COMPUTATIONAL INTELLIGENCE METHODS FOR HIGHWAY INFRASTRUCTURE MANAGEMENT SYSTEMS

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ABSTRACT

Given the need to explore innovative ways to address road condition evaluation problems, this work provides an overview of some promising methods of analysis, based on computational intelligence techniques. A non conventional methodology that combines different fields of knowledge is proposed to help making decisions for highway management systems and road condition evaluation. Artificial Neural Networks and Fuzzy Logic are proposed to assess road performance of existing flexible pavement highways and to identify rehabilitation alternatives, based on non-destructive testing data collected along the road.

Keywords: Highway performance, fuzzy logic, artificial neural network, non-destructive testing, flexible pavements.

INTRODUCTION

Due to the continuous development of highway infrastructure worldwide, it is necessary to promote and implement management systems, in order to focus human efforts and investments to provide road conservation and good conditions of stability, functionality and security for road transportation system.

Road condition assessment is an important input for any highway infrastructure management system; thus there is a permanent challenge to involve efficient methods, techniques and models that instil more confidence about road evaluation problems, to obtain rehabilitation solutions attached to real road conditions.

In this way, computational intelligence-CI has demonstrated to be an efficient, non deterministic and very realistic approximation to solve engineering problems. Here, CI is addressed as an analysis method close to the representative physical phenomenon of roads behaviour, to find performance parameters useful for making decision process; in particular, an artificial neural networks and fuzzy logic based methodology is proposed to evaluate road performance from non destructive testing data processing.

In order to give a general framework, main concepts about highway management systems, road condition evaluation and computational intelligence are presents first. Latter, some relevant investigations about computational intelligence applied to highway engineering analysis are described. Finally, a proposal of computational intelligence methodology applied to highways infrastructure evaluation is exposed. For illustration and validation purposes, a structural evaluation of road is provided.

HIGHWAY MANAGEMENT SYSTEMS AND ROAD CONDITION EVALUATION

In order to administrate the existing road infrastructure, there are usually three levels of analysis that can be achieved by highway management systems: *strategy level* to analyze networks or sub-networks managed by any organization; *program level* to plan investments for one or more years, where many projects can be selected by priorities; *project level* to analyze one or a few roads as investment alternatives. This article focuses on the latter level.

On the other hand, the American Association of State Highway and Transportation Officials - AASHTO, propose three phases for rehabilitation selection process, as shown in figure 1.

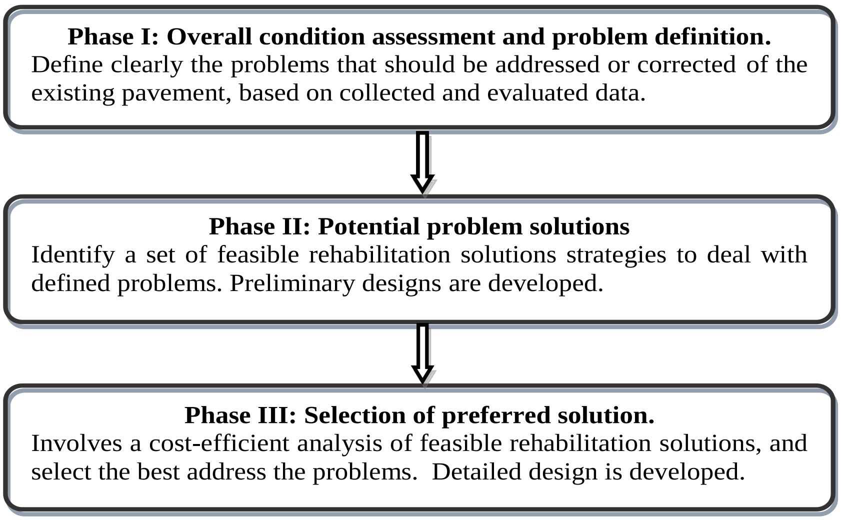


Figure 1 – Highway rehabilitation selection process. Adapted from AASHTO guide 1993.

The main interest in this paper is phase I and phase II, due to the hard work that must be done to assess overall condition, problem definition and setting up potential solutions.

According to the National Cooperative Highway Research Program – NCHRP, phase I can be established by assessing the following aspects: Structural adequacy related with the response of the pavement to traffic loads; functional adequacy related with pavement surface features; subsurface drainage adequacy; durability material adequacy; shoulder condition; maintenance history; variability of pavement condition within a project; miscellaneous constraints like lateral clearance and traffic control restrictions.

