# Scenario Analysis in Expressway Management via Modeling Bayesian Networks

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## ABSTRACT
The enterprise risk management is crucial for high-stakes investment corporations. The contemporary value-based management seeks to maximize the shareholder value. To achieve value creation, enterprises need to identify the key value drivers, also called key risk factors where they cause unexpected value and loss. Key value drivers are the variables that can be maximized to raise the entire enterprise value and influenced by the corporate strategy. This study presents an approach to applying Bayesian Network to determine key value drivers or key risk factors for the prediction of enterprises value, economic profit of Expressway Authority in Thailand. The experimental results showed that this technique provides high prediction accuracy. The eight key risk factors that affect the enterprise value comprise Traffic volume per day, Time of travel, Cost of Route Maintenance, Income from rental area, Speed of toll collection, Volume per capacity rate, Rate of Accident, and Income from Tollway. The results of multiple regression analysis indicated that all the independent variables (eight key risk factors) in the Bayesian Network model directly affected the dependent variable or economic profit. Furthermore, the model is applicable for scenario analysis in expressway management to discover the factors that would increase economic profit. The experiments on various scenarios reported that the high level of service quality must be sustained if the enterprise desires to increase the economic profit.

## General Terms
Machine Learning, Bayes Theorem, Decision Support System

## Keywords
Bayesian Networks, Expressway Management, Enterprise Value, Scenario Analysis, Enterprise Risk Management

## 1. INTRODUCTION
The expressway networks play an important role in Thailand economic development, especially in enhancing the logistics systems. The Expressway Authority of Thailand, a state enterprise, is responsible for project planning, managing the construction, operating, and maintaining expressway networks. While the investment amount is huge, the return on investment will be gained after the operation phase. Due to high-stakes investment caused by a large number of uncertainty factors or risks during the operation phase, the enterprise risk management, performance measurement, and future plans should be well-prepared. Future plans can be established based on scenarios analysis, which is a main method of projections. Scenario analysis is a process of analyzing possible future events by considering alternative possible outcomes (scenarios). Rather than showing one exact picture of the future, the method consciously presents several alternative future developments. Consequently, a scope of possible future outcomes is observable. Not only are the outcomes observable, but also the development paths leading to the outcomes. It is useful to generate a combination of an optimistic, a pessimistic, and a most likely scenario. We can expose corporation outcomes through performance measures. Key performance measures determine an organization's strategy, which in turn, is linked to its operations. Nowadays, many organizations, including those in Thailand, have adopted a new breed of performance measures that are based on shareholder value (enterprise's value), known as value-based management. Shareholder value is the financial value created for shareholders by the companies in which they invest. Companies are choosing to employ a system of measuring the shareholder value for many reasons (Copeland *et al.* 1994 cited in [1]). First, value is the best metric of performance as it is the only measure that is comprehensive and useful for decision-making. By increasing the shareholder value, companies can maximize the value for other stakeholders namely customers, labors, government (through taxes paid), and suppliers of capital. Second, shareholders are the only stakeholders of a company who simultaneously maximize everyone's claim in seeking to maximize their own. Finally, companies that are unable to create their shareholder value will find that capital flows away from them and towards their competitors who are creating their shareholder value. To achieve value creation, enterprises need to identify the key value drivers, or the variables that can be maximized to raise the entire enterprise value and influenced by the corporate strategy. They are also called key risk factors in another perspective where they cause unexpected value and loss. These key value drivers are varied for different industries or enterprises. Identifying key value drivers can be derived from efforts to model the determinants (key value drivers) of firm profit within an industry. Value creation is the process of enterprise risk management that transforms the resources or enterprise's capital to outcome or enterprise's value based on their causal relationship, which can visualize scenarios via the causal model or cause and effect diagram. Due to the problems of identifying the relationships of the risk factors and the subjectivity of risk management and ineffectiveness of some methodologies, such as Heuristic-based approach or analytical methods when applied

