Infrastructure Asset Management System

Methodologies for Infrastructure Asset Management System in U.S.

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Abstract

Infrastructure asset management is a methodology for programming infrastructure capital investments and adjusting infrastructure service provision to fulfill established performance, considering the life-cycle perspective of infrastructure. In this study, the methodologies for infrastructure asset management system implemented in sewer management system, bridge management system, pavement and highway management system, and embankment dam management system are described with focus on the system in U.S. As the major methodology to support the decision-making for asset mangers to better allocate the limited funds to the area needing it the most. various demand forecasting methodologies used in wastewater, water, transportation, electricity, and construction are also introduced for their applicability towards infrastructure asset management

Keywords: Infrastructure Asset Management, Demand Forecasting

1. Introduction

Asset management is defined as a systematic process of maintaining, upgrading, and operating physical assets cost-effectively, while facilitating more organized, logical approach to decision-making (FHWA and AASHTO, 1996). Infrastructure asset management is a methodology for programming infrastructure capital investments and adjusting infrastructure service provision to fulfill established performance, considering the life-cycle perspective of infrastructure. With the recent increasing need for infrastructure rehabilitation, the need for an effective infrastructure management system is crucial under budgetary constraints. Though advances in information technology help make it possible to integrate disciplinary information systems to support decision-making, most efforts are still in their infancy in U.S. (Garvin, 2001). Moreover, there is no systematic methodologies for the management of infrastructure asset introduced yet in Korea.

Due to limited funds, the one of the most difficult and crucial task in managing an aging infrastructure is the prioritization of maintenance and repair expenditures to better allocate funds (Chouinard et al., 1996). As infrastructures approach their design lives, there is an increasing demand for new construction, and rehabilitation projects to create and/or extend the design life so that the potential for loss of function or down time can be minimized. As the major methodology to support the decision-making for these, demand forecasting tools have been widely used for its implementation in management of infrastructure assets such as transportation, housing, and utilities (i.e., electricity, water). This can allow asset mangers to better allocate the limited funds to the area needing it the most. In order to accomplish the difficult task of efficient allocation of funds, it is important to forecast future demand to identify problematic areas and develop necessary management schemes to prevent any failure of infrastructure system. Hereby, this paper introduces the methodologies of infrastructure asset management system implemented in U.S. and presents the brief description of the various demand forecasting models implemented in major infrastructure asset management system.

2. Infrastructure Asset Management System

In U.S., the Office of Asset Management in U.S. FHWA serves as an advocate for asset management,

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system preservation, pavement management and analysis, bridge management and inspection, and construction and maintenance activities, as well as technology development, outreach, and partnering initiatives. (FHWA, 2003).

2.1 Sewer Management System

A multiple objective mathematical model using integer linear programming for the planning of the rehabilitation of combined sewer systems was developed by Reyna (1993). In this model, the overall structural performance, hydraulic performance, disruption level, and annual maintenance and claim costs, constrained by the maximum annual construction costs, were optimized to give the best set of rehabilitation plan. In the model, the life cycle cost analysis was performed by estimating annual maintenance and claim unit cost. In solving the linear programming model, a bilinear relationship between the maintenance and claim unit cost for existing and rehabilitated segments and their structural condition index and pipe diameter was assumed. Faced with the difficulty of solving integer programming for large networks, Reyna tried to overcome this difficulty by using a prioritization scheme. A weighting system, based on structural, hydraulic, and cost, was employed to help prioritize between sewer pipes.

