Soft Computing-Based Infrastructure Life-Cycle Cost Analysis Tools

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Abstract

Life cycle cost analysis (LCCA) is a key component in the transportation infrastructure management process. Both deterministic and probabilistic LCCA approaches have been used by transportation agencies. Probabilistic methods allow decision makers to evaluate the risk of an investment utilizing uncertain input variables, assumptions, or estimates. However, if the uncertainty in the input is of an ambiguous rather than random nature, soft computing techniques can be more appropriate than the probabilistic methods. This paper discusses the framework to develop enhanced infrastructure LCCA tools using soft computing techniques. The feasibility and practicality of the approach is illustrated with a prototype LCCA algorithm (considering only agency costs) that uses fuzzy logic for pavement maintenance and rehabilitation (M&R) treatment selection and timing.

Introduction

The task of maintaining existing transportation infrastructure networks has become more challenging than ever before due to increasing deterioration, increasing demands, and shrinking financial and human resources. Transportation infrastructure systems have gradually deteriorated due to environmental wear and general use that, in many cases, significantly exceeded the design expectations. This has resulted in a decrease in the level of service provided to the public. In the United States, this decrease has been clearly manifested in a recent survey conducted by the American Society of Civil Engineers (ASCE 2003). According to this survey, one third of U.S. roads are in poor or mediocre condition, and road conditions contribute to as many as 13,800 highway fatalities annually.

To revert this trend, transportation agencies are embracing an asset management philosophy. Asset management combines engineering principles with business practice and economic theory, serving as today's best approach for balancing growing demands, aging infrastructure, and constrained resources (FHWA 1999; OECD 2001). This management philosophy requires the use of objective performance-oriented tools, such as engineering economic analysis, to select projects and to evaluate the consequences of different budget and performance scenarios.

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Life-cycle cost analysis (LCCA) is an economic analysis tool that is increasingly being used to support infrastructure and asset management decisions. This technique relies on estimates of the future of infrastructure performance, maintenance and rehabilitation actions, and user cost. Since these estimates are often based upon uncertain, ambiguous (different solutions for the same set of data), subjective, and sometimes incomplete information, soft-computing techniques emerge as a very helpful alternative for developing LCCA tools. Soft-computing encompasses computational techniques that tolerate imprecision, uncertainty, and ambiguity. In particular, fuzzy logic techniques could provide a complete approach for the treatment of these types of information. This paper explores the framework to develop enhanced transportation infrastructure LCCA tools using soft computing techniques. A prototype fuzzy logic-based LCCA algorithm (considering only agency costs) is presented. This algorithm could serve as part of the proposed generic framework.

Engineering Economic Analysis

Engineering economic analysis encompasses a collection of techniques that can be used to select, evaluate, recommend, and prioritize investment options according to their level of economic efficiency. Tools such as life-cycle cost analysis (LCCA), benefit cost analysis (BCA), risk analysis, and impact analysis can be used to either identify possible alternatives to achieve performance objectives at the lowest long-term cost or to provide maximum benefits for a given investment level. Economic analysis is a critical component of a comprehensive project evaluation methodology, since it can identify, quantify, and value the economic benefits and costs of the projects for a multiyear period (FHWA 2003).

Life-cycle cost analysis is a decision-support tool commonly used to account for all costs associated with a certain investment. For transportation infrastructure projects, LCCA includes costs for: construction, operation, logistics, maintenance, and disposal, and it also includes both user and nonuser (agency) costs. LCCA includes the following activities: (1) developing alternatives to accomplish the objectives of a project, (2) determining the schedule of initial and future activities necessary for each alternative, (3) estimating the costs associated with these activities (or expenditure streams), (4) discounting and adding these costs to compute the total life-cycle costs, and (5) evaluating the results (FHWA 2002). Life-cycle cost analysis can play an important role in transportation infrastructure management, supporting alternative evaluation, project selection, and budget allocation. The Federal Highway Administration (FHWA) has encouraged and in some cases mandated the use of LCCA in analyzing all major investment decisions (FHWA 1998).

