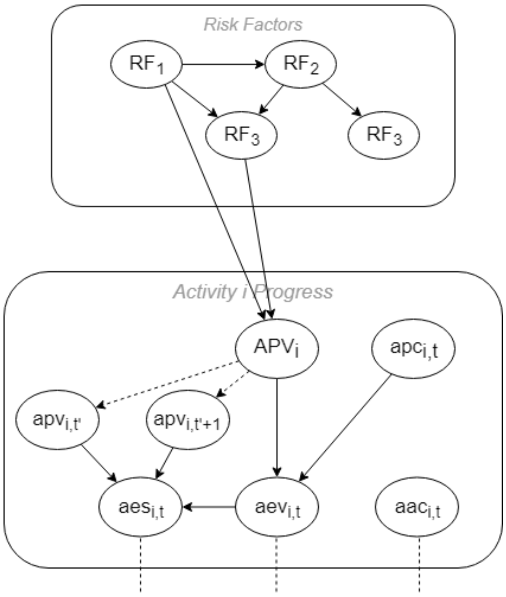

Figure 4 ESM Activity Progress Fragment

4.3 Project Progress

Figure 5 shows the relation between activity progress fragments and the project progress fragment. The planned value PV_t, earned value EV_t and actual costs AC_t of the project at t are calculated by summing up $apv_{i,t}$ and $aev_{i,t}$ distributions and $aac_{i,t}$ values from each activity i fragment as follows:

$$PV_t = \sum_i apv_{i,t}$$

$$EV_t = \sum_i aev_{i,t}$$

$$AC_t = \sum_i aac_{i,t}$$

CV, *SV*, *SPI*, *CPI*, *EAC* and *TEAC* metrics are calculated from these distributions as described in Section 2.

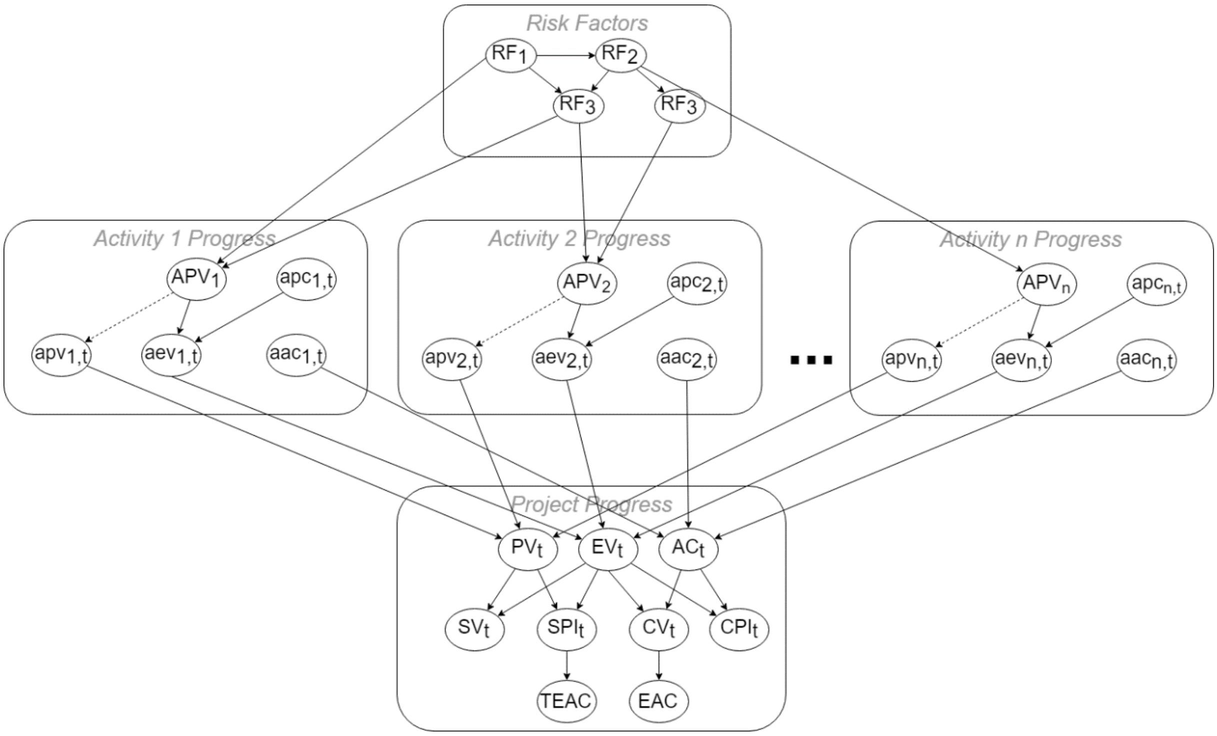

Figure 5 Project Progress Fragment

4.4 Application: Student Project

We used the student project example shown in Section 2 to demonstrate the application of the proposed Bayesian EVM approach, and to illustrate its differences and capabilities compared to the traditional EVM approach.

