Using genetic algorithms to optimize material and construction variables for Performance-Related specifications

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Abstract - *The Highway construction acceptance procedure must be designed to encourage the control of Materials and Construction (M&C) variables that present most strongly long-term performance. Therefore, many highway agencies moved away from the oldest types of Specifications (Method-type and End-result specifications) to develop Performance-Related Specifications (PRS). PRS consider the long–term performance and the Life Cycle Cost (LCC) of the pavement and relate them to the M&C variables. Reward or punishment assessed for the contractor is based on comparing LCC of as-constructed to as-designed pavements. In this research, the finite element method represents the behavior of the pavement materials and evaluate the pavement response (horizontal tensile strain εt at the bottom of the asphalt layer and vertical compressive strains εc at the top of the subgrade soil) using the nonlinear elastic orthotropic axisymmetric finite element model with the help of Ansys. The anticipated performance of as-constructed pavement depends mainly on the M&C variables that the contractor used. To ensure the quality of the as-constructed pavement, the M&C variables can be optimized using optimization methods to select the optimum values for M&C variables to achieve optimum performance. The aim of this research is selecting the optimum values of M&C to maximize the pavement performance of as-constructed pavement. A case study was developed to verify the optimization process. Genetic Algorithms (GA) method is selected as it can deal with multiple variables and can be applied to achieve any fitness function so the contractor can find the optimum solutions without performance loses. Also, a computer application structured into several subroutines and modules was developed to demonstrate the case study. V-model of verification and validation is applied to this computer application to investigate its capability of satisfying the required specification and standards.*

Key Words: Flexible Pavements, Performance-Related Specifications, Long–Term Performance, Optimization, Genetic Algorithms.

1.INTRODUCTION

In Method-Type Specifications, the contractor will be assured full bid price if the inspector verifies M&C prescribed by the agency.

The major deficiencies in Method -Type Specifications are the penalties for the contractor's nonconformance based on the inspector's judgment and statistical concepts are not used to evaluate the highway pavement and the payment schedule.

End-Result Specifications shifted the responsibility of the constructions, and quality control from the agency to the contractor, and the agency accepts, or rejects based on the acceptance test results. Limitations of test results, percent defective limitations-specified for evaluating the highway pavement and considering the variability of the results to minimize the risks to the agency and the contractor using a sound acceptance plan. The deficiency of End-Result Specifications is the dependence of payment schedules on the past ability of the contractor to perform and neglecting the long-term performance. The main advantage of this type is that payment provided to the contractor is related to the expected performance of the as-constructed pavement [1].

In PRS, the payment is determined by comparing LCC of the as-constructed pavement with the as-designed pavement. The main advantage of PRS is that payment provided to the contractor is related to the expected performance of the as-constructed pavement [2].

The aim and scope of this research are selecting the optimum values of M&C variables to maximize the pavement performance of as-constructed pavement to provide the contractor alternatives to achieve the as-designed performance using GA. A computer program was developed to demonstrate the process and show the final results that represent the optimum solutions as alternatives which help the contractor to choose from. To achieve the objectives of this research, main steps should be conducted as follows:

1. Inputting M&C variables for the as-designed pavement, environmental, traffic and load, cost and distress data.
2. GA's randomization of M&C variables for the as-constructed pavement based on specific constraints.
3. Calculating Fundamental Material Properties (FMP) and Fundamental Pavement Response Variable (FPRV).
4. Predicting pavement performance indicators.
5. Acceptance plan.
6. GA's crossover, mutation, selection, and reproduction.

2. METHODOLOGY

The main objective of this research is to simplify the previously mentioned framework by utilizing several user-friendly models to select the optimum values for M&C variables of PRS for flexible pavements using GA to provide the contractor with different alternatives to achieve the as-designed performance. Fig-1 shows the conceptual framework, that was developed to achieve these aims. The input variables used in this research are divided into four categories:

M&C variables as mentioned in Table-1, environmental variables, traffic and load data, and cost and distress data.

Table -1: M&C selected and controlled by the contractor

Variable	Symbol	Unit
The thickness of the asphalt layer	h_{asp}	Inch
The thickness of the base coarse layer	h_{base}	Inch
Absolute viscosity of bitumen measured at 70° F	V_{is}	Poises
Percentage by weight of passing (No. 200) sieve	P_{200}	%
Air voids percentage by volume	V_v	%
Asphalt percentage by weight of mix	P_{ac}	%
California Bearing ratio of Base coarse layer	CBR_{base}	%
California Bearing ratio of Subgrade	CBR_{soil}	%

The only environmental factor applied in this research is the pavement temperature because it affects the stiffness of asphalt and consequently the dynamic modulus of the asphalt concrete mixture.

