Soft Computing Applications for Urban Pavement Maintenance Management System

Yogesh U. Shah, Dr.S.S. Jain, Dr. Devesh Tiwari and Dr.M.K. Jain

Abstract--- Urban Pavement Maintenance Management (UPMM) framework involves decision making related to condition assessment, performance prediction, prioritization and resource optimization which are often based on data that is uncertain, ambiguous, and incomplete and incorporate engineering judgment and expert opinion. Soft computing techniques are particularly appropriate to support these types of decisions because these techniques are very efficient at handling such subjective data. This paper presents a review of the application of soft computing techniques in UPMMS. The three most used soft computing constituents, artificial neural networks, fuzzy systems, and genetic algorithms are reviewed, and the most promising techniques for the different pavement management functions are identified. Based on the applications reviewed, it can be concluded that soft computing techniques provide appealing alternatives for supporting many pavement management functions. Although the soft computing constituents have several advantages when used individually, the development of practical and efficient intelligent tools is expected to require a synergistic integration of complementary techniques into hybrid models.

Keywords--- Pavement Maintenance Management System, Soft Computing; Artificial intelligence, Neural Networks, Fuzzy Sets

I. INTRODUCTION

A. General

Urban Pavement Management System is very challenging and timely issue. The sound pavement management system plays a vital role in encouraging a more productive and competitive national economy. The increasing demands of roads because of rapid urbanization, shrinking financial and human resources, and increased deterioration of pavements have made the task of maintaining our pavement networks more difficult than ever before. In absence of proper and timely maintenance many of the nation’s pavement network systems are reaching the end of their service lives.

In many cases, pavement management decisions, such as pavement condition evaluation, pavement performance prediction models, deciding MR&R strategies, prioritization, life-cycle cost analysis and optimization, are based on data that is uncertain, ambiguous and sometimes incomplete; furthermore, they incorporate engineering judgment and expert opinion. The soft computing applications offer an appealing alternative because this emerging computational paradigm combines several problem-solving technologies that provide complementary reasoning and searching methods to solve real-world problems that involve imprecision, uncertainty, subjectivity, and partial truth. The main technologies included in the soft computing umbrella are artificial neural networks, fuzzy logic and genetic algorithms. The objective of this paper is to review applications of soft computing techniques in urban pavement management systems, highlighting the advantages over traditional approaches. It also provides a quick overview of the soft computing techniques that hold the most promise to enhance the urban pavement management process.

II. SOFT COMPUTING TECHNIQUES

Soft Computing Techniques have been recognized as attractive alternatives to the standard, well established “hard computing” paradigms. Traditional hard computing methods are often too cumbersome for today’s problems. They always require a precisely stated analytical model and often a lot of computational time.

Soft computing techniques have proven effective for pavement and infrastructure management applications because they allow for the handling and processing of subjective and ambiguous information, as well as incomplete data sets. Many soft computing techniques, artificial neural networks, fuzzy systems, and genetic algorithms, have been used in infrastructure management with various degrees of success (Flintsch 2003).

Table 1 presents a summary of the main advantages for these soft computing techniques. However, each soft computing constituent has its own limitations to develop a practical and efficient system. Artificial Neural Networks always require reliable training pattern information which is often difficult to obtain. And it won’t perform well when the inputs are out of the range of the training set. Fuzzy Logic Systems need carefully defined 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. Evolutionary computing could produce “good” solutions but cannot guarantee the solutions are true optimum. These limitations could be offset to some extent by using hybrid systems (Zadeh 2001).
Obviously, more efforts are needed to develop and implement such a system.

### Table 1: Advantages of Soft Computing Techniques (after Litak and Litak, 2004)

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<tr>
<th>Soft Computing Technique</th>
<th>Important Characteristics</th>
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<td>Artificial Neural Networks</td>
<td>Excellent pattern recognition capabilities. Can be trained to solve, recognize, and search the shape of elements of databases, solve combinatorial optimization problems, recognize without definitions, and make generalizations.</td>
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<td>Fuzzy Logic Systems</td>
<td>Possibility of introducing and using subjective information (including rules from experience, intuition, and heuristics) and providing functional transparency. Type-2 Fuzzy Logic Systems are also capable of handling uncertainty.</td>
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<tr>
<td>Genetic Algorithms</td>
<td>Can produce “good” solutions for different combinatorial optimization problems; can tune Fuzzy Logic Systems, and can be used in the Neural Networks training process.</td>
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<tr>
<td>Hybrid Systems</td>
<td>Synergistically integrate complementary members to combine their advantages and allow achieving tractability, robustness, low solution cost, and better support with reality.</td>
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### A. Artificial Neural Network