The traditional EVM disregards the uncertainties regarding completion percentages and planned values in its calculations. Although the student thinks she completed 30% of the analysis activity, it is often difficult to provide an accurate figure for this especially when the activity is not close to completion. Our approach extends the traditional EVM analysis in three aspects:

1. The proposed framework enables the project manager to define completion rates by using statistical distributions to reflect the uncertainty regarding their estimates. The

Beta distribution is a suitable statistical distribution for this case as it is bounded between 0 and 1, and it has a flexible shape. Other distributions that are bounded between 0 and 1 can also be used for defining the completion percentages. Table 4 shows the statistical distributions used for defining each activity completion percentage, their mean and 90% confidence interval.

Table 4 Completion Percentage Distributions for Student Project Example

	Literature Review	**Modelling**	**Experiments**	**Analysis**
Distribution	Beta(80,20)	Beta(70,30)	Beta(20,30)	Beta(6,14)
Mean (90% CI)	0.80 (0.73 – 0.86)	0.70 (0.62 – 0.77)	0.40 (0.29 – 0.52)	0.30 (0.15 – 0.48)

2. Our framework enables the modelling of the causal relations between the risk factors and project activities. In this example, the student identified technical problems regarding the modelling software, problems regarding acquiring data, having unexpected results from the experiments and high workload in the exam period as the four main risk factors. These risk factors were modelled by a BN fragment and their relations to the *PV* of different activities are defined as shown in Figure 6. The parameters of the risk factors BN fragment are shown in Table 5.

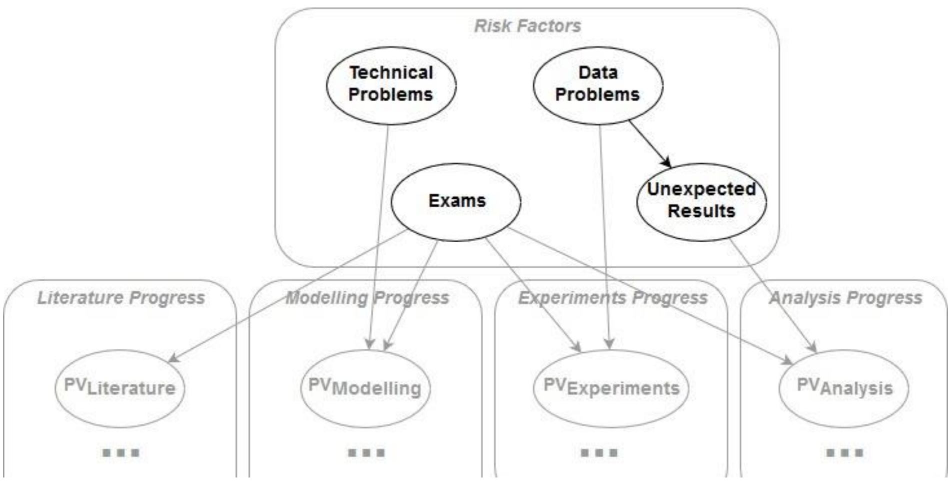

Figure 6 Risk Factors Fragment for Student Project Example

Table 5 Parameters of Risk Factors for Student Project Example

Parameters of Risk Factors BN Fragment
P(*Exams*) = 0.8
P(*Technical Problems*) = 0.3
P(*Data Problems*) = 0.4
P(*Unexpected Results*| *Data Problems*) = 0.50
P(*Unexpected Results* | ¬ *Data Problems*) = 0.17

3. The planned values are also defined by statistical distributions in our framework to reflect the uncertainty regarding plans. If PV of an activity could be affected by a risk factor, we use a mixture distribution conditioned on the risk factor for defining the PV. In this example, the student used mixtures of normal distributions to define the uncertainty regarding *PV* (Table 6).

