ROAD-PERFORMANCE ASSESSMENT FOR MANAGEMENT SYSTEMS
- A SOFT COMPUTING BASED APROACH –

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ABSTRACT

With the aim of exploring innovative ways to address road-performance evaluation in México, this work provides an approach to some promising methods of analysis based on soft computing techniques. A non-conventional methodology that combines Artificial Neural Networks - ANNs and Fuzzy Logic - FL, is presented to help making decisions for road management systems in project level for existing asphalt concrete pavements, based on non-destructive testing data. Here ANNs are intended to mechanical parameters estimation of pavements and FL is used to represent qualitative parameters and creating rules to facilitate selection of rehabilitation alternatives.

A case study was considered to evaluate benefits, limitations and accordingly, think of its applicability to larger scale. The main benefits identified of this methodology for road performance assessment are: quantitative and qualitative parameters can be considered into analysis; condition assessment and problem definition can be clearly established, taking into account most of significant parameters; straightforward multivariate non-linear regression analysis is feasible; efficiency is demonstrated trough low computational cost to perform real time analyses and reliable results.

1. INTRODUCTION

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.

Previous research and case studies have shown that soft computing tools are efficient, non-deterministic and very realistic approximations to deal with highway management problems.

This report is part of the efforts being made by the “Instituto de Ingeniería” of the “Universidad Nacional Autónoma de Mexico, UNAM” to implement soft computing based solutions for some civil engineering problems. For road condition assessment in particular, successful outcomes have been found in terms of processing non-destructive testing – NDT data, parameter identification and potential solutions identification, useful for making decision processes.

Beyond identifying limitations and advantages of soft computing methods over traditional procedures, this work intend to exploit the ability of ANNs and FL to simulate complex non-linear pavement’s problems. Here, both tools are combined as an analysis method close to the representative physical phenomenon of roads, which is evaluated by comparing the observed and predicted behaviour.

In order to give a general framework, main concepts about highway management systems, road condition evaluation and soft computing tools are presented in the first sections. Later, some relevant investigations about soft computing applied to highway engineering analysis are described. Finally, soft computing tools applied to structural evaluation of a case study is exposed.

2. PAVEMENT EVALUATION AND MANAGEMENT SYSTEMS

There are usually three levels of analysis that can be achieved by pavement management systems: strategy level to analyse 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 analyse one or a few roads as investment alternatives. This article focuses on the latter level, assessing the phases for rehabilitation selection process shown in figure 1.

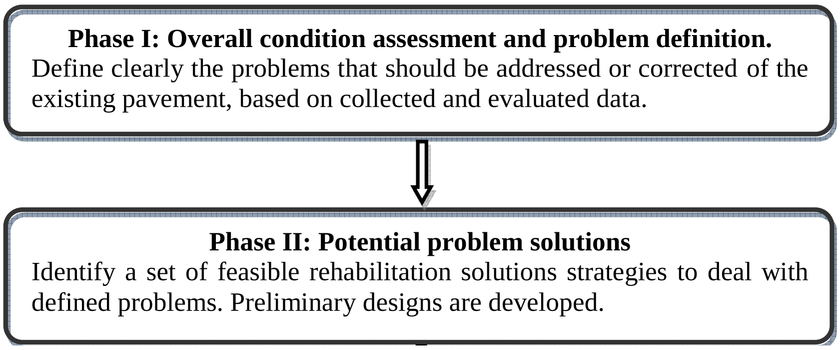


Figure 1 – Phases considered for pavement rehabilitation selection process. Adapted from AASHTO guide 1993.

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.

The main interest now, is to focus on structural condition, which can be evaluated by layer thicknesses and many other parameters. In this way, main criteria of NCHRP to judge the structural adequacy of existing pavements are assumed: layer modulus, cracking, rutting and shoving distresses. Table 1 summarizes the relevant distresses and severity levels, for interstate highways in particular. Additionally, potholes were considered as structural damages too.

All these parameters can be determined by means of non-destructive testing. For this study, damages and severity levels were determined by visual inspection, rutting by laser sensors measurements and strength parameters by Falling Weight Deflectometer-FWD tests. Layer thicknesses were determined by means of destructive testing.

Non-destructive techniques produce huge amounts of information, from which pavement conditions can be assessed. To carry out this task, in this paper a soft computing approach is proposed both to process information and to model properly pavement's structural system.

