Advances in Engineering Software 116 (2018) 67–79

Contents lists available at ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Research paper

A comparative study of machine learning approaches for modeling concrete failure surfaces

Uwe Reuter*,[a], Ahmad Sultan[a], Dirk S. Reischl[b]

[a] Technische Universität Dresden, Faculty of Civil Engineering, Dresden 01062, Germany
[b] Technische Universität Dresden, Faculty of Civil Engineering, Institute of Concrete Structures, Dresden 01062, Germany

ARTICLE INFO

Keywords:
Artificial neural network
Support vector machine
Support vector regression
Concrete failure surface

ABSTRACT

This study introduces an enhanced approach for concrete failure criterion, which is strongly needed for a realistic simulation of concrete behavior, by employing machine learning approaches instead of the traditional models of failure surfaces. Since the shape of concrete failure surfaces is not exactly known, a general shape function for verification purposes of the machine learning approaches is introduced. Artificial neural networks, support vector machines, and support vector regression are adapted to model realizations of this general shape function with different noise levels. After the successful fitting of these surfaces, the algorithms are employed to model the failure surface of C25 concrete starting from 88 experimental tests. The three approaches are able to fit the experimental data with low error and are compared to one another. Drucker–Prager and Bresler–Pister surfaces are solved for the same experimental data and compared with the support vector regression surface. The main advantage of machine learning approaches is that they are model-free approaches which eliminate the need of new models for new concrete types.

1. Introduction

Concrete strength is still described by a single value of compressive strength, but its complex behavior is pushing toward a more comprehensive and accurate description. The pure tension, shear and torsion stresses were studied thoroughly and linked to the compression strength. The compound stress situations were also studied in the past decades and therefore the failure surface was proposed. Many models were early introduced like Rankine, von Mises, Tresca and Mohr–Coulomb [1–4]. These simple models were easy to handle with hand calculations but were not able to describe the failure surfaces accurately. By applying optimization algorithms more complex models were introduced like Drucker–Prager [5], Bresler–Pister [6], Ottosen [7] and others [8–11]. These approaches were able to describe the failure surfaces more accurately but had two disadvantages; the complexity and the limitation to a predefined model. Wai-Fah Chen states that "No one mathematical model can describe the strength of real concrete materials completely under all conditions. Even if such a failure criterion could be constructed, it would be far too complex to serve as the basis for the stress analysis of practical problems" [1]. This statement is what this study is trying to overtake by applying machine learning approaches.

With the development of machine learning algorithms [12,13], it became motivating to use such approaches to develop new models for concrete strength. Machine learning is a computer science subfield that provides a broad range of model-free approaches classified into three categories unsupervised learning, reinforcement learning and supervised learning [14]. The focus in this paper is on three well-known supervised learning approaches; artificial neural networks (ANNs), support vector machines (SVMs) and support vector regression (SVR), in order to study their suitability for modeling concrete failure surfaces especially with respect to accuracy and efficiency as well as their potential to cope with uncertain experimental data. These three approaches are adapted to model a concrete failure surface for each approach. The obtained failure surfaces are compared with Drucker–Prager and Bresler–Pister surfaces as two conventional approaches.

The goal of this study is to develop a new comprehensive, accurate and simple failure criterion for concrete free of any predefined models and completely depending on the experimental tests. This would be a great step toward a more realistic analysis of concrete behavior.

2. Concrete failure surface

A material failure surface [1] is a representation of the failure limits in three dimensional space where axes are the principal stresses σ_i in the

* Corresponding author.
E-mail address: uwe.reuter@tu-dresden.de (U. Reuter).

https://doi.org/10.1016/j.advengsoft.2017.11.006
Received 7 July 2017; Received in revised form 6 October 2017; Accepted 28 November 2017

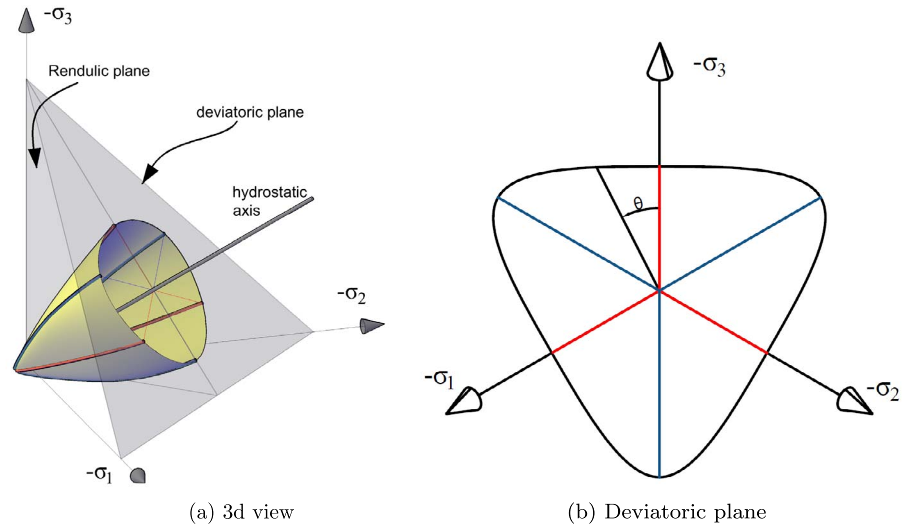

Fig. 1. Concrete failure surface.

three principal directions n_i ($i=$ 1, 2, 3). Thus, in this kind of stress space, one is interested in the geometry of the stress rather than the orientation of the stress state with respect to the material of the body. Points inside the surface represent cases where concrete is still bearing stresses and points on the failure surface determine failure states of the concrete, whereas points outside the failure surface are stress cases that cannot be reached.