Table 6 Parameters of PV for Student Project Example

	Exams: True	***Exams: False***		
Literature	Normal(260, 10)	Normal(210,15)		
	Tech. Pr.: True, Exams: True	***Tech. Pr.: True, Exams: False***	***Tech. Pr.: False, Exams: True***	***Tech. Pr.: False, Exams: False***
Modelling	Normal(220,20)	Normal(160,15)	Normal(130,15)	Normal(105,10)
	Data Pr.: True, Exams: True	***Data Pr.: True, Exams: False***	***Data Pr.: False, Exams: True***	***Data Pr.: False, Exams: False***
Experiments	Normal(230,25)	Normal(215,15)	Normal(150,15)	Normal(140,10)
	Unexp. Res.: True, Exams: True	***Unexp. Res.: True, Exams: False***	***Unexp. Res.: False, Exams: True***	***Unexp. Res.: False, Exams: False***
Analysis	Normal(130,30)	Normal(120,30)	Normal(60,15)	Normal(50,10)

AC values of each activity are known as shown in Table 2 and these are instantiated in the BN model. Once the *PV* and completion percentage distributions and *AC* values were defined, we calculated the posterior distribution of *EV, SPI* and *CPI* by using our framework. Figure 7 shows the posterior distributions of the project *EV*, *SPI*, *CPI*, *EAC* and *TEAC* values.

