Local Calibration for Mechanistic-Empirical Design using Genetic Algorithm

Amr Ayed, University of Waterloo

Susan Tighe, University of Waterloo

Paper prepared for presentation

at New Developments in ME Pavement Design session

of the 2015 Annual Conference of the
Transportation Association of Canada
Charlottetown, PEI

ABSTRACT

The Mechanistic Empirical Pavement Design Guide (MEPDG) is expected to be adopted by most transportation agencies and pavement engineers in the next few years. As a part of mechanistic-empirical pavement design procedure, it is required to locally calibrate distresses to match up analysis results with local measured data. However, it has been a challenging task for pavement practitioners and experts to calibrate distress models inherited in the design procedure due to the way the M-E design tool is processing the data. The literature review showed that the vast majority of calibration techniques currently in use are solely based on statistical analysis and trial and error approach for different combination of local calibration coefficients to find the best set that produces results closer enough to observed data in the field. This approach lack accuracy due to limited trials that can be evaluated and the absence of mathematical algorithm to guide the trial selection at the start of each MEPDG analysis cycle to find the optimum set of calibration coefficients.

This study will investigate the possibility of using genetic algorithm (GA) to calibrate MEPDG distresses. Framework of calibration system will be designed to simulate the MEPDG calibration process within the genetic algorithm context. Site specific data from different locations will be used as inputs to MEPDG and initial calibration coefficient seeds will be presented to the system to produce initial distress output and compared to measured field data. The genetic algorithm will then be employed to guide the selection of new calibration set each time analysis cycle is performed and crossover and mutation processes will be used to produce new sets of chromosomes and presented to the calibration system for new evaluation cycle in an automated process to overcome drawbacks of the traditional trial and error approach. Calibration framework design and development will be discussed in this study along with results and advantages of using the genetic algorithm approach over traditional ones.

INTRODUCTION

Major Changes have been made in the way pavements are modeled and analyzed in the newly developed Mechanistic-Empirical Pavement Design Guide (MEPDG) compared with the 1993 American Association of State Highway and Transportation Officials (AASHTO) Pavement Design Guide. The (MEPDG) is proposed as an advanced pavement design tool that integrates up-to-date pavement practices. Since MEPDG was released in 2004, transportation agencies have continuously worked on calibrating and evaluating the program with regard to implementation for provincial and local agencies in Canada.

MEPDG requires three categories of input data: traffic, climate, and pavement structure (1). There are also three levels of data precision: Level 1 requires site-specific data based on laboratory or field tests, Level 2 inputs are derived from other material properties measured in the laboratory or field tests, and Level 3 is estimated from designers' experience.

BACKGROUND

Today, many provincial and local agencies are collecting pavement condition data (e.g. rutting, cracking and IRI) using automatic road surveyors in a continuous manner across the entire highway network. These data, often stored in the pavement management systems (PMS), indicate not only the average but also the variation of the pavement performance over age. These data can be used in the local evaluation of the MEPDG design reliability as reported previously in several studies (2 and 3).

Within the MEPDG context, functional performance for all pavements types is defined by time (pavement age) dependent pavement roughness quantified as a predicted International Roughness Index (IRI). IRI is predicted using a regression equation with computed pavement distresses, initial IRI, and "site/climate" factors as the primary independent variables. The roughness in M-E design is measured using the following equations (4)

$$IRI = IRI_o + 0.0150(SF) + 0.400(FC_{Total}) + 0.0080(TC) + 40.0(RD)$$

where:

IRI_o = Initial IRI, in./mi,
SF = Site factor,
FC_{Total} = Area of fatigue cracking (combined alligator, longitudinal, and reflection cracking in the wheel path), percent of total lane area. All load related cracks are combined on an area basis-length of cracks is multiplied by 1 ft to convert length into an area basis,
TC = Length of transverse cracking (including the reflection of transverse cracks in existing HMA pavements), ft/mi, and
RD = Average rut depth, in.

and

$$SF = Age[0.02003(PI + 1) + 0.007947(Precip + 1) + 0.000636(FI + 1)]$$

where:

Age = Pavement age, yr,
PI = Percent plasticity index of the soil,

FI = Average annual freezing index, °F days, and
Precip. = Average annual precipitation or rainfall, in.