Table 1 – Structural condition parameters for pavement assessment

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

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

3. SOFT COMPUTING

This technique merges elements of adaptation, learning, evolution and fuzzy logic, to develop "intelligent" programs that allow modelling complex and variable systems. Hence, it 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 great potential to be considered as an alternate analysis method.

3.1. Fuzzy Logic - FL

Through FL it is possible to consider fuzzy concepts like more, less, very, low, medium; these are in between values of crisp concepts from classical logic such as yes/no; true/false, belong/not belong, zero/one.

Some parameters collected to evaluate road conditions are qualitative and therefore not suitable for analytical or numerical analysis. That is the case of damage severity levels 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 a problem is, and the feasible solutions which would be more appropriate.

FL let overcome this constraint, expressing qualitative parameters in a mathematical way to process them, later, by computational means. Membership functions can be defined so that a proposition is neither true nor false, but may be in part true and in part false, to any degree.

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 are shown in figure 2. Here trapezoidal or triangular functions could be suitable fuzzy logic representations. In fact there are many other possibilities.

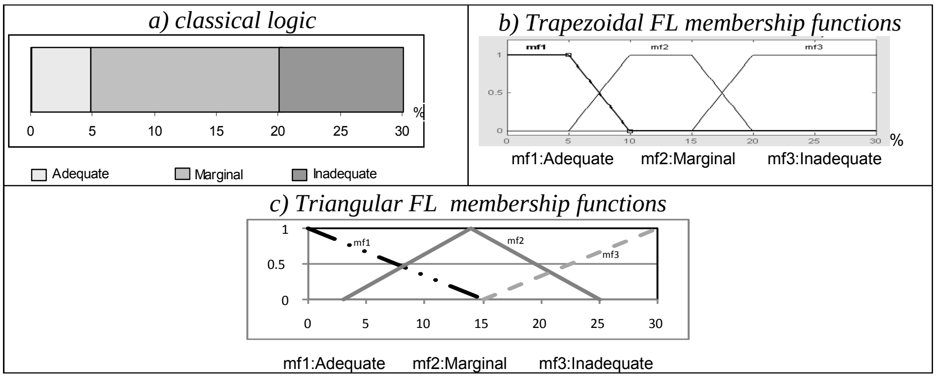


Figure 2 –Fatigue cracking adequacy representation

3.2. Artificial Neural Networks - ANNs

ANNs have been deemed as mathematic-statistical computational tools, useful to model complex nonlinear 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 behaviour in particular. Results of modelling depend on how the neurons are interconnected (architecture) and the strength of these 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 nonlinear problems.

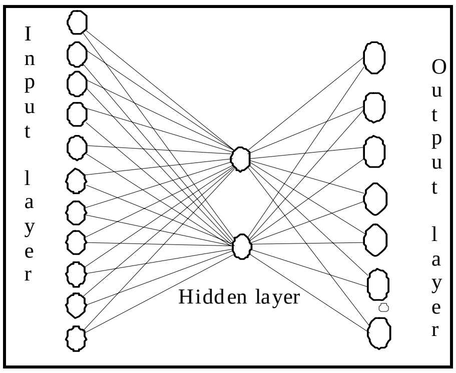


Figure 3 – Basic configuration of Artificial Neural Network model

There are two stages in ANN models: the first is the training stage, where learning is achieved to get knowledge from a data set. The second stage is testing to evaluate the ANN capabilities to yield reasonable outputs for new data input sets, different from those used during the learning stage.

The learning process, in turn, could be supervised if a desired output is given for the specified inputs. Here connections weights are adjusted until any error criterion is satisfied when comparing computed and desired (target) 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 modelling: Architecture, learning rules, error function, input function, transfer function. All those elements depend on data base and the type of problem to address.

3.3. Highway Assess Using Soft Computing

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 and wrote a state of the art about artificial intelligence-based decision to support technologies in pavement management. These 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 the reported cases were developed using synthetic data, and therefore the authors made the following statement: “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 soft computing tools have been more frequently used. For example, Abdallah et al (2000) developed an ANN model to predict the remaining life of a flexible pavement, taking into account different agencies criteria. In their study, synthetic non-destructive testing data was used to develop the model, and await actual data to validate the methodology.

Williams et al (2004) showed that FL was the most appropriate method 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) summarized 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 did not show directly the infrastructure condition; accordingly, some data needed to be interpreted by a human skilled analyst, whose criterion could be unreliable or subjective, since he is challenged by many factors. The authors found 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 soft computing played an important role to solve particular problems in highway engineering. For instance, to get structural properties of pavement layers, Goktepe et al (2005) mention some studies conducted from 1993 (Meier and Rix) to 2003 (Terzi, Saltan and 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 and 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 modelling ability of soft computing tools.