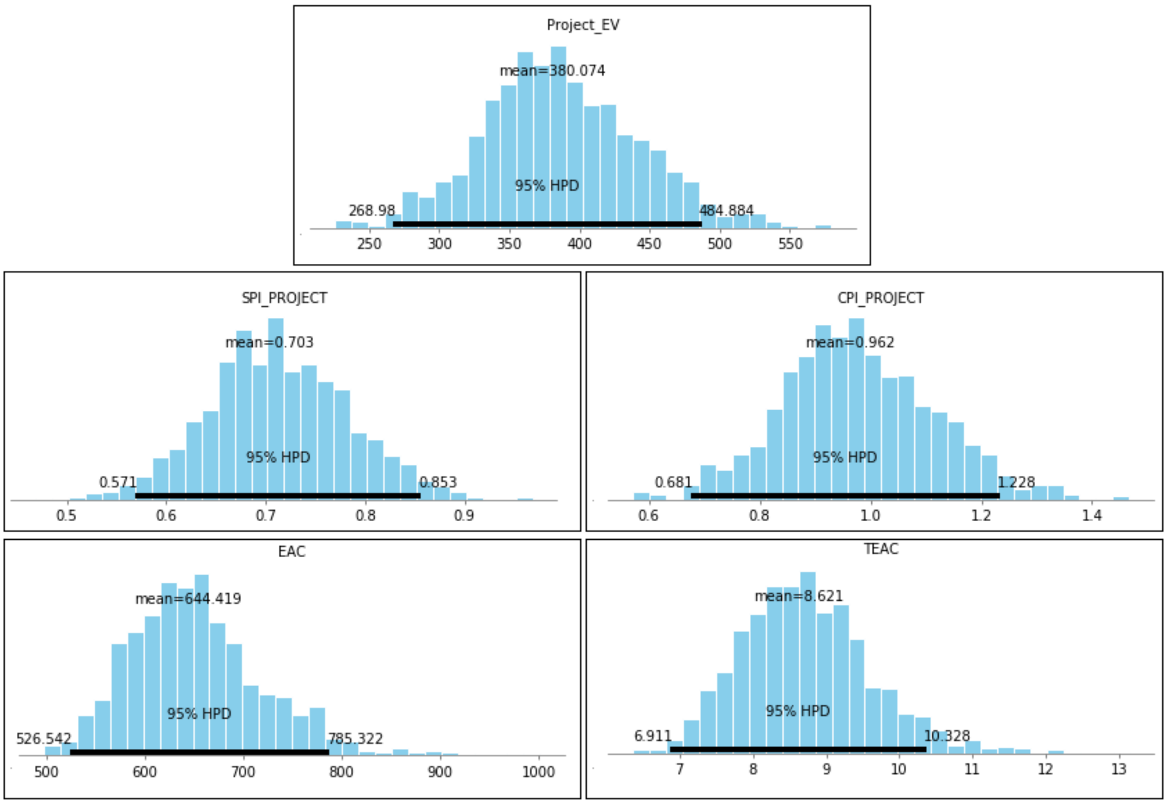

Figure 7 Posterior distributions of Bayesian EVM model for student project

As parameters are defined as probability distributions in our Bayesian EVM model, the posterior distributions of performance indices were calculated. The posterior distribution of the overall project *EV* has the mean value of 380.07 and standard deviation of 55.67; and with 90% probability it is between the values of 290.36 and 474.34. This gives us more information than the point value of 401 we get from traditional EVM calculations. *SPI* of the project has the mean value of 0.70, standard deviation of 0.07 and with 90% probability the *SPI* is between 0.59 and 0.83. Project CPI is a distribution with the mean value of 0.96 and standard deviation of 0.14. CPI is between 0.74 and 1.20 with 90% probability. Note that, unlike the proposed BN model, the traditional EVM approach shown in Section 2 did not provide any information about the uncertainty of these performance indices.

The posterior distribution of EAC has the mean value of 644.42 and standard deviation of 70.26. The uncertainty of this estimate is large due to high variance in the estimates of risk factor effects. With 90% probability, EAC is between the values of 545.74 and 770.44. This shows that if everything goes as planned project completion may cost much less than what the student would believe based on traditional EVM method. However, if risk factors affect the flow of the project heavily, it might cost much more than what she estimated using only the traditional EVM method. Including risks and uncertainties in the calculations would assist the student to understand the variance and uncertainty regarding the project control metrics. The posterior of TEAC has the mean value of 8.62, the standard deviation of 0.91. Depending on the risk factors, TEAC can be between 7.26 and 10.21 months with 90% probability.

Including risk factors in the model enables us to make scenario analyses in project control. For example, suppose the student did not have a high workload in the exam period, and she experienced technical problems regarding the use of the modelling software. We instantiated those variables in the BN model and calculate it to update the EVM metrics (see Table 7). Entering this scenario to the BN decreased the expected value and standard deviation of PV of each activity. In other words, the amount of work expected to complete each work is smaller under given scenario, as a higher workload in exam period was initially considered to be very likely and expected to affect all activities but this did not happen in this scenario.

Table 7 Scenario Analysis Results for Student Project, *Exams = False* and *Tech. Pr. = True*

	Default BN				**Scenario *Exams = False, Tech. Pr. = True***			
	Mean	**SD**	**5%**	**95%**	**Mean**	**SD**	**5%**	**95%**
Lit. Rev. PV	250.27	27.19	195.31	288.28	209.52	14.20	185.81	232.37
Modelling PV	137.05	38.60	90.29	224.57	105.10	9.88	88.46	121.07
Experiments PV	163.32	39.75	117.33	249.94	140.03	9.71	124.35	155.79
Analysis PV	63.37	30.83	27.72	120.14	49.68	10.41	33.12	67.50
Project EV	380.07	55.67	290.36	474.34	312.15	20.53	278.34	345.55
Project SPI	0.70	0.07	0.59	0.83	0.70	0.03	0.65	0.76
Project CPI	0.96	0.14	0.74	1.20	0.79	0.05	0.70	0.87
EAC	644.42	70.26	545.74	770.44	639.66	31.26	589.74	693.00
TEAC	8.62	0.91	7.26	10.21	8.59	0.41	7.93	9.29

4.6 PROPCOT

The proposed framework and the examples and case studies shown in this paper can be calculated by the PROPCOT Python script and are available in PROPCOT (2020). PROPCOT is able to collect input parameters for the framework from a spreadsheet file. For simplicity of use, at most two binary risk factor parents can be defined for each work package in the spreadsheet. The source code for PROPCOT is also available to enable building of more complex risk factor models and extending of the tool.

5. Case Study: Construction of a Biofuel Refinery

In this section, we apply the proposed method to data from a real construction project of a biofuel refinery. The project data is taken from the project database of Gent University Operations Research & Scheduling Research Group (Batselier & Vanhoucke, 2015; Vanhoucke et al., 2016). The project consists of 23 activities that are planned to be completed between 2nd March 2015 and 15th July 2016. We evaluate the project's progress on 29th July 2015. Note that, both fixed and variable costs were recorded for each activity in the project dataset (Batselier & Vanhoucke, 2015; Vanhoucke et al., 2016). We only used variable costs of each activity for PV and EV calculations as variable costs reflected activity progress in the project dataset. We excluded activities with zero variable costs as these activities represented lead times and waiting times in the project. As a result, we considered 16 activities for EVM, and five of these activities are planned to be started and actually started before 29th July 2015, i.e. "Tanks-Preparation", "Skids-Preparation", "Civil-Preparation", "Automation-Preparation" and "Analytics-Preparation". Table 8 shows the activity details and observed parameters. The first group in Table 8 contains the five activities that have started before the project control moment; the second group contains is the future activities that do not affect the current project control parameters.