The successful implementation of LCCA is affected by several technical issues (FHWA 1999): selecting an appropriate discount rate, quantifying non-agency costs such as user costs, securing creditable supporting data, including traffic data, projecting costs and travel demand throughout the analysis period, estimating salvage value and useful life, estimating maintenance costs and effectiveness, and modeling asset deterioration. These issues translate into many sources of uncertainty in the LCCA analysis.

Before conducting an LCCA, the analyst must define the general parameters, such as analysis period and discount rate. The analysis period should be long enough to reflect the performance difference among alternative projects. The FHWA (1998) recommends an analysis period of at least 35 years, but some states require a longer analysis period (e.g., 50 years in Virginia). For discount rate, Walls and Smith (1998) and Kirk and Dell'Isola (1995) recommend the use of real discount rates and real dollars. In the United States, the Office of Management and Budget (OMB) annually publishes the discount rate for economic analysis in Appendix C of its Circular A-94.

Once the analysis period is determined, the following five categories of costs should be evaluated and calculated for the project's life-cycle (NCHRP 2001):

- Agency Costs (construction, rehabilitation, maintenance, salvage return, engineering and administration, and investment)
- Vehicle Operating Costs (gas, tires, vehicle maintenance, depreciation, etc.)
- Travel Time Costs (dollar value of time spent on the roadway)
- Accident Costs
- Environmental Costs

Agency costs are those associated with the design, construction, and maintenance of the facilities. For many agencies, existing pavement and bridge management systems provide pavement condition and usage information, as well as pavement deterioration models and appropriate maintenance and rehabilitation options and costs. Such information is already enough to determine agency costs.

The other four categories of costs are associated with the use of the facility. Many agencies in the U.S. only consider project costs in their LCCA procedures because of the difficulties associated with the quantification of user costs. However, user cost can account for up to 95% of the total highway transportation cost and should not be ignored. Several models for estimating direct user costs as a function of infrastructure condition and user delay costs as a function of lane closure practices have been proposed (Memmott et al. 1999; Kerali 1999; Pappagiannakis and Delwar 2001; Walls and Smith 1998). Since the uncertainty in these costs is usually very significant and the determination of them requires a large amount of information that it is costly and not always available, the use of soft computing tools, which are effective for handling uncertain, subjective, and incomplete data, may help incorporate these user costs into the LCCA process.

Currently, there are two main LCCA approaches used by local and state agencies: deterministic and probabilistic. Flintsch (2004a) reviewed and compared existing economic analysis tools for supporting project, network-, and strategic-level pavement management decisions.

Deterministic methods are relatively easier to implement, but they cannot provide any risk assessment on the uncertainty associated with future events. In the deterministic methods, all input variables (costs) are assumed to be known and given a single, fixed value. The primary formula used to calculate the total present worth over the life-cycle of the facility under investigation is the following:

$$LCC = InitialCost + \sum_{k=1}^{n} FutureCost_{(k)} \times \left[\frac{1}{(1+i)^k} \right] \qquad (1)$$

where,
LCC = total present worth of life-cycle costs
$InitialCost$ = project costs in the first year
$FutureCost_{(k)}$ = project costs in year k
K = year
N = analysis period
I = discount rate

The uncertainty in the physical and economic aspects considered in the engineering economic analysis has been addressed by adopting probabilistic (risk analysis) approaches. Probabilistic LCCA methods allow for consideration of the variability, *i.e.* probability distribution, associated with the different costs incurred over the life cycle of the pavement or facility studied. However, it is relatively difficult to collect all of the information that is needed for applying this approach.

In a probabilistic model, each variable is given an associated probability distribution function (PDF). Probabilistic LCCA tools conduct a simulation (typically using Monte Carlo simulation) to sample the input and generate a PDF for the output economic indicators considered in the analysis. Walls and Smith (1998) proposed a probabilistic methodology for pavement LCCA, which used Monte Carlo simulation. A package of risk analysis Excel Add-in tools was developed. StratBencost (NCHRP 2001) uses a similar approach and provides default median and ranges for all variables relevant to the user costs.

The main advantage of the probabilistic approach is that it allows decision makers to evaluate the risk of an investment due to uncertain input variables, assumptions, or estimates (FHWA 1998). The probabilistic approach implicitly assumes that the uncertainty is of random nature and that it can be modeled using a PDF. If the uncertainty in the input is of an *ambiguous* nature, soft computing applications may provide a better life-cycle cost assessment than the probabilistic approach.

Soft Computing Applications for Life Cycle Cost Analysis

Soft computing is an umbrella of computational techniques that handles both subjective and numerical information, and it also tolerates imprecision, uncertainty, and ambiguity (Zadeh 1997). Soft computing includes three principal constituents: fuzzy mathematical programming, neural networks, and probabilistic reasoning –subsuming belief networks, genetic algorithms, chaotic programming, and parts of machine learning (Zadeh, 2001). Although the specific techniques included under the soft computing umbrella have evolved since the introduction of the term, the overarching concept has been the same: the integration of complementary reasoning techniques to develop systems that "tolerate imprecision, uncertainty, and partial truth to achieve tractability, robustness, and better rapport with reality" (Zadeh, 1997).

Soft computing techniques were selected for the development of robust and flexible LCCA procedures and tools for the following reasons:

1. Available information may be uncertain, ambiguous, and incomplete (information availability for different transportation infrastructure projects is highly variable).
2. Both objective (numerical) and subjective (linguistic) information may be available and should be considered in the analysis. While some relevant factors are easily quantifiable in economic (monetary) terms, other factors, such as environmental effects, comfort, aesthetics, versatility, and mobility considerations, may be better evaluated using subjective terms.
3. Economic analysis of transportation infrastructure projects often requires a lot of expert knowledge, and the resource allocation tradeoffs that LCCA supports often involve conflicting asset performance and economical objectives and constraints.

The main advantages of the three soft computing constituents most used in infrastructure management are discussed below. A comprehensive review of the applications of these techniques to support infrastructure management is presented in Flintsch (2004b).

Fuzzy logic techniques provide a convenient way for incorporating engineering expertise and prior knowledge into the decision of maintenance and rehabilitation treatment along the infrastructure's life span. They are very efficient for handling subjective and uncertain information that is always involved in the decision-making process but difficult to be processed by "crisp" mathematical methods. Furthermore, fuzzy programming techniques appear to provide an effective way to make the resource optimization more flexible by relaxing (fuzzifying) the constraints or objectives in optimization models. On the other hand, the main difficulty associated with the uses of these techniques is related with the definition of the needed membership functions and inference rules. Expert opinions are one of the major sources to design the fuzzy system, but inevitably, subjective bias would be included in the system.

Artificial neural networks are capable of modeling complex linear or nonlinear functions with very good prediction capabilities if proper values are assigned to network connection weights. Neural networks can be trained to save, recognize, and search the shapes or elements of databases, solve combinatorial optimization problems, recognize without definitions, and make generalizations. This feature makes this computational architecture particularly appropriate for conducting complex analysis such as modeling future infrastructure conditions. For example, neural network can be used to predict transportation infrastructure conditions based on history records of other infrastructures under similar environments. The main limitation of neural networks is that they require reliable and abundant training pattern information which is often difficult to obtain.

Evolutionary computation techniques are heuristics that can produce "good" solutions for difficult combinatorial optimization problems, can tune Fuzzy Logic Systems, and can be used in the Neural Networks training process. The most common of these heuristics, genetic algorithms, are effective to overcome local optimum limits and are usually efficient when large amounts of independent variables exist in the programming problem, just like decisions based on LCCA over a large transportation infrastructure network. Evolutionary computing could produce "good" solutions but cannot guarantee the solutions are true optimum.

Most of the limitations discussed in the previous paragraphs could be offset to some extent by using hybrid systems. These systems synergistically integrate complementary soft-computing members to combine their advantages and allow achieving tractability, robustness, low-solution cost, and a better rapport with reality (Zadeh 2001).

Fuzzy Logic-Based LCCA Algorithm

As mentioned, the determination of all the cost incurred through the life cycle of a facility is by nature uncertain and often requires significant subjective judgment and expert knowledge Thus, a fuzzy logic approach emerges as an appealing alternative for developing robust LCCA tools. This section presents a simple fuzzy logic-based LCCA model developed to test this hypothesis.

The LCCA model uses fuzzy logic to estimate future pavement maintenance and rehabilitation costs. Fuzzy logic systems are an extension of the traditional rule-based reasoning (expert systems), which incorporate imprecise, qualitative data in the decision-making process by combining descriptive linguistic rules through fuzzy logic (Zadeh 1973). The design of the fuzzy system requires the definition of a set of membership functions (which enable the system to handle uncertainty) and a set of rules. Smooth relationships can be achieved by using descriptive expressions, such as poor, fair, or good to categorize linguistic input and output variables. Fuzzy logic was developed to provide soft algorithms for data processing that can both make inferences about imprecise data and use the data. It enables the variables to partially belong to a particular set, and at the same time, it makes use of the generalizations of conventional Boolean logic operators in data processing.

Fuzzy logic systems use fuzzy sets. While a traditional crisp set only allows its members' membership function to take values of one or zero (either belongs to the set or not, respectively), members of a fuzzy set can have a membership function in the interval [0, 1]. As a result, a member can belong to a fuzzy set with a certain degree of membership between zero and one. Examples of the membership functions for the various levels of the input variables used in the LCCA model are presented in Figure 1.

A rule-based fuzzy logic system is composed of four parts (Zadeh, 2001): a rule base, an input processor (fuzzifier), an inference engine, and an output processor (defuzzifier). The rules of the fuzzy logic system store the *knowledge* of the system. The rules can be provided by experts, extracted from collected cases or examples, or derived from a combination of both. The rules in fuzzy logic systems are often expressed in the form of IF-THEN statements. The input and output processors provide mappings between crisp numbers or verbal statements and fuzzy sets. The inference engine handles the application of pertinent rules.

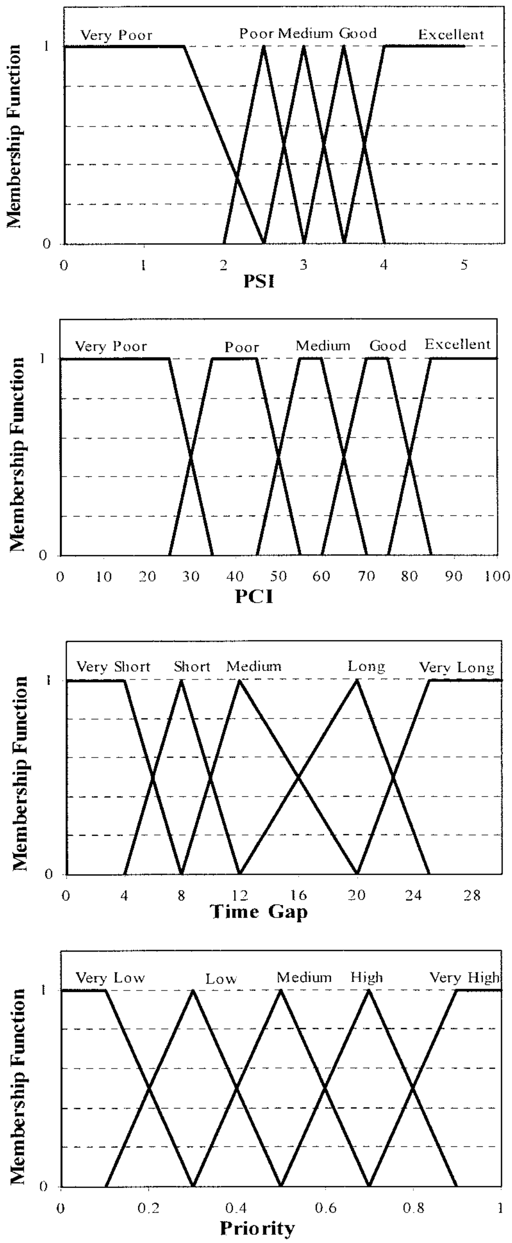

FIGURE 1. Membership functions for the variables considered.

The selection of membership functions, rules, and inference engines depends upon the information available and the condition of each individual case. In general, manually building a fuzzy logic system is difficult and time consuming. Neuro-fuzzy systems have been recommended for extracting rules from existing data. These hybrid soft-computing tools take advantage of the learning algorithms used in artificial neural networks (Nauck et al., 1997; Flintsch, 2002).

Agency Costs Model

Agency cost determination is a major part of LCCA; it includes the evaluation of all pavement construction, maintenance, and rehabilitation costs incurred during the analysis period. Although they can be uncertain, initial construction costs can generally be obtained with a certain degree of precision from construction bids, contracts, or pavement management systems. On the other hand, future treatment and expenditures are unknown at the time of conducting the LCCA and can only be estimated based upon agency policies (e.g., PMS) or treatment cost of similar projects. Therefore, the main source of uncertainty in the agency cost comes from unknown pavement performance and future pavement maintenance, rehabilitation, and repaving actions. As a first step and to demonstrate the feasibility of the approach, fuzzy systems were used for treatment selection and timing; however, they can also be used for modeling pavement deterioration as discussed later in the paper.

Agency decisions concerning the timing and type of maintenance, rehabilitation, and repaving (MR&R) actions are mainly based upon pavement condition and/or time since last treatment. Fuzzy logic techniques can be used to predict future pavement conditions and to determine the necessary MR&R actions. The prototype model presented in this paper (Figure 2) uses deterministic models to predict pavement condition based upon pavement structure, age, and traffic, as well as a fuzzy logic model to select treatments based upon pavement condition and time since last treatment.

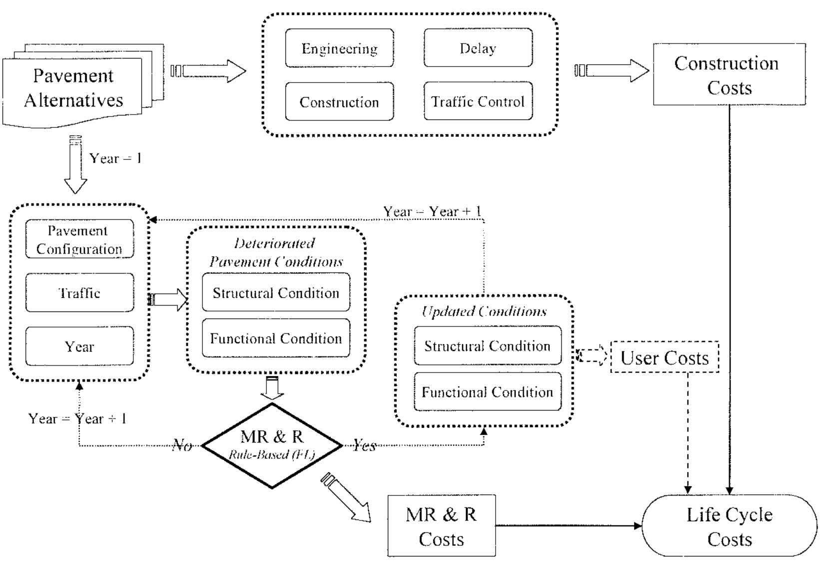

FIGURE 2. Fuzzy logic-based LCCA framework.

User Costs Considerations

User cost may include vehicle operating costs, travel time, and accident and environmental costs. Accident cost analysis involves an estimation of accident rates; that is, which kind of accident and how often it will happen. The estimation should be based upon the roadway geometric characteristics, pavement condition, and traffic distribution, among other factors. Both vehicle operating and travel time cost estimation need information about traffic and pavement conditions, as well as cost of time, gasoline, repairs, etc. Environmental costs include emissions and noise, among other factors. These costs are estimated based upon often uncertain, incomplete, and sometimes ambiguous information. Although the user costs are of great importance, they were not considered in this, the feasibility study, because it was preferred to have a simpler application for evaluating the technology. This is also consistent with current agency practices in the U.S., which in general do not consider user costs. However, the overall framework of the application being considered includes user cost as shown by dotted lines in Figure 2.

