Case Studies of Asphalt Pavement Analysis/Design with Application of the Genetic Algorithm

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Abstract. The primary purpose of this study is to demonstrate the applicability of the genetic algorithm (GA) to solve nonlinear optimization problems encountered in asphalt pavement design. The fundamentals of the GA are briefly discussed, and four case studies are presented. The first case study is an example showing the backcalculation of layer moduli with deflection data from a falling weight deflectometer and a layered-elastic program. The second case study demonstrates how to construct the master curve, either from a mix flexural frequency sweep test or from a binder rheometer test, and how to apply that master curve in pavement design. The third case shows how to apply the GA to characterize the binder discrete relaxation spectrum with a generalized Maxwell solid model. The last case study illustrates how to apply the GA to define the mix fatigue damage process of a flexural controlled-deformation beam fatigue test and the permanent shear strain accumulation process of a controlled-load repetitive simple shear test with constant height using a three-stage Weibull approach, and how to apply the three-stage Weibull approach in predicting pavement performance. The results indicate that the GA is promising and successful in resolving the nonlinear optimization problem although the GA presents some difficulty in terms of computing efficiency in the case study of backcalulation of layer moduli.

1 Introduction

The Genetic Algorithm (GA) has long been used as an optimization tool in resolving numerical problems, especially the problem of nonlinear optimization. However, little has been done to apply GAs to asphalt pavement design until recently. The backcalculation of pavement layer moduli, design of pavement structures, and scheduling of pavement maintenance operations are the major applications of

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GAs. This paper presents the use of GAs for the backcalculation of pavement moduli focused in the sensitivity analysis of GAs, the characterization of mix master curve, the binder relaxation spectrum, and the material performance models of asphalt concrete using three-stage Weibull approach.

Kameyama et al. developed a method for backcalculating pavement layer moduli from surface deflections with the GA [1], with the deflections calculated by layered-elastic theory as the input condition. FWA et al. [2] stressed that although the strength of the GA-based methods for backcalculation lies in its superior global search ability, its computation time needs to be reduced before the method can be considered for routine backcalculation analysis in practice. The GA has replaced traditional calculus methods used to search for best-fit stiffness profiles of in situ pavement systems based on non-destructive test methods [3].

GAs have been used by Liu and Wang [4] for design of flexible pavement structure and by Hadi and Arfiadi [5] for design of rigid structures.

Shekharan used GAs to develop solutions to pavement deterioration models [6], and Attoh-Okine presented the application of the GA in predicting roughness progression in flexible pavements [7]. GAs have been merged with artificial neural networks and fuzzy logic to efficiently identify the distresses to be treated [8]. The advantages of such approaches in the design of decision support systems have been described by Loia et al. [9].

The GA is a technique inspired by the Darwinian theory of survival of the fittest [10]. It mimics the natural process of evolution to develop an optimum solution. GAs operate on a set of randomly generated solutions. For each of the solutions, the values of fitness function, which indicate the proximity of the solution to the optimum solution, are evaluated. The solutions with good fitness values are combined in an attempt to produce a better solution set. Replacing solutions with poor fitness with new solutions completes one iteration, or generation of the algorithm. This process is repeated until a sufficiently good fit is obtained.

The general procedure to conduct a GA analysis is [11]:

1. *Define the problem.* The parameter definition and fitness function associated with the problem should be clearly identified before conducting a GA-based analysis. The rest of the GA procedure is to find an optimum set of parameters— that is, a good gene—that minimize the fitness function. Intuitively, the residual sum of squares (*RSS*) is a good choice for the fitness function, given that the objective is to have the measurements and predictions as close as possible to model fitting.
2. *Generate N (even number) genetic starting strings.* From the problem definition, a total of p parameters $(t1, t2, t3, \ldots, tp)$ are selected to construct a gene string (or gene). A gene $\mathbf{\Lambda}_i$ consists of values $\left\{S_{t1}^{(i)}, S_{t2}^{(i)}, S_{t3}^{(i)}, \ldots, S_{tp}^{(i)}\right\}$ of p parameters, which are generated by using a uniform distribution over a specified range of each parameter. A gene pool is defined as a set of genes, that is, $\{\mathbf{\Lambda}_1, \mathbf{\Lambda}_2, \ldots, \mathbf{\Lambda}_N\}$: