Learning Bayesian Network to Explore Connectivity of Risk Factors in Enterprise Risk Management

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Abstract

Enterprise Risk Management provides a holistic top-down view of key risks facing an organization. Developing techniques that can exhibit the inter-connectivity of risks are required to effectively manage risks on an enterprise-wide. This research thus proposed Bayesian Network learning technique to explore the correlated risks in portfolio risk management using the Expressway Authority of Thailand for empirical study. The comparisons of three Bayes Net algorithms for building the risk map were also conducted. The results showed that TAN classifier was best suited for establishing the causality model of Bayesian risk map to strengthen portfolio risk management in this work. The findings from the study also indicated that all the twenty six key risk indicators, derived from expert judgment, were related in hierarchy and directly affected the portfolio risk value, or economic profit. The study found that number of new car's registration, customer life time value, and safety cost efficiency were the root causes of the portfolio risk of expressway enterprise.

Keywords: *Bayesian Network learning, Risk Map, Portfolio Risk, Enterprise Risk Management*

1. Introduction

With the ever-growing complexity of business environments, risks are more and more interconnected. Thus, a paradigm of the way to view enterprise risk management is shifted from a silo perspective to holistic view. Only through understanding the inter-connectivity of risks, the decision maker arrives at a holistic view of the risk system. However, the traditional techniques of risk analysis that provide a decision maker with both quantitative and qualitative analysis, namely checklists techniques (risk references), cause-effect diagrams, influence diagrams, failure mode and effect analysis (FMEA), fault tree analysis (FTA), event trees, risk matrices (probability and impact grids), sensitivity analysis, Monte Carlo simulations, project evaluation and review techniques (PERT), and critical path analysis (CPA), fail to highlight this important property of real-world risks [20]. In addition, most of these techniques are effective to record and monitor individual risk factors, but few can visualize how risks are interrelated. Some useful techniques, for example, concept mapping and soft system approaches are recommended to assist with the holistic approach. However, for the business managers, most of these techniques are qualitative, and unreliable. Therefore, it is essential to develop techniques that can introduce the complexity of inter-connectivity, whilst simplify practicable and reliability in real-world business. This paper thus proposes a method from machine learning community, called Bayesian Network learning, to discover the correlated risks in order to strengthen the enterprise risk management. Expressway Authority in Thailand (EXAT), a state enterprise responsible for expressway management, is selected as the case study. Expressway or toll way is one of the important infrastructures of countries. The expressway networks are significant for the national economic development, especially in enhancing the logistic systems. However, while the investment amount is huge, the return on investment will be gained after the operation phase. Moreover, there are a large number of uncertainty factors or risks that could influence the performance of an expressway enterprise during the operation phase. In order to well manage the expressway operation and to achieve Stakeholders Value Creation Maximization, it is essential to efficiently discover and manage the enterprise risks via enterprise risk management based on portfolio risk view.

Bayesian Network has been widely used in the context of classification. The goal of learning a Bayesian Network is to find both the structure and the parameters of the network that best fit the training data, according to a given scoring function [9]. Therefore, the technique could be applied for exploring the connectivity of risk factors in a risk system that is similar to the network structure obtained from Bayesian learning. In addition, the weights of risk correlation can be expressed in terms of the probability values resulted from parameter learning. Moreover, Bayesian Network can also be used as a model to evaluate, map, and visualize risks that are based on portfolio view of enterprise risk management.

Since there are several different Bayesian classifiers and some classifiers perform better than others on different datasets. This research also explores which classifier will work best on a given real-world business dataset.

The remaining of this paper is organized as follows. Section 2 briefly reviews the literature. Section 3 describes the research methodology, and proposes the key risk indicators derived from the empirical exploration based on EXAT expert judgment. Section 4 reports the experimental results and presents the graphical connectivity of key risk factors. Section 5 concludes the work presented in this paper.