to complicated problems, this paper proposes an approach to managing enterprise risk using Bayesian Networks to analyze key risk factors and to predict the enterprise value and performance during operation. Modeling scenarios via Bayesian networks is the method for uncertainty reasoning and knowledge representation that was advanced at the end of the $20^{th}$ century. Bayesian probability theory is a branch of mathematical probability that allows one to model uncertainty and to predict their outcomes of interest by combining common-sense knowledge and observed evidence. After establishing all the variables in a model, one must deliberately associate the variables that cause changes in the system to those variables on which they influence [2]. In general, a Bayesian network describes the joint probability distribution for a set of variables. The network or graph visualization represents the cause-and-effect relations among variables, pointed out by arcs. The degree of relationship is interpreted in terms of conditional probabilities according to Bayes theorem. Bayesian Networks allow stating conditional independence assumptions that apply to subsets of the variables, providing more tractable and less constraining than the global assumption of conditional independence. The output of Bayesian network model can be a probability distribution of interval estimates of performance.

## 2. SHAREHOLDER VALUE MEASUREMENT

Based on the value based management (VBM) approach, a continuous process begins with strategic planning to achieve competitive advantages which produce superior growth in economic profits and returns to shareholders. The value of enterprise is the economic efficiency of enterprise and economic performance on the basis of their overall operations of the overall judgment. In general, enterprise core performance is the financial benefits. And the value of enterprise is based on current and the past profits ability of enterprise and development potential [3]. The most common method for measuring shareholder value is Economic Value Added (EVA) or Economic Profit (EP). EP is an estimation of a company's true economic profit after making corrective adjustment to accounting numbers. In fact, EP measures the company's value creation from the economic points of view. The most attractive advantage of EP compared with traditional profit measures is that the calculation of EP considers the opportunity cost of equity capital. The opportunity costs explain why shareholders invest in a certain company instead of the other company. Following this way, investment by shareholder is the same as loans from creditors. Shareholder value using EP measure is the focus of this research. The basic formula of EP is shown as Equation 1.

$$\mathrm{EP} = (\mathrm{NOPAT} + \mathrm{Adj}_{\mathrm{Nopat}}) - ((\mathrm{WACC})(\mathrm{Capital} + \mathrm{Adj}_{\mathrm{Capital}})) \quad (1)$$

where EP equals to net operating profits minus a charge for cost of invested capital,

NOPAT denotes net operating profit after taxes,

Capital denotes total capital of a company,

Adj $_{\mathrm{Nopat}}$ and Adj $_{\mathrm{Capital}}$ denote the adjustments made by Stern Stewart on NOPAT and capital,

WACC refers to weighted average cost of capital, including capital invested by shareholders and creditors.

If the operating profit is greater than the cost of capital, value is created. Otherwise, value is destroyed (i.e. shareholder value is created when EP> 0, and destroyed when EP ≤ 0). A company can increase its economic profit in the following ways [1]:

(1) Increasing NOPAT by increasing operating income.

(2) Reducing the capital charge by reducing the company's capital and cost of capital.

## 3. KEY VALUE DRIVERS

Key value drivers or key success factors can be regarded as key risk factors if they cause unexpected value and loss (opportunity loss and damage). Value drivers are varied for different industries or enterprises. They are variables influenced by management strategies and decisions that can significantly affect the competitive advantage of the various firms in an industry. More specifically, identifying key value drivers can be derived from efforts to model the determinants of firm profit within an industry. There are a number of strategic models that can be used to illustrate the role of value drivers. This paper opts to modify the two classical models like Porter's and Ansoff's models. The Porter's model primarily focuses on cost driver capability for differentiation, strategy focus, and productivity. While the Ansoff's model focuses on product-market expansion strategy that comprises consolidation and productivity; market penetration; operational repositioning; strategic repositioning; related product/ market development; unrelated product/market development and diversification. The concept of value drivers also suggests causal relationships between resources and organizational value creation. Traditionally, those resources were physical or financial capital. Nowadays, the concept of intellectual capital has been identified as a key resource and driver of organizational performance and value creation. And how resources interact to create value or how intangible assets are converted into tangible outcomes can be visualized via Kaplan and Norton's approaches such as strategy map, cause-and-effect diagram based on the perspectives of the balanced scorecard. This paper thus applies the concept of strategy map for assessing key value drivers or key risk factors from both the financial and nonfinancial dimensions.