Table 8 Biofuel Refinery Construction Activities

ID	Work Package	PD	PV	PC	AC
1	Tanks – Preparation	249 day(s)	€ 56,025.00	43%	€ 24,300.00
3	Skids – Preparation	45 day(s)	€ 10,125.00	100%	€ 10,125.00
12	Civil – Preparation	85 day(s)	€ 38,250.00	74%	€ 28,350.00
19	Automation – Preparation	220 day(s)	€ 49,500.00	10%	€ 5,175.00
21	Analytics – Preparation	260 day(s)	€ 58,500.00	17%	€ 9,675.00
2	Tanks – On Site	1 day(s)	€ 1,350.00	0%	€ 0.00
6	Skids – On Site 1	65 day(s)	€ 117,000.00	0%	€ 0.00
7	Skids – On Site 2	20 day(s)	€ 36,000.00	0%	€ 0.00
8	Skids – Commissioning	45 day(s)	€ 121,500.00	0%	€ 0.00
10	Utilities – Lead Time	140 day(s)	€ 94,500.00	0%	€ 0.00
11	Tie-inns	5 day(s)	€ 2,250.00	0%	€ 0.00
13	Civil – On Site	80 day(s)	€ 360,000.00	0%	€ 0.00
14	Labo Container	100 day(s)	€ 90,000.00	0%	€ 0.00
16	Piping – On Site	55 day(s)	€ 99,000.00	0%	€ 0.00
18	Electrical – On Site	30 day(s)	€ 13,500.00	0%	€ 0.00
20	Automation – On Site	20 day(s)	€ 4,500.00	0%	€ 0.00
22	Analytics – On Site	25 day(s)	€ 5,625.00	0%	€ 0.00

The traditional EVM results are given in Table 9. *SPI* for the project is greater than 1. *CPI* is less than 1 by a small margin. Based on these values, Project cost at completion is estimated to be € 81,208.09 and project is expected to take approximately 13.8 months to complete.

Table 9 Traditional EVM for Biofuel Refinery Construction

Project Definition			Project Progress			Metrics		Predictions	
Work Package	**PV_{Total} (€)**	**PV_{July} (€)**	**PC %**	**AC (€)**	**EV (€)**	**SPI**	**CPI**	**TEAC (Months)**	**EAC (€)**
Tanks	55000	19800	40%	24300	22000	1.11	0.91		
Skids	9000	9000	100%	10125	9000	1.00	0.89		
Civil	38000	25080	70%	28350	26600	1.06	0.94		
Automation	50000	5000	10%	5175	5000	1.00	0.97		
Analytics	58000	5220	20%	9675	11600	2.22	1.20		
PROJECT	**210000**	**64100**	**67%**	**77625**	**74200**	**1.16**	**0.96**	**~ 13.8**	**81208.09**

5.1 Application of Bayesian EVM to Case Study

The project data from database (Batselier & Vanhoucke, 2015; Vanhoucke et al., 2016) only contained planned values, completion percentages and actual cost of each activity. In order to illustrate the application and capabilities of the proposed framework, we defined risk factors for the activities that have started, and probability distributions associated with planned values and completion percentages in this case study. Figure 8 shows the BN fragment of the risk factors in the case study, the marginal probabilities of each risk factor are given in Table 10.

