USE OF SOFT COMPUTING APPLICATIONS TO MODEL PERVIOUS CONCRETE PAVEMENT STRUCTURE IN COLD CLIMATES

Introduction

The Pervious Concrete Pavement Structure (PCPS) is of significant importance regarding stormwater management and water quality control. Engineers realized that runoff has potential impacts on surface and groundwater supplies. By developing the land, the runoff volume increased, leading to downsream flooding and bank erosion. Not only does the pervious concrete pavement reduce the effect of land development by decreasing the runoff, but also it protects the water supplies (ACI 522R-06, 2006). Most importantly from a pavement engineering prespective, having a reduced amount of runoff may improve the level of road safety. In addition, it has several other potential beneficial aspects such as reducing noise, minimizing heat, protecting the native ecosystem, recharging the ground water, and protecting natural landscape. To benefit from the PCPS, it should be effectively managed by incorporating adequate performance models.
In order to develop a performance model, two major steps should be taken: development of an appropriate condition index and acquiring adequate performance data to calibrate and validate model overtime. Several types of condition indices have been broadly developed such as the Pavement Condition Index (PCI) and Present Serviceability Index (PSI). The degree of pavement deterioration is commonly indicated by the particular distress type as well as its severity and density. The Ministry of Transportation of Ontario (MTO), for instance, proposes weighting factors for different distress types to estimate Distress Manifestation Index (DMI) as a condition indicator of various types of pavements considering severity and density of each distress type observed, whereas ASTM defines specific deduct value curves to quantitatively rate the manifestation of each distress

type based on accurate assessment of its severity and density in order to estimate PCI.

Since the PCPS use is limited in colder climates and long term field performance data is not available, gathering detailed performance data would a challenge. Hence, it is of importance to develop an efficient and reliable method to evaluate the pavement condition using the limited available data. Over time, as more data is available the models will be modified and updated. This paper proposes a subjective methodology for condition evaluation of the PCPS resulting in developing performance models.

Fuzzy set has been widely employed to incorporate subjective judgment and qualitative evaluation in pavement management systems (PMS). Bandara (2001) developed a pavement maintenance prioritization plan applying rapid visual condition evaluation incorporating fuzzy sets. Moreover, fuzzy set presentations were utilized to determine a pavement performance rating for various condition states in order to tackle the Network Optimization System (NOS) problem by Wang (1997). The fuzzy set approach is employed herein to account for subjectivity associated with different data involving in estimation of the pavement condition index of pervious concrete (i.e. severity, density, and weighting factor of each distress type) to obtain a novel condition index for PCPS based on the MTO methodology. Most importantly, this paper develops a Markov model to predict the performance of the PCPS incorporating a simulation technique.

Condition Evaluation of Pervious Concrete Pavement Structures

Two major items should be provided to develop an adequate condition index: a database encompassing pavement performance information (involving various distresses including the severity and density) and a methodology to combine all distress types into a single index by dedicating appropriate weights.

Firstly, a database encompassing 24 pervious concrete pavement sites is applied (Delatte 2007). The subjective pavement condition data base includes severity and density of different distress types observed on the various pervious concrete pavement sites. The four most commonly observed distress types are clogging, raveling, cracking, and polishing.

The descriptions employed to define severity, density, and weighting factor include none, minimal, moderate, and severe are used to express severity and density, while important, moderately important, very important, and extremely important describe the weighting factors.

Secondly, an adequate condition index should be specified. In this paper, the MTO methodology is applied to combine all distress types into a single index. Ministry of Transportation of Ontario (MTO) developed the MTO Pavement Condition Index and Distress Manifestation Index (DMI). DMI describes overall pavement surface condition applying various distress types observed on a pavement section. Then, DMI is estimated by computing weighted summation of severity and density of distress types. The weighting factors corresponding to polishing, cracking, raveling, and clogging for the pervious concrete pavement structures are 1.0, 1.5, 2.0, and 2.5, respectively. These weights are presented according to the relevant literature and experienced engineers' judgments and simply show the effect of various distress types on the overall pavement surface condition. For instance, clogging is extremely important distress type in terms of functional performance of the pervious concrete pavements. Raveling and polishing are very important and important criteria, respectively, representing surface distresses. Ultimately, cracking which expresses structural adequacy of pervious concrete pavements is moderately important.

The DMI varies between 0 and 10 which 0 shows the poorest condition of a pavement section, while 10 presents a new installed or rehabilitated pavement. DMI is estimated for different pervious concrete pavement structures deploying Equation 1.

$$\boldsymbol{DMI} = \mathbf{10} \times \frac{DMI_{max} - \sum_{i=1}^{n} W_i \ (s_i + d_i)}{DMI_{max}} \qquad \text{Equation 1}$$

Where:

DMI = distress manifestation indx
i = distress type
W_i = weighting factor ranging from 0.5 to 3.0
S_i = severity of distress ranging from 0.5 to 4.0
d_i = density of distress occurrence ranging from 0.5 to 4.0

DMI_{max} = the maximum theoretical value dedicated to an individual pavement distress (56 for pervious concrete)

Fuzzy Representation of the Pavement Performance Data

Two types of ambiguity are inherent in collecting performance data (severity, density, and weighting factor of each distress). First, distress severity and density data is affected by the level of training and consistency amongst evaluators (Tighe 2008). However, these uncertainties and inconsistencies associated with the subjective rating can be dealt with representing fuzzy set. Functions are applied in fuzzy sets to indicate a value that would be a member of the set to a number between 0 and 1, representing its real degree of membership. Accordingly, a degree of 0 means that the associated value is not in the set, while value 1 expresses the corresponding value is completely a representative of the set. A linear membership function, namely Triangular Fuzzy Numbers (TFNs), is the simplest and suitable function to represent severity, density, and weighting factors.

Severity and density levels (i.e. minimal, moderate, and severe) of each distress type which were subjectively rated have been modeled as fuzzy members (TFNs) in a [0.5, 4] scale based on MTO methodology considering possible magnitude of uncertainty. An Individual triangular fuzzy set is proposed for both severity and density illustrated in Figure 1.

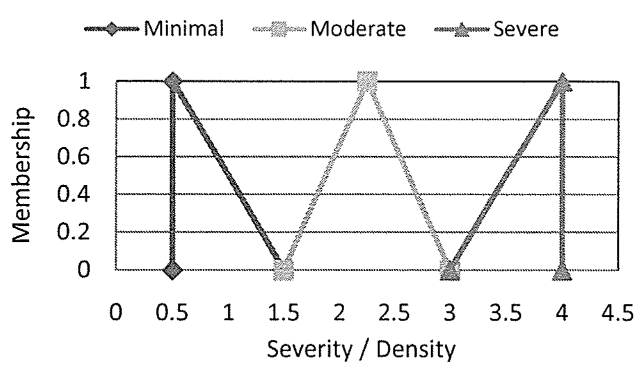

Figure 1 TFNs for various severity/density levels

Likewise, the weighting factors in the scale of [0.5, 3.0] were applied in this study based on MTO methodology. The fuzzy set representations of the weighting factors of different distresses are illustrated in Figure 2.

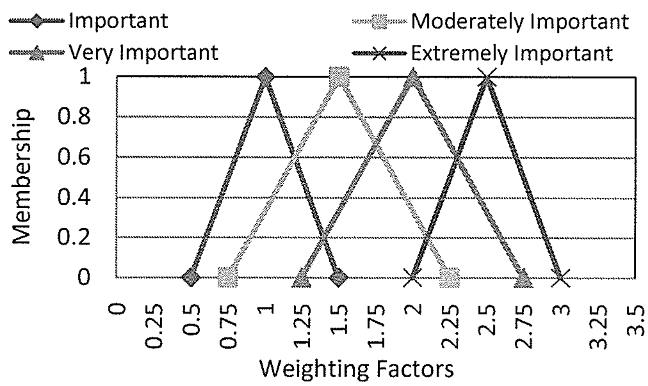

Figure 2 TFNs for various weighting factors

Fuzzy Representation of the Pavement Condition Index

Since the variables in Equation 1 (i.e. s_i : severity, d_i : density, w_i : weighting factor) are represented in the fuzzy sets, the fuzzy mathematics is required to calculate Distress Manifestation Index (DMI). Although fuzzy number operations can be executed using the extension principle (Zadah 1965), the concept of an alpha-level set or an "α-cut" is proposed herein to simplify the fuzzy calculations. All of the computations are executed on left and right domains of each fuzzy number at the selected α. For instance, as shown in Figure 1, for the α-cut of [0.0], the severity and density of moderate condition is restricted to the domain of 1.5 to 3.0. Fuzzy set mathematical operations (summation, subtraction, etc.) can be easily executed such as conventional Mathematics applying left and right domains.

It is worth mentioning that all of the combinations regarding different domains at each α-level should be considered to carry out the mathematical operations. Then, the maximum and minimum values are assigned to the right and left domains of the result at the associated α-level, respectively. In this study, in order to compute the condition index (DMI), three major criteria (i.e. severity, density, and weighting factors) are estimated for four distress types (i.e. clogging, raveling, cracking, and polishing). Therefore, in total, there are 12 variables (i.e. 12 = 3 x 4) which lead to 2^{12} (i.e. 4,096) permutations. To execute the computational procedure to obtain the pavement condition index (DMI), six α-values from 0.0 to 1.0 at 0.2 intervals are used so that 24,576 (i.e. 24,576 = 6 x 4,096) permutations are required to be completely and accurately fulfilled for each pervious concrete pavement site (totally 589,824 = 24 x 24,576) which appears to be a computationally complex problem. The writer developed a powerful computer program to execute the fuzzy computational process in an efficient and precise manner. The final result of the computations is an aggregated fuzzy rating that expresses the Distress Manifestation Index (DMI) of the respected PCPS. Table 1 summarizes the α-level cut representations of the DMI of some of the PCPS, for illustration.

Consequently, the data in Table 1 can be applied to build the membership function of fuzzy condition index (DMI). Some of pavement membership functions are illustrated in Figure 3.

Table 1 α-Level Cut Representation of Fuzzy Condition Index

Rating Interval	Pervious concrete Pavement site number						
	S1	S2	S3	S4	S5	S6	S7
α=0	[2.40, 7.83]	[6.00, 8.00]	[5.13, 8.77]	[4.88, 7.88]	[6.75, 9.58]	[2.56, 8.13]	[3.00, 7.79]
α=0.2	[3.08, 7.43]	[6.13, 7.76]	[5.60, 8.52]	[5.22, 7.61]	[7.36, 9.52]	[3.32, 7.75]	[3.61, 7.43]
α=0.4	[3.73, 7.00]	[6.27, 7.51]	[6.05, 8.25]	[5.55, 7.33]	[7.91, 9.45]	[4.04, 7.35]	[4.19, 7.05]
α=0.6	[4.35, 6.53]	[6.40, 7.24]	[6.48, 7.95]	[5.86, 7.04]	[8.41, 9.38]	[4.72, 6.91]	[4.74, 6.63]
α=0.8	[4.94, 6.03]	[6.53, 6.96]	[6.90, 7.63]	[6.15, 6.74]	[8.86, 9.32]	[5.35, 6.44]	[5.25, 6.20]
α=1	[5.50, 5.50]	[6.67, 6.67]	[7.29, 7.29]	[6.42, 6.42]	[9.25, 9.25]	[5.94, 5.94]	[5.73, 5.73]

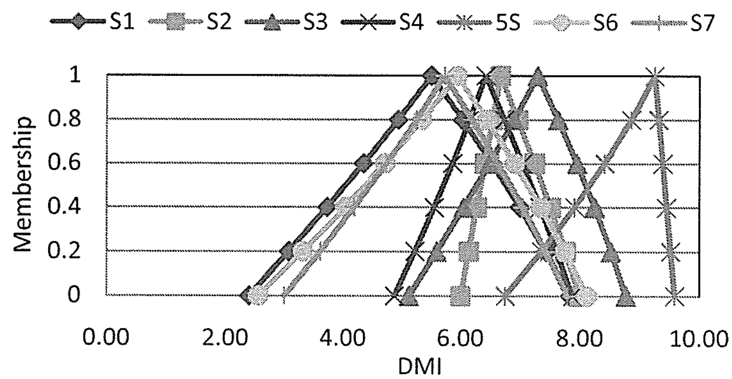

Figure 3 Fuzzy condition indices for the selected pervious concrete pavement sites

Figure 3 illustrates that the pervious concrete site S5 performs considerably better with a DMI of 9.25 than the others, while site S1 pavement condition is the worst with the DMI of 5.5. Moreover, it can be observed that the uncertainty of the condition index value of site S2 is the lowest, whereas that of site S6 is the highest. In other words, Table 1 (at level α=0) demonstrates that the condition index of site S2 is restricted to a domain of 6.00 to 8.00 (narrower range, less uncertainty), while that of site S6 is restricted to a domain of 2.56 to 8.13(wider range, more uncertainty).

Markov Model of the PCPS

In order to develop a Markov model, a condition indicator and states (condition rating), a current condition probability vector, stages (duty cycles), and transition probability matrices should be practiced which are depicted below.

Condition Indicator

Condition indicators measure how well a pavement serves the users. As mentioned earlier, the DMI is applied herein as a performance indicator that is an aggregated measure to support the network level decisions. The DMI ranges from 0 to 10. It is proposed to divide the

DMI into three states: Good, Fair, and Poor which their boundaries are (7, 10), (4, 7), and (0, 4) respectively.

It is worth mentioning that although more condition states provide detailed Transition Probability Matrices (TPMs), they simultaneously reduce the reliability of TPMs. Namely, the probabilistic process suffers from decrease of reliability of data with increase of condition states. That is, the more the number of states, the more uncertain and inconsistent data would be collected from experts to build the TPMs. Hence, this research suggests only three condition states to overcome this problem.

Moreover, it is assumed that a pavement can shift only form a higher state to a lower state (q_{ii}) or stay at the same state (p_{ii}). This assumption, also, reduces the level of uncertainty and inconsistency since in each row of TPMs there is only one variable.

$$p_{ii} = prob[\,X(t+1) = i/X(t) = i] \qquad \text{Equation 2}$$

$$q_{ii} = prob[\,X(t+1) = i-1/X(t) = i] \qquad \text{Equation 3}$$

$$p_{ii} = 1 - q_{ii} \qquad \text{Equation 4}$$

Where:

p_{ii} = probability of staying at state i over stage t

q_{ii} = probability of shifting from state i to state i-1 over stage t

Current Condition Probability Vector

The Markov Chain model starts with a condition probability vector reflecting the initial or current condition of a given pavement section. The condition probability vectors of current condition of PCPS are estimated based on their fuzzy representations as presented earlier in Table 1. In order to define a probability condition vector for each pavement site, the probability of being in each condition state should be estimated applying fuzzy set which is a tedious task. So, a suitable probability distribution function is employed instead of a fuzzy membership function to be able to compute the probability of being in each condition state. Regarding the fact that the membership functions are in triangular form, the triangular probability distributions are utilized with the same criteria (i.e. min, most probable, and max values). For instance, the fuzzy membership function of site S1 presented in Figure 4 can be represented as the corresponding triangular probability distribution shown in Figure 5.

The triangular probability distribution of current condition vector of site S1 is expressed as follows.

Equation 5

$$TPD_{S1} = T_{S1}(Min, Most\ Probable, Max) = T_{S1}(2.40, 5.50, 7.83)$$

Where:

TPD_{s1} = triangular probability distribution of site S1

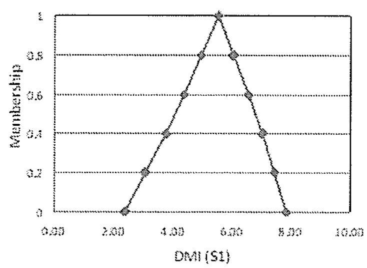

Figure 4 Fuzzy DMI

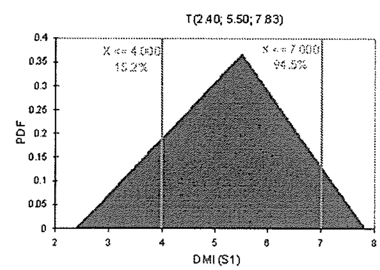

Figure 5 PDF of DMI

The triangular distribution functions can be readily applied to determine the current condition probability vector of each pavement site. For example, the probability of being in poor condition state (P_p) is equal to area under the curve of triangular probability density function (Figure 5) which X is less than four. The following formulas are used to indicate the current condition probability vector of each pavement site incorporating corresponding triangular distribution functions.

$P_G = P(X \geq 7)$ Equation 6

$P_F = P(4 < X < 7)$ Equation 7

$P_P = P(X \leq 4)$ Equation 8

Where P_G, P_F, and P_P are the probability of being in Good, Fair, and Poor condition state, respectively. Using Equations 6-8, it is obtained from Figure 5 that P_p, P_F, and P_G of DMI(S1) are equal to 15.2%, 79.3% (i.e. 94.5% - 15.2%), and 5.5 % (i.e. 100% - 94.5%), respectively. The current probability condition vectors of the entire PCPS are calculated and some of them are represented for illustration in Table 2.

Table 2 Probability Condition Vectors of Selected Sites

Probability	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
P_G	0.06	0.38	0.55	0.17	0.99	0.10	0.06	0.09	0.09	0.29
P_F	0.79	0.64	0.45	0.83	0.01	0.79	0.86	0.83	0.84	0.71
P_P	0.15	0.00	0.00	0.00	0.00	0.11	0.08	0.08	0.07	0.00

Stage (Duty Cycle)

Stage (duty cycle) in a pavement deterioration is defined as one year of traffic and environmental degradation. The non-homogeneous approach expresses different TPMs for the various stages. An ideal approach is to develop individual TPM for each stage. But, on one hand this approach dramatically increases the uncertainty and decrease the reliability of data presented in TPMs and on the other hand it is hardly feasible to build non-homogeneous TPMs regarding the lack of long term performance evaluation of the pervious concrete pavement structures. Thus, the zoning scheme is selected representing a period of three years throughout the planning horizon (i.e. 12 years). It is assumed that the rate of deterioration is constant in each zone (i.e. TPMs are identical in each zone). However, the deterioration rate is supposed to vary from one zone to another. The 3-year period of a zone is a realistic assumption since a distress survey is approximately carried out every three years.

Since the deterioration rate is assumed to be constant within each zone, the homogeneous Markov Chain (i.e. individual TPM) is developed for each zone. On the contrary, the deterioration rate is shifted from one zone to another. Namely, the non-homogeneous Markov Chain (i.e. different TPMs) is utilized for transition from one zone to another. Therefore, the combination of non-homogeneous and homogeneous Markov Chain is proposed as an efficient approach to develop a performance model for the PCPS to reflect changes that may occur in terms of deterioration rate.

Transition Probability Matrices (TPMs)

Two main approaches are being used to develop TPMs: applying subjective data and utilizing long term condition performance data. The later approach is not applicable to this study due to limited knowledge of long term performance of the PCPS. Consequently, the subjective approach is selected to build the different TPMs for various zones based on relevant literature and a panel of experienced engineers. Then, the results obtained in terms of subjective probability reflect any uncertainty inherent in subjective data which can be represented as triangular or normal distribution functions.

The triangular distribution function is selected to express the elements of TPMs regarding the fact that the triangular distribution matches with the other subjective data representations (e.g. condition state). However, other distribution functions such as Normal distribution can be easily replaced in this methodology. Consequently, the different TPMs for various zones can be developed. TPM_{Z1} (zone 1) is presented as follow for illustration.

$$TPM_{Z1} = \begin{array}{c} \\ \text{Good} \\ \text{Fair} \\ \text{Poor} \end{array} \begin{array}{c} \begin{array}{ccc} \text{Good} & \text{Fair} & \text{Poor} \end{array} \\ \begin{bmatrix} T(0.70, 0.85, 1.00) & T(0.00, 0.15, 0.30) & 0 \\ 0 & T(0.55, 0.70, 0.85) & T(0.15, 0.30, 0.45) \\ 0 & 0 & 1 \end{bmatrix} \end{array}$$

Where TPM_{Z1}, TPM_{Z2}, TPM_{Z3}, and TPM_{Z4} are TPMs associated with time zone one, two, three, and four. T represents the triangular distribution function. It is noted that these TPMs were built based on the relevant available data. However, the ideal approach is to update the existing TPMs and add more TPMs representing different types of PCPS. This could certainly be done once long term PCPS performance data is available.

Future Probabilistic Performance of the Pervious Concrete Pavement Structures

In order to estimate the future condition of the PCPS Equation 9 can be applied.

$$DMI\ (t) = DMI(0) \times \prod_{i=1}^{t} TPM_{\ i} \quad t = 1, 2, .., 12 \qquad \text{Equation 9}$$

Where DMI(t) is the probability condition vector expressing the performance of a pavement at the end of stage t, while DMI(0) is the initial probability condition vector.

In order to calculate the future performance of a pavement (DMI (t)), the multiplication of probability distribution functions (TPM_i) to both single value (DMI(0)) and other probability distribution functions (TPM_j) should be performed. A simulation technique (Latin

Hypercube Simulation (LHS)) is employed to execute this operation. It performs several iterations to obtain probability distribution functions of a response value (DMI(t)). The mean value of the probability distribution function of the response value is selected to address each element of the probability condition vector. Table 3 presents the probability condition vectors of some selected pavement sites after the first stage. In order to simply compare the performance of various sites a single expected value of pavement condition is computed for each site using Equation 10.

$$E.V._{DMI}\ (t) = AVE_{DMI} \times DMI\ (t) \qquad \text{Equation 10}$$

Where $E.V._{DIM}(t)$ is the expected value of the probability condition vector of a pavement after stage t. AVE_{DMI} is the vector of average of various state boundaries. AVE_{DMI} is equal to (8.5, 5.5, 2.0). The expected value of the probability condition vector of some pavement sites after first stage (i.e. one year) is also presented in Table 3.

Table 3 The Probability Vector and Expected Value of the Condition Indicator after the First Stage

DMI	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
P_G	0.05	0.32	0.47	0.15	0.84	0.09	0.05	0.07	0.08	0.25
P_F	0.56	0.49	0.39	0.60	0.15	0.57	0.61	0.60	0.60	0.54
P_P	0.39	0.19	0.13	0.25	0.00	0.35	0.33	0.33	0.32	0.21
$E.V._{DMI}$ (1)	4.27	5.80	6.45	5.08	8.02	4.55	4.49	4.55	4.61	5.49

The expected values of the probability condition vector represented in Table 3 are the mean value calculated by the simulation technique. However, an accurate result is specified by a probability distribution function rather than single value. Several probability distribution functions have been tried to match this data. Different indicators are employed to assess the goodness of fit of the various probability distribution functions (e.g.Chi-square, Anderson-Darling, and Kolmogorov-Smirinov values).

This process can be similarly carried out for various stages of each pavement site. For example, Figure 6 shows the probabilistic performance of the pavement site S5 throughout the planning horizon using the best distribution functions after each stage (i.e. one year). It is noted that the current condition of site S5 is presented by the triangular distribution function and the predicted condition of site S5 is represented by different types of probability distribution functions (mentioned in Figure 6) for each year within the planning horizon. Namely, each curve in Figure 6 shows the condition of site S5 in particular year.