2. Literature Review

2.1 Enterprise Risk Factors

Nowadays, enterprise risk management based on holistic view can be implemented within the framework of the value based enterprise risk management (VBRM) approach. VBRM could be defined as the strategic enterprise process of identifying, assessing and responding to the collective risks and opportunities that may affect the enterprise's ability to attain its strategic goals, optimize its stakeholders' value, and improve its overall stewardship and management. Hence, tt can be assumed that an enterprise risk is the corporate competitiveness risk, which arises from four dimensions consisting of the environment risk, resource risk, strategy risk, and capacity risk ([8], [11], [13], [14], [21]).

In the expressway enterprise operation, the factors influencing the enterprise value mostly come from the internal and external environments of enterprise. The external risk factors are uncontrollable and difficult to be prevented, for example, the change of political situation, economic policy, environmental protection, market situation, community support, regulation reformation or otherwise. On the other hand, the internal risk factors mostly appear in three ways: i) financial benefit factors including maintenance costs, overhead expenses, traffic, toll, the earning of rational exploitation, and otherwise; ii) the ability/ efficiency of management factors consisting of the efficiency of organization function, resource management, commercial competition, the ability of managers; and iii) the services capacity risk comprising the freeway capacity, running speed, toll system, monitor or communications system, the attitude of service, and so on [4,15-18].

2.2 Bayesian Network

Bayesian Network (also known as Bayesian Belief Network, Causal Probabilistic Network, Probabilistic Cause-Effect Model, or Probabilistic Influence Diagram) is interpretable and flexible probabilistic graphical model that describes the probability distribution governing a set of variables by specifying a set of conditional independence assumptions along with a set of conditional probabilities. A Bayesian network is represented by a directed acyclic graph (DAG), associated with sets of local conditional probabilities attached to each node, called Conditional Probability Table or CPT [3]. The network arcs represent the assertion that the variable labeled in each node is conditionally independent of its nondescendants in the network given its immediate predecessors in the network. A Bayesian network represents a probability distribution on the joint distribution that can be decomposed according to the chain rule as shown in Equation 1.

$$P(X_1, \dots, X_i) = \prod_{i=1}^{n} P(X_i / X_1, \dots, X_{i-1}) = \prod_{i=1}^{n} P(X_i / \pi(X_i)) \quad (1)$$

where $\pi(X_i) = \varnothing P(X_i / \pi(X_i)$ is marginal probability of X_i, $P(X_i)$

This decomposition of the joint distribution leads to powerful inference algorithms that enable Bayesian networks to analyze large amount of data and extract useful knowledge for decision making, controlling, predicting and reasoning the behaviors of a system, in addition to diagnose the cause of a phenomenon.

In order to perform Bayesian inference, prior probabilities and posterior probabilities are required.

Let X, and Y be two stochastic variables, and suppose that $X = x$ and $Y=y$ be evidence. Before considering the evidence $Y=y$, the prior probability of the event $X = x$ or $P(X = x)$ should be estimated first. After taking into account of the evidence $Y=y$, according to Bayes theorem, the posterior probability $P(X=x|Y=y)$ can be calculated as shown in Equation 2.

$$P(X = x|Y = y) = \frac{P(X=x, Y=y)}{P(Y=y)} = \frac{P(X=x)P(Y=y/X=x)}{P(Y=y)} \quad (2)$$

where $P(X = x|Y = y)$ is the probability of the joint event $P(X = x \wedge Y = y)$. If X, Y are independent, then $P(X=x|Y=y) = P(X=x)$.

2.2.1 Learning Bayesian Network

The methods to construct Bayesian networks can be majorly classified into two categories: i) top-down modeling methods, and ii) reverse-engineering methods. Top-down modeling methods seek for direct solutions to Bayesian network structure and parameter assignments from any prior knowledge resources and domain experts. In contrast, reverse-engineering approaches utilize machine learning algorithms to train (learn) Bayesian network structure and parameters from a collection of past observations. The advantage of the latter approaches is that, a training machine can automatically determine a best Bayesian network model with structure and parameters that optimally fits to the training data under the judgments of an object function or scoring function [1]. This study uses the reverse-engineering methods to construct the Bayesian network models, which can visualize the correlation of risk factors.