Traffic data include Equivalent Single Axle Load (ESAL), no. of vehicles, wheel load, tire pressure, and growth factor.

Cost and distress data can be summarized as distress failure level due to rutting, fatigue cracking, and roughness in addition to agency and user costs for these failures, bid price to the contractor, and interest rate.

These data are compiled together in a finite element model to compute FPRV ε_c and ε_t.

The number of repetitions to failure (N_f) due to rutting, fatigue, and roughness is used as a performance indicator. There is a possibility to choose from many models to get (N_f) such as Anderson, 1990.

Then cost analysis is derived from calculating the pay factor as shown in Fig-2, and the fitness function of the optimization process to maximize the difference between equivalent uniform annual cost A_n for the as-designed and the as-constructed pavements ΔA_n.

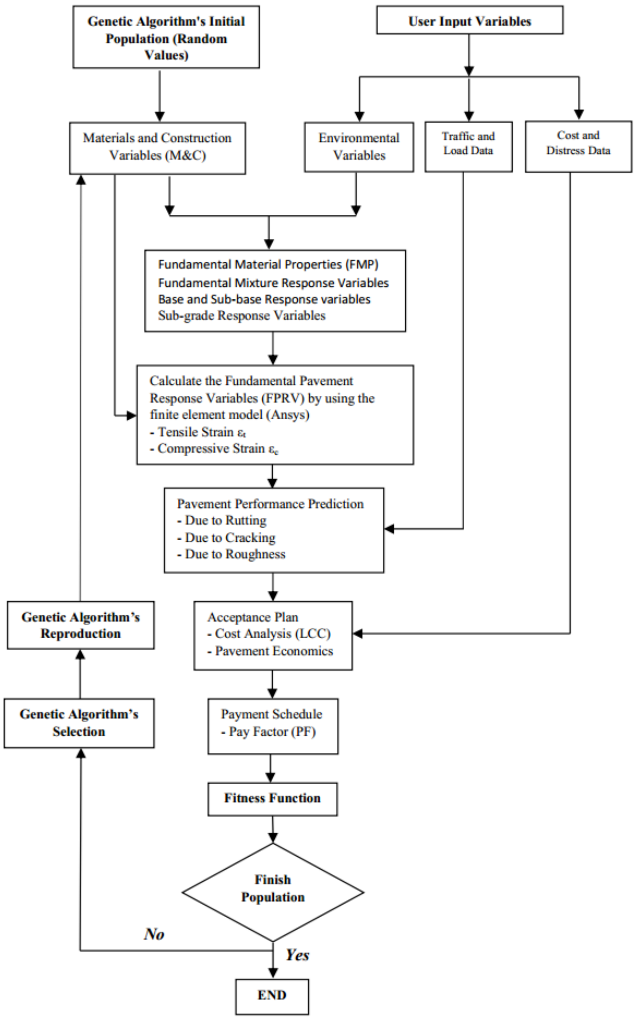

Fig -1: Main framework flowchart

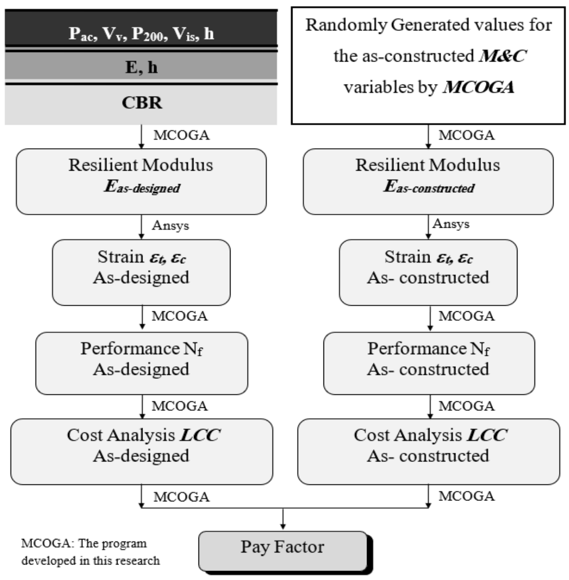

Fig -2: Calculating pay factor

3. GENETIC REPRESENTATION

The algorithm is initialized with a finite set of potential solutions called the population. Each possible solution, referred to as a chromosome. However, for building a chromosome, its genes must be identified first. In this case, the eight variables for the as-constructed pavement as mentioned in Table-1 are the genes' values. Moreover, chromosomes have a number as an index in each population. Every chromosome has a value represented by pay factor and fitness represented by ΔA_n. Each chromosome is designed to represent a solution for the problem, and it does not have repeated node index. It also encoded in bit string encoding. Hence, every chromosome in this research has eleven genes in total and can be represented as shown in Fig-3.

Index	h_{asp}	h_{base}	V_{ls}	P_{200}	V_v	P_{ac}	CBR_b	CBR_s	PF	ΔA_n

Fig -3: Genetic representation of the chromosome

Each chromosome's value is calculated from PRS procedures [3]. Firstly, the initial population is constructed, and its chromosomes are first randomly generated within the specified limits for each M&C variable. Once the generation of the initial population's chromosomes is completed, each chromosome's fitness ΔA_n is calculated. After estimating the fitness for all chromosomes in the first population, the chromosomes and their fitness are stored in the algorithm's database to avoid duplicated analysis for chromosomes that have been evaluated before and may they appear in future generations. These solutions are evaluated by a fitness function which is maximize ΔA_n.

New populations' generation is performed in two subsequent processes: selection and reproduction. The selection process is carried out to choose a pair of chromosomes to perform the reproduction process [5]. In this research, "roulette wheel" selection and elitism are used. Chromosomes with higher fitness have more probability of selection. Then these selected chromosomes sorted descending due to its fitness ΔA_n. After selecting a pair of parent chromosomes, the crossover process is carried out and suggested in our research as shown in Fig-4.

Selected Node

P_1	5	10	1	5	4	5	60	10
P_2	6	12	0.5	6	5	6	70	15

P_1	5	10	1	5	5	6	70	15
P_2	6	12	0.5	6	4	5	60	10

Fig -4: One point crossover process

After performing crossover, A one gene mutation process, is suggested and carried out, based on specific constraints, to allow new chromosomes to be created as shown in Fig-5.

Selected Gene

Before Mutation

P_1	5	10	1	5	4	5	60	10	PF_1	ΔA_{n1}

After Mutation

P_1	5	10	1	8	4	5	60	10	PF_2	ΔA_{n2}

Fig -5: One gene mutation process

The fit chromosomes are assigned a high probability to "reproduce" in the next generation. The algorithm proceeds to generate more good solutions in each iteration and eventually converges to a population with a distribution of reasonable solutions after several generations [6]. The last generation represents the optimum solutions and the best of the family tree and arranged from greatest to least as alternatives for the contractor to choose from.

As each operator probability may vary through the generations, this research suggested that crossover probability to be 0.85 and mutation probability to be 0.01 however the developed program let the user to input them.

4. IMPLEMENTATION

A program is created in Visual Basic 6.0® environment to demonstrate the case study presented in this research with a friendly graphical user interface. This program named MCOGA that stands for (Material and Construction variables Optimization by Genetic Algorithms).

MCOGA is structured into several subroutines and involves 2 Modules and 7 forms and run through two stages as shown in Figure Fig-6. The first module (Module PRS.bas) is for PRS and the second module (modBitOps.bas) is for GA. The first stage is a frontend and contains three substages and the second stage is a backend and involves two substages and can be summarized as follows:

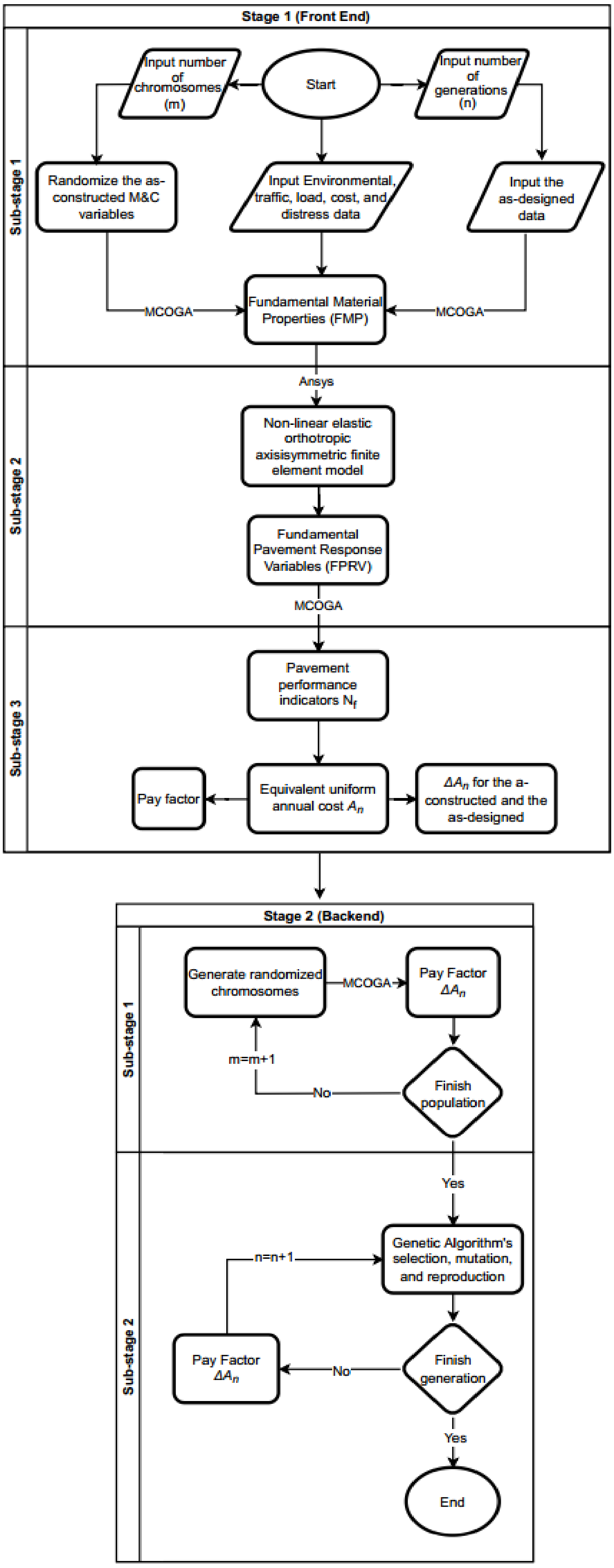

Fig -6: Organization of modules and subroutines

1.1 First stage

1. The first substage runs through 3 forms as follows:

7. The first form is to input GA data that the user chooses to control the optimization process and randomizing the as-constructed M&C variables to form the first chromosome in the initial population as shown in Fig-7.

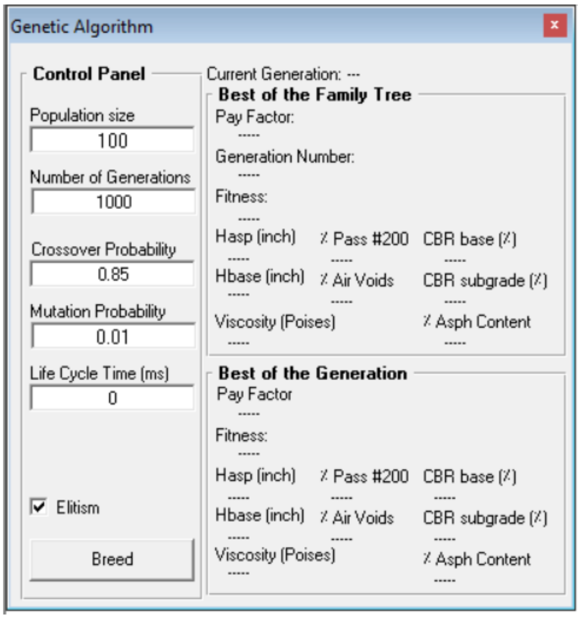

Fig -7: Input genetic algorithms data

8. The second form as shown in Fig-8 is to input the limits of M&C variables which can be determined from The Asphalt Institute or AASHTO.

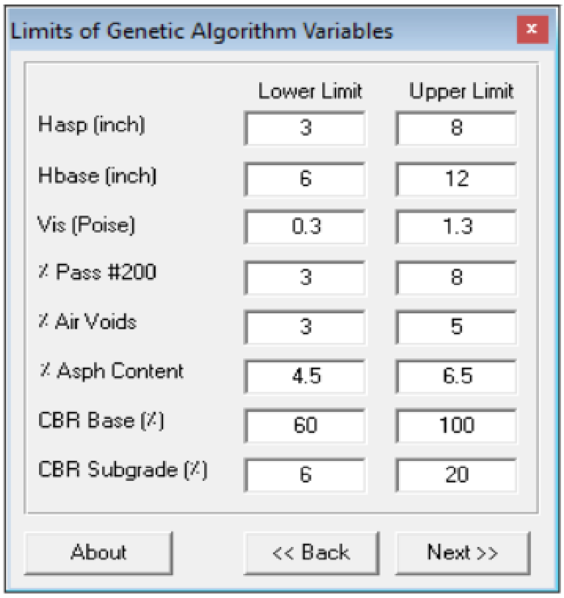

Fig -8: Input limits of M&C variables

Table-2 summarizes these values according to (Akhter, 1985) [4].

Table -2: GA Limits for M&C variables (According to Akhter)

Variable	Upper Limit	Lower Limit	Unit
h_{asp}	3	8	Inch
h_{base}	6	12	Inch
V_{is}	1.3	4.3	Poises
P_{200}	0.4	10.6	%
V_v	0	15.9	%
P_{ac}	3	10.2	%
CBR_{base}	60	100	%
$CBR_{subgrade}$	6	20	%

9. The third form is to input the as-designed M&C variables, traffic, load, environmental, cost, and distress data and calculating FMP for both the as-designed and the as-constructed pavements as shown in Fig-9.

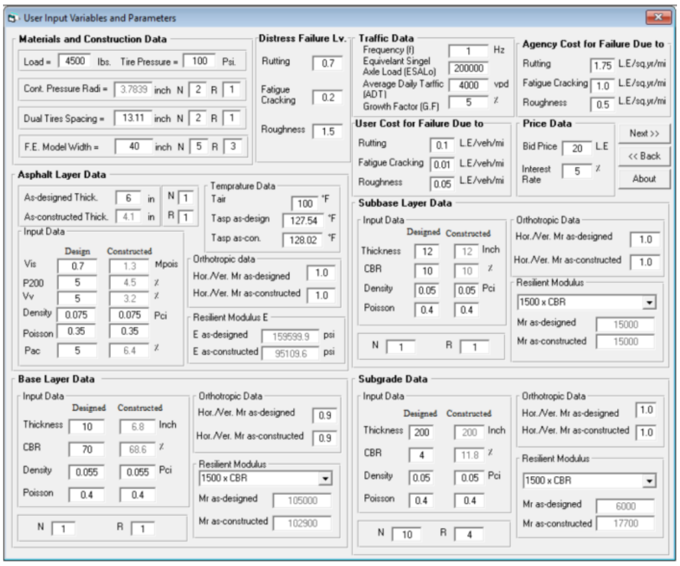

Fig -9: input all M&C and environmental variables and traffic, load, distress, and cost data

2. The second substage is a link programed to transform the stored data from VB6 to Ansys and calculate FMRV in terms of horizontal tensile strain ε_t at the bottom of the asphalt layer and vertical compressive strains ε_c at the top of the subgrade soil using nonlinear elastic orthotropic axisymmetric finite element model with the aid of Ansys® then transform the output from Ansys to VB6 again as shown in Fig-10.

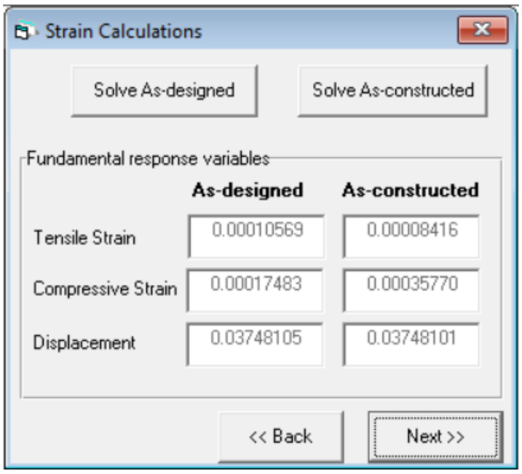

Fig -10: The link with Ansys to calculate FPRV

3. The third substage runs through 3 forms as follows:

10. The first form as shown in Fig-11 uses the output that contains FPRV from Ansys as inputs to predict pavement performance in terms of number of repetitions to fail N_f for rutting, fatigue cracking, roughness using several methods for both the as-designed and the as-constructed pavements.

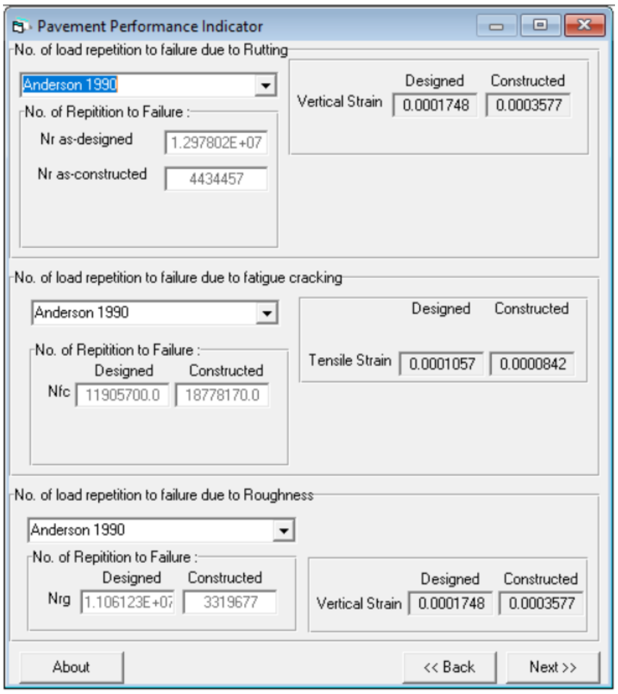

Fig -11: Number of load repetition to failure due to different distresses

11. The second form calculates the distress level at each year and the year of failure due to rutting, fatigue cracking, and roughness for both the as-designed and the as-constructed pavements as shown in Fig-12.