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.

4. SOFT COMPUTING APROACH FOR ROAD-PERFORMANCE ASSESSMENT - A CASE OF STUDY

A road section in Mexico, with available information about non-destructive testing data, was considered as case of study; road conservation and monitoring is in charge of Secretaría de Comunicaciones y Transportes – Veracruz (Orozco, 2005). Results of traditional analysis are available too for comparison purposes.

General characteristics of the analysed road section are presented first; subsequently, mechanical parameter identification through ANNs modelling is described; later, the inclusion of FL is described to represent pavement's qualitative parameters and to develop fuzzy inference rules for decision-making processes related to rehabilitation alternatives.

4.1. Characteristics of Corridor

Based on available testing data, and taking into account the response and condition of pavement, two types of pavement structures can be identified along the 28 km length of analysed road (K112 to K140), as shown in figure 4.

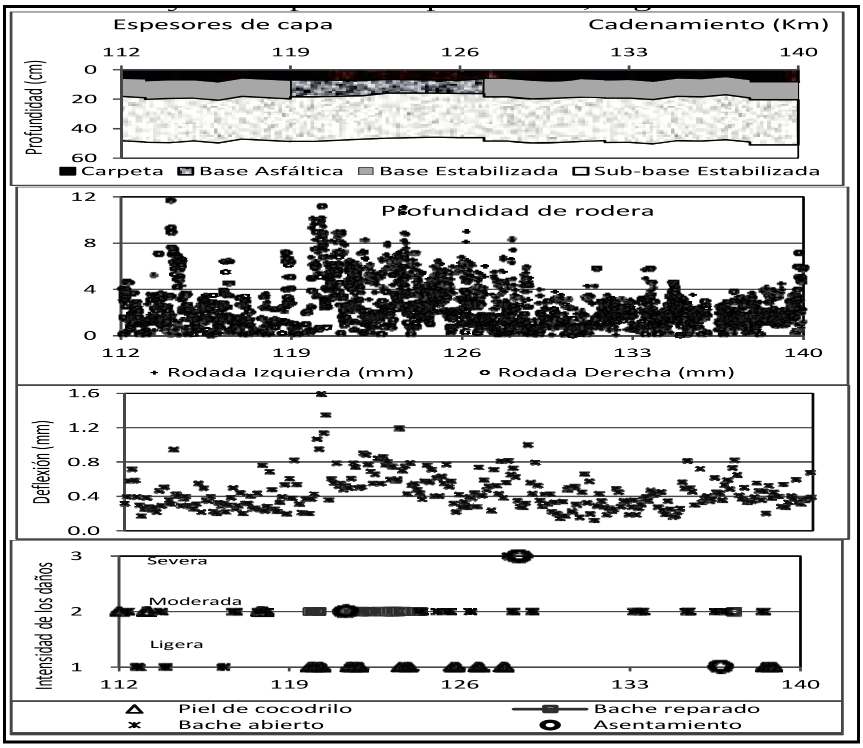


Figure 4 - Main features of corridor. (Modified from Orozco, 2005)

In the first 8 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 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.

4.2. Parameter identification

In this stage, stiffness related parameter is estimated. A common practice to estimate the stiffness (modulus) of pavement layers is based on the layer thicknesses of the pavement structure and non-destructive deflection testing, which measures the instantaneous deflection basin response to an impulse load applied on the pavement surface, similar to traffic load. Figure 5 shows a general arrangement for typical impact load deflection test.

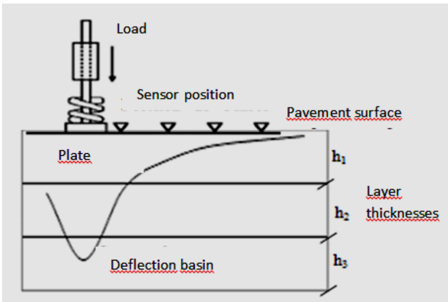


Figure 5 – Impact load deflection test

Variables needed for parameter identification, were classified as seen in table 2.

