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Large engineering project risk management using a Bayesian belief network

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ABSTRACT

This paper presents a scheme for large engineering project risk management using a Bayesian belief network and applies it to the Korean shipbuilding industry. Twenty-six different risks were deduced from expert interviews and a literature review. A survey analysis was conducted on 252 experts from 11 major Korean shipbuilding companies in April 2007. The overall major risks were design change, design manpower, and raw material supply as internal risks, and exchange rate as external risk in both large-scale and medium-sized shipbuilding companies. Differences of project performance risks between large-scale and medium-sized shipbuilding companies were identified. Exceeding time schedule and specification discontent were more important to large-scale shipbuilding companies, while exceeding budget and exceeding time schedule were more important to medium-sized shipbuilding companies. The change of project performance risks was measured by risk reduction activities of quality management, and strikes at headquarters and subcontractors, in both large-scale and medium-sized shipbuilding companies. The research results should be valuable in enabling industrial participants to manage their large engineering project risks and in extending our understanding of Korean shipbuilding risks.

1. Introduction

Project risk management, one of the main subjects of project management (Raz & Michael, 2001), is the planning, organization, monitoring and control of all aspects of a project and it consists of risk identification, risk qualification, risk response development, and risk response control (Saynisch, 2005). Miller and Lessard (2001) pointed out that understanding and managing project risks in large engineering projects are challenging tasks at the early phase. The failure of large engineering projects has highlighted the importance of risk management mainly in the defense, construction and oil industries due to the serious damages that may be incurred (Williams, 1995). Active research has investigated process modeling and the methodologies of project risk management, in order to develop a systematic approach and integrated methodology of project risk management (del Cano & de la Cruz, 2002; Raz & Michael, 2001).

The use of diagrams such as cause and effect diagram and influence diagram is one of the methodologies for project risk management. A diagram is suitable for the modeling of conditional probability relationships among risks, and is useful when handling complex problem. However, it is not easy to construct relationships and it is more complex than intuition-based analysis, so it has not been applied to project risk management as a widely used methodology (Han & Diekmann, 2001; Lyons & Skitmore, 2004; Raz & Michael, 2001; Simister, 1994).

A Bayesian belief network is a graphical model that presents probabilistic relationships among a set of variables by determining the causal relationships among them (Heckerman, 1997). Because a Bayesian belief network constructs a cause and consequence diagram easily, it could be a suitable methodology for project risk management with systematic and integrated processes. Therefore, this study presents a project risk management procedure using a Bayesian belief network, applies this procedure to the Korean shipbuilding industry, and performs a project risk comparison between large-scale and medium-sized shipbuilding companies.

2. Literature review

2.1. Project risk management

The main purpose of project risk management is to identify, evaluate, and control the risks for project success. The measurement of project success is difficult because it may be changed by project phase, and many stakeholders have different criteria to evaluate project success. However, the project success criteria are generally measured by time overrun, cost overrun, and technical performance (Baccarini & Archer, 2001; Williams, 1993).

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Table 1
Examples of project risk management process

Chapman	Cooper et al.	NASA	Boehm	Patterson and Neailey	Tummala and Leung	Zhi
Various industries	Various industries	Various industries	Software development	Automotive manufacturing	Utility sector	Construction
Define/focus	Establish the context	Risk planning				Risk classification
Identify	Identify the risks	Risk identification and characterization	Risk identification	Risk identification	Risk or hazard identification	Risk identification
Structure/ownership				Risk assessment	System hazard analysis	Risk assessment
Estimate	Analyze the risks	Risk analysis	Risk analysis Risk prioritization	Risk analysis	Ranking of hazards	
Evaluate			Risk management planning		Development of action plans	
Plan	Evaluate the risks	Risk mitigation and tracking	Risk resolution	Risk reduction/ mitigation	Risk evaluation	Risk response
Manage	Treat the risks		Risk monitoring	Risk monitoring/loop	Risk control and monitoring	

Various studies have proposed the process of project risk management for project success, as shown in Table 1 (Boehm, 1991; Chapman, 1997; Cooper, Grey, Raymond, & Walker, 2005; NASA, 1995; Patterson & Neailey, 2002; Tummala & Leung, 1996; Zhi, 1995). Though some studies used a detailed process for specific application (Kwak & Stoddard, 2004), or a modified process for evaluating the risk ranking of various projects (Baccarini & Archer, 2001), the general project risk management process consisted of four phases: risk classification and identification, risk assessment, risk analysis, and risk control.

