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Evaluate The Asphalt Pavement Performance Of Rut Depth Based On Intelligent Method

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Abstract - The development of highway at Kurdistan in Iraq, requirement of road users is increasing. The key problem is to design the asphalt pavement construction to ensure pavement performance. Evaluation of asphalt pavement performance is very important method it concerned with quantitative and uncertain information. Fuzzy Petri net (FPN), as one type of high level Petri net, has shown a lot of attention recently due to its sufficiency, for knowledge representation and logic reasoning. In this paper we present an intuitive approach of FPN model for asphalt pavement performance evaluation. The model is based on the theory of FPNs is used to describe a formal model of knowledge representation for vague information of asphalt pavement (i.e. rut depth).The proposed approach is to bring asphalt pavement performance evaluation within the powerful modeling method of FPN tools. The input values in our model the surface thickness (*ST*), traffic count (*TC*) and age (*A*) can be formulated as uncertain fuzzy tokens to determine the rut depth values at time instance (*t*+1). The FPN components and functions consist of some types of fuzzy operators AND operator (*MIN*) and OR operator (*MAX*) of If-parts and Then-parts in fuzzy rules.

Index Terms— *Asphalt Pavement Performance; Fuzzy Petri net; fuzzy reasoning; Rut Depth.*

I. Introduction

In asphalt pavement construction permanent deformation is one of the major harasses that influence asphalt pavement performance. Asphalt pavement scientists tend to agree that predictive model is a critical element in determining restoration strategies to reducing expends. However, the cause of rutting is complicated and is a function of molding variables, which results in the poor performance of many of the existing models [I, 2, 3]. PNs and fuzzy logic exhibit a graphical and mathematical method to model, and simulate different systems. It is used for representing fuzzy rules (FRs) in the knowledge base, and executing fuzzy reasoning to evaluate the truth degrees of goal propositions. Straight with the speedy advance of the expert system, the characterizations of FRs are more and more complex. Thus, researchers conducted their researches with extended FPN theory and developed many improved FPN models, which include FPNs reasoning system generalized FPNs and more ever reversed FPNs, incorporating the fuzzy logic with Fuzzy Petri Nets it has been widely used to deal with these types of problems [4, 5, 6].

The explanation of how to reach conclusions is expressed through the movements of tokens in FPNs [7]. The field of fuzzy Petri nets may have an important impact in understanding how the systems work, giving at the same time a way to describe, manipulate, and analyse them. The application of modeling the asphalt pavement performance evaluation [8, 9], FPNs as a new tool for predicting the asphalt pavement values at time instance (*t*+1) for each input variables surface thickness (*ST*), traffic count (*TC*) and age (*A*) at time instance *t* are investigated in this paper.

The method presented in this paper develops a fuzzy model that can predict the values for each input variables.

We compare our method to the fuzzy logic of MATLAB to validate our model. The comparison is made in terms of the asphalt pavement value measure of the input variables.

The similarity that we have discovered is that they both have the same conclusions.

The organization of this paper is as follows: In section 2, fuzzy Petri nets concept are described. In Section 3, fuzzy inference systems are presented. In section 4, asphalt pavement with example and simulation are presented. In section 5 we explained the details of methods of modeling asphalt pavement and describes experimental and simulation results. Finally, we presented the conclusions of model in Section 6.

II. FUZZY PETRI NET CONSEPTS

Chen *et al.* [5] develop an FPN model to represent knowledge rules of a decision support system and gave an efficient algorithm for knowledge reasoning. The classical FPN structure can be defined as an 8-tuple [5]:
The tuple *FPN* = (P, T, D, I, O, F, α, β) is called a fuzzy Petri net if:

1. $P = \{p_1, p_2, ..., p_n\}$ is a finite set of places, corresponding to the propositions of FPRs;
2. $T = \{t_1, t_2, ..., t_n\}$ is a finite set of transitions, $P \cap T = \emptyset$, corresponding to the execution of FPRs;
3. $D = \{d_1, d_2, ..., d_n\}$ is a finite set of propositions of FPRs. $P \cap T \cap D = \emptyset$, $|P| = |D|$, d_i ($i = 1,2,..., n$) denotes the proposition that interprets fuzzy linguistic variables.
4. $I : P\times T \rightarrow \{0, 1\}$ is an $n\times m$ input incidence matrix defining the directed arcs from propositions (P) to rules (T).
5. $O : P\times T \rightarrow \{0, 1\}$ is an $n\times m$ is an output incidence matrix defining the directed arcs from rules to propositions.
6. $F = \{\mu_1, \mu_2, ..., \mu_m\}$ where μ_i denotes the certainty factor (CF $=\mu_i$) of R_i, which indicates the reliability of the rule R_i, and $\mu_i \in [0,1]$;
7. $\alpha : P \rightarrow [0,1]$ is the function which assigns a token value between zero and one to each place;
8. β: $P \rightarrow D$ is an association function, a bijective mapping from a set of places to a set of propositions.

Moreover, this model can be enhanced by including a function Th: $T \rightarrow [0, 1]$ which assigns a threshold value $Th(t_j) = \lambda_j \in [0, 1]$ to each transition t_j, where $j= 1,\dots, m$. Further more, a transition is enabled and can be fired in FPN models when values of tokens in all input places of the transition are greater than its threshold.

III. FUZZY INFERENCE SYSTEM MODEL

This paper proposes a linguistic reasoning of fuzzy Petri net model with respect to the linguistic reasoning algorithm for knowledge representation and reasoning. The linguistic production fuzzy rules in the knowledge base system of a decision support system are modeled by FPN, where the truth degrees of the propositions in the linguistic production rules and the certainty factors of the rules are represented in the paper.

The mechanism described in this paper is Mamdani approach [10] that is able to overcome the drawbacks specific to ordinary Petri nets.

The model describing the concept of dynamic processes compute the states, at a time instant of asphalt pavement performance, from the information of the inputs surface thickness (*ST*), traffic count (*TC*) and age (*A*), at time instant *t*:

$$x(t + 1) = f(st, tc, a) \qquad (1)$$

As shown in function (2), no more processing is done in this layer

$$O_i^{(1)} = \mathrm{st}, \mathrm{tc}, \mathrm{a} \qquad (2)$$

Where *st*, *tc*, *a* are the variable value of the i^{th} asphalt pavement inputs surface thickness (*ST*), traffic count (*TC*) and age (*A*), at time instant *t*, and $O_i^{(1)}$ is the i^{th} output of layer 1.

These values of the three inputs variables, can be assigned linguistic labels, e.g., `low-expressed' (L), `medium-expressed' (M), and `high expressed' (H). By using the center of gravity method as the defuzzification using function (3) we can find the crisp value of input variables surface thickness (*ST*), traffic count (*TC*) and age (*A*).

$$app = \frac{\sum_{i=1}^{n} (low, medium, high)i \times y_i}{\sum_{i=1}^{n} (low, medium, high)i} \quad \textbf{(3)}$$

where: *app* is the asphalt pavement performance of output layer from the *i*-th rule, y_i is the gravity's horizontal of output area from the *i*-th rule.

To get the results of the model we apply the *max* function to all the resulting implications performs the aggregation approach.

The proposed model reasoning algorithm can perform ordered linguistic inference automatically, which allows the rule-based decision making systems based on the fuzzy model to carry out linguistic reasoning in a more flexible and intelligent manner.

To explain our algorithm, we use a fuzzy model shown in Fig. 1. The net contains twenty seven production rules of the asphalt pavement performance rut depths transitions $T_1, T_2,\ldots,T_{27}$ with appropriate input and output places representing the propositions forming the surface thickness (*ST*), traffic count (*TC*) and age (*A*) rules. To keep the model working with the same weight for all rules the certainty factor value with be one for all rules (i.e. CF = 1).