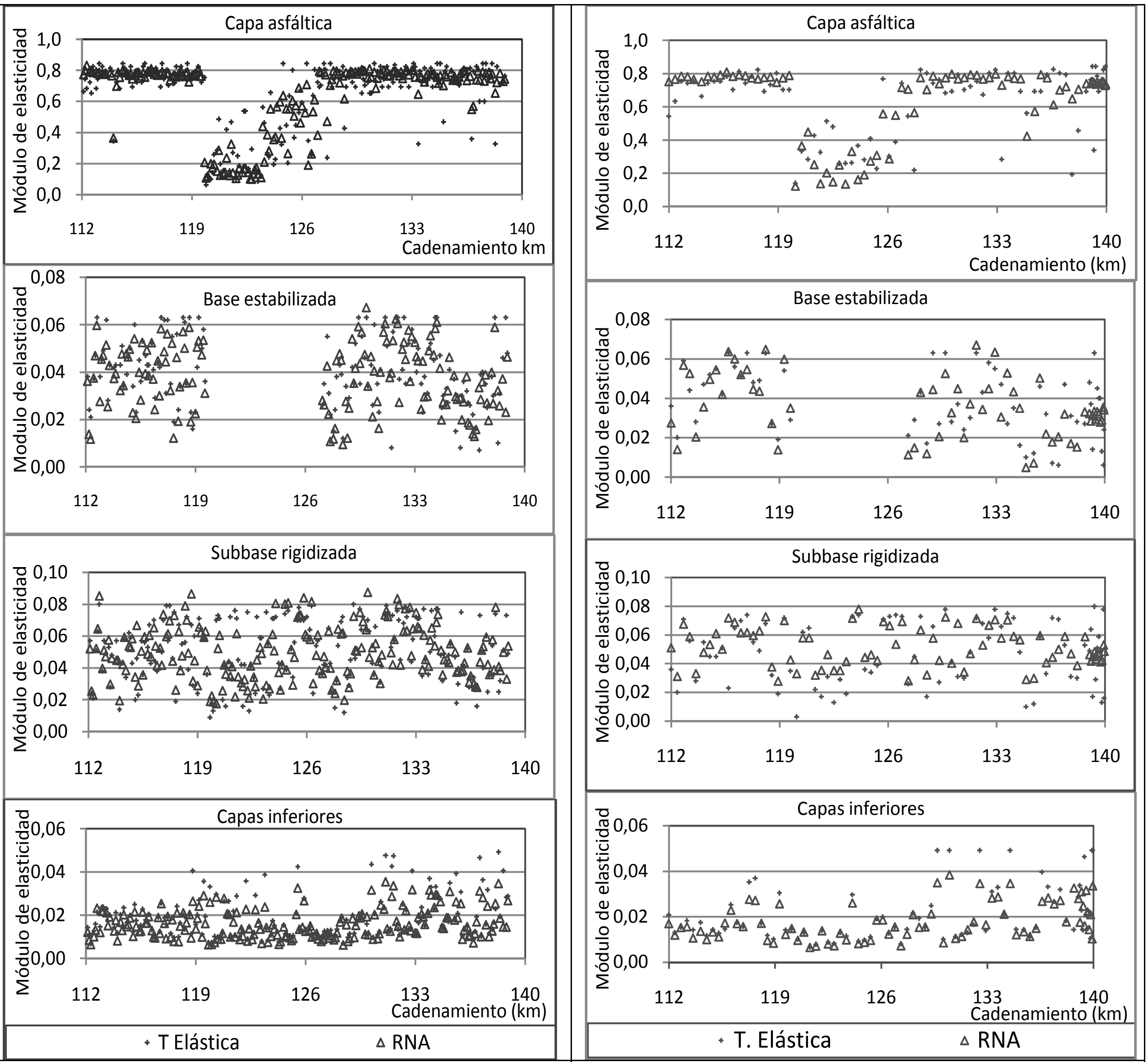
Table 2– Variables considered for parameter identification

Type	Variable
Structural features	Layer thickness and depth Type of layer material (Poisson ratio)
Testing	278 Deflection tests (applied load, sensors position, measured deflections)
Strength	Layer modulus (elastic theory traditional analysis)

ANN is proposed to model deflection basin and estimate layer modulus. For this purpose input variables are: applied load, layer thicknesses and depth, Poisson ratio and measured deflections; layer moduli estimated 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 modelling; as a result reinforced learning shows better performance than supervised learning through an ANN with following features: one hidden 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 modelling.

Figure 6 illustrates layer modulus estimated along the analysed road for ANNs training and testing stages; comparison with results obtained by traditional elastic theory is made too. The comparative analysis indicates the great capacity of ANN model to reproduce the pavement response under deflection tests.



a) Training stage   b) Testing stage

Figure 6 – Layer modulus estimations (kg/cm^2*10^5)

4.3. Structural condition assessment

Mapping the actual structural road condition is feasible through an intuitive analysis that integrates quantitative parameters (deflection, modulus) and qualitative variables (distresses severity levels).

With the aim to involve qualitative parameters into analysis, fuzzy representation of each distress adequacy level has to be defined. First, membership functions are proposed to map NCRHP criteria; figure 7 shows an example of fatigue cracking representation.

Then qualitative labels are defined to describe any specific condition of pavement: excellent, very good, good, fair, poor and dreadful, as specified in the table 3.

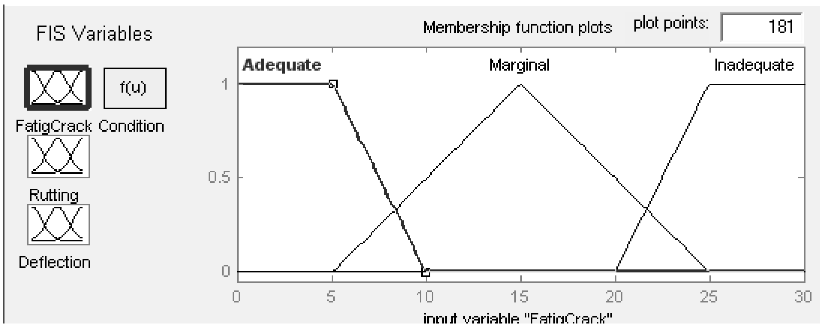


Figure 7 – Fuzzy representation of parameters

Here rules are defined to describe any specific condition of pavement, ranging between two extreme conditions: IF all parameters are adequate, THEN the pavement condition is excellent; IF all parameters are inadequate, THEN the pavement condition is dreadful. Additional rules for intermediate conditions like very good, good, fair and poor categories are defined.

Table 3 – Inference rules

1. If (FatigCrack is Adequate) and (Rutting is Adequate) and (Deflection is Adequate) then (Condition is Excellent) (1)
2. If (FatigCrack is Marginal) and (Rutting is Marginal) and (Deflection is Marginal) then (Condition is Good) (1)
3. If (FatigCrack is Inadequate) and (Rutting is Inadequate) and (Deflection is Inadequate) then (Condition is Dreadful) (1)
4. If (FatigCrack is Inadequate) or (Rutting is Inadequate) or (Deflection is Inadequate) then (Condition is Fair) (1)
5. If (FatigCrack is Adequate) and (Rutting is Adequate) and (Deflection is Marginal) then (Condition is VeryGood) (1)
6. If (FatigCrack is Marginal) and (Rutting is Adequate) and (Deflection is Adequate) then (Condition is VeryGood) (1)
7. If (FatigCrack is Adequate) and (Rutting is Marginal) and (Deflection is Adequate) then (Condition is VeryGood) (1)
8. If (FatigCrack is Adequate) and (Rutting is Marginal) and (Deflection is Marginal) then (Condition is Good) (1)
9. If (FatigCrack is Marginal) and (Rutting is Adequate) and (Deflection is Marginal) then (Condition is Good) (1)
10. If (FatigCrack is Marginal) and (Rutting is Marginal) and (Deflection is Adequate) then (Condition is Good) (1)
11. If (FatigCrack is Inadequate) and (Rutting is Inadequate) and (Deflection is Marginal) then (Condition is Poor) (1)
12. If (FatigCrack is Inadequate) and (Rutting is Marginal) and (Deflection is Inadequate) then (Condition is Poor) (1)
13. If (FatigCrack is Marginal) and (Rutting is Inadequate) and (Deflection is Inadequate) then (Condition is Poor) (1)

A representation of these fuzzy inference rules is presented in figure 8, using only three parameters: fatigue cracking, rutting and deflection. Here the condition is rated between 0 (dreadful) and 1 (Excellent).

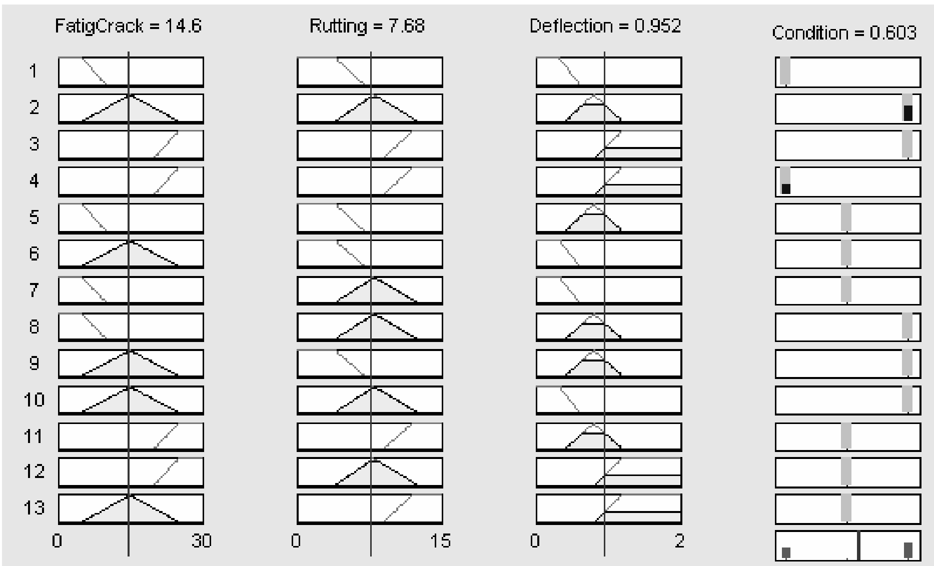


Figure 8 – Graphical representation of rules defined

Now, a Fuzzy Inference System is used to evaluate pavement's condition at any specific site, by combining all representative parameters. A summary of results is presented in table 4.

Table 4 – Results of Fuzzy Inference System

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 K140	Poor	Marginal potholes and patching; low base layer modulus

4.4. Potential Solutions Identification

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. Sector No. 1, 6 and 9 fall into this category.

Sector No. 4 is classified into fair condition, because it exhibits only one marginal damage and eventual low base layer modulus; however, solutions depend on the type of distress.

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

Table 5 shows basic rehabilitation solutions suggested by NCHRP; although these criteria are considered appropriate, they do not necessarily take into account the amount and diversity of damages, severity levels and stiffness condition of pavement layers. Then, additional criteria based on experts and own experiences are involved to increase the feasible rehabilitation solutions.

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

Rule 1: IF fatigue cracking is Inadequate, THEN full OR partial depth repair, OR recycling
Rule 2: IF fatigue cracking OR reflective cracking is marginal, THEN crack sealing
Rule 3: IF block OR longitudinal cracking is inadequate OR marginal, THEN crack sealing
Rule 4: IF reflective cracking is inadequate, THEN full or partial depth repair
Rule 5: IF shoving is inadequate, THEN level up overlay
Rule 6: IF pothole is inadequate, THEN full OR partial depth repair
Rule 7: IF Rutting is inadequate, THEN level up overlay OR cold milling OR in situ recycling

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.

Finally, integrated solutions for the analysed road are proposed in table 6, taking into account the structural condition of pavement, distreses types and severity levels.

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

It is worth to mention that tradicional analisis conducted in the same corridor recomends only one solution: milling and 5 cm overlay throughout the corridor (Orozco 2005).

Table 6 – Rehabilitation solutions for a case of study

No.	SECTOR	FEASIBLE SOLUTION
1	1K112 to K114.5	Hot or cold in situ recycling, or cold milling
2	K114.5 to K116.5	
3	K116.5 to K118	Local partial depth repair (potholes)
4	K118 to K119.5	Hot or cold in situ recycling; structural reinforcement overlay.
5	K119.5 to K124	Full depth repair.
6	K124 to K127	Hot or cold in situ recycling, or cold milling.
7	K127 to K129	Full depth repair.
8	K129 to K133	
9	K133 to K140	Local partial depth repair (potholes) and structural reinforcement with overlay

CONCLUSIONS

Previous investigations show the exceptional ability of computational intelligence tools for modelling highway infrastructure problems related to overall condition evaluation. Efforts should be focused to gather actual field data against which novel alternatives to model road-performance be tested.

Based on previous investigations, theoretical foundations, experience and practice, a non-conventional way to address structural problems of highways in México is presented. It combines different fields of knowledge, involving ANN and FL techniques to analyse technical information previously collected along flexible pavement highways.

Here FL is used to account for qualitative parameters representation and for creating rules to facilitate selection of rehabilitation alternatives. ANN is proposed for estimating layer modulus. The results show its great capacity to reproduce the pavement response under deflection tests.

Fuzzy representation of parameters considered in the case of study, along with fuzzy rules defined, lead to full description of corridor and to develop recommendations *ad hoc* to particular conditions along the road.

The main 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 most significant parameters through multivariate analysis. Efficiency is achieved trough low computational cost to perform real time analysis and accurate results.

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