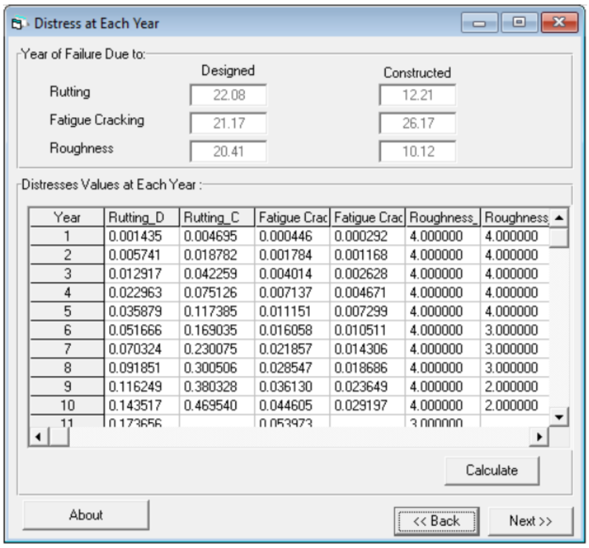

Fig -12: Calculating the year of failure and distress each year

12. The third form is to calculate LCC represented by equivalent uniform annual cost A_n for both the as-designed and the as-constructed pavements and payment schedule to calculate contractor's pay factor as the value for the first chromosome in the initial population.

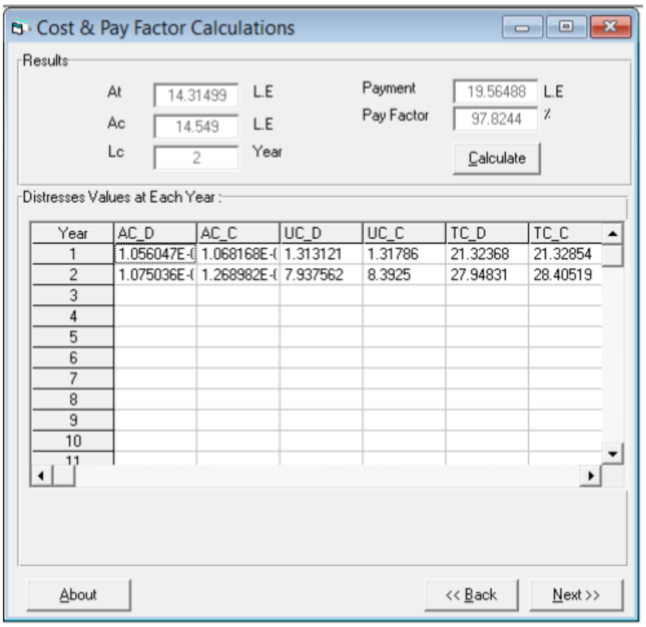

Fig -13: Cost, payments, LCC, and pay factor calculations

1.2 Second stage

1. The first substage in the second stage coded to run in background which repeats the previous steps to randomly generate the rest of chromosomes in the initial population and calculate the values and fitness for each of them to complete the initial population.

2. The second substage coded to run in background and executed to generate new generations using selection, crossover, mutation, and reproduction techniques as mentioned before then evaluating the objective (fitness) function which is to maximize ΔA_n by comparing the fitness of all chromosomes to their predecessor in this generation and sorting all the results fitness from the largest to the lowest and repeating the previous procedures to produce next generations till the last generation and representing all optimum solutions as alternatives sorted from best to least without losing the quality or performance drop.

5. CASE STUDY

A case study was presented to verify the optimization process. The input data can be summarized as mentioned in tables from Table-3 to Table-9.

Table-3 contains genetic algorithms data, which controls the optimization process without using elitism, as inputs of the first form as shown in Fig-7.

Table -3: Case study's genetic algorithms data

Parameter	Value	Units
Population Size	100	-
Number of Generations	1000	-
Crossover Probability	0.85	%
Mutation Probability	0.01	%

Table-4 contains the limits of M&C variables, as inputs of the second form as shown in Fig-8.

Table -4: Case study's GA Limits for M&C variables

Parameter	Unit	Upper Limit	Lower Limit
h_{asp}	Inch	3	8
h_{base}	Inch	6	12
V_{is}	Poises	0.3	1.3
P_{200}	%	3	8
V_v	%	3	5
P_{ac}	%	4.5	6.5
CBR_{base}	%	60	100
$CBR_{subgrade}$	%	6	20

Tables from Table-5 to Table-9 represents the inputs of the third form as shown in Fig-9 in this case study FMRV is chosen to be (1500 x CBR). Table-4 summarizes M&C variables for the as-designed pavement and all parameters for the as-designed and the as-constructed pavements. Table-6 contains traffic and load data. Table-7 represents environmental data. Table -8 contains distress levels and cost data. Table-9 represents the nonlinear elastic orthotropic axisymmetric finite element model data.

Table -5: Case study's M&C variables.

Parameter	Value	Unit
Material and Construction variables		
D_1	6	Inch
D_2	10	Inch
V_{is}^D	0.7	Poises
P_{200}^D	5.3	%
V_v^D	3.67	%
P_{ac}^D	5	%
CBR_{base}^D	80	%
$CBR_{subgrade}^D$	5.5	%
$Dens_{D1}$ and $Dens_{C1}$	0.075	Pci.
$Dens_{D2}$ and $Dens_{C2}$	0.055	Pci.
$Dens_{D3}$ and $Dens_{C3}$	0.05	Pci.
η_{D1} and η_{C1}	0.35	-
η_{D1} and η_{C1}	0.4	-
η_{D1} and η_{C1}	0.4	-

Table -6: Case study's traffic and load data.

Parameter	Value	Unit
Traffic and Load Data		
f	1	Hz
ESAL	200000	-
ADT	4000	Vehicle / Day
G.F.	5	%
P	4500	lbs.
ρ	100	Psi
a	3.7839	Inches

Table -7: Case study's environmental data.

Parameter	Value	Unit
Environmental Data		
T_{air}	77	ºF
T_{asp}^D	98.91	ºF
T_{asp}^C	98.95	ºF

Table -8: Case study's distress levels and cost data.

Parameter	Value	Unit
Cost Data		
Rutting distress Agency Cost	1.75	LE /yard²/Mile
Rutting distress User Cost	0.1	LE/vehicle/mile
Fatigue distress Agency Cost	1	LE /yard²/Mile
Fatigue distress User Cost	0.01	LE/vehicle/mile
Roughness distress Agency Cost	0.5	LE /yard²/Mile
Roughness distress User Cost	0.05	LE/vehicle/mile
Bid Price	20	LE/yard²
Interest Rate	5	%
Distress Failure Level		
Rutting	0.75	-
Fatigue Cracking	0.2	-
Roughness	0.51	-

Table -9: Case study's finite element model data.

Parameter	Value	Unit
Finite Element Data		
N_a	1	-
R_a	1	-
CC	13.11	Inches
N_{cc}	2	-
R_{cc}	1	-
W	40	Inches
N_w	5	-
R_w	3	-
D_1	6	Inches
D_2	10	Inches
D_3	200	Inches
N_1	1	-
N_2	1	-
N_3	10	-
R_1	1	-
R_2	1	-
R_3	4	-

As mentioned before the program then generates a link with Ansys to calculate FPRV (ε_c and ε_t), As shown in Fig-10, to calculate N_f for rutting, fatigue, and roughness for the first chromosome, as shown in Fig-11 and calculates the year of failure and the year of failure due to each distress, as shown in Fig-12.

The program reactivates the first window while generating new generations and shows the optimum solution of the current generation and the best of family tree, as shown in Fig-7.

The V-model is applied to verify and validate the developed program. Verification activities were done before coding to check that the developed program built right and run correctly without any bugs or errors.

However, validation was done by running MCOGA with case study parameters then input the same parameters in PRS program created by (Galal, 2003) [7] and apply trial and error methodology to verify MCOGA outputs as shown in Table-10.

It is obvious that all variables are within the limits, reasonable and logical and the results are approximately the same from PRS program and MCOGA. Also, the pay factors (values) for all alternatives are within the interval [95-105] and their fitness are approximately the same. So, the program gives alternatives that the contractor can rely on without performance drop.

Table -10: Outputs comparison of MCOGA and PRS.

MCOGA											PRS	
Ch.	h_{asp}	h_{base}	V_{is}	P_{200}	V_v	P_{ac}	CBR_{base}	CBR_{sub}	PF	Fitness	PF	Fitness
1	7.4	11.6	1.1	4.2	4.6	5.3	74	6	99.02608	0.104755	99.02607	0.104754
2	5.3	11.3	1.3	3.4	3.5	4.8	89.9	6.6	99.03731	0.103548	99.0373	0.103547
3	6	10.9	1	3.2	4.5	4.8	93.9	6.7	99.06013	0.101092	99.06012	0.101091
4	5.1	11.6	0.4	3	3.7	5.1	90.1	8.4	99.08801	0.098094	99.088	0.098093
5	5.4	11.9	0.5	3.4	3.9	5.2	92.6	9.3	99.08827	0.098066	99.08826	0.098065
6	3.9	11.8	1.3	7	3.3	4.6	81	8.9	99.13288	0.093268	99.13287	0.093267
7	7.2	11.1	1.1	7.6	4.2	6	95.4	8.8	99.14372	0.092102	99.14371	0.092101
8	6.9	9.8	0.6	7.9	3	5.3	98.7	6.7	99.16409	0.089911	99.16408	0.08991
9	7.6	11.5	1.2	7.9	3.8	5.6	87.8	9.9	99.18497	0.087666	99.18496	0.087665
10	6.9	11.6	1.3	3.6	4.2	5.5	62	7.2	99.19266	0.086839	99.19265	0.086838
11	7.8	10.5	0.6	4.3	3.5	5	73.8	6.7	99.20609	0.085394	99.20608	0.085393
12	5	12	1.3	6	3.7	6.1	83.4	11.7	99.22809	0.083028	99.22808	0.083027
13	3.6	12	0.4	6.6	3.4	6.4	70	10.5	99.25475	0.080161	99.25474	0.08016
14	6	10.9	1	3.2	5	5.3	93.8	10.4	99.28508	0.076898	99.28507	0.076897
15	8	10.3	1.1	4.4	4.6	4.5	95.8	9.4	99.29855	0.075448	99.29854	0.075447
16	7.1	10.7	1	3	4.9	5.3	92.3	9.9	99.30296	0.074974	99.30295	0.074973
17	3.7	11.7	1.3	7.2	3.6	6.3	78.7	12	99.32702	0.072387	99.32701	0.072386
18	5.9	11.8	0.4	7.6	4	5.3	77.3	11.6	99.33526	0.0715	99.33525	0.071499
19	6.2	9.9	0.4	4.7	4.2	4.7	79.9	7.3	99.35362	0.069526	99.35361	0.069525
20	5.6	10.1	1.3	5.3	4.7	5.4	96.1	9.4	99.36502	0.068298	99.36501	0.068297
21	6.8	11.1	0.6	7.2	3.1	6.4	71.7	9.3	99.36627	0.068164	99.36626	0.068163
22	6.2	11.7	0.3	3.3	4.9	5.3	87.3	13.5	99.37138	0.067616	99.37137	0.067615
23	4.2	11	0.6	3.3	3.7	5.4	80.1	10.8	99.38956	0.06566	99.38955	0.065659
24	4.7	11.2	0.6	4.4	4.7	5.4	91.8	13.3	99.40913	0.063555	99.40912	0.063554
25	3.1	11.9	1.2	4	3.3	5.7	70.9	12.7	99.42554	0.061789	99.42553	0.061788
26	4.4	10.9	0.5	4	4.5	5.3	89.3	12.4	99.44438	0.059763	99.44437	0.059762
27	4.8	11.9	0.7	6.9	3.5	6.1	99.9	18.4	99.45922	0.058167	99.45921	0.058166
28	3	11	1	7.6	3.2	6.1	91	13.4	99.46516	0.057528	99.46515	0.057527
29	5.5	11.8	0.3	4.1	4.6	4.6	61.7	10.9	99.47919	0.056019	99.47918	0.056018
30	7.9	8.5	0.6	7.5	4.9	5.6	97.6	6.6	99.48454	0.055444	99.48453	0.055443
31	6.7	11.1	0.6	5.1	4.1	4.7	75.5	11.2	99.486	0.055286	99.48599	0.055285
32	7.1	12	0.7	4.7	4.9	6.4	82.9	15.7	99.48714	0.055164	99.48713	0.055163
33	7.1	12	0.7	4.7	4.9	6.4	82.9	15.7	99.48714	0.055164	99.48713	0.055163
34	7.9	10.7	0.9	7.4	3.1	6	89.1	12.7	99.56219	0.047091	99.56218	0.04709
35	6.8	11.6	0.7	4.4	4.7	6.3	80.4	14.9	99.57508	0.045705	99.57507	0.045704

6. CONCLUSIONS

A neat framework is developed to select the optimum values of M&C variables for PRS for flexible pavements that maximize the difference between equivalent uniform annual cost A_n for the as-designed and the as-constructed pavements □□□ using GA with a computer program, to facilitate these complicated calculations coded in VB6, which is verified and validated with V-model.

A case study was developed to verify the optimization process and showed that GA is an effective and effortless method to select M&C variables and gave reasonable optimization results. It also confirms that we can rely on GA to optimize any other variables.

6. RECOMMENDATIONS

Based on this study, the following recommendations were performed for further studies such as applying GA optimization methodology to select M&C variables for PRS for rigid pavements. Also, more M&C variables, models for calculating FMRV, models for predicting temperature profile, environmental effects, models to predict rutting, fatigue cracking, roughness distresses can be considered in further studies.

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