An important property of concrete failure surface is its six-fold symmetry. This follows from the assumed isotropy of concrete as the labels 1, 2, 3 attached to the coordinate axes are arbitrary. The hydrostatic axis is the diagonal which has equal distances from all three axes, so every point on this axis is characterized by $\sigma_1 = \sigma_2 = \sigma_3$. The deviatoric plane is the plane perpendicular to the hydrostatic axis. Fig. 1b shows the deviatoric plane with the projection of the principal axes on it. The angle θ is called the angle of similarity and it is measured from the projection of any axis on the deviatoric plane and in both directions from $\theta = 0$ to $\theta = 60$. The meridian that corresponds to $\theta = 0$ is called the tensile meridian which is marked red. The meridian corresponding to $\theta = 60$ is called the compressive meridian and it is marked blue. As a result, there are 3 compressive meridians and three tensile meridians in the whole failure surface. Rendulic plane is the plane where two stresses are equal e.g. $\sigma_1 = \sigma_2$. This plane passes through both compressive and tensile meridians.

The oldest assumptions used for concrete failure surface were the maximum tensile stress criterion which was proposed by Rankine in 1876, shearing stress criteria of Tresca (1864) and von Mises (1913) [4], and Mohr–Coulomb criterion (1900). These one and two-parameter models were suitable for hand calculations but suffered from rough approximations so they were used for specific problems only.

More complex models were proposed afterwards. Drucker and Prager (1952) assumed a model with two parameters. Then three-parameter models were proposed by Bresler–Pister (1958) [6] and Willam–Warnke (1974) [15]. The development continued by increasing the number of parameters and many 4 and 5-parameter models were developed in the past years [7–11]. All these models had predefined shapes and their parameters needed an optimization to fit the experimental data. This was the main disadvantage of these models. Two common conventional models are introduced in the following to be compared later with the machine learning based models.

2.1. Drucker–Prager model

This model was developed in 1952 based on studies of soil mechanics [3,5] as a two parametric model. It represents a dilatation of von Mises criteria about the influence of the hydrostatic stress component, or a smooth approximation to Mohr–Coulomb surface. It is described by the formula

$$\alpha I_{1\sigma} + \sqrt{J_{2\sigma}} - \beta = 0 \tag{1}$$

where $I_{1\sigma}$ is the first invariant of the stress tensor, $J_{2\sigma}$ is the second invariant of the deviatoric stress tensor, α and β are the two parameters that define the surface according to the concrete properties and tests. The main disadvantages are that the meridians are straight lines (linear) and the cross section in the deviatoric plane is limited to circular as shown in Fig. 2.

2.2. Bresler–Pister model

Bresler and Pister developed in 1958 [1,6] a three parametric model assuming that the meridians have a parabolic formula and neglecting the difference between the meridians. It was described by the formula

$$\frac{\tau_{oct}}{|f_c|} = a - b\cdot\frac{\sigma_{oct}}{|f_c|} + c\cdot\left(\frac{\sigma_{oct}}{|f_c|}\right)^2 \tag{2}$$

where a, b, c are the three parameters, f_c is the uniaxial compressive strength tested with rigid plates, σ_{oct} is the octahedral normal stress and τ_{oct} is the octahedral shear stress. This model has circular cross sections in the deviatoric plane which is considered as the main disadvantage of it (see Fig. 3).

3. Machine learning approaches

3.1. Artificial neural networks

Artificial neural networks (ANNs) [14,16–19] are an analogy of the

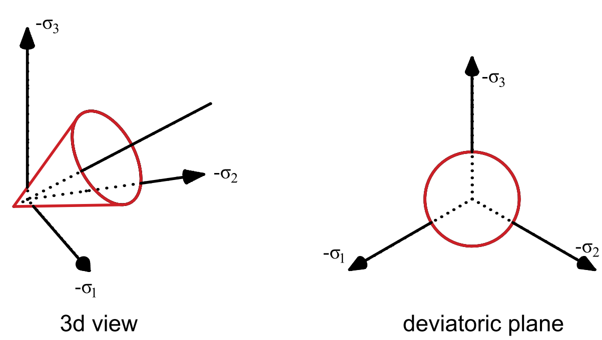

Fig. 2. Drucker–Prager model.