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Evaluation of Residual Fatigue Strength of Concrete Based on Machine Learning Approaches

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ABSTRACT

This study utilizes the machine learning technique to solve the complex fatigue problem of concrete materials. To this end, several learning algorithms were addressed including the random forest (RF), support vector machine (SVM), and artificial neural networks (ANNs) models. Extensive experimental data were collected from literature to train the machine learning models for estimating the maximum number of cycles at failure (i.e., the so-called fatigue life). A machine learning model providing the best correlation was chosen through verifications. On this basis, a strength degradation model of concrete under fatigue loading was finally proposed to evaluate the residual strength of concrete after fatigue damage, which is a key factor in determining the remaining service life of concrete structures.

1. INTRODUCTION

Serious consequence of fatigue failure is anticipated, and thus it is considered as one of the critical issues in the built environment made of concrete despite long lasting research efforts. Satisfactory performance is essentially required under long-term and sustained loading conditions with various intensity and frequency (Cladera et al. 2020, Schlafli and Bruhwiler 1998_ENREF_5). However, detrimental effects of fatigue in terms of strength, deformation capacity, and durability performance have not been fully explored yet, especially for safe structural design of fatigue-sensitive bridges and industrial buildings (Zhang et al. 2020). The internal resistance mechanism in an RC member basically originates from two components: compressive resistance provided by concrete and its counterpart provided by reinforcements in tension (Zhang et al. 2021). The existing studies (Sparks and Menzies 1973, Medeiros et al. 2015) reveal that there are inter-related mechanisms among key variables including the compressive strength, aspect ratio of test specimen, maximum stress level, minimum stress to maximum stress ratio, and fatigue loading frequency. In addition, it is very hard to justify how much service life (or residual strength) remains after fatigue damage even though extensive fatigue

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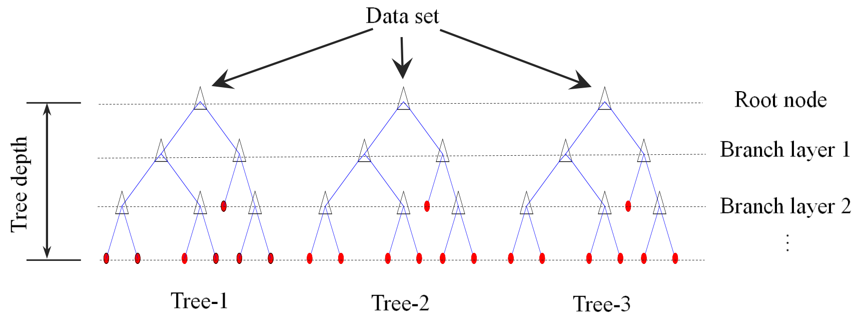
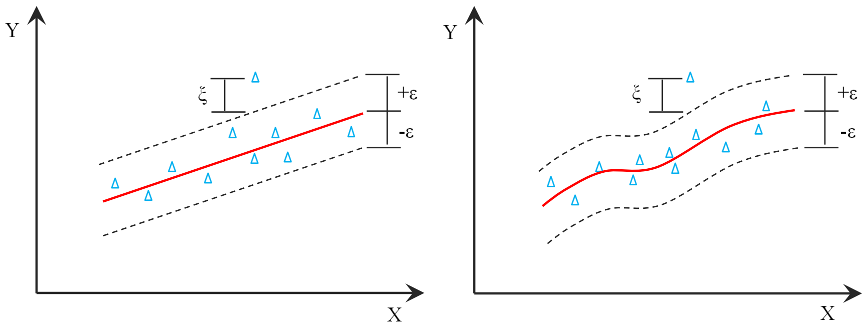
test results are available (Benard 2017). This is because fatigue testing is usually terminated after reaching target loading cycles before fatigue failure. In view of these limitations, this study utilizes the machine learning technique to solve this complex fatigue problem of concrete materials with high uncertainty. Based on the well-trained machine learning model, a strength degradation model of concrete under fatigue loading for estimating the residual strength of concrete after fatigue damage is finally proposed.

2. MACHINE LEARNING MODELS

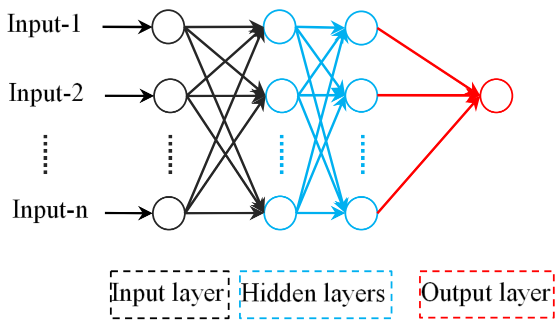
Three machine learning models were trained by a total of one thousand and ten sets of experimental data collected from literature, as shown in Fig. 1. All the five PC wall specimens consisted of two individual PC wall piers. 15 % of the test data was randomly selected and separated as the cross-validation data to prevent over-fitting. The learning model can be considered a stable and reliable model only when the model has good performance for both training data set and testing (cross-validation) data set.



(a)



(b)

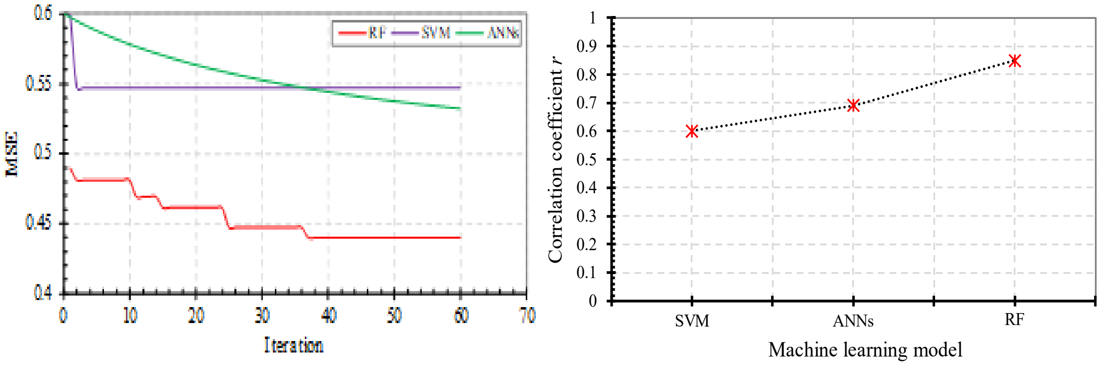


(c)

Fig. 1 Machine learning models: (a) random forest model; (b) support vector machine; (c) artificial neural networks

3. LEARNING RESULTS AND DISCUSSION

The mean square error (MSE) and correlation coefficient (r) of the machine learning models are presented in Fig. 2. It can be seen that the MSE steadily decreases as the number of training trails increases till reaching convergences. The MSE from the random forest model was the smallest