Based on the reverse-engineering methods, learning the structure implies learning the conditional independence from observations. There are two groups of approaches for structure learning: constraint-based method, and search-and-score method [5]. In the constraint-based method, probabilistic relations using the Markov property with conditional independence test is used to learn and analyze the network structure and then a graph is built which satisfies the corresponding d-separation statements. However, this study does not deal with constraint-based algorithms. The search-and-score method comprises two elements: a search procedure for a network structure and a score (metric) evaluating each structure found in the search [6]. The best Bayesian network is the one that best fits the data and leads to the scoring based algorithms that seek a structure which maximizes the scoring function [5].

2.2.2 Bayesian Network Classifiers

There are several algorithms (classifiers) based on the search-and-score method. This study focuses on three classifiers, which have the potential to learn the dependencies and causal relationship among the variables, i.e., Tree Augmented Naïve Bayes (TAN), K2, and Hill Climbing [7, 12]. Fig. 1 illustrates the structure of the Bayesian classifiers considered in this paper.

TAN is an extension of the Naive Bayes classifier. It removes the Naive Bayes assumption that all the features are independent. The dependencies between variables, other than the class, are also taken into account. By adding a tree-like structure to Naive Bayes, each attribute may have, in addition to the class attribute, one another parents from amongst the others.

K2 is a score-based greedy search algorithm for learning Bayesian networks from data. It maximizes the probability of an optimal graph topology, given a dataset, by using a Bayesian score to rank different graphs. The algorithm is restricted by an order on the variables.

Hill Climbing (HC) is an algorithm used for adding, deleting and reversing arcs. The search is not restricted by an order on the variables (unlike K2). HC will follow the graph from node to node, always increasing the value of the solution, until a local maximum is reached. This study compared the performance among these three classifiers to select the best model to strengthen enterprise risk management.

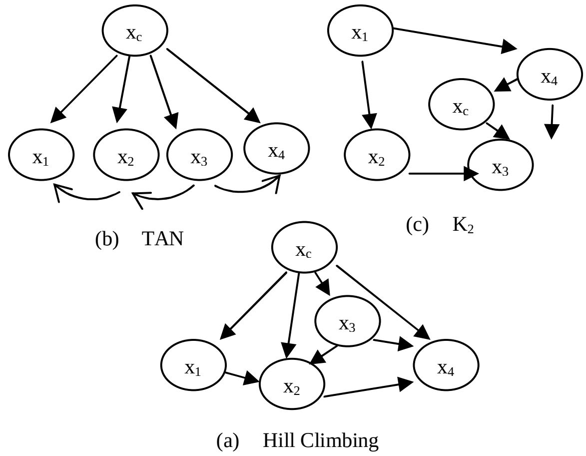

Fig. 1 Different Bayesian network structures of TAN, K2, and Hill Climbing [12]

3. Research Methodology

Starting from the process of data selection to discover key risk indicators (KRIs), the methods of screening through in-depth interviewing the EXAT executive manager, systematic thinking based on expert method, and the confirmatory analysis with statistic methodology were conducted. Finally, the twenty six key risk indicators (KRIs) were derived (see table 1 in appendix). The learning algorithm of Bayesian Network consists of five steps: 1) construction, 2) initialization, 3) network learning, 4) predicting, and 5) reasoning of network. However, this study does not focus on the fourth and fifth steps.

(1) Construction of the Bayesian network is to determine the nodes and the structure of network. According to the features of the portfolio risk, the metric is economic profit, and the KRIs influencing economic profit are variables labeled on nodes.

(2) Initialization of the Bayesian network is to determine the probability distribution or conditional probability distribution of each node. It can be obtained by either historical data or expert judgment.

(3) Network learning includes parameter learning and structure learning. This study focuses on data driven, i.e. structure and parameter learning through algorithms. The connectivity of risk factors, and correlation value—probability value, will be shown in this step. The output can be called the risk map or risk model.

(4) Predicting is the estimate of future portfolio risk or economic profit after having obtained the posterior probability.

(5) Reasoning of the network consists of scenario analysis and causal analysis, which assess the impact of risk factors on the portfolio risk.

The open-source software WEKA [2] was used for testing. It is a free software package implemented with Java language. The assessment method of 10-fold cross validation was used for evaluating the performance of the model constructed from three classifiers.