Neural networks can be used for a wide variety of learning tasks. They should be considered a mathematical tool, similar to regression analysis. The key feature of neural networks over regression analysis is that neural networks use non-linear mathematics and therefore can be used to model highly complex and non-linear functions. (Grup et al. 1998)

A learning task consists of a set of data from which training examples are formed. Each training example usually comprises input data and the desired network response. When applying a neural network to learn from this set of data, the training of the network requires a number of decisions related to the use of the available training methods. Selecting the appropriate method consists of configuring a neural network and selecting algorithms (learning rules) for training the network. A network accepts an input vector and generates a response in the form of an output vector.

### B. Fuzzy Logic

Fuzzy logic systems (Zadeh 1965, 1973) 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. The design of the fuzzy system requires the definition of a set of membership functions and a set of fuzzy rules. When various rules are activated, the binary rules that define conventional expert systems usually result in discontinuities at the exit of a system. This does not resemble human behavior, where a smooth relation usually exists between cause and consequence. Smooth relationships can be achieved by using fuzzy rules that include 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 (up to a certain degree) belong to a particular set and, at the same time, makes use of the generalizations of conventional Boolean logic operators in data processing. Fuzzy systems are convenient to model expert opinions because they handle linguistic rules efficiently and are fault-tolerant regarding small changes in the input or system parameters. One of the limitations of fuzzy systems is that they do not have formal algorithms to learn from existing data. The main advantage of this approach is the possibility of introducing and using rules from experience, intuition, and heuristics, and the fact that a model of the process is not required. Fuzzy systems also provide functional transparency.

### C. Genetic Algorithm

Genetic Algorithms (GAs) are adaptive heuristic search algorithms that are based on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem. First pioneered by John Holland in the 60s, Genetic Algorithms have been widely studied, experimented and applied in many fields in engineering worlds. GAs were introduced as a computational analogy of adaptive systems. They are modelled loosely on the principles of the evolution via natural selection, employing a population of individuals that undergo selection in the presence of variation-inducing operators such as mutation and recombination (crossover). A fitness function is used to evaluate individuals, and reproductive success varies with fitness. The paradigm of GAs described above is usually the one applied to solving most of the problems presented to GAs. Though it might not find the best solution, more often than not, it would come up with a partially optimal solution.

### D. Hybrid Systems

Although the soft computing constituents have several advantages when used individually, the development of a practical and efficient system often requires a synergistic integration of the complementary members into hybrid systems (Zadeh 2001). For example, while assessing the feasibility of using fuzzy technologies for life-cycle cost analysis for complex weapon design, Senglaub and Bahill (1995) concluded that the technique had potential only in a hybridized environment—not as a standalone solution. A combined hybrid system makes it possible to “achieve tractability, robustness, low solution cost, and better rapport with reality” (Zadeh 1997). The full potential of soft computing techniques resides in the development of truly “intelligent” decision support tools. Hybrid soft computing architectures can cleverly combine several techniques that add to their capabilities and benefits. Fuzzy logic provides a methodology for approximate reasoning and for computing with words; neural networks are efficient for curve fitting learning and system identification; genetic algorithms are efficient random search and optimization heuristics. The combined tools may handle uncertain, subjective, incomplete, and/or ambiguous information, generate knowledge by learning from examples and/or experts, and improve their performance as they are used.

### E. Expert Systems

In artificial intelligence, an expert system is a computer system that emulates the decision-making ability of a human expert. Expert systems are designed to solve complex problems by reasoning about knowledge, like an expert, and not by following the procedure of a developer as is the case in conventional programming. The first expert systems were created in the 1970s and then proliferated in the 1980s. Expert
systems were among the first truly successful forms of AI software.

An expert system has a unique structure, different from traditional programs. It is divided into two parts, one fixed, independent of the expert system: the inference engine, and one variable: the knowledge base. To run an expert system, the engine reasons about the knowledge base like a human. In the 80s a third part appeared: a dialog interface to communicate with users. This ability to conduct a conversation with users was later called "conversational". Ismail, N. et al. (2009) provided a brief overview of current developments and implementation of expert system in pavement management for both highway and airport networks.