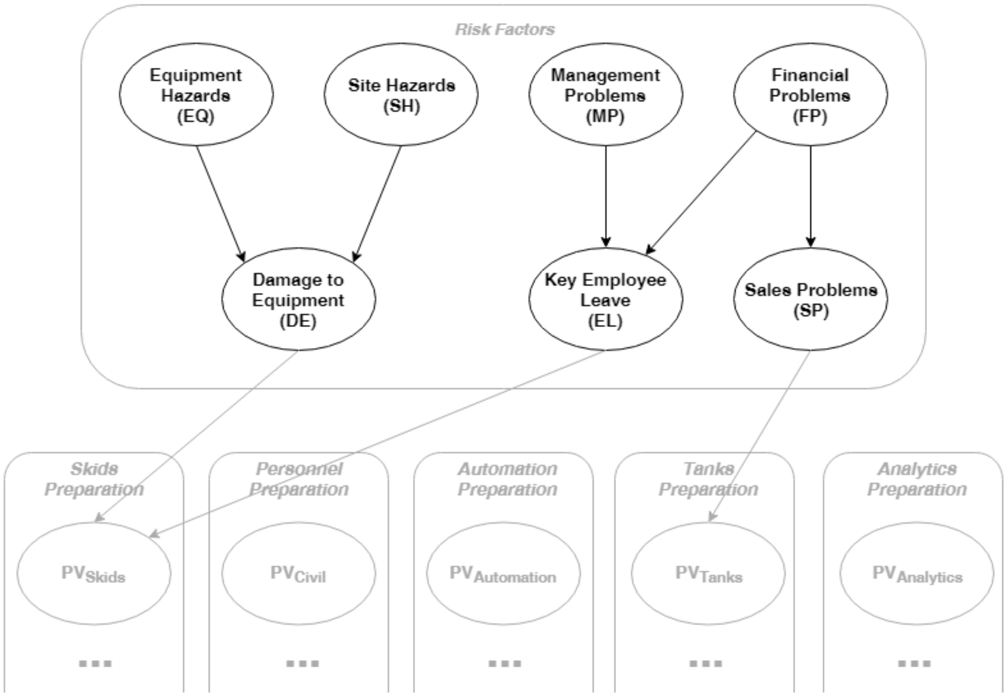

Figure 8 Risk Factors Fragment for Biofuel Refinery Construction

Table 10 Probabilities of Risk Factors for Biofuel Refinery Construction

Probabilities in Risk Factors BN Fragment		
P(*EH*) = 0.4	P(*DE* | *EH, SH*) = 0.6	P(*EL* | *MP, FP*) = 0.55
P(*SH*) = 0.3	P(*DE* | *EH*, ¬*SH*) = 0.4	P(*EL* | *MP,* ¬*FP*) = 0.22
P(*MP*) = 0.4	P(*DE* | ¬*EH*, *SH*) = 0.15	P(*EL* | ¬*MP, FP*) = 0.43
P(*FP*) = 0.18	P(*DE* | ¬*EH*, ¬*SH*) = 0.1	P(*EL* | ¬*MP,* ¬*FP*) = 0.18
P(*SP* | *FP*) = 0.6		
P(*SP* | ¬*FP*) = 0.2		

*PV*s are defined as mixture distributions in Bayesian EVM models. *PV* values for the activities that are affected by risk factors and the distributions that define them are given in Table 11. Probability distributions representing the activity completion percentages of this project is shown in Table 12. Note that, we avoided defining highly precise completion rates for the expected values of the completion rates due to the difficulties regarding this as discussed in Sections 4.2 and 4.4.

Table 11 Parameters of PV for Biofuel Refinery Construction

	SP: True	***SP: False***		
Tanks	Normal(60000,1000)	Normal(55000,1000)		
	DE: True, EL: True	***DE: True, EL: False***	***DE: False, EL: True***	***DE: False, EL: False***
Skids	Normal(12000,1000)	Normal(10000,1000)	Normal(11000,1000)	Normal(9000,1000)

Table 12 Completion Percentage Distributions for Student Project Example

	Tanks	**Skids**	**Civil**	**Automation**	**Analytics**
Distribution	Beta(40,60)	1	Beta(7, 3)	Beta(1,9)	Beta(10,40)
Mean (90% CI)	0.40 (0.32 – 0.48)	1	0.70 (0.45 – 0.90)	0.10 (0.01 – 0.28)	0.20 (0.12 – 0.30)

Figure 9 shows the posterior distributions of the project EV, SPI, CPI, EAC and TEAC values from the Bayesian EVM model. The expected value of SPI is above 1 while CPI is below 1. The probability that SPI is greater than 1 is 0.97, whereas the probability that CPI is greater than 1 is 0.20. *EAC* of this project, which represents the cost estimate of the project, is between € 202,072.90 and € 247,846.70 with 90% probability. *TEAC,* which represents the duration estimate of this project, i.e. TEAC, has an expected value of 13.92 months, and it is between 12.53 and 15.62 months with 90% probability. In other words, the project is likely to be on time and over budget. This example shows the limitations of decision support provided when using only expected values, and the necessity for calculating the uncertainty regarding project performance estimates. Note that, the amount of discrepancy between values of indices depends on the risk factor probabilities and probability distributions of activity completion times used while calculating the uncertainty in project control. The proposed approach guides the project manager to think about and plan these uncertainties and compute their effects on the project progress.