As shown in the previous equations, the independent variables are correlated to other parameters related to other distresses and climatic parameters that are being predicted/calculated within the MEPDG environment and therefore, the IRI model cannot be calibrated outside MEPDG and it needs to be executed iteratively to calculate all inputs needed for IRI model.

SCOPE AND STUDY OBJECTIVES

The current study will introduce a new methodology to locally calibrate international roughness index (IRI) models included in the MEPDG. The research effort in this study was undertaken using the research grade MEPDG (version 1.1). Measured roughness and site specific data from different local municipalities in Ontario will be used to calibrate IRI models. Literature review revealed that variables such as age, traffic, subgrade condition, road function class, pavement thickness are most significant to IRI deterioration models (4). Therefore, selected section from various Ontario municipalities PMS database for the study will be classified based on design of experiment (DOE) that accounts for factors that are known to highly influence the pavement performance. For this study, three parameters were selected to classify the pavement condition:

- Thickness – 3 levels (thin, medium, thick) based on equivalent granular thickness (EGT)
- Traffic – 3 levels (low, medium, high) based on average annual daily traffic (AADT)
- Subgrade – 2 levels (weak, strong) based on local knowledge of soil properties

Three sections in each DOE class as shown in table 1 are selected to represent different function classes for local, collector and arterial respectively. The three factors, thickness, traffic and subgrade, have different cutoff numbers for each function class and classified in each function class based on the distribution of each factor. In some conditions, no matching sections were found in the database to represent a particular condition. For example, no local sections (0) were found in thin thickness, strong subgrade and medium traffic category and only collector and arterial sections were used (0, 1, 1). Material, traffic and site specific inputs for selected sections were collected from different PMS database and entered into MEPDG and a total of 42 MEPDG design models were prepared for each section.

Table 1: Number of Sections with Records for different DOE Classes

	Thickness	Subgrade	Traffic		
			Low	Medium	High
RCI	Thin	Weak	0, 1, 0	0, 0, 1	1, 1, 1
		Strong	1, 0, 1	0, 1, 1	1, 0, 0
	Medium	Weak	0, 1, 1	0, 1, 1	0, 1, 1
		Strong	1, 1, 1	1, 1, 1	1, 1, 1
	Thick	Weak	1, 1, 1	1, 1, 1	1, 1, 1
		Strong	1, 1, 1	1, 0, 1	1, 1, 1

PROBLEM STATEMENT

The literature review revealed that most of the research efforts to calibrate MEPDG models, including IRI, are being done mainly based on “trial and error” statistical approach. In other word, local roughness calibration coefficients set (C1, C2, C3 and C4) are initially introduced to MEPDG and calculated IRI output is compared to measured IRI and the deference is evaluated against predefined threshold. Different combinations of calibration coefficients sets are repeatedly entered and the set with the least difference is selected as the best calibration coefficients set for particular condition. This process lack the mathematical means to guide the search for next calibration set based on the previously selected set result.

Optimization algorithms, including genetic algorithms, are suitable to resolve these problems where guidance engine is employed to direct the search for the optimum solution. Kim et al carried put a study to use the genetic algorithm to calibrate rut and alligator crack in MEPDG (5). The study used apads.exe engine module included in MEPDG to predict future distresses. However, this module cannot be used outside the MEPDG context and special software module was developed for this study to have apads.exe work as a standalone module and therefore, cannot be used for other studies or by public agencies.