This study used the monthly statistic of the twenty six KRIs needed in the financial reports, the performance reports, and the statistical reports since 2005-2010 of fiscal year.

4. Experimental Results

4.1 Performance of Classifiers

The performance of candidate classifiers was evaluated using the standard metrics of accuracy, precision, recall, F-measure, and ROC area for risk classification. The values of these metrics were calculated using the predictive classification table, known as Confusion Matrix (Table 2), seeing details in [10]. Additionally, another statistical analysis was carried out to assess the performance of the different classifiers for comparisons [7]: mean absolute error which is the range of possible values in terms of the unit of measurement, and the weighted average of all the absolute errors found from cross validations; and relative absolute error which is a ratio of the mean absolute error of the learning algorithm over the mean absolute error found by predicting the mean of the training data. The lower the percentage, the better the performance of the classifier compared to just predicting the mean.

The testing results of the three classifiers are shown in Table 3. According to Table 4, it reported that TAN yielded the highest accuracy of 84.722%. Thus, TAN was chosen to build Bayesian Network model for representing the risk map with the identified key risk factors and the correlation of risk factors defined in portfolio risk.

Table 2: Confusion matrix

		PREDICTED	
		IRRELEVANT	RELEVANT
ACTUAL	IRRELEVANT	TN	FP
	RELEVANT	FN	TP

According to Table2,

TN (True Negative): Number of correct predictions that an instance is irrelevant.

FP (False Positive): Number of incorrect predictions that an instance is relevant.

FN (False negative): Number of incorrect predictions that an instance is irrelevant.

TP (True Positive): Number of correct predictions that an instance is relevant.

Table 3: Statistical analysis of classifiers

Classifier	Mean Absolute Error	Relative Absolute Error
TAN	0.115	29.122%
K_2	0.222	56.458%
Hill Climbing	0.197	49.982%

Table 4: Performance results of classifiers

Classifier	Accuracy	Precision	Recall	F-Measure	ROC Area
TAN	84.722%	83.9%	84.7%	84.2%	93.8%
K_2	69.444%	71.5%	69.4%	70.2%	82.7%
Hill Climbing	76.389%	76.4%	76.4%	76.4%	84.5%

4.2 Bayesian Risk Map

The best Bayesian Network model, derived from TAN, is shown in Fig. 2.