Case Study

This section presents an example that illustrates the use of the developed fuzzy logic model for project-level LCCA. The example evaluates different MR&R policies for a flexible pavement structure, which consisted of 40mm (1.5in) of hot mix asphalt (HMA) wearing course, a 180mm (7in) HMA base layer, a 75mm (3in) asphalt-treated open-graded drainage layer, and 220mm (8.5in) of cement-treated aggregate subbase. Cost data from the Virginia Department of Transportation (VDOT, 2002) were used to calculate the project cost. The initial construction cost (without considering non-pavement items) was $204,475.92 per lane-mile. Routine maintenance costs were assumed similar for all alternatives. Initial traffic was 306,301 annual equivalent single axle loads (ESALs), and a traffic growth rate of 4% was assumed.

Future MR&R costs were estimated using fuzzy logic models that select treatments based upon user-defined rules. The variables considered are pavement structural and functional condition, which were measured using the Present Serviceability Index (PSI) and Pavement Condition Index (PCI) respectively and time since last treatment (time gap). The AASHTO pavement design equation (AASHTO 1993) was used to predict PSI progression. An S-shaped regression equation that was developed for new flexible pavements at the Washington State DOT (Jackson and Mahoney 1990) was used for predicting PCI.

Decision Making Model

Figure 3 presents the project selection algorithm used in this example. The algorithm consists of two rule-based fuzzy logic models, a trigger model, and a policy model. Users can define rules for both models. The trigger model computes the priority of a do-nothing policy, while the policy model is used to evaluate the priority of specific MR&R treatments.

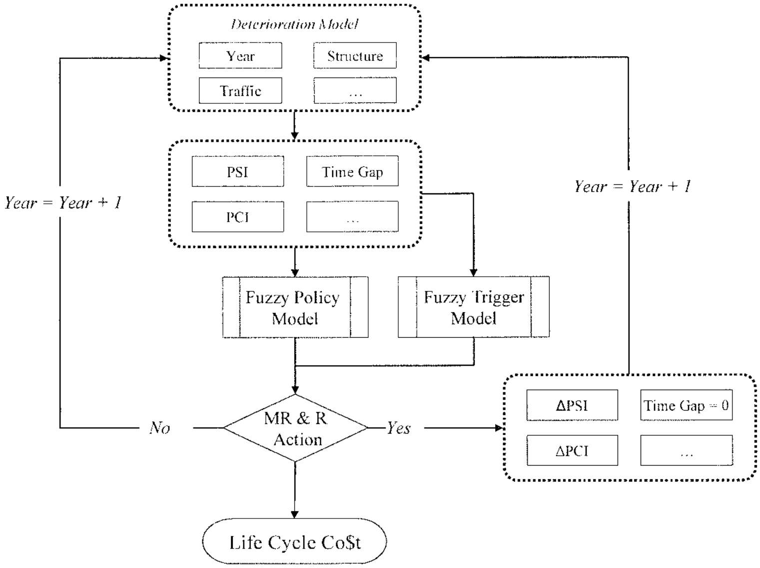

FIGURE 3. Fuzzy logic-based project selection algorithm.

For each year, the algorithm evaluates the *priorities* of a do-nothing policy and the various treatments defined by the policies/criteria provided in the form of user-defined fuzzy rules. If the priority of a treatment exceeds that of the do-nothing alternative, the treatment is applied and the pavement variables adjusted accordingly. Otherwise, only routine maintenance is applied, and the pavement is deteriorated according to the default prediction curves. The process is repeated for each year in the analysis period. The life-cycle costs are then computed annually using user-defined typical cost for the different treatments. The algorithm was implemented in a MatLab-based computer program that provides default values for all the input variables and criteria.

MR&R Policies

The membership functions for the various pavement variables and levels (linguistic descriptions) considered in this case study were presented in Figure 1. Table 1 summarizes the fuzzy logic-based model. Five MR&R policies were evaluated in this case study:

- Preventive maintenance
- Thin overlay (50mm [2in])
- Medium overlay (100m [4in])
- Thick overlay (150mm [6in]) and
- Reconstruction

Six groups of fuzzy logic rules were developed – one for the do-nothing policy (trigger model) and one for each of the five policies investigated. The case study only considered one treatment in each policy. This is a simplification used only to illustrate the approach and verify the reasonableness of the algorithms.