METHODOLOGY

To overcome this problem, a genetic algorithm (GA) framework was prepared to optimize calibration coefficients. Initial trials attempt to use linear programming optimization approach included with Microsoft Excel software (Solver), however, MEPDG outputs results are in Excel format which conflict and prevent Excel solver from executing repetitive trials. Therefore, the genetic algorithm was found to be the best optimization technique for this problem.

The implemented GA framework includes MEPDG engine that receives initial coefficients seeds for C1, C2, C3 and C4 from GA and then call MEPDG program, open calibration screen for IRI as shown in Figure 1, insert the parameters, execute the analysis based on the passed coefficients, close the MEPDG program and read results file to get predicted IRI at different ages. It was essential to automate this process so that it can be included in an iterative process later within a genetic algorithm as explained in the next section.

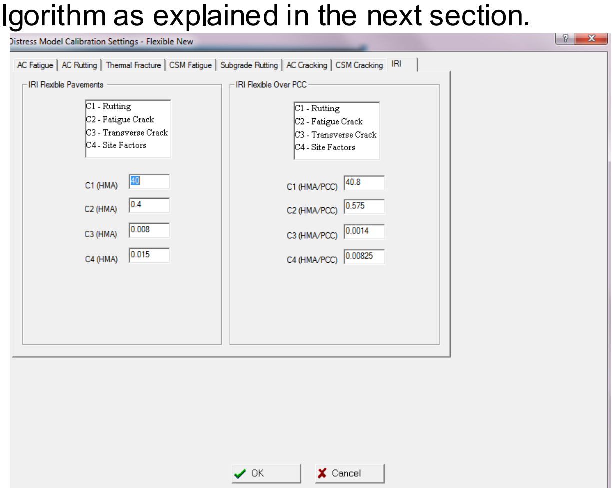

Figure 1: MEPDG Screen for entering Roughness Calibration Parameters

GENETIC ALGORITHM

Genetic algorithms (GA) are inspired by Darwin's theory about evolution. Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new generation. This is motivated by a hope, that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied. The GA has been successfully used to solve many optimization problems in the pavement industry (6). This includes solving multi-objective pavement maintenance and rehabilitation programming problems at project level and network level analysis (7 and 8).

Modeling approach

The genetic algorithm was employed in this study to locally calibrate IRI models included in the MEPDG. As shown in Figure 2, the process start by randomly generating four initial seeds (chromosomes) for calibration coefficients, each chromosome consists of (C1, C2, C3 and C4) representing different roughness calibration coefficients combination. Subsequently each chromosome is introduced to the automated MEPDG engine to execute the analysis and store roughness results in a database to be used later and pass it back to GA. The advantage of storing analysis results the possibility it can be used later if the same chromosome was chosen later or generated randomly as part of next generations and save MEPDG reprocess time. The genetic algorithm calculates the fitness of each chromosome using the following equations:

$$Fitness = \frac{Calculated\ Roughness}{Measured\ roughness} * 100\ (where\ Calculated\ Roughness > Measured\ Roughness)$$

$$Fitness = \frac{Measured\ roughness}{Calculated\ Roughness} * 100\ (where\ Calculated\ Roughness < Measured\ Roughness)$$

The closer the fitness to 100%, the more the chromosome has chance to survive for next generation. The next step is identifying best and worst chromosomes in the current generation. The worst chromosome(s) will be killed to leave room for offspring generated as a result from crossover and mutation by the best chromosomes. Next, fittest parent's pair is selected to generate new offspring by crossover. Mutation of single chromosome gene was performed on random bases only when a random mutation rate exceeds 25%. Mutation of all chromosomes was applied when all chromosomes have same fitness. Fitness for new generation chromosomes are evaluated again and process is repeated until fitness meets predefined accuracy level (accuracy > 95%). Figure 3 shows the interface for the genetic algorithm program that has been developed to calibrate the MEPDG roughness.

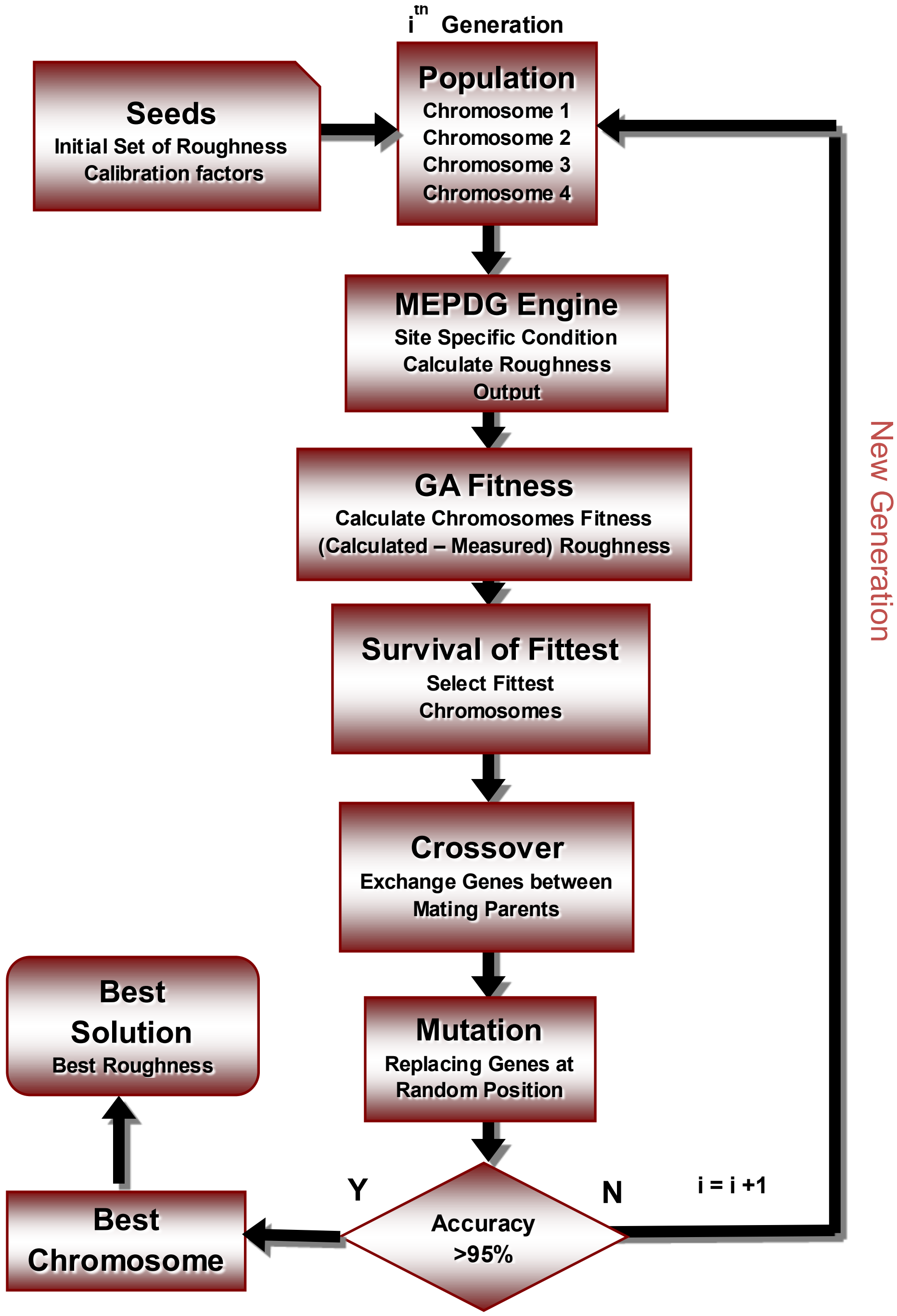

Figure 2: Framework for Genetic Algorithm used in the Calibration

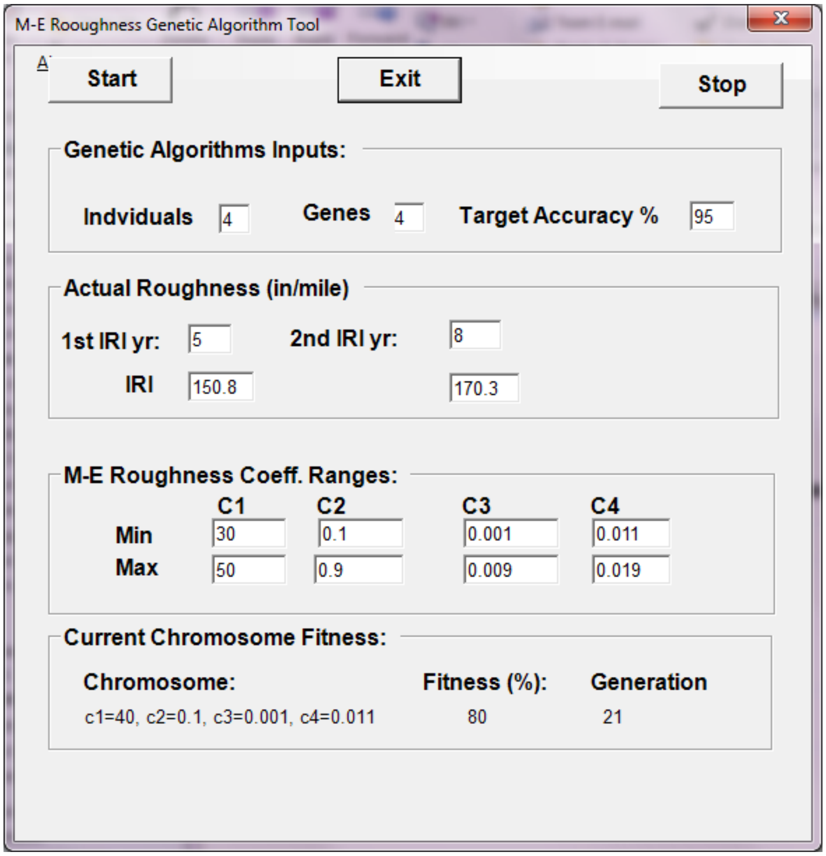

Figure 3: Screenshot from Developed Genetic Algorithm Tool for Roughness Calibration

RESULTS

Table 2 shows the results for the fittest chromosomes for each DOE category. For example, 3 sections (local, collector and arterial respectively) were calibrated for thin thickness, weak subgrade and high traffic. The best fitness achieved for each section was (92%, 90%, 74%) respectively. Categories where no section found were designated with NA results. Table 3 shows the details for each section optimum solution along with the measured IRI and the calculated IRI resulted from the GA. As can be seen from table 2 and table 3, most of the sections showed good chromosomes fitness above 90% with slight difference between predicted and measured roughness which suggest that GA is a promising tool that can be used to locally calibrate MEPDG distress coefficients. Few sections showed low fitness below 90%, however, this fitness can be improved by changing the mutation rate (and or crossover positioning) to produce fitter solution to the problem.

Table 2: Fitness Results for MEPDG Roughness Calibration

Thickness	Subgrade	Traffic		
		Low	Medium	High
Thin	Weak	NA, 96, NA	NA, NA, 93	92, 90, 74
	Strong	54, NA, 94	NA, 97, 96	95, NA, NA
Medium	Weak	NA, 94, 95	NA, 93, 74	NA, 83, 89
	Strong	89, 85, 84	91, 92, 82	92, 93, 84
Thick	Weak	93, 95, 95	95, 92, 93	93, 87, 59
	Strong	78, 81, 97	93, NA, 90	97, 90, 92