Lee and Ro (1988) developed a sanitary sewer maintenance scheme for the City of San Diego. The City of San Diego works with about $30 million a year to maintain over 5,300 sewer segments and manholes on 117 trunk sewers. Finding a way to efficiently manage all sewer networks under constrained budget constantly challenges to the decision makers. For sewer maintenance, the sewers were prioritized according to a numeric value assigned during the two levels of the evaluation process. The first level is based on the structural condition of the sewer and the second system is based on the consequence of failure. Currently, the City of San Diego televises the problematic sewer sections as needed. This method of maintenance will soon change as the City of San Diego has a goal of televising every mile of their sewer system within the next four years in order to develop a more standardized and organized data for maintenance prioritization. Once televised, the televised sewer segments are assigned a numerical value based on a set of evaluation criteria. The evaluation criteria include: structural condition (i.e. cracks, offsets, alignment, etc.), root intrusion, infiltration, flow rate and other factors that might influence the performance of the sewer. After assigning the severity point value, the total value is calculated by summing up all the severity point values for all categories. Once the severity points for all sewer segments have been calculated, the first priority will be assigned to the one with highest severity points (Lee and Ro 1988).

Table 1. Sewer Maintenance Priority Scheme

Description	Severity Rating		
	Sewer A	Sewer B	Sewer C
Circular Crack		150	150
Open Crack	250		
Root	50	50	
Sag			
Grease		50	50
Connection Infiltration	250		250
Tot	550	250	450

An illustrative example of San Diego's sewer maintenance prioritization scheme is shown in Table 1.

2.2 Bridge Management System

A bridge management system, PONTIS, addresses economic efficiency by identifying the actions which minimize the life cycle costs. A detailed description of PONTIS can be referred to Wells et al. (1993). PONTIS addresses economic efficiency by identifying the actions that minimize the life cycle costs. By combining expert opinions with a data manager, the difficulty of obtaining accurate and complete data on construction and maintenance history is relieved. Markovian deterioration modeling process has been used to forecast the future structural condition of the bridge. In PONTIS, the bridge is divided into individual elements composed of the same material where each element is expected to have the same deterioration rate. The maintenance, repair and rehabilitation actions are separated from improvement actions in the optimization routine. PONTIS also employs a top-down analytical approach by optimizing over the network before determining individual bridge projects. Key features of PONTIS include:

- Data and analytical models: (1) an inventory of the State's bridges to include condition data, (2) engineering and economic models to include deterioration prediction models, (3) an array of improvement options, and (4) updating procedures;
- Procedures to identify optimal maintenance, repair, and rehabilitation strategies;
- Procedures to identify and rank capital improvements based on economic criteria; and
- An integration model that develops a consolidated master list of recommended maintenance and capital improvements.

To date, 37 States have procured a license to implement PONTIS. However, significantly fewer than 37 are using the model of decision-making. One issue is the requirement to populate the PONTIS database with information on bridge elements data that are not readily available because bridge inspectors must be trained to conduct element-level inspections. Another issue is that

States have found it difficult to obtain adequate data on current and historical maintenance and repair cost estimates.

Another bridge management system, similar to PONTIS, is BRIDGIT (Czepiel 1995). BRIDGIT is developed jointly by the National Cooperative Highway Research Program (NCHRP) and the National Engineering Technology Corporation. BRIDGET performs all functions of PONTIS. BRIDGET also use Markovian deterioration modeling to predict future deterioration and incorporates it to simulate life cycle cost analysis. The main difference between PONTIS and BRIDGIT is in the optimization model. BRIDGET is able to perform multi-year analysis and consider delaying maintenance and rehabilitation actions on a particular bridge to a later date. Another difference between PONTIS and BRIDGIT is the ability of BRIDGIT to define and distinguish between specific protection systems for elements when determining feasible options. The greatest disadvantage of BRIDGIT is the speed when compared to PONTIS.

2.3 Pavement and Highway Management System

Butt et al. (1994) provides a detailed description of a pavement management system called MicroPAVER. MicroPAVER system involves systematic and consistent method for selecting maintenance and rehabilitation needs and determining priorities and the optimal time for repair by predicting future pavement condition. MicroPAVER covers all aspects in pavement management system, which includes network definition, condition rating procedure, condition prediction modeling, budget forecasting, life cycle cost analysis of maintenance and rehabilitation strategies, and prioritization scheme.

MicroPAVER incorporates dynamic programming for the optimization for pavement management systems in conjunction with a Markov chain prediction model. For deterioration modeling, pavement sections are grouped based on surface type, distress modes, and traffic levels. Using Markov chain theory, prediction curves are fitted to obtain transition probability that help define future performance. The transition probabilities are used in the dynamic programming to minimize the life cycle cost of maintenance. The dynamic programming provides optimal maintenance strategies throughout the useful life.

Prioritization methods for pavement management based on benefit/cost ratio has been studied by Falls et al. (1993) and Butt et al. (1994). In the benefit/cost analysis, cost to maintain and rehabilitate pavement is compared against the benefit (i.e., vehicle operating savings, savings in value) from rehabilitating the pavement. In the benefit/cost ratio method, all the pavement sections in the given network are ranked with the use of weighted optimal benefit/cost ratios. For example, the higher the weighted optimal benefit/cost ratio of a section is, the higher the priority of that section will be for repair. The available budget is allocated to the pavement sections by selection of one section at a time form the ranked sectionlist. The prioritization is stopped when the available budget is completely exhausted. Routine maintenance is done for the sections that do not receive major rehabilitation. Optimal maintenance and repair recommendations and the corresponding benefit/cost ratios for each state are produced with the use of dynamic programming.

For prioritization using incremental benefit/cost ratio, benefits from limited maintenance and repair funds are maximized for one pavement section at time (project-level optimization) or for a group of pavement sections to maximize the overall benefits (network-level optimization). The output of the incremental benefit/cost ratio is a list of sections to be repaired, type of maintenance and repair alternative selected, cost of maintenance and repair alternative, section benefit, and total network benefits. The prioritization process, using incremental benefit/cost ratio, is composed of five elements: benefit, cost, routine maintenance, budget optimization, and PCI adjustment.

In the benefit computation, each section of pavement is grouped according to the pavement condition index (PCI) value. The benefits of all feasible maintenance and repair alternatives are obtained for the pavement section. It is then multiplied by user defined weights to obtain the weighted benefits for all maintenance and repair alternatives for the section. In the cost computation, the present-worth costs and initial costs of all feasible maintenance and repair alternatives are obtained. The initial costs of all feasible maintenance and repair alternatives of a section are multiplied by the section area and inflation rate, and the inflated initial costs of each pavement section are stored for use in the budget optimization module. In routine maintenance all feasible maintenance and repair alternatives of a section are identified, and the corresponding inflated initial costs, present-worth costs, and weighted benefits are obtained. The available budget is obtained and this information is used in the incremental benefit/cost ratio program to produce the optimal maintenance and repair recommendations. The PCI adjustment module recomputes the pavement condition index values for each section when the recommended maintenance and repair alternatives are performed.

The State of Washington has been actively involved in defining policy goals and improving action strategies to help better allocate the limited funds and more effectively develop maintenance strategies for highway infrastructures. The ranking methodology for highway mobility improvements used by the Washington State Department of Transportation (WSDOT) has four basic steps. First, submission of requests for projects from WSDOT regional offices. Second, the submissions are screened for program eligibility. Third, five categories (cost-efficiency, community support, environmental impact, modal integration, and land-use) of evaluation criteria are calculated and reviewed for each project. Finally, project rankings are computed using a priority index (Niemeier and Rutherford 1996).

The ranking system developed by WSDOT establishes, for each biennium cycle, an ideal project. The ideal project is assigned all the best scores attained in each of the five categories mentioned above. Similarly, the least desirable project is characterized by having worst scores in all five categories. Once the rankings are established, the projects are ranked according to their calculated Euclidean distance from the least and the ideal projects for the programming cycle. Criteria weights for 1995-1997 biennium cycle, developed by WSDOT, is shown in Table 2.

Table 2. Criteria Weights for 1995-1997 Biennium (Niemeier and Rutherford 1996)

Category	Weight (%)
Cost-efficiency	65
Community support	14
Environmental impact	8
Modal integration	7
Land use	6
Total	100

2.4 Embankment Dam Management System

A function-based condition indexing was developed by Chouinard et al. (1996) to prioritize maintenance and repair for embankment dams within the U. S. Army Cops of Engineers. The basis for this prioritization scheme is the overall condition of the facilities, i.e., facilities in the worst condition are given the highest priority. Each component of a given facility is rated in terms of its ability to perform its intended function. In another words, the condition of the facility is rated separately for each function by explicitly considering the components of each functional system. Since a particular infrastructure system may perform several functions, a condition assessment is conducted for each of its functions. The overall condition is developed by combining the condition index of each functional system through a weighted summation that reflects the relative importance of the various functions.

The condition index of each component is found using a generic condition indexing scale (i.e. numbers ranging from 0 to 100, 100 being the best condition and 0 being the worst condition) and through definitions of ideal and failed condition provided by experts. The condition index of a particular facility is found from a weighted combination of the condition indices that meet the objective of facility for the functional system. The weighting functions are based on the importance of the components. For example, the condition index of the most important component is given proportionately greater weight. In order to obtain the condition index for the facility, the condition index found for all objectives are summed together along with the associated weighting functions.

3. Demand Forecasting Methodologies

As a planning tool for management of different infrastructure assets (i.e. water, wastewater, transportation, and housing), demand forecasting has been commonly used. In this study, the various demand forecasting models implemented in different areas are reviewed from prior studies in order to ensure the feasibility of their adaptation in Korean infrastructure asset management system.

3.1 Forecasting of Wasterwater Demand

Forecasting of sanitary sewer flow under dry conditions was performed by Djebbar and Kadota (1998). In their study, an ANNs was used to forecast sanitary sewer flows in Vancouver, CA, under dry weather conditions. In the model, the input variables for the model were total area, population, dwelling units, commercial area, industrial area, institutional area, and other non-residential area. The output of the model was the average dry weather sanitary flow. The ANN model was developed using feed-forward network in conjunction with back propagation training algorithm. One hidden layer with three hidden nodes was selected for the model. The validation of the model was performed comparing the forecasted value with that of the measured value, and an average error less than 16% was produced.

3.2 Forecasting of Waster Demand

Many forecasting methods such as time-series models (Billing and Agthe,1998), memory based learning techniques i.e., artificial neural network, multiple regression (Billing and Agthe, 1998), (Takashi et al., 1993), (Weber, 1993), auto regressive integrated moving average models (Hartley and Powell, 1991) and IWR-MAIN (Institute for Water Resources Municipal And Industrial Needs) (Dziegielewski and Boland,1989) have been applied to develop demand forecasting model for water demand. From the study of various modeling methods and data acquisition techniques for water demand forecasting by Weber (1993), it was noted that the selection of water demand forecasting methods is highly dependent on the availability and the amount of data that can be assembled for the forecasting purpose. Typically, the underlying method of analysis used to forecast water demand is regression analysis. About 85 to 95 percent of water demand forecasting models are developed using the regression techniques (Weber, 1993).

3.3 Forecasting of Wasterwater Treatment Plant Performance

Forecasting wastewater treatment plant performance was accomplished using a time series model by Berthouex and Box (1996), which utilized a time-series forecasting model to predict effluent quantity in one to two days in the immediate future. The time series model used has the form of an exponentially weighted moving average, where the time series transfer function model produces a numerical estimate of effluent quality for one or more days ahead. The selection of the time-series modeling for the demand forecasting was justified by reasoning that regression models have poor performance, considering the auto-correlated data, dependence between input variables, dynamic relations between input and output variables, and parsimonious use of variables. It was found that ordinary least squares used in regression analysis is only appropriate for uncorrelated data. But in the case of wastewater data, a proper allowance must be made for serial dependence that is likely to occur between successive observations which can be captured using time series models (Berthouex and Box, 1996).

3.4 Forecasting of Transportation Demand

In transportation, demand is frequently forecasted to aid in the planning stage or in the management stage. Deutsch et al. (1994) conducted a study where the comparison of stochastic models was performed to evaluate their transportation performances. Based on demand forecasts for each of the distribution centers and the shipping costs from the plants to the distribution centers, the best combination of shipments from the plants to meet the demands subject to the capacity constraint of each plant was explored, where the information provided for demand forecasting were the historical demand data, cost data, and the capacity of each plant. The methodology and benefit of using the Space-Time AutoRegressive Integrated Moving Average (STARIMA) was presented to formulate stochastic demand, and the comparison of the Space-Time AutoRegressive Integrated Moving Average (STARIMA) model with 2 basic statistical models-expected value and stochastic approximation was performed. The moving average technique could also be compared to more popular and powerful modeling approach, such as multiple regression or artificial neural networks.

3.5 Forecasting of Construction Demand

Numerous attempts have been made in trying to forecast construction demand using various methodologies, such as multiple regression and artificial neural network. Tang et al. (1990) forecasted construction demand in Thailand using the stepwise regression technique, which showed that the demand for residential construction in Thailand relied heavily on per capita income, price index, interest rate, and the size of population. For non-residential construction demand, the industrial production index and index of profit expectations were significant indicators. In public construction demand analysis, the ratio of government revenues to the construction cost index was the biggest contributor to public construction demand.

3.5.1 Using Multiple Regression Model

Akintoye and Skitmore (1994) discussed the development of a model to forecast the private sector construction demand in the United Kingdom. The results showed that the ex post forecasting (i.e., the model is simulated beyond the estimated period, but not further than the last date for which the data is available) accuracy identified a positive bias in respect of private sector housing and commercial work models. It was also found that the private sector industrial model consistently underestimated private sector industrial demand. The study by Kellingsworth (1990) identified significant economic indicators for industrial construction for identifying and testing for significant variables to be included in the forecasting model. These indicators were then applied to a multiple regression demand forecasting model to verify their significance and accuracy of the model.

3.5.2 Using ANNs Model

ANN using back propagation training algorithm was applied to forecast residential construction demand in Singapore by Hua (1996), where it was found that the ANN model generated superior construction demand forecast when compared to the conventional multiple regression models. Yang and Parker (1997) also applied the back-propagation neural network (BPNN) and general regression neural network (GRNN) in order to forecast residential construction demand in U.K. The results of the study showed that GRNN was able to better estimate dramatic changes in demand, while BPNN gave better long term forecasting.

4. Conclusion

In this chapter, a brief review of methodologies for the various infrastructure asset management system (sewer, pavement, bridge, embankment dams) in U.S. has been presented. The demand forecasting models used in wastewater, water, wastewater treatment plant performance, transportation, and construction has also been introduced in brief. The forecasted demand then can be used to identify "critical" areas for optimal rehabilitation and maintenance fund allocation. It is recommended that more extensive review of the mathematical methodologies and their feasibility towards their implementation of Korean infrastructure asset management system should be performed so that the optimal methodology applicable to the each of systems in Korea can be determined.