Table 1 summarizes the main criteria to judge the adequacy of existing flexible pavements, proposed by NCHRP, depending on relevant distresses and severity levels, for interstate highways in particular.

Table 1 – Overall condition assessment for flexible pavement highways

EVALUATION	VARIABLE OR DISTRESS TYPE	ADEQUACY LEVEL		
		Inadequate	**Marginal**	**Adequate**
STRUCTURAL	Fatigue Cracking, (% of wheel path area)	>20	5 to 20	<5
	Longitudinal Crackingin in wheel path (ft/mi)	>1060	265 to 1060	<265
	Reflection Cracking width (in)	> 0.5	0.25 to 0.5	< 0.5
	Transverse Cracking spacing (ft)	< 100	100 to 200	> 200
	Rutting, mean depth of both wheel paths (in)	> 0.4	0.25 to 0.4	< 0.25
	Shoving (% of wheel path area)	>10	1 to 10	None
	Strength	**Low**	**Mean**	**High**
	Asphalt Concrete Modulus (psi)	300000	500000	1500000
	Cement treated base	250000	600000	1000000
	Asphalt treated base	100000	250000	500000
	Granular base	15000	30000	40000
	Soil cement	50000	75000	100000
	Granular subbase	8000	15000	25000
	Coarse Subgrade	7000	12000	20000
	Fine subgrade	3000	5000	7000
FUNCTIONAL	Smoothness	**Inadequate**	**Marginal**	**Adequate**
	IRI (in/mile)	>175	100 to 175	<100
DRAINAGE	Asplat Concrete Stripping	Signs of stripping	No signs of stripping	No signs of stripping
	AC pumping (fines from underlying layers)	Signs of pumping	No signs of pumping	No signs of pumping
DURABILITY	Raveling	Loss of coarse aggregate	—	Loss of fine aggregate
	Rutting, mean depth of both wheel paths (in)	Same as structural adequacy		
	Shoving (% of wheel path area)	Same as structural adequacy		
	Block Cracking	Noted	—	None
	Bleeding (% of wheel path area)	>10	5 to 10	<5
	Stripping in Treated Base or Subbase	Unable to recover majority of cores. Some pumping of fines onto shoulder may be observed	Unable to recover some cores. Some pumping of fines onto shoulder may be observed	Cores are predominantly intact. No sign of pumping of fines from beneath pavement
	Unbound granular layers contamination	Contamination with fines from subgrade		
MAINTENANCE	%Surface area with deteriorated patching and other repairs	>15	8 to 15	<8

Adapted from "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures". ARA, Inc. y ERES Consultants Division NCHRP-TRB-NRC-2004.

It is necessary to handle a huge amount of information to assess an overall highway condition; accordingly, computational intelligence can play an important role, both to process information, so as to model properly any structural system of flexible pavement.

COMPUTATIONAL INTELLIGENCE

This branch of artificial intelligence merges elements of adaptation, learning, evolution and fuzzy logic, to develop "intelligent" programs, that allows modeling complex and variable systems. Hence, computational intelligence offers a possibility to involve a more humane way of thinking and reasoning on computer programming algorithms. Highway engineering has shown a special interest on Artificial Neural Networks and Fuzzy Logic applications, to solve specific problems related with pavement evaluation; there are successful experiences that reveal the large potential to be considered as an alternate analysis method.

Fuzzy Logic - FL

Through FL it is possible to consider fuzzy concepts like more, less, very, low, medium; those are intermediate values between crisp concepts from classical logic such as yes/no; true/false, belong/not belong, zero/one. In this way, ranges of values can be defined between crisp boundaries trough membership relations or functions, i.e. an element belongs to a fuzzy set with a certain degree of membership. Therefore, a proposition is neither true nor false, but may be in part true and in part false, to any degree.

Some parameters collected to evaluate the road condition are qualitative and therefore can't be considered into analytical or numerical traditional analysis. That is the case of severity levels of damage expressed as linguistic variables like adequate, marginal, inadequate, or severe, moderate, light, or high, medium, low; these qualities must be considered into analysis to establish how serious the problems are, and the feasible solutions which would be more appropriate. FL let overcome this constraint, expressing those parameters in mathematical way to process them, later by computational means.