CONCLUSIONS

The current study showed that genetic algorithm (GA) can be employed to locally calibrate mechanistic empirical design guide. As a part of this study, MEPDG engine was developed to receive roughness calibration coefficients, execute analysis and calculate roughness output. The GA framework mechanism generates initial coefficients seeds and receives output from MEPDG engine to calculate chromosome fitness in each cycle in an iterative process that is guided by GA routine. A design of experiment (DOE) was implemented to identify the factors that are highly impacting the roughness performance. The DOE resulted in 18 site specific conditions. The objective was to elect three sites in each category condition from different sites in Ontario that represents local, collector and arterial function classes respectively. Accordingly, 42 sections were available for calibration in this study. The calculated fitness for most of the sections in the DOE indicated that the genetic algorithm is a promising tool that can be used in the calibration of MEPDG and these resulted models are perfectly calibrated to represent the current condition in most of the cases. The optimization-based technique will definitely provide near optimum local calibration coefficients and help pavement industry and transportation agencies to accurately calibrate MEPDG compared to traditional “trial and error” based technique. These coefficients can be enhanced by increasing the number of individuals in each population or use more samples in each condition to improve the calibration results.

Table 3: Calibration Results for each Selected Section in the DOE

	Thickness	Subgrade	Traffic	C_1	C_2	C_3	C_4	Fitness	Measured IRI		GA IRI	
									1	2	1	2
Local	Thin	Strong	Low	42	0.8	0.003	0.018	54.2	170.5		92.5	
	Thin	Strong	High	43	0.6	0.004	0.017	94.9	95.1		90.2	
	Thin	Weak	High	38	0.6	0.006	0.016	92.2	110.9		102.2	
	Medium	Strong	Low	49	0.4	0.008	0.019	89.0	101.1	114.3	94.1	97.1
	Medium	Strong	Medium	47	0.7	0.005	0.019	91.4	141.8	165.3	138.1	141.3
	Medium	Strong	High	44	0.3	0.001	0.017	92.3	92.2	107.5	90.1	93.4
	Thick	Strong	Low	50	0.8	0.005	0.017	77.8	114.3		88.9	
	Thick	Strong	Medium	33	0.5	0.001	0.014	93.4	125.4		134.2	
	Thick	Strong	High	47	0.5	0.003	0.016	97.0	69.9	79.1	71.4	75.9
	Thick	Weak	Low	50	0.1	0.007	0.019	93.2	146.2		136.2	
	Thick	Weak	Medium	36	0.2	0.008	0.011	94.7	117.9		124.5	
	Thick	Weak	High	31	0.1	0.008	0.016	92.8	54.7	67.8	63.7	68.1
Collector	Thin	Strong	Medium	43	0.3	0.001	0.014	97.1	63.8		61.9	
	Thin	Weak	Low	39	0.4	0.002	0.015	96.3	117.9		122.4	
	Thin	Weak	High	43	0.3	0.001	0.015	90.2	146.2		131.9	
	Medium	Strong	Low	46	0.7	0.005	0.019	84.6	170.5	231.9	164.4	168.6
	Medium	Strong	Medium	38	0.3	0.001	0.015	92.0	165.3	175.8	155.1	158.6
	Medium	Strong	High	50	0.4	0.003	0.015	92.9	110.9	137.5	129.2	137.4
	Medium	Weak	Low	42	0.4	0.006	0.018	94.3	110.9	133.3	121.8	130.1
	Medium	Weak	Medium	40	0.9	0.002	0.015	92.7	101.1	121.6	116.6	123.3
	Medium	Weak	High	46	0.8	0.005	0.012	82.6	65.7	79.1	83.8	91.0
	Thick	Strong	Low	46	0.2	0.005	0.017	81.0	98.0	110.9	82.8	86.0
	Thick	Strong	High	30	0.6	0.004	0.012	90.5	117.9	129.3	133.6	139.5
	Thick	Weak	Low	37	0.4	0.001	0.018	94.6	110.9	129.3	111.3	115.8
	Thick	Weak	Medium	44	0.2	0.009	0.017	91.9	192.8	198.8	177.1	182.7
	Thick	Weak	High	44	0.6	0.004	0.018	87.2	81.5	117.9	103.3	112.5
Arterial	Thin	Strong	Low	38	0.8	0.001	0.011	93.7	150.8		160.6	
	Thin	Strong	Medium	48	0.1	0.008	0.013	96.2	137.5		143.0	
	Thin	Weak	Medium	49	0.4	0.006	0.019	92.8	155.5	165.3	143.1	154.7
	Thin	Weak	High	38	0.4	0.007	0.011	73.5	72.1	98.0	104.4	125.6
	Medium	Strong	Low	45	0.5	0.007	0.019	83.9	95.1	98.0	79.2	82.8
	Medium	Strong	Medium	46	0.8	0.002	0.018	81.5	155.5	165.3	127.8	133.7
	Medium	Strong	High	44	0.6	0.007	0.018	83.9	117.9	117.9	98.9	
	Medium	Weak	Low	46	0.3	0.001	0.018	94.7	110.9	117.9	103.2	113.6
	Medium	Weak	Medium	46	0.3	0.009	0.017	74.4	146.2	192.8	119.0	130.0
	Medium	Weak	High	45	0.4	0.002	0.018	89.3	137.5	165.3	128.9	140.2
	Thick	Strong	Low	40	0.4	0.002	0.016	96.6	133.3	146.2	136.2	139.3
	Thick	Strong	Medium	41	0.4	0.006	0.018	90.0	146.2	155.5	133.7	137.7
	Thick	Strong	High	36	0.3	0.001	0.018	91.9	121.6	150.8	123.2	128.2
	Thick	Weak	Low	35	0.3	0.001	0.017	95.0	110.9	133.3	115.6	125.4
	Thick	Weak	Medium	32	0.5	0.007	0.011	93.4	76.7	86.7	84.4	90.5
	Thick	Weak	High	49	0.4	0.006	0.018	58.8	150.8		88.6	