Reference

1. Akintoye, A. and Skitmore, M., "Models of UK Private Sector Quarterly Construction Demand." Construction Management and Economics, E. & F.N. Spon, London, England, No.12, 1994, pp3-13
2. Berthouex, P. M. and Box, G. E., "Time Series Models for Forecasting Wastewater Treatment Plant Performance." Water Research, Pergamon Press, Oxford, England, 30 (8), 1996, pp1865-1875
3. Billings, R. B. and Agthe, D. E., "State-Space versus Multiple Regression for Forecasting Urban Water Demand." Journal of Water Resources Planning and Management, ASCE, 124 (2), 1998, pp113-117
4. Butt, A. A., Shahin, M. Y., Carpenter, S. H., and Carnahan, J. V., "Application of Markov Process to Pavement Management Systems at Network Level." Third International Conference on Managing Pavements, Transportation Research Board, No.2, 1994, pp159-172
5. Chouinard, L.E., Andersen, G.R., and Torrey III, V.H., "Ranking Models Used for Condition Assessment of Civil Infrastructure Systems." Journal of Infrastructure Systems, ASCE, 2(1), 1996, pp23-29
6. Czepiel, E., "Bridge Management Systems: Literature Review." Technical Report No. 11, Infrastructure Technology Institute, Northwestern University, March 1995
7. Deutsch, S. J., Patel, M. H., and Dieck Assad, A. J., "Comparison of Stochastic Approaches to the Transportation Problem: A Case Study." IEEE Transactions on Engineering Management, 41 (2), 1994, pp152-164
8. Djebbar, Y. and Kadota, P. T., "Estimating Sanitary Flows Using Neural Networks." Water Science Technology, 38 (10), 1998, pp215-222
9. Dziegielewski, B., and Boland, J. J., "An Annotated Bibliography on Techniques of Forecasting Demand for Water." U.S. Army Corps of Engineers Institute for Water Resources, IWR-Report 81-C03, Fort Belvoir, Virginia. 1981
10. Falls, L. C., Khalil, S., Haas, R. and Hudson, W. R., "Cost-Benefit Evaluation of Network Level Pavement Management." Proceedings of the Infrastructure Planning and Management, ASCE, 1993, pp152-156
11. Federal Highway Administration, Office of Asset Management, U.S. Department of Transportation. Research and Development Activities, Washington, D.C., U.S.A. 2003
12. Federal Highway Administration and the American Association of State Highway and Transportation Officials. Asset Management: Advancing the State of the Art Into the 21st Century Through Public-Private Dialogue, Washington, D.C., U.S.A 1996
13. Garvin, M., Challenges of Infrastructure Asset Management, First Annual Conference on Infrastructure Priorities, Washington, D.C. Oct. 24-26, U.S. 2001
14. Hua, G. B., "Residential Construction Demand Forecasting Using Economic Indicators: A Comparative Study of Artificial Neural Networks and Multiple Regression." Construction Management and Economics, E. & F.N. Spon, London, England, 14, 1996, pp25-34
15. Kellingsworth, R. A. Jr., "A Preliminary Investigation into Formulating a Demand Forecasting Model for Industrial Construction." Cost Engineering, 32 (8), 1990, pp11-15
16. Lee and Ro., "CCTV Inspection of Concrete Sewers (Supplemental Report) for the City of San Diego Metropolitan Wastewater Department." Report,Lee and Ro, Inc. San Diego, CA. U.S.A. 1998
17. Niemeier, D. A. and Rutherford, G. S., "Statewide Programming: Implementing Transportation-Policy Objectives." Journal of Infrastructure Systems, ASCE, 2(1), 1996, pp30-39
18. Reyna, S. M.,. "Optimal Planning of Sewer Systems Rehabilitation." Ph. D. Dissertation, School of Civil Engineering, Purdue University, West Lafayette, Indiana. U.S.A. 1993
19. Tang, J., Karasudhi, P. and Tachopiyagoon, P., "Thai Construction Industry: Demand and Projection." Construction Management and Economics, E. & F.N. Spon, 8, 1990, pp249-257
20. Weber, J. A., "Integrating Conservation Targets into Water Demand Projections." Journal of American Water Works Association, 85 (8), 1993, pp63-70
21. Wells, D. T., Scherer, W. T., and Gomez, J. P., "The State of the Art of Bridge Management Systems." Proceedings of the ASCE Conference on Infrastructure Planning and Management, Denver, Colorado. U.S.A.1993
22. Yang, Z. R. and Parker, A., "Applying Artificial Neural Networks to UK Construction Demand Forecasting (Private Sector)." Dept. of Land & Construction Management. University of Portsmouth, Portsmouth, England, 1997 http://www.rics.org.uk/research/cobra97/zang.html