Any distress level cited in table 1 could be represented in classical and fuzzy logic. For instance, crisp and fuzzy concept related to fatigue cracking adequacy is shown in figure 2. Here trapezoidal or triangular functions could be suitable fuzzy logic representations.

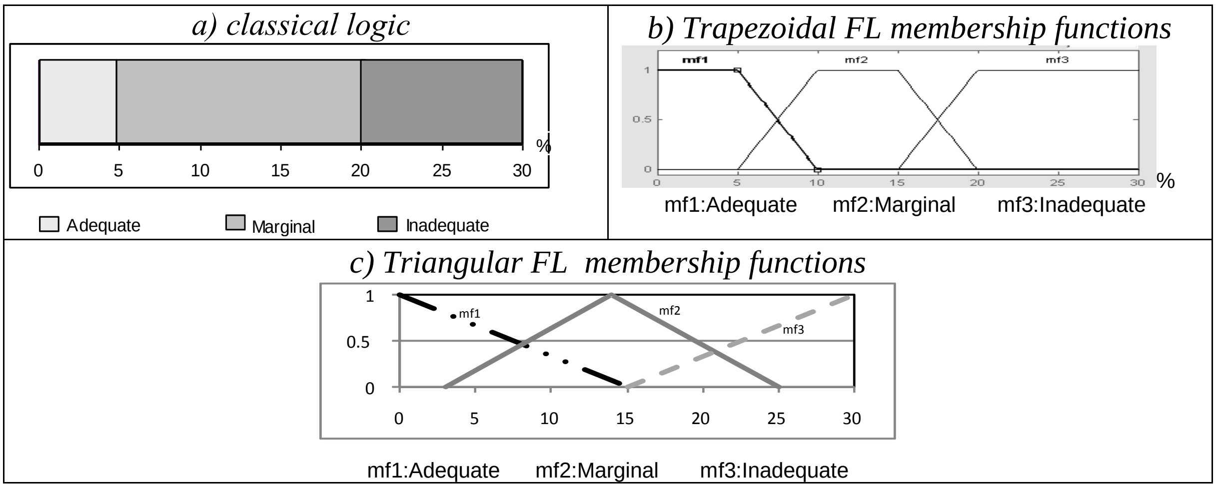


Figure 2 –Fatigue cracking adequacy representation

Artificial Neural Networks - ANNs

In practical terms, ANNs have been deemed as mathematic-statistical computational tools, useful to model complex non lineal problems, either for searching relationships for multivariate analysis in regression problems, or to recognize patterns in a data set for classification purposes.

ANNs are inspired on biological neural networks, and especially in the complex structure and efficiency of human brain; here intelligence is the result of high connectivity between the large amounts of brain neurons. In similar way, ANNs are formed by interconnected processing neurons that receive, process and transmit signals or information to others which are connected; each link have associated a value called weight, which can be fitted to simulate any feature or behavior in particular. Results of modeling depend on how the neurons are interconnected (architecture) and the strength of those connections (weights values).

An ANN is a parallel multilayer structure, formed by an input layer, hidden layers and output layer; each layer is constituted respectively by input neurons, hidden neurons and output neurons, as is shown in figure 3. Complex architectures have been associated to non lineal problems.

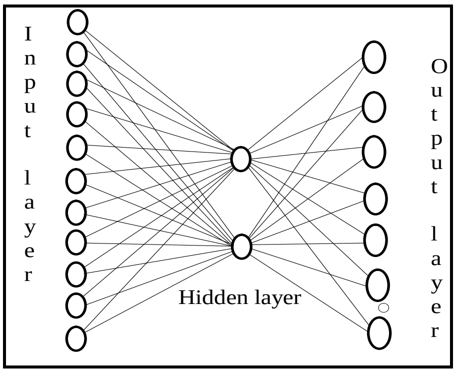


Figure 3 – Basic configuration of Artificial Neural Network model.

There are two stages in ANN models: the first is the *training* stage, were learning is achieved to get knowledge from a data set. The second stage is *testing* to reach generalization that is the capability to generate reasonable outputs for new data input sets, different from that used during learning stage.

The learning process in turn, could be *supervised* if desired output is given for the specified inputs. Here connections weights are adjusted until any error criterion is satisfied when comparing computed and desired output. *Reinforced* learning is useful when there are traces about the output for each input. In contrast, *unsupervised* learning does not need desired outputs, because ANN receives inputs or patterns, find out significant features and learns how to classify them into suitable categories.