III. CRITICAL REVIEW OF SOFT COMPUTING APPLICATIONS IN UPMMS

Soft computing techniques hold great promise in supporting pavement management development because the decisions supported by PMS often require a great deal of expert knowledge and often involve handling and processing subjective and sometimes ambiguous and incomplete information. Some of the most significant implemented and potential urban pavement management applications are discussed in the following sections and summarized in Table 2.

A. Pavement Condition Evaluation

Evaluation is a key part of pavement management because it provides the means for seeing how well the planning, design, and construction objectives have been satisfied. The pavement evaluation includes evaluating both the functional and structural condition of the pavement. Generally, indices are developed to represent the pavement condition. Soft computing techniques are particularly appropriate in such cases because they can estimate functions from samples without requiring a mathematical formulation of the dependence of output on input values.

Haas, C. (1985) described the development of a prototype of an automated distress data collection system for which the objective was to efficiently process, analyze and store the data and produce consistent and repeatable results. The systems were developed using Knowledge Based Expert System (KBES). Juang and Amirkhanian (1992) documented the development of unified pavement distress index (UPDI) using the theory of fuzzy sets. Zhang (1993) discussed the formulation of a comprehensive ranking index for flexible pavements. A model called the overall acceptability index (OAL), based on fuzzy set theory, was developed. Four parameters viz. roughness, surface distress, structural capacity and skid resistance were considered for OAL. Shoukry et al. (1997) adopted a fuzzy logic approach to derive a universal pavement distress evaluator defined as Fuzzy Distress Index (FDI). Arliansyah et al. (2003) proposed a method to determine membership functions used in pavement condition assessment based on experts’ opinions about the range values of linguistic rating terms of pavement parameters. The fuzzy pavement condition index (FPCI) was evaluated. Terzi (2007) used artificial neural networks (ANN) in modelling the present serviceability ratio (PSR) for the flexible pavements. Koduru et al. (2010) showed a methodology using fuzzy logic for the categorization of distresses. Also an expert system was developed in C language using fuzzy logic for reasoning. Sarsam (2010) evaluated the pavement sections using an expert system based VEPAPSC (Visual Evaluation of Asphalt Concrete Pavement Surface Condition) and determined the present condition rating (PCR).

B. Pavement Performance Prediction Models

The next part of UPMMS is to develop the prediction models for pavement deterioration using the existing pavement condition. Various types of prediction models developed include empirical-mechanistic, mechanistic, regression and markov chain models. Neural networks and other soft computing techniques are increasingly used instead of the traditional regression methods because this process involves significant subjectivity and uncertainty.

Hybrid systems (Ritchie et al. 1991; Chou et al. 1995) have been used for detecting and classifying distresses from visual images. Huang and Moore (1997) compared multiple linear regression and artificial neural network (ANN) for predicting roughness distress level (RUGDL) probability for bituminous pavements as defined by Kansas Department of Transportation (KDOT) PMS. Roberts (1998) used two types of ANN viz. quadratic function and dot product to predict the roughness from several pavement characteristics and traffic. Yang et al. (2003) predicted three key indices – crack rating, ride rating and rut rating using three ANN models.

Omar Smadi (2001) developed the KBES model for pavement condition forecasting in conjunction with a deterministic performance model. Performance curves developed using regression analysis (age vs. condition) were used as the initial input to the KBES. Bandara et al. (2001) developed a fuzzy Markov model for predicting future pavement condition by incorporating subjective probability assessments regarding pavement condition deterioration rates. Genetic algorithms have also been used to develop several pavement deterioration models (Shekharan 2000) and to combine expert knowledge and performance data for the development of transition provability matrices (Hedfi and Stephanos 2001). Bianchini and Bandini (2010) proposed a neuro-fuzzy model to predict the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of an existing pavement.

C. Deciding MR&R Strategies

The identification of road sections in need of maintenance, rehabilitation, replacement, or improvement, as well as appropriate strategies for these sections, is a critical pavement management function that involves a great deal of knowledge about the condition of the assets, the effectiveness of the corrective strategies, and the impact of the action on the system performance.

