Analyzing Taiwan Bridge Management System for Decision Making in Bridge Maintenance
A Big Data Approach

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Abstract: The Taiwan Bridge Management System (TBMS) has been online for 15 years and has an inventory of 33,275 bridges, including all kinds of bridges and culverts in Taiwan. Currently, the number of fields in all tables in the databases of TBMS is around 6,500 with more than 3 million data records in its databases. Meanwhile, bridge inspection data and maintenance data are increasing at a speed of 15,000 records annually. Thus, the TBMS databases are deemed as “Big Data.” There are more than 9,500 bridges that are over 20 years old with another 7,200 bridge having unknown built years in the TBMS. The bridges in Taiwan have stepped into the stage where maintenance is crucial and frequently required. Therefore, this research aims at analysing the database in the TBMS using “Big Data” approach for determining maintenance strategies for these bridges. This paper describes results of the first year’s research efforts. Relevant literature in bridge maintenance, prioritization, and life-cycle bridge management were firstly reviewed. Concepts, theories, techniques, and available software for analysing “Big Data” were also intensively examined and summarized. In next year, functions will be programmed and applied to the TBMS databases using appropriate “Big Data” software to obtain useful information in bridge deterioration, repair methods, and maintenance costs.

1 INTRODUCTION

The Taiwan Bridge Management System (TBMS) has been online since 2000 (TBMS, 2014). Its inventory includes 33,275 bridges with 6,524 fields in all tables, and the total amount of data records is 3,457,274 which increase 15,000 records annually. Among these fields, there are 475 fields containing kernel management information of a bridge such as inventory data, inspection results, and repair records. Thus, the databases in the TBMS have met the definition of “Big Data.”

Table 1 shows the amount of bridge components which are deemed necessary for maintenance actions. It also shows that the number of seriously deteriorated components still increase gradually, even though maintenance activities have been expedited by responsible agencies for many of such components.

Due to limited budgets, especially for local governments, prioritization of bridge maintenance is always a tough task for the bridge management agencies, in addition to determining which option is better between maintaining and rebuilding of the bridge. Life-cycle cost analysis is a feasible solution for such problem; however, such technique requires an appropriate deterioration prediction model which does not yet implemented in the TBMS.

Table 1: Amount of bridge components need maintenance actions.

Road level	2010	2011	2012	2013	2014
City/ County	1,200	463	575	578	857
Freeway/ Highway	17	18	16	24	35
Railways	0	26	28	3	2
Total	1,217	507	619	605	894

In order to effectively evaluate cost efficiency of repairing work and rebuilding of bridge, this research aims to analyze the TBMS databases to obtain characteristics of bridge deterioration in Taiwan that are useful for determining maintenance

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strategies. This two-year research project has two stages. For the first year, in addition to literature review in bridge maintenance, techniques and available software related to big data are thoroughly investigated; and application of these techniques and software to the TBMS databases is planned to be performed in the second year.

For this research, it is anticipated to obtain maintenance information such as repairing method, repairing cost, maintenance period, progressive of deterioration conditions, and factors that trigger the repairing actions. Finally, a decision support and evaluation model for rebuilding of deteriorated bridges will be established from this research.

2 LITERATURE REVIEW

2.1 Factors caused Bridge Deterioration in Taiwan

Su (Su, 2003) collected 935 bridge inspection data in Taichung to analyze the relevancy between bridge deterioration and its environment by a logistic regression. The study discovered that the age of bridge, the distance to sea, and using of I-type girders are the major factors that caused deterioration. In addition, Lin (Lin, 2007) successfully established a service life prediction model for expansion joint that obtained a 9% difference between the predicted and the actual service year, he also discovered that horizontal acceleration, number of spans and traffic flow are the most significant factors in determining the service life of an expansion joint.

2.2 Prioritization of Bridge Maintenance

For both central and local governments, distribution of bridge maintenance budgets is always a difficult task. Chen (Chen, 2007) established a model to calculate a danger factor (DF) for a bridge by assigning weights to its major components based on their deterioration ratings multiplied by a traveller's factor determined by level of road that bridge was on; then the component having the highest value was normalized to represent the DF of the bridge. The DF can be used for both prioritization of bridge maintenance and distribution of maintenance budgets. This model is currently incorporated by the TBMS.

2.3 Effectiveness of Maintenance Budget

Budget spent for bridge maintenance needs to be effective. Feasible ways to check the effectiveness of is to investigating results of maintenance within a time period or under limited budgets. Weng (Weng, 2009) compared the same amount of cost spent within a time period for fixing or replacing certain components to find which way is more effective. Lay (Lay, 2001) developed a maintenance cost analysis model that allowed the user to input the amount of budget for a given number of years, and the model would allocate the budget to the bridges to achieve the most effective result. Huang (Huang, 2007) proposed a concept of concurrently maintaining multiple components on a bridge to reduce the overall time spent for repairing various components of the bridge.