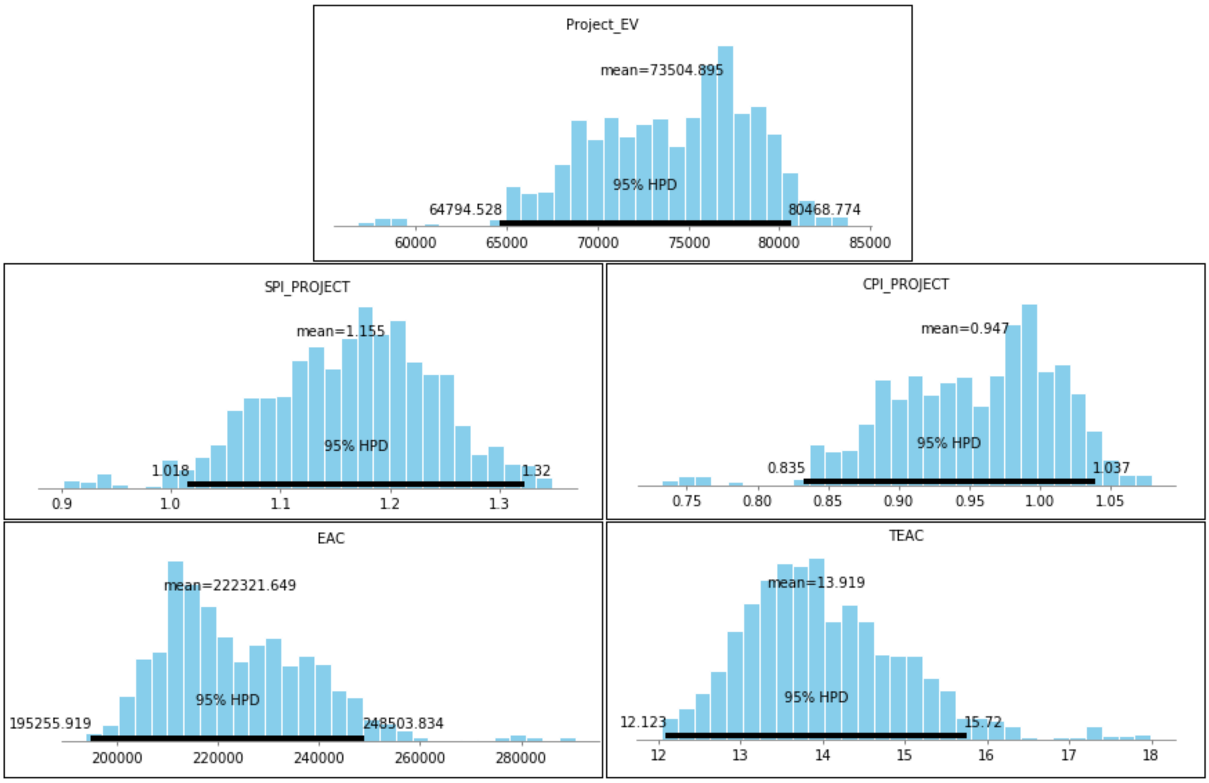

Figure 9 Posterior distributions of Bayesian EVM model for Biofuel Refinery Construction

We can use our framework for a 'what-if' risk scenario analysis in this case study. The BN model also enables the use of diagnostic inference by instantiating the targeted performance indices and revising the probability distribution of other EVM parameters according to these targets. Suppose there has been a sales problem before the project control moment, and we would like to assess the activity PC, and project PV and EV values are likely to be if the project is completed in time and within budget under this scenario. We instantiated the value of 'Sales Problem' variable as 'True', and the values of *SPI* and *CPI* to be greater than or equal to 1 and revised the posteriors of EVM parameters in the BN. Note that, the *SPI* and *CPI* values greater than or equal to 1 reflect the case that the project is expected to be completed on time and within budget. Table 14 shows that the expected CR of activities are 2% - 7% higher than our current estimates, and the expected value of the project EV is 84154 when the SPI and CPI are greater than or equal to 1.