A hard work must be done to identify all elements involved in ANN modeling: Architecture, learning rules, error function, input function, transfer function. All those elements depend on data base and the type of problem to address.

Highway Assess Using Computational Intelligence

As part of research efforts to apply ANN in pavement maintenance in Sweden, Sundin & Braban-Ledoux (2001) reviewed almost 40 articles published from 1987 to 1999, to settle a state of the art about artificial intelligence based decision support technologies in pavement management. Authors summarize main findings and potential of expert systems, ANN, FL, genetic algorithms and hybrid systems for diagnosis, analysis, design and choice phases of pavement management decision process.

Unfortunately many of those reported cases were developed using synthetic data, and therefore the authors cite:

> "The real challenge is to develop an application that performs significantly better than the models commonly used by pavement engineers on the basis of real data collected from field."

In the last decade, the Texas Department Transportation and the Federal Highway Administration have conducted many projects where computational intelligence tools are ever more frequent used. For example, Abdallah et al (2000) developed an ANN model to predict remaining life of flexible pavement, taking into account different agencies criteria. At that stage, synthetic non destructive testing data was used to propose de model, and actual data expect to be used later to validate the methodology.

In that direction, Williams et al (2004) showed that FL method was the most appropriate for processing non destructive testing - NDT data via data fusion technique, in order to get representative values of mechanical parameters of pavement layers determined from different sources. Abdallah et al (2005) used this method in some case studies, with real data collected from field.

Yella et al (2006) summarize the findings of a large number of research papers using artificial intelligence techniques such as neural networks, machine learning, expert systems, ease-based reasoning and fuzzy logic, in a wide variety of problems in railway infrastructure inspection area. They put special interest on processing NDT information, usually performed as signals, images and so on, which often do not show directly the infrastructure condition; so, data need to be interpreted by a human skilled analyst, whose criterion could be unreliable or subjective, since he is challenged by many factors. The authors find significant advantages of computer-based techniques to: automate the knowledge of analysts, interpretation of large volume of NDT data and to improve speed and accuracy of analysis.

There are many other investigations in which computational intelligence have played an important role to solve any particular problem in highway engineering. For instance, to get structural properties of pavement layers, Goktepe et al (2005) mention some studies conducted from 1993 (Meier y Rix) to 2003 (Terzi, Saltan y Yildirim), in which ANN and FL are used to estimate mechanical properties of pavements, such as layer modulus based on NDT information. More recent works conducted by Reddy et al (2004 & 2006), Goktepe et al (2006), Rakesh et al (2006), Saltan et al (2006 & 2007), Sharma & Das (2008), have been focused on finding more accurate and efficient structural models, using optimization algorithms and hybrid models for structural condition evaluation.

All these studies show the exceptional modeling ability of computational intelligence tools; according to this background, the major benefits of using techniques such as artificial neural networks and fuzzy logic are: quantitative and qualitative information collected by different sources along any highway can be considered for analysis; overall condition assessment and problem definition can be clearly established, taking into account the whole significant parameters through multivariate analysis. Efficiency has been demonstrated trough low computational cost to perform real time analysis and accurate results.

Despite the successful experiences obtained, there are still some constraints: Goktepe et al (2006) remark the need to be careful with the use of ANN, because causal material model and mechanical analysis do not exist to estimate mechanical responses of pavements; here results depend strongly on quality and quantity of data set learning. In contrast, most authors consider those techniques as approximations that engage all mechanic laws that influence natural complex systems difficult to model, without falling into simplified assumptions of traditional theoretical models.

PROPOSED METHODOLOGY

Based on practice and experience, state of the art and theoretical knowledge about pavement engineering and computational intelligence, the basic plan sown in table 2, is formulated to asses an overall condition of highway infrastructure.