From Table I, we can see that the rule-based system of the goal places become impotent to get the values of goal places of asphalt pavement performance rut depths and applying the traditional Min-Max operation. In extant the fuzzy model, the truth values of input places are restricted to be fuzzy values between 0 and 1, which are usually determined by multiple decision makers according to the data gathered from the considered system.

We consider the three cases of lower medium and high values of the given intervals to arrange elements of the initial marking vector $\theta = \theta_1, \theta_2, \ldots. \theta_m$, where $\theta_i \in [0,1]$ means the truth degree of the input place $p_i = (i = 1,2,..., m)$.in our mode the values of initial marking vector will be $\theta = (1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0)$.
So, for any input place *pi*, all the factors are to be evaluated by fuzzy model by means of set of expressions over a three-point linguistic term set *VST*, *V TC*, and *VA* as shown below:

$$V\,ST = [\mu_{low\_}\,ST, \mu_{medium\_}\,ST, \mu_{high\_}\,ST]^T, \qquad (4)$$

Similarly, *TC* and *A* is defined as:

$$V\,TC = [\mu_{low\_}\,TC, \mu_{medium\_}\,TC, \mu_{high\_}\,TC]^T,$$
$$VA = [\mu_{low\_}\,A, \mu_{medium\_}\,A, \mu_{high\_}\,A]^T,$$

In this case a 3-d membership vector for the fuzzy sets low, medium, and high corresponding to fuzzy value of the asphalt pavement performance evaluation is asphalt pavement rated and is given.

Table 1. Fuzzy production rules for Rut depths

IF		***THEN***	
Surface Th.	*Traffic Count*	*Age*	*Rut depths*
L	L	L	L
L	L	M	L
L	L	H	L
L	M	L	L
L	M	M	L
L	M	H	L
L	H	L	M
L	H	M	M
L	H	H	M
M	L	L	L
M	L	M	L
M	L	H	L
M	M	L	L
M	M	M	M
M	M	H	M
M	H	L	M
M	H	M	H
M	H	H	H
H	L	L	M
H	L	M	L
H	L	H	M
H	M	L	M
H	M	M	M
H	M	H	M
H	H	L	H
H	H	M	H
H	H	H	H

Using the concepts of fuzzy operator "*AND*" or "*OR*" we can check the firing strength of each rule in our model. To perform *MIN* or *MAX* composition operation [6, 11] the model Fig. 1 shown the following *MIN* rules:

$FR_1 : MIN(\mu_{low}(ST), \mu_{low}(TC), \mu_{low}(A))$
$FR_2 : MIN(\mu_{low}(ST), \mu_{low}(TC), \mu_{medium}(A))$
$FR_3 : MIN(\mu_{low}(ST), \mu_{low}(TC), \mu_{high}(A))$
$FR_4 : MIN(\mu_{low}(ST), \mu_{medium}(TC), \mu_{low}(A))$
$FR_5 : MIN(\mu_{low}(ST), \mu_{medium}(TC), \mu_{medium}(A))$
$FR_6 : MIN(\mu_{low}(ST), \mu_{medium}(TC), \mu_{high}(A))$
$FR_7 : MIN(\mu_{low}(ST), \mu_{high}(TC), \mu_{low}(A))$
$FR_8 : MIN(\mu_{low}(ST), \mu_{high}(TC), \mu_{medium}(A))$
$FR_9 : MIN(\mu_{low}(ST), \mu_{high}(TC), \mu_{high}(A))$
$FR_{10} : MIN(\mu_{medium}(ST), \mu_{low}(TC), \mu_{low}(A))$
$FR_{11} : MIN(\mu_{medium}(ST), \mu_{low}(TC), \mu_{medium}(A))$
$FR_{12} : MIN(\mu_{medium}(ST), \mu_{low}(TC), \mu_{high}(A))$
$FR_{13} : MIN(\mu_{medium}(ST), \mu_{medium}(TC), \mu_{low}(A))$
$FR_{14} : MIN(\mu_{medium}(ST), \mu_{medium}(TC), \mu_{medium}(A))$
$FR_{15} : MIN(\mu_{medium}(ST), \mu_{medium}(TC), \mu_{high}(A))$

$FR_{16} : MIN(\mu_{medium}(ST), \mu_{high}(TC), \mu_{low}(A))$
$FR_{17} : MIN(\mu_{medium}(ST), \mu_{high}(TC), \mu_{medium}(A))$
$FR_{18} : MIN(\mu_{medium}(ST), \mu_{high}(TC), \mu_{high}(A))$
$FR_{19} : MIN(\mu_{high}(ST), \mu_{low}(TC), \mu_{low}(A))$
$FR_{20} : MIN(\mu_{high}(ST), \mu_{low}(TC), \mu_{medium}(A))$
$FR_{21} : MIN(\mu_{high}(ST), \mu_{low}(TC), \mu_{high}(A))$
$FR_{22} : MIN(\mu_{high}(ST), \mu_{medium}(TC), \mu_{low}(A))$
$FR_{23} : MIN(\mu_{high}(ST), \mu_{medium}(TC), \mu_{medium}(A))$
$FR_{24} : MIN(\mu_{high}(ST), \mu_{medium}(TC), \mu_{high}(A))$
$FR_{25} : MIN(\mu_{high}(ST), \mu_{high}(TC), \mu_{low}(A))$
$FR_{26} : MIN(\mu_{high}(ST), \mu_{high}(TC), \mu_{medium}(A))$
$FR_{27} : MIN(\mu_{high}(ST), \mu_{high}(TC), \mu_{high}(A))$

From other side we have the *max* composition operation rules as following:

Low: $MAX(FR_1, FR_2, FR_3, FR_4, FR_5, FR_6, FR_{11}, FR_{12}, FR_{13}, FR_{20})$,
Medium: $MAX(FR_7, FR_9, FR_{14}, FR_{15}, FR_{16}, FR_{19}, FR_{21}, FR_{22}, FR_{23}, FR_{24})$,
High: $MAX(FR_{17}, FR_{18}, FR_{25}, FR_{26}, FR_{27})$,

According to the result of *min* and *max* composition operations the next step will be the defuzzification operation as shown in function 3, the output is used to make a final decision.

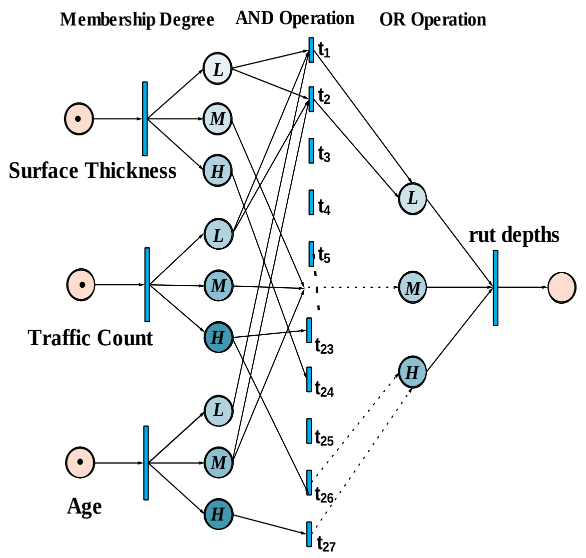

Fig.1. Fuzzy model of mamdani method with surface thickness (*ST*), traffic count (*TC*) and age (*A*) and rut depths output.