Table 13 Scenario Analysis Results for Biofuel Refinery Construction, CPI ≥ 1 and SPI ≥ 1

	Scenario *Sales Problem = True*				Scenario *Sales Problem = True, CPI ≥ 1, SPI ≥ 1*			
	Mean	**SD**	**5%**	**95%**	**Mean**	**SD**	**5%**	**95%**
Skids PC	1	0	1	1	1	0	1	1
Civil PC	0.70	0.14	0.45	0.90	0.77	0.11	0.58	0.93
Automation PC	0.10	0.09	0.01	0.28	0.14	0.10	0.01	0.33
Tanks PC	0.40	0.05	0.32	0.48	0.42	0.05	0.34	0.49
Analytics PC	0.20	0.06	0.12	0.30	0.22	0.06	0.13	0.32
Project EV	77108.0	8476.8	63439.0	91272.0	84154.0	82968.0	78108.0	94328.0
Project PV	66796.0	1644.8	64170.0	69575.0	67055.0	1666.7	64431.0	69848.0

6. Conclusion

This paper presented a Bayesian framework for project control that models EVM and ESM using BNs. The proposed approach overcomes a limitation of EVM and ESM by incorporating uncertainty and risk factors associated with projects into project control. In the proposed approach, the uncertainty regarding planned values and activity completion percentages can be modelled with statistical distributions, and the effect of different risk factors to these variables can be explicitly modelled and computed. The proposed approach calculates the probability distribution and uncertainty of all project control metrics and enables 'what-if' scenario analysis for different risk scenarios. We used a student project example to illustrate the use of the proposed approach and applied it to real project data from a construction project to demonstrate its applicability to larger projects in different domains.

Defining planned values and activity completion percentages by probability distributions is a major benefit of the proposed approach, since both of these factors are inherently uncertain. It is often difficult to determine what percentage of the work related to an activity is completed unless it has not been started yet or it is fully finished. For example, the difference between 55% complete or 65% complete may not be accurately stated for an R&D related activity in a project. The proposed approach overcomes this by defining PC by using a probability distribution. The project manager may use a distribution of Triangular (0.4, 0.5, 0.7) to represent the judgement that the activity is more than 40% and less than 70% complete, and it is most probably 50% complete. Similarly, the uncertainties regarding PVs can be represented by using probability distributions, and the Bayesian framework enables using the whole probability distributions of these variables, rather than using only summary statistics, in its computations for EVM and ESM.

Integrating risk factors into EVM aids project managers to explicitly plan the relevant uncertainty and risks therefore enables more accurate estimation of project planned values and a more realistic approach for project control. Project planned values are often estimated by project managers or the responsible managers for specific activities. It is often easier for domain experts to estimate planned values under different scenarios and to combine them by using a modelling tool rather than giving an aggregate estimate which covers all possible scenarios. Moreover, when some risk factors realise, project managers often need to adjust the plan regarding the effect of those factors. Hence the parameters of the EVM approach need to be adjusted too according to the change in plans. Our approach enables these adjustments to be done by the modelling tool. This also makes it possible to do 'what-if' scenario analysis at any stage of the project by instantiating risk factors in the BN model and updating the posterior probability distributions of the project metrics. Risk factors are modelled as discrete variables in our framework as project risks are often considered in terms occurrence of specific risk events. The framework also supports a continuous or a hybrid BN fragment for risk factors when required as the rest of the BN structure is also a hybrid BN.

Our proposed approach offers an extended EVM and ESM-based project control by handling uncertainty using Bayesian reasoning. Diagnostic reasoning can be used in our tool by instantiating targeted TEAC, EAC or performance indices and revising the probability distributions of risk factors and EVM parameters. This will aid the decision maker to examine the project progress and risk expectation required to achieve these targets. However, there is a limitation of EVM and ESM-based approaches in diagnosing the cause of the delay or extra costs. In EVM and ESM a project that is delayed or over-budget may have two causes. Firstly, planning may be insufficient or inaccurate so that even though the project is progressing with normal conditions, the performance indices may be worse due to inaccuracies of PVs. Secondly, PVs may be accurate, but the project may be progressing slower or more costly due to other risk factors. A limitation of EVM, ESM, and therefore the proposed approach, is that they cannot distinguish which of these causes led to delay or over-budget. In other words, EVM and ESM shows us the schedule and cost performance of a project, but they do not show us what caused this. As further research, we plan to modify our Bayesian EVM framework to exploit the 'explain-away' type of reasoning in BNs to add this functionality. MCDM approaches could also be integrated to BNs (Yet & Tuncer Şakar, 2019) and other predictive approaches to provide improved project control (Kou et al., 2012, 2014). We also plan to extend PROPCOT by developing comprehensive and user-friendly application interfaces to enable integrating the proposed approach with widely available project management software.

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