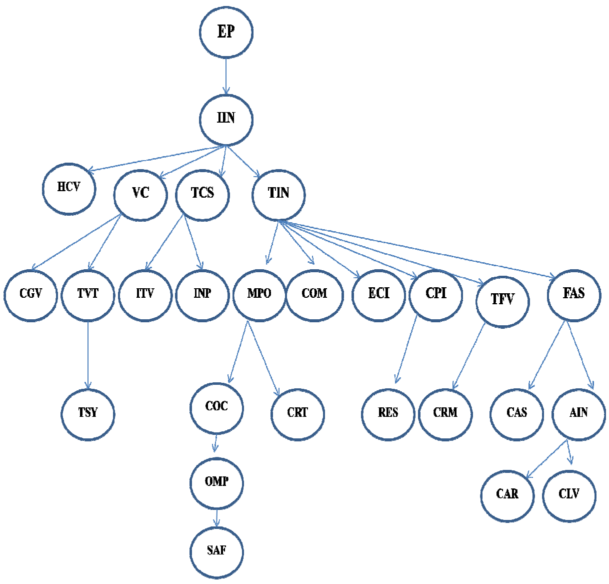

Fig. 2 Bayesian risk map for portfolio risk management of expressway enterprise

According to the resulting risk map or risk model, it implied that all risk factors correlate both directly and indirectly based on the assumption of conditional independence of Bayesian Networks. Furthermore, due to the findings that TAN algorithm was best suited for constructing the cause and effect model in this work, the connectivity of risk factors derived from the model could be assumed to suit for the portfolio risk of expressway enterprise. It reflected that the class node, i.e. the value of portfolio risk or economic profit (EP), depended on the twenty six attribute nodes, which affecting each other in hierarchy as well. It was found that an Interest or dividend income (IIN) is the first cause. Human capital value (HCV), Traffic volume per toll capacity ratio (VC), Toll collection speed (TCS), and Toll income per day (TIN) are the second causes. Corporate governance efficiency (CGV), Travelling time (TVT), IT resource value (ITV), Innovation management process value (INP), Operating profit margin (MPO), Information service providing value (COM), the current economic climate (ECI), the cost of living and inflation. (CPI), Traffic volume per day (TFV), and Net Fixed Assets Turnover Ratio (FAS) are the third causes. Convenient provision value (TSY), Cost control efficiency (COC), Customer retention (CRT), Incident resolution speed (RES), Customer management process value (CRM), Net cash ratio (CAS), and Area income (AIN) are the fourth causes. Operation Management process value (OMP) is the fifth cause. Number of new car's registration (CAR), Customer life time value (CLV) and Safety cost efficiency (SAF) are the root causes. Based on the empirical results, the technique would be used by decision makers for properly manage risks on an enterprise-wide.

5. Conclusions

In this study, the connectivity of risk factors in enterprise risk management was discovered for the domain of the expressway enterprise using EXAT as the case study. According to the performance comparison results, TAN algorithm was selected for learning the Bayesian Network to construct the risk map, which supports the decision in enterprise risk management based on holistic view. The empirical study also showed that the proposed model was accurate in representing the inter-connectivity among the twenty-six key risk indicators discovered.

Appendix

Table 1: All variables or key risk factors influencing portfolio risk of expressway enterprise

Risk Indexes	***Variables Name (KRIs)***	***Explanation***
Socio-economic risk	Coincident index (ECI)	The statistical tools used to measure the current economic climate.
	Customer price index (CPI)	The statistical tools used to measure the cost of living and inflation.
	Number of new car's registration. (CAR)	The number of registered cars in Bangkok and its vicinity.
Structural value risk	Human capital value (HCV)	Total revenue: personal expense
	IT resource value (ITV)	Total revenue: IT expense
	Corporate governance efficiency (CGV)	Total revenue: Committee meeting fee
Process value risk	Operation Management process value (OMP)	Net toll revenue : Operation expense
	Customer management process value (CRM)	Net toll revenue : Marketing expense
	Innovation management process value (INP)	Total revenue : R&D expense
Viability risk	Operating profit margin (MPO)	(Operating profit x100): Net Toll revenue
	Cost control efficiency (COC)	(Operation cost x100): Net toll revenue
	Net cash ratio (CAS)	Net Cash flow: Net toll revenue
Opportunity value risk	Traffic volume per day (TFV)	The average of traffic volume per day
	Toll income per day (TIN)	The average of toll income per day
	Area income (AIN)	The number of income from area exploitation
	Interest or dividend income (IIN)	The number of income from interest or dividend
	Net Fixed Assets Turnover Ratio (FAS)	(Net toll revenue x100) : fixed assets
Toll quality risk	VC ratio (VC)	Traffic volume per toll capacity ratio
	Safety cost efficiency (SAF)	(Maintenance cost x100) : Accident quantity
	Convenient provision value (TSY)	Net toll revenue : Expense of providing tolling technology
Service quality risk	Toll collection speed (TCS)	The average of time to be used for toll collection
	Information service providing value (COM)	Net toll revenue: Expense. of providing information service
	Travelling time (TVT)	The average of travelling time
	Incident resolution speed (RES)	The average of time to be used for incident resolution
Brand image risk	Customer life time value (CLV)	CLV=m(r/1+i-r); m=Operating profit margin, r=customer retention, i=weighted average cost of capital (WACC)
	Customer retention (CRT)	(Traffic volume$_t$ - Traffic volume$_{t-1}$) x100 : Traffic volume$_{t-1}$
Portfolio risk	Economic profit (EP)	$\mathrm{EP} = (\mathrm{NOPAT} + \mathrm{Adj}_{\mathrm{Nopat}}) - ((\mathrm{WACC})(\mathrm{Capital} + \mathrm{Adj}_{\mathrm{Capital}}))$

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