IV. Modeling of asphalt pavement performance evaluation

Referring to highway maintenance technical specifications in Iraq, high-grade asphalt pavement performance evaluation indicators are divided into three variables: surface thickness (ST), traffic count (TC) and age (A). Using the *IF-THEN* statements, the estimation procedure for the FPN model can be described by the following two step process.
Evaluate the consequent proposition: The "fired" consequents (THEN) are aggregated into predictions for the outputs. Before the above steps can be discussed in detail, the fuzzy membership function is discussed.
The fuzzy terms and membership function for our FPN model are included in the fuzzy rule Fig. 2. Any input value can be described through a combination of membership values in the linguistic fuzzy sets. In order to measure these input and output metadata universally, we normalize them into the same standard scale of [0, 1]. The values of linguistic variables are fuzzified to obtain the membership degree by membership function. For example, μ_{low_st} =(0.35) = 0.5, and $\mu_{medium\_}$ *st* =(0.35) = 0.5, means the value, 0.35 belongs to medium with truth value of 50% while 50% belongs to low.

The membership degrees of these input data are calculated by membership functions. These membership function value can be used as the degree of truth of each antecedent proposition in our FRBPN model. However, the degree of truth of all input propositions listed as:

TS = 0.375
$\mu_{TS\_Low}(0.375) = 0.5$
$\mu_{TS\_Medium}(0.375) = 0.5$
$\mu_{TS\_High}(0.375) = 0.0$

TC = 0.125
$\mu_{TA\_Low}(0.125) = 1$
$\mu_{TA\_Medium}(0.125) = 0.0$
$\mu_{TA\_High}(0.125) = 0.0$

A = 0.5
$\mu_{A\_Low}(0.5) = 0.0$
$\mu_{A\_Medium}(0.5) = 1$
$\mu_{A\_High}(0.5) = 0.0$

Since we are dealing with rules that have the AND connector, we get an output that is a minimum of the *n* inputs, i.e. the output set *S* for Rule1 is cut at the membership value of the following :

MIN (μ_{TS_low} (0.375) = 0.5, μ_{TC_low}(0.125) = 1, μ_{A_low}(0.109) = 1).

The reasoning for all rules is similar. For example, with *TS* input data the firing strength of each activated rule is calculated by the *MIN* and *MAX* composition operator, respectively. It yields

$FR_1 = 0.5$,	$FR_{15} = 0.0$,
$FR_2 = 0.0$,	$FR_{16} = 0.0$,
$FR_3 = 0.0$,	$FR_{17} = 0.0$,
$FR_4 = 0.0$,	$FR_{18} = 0.0$,
$FR_5 = 0.0$,	$FR_{19} = 0.0$,
$FR_6 = 0.0$,	$FR_{20} = 0.0$,
$FR_7 = 0.0$,	$FR_{21} = 0.0$,
$FR_8 = 0.0$,	$FR_{22} = 0.0$,
$FR_9 = 0.0$,	$FR_{23} = 0.0$,
$FR_{10} = 0.5$,	$FR_{24} = 0.0$,
$FR_{11}= 0.0$,	$FR_{25} = 0.0$,
$FR_{12} = 0.0$,	$FR_{26} = 0.0$,
$FR_{13} = 0.0$,	$FR_{27} = 0.0$,
$FR_{14} = 0.0$,	

However, our main goal here is to construct semantically meaningful fuzzy model, allowing us to attach intuitive linguistic fuzzy sets such as low, medium, and high, and each describing a different level of asphalt pavement performance evaluation in asphalt pavement. For this purpose the fuzzy membership functions with overlap ½ are plotted in Fig. 2 with respect to the biological concept (concentration).

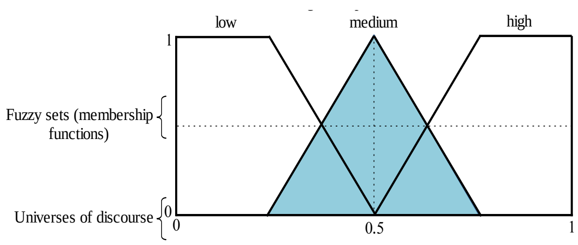

Fig.2. fuzzy membership functions of inputs and outputs

The applications of FPN are ideal to describe some scientific idea and provide good tools. We develop a FPN algorithm that can predict the values for each input variables. In particular we refer to the processes known as fuzzy logic methods to model asphalt pavement performance evaluation.