## 4. BAYESIAN NETWORKS

Bayesian Network (also known as Bayesian Belief Network, Causal Probabilistic Network, Probabilistic Cause-Effect Model, or Probabilistic Influence Diagram) is a 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 [4]. 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. Bayesian networks are useful for prediction and reasoning. 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. This process belongs to unsupervised learning in machine learning theory. The advantage of this class 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 [5]. This study uses the reverse-engineering methods to construct the Bayesian network model. An example of Bayesian networks is shown in Figure 1.

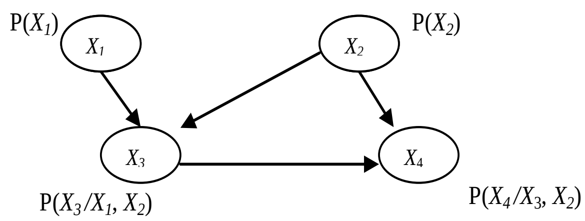



**Figure 1. Example of Bayesian Network [6]**

## 4.1 Calculation of Bayesian Networks

For variables $X_i\ (i = 1, \ldots, n)$ given $\pi(X_i), X_i$ is conditionally independent on all non-parents nodes, a joint distribution probability of $n$ variables can be decomposed according to a chain rule as shown in Equation 2.

$$P(X_1, \ldots, X_i) = \prod_{i=1}^{n} P(X_i/X_1, \ldots, X_{i-1}) = \prod_{i=1}^{n} P(X_i/\pi(X_i)) \tag{2}$$

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

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 3.

$$\mathrm{P}(X = x|Y = y) = \frac{\mathrm{P}(X=x, Y=y)}{\mathrm{P}(Y=y)} = \frac{\mathrm{P}(X=x)\mathrm{P}(Y=y/\mathrm{X=x})}{\mathrm{P}(Y=y)} \tag{3}$$

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

## 4.2 Inference of Bayesian Networks

The inference of Bayesian Networks can be categorized into three types: one is the inference of posterior probability, another is the maximum a posterior hypothesis (MAP), and the other is the most probable explanation (MPE). In this paper, the Bayesian Network model is applied for the scenario analysis of enterprise risk management. The inference of posterior probability is employed for analyzing the risk factors and predicting the enterprise value and performance. In particular, the known values or evidences are used to calculate other variables' posterior probability. There are four types of posterior probability inference defined as following [6]:

1) Diagnostic inference, which can infer the causes in the light of the results.

2) Predictive inference, which can forecast the results according to the causes.

3) Intercausal inference, which can reveal the relationship between different reasons with the same result.

4) Mixed inference, which includes all the ways mentioned above.

## 4.3 Bayesian Networks Learning

Using the Bayesian network learning methods comprise five steps: construction, initialization, network learning, predicting and reasoning of network.

(1) Construction of the Bayesian network is to determine the nodes and the structure of network. According to the features of the shareholder value, economic profit and the key value drivers or the key risk indicators (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.

(4) Predicting is the estimate of future 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 or key value drivers on the shareholder value and performance.

WEKA is a free software package implemented with Java language. It incorporates a large number of machine learning algorithms for data mining tasks. In this study, WEKA is used for creating the prediction model, including causal map; probabilistic values; and inferences diagram. The assessment method of 10-fold cross validation is used for evaluating the performance of the model constructed. The obtained results will be compared to statistical analysis methods. The model can be then used for enterprise value prediction and scenario analysis. This paper provides some examples that show how Bayesian networks can help making a decision. WEKA offers various search algorithms. This study chose TAN search algorithm, which has exhibited excellent performance in data mining [7]. The algorithm can produce a causal-effect graph, which is formed by calculating the maximum weight spanning tree using score based method.