REFERENCES

1- Zaghloul, S., Abd El Halim, A., Ayed, A., Vitillo, N. and Sauber, S. "*Sensitivity Analysis of Input Traffic Levels on MEPDG Predictions*", TRB 85th Annual Meeting, Washington, DC, *2006*.

2- Wu,Z., Yang, X. and Zhang, Z "*Evaluation of MEPDG Flexible Pavement Design using Pavement Management System Data: Louisiana Experience*", International Journal of Pavement Engineering, Vol. 14, No. 7, 674–685, *2013*

3- Hamdi, A., Tighe, S., and Ningyuan, L. "*Canadian Calibration on Mechanistic-Empirical Pavement Design Guide to Estimate International Roughness Index using MTO Data* ", Chinese Society of Pavement Engineering, International Journal of Pavement Research and Technology, Vol.7 No.2, Mar. *2014*

4- Baus., R. L. and Stires, N. R. "*Mechanistic-Empirical Pavement Design Guide Implementation* ", FHWA/SCDOT Report No. FHWA-SC-10-01, *2010*.

5- Jadoun, F., and Kim, Y. *Calibrating Mechanistic-Empirical Pavement Design Guide for North Carolina* ", Transportation Research Record, (2305), pp. 131-140., *2012*

6- Golroo, A. and Tighe, S. "*Optimum Genetic Algorithm Structure Selection in Pavement Management*", Asian Journal of Applied Sciences, 5: 327-341., *2012*

7- Chikezie, C., Olowosulu, A. and Abejide, O. "*Multiobjective Optimization for Pavement Maintenance and Rehabilitation Programming using Genetic Algorithms*", World Scholars Resource Library, 5 (2013), pp. 76–83

8- Morcousa,G., and Lounisb, Z. "*Maintenance optimization of infrastructure networks using genetic algorithms*", Automation in Construction, Volume 14, Issue 1, January 2005, Pages 129–142