Fig. 1 shows an overview of the fuzzy modeling process. This schematic indicates the components that have to be defined for our application, including inputs considered in the model value can be inferred in terms of three degrees low (L), medium (M), and high (H).

Procedure FPN presented below to predict asphalt pavement performance value of the tow fuzzy inputs. After the construction of the FPN model is over, we initialize the beliefs of the propositions rules mapped at the appropriate places.

Depending on the rule is demonstrated as part of the fuzzy model, it is discarded from the set of rules. However, the processing system described above is repeated for each rule. A set of decision-maker model based on the linguistic variable term sets to obtain the initial truth values vector θ = (1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0) based on domain experts' knowledge and experience. Based on the concepts of FPN we presented the concepts of each one in the fuzzy Petri net for computation of the inference engine system of Fig. 1. We have variables surface thickness (ST), traffic count (TC) and age (A) for the rules in the model. Then calculate the membership degree of the proposition of variables. Also calculate the enabling transitions by the AND operator (*MIN*). To explain the max firing of each enabling transitions an OR operator (*MAX*) is used for this case. Through all these steps the calculation of a conclusion of the output for each subsystem by defuzzyfication method to get the results of asphalt pavement performance ruts depths.

In this paper, the implication relationship of the antecedent and consequent proposition in fuzzy Petri net models is used to establish the elements for fuzzy rules follow the Mamdani model [7].

As illustrated in Fig. 1, the model of FPN is used to describe the fuzzy inference reasoning system. The properties of the proposition set of places and the firing transitions for FPN model are described in details.

The model can avoid information distortion and loss which occur formerly in the linguistic information low, Medium, and High: represents the value of places. Each place with a token represents the value of a consequent proposition of a fuzzy rule. Multiple factors can be considered in evaluating the truth degrees of input places, which makes the model more realistic and more flexible. The value of a proposition of the winning fuzzy rule from the fuzzy rules in each model is calculated by the centroid method.

V. EXPERIMENTAL AND SIMULATION RESULTS

We use an asphalt pavement construction to ensure pavement performance example from to illustrate the model presented in this study. Asphalt pavement is one of the types of problems has been widely shown in high way systems, as example Fig. 3 illustrate the model presented in this study. As shown in Fig. 1, the fuzzy rule base of the reasoning process as a part in the main system to determine the value of $x(t+1)$ (i.e. the predicted value of asphalt pavement performance) is constructed of FPN model. The fuzzy membership functions of input variables surface thickness (*ST*), traffic count (*TC*) and age (*A*) 0.5 are described in section 3. We input a crisp data into this corresponding membership functions, and get the membership degree for all variables.

To explain our method a value of each input variable is presented. For example, the normalized value for each input data as follows: the surface thickness (*ST*) = 0.375, traffic count (*TC*) 0.125 and age (*A*). The membership function value can be used as the truth degree of each antecedent proposition in our FPN models. For each input data the firing strength of each activated rule is calculated by the *MIN* and *MAX* composition operator, respectively. It yields rut depth values:

When we are dealing with two or more rules, we have an OR operation between all the rules. Therefore we "maximize" all the fired rules to a single set. It yields

Low: $MAX(FR_1, FR_2, FR_3, FR_4, FR_5, FR_6, FR_{10}, FR_{11}, FR_{12}, FR_{13}, FR_{19}, FR_{20}) = MAX(0.5, 0, 0, 0, 0, 0, 0.5, 0, 0, 0, 0) = 0.5$,

Medium: $MAX(FR_7, FR_8, FR_9, FR_{14}, FR_{15}, FR_{16}, FR_{21}, FR_{22}, FR_{23}, FR_{24}) = MAX(0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0$,