In the expressway operation enterprise, the factors influencing the shareholder value mostly come from the internal and external environments of expressway projects. The external risk factors are uncontrollable and difficult to prevent. The internal risk factors appear mostly in 3 ways: financial benefit, the ability/efficiency of management, and the services [8, 9, 10, 11, 12, 13]. This paper focuses on the internal key risk factors or financial and operational drivers of an expressway operation enterprise from the perspective of Thailand's expressway corporation. All variables or key value drivers (key risk indicators) from empirical exploration are shown in Table 1. This study used monthly quantitative (non-) financial data, part of the financial perspective, amassed from financial report since 2005-2010 of fiscal year. And, the key performance indicators of operational activity are also used as the key value measures, obtained from the performance report since 2005-2010 of fiscal year. However, due to small sample size (72 records), selection of relevant variables is suggested for developing a useful model. Variable selection is important on account of irrelevant and redundant features may confuse the learning algorithm and obscure the predictability of truly effective variables. Therefore, a small number of predictive variables are preferred. In this study, the variables are selected based upon the correlations and conditional correlations among variables.

# 5. EXPERIMENTAL RESULTS

## 5.1 Prediction Model

The pre-processing of feature/ variable selection was performed using the Correlation Coefficient analysis. The variables that have significant correlation are assumed to be related with the economic profit or the value of economic profit depends on these variables. Based on the analysis results, variables: x4, x5, x10, x13, and x17 are eliminated.

**Table 1. All variables or key risk factors influencing shareholder value**

| Variable Name | Explanation |
|---|---|
| Traffic (x1) | Traffic Volume per day |
| Toll revenue (x2) | Income from Tollway |
| Area income (x3) | Income from rental area |
| Interest income (x4) | Interest Income |
| Interest cost (x5) | Interest Expense |
| v/c ratio (x6) | Volume per capacity rate |
| toll receive speed (x7) | Speed of toll collection |
| drive time (x8) | Time of travel |
| Rescue speed (x9) | Speed of rescue |
| Accident Quan. (x10) | Volume of Traffic Accident |
| Accident rate (x11) | The rate of Accident |
| route maintenance cost (x12) | Cost of Route Maintenance |
| device maintenance cost (x13) | Cost of Equipment maintenance |
| R&D cost (x14) | Cost of Research and Development |
| Training cost (x15) | Cost of Training |
| Marketing cost (x16) | Spending on Marketing |
| Overhead cost (x17) | Cost of Overhead |
| EP (x18) | Economic Profit per month |

The *k*-fold cross validation is a standard performance evaluation method for machine learning algorithms. The method starts with partitioning the dataset into *k* disjoint subsets. The assessment of model performance will iterate *k* times. For the $i^{th}$ iteration, the $i^{th}$ subset is selected as the test dataset, and the remaining subsets are merged into the training dataset used for model construction. It is observed that each subset is used as a test dataset once. Typically, the model performance is measured by accuracy rate. The accuracy rate of the model using *k*-fold cross validation is the average value calculated from *k* iterations. In this study, 10-fold cross validation was used to evaluate the model performance.

Bayesian learning can be used with discrete or continuous variable type. Prior to model construction, the preprocessing of discretization was performed in this study to convert continuous variable values into discrete (to divide the continuous cumulative probability distribution into *n* equally probable intervals).

During the discretization process, one problem that researchers face is to decide the number of states for discretization. We started from two states to five states and tested the model with all samples. When continuous variables were discretized into 2 states, the model's accuracy in predicting economic profit was 90.28%. When the number of discretization states increased to 3, 4, and 5, the model's accuracy in predicting economic profit is 94.44%, 80.56%, and 79.17%, respectively. When the number of states for discretization was further increased, the model's performance continued to drop. The findings showed that discretizing continuous variables into 2 or 3 states led to the best performance.