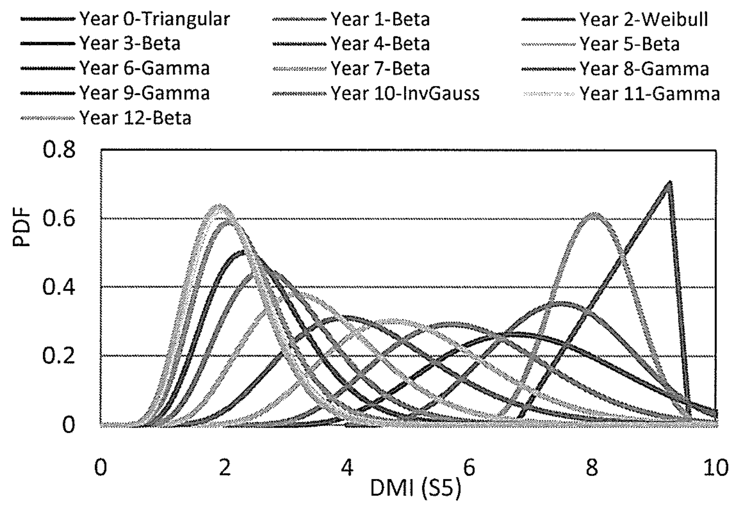

Figure 6 Probabilistic presentation of pavement performance

The performance prediction model of the PCPS can be developed incorporating both the expected value and the probability distribution function of the associated condition indicator throughout the service life. The performance prediction model has been illustrated in Figure 7 for site S5 over the entire zones (i.e. 12 years) utilizing both the expected values and some of the probability distribution functions.

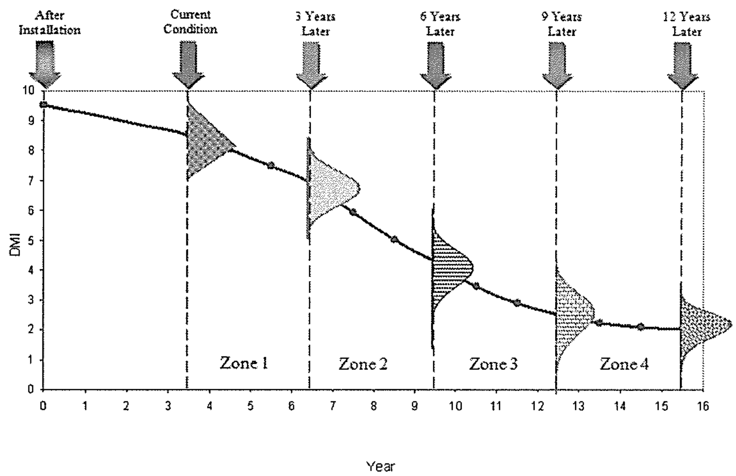

Figure 7 Performance prediction model for site S5

It is assumed that the initial condition index of site S5 after installation is equal to 9.5 in terms of DMI. Also, it is noted that site S5 is 3.5 years old at the current time. It is observed from Figure 7 that at each time zone the trend/deterioration rate is constant, whereas from one zone to another the trend/deterioration rate change can be obviously realized.

Conclusion

The findings drawn from the proposed methodology fulfilled the scope and objective of this study. The main conclusions are presented as follows:

1. The weighting factors of various distress types were subjectively introduced considering the impact on the pavement condition index.
2. The condition of various pervious concrete pavement sites was evaluated based on DMI according to the MTO methodology and represented in fuzzy sets (using membership functions).
3. The transition probability matrices were develop for various time zones throughout the planning horizon

4. The future performance measure of pavements was presented in form of single value and probability distribution functions
5. A computer program was developed to execute the entire complicated and time consuming fuzzy set mathematical computations.

Future Steps

Continuous data is being collected to further validate and calibrate the models presented in this study.

References

ACI 522R-06, (2006), *Pervious Concrete*, American Concrete Institute.

Bandara,N., Gunaratne,M., (2001), *Current And Future Pavement Maintenance Prioritization Based on Rapid Visual Condition Evaluation,* Journal of Transportation Engineering, 127 (2), pp. 116-123.

Delatte, N., Miller, D., Mrkajic, A., (2007), *Field Performance Investigation on Parking Lot and Roadway Pavements* Report to the RMC Research & Education Foundation.

Tighe, S., L. Ningyuan, T. Kazmierowski, Evaluation of Semiautomated and Automated Pavement Distress Collection for Network-Level Pavement Management. TRB 87^{th} Annual Meeting CD-ROM.

Wang,K., Liu,F., (1997), *Fuzzy Set-Based and Performance-Oriented Pavement Network Optimization System Journal of Infrastructure Systems*, 3 (4), pp. 154-159.

Zadah, L. A. (1965). ''Fuzzy sets.'' *Information and Control*, 8, 338–353.