Table 2 – Neuro-fuzzy based methodology for condition assessment of highways

STAGE	DESCRIPTION	METHOD
Organizing data base	Classify significant variables by condition type to assess, according to NCHRP: structural, functional, drainage, durability, maintenance	Empirical knowledge
Preliminary Analysis	Graphic variables relationships to see global behavior, responses of pavement, preliminary zones and eventual atypical data.	Empirical knowledge
Parameter Identification	Parameters associated with each condition type, are derived or computed from data base.	Artificial Neural Network System
Assessing adequacy by condition type	Define problems to address by each condition type. FL is used for setting up membership functions for qualitative parameters such as severity levels of distress. ANN is used for mapping the real condition of whole road, trough relations identified between input variables and response observed. Homogeneous and transitions zones could be defined by FL.	Hybrid Neural – Fuzzy System + Empirical Knowledge
Potential solutions	As rehabilitation alternatives depend on road condition, FL is used for creating rules to facilitate selection of potential solutions, based on NCHRP criteria.	Empirical knowledge + Fuzzy Logic Rules

Implementation of proposed methodology

To show an application of mentioned strategy, a detailed methodology for ***structural assessment*** of highways is developed. A case of study was considered through a road section 28 km long in Mexico, with available information about non destructive testing measure on the pavement surface; results of traditional analysis are available too for validation purposes.

Stage 1: Organizing data base

Variables needed for structural adequacy assessment, can be classified as seen in table 3.

Table 3– Variables considered for structural evaluation

Type	Variable
Structural features	Layer thickness and depth Type of layer material (Poisson ratio)
Testing	Distresses and severity levels (see table 1) 278 Deflection tests (applied load, measured deflections and basin area)
Strength	Layer modulus, structural index, structural rating

Stage 2: Preliminary analysis

Based on available non destructive testing data, and taking into account the response and condition of pavement, two types of pavement structures can be identified along the analyzed road. In the first 7.5 km and the last 13 km of the road, the pavement is formed by 7 cm of asphalt concrete, 12 cm of granular base, 30 cm of cement stabilized sub-base, for a total thickness of 49 cm. In the 7.5 km intermediate zone, the total thickness is about 42 cm because the base layer doesn't exist; instead there is an asphalt base layer of 5 cm thick. In this last sector, the pavement exhibits the highest level of deflections, rutting and structural distresses.

Stage 3: Parameter identification

In parameter identification stage, stiffness related parameter is estimated. A common practice is estimation of layer modulus based on layer thickness of pavement structure and non destructive deflection testing, which measure the instantaneous deflection basin response to an impulse load applied on the pavement surface, similar to traffic load.

ANN is proposed to model deflection basin and estimating layer modulus. For this purpose input variables are: applied load, layer thicknesses and depth, Poisson ratio for each layer and measured deflections; layer modulus estimated previosly by elastic theory are deemed as rough outputs.

The first task is to identify the best network architecture to simulate the problem. Using actual field data, a sensitivity analysis was conducted to determine all elements involved in ANN modeling; as a result reinforced learnig shows better performance than supervised learnig through an ANN with following features: one hiden layer with 4 hidden neurons, Jordan recurrent architecture, Jacob enhanced back-propagation rule learning, mean absolute error function, dot product input function and sigmoid transfer function. An error of 1.7% was obtained in less than 2 minutes of processing demonstrating the accuracy and computational efficiency of ANN modeling. Figure 4 ilustrates layer modulus estimated along the analized road from both neural model and traditional elastic theory. Shaded areas indicates typical layer modulus values.