Figure 2 illustrates the structure of Bayesian Network generated by WEKA after data pre-processing described earlier. It is observed that x9, x14, x15, and x16 disappear since they are disconnected nodes.

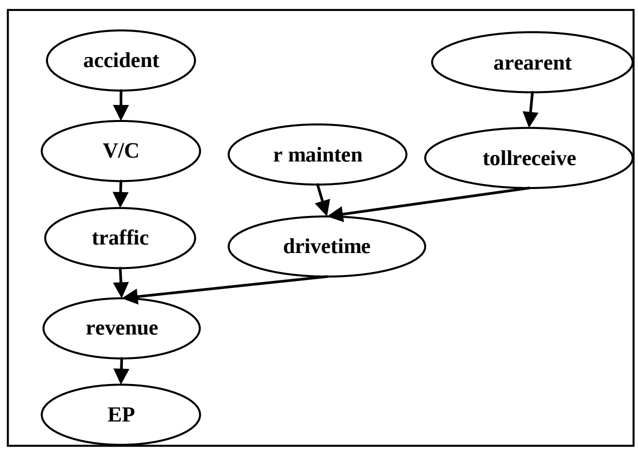



**Figure 2. Structure of Bayesian Network for Expressway Management**

Example of conditional probability tables attached to nodes: ep, revenue, and V/C are shown in Figure 3. The values of conditional probability contained in each table were computed by WEKA based on 72 data records of Thailand's expressway management corporation.

The result of model testing is shown in Figure 4, which reports the model accuracy rate of 94.44%. According to the experimental result, the approach to modeling Bayesian Network is promising for identifying key risk factors used in expressway performance management.

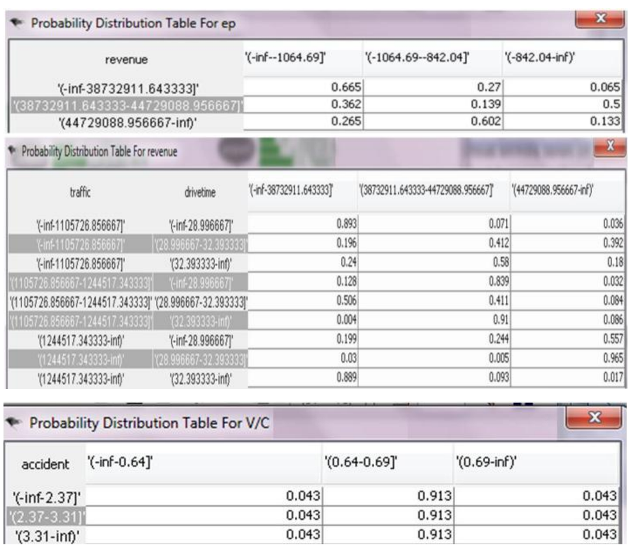
## 5.2 Statistical Analysis

This paper compares the performance of the Bayesian network model in Figure 2 with a statistical analysis technique, i.e. multiple regression analysis using SPSS software package as a tool. Using the same eight variables, multiple regression yields the coefficient of determination (R Square) valued 23.4% (see Table 2). This indicates that Traffic volume per day (Traffic), Time of travel (drivetime), Cost of Route Maintenance (routemaintencost), Income from rental area (areaincome), Speed of toll collection (tollreceivespeed), Volume per capacity rate (V/C ratio), The rate of Accident (accidentrate), Income from Tollway (tollrevenue) can explain the variation of the shareholder value (dependent variable) by 23.4%.