2.4 Bridge Life-cycle Management

Many researchers have promoted life cycle cost concept for bridge management for many years. However, current practice in most bridge construction bids still not yet considers maintenance costs. Zhu (Zhu, J. and B. Liu, 2013) established an optimal model for calculating bridge total life cycle cost for RC beam bridges, considering travellers' cost and social cost. Safi (Safi, M., H. Sundquist, and R. Karoumi, 2014) analyzed the Sweden bridge management system to find a total maintenance cost for bridge components. The research results also showed that the total maintenance cost is 15% to 25% of life cycle cost of a bridge, while different types of bridges may have more than 50% difference in construction cost.

2.5 Summary

Several studies in deterioration factors and maintenance prioritization have obtained certain valuable results for the bridges in Taiwan. However, actual maintenance frequency, costs, and methods of various bridge components could be used to generate a life cycle cost model which is crucial to obtain a more effective maintenance strategy. In addition, decision making between continuing maintenance actions and rebuilding of a new bridge still not yet clarified. Thus, answers to these doubts by digging into the actual inspection results and maintenance records in the TBMS have become the major objectives of this research.

3 TAIWAN BRIDGE MANAGEMENT SYSTEM (TBMS)

Supported by the Institute of transportation, Ministry of Transportations and Communications, the TBMS was developed by National Central University in 1999. TBMS is used by all the governmental agencies which are responsible for bridge management. There are 9 modules in TBMS, such as Inventory, Inspection Data, Maintenance Records, Statistic, Decision Support, etc., as shown in Figure 1. This research focuses on data in three of these modules; they are Inventory, Inspection Data, and Maintenance Records modules, as described below.

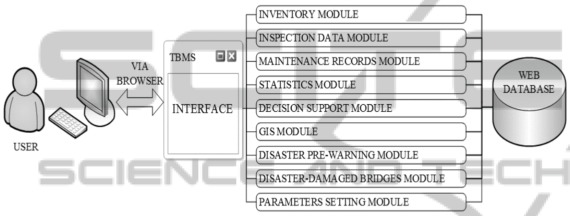

Figure 1: Major functional modules of the TBMS.

3.1 Inventory Module

There are 33,275 bridges in the inventory module, among which only 28,000 bridges are still in use or under maintenance, the rest were destroyed by natural disasters, closed or demolished due to serious deterioration. In this module, there are four tables that describe the basic data of a bridge. Bridge main inventory table is the top layer of data structure in this module; below which are abutment, pier, and span tables. The main inventory table consists of six kinds of data such as management, geometry, structure, particular structure, river, and design; the total number of fields is 147 with roughly 33,000 records since year 2000.

The abutment, pier, and span tables have data fields describing detailed geometry and design information with 42, 58, and 39 fields and around 9,700, 24,000, and 90,000 records, respectively.

3.2 Inspection Data Module

The methodology of regular bridge inspections used by the TBMS is called DER&U (MOTC, 2011). In this methodology, four indices are used to evaluate the condition of a bridge component: "D" represents the degree of deterioration; "E" represents the extent of the deterioration; "R" represents the deterioration's relevancy to bridge safety; and "U" represents the urgency for repairing the deterioration. All of these indices are numerically rated on an integer scale from 0 to 4 to describe the status of the deterioration, as exhibited in Table 2. For a concrete bridge, 21 components need to be inspected, for other types of bridges the number of components may up to 25.

Table 2: The DER&U evaluation criteria.

	0	1	2	3	4
D	Component not existing	Good	Fair	Bad	Serious
E	Unable to inspect	Less than 10%	10~30%	30~60%	Over 60%
R	Relevancy uncertain	Minor	Limited	Major	Large
U	Urgency uncertain	Routine	In 3 years	In 1 year	Immediately

This inspection data module stores visual inspection results of all bridges. It has three layers of data structure; they are main, overall, spans and piers inspection sheets. These inspection sheets have 21, 69, and 51 fields to record the inspection results and currently they have around 276,000, 277,000, and 2,000,000 records, respectively. Since current regulation requires at least inspecting bridge once per two years, these records increase roughly 15,000 annually. Notably, if deterioration is found during inspection, it is required to input a suggested repairing method by the inspector. Thus, at the bottom of the data structure, the suggested repairing method is also recorded by 34 fields; it has 521,000 records in the TBMS now.

3.3 Maintenance Records Module

In this module, there are seven tables used to record a maintenance work such as maintenance contract, contractor, and detail records of maintenance activities, etc. Currently, 54,000 maintenance records are stored in this module. The time for maintenance, method used, costs and quantity of repaired components of a bridge are deemed as crucial information in this research.

4 BIG DATA ANALYSIS TECHNIQUES

This research reviews current techniques and software for big data analysis. These techniques are normally referred to data mining techniques for finding meaningful information from the big data; such as supervised learning, unsupervised learning, affinity grouping, market basket analysis, clustering, and description, etc. As for the definition of data mining, it means data with particular relevancy could be found by statistics, analysis, machine learning or expert system (Wikipedia, 2014). These data mining techniques are described below.

4.1 Big Data Analysis Techniques

4.1.1 Artificial Neural Network

Artificial neural network (ANN) is a mathematic model simulating neurons connected as a network in human brains. ANN is a tool in nonlinear statistics used for investigating the relationships among data. ANN consists of nodes, existing on a number of layers; and links, connecting these nodes meanwhile representing the weights of transmitted messages between nodes. In sum, ANN is a learning machine with a black box formed by these nodes and links, after learning from a huge amount of input data sets and their corresponding output answers, the trained ANN can be used in many areas for prediction or recognition.