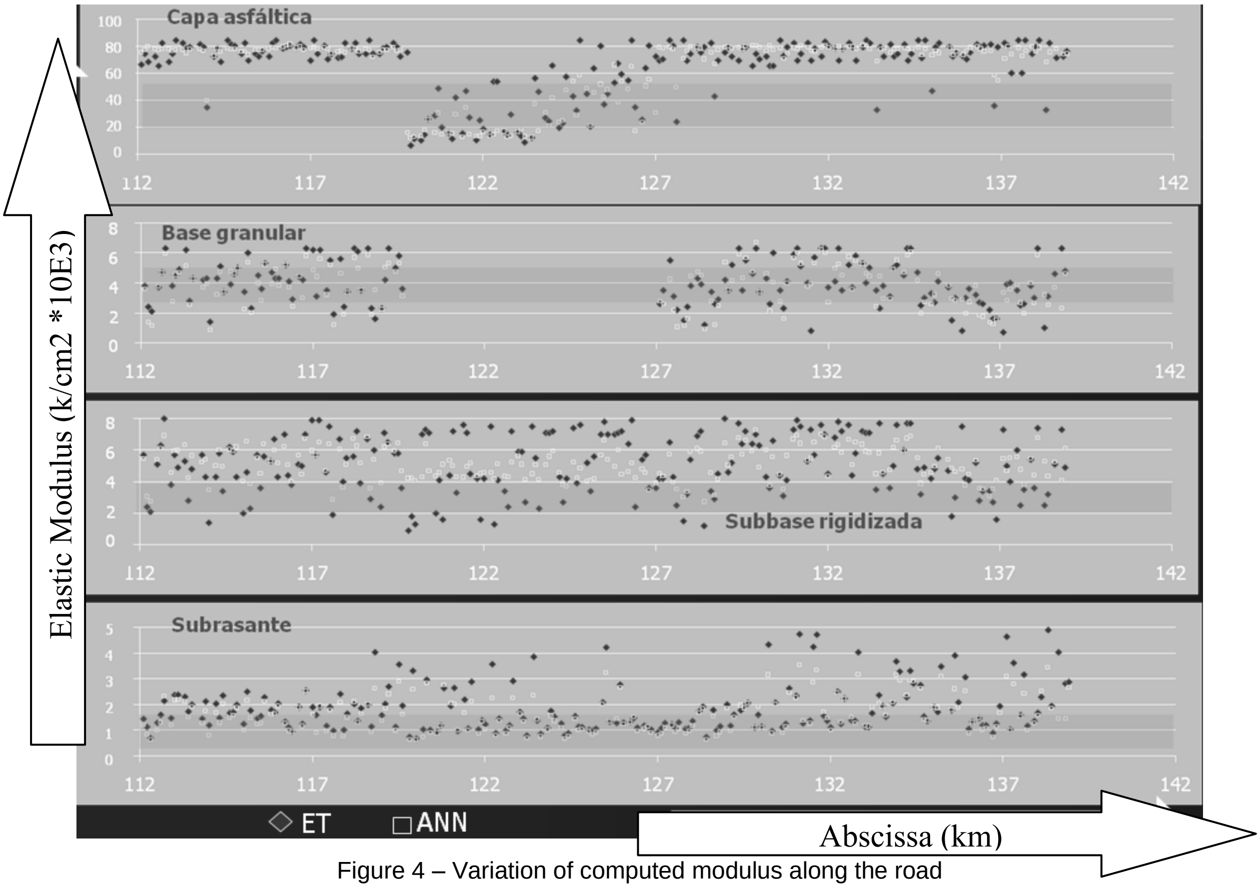


Figure 4 – Variation of computed modulus along the road

On the other hand, figure 5 illustrates results obtained through ANN deflection basin modeling. The comparative analysis between computed and measured deflections indicates the great capacity of ANN model to reproduce the pavement response under deflection tests. An error of 1.8% was obtained in less than three minutes of processing. It is important to notice that values away from measured deflections match with sites where pavement exhibit severe structural damages.

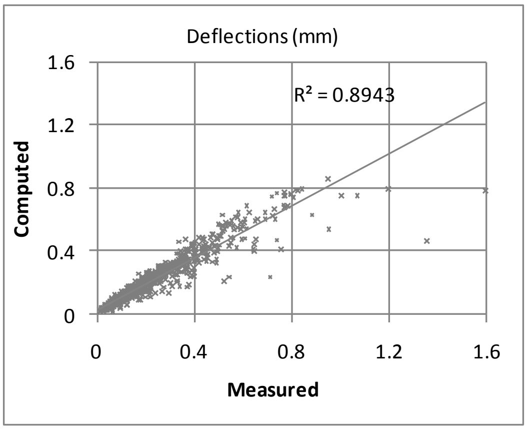
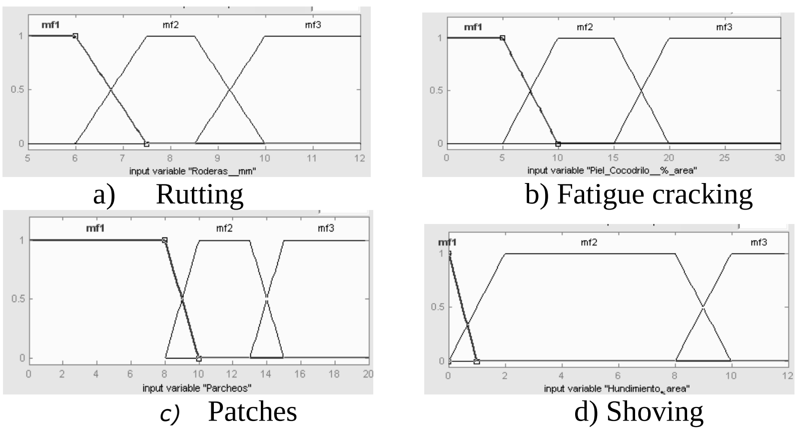