The relationships of each variable can be seen in Table 3. It can be concluded that the independent variables are significant, i.e. the independent variables in the model have the relationship to the dependent variable. The estimation of multiple regression is as follow:

$$Y = -577.321 + 0.002\,X1 - 0.0702\,X2 + 11.381\,X3 - 2230.488\,X6 - 37.552\,X7 + 20.962\,X8 + 51.581\,X11 - 0.145\,X12$$

The result of statistical analysis thus confirms that the independent variables, key risk factors, used in the model constructed by Bayesian network learning are reliable for the predication of the dependent variable, economic profit.



Probability Distribution Table For ep

| revenue | '(-inf--1064.69]' | '(-1064.69--842.04]' | '(-842.04-inf)' |
|---|---|---|---|
| '(-inf-38732911.643333]' | 0.665 | 0.27 | 0.065 |
| '(38732911.643333-44729088.956667]' | 0.362 | 0.139 | 0.5 |
| '(44729088.956667-inf)' | 0.265 | 0.602 | 0.133 |

Probability Distribution Table For revenue

| traffic | drivetime | '(-inf-38732911.643333]' | '(38732911.643333-44729088.956667]' | '(44729088.956667-inf)' |
|---|---|---|---|---|
| '(-inf-1105726.856667]' | '(-inf-28.996667]' | 0.893 | 0.071 | 0.036 |
| '(-inf-1105726.856667]' | '(28.996667-32.393333]' | 0.196 | 0.412 | 0.392 |
| '(-inf-1105726.856667]' | '(32.393333-inf)' | 0.24 | 0.58 | 0.18 |
| '(1105726.856667-1244517.343333]' | '(-inf-28.996667]' | 0.128 | 0.839 | 0.032 |
| '(1105726.856667-1244517.343333]' | '(28.996667-32.393333]' | 0.506 | 0.411 | 0.084 |
| '(1105726.856667-1244517.343333]' | '(32.393333-inf)' | 0.004 | 0.91 | 0.086 |
| '(1244517.343333-inf)' | '(-inf-28.996667]' | 0.199 | 0.244 | 0.557 |
| '(1244517.343333-inf)' | '(28.996667-32.393333]' | 0.03 | 0.005 | 0.965 |
| '(1244517.343333-inf)' | '(32.393333-inf)' | 0.889 | 0.093 | 0.017 |

Probability Distribution Table For V/C

| accident | '(-inf-0.64]' | '(0.64-0.69]' | '(0.69-inf)' |
|---|---|---|---|
| '(-inf-2.37]' | 0.043 | 0.913 | 0.043 |
| '(2.37-3.31]' | 0.043 | 0.913 | 0.043 |
| '(3.31-inf)' | 0.043 | 0.913 | 0.043 |

**Figure 3. Example of Conditional Probability Tables**

**= = = Run information = = =**
**Scheme: weka. Classifiers. bayes. BayesNet- D- Q weka. classifiers. bayes. net. Search. Local. TAN- - -S**
**Relation: shareholder- weka. filters. unsupervised. Attribute. Remove- R3-6,8-9, 14,17-18,22-28-weka.filters**
**Instances: 72**
**Attributes: 9**
**revenue**
**traffic**
**areareent**
**v/c**
**tollreceive**
**drivetime**
**accident**
**r mainten**
**EP**
**Test mode: 10- fold cross- validation**
**Time taken to build model: 0.02 seconds**
**= = = Stratified cross-validation= = =**
**= = =Summary= = =**

| | | |
|---|---|---|
| **Correctly Classified Instance** | **68** | **94.444%** |
| **Incorrectly Classified Instances** | **4** | **5.5556%** |
| **Kappa statistic** | **0.905** | |
| **Mean absolute error** | **0.0512** | |
| **Root mean squared error** | **0.1869** | |
| **Relative absolute error** | **12.8349%** | |
| **Root relative squared error** | **41.9407%** | |
| **Total Number of Instances** | **72** | |