4.1.2 Decision Tree

A decision tree consists of a decision diagram and possible solutions. It can describe process and procedures including random events and their associated resources or costs. A decision can be used as a prediction model in which nodes represent issues while paths represent possible properties. Normally, a decision tree has only one single output as the answer after evaluation. If plural answers are needed, multiple decision trees should be built accordingly.

4.1.3 Genetic Algorithms

Genetic algorithm (GA) simulates biological hereditary and evolution to solve the problems through coding (Wikipedia, 2014). There are many arithmetic operators simulate different characteristics of evolution in various genetic algorithms. In a genetic algorithm, the solution of a problem is called individuality representing a sequence of variable, and the function is called chromosome. Individualities are generated by inheritance or mutation, selection or crossover. Each of the individuality's suitability is evaluated and prioritized by its evaluation result; individualities with higher suitability values are then chosen to produce a new generation. Optimum solutions can be found after a number of generations.

4.1.4 Genetic Algorithms

Fuzzy logic was established by Prof L.A. Zadeh in 1965. While classical logic considers that true or false be described by a binary and discrete variable; i.e., either 0 or 1, fuzzy logic is able to represent a linguistic description as partial true truth or false using a decimal number between 0 and 1. Definition of utility functions; i.e., determining the relationship between the linguistic description and its corresponding decimal number, is crucial in the application of fuzzy logic.

4.1.5 Regression

Regression is a statistic method to display the relationship, direction, and strength of multiple variables. It's also a model to predict the variation of variables. There are seven commonly used regression models such as simple-linear regression, non-linear regression and multiple regression, etc.

4.2 Big Data Analysis Software

Big data analysis has become a popular issue recently. After a thorough review of current available software, 11 kinds of popular software packages are found. They are Matlab, SAS, R, Python, Julia, Java, Hadoop and Hive, Scala, Kafka and Storm, Octave, and GO. Among which, Matlab and SAS are widely used by academia, while R is incorporated by many famous portals. Thus, this research plans to utilize these three kinds of software packages to perform the big data analysis; their characteristics are depicted below.

4.2.1 Matlab

Matlab is commercially available software developed by MathWorks. It can be used for algorithm generation, data visualization, data mining, data analysis and calculation. Its latest version is R204b which allows the user to establish user surfaces by its programing language or by calling other programs written by C, C++, JAVA, Python or FORTRAN.

Matlab also provides an easy-to-use tool box established based on various techniques such as generic algorithm, neural networks and ANN, allowing the use to perform functions such as optimal analysis, statistics, signal processing, image-processing, vector analysis, and matrix calculation. Notably, raw data preparation is crucial for Matlab since that may affect calculation efficiency.

4.2.2 Statistics Analysis System (SAS)

Developed by SAS Institute Inc., SAS has been commonly used in commercial areas for decades (Wikipedia, 2014). The initial version of SAS was written in language C, and now JAVA and C++ are also included. Its latest version is 9.4, including 10 main modules for data mining, graphics and presentation, econometrics and time series analysis, clinical trial analysis, statistics analysis, interactive matrix language, quality control, and database transfer, etc.

4.2.3 R

R was developed by Professors Ihaka and Gentleman at the University of Auckland in New Zealand. R is written for statistic, drawing, and data mining. R is capable of performing 25 kinds of statistic and numerical analysis functions such as obtaining mean value, standard deviation, plotting of histogram, and executing regression process. Most importantly, the source code of R is available freely. Its famous users include Google, Facebook, Bank of America, and New York Times.

In addition to the above functions, R can be used for matrix calculation; its efficient performance can be comparable to GNU Octave and Matlab. Thousands of added software tools based on various analysis techniques for economics and finance have been established on R by various languages such as LaTeX, JAVA, C, and FORTRAN.

4.3 Research Process and Anticipated Results

The next step of this research taken is to formulate single data records which consists of data of fields from tables of bridge inventory, span, pier, abutment, main inspection, detail inspection, suggested maintenance method, and maintenance record. Data records have missing data in any field or have logic inconsistence will be eliminated. These records will be input to the three software packages; Matlab, SAS, and R as mentioned above. The anticipated results will be a maintenance frequency for all the bridge components, most maintained bridge components, actual maintenance costs for bridge components, and the relationship between deterioration and bridge inventory data. Finally, an evaluation model will be established for determining continuation of maintenance or rebuilding of a bridge based on these findings.

5 CONCLUSIONS

This research collected relevant literature in bridge maintenance and life cycle costs analysis in Taiwan. It was found that models for calculating bridge life cycle costs still not yet established, nor the effectiveness comparison between maintenance and rebuilding of a deteriorated bridge. These have become goals of this research and are intended to be solved by digging into the big databases of the TBMS which has already been used for 15 years. This research also surveyed available software packages for big data analysis and will soon apply them to find relevant maintenance information for decision making in bridge maintenance in Taiwan.

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