High: $MAX(FR_{17}, FR_{18}, FR_{25}, FR_{26}, FR_{27}) = MAX(0, 0, 0, 0, 0) = 0.0$,

According to the result of *max* operation the defuzzification of output is used to make a final decision. We adopt the "center of gravity" method in to solve this problem. Then, the defuzzification of *rut depths* is calculated as *rut depths* = 0.2, by the centroid of the aggregate output membership function in the each FPNs model. Following the steps of the reasoning process, the final winning rule in the FPN model is FR_{10} (*IF TS is Medium and TC is Low and A is Low THEN the rut depths is Low*), The fuzzy model of the MATLAB tools is also used to compare the inference results under the same conditions with the value of *rut depths* = 0.213. The predicted values of the outputs *rut depths* are shown in Fig. 4, x-axis

Fig.3. permanent deformation (rutting)

Represents the time points of observations of different inputs and y-axis represents predicted values. The results prove the accuracy and efficiency of our method.

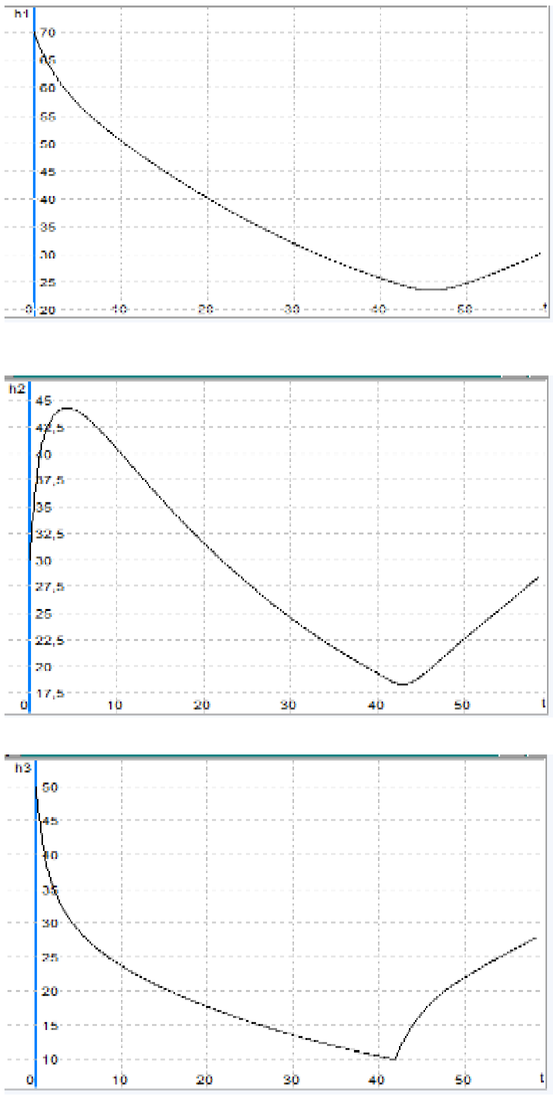

Fig.4. profile of variables, low, medium and high

VI. CONCLUSION

The key problem is to design the asphalt pavement construction to ensure pavement performance. Evaluation of Asphalt pavement Performance is very important method it concerned with quantitative and uncertain information.

This paper, introduced an intelligent model for FRs based reasoning system to asphalt pavement performance evaluation and reasoning. FPNs are a very important knowledge representation and inference tool which have been widely used in many areas and industries.

The fuzzy set method is used to establish the fuzzy rules to prediction of the asphalt pavement performance evaluation. FPNs are a very important knowledge representation and inference tool which have been widely used in many areas and industries.

The motivation for using FPNs models is the ability to translate vague information into linguistic constructs that can then be easily converted into testable hypotheses. It is also worth remarking that the quality values assigned by FPN to determine asphalt pavement values at time instance (t+1) of the input variables are much more informative. We have shown here, that the FPN model is appropriate and can reach the same accuracy performance of available software.

The validation of our model was achieved by comparing the results obtained with fuzzy logic using the MATLAB Toolbox both methods have the same reasoning outcomes.

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