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Original Research Article

A new approach for modeling of flow number of asphalt mixtures

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ABSTRACT

Flow number of asphalt-aggregate mixtures is an explanatory parameter for the analysis of rutting potential of asphalt mixtures. In this study, a new model is proposed for the determination of flow number using a robust computational intelligence technique, called multi-gene genetic programming (MGGP). MGGP integrates genetic programming and classical regression to formulate the flow number of Marshall Specimens. A reliable experimental database is used to develop the proposed model. Different analyses are performed for the performance evaluation of the model. On the basis of a comparison study, the MGGP model performs superior to the models found in the literature.

1. Introduction

Rutting is mainly caused by traffic loads that led into pavement permanent deformations. The accumulation of the deformations results in progressive development of rutting phenomenon. The negative effects of rutting on the pavement performance are well-understood [36]. Mechanistic-empirical, constitutive modeling and simple performance testing approaches are commonly used for the analysis of the rutting potential of asphalt mixtures [21]. More, there has been recent research on viscoelastic, viscoplastic and damage material models [6,17]. Significant dependence on these methods on the empirical data and accurate characterization of the asphalt behavior are considered as their limitations. Rut susceptibility can be also analyzed during asphalt mix design. In the well-known Superpave mixture design method, there is no direct test method to evaluate the permanent deformation resistance of mixtures. This limitation motivated different researchers to use a rutting resistance indicator parameter, called flow number. This parameter can be measured through a repeated load permanent deformation test. In fact, the flow number denotes the number of cycles after which the asphalt experiences the tertiary deformation [40]. However, performing dynamic tests to determine the flow number is a sensitive and cumbersome procedure. This issue implies the importance of developing a precise model that can correlate the flow number with mix design parameters.

A viable approach to determine the flow number is to computational intelligence (CI). The CI-based method can automatically learn from the experimental data and design computer models. These techniques have been applied to different civil engineering tasks. For example, in the field of hydraulic engineering, Azamathulla [3] and Azamathulla et al.

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[4] utilized a robust CI method called genetic programming (GP) to predict the scour below submerged pipeline and scour depth downstream of sills. One of the most widely used CI methods, artificial neural network (ANN), is applied to the modeling of soil properties [8,9], factor of safety of soil nailed slopes [15], as well as other geotechnical and earthquake engineering problems [28,29,31]. On the structural domain, the CI methods are utilized for tackling various problems such as modeling true stress of dynamic strain aging regime of austenitic stainless steel [16], modeling of shear strength of RC deep beams [13], structural assessment and damage identification [27,28], etc. There are also studies on application of CI in behavioral modeling of asphalt pavements and materials such as estimation of polypropylene concentration of modified bitumen images [38], determine static creep behavior and optimal polypropylene amount in bituminous mixtures [37], prediction of the dynamic modulus of hot-mix asphalt (HMA) [5], predict asphalt mix performance [23]. However, a common limitation of most of the CI techniques is that they cannot provide practical prediction equations. To cope with this issue, Koza [22] proposed the GP method which is capable of generating computer programs following the Darwinian natural selection theory. GP and its variants have been widely used for the analysis of civil engineering systems [1]. There are also limited studies on the application of GP to the analysis of pavement systems. Alavi et al. [2], Gandomi et al. [12] and Mirzahosseini et al. [24] proposed new models for the prediction of flow number using different GP-based methods. Gopalakrishnan et al. [19] developed asphalt mix stiffness predictive equations utilizing GP. A comparative analysis of ANN and GP in backcalculation of pavement layer thickness was carried out by Saltan and Terzi [30]. Terzi [39] employed a branch of GP to model the deflection basin of flexible highway pavements.

This study proposes a new approach called multi-gene genetic programming (MGGP) for the formulation of the flow number of asphalt mixtures. The MGGP method combines GP with statistical regression to evolve a number of sub-programs with both linear and non-linear terms. The MGGP model is calibrated using an experimental database that has been already developed by the authors. Aggregate, bitumen and asphalt mixture characteristics are used to formulate the flow number. A comparative study is conducted to verify the performance of MGGP against different CI methods.

2. Evolutionary computation

Inspired by the natural evolution, evolutionary computation (EC) methods generate computer models to solve complicated problems. Some of the well-known branches of EC are genetic algorithms (GA), evolutionary strategies (ESs), and evolutionary programming (EP) [11]. These techniques are collectively known as evolutionary algorithms (EAs). CI includes EAs with ANN and fuzzy logic. In general, an EA consists of an initial population of random individuals improved by a set of genetic operators (e.g., reproduction, mutation and recombination). The individuals are encoded solutions in form of binary strings of numbers evaluated by some fitness functions [7].

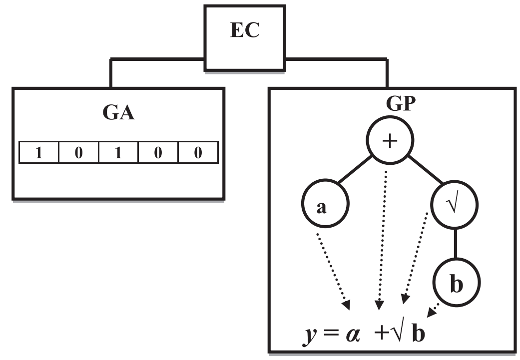

Fig. 1 – A comparative illustration of encoded solutions by GA and GP.

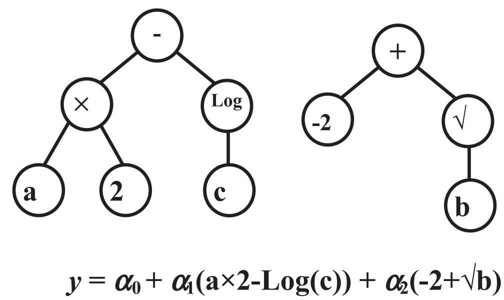

Fig. 2 – A model generated by MGGP.

GP and GA are shown to be a suitably robust EA for dealing with a wide variety of complex civil engineering problems [22]. There are notable differences between these methods. Fig. 1 shows a comparison of the encoded solutions (individuals) by GA and GP. As it is seen, the solution provided by GA is a string of numbers while GP directly outputs computer programs represented as tree structures [1,22]. The final output of GP is a single tree expression. MGGP is an extension to GP where the solution is a weighted linear combination of different GP computer programs [14,15,33]. In contrast with other CI methods, MGGP has been applied to few fields in engineering domain [14–16,25]. Fig. 2 shows a typical program evolved by MGGP. It can be observed from Fig. 3 that the model is linear in parameters with respect to the coefficients α_0, α_1 and α_2 despite using nonlinear terms. In the MGGP algorithm, ordinary least squares analysis is performed to determine these coefficients [34]. Comprehensive details about MGGP can be found in [14,15,33].

3. Empirical model for the flow number

On the basis of a literature review [2,12,20,36], several parameters affecting rutting are determined in this study. Accordingly, the MGGP-based formulation of flow number (F_n) is considered to be as follows:

$$\mathrm{Log}(F_n) = f\left(\mathrm{CP}, \mathrm{FP}, \mathrm{BP}, \mathrm{V_a}, \mathrm{VMA}, \frac{M}{F}\right) \quad (1)$$

where CP, FP, BP, V_a, and VMA are percentages of coarse aggregate, filler, bitumen, air voids, and voids in mineral aggregate. M/F is the ratio of Marshall stability to flow