In each phase of a project risk management process, common methodologies proposed by Lyons and Skitmore (2004), Raz and Michael (2001) and Simister (1994) are as follows:

In the risk identification phase, the main methodologies are brainstorming, document review, Delphi technique, checklist analysis, and assumptions analysis. The risk analysis phase can be divided into qualitative risk analysis and quantitative risk analysis. The former includes risk probability and impact assessment, and probability and impact matrix, while the latter includes sensitivity analysis, expected monetary value analysis, and decision tree analysis using utility theory (de Klert, 2001). Other methodologies include simulation (Duffey & van Dorp, 1999), cause and effect diagram, influence diagram, game theory, and fuzzy theory (Carr & Tah, 2001; Kuchta, 2001). Fault tree and event tree analyses are also used in technical risk analysis as quantitative risk analysis (Molak, 1997; NASA, 1995). Since various methodologies exist in each process of project risk management, del Cano and de la Cruz (2002) recommended suitable methodologies with consideration for project scale, complexity, and organization risk maturity level. They also suggested that most of the methodologies are suitable for large engineering projects.

However, Han and Diekmann (2001) described the following disadvantages of these methodologies: intuition-based analysis and analytical methods are unsuitable for complex problems, a statistical approach requires tremendous effort in data collection, a decision tree has complexity in the form of correlated variables, simulation needs a mathematical model and the probability density function needs to be defined for each variable, a neural network is highly sensitive to data set, and an influence diagram requires detailed representation of the relationships. Han and Diekmann (2001) therefore used the cross impact analysis method for construction project go/no-go application. However, the cross impact analysis method has the disadvantages of demanding the experts' estimation of conditional probabilities or joint probabilities of event pairs, or the marginal probability of events (Weimer-Jehle, 2006).

A Bayesian belief network is used in this study for large engineering project risk management because it can easily present a detailed representation of the relationships and calculate conditional probabilities of risk items which are the disadvantages of the influence diagram and cross impact method.

2.2. A Bayesian belief network

A Bayesian belief network, also called a causal network or belief network, is a powerful tool for knowledge representation and reasoning under conditions of uncertainty (Cheng et al., 2002), and visually presents the probabilistic relationships among a set of variables (Heckerman, 1997). It is frequently applied in real-world problems such as diagnosis, forecasting, automated vision, sensor fusion, and manufacturing control (Heckerman, Mamdani, & Wellman, 1995). It has been extended to other applications including transportation (Ulegine, Onsel, Topcu, Aktas, & Kabak, 2007), ecosystem and environmental management (Uusitalo, 2007), and software risk management (Fan & Yu, 2004). A Bayesian belief network has many advantages such as suitability for small and incomplete data sets, structural learning possibility, combination of different sources of knowledge, explicit treatment of uncertainty and support for decision analysis, and fast responses (Uusitalo, 2007). It is therefore applied to decision support systems with uncertainty.

A Bayesian belief network consists of qualitative and quantitative parts (van der Gaag, 1996). The qualitative part of a Bayesian belief network, so-called structural learning, is the graphical representation of independence holding among variables and has the form of an acyclic directed graph. There are two methods for structural learning using data. One is a Bayesian approach based on scoring and searching, the other is a constraint-based approach based on independence test. A Bayesian approach finds the optimal model structure from data after a Bayesian belief network is constructed by the user's priori knowledge, and a constraint-based approach finds the optimal model structure from conditional dependences in each pair of variables. However, a constraint-based approach is commonly used due to its computational simplicity compared to the Bayesian approach (Uusitalo, 2007).

A PC algorithm which is widely used in the constraint-based approach connects all nodes, deletes connections according to the conditional independence from any node as a center to neighbor nodes, and finally represents the directions (Spirtes, Glymour, & Scheines, 1993). Abellan, Gomez-Olmedo, and Moral (2006) highlighted the advantages of a PC algorithm in having an intuitive basis and the ability to recover a causal structure of an equivalent true model for the data. Therefore, this study used a PC algorithm based on Spirtes et al. (1993).

The quantitative part of a Bayesian belief network, the so-called parameter learning, finds dependence relations as joint conditional probability distributions among variables using cause and consequence relationships from the qualitative part and data of vari-