**Figure 4. Result of Model Testing**

**Table 2. Model summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin- Watson |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .483[a] | .234 | .136 | 242.75294 | .234 | 2.403 | 8 | 63 | .025 | 1.703 |

a. Predictions: (Constant), accidentrate, V/Cratio, routemaintencost, drivetime, areaincome, tollreceivespeed, tollrevenue, traffic

b. Dependent Variable: ep

**Table 3. Coefficient**

| Model | Unstandardized Coefficients | | Standardized Cofficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| 1 (Constant) | -577.321 | 955.962 | | -.604 | .000 |
| tollrevenue | -7.020E-6 | .000 | -.130 | -.224 | .023 |
| traffic | .002 | .002 | .643 | 1.015 | .031 |
| areaincome | 11.381 | 22.010 | .067 | .517 | .049 |
| V/Cratio | -2230.488 | 1398.535 | -.292 | -1.595 | .016 |
| tollreceivespeed | -37.552 | 15.798 | -.358 | -2.377 | .021 |
| drivetime | 20.962 | 17.952 | .157 | 1.168 | .024 |
| routemaintencost | -.145 | .120 | -.149 | -1.212 | .030 |
| accidentrate | 51.581 | 72.956 | .094 | .707 | .048 |

## 5.3 Scenario Analysis

In this section, we demonstrate some results by using the learned Bayesian Network model for performance prediction and enterprise risk assessment based on scenario analysis. The initialized probability values are shown in Figure 5. The probability that Economic Profit value will decrease less than -1064.69 million baht is 0.4375 in this Figure. It reflects the current situation, meaning the enterprise is approaching to get opportunity loss or failure. Therefore, the manager needs to mitigate that risk by improving and controlling the key risk factors. Referring to the relationship presented in the Bayesian Network structure, Economic profit is directly influenced by revenue (Income from Tollway). Revenue is affected by traffic (Traffic volume per day), and drivetime (Time of travel). In scenario analysis, we will explore how to increase economic profit based on the impacts of three scenarios on the level of service, by measuring V/C (Volume per capacity rate) and tollreceive (Speed of toll collection).

The first scenario is optimistic, where V/C increases in the highest interval that means the expressway may be used efficiently and tollreceive decreases in the lowest interval that means the tollbooth could let car off fast. Both situations reflect the high level of service quality. The probabilistic result of Economic Profit value increase more than -842.04 million baht is 0.3150 as shown in Figure 6. While the increase of service quality is on the highest level, the probabilistic results of traffic, drivetime, and revenue, in the middle interval, also increase are 0.9314, 0.6245, and 0.5617 in orderly.

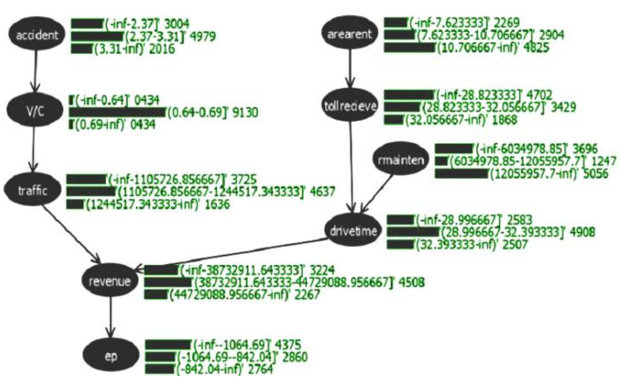



**Figure 5. Bayesian Model in Initialized State**

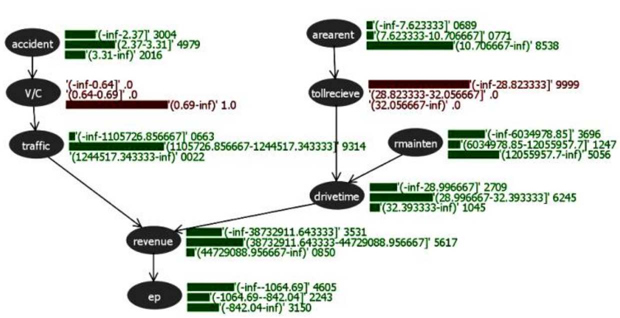



**Figure 6. Optimistic Scenario**

The second scenario is stable based on the current trend. As shown in Figure 7, the probabilistic result of Economic Profit value in the highest interval decrease is 0.2825. And the probabilistic results of traffic, drivetime, and revenue in the middle interval, also decrease are 0.4431, 0.4253, and 0.4663 in orderly.

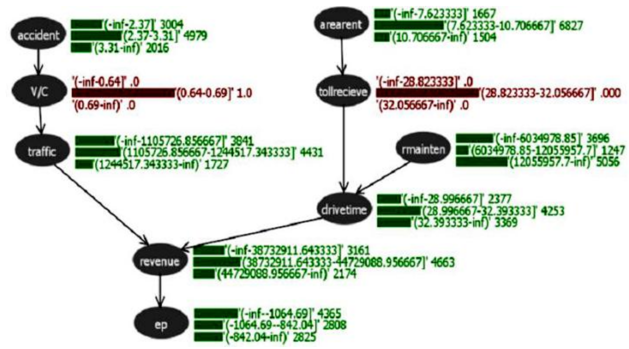



**Figure 7. Stable Scenario**

The third scenario is pessimistic as shown in Figure 8, where V/C decreases in the lowest interval that means the expressway may be used inefficiently, and tollreceive increases in the highest interval that means the tollbooth may face the congestion situation. Both situations reflect the low level of service quality. The probabilistic result of Economic Profit value increase is 0. 2996.

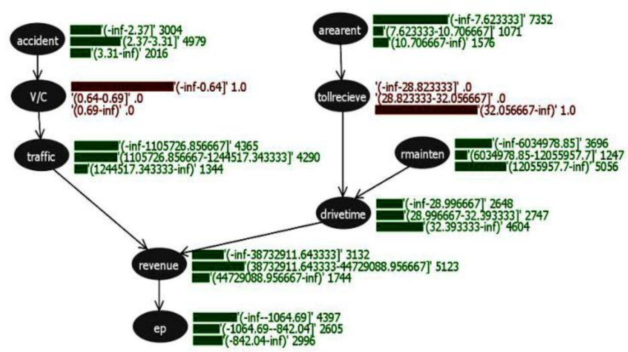



**Figure 8. Pessimistic Scenario**

**Table 4. Probability of falling in traffic, drivetime, and revenue under different scenarios**

| | Traffic | Drivetime | Revenue | EP |
|---|---|---|---|---|
| Optimistic scenario | 0.9314 | 0.6245 | 0.5617 | 0.3150 |
| Stable scenario | 0.4431 | 0.4253 | 0.4663 | 0.2825 |
| Pessimistic scenario | 0.4290 | 0.2747 | 0.5123 | 0.2996 |

The differences of outcomes as summarized in Table 4 would be caused by the level of service quality. Hence, it could be inferred that the high level of service quality must be sustained if the enterprise desires to increase the economic profit. As a consequence, the expressway enterprise needs to create the risk management strategy, especially that influencing the service risks.

## 6. CONCLUSION

The focus of this research is to apply Bayesian Networks for enterprise risk management. The software package, WEKA, is used to learn the Bayesian Network from the dataset of the Expressway Authority of Thailand, which is the expressway enterprise in Thailand. The data preprocessing of feature selection and discretization were performed prior to model construction. The model performance was evaluated by 10-fold cross validation due to small size of the dataset. The results showed that Bayesian Network technique is reliable with high prediction accuracy. The model can identify the key value drivers of economic profit. Further, the variables existing in the Bayesian Network model were examined by statistical analysis technique, i.e. multiple regression analysis. The results showed that the independent variables, key risk factors, in the model can be used to predict the dependent variable, economic profit. Additionally, the Bayesian Network model is applicable for scenario analysis in expressway management. The results from various scenarios could help a manager making the decision. Therefore, Bayesian Network is useful for building decision support systems.

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