Early on, the performance of rule-based expert systems was compared with artificial neural networks for selecting sections for crack routing and sealing (Hajek and Hurdal 1993). It was concluded that the two techniques exhibited complementary strengths, thus, it was recommended that these techniques be combined into a hybrid system. A case study
was reported in which a fuzzy logic system was developed for selecting pavement maintenance and rehabilitation (M&R) treatments (Grivas and Shen 1995). The system also provided the degree of confidence (certainty) in the proposed treatment. A fuzzy logic, multiobjective, decision-making model has been used for selecting an M&R treatment from a set of feasible treatments prepared using a rule-based expert system (Prechaverakul and Hadipriono 1995). Similarly, neural networks have been used for selecting candidate pavement rehabilitation projects (Flintsch et al. 1996) and for recommending appropriate pavement M&R treatments based on pavement distress (Alsugair and Al-Qudrah 1998). Genetic adaptive neural networks have been used for selecting “optimum” M&R strategies (Taha and Hanna 1995; Abdelrahim and George 2000). Omar Smadi (2001) developed the KBES model for treatment selection is a decision tree of “if-then-else” rules based on historical information and expert opinions of field maintenance engineers, design engineers, and construction engineers. An adaptive neuro-fuzzy model, which allows for the combination of expert knowledge with knowledge acquired from examples, has recently been proposed for pavement treatment selection (Flintsch 2002).

D. Prioritization

An integral component of any pavement management system is a procedure for establishing priority order by using a method that will lead to a more realistic and rational way of establishing candidate projects for priority programming at the network-level PMS. Priorities can be determined by many methods, ranging from simple subjective ranking to the true optimization method.


E. Optimization

The optimization approaches require the formulation of the decision problem as a mathematical model in which the objective one wished to pursue (i.e. maximizing improvement) and the constraints one has to satisfy (i.e. budget, manpower, equipment etc.) are stated as mathematical decision techniques.

Wang and Liu (1997) described the application of fuzzy set representations for different pavement factors introduced to determine the pavement performance ratings for various pavement condition states, which are necessary to generate the objective function. In these performance-oriented NOS, a uniform annual budget was used as a constraint. Fwa et al. (2000) presented a genetic-algorithm-based procedure for solving multi-objective network level pavement maintenance programming problems. Chan et al. (2001) applied genetic algorithm (GA) for optimizing the resource allocation for pavement maintenance programming.

Omar Smadi (2001) developed the KBES model using deterministic dynamic programming for the resource allocation model and was also used for project selection through optimizing a multi-year pavement management program. Chan et al. (2003) employed the genetic-algorithm (GA) optimization technique to allocate the total funds available to the district or regional agencies in order to best achieve specified central and regional agencies’ goals subject to operational and resource constraints. Choi (2004) focused on the analysis of a data set from the long-term pavement performance (LTTP) database to quantify the contribution of material & construction variables of asphalt concrete on pavement performance (i.e., international roughness indicator) using a back-propagation neural network (BPNN) algorithm. Bosurgia and Trifiroa (2005) defined a procedure to make use of the available economic resources in the best way possible for resurfacing interventions on flexible pavements by using artificial neural networks and genetic algorithms.

IV. CONCLUSIONS

Urban Pavement Maintenance Management (UPMM) framework involves decision making based on data that is uncertain, ambiguous, and incomplete and incorporate engineering judgment and expert opinion. Soft computing tools are particularly appropriate because these techniques can handle both numerical (even imprecise, uncertain, ambiguous and incomplete) and subjective information.

The applications of three soft computing techniques viz: artificial neural network, fuzzy logic systems and genetic algorithms for UPMM were reviewed and the most efficient technique for different PMS functions were identified. The knowledge of expert system to PMS was also discussed. The conclusions drawn from this study are as follows:

- Neural, fuzzy, and neuro-fuzzy models are recommended for condition assessment and performance prediction. Adaptive hybrid soft computing applications, which are able to acquire knowledge, could be used to develop pavement condition assessment and performance models that are updated automatically as part of the feedback process.
- Models that allow for the combination of expert knowledge with knowledge acquired from examples (numerical data) are ideal for project and treatment selection, and prioritization. Neural networks, fuzzy systems, and combination thereof have been used with successful outcomes in most of the cases. Fuzzy, multi-attribute, decision-making models can be used for developing flexible project selection and prioritization tools.
- Genetic algorithms, fuzzy mathematical programming, and advanced hybrid systems are best suited for enhancing optimization procedures. Fuzzy optimization techniques, which are able to resolve linear or dynamic programming problems with fuzzy parameters, constraints and/or objective functions, could increase the flexibility and solution stability of the programming process.
Knowledge based expert system were found to be suitable for pavement condition assessment and performance prediction models. It had its application for models selecting the MR&R strategies.

REFERENCES


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