Figure 5 – Computed and measured deflection relationship

Stage 4: Structural Adequacy Assesment

With the aim to involve qualitative parameters into analysis, fuzzy representation of each distress adequacy level have to be defined first. Based on experts recommendations, trapezoidal membership functions that better map the NCRHP criterias are proposed, as shown in figure 6.



mf1 = Adequate *mf2 = Marginal* *mf3 = Inadequate*

Figure 6 - Membership functions for damage severity levels

Now, a hybrid neuro – fuzzy system is proposed for mapping the real structural condition of whole road: estimated layer modulus and FL membership functions for damage levels can be integrated with whole aditional structural information as input in a new ANN model; available indicators such as structural rating and structural Index are asumed as desired outputs.

As a result, relations between input variables and response derived can be established; then FL rules could be definen to describe any specific condition of pavement, ranging between two extreme conditions: IF all parameters and indicators are adequate, THEN the pavement condition is excellent; IF all parameters and indicators are inadequate, THEN the pavement condition is dreadful. Additional rules for intermediate conditions like very good, good, fair and poor categories are defined.

For the case of study, homogeneous sectors are defined in table 4 from pavemen condition assesment.

Table 4 – Homogeneous zone definition

No.	SECTOR	STRUCTURAL CONDITION	OBSERVATIONS
1	1K112 to K114.5	Poor	Marginal potholes and rutting
2	K114.5 to K116.5	Very good	
3	K116.5 to K118	Good	Marginal potholes
4	K118 to K119.5	Fair	Marginal rutting; eventual low modulus in base layer.
5	K119.5 to K124	Dreadful	Marginal potholes, fatigue cracking and patching; inadequate to marginal rutting; low modulus in asphalt and subbase layers.
6	K124 to K127	Poor	Marginal potholes, fatigue cracking and rutting.
7	K127 to K129	Dreadful	Marginal to inadequate potholes; marginal fatigue cracking and rutting; inadequate shoving; low base layer modulus.
8	K129 to K133	Very good	
9	K133 to K135	Fair	Marginal potholes and eventual low modulus in base layer
10	K135 to K137.5	Poor	Marginal potholes; low base layer modulus
11	K137.5 to K140	Poor	Marginal potholes and patching

Stage 5: Potential solutions

Based on NCHRP criteria, a pavement is considered that has failed If any current distress level exceeds values specified under the “inadequate” category; in those cases large-scale corrective actions are needed. That is the case of sectors No. 5 and 7.

Pavement with one or more structural related distresses in the “marginal” category will need any rehabilitation activity soon before pavement reach inadequate structural condition. Sectors No. 1, 6, 10 and 11 fall into this category.

Sectors No. 4 and 9 are classified into fair condition, because they exhibit only one marginal damage and eventual low base layer modulus; however, derived solutions depends on the type of distress.

Sectors No. 2 and 8 only need routine preventive actions, and sector No. 3 need full or partial depth repair at specific sites of potholes.

Although NCHRP criterias for solution identification are considered appropriate, they are not always enough to take into acount the large amount of damages, severity levels and stifness condition of pavemen layers. Then, aditional criteria based on experts and own experience are involved to increase the feasible rehabilitation solutions. Table 5 shows basic suggestions of NCHRP.

Table 5 – Main rehabilitation strategies for structural distresses

DISTRESS TYPE	REPAIR SOLUTION	PREVENTIVE SOLUTION	OTHER SOLUTIONS
Fatigue cracking	Full depth repair	Crack sealing	Partial depth repair, cold milling, hot or cold in situ recycling, overlay
Block cracking	Crack sealing		
Longitudinal cracking	Crack sealing		Full depth repair, hot or cold in situ recycling, overlay
Reflective cracking	Full or partial depth repair	Crack sealing	
Shoving	Level up overlay		
Potholes	Full depth repair	Crack sealing and seal coating	Partial depth repair
Rutting	Level up overlay or cold milling		Hot or cold in situ recycling

Adapted from "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures". ARA, Inc. y ERES Consultants Division NCHRP-TRB-NRC-2004.

Bearing in mind the above relevant conditions, FL is used now for rules definition process in order to facilitate selection of alternatives; below are some rules derived.

Rule1: IF fatigue cracking is Inadequate, THEN full OR partial depth repair, OR recycling is needed

Rule2: IF fatigue cracking is marginal, THEN crack sealing is recommended

Rule 3: IF block cracking is inadequate OR marginal, THEN crack sealing is needed

Rule 4: IF longitudinal cracking is inadequate or marginal, THEN crack sealing is needed

Rule 5: IF reflective cracking is inadequate, THEN full or partial depth repair is needed

Rule 6: IF reflective cracking is marginal, THEN crack sealing is recommended

Rule 7: IF shoving is inadequate, THEN level up overlay is needed

Rule 8: IF pothole is inadequate, THEN full OR partial depth repair is needed

Rule 9: IF Rutting is inadequate, THEN level up overlay OR cold milling OR in situ recycling is needed

Finally, depending on the structural condition of pavement, distreses types and severity levels, integrated solutions are proposed in table 6, for the particular analized highway.

Table 6 – Rehabilitation solutions for a case of study

No.	SECTOR	STRUCTURAL CONDITION	FEASIBLE SOLUTION
1	1K112 to K114.5	Poor	Hot or cold in situ recycling, or cold milling
2	K114.5 to K116.5	Very good	
3	K116.5 to K118	Good	Local partial depth repair (potholes)
4	K118 to K119.5	Fair	Hot or cold in situ recycling; structural reinforcement overlay.
5	K119.5 to K124	Dreadful	Full depth repair.
6	K124 to K127	Poor	Hot or cold in situ recycling, or cold milling.
7	K127 to K129	Dreadful	Full depth repair.
8	K129 to K133	Very good	
9	K133 to K135	Fair	Local partial depth repair (potholes) and structural reinforcement with overlay
10	K135 to K137.5	Poor	Local partial depth repair (potholes) and structural reinforcement with overlay
11	K137.5 to K140	Poor	Partial depth repair.

In this way a complete structural evaluation is made, integrating elements from empirical knowledge, FL, ANN and hybrid systems.

CONCLUSIONS

Previous investigations show the exceptional ability of computational intelligence tools for modeling highway infrastructure problems related to overall condition evaluation. Most of the reported cases were developed using synthetic data; therefore efforts have to be made to develop novel alternatives to model those problems, on the basis of actual field data.

Based on previous investigation, theoretical foundations, experience and practice, a general method is proposed to asses an overall condition of highway infrastructure. In order to show an application of proposed methodology, an innovative non conventional way to address structural problems of highways is developed; this methodology combines different fields of knowledge, involving ANN and FL techniques to analyze technical information previously collected along flexible pavement highways.

Here FL is used for qualitative parameters representation, homogeneous zones definition and for creating rules to facilitate selection of rehabilitation alternatives. ANN is proposed for estimating layer modulus and modeling deflection basin purposes, in parameter identification stage; here ANN modeling shows a great capacity to reproduce the pavement response under deflection tests. For adequacy assessment stage, ANN is proposed for mapping the real structural condition of entire road.

The methodology is proposed for project level analysis of flexible pavement highway management system; special interest is focused on condition assessment, problem definition and setting up potential solutions, taking into account the NCHRP criterion.

The main benefits identified of neuro-fuzzy modelling of highways performance are:

1. Quantitative and qualitative information collected by different sources along any highway, can be considered into analysis.

2. Condition assessment and problem definition can be clearly established, taking into account the whole significant parameters of highway infrastructure.

3. Structural parameters can be estimated using non destructive testing processing information.

4. Multivariate non-linear regression analysis is feasible through ANN to model complex pavement problems.

5. Definition of homogeneous zones based on road condition, with the capability to identify transitions zones instead of crisp boundaries defined by traditional models. Sector No. 4 is an example of transition zone.

6. Efficiency has been demonstrated trough low computational cost to perform real time analysis and accurate results.

Rather than identify limitations and advantages of computational intelligence methods over traditional analysis, the main interest in this work was to show the ability of neuro-fuzzy model to represent reality, evaluated by means of relationships between observed and predicted behaviors.

FINAL REMARK

The proposed methodology is part of the efforts being made by that the “Instituto de Ingeniería” of the “Universidad Autónoma de Mexico” to implement soft computing based solutions for some civil engineering problems. For highway engineering in particular, succesfull preliminary results have been found for processing NDT information and parameter identification. It soon expects to complete the implementation of this methodology so that could be used as an additional tool in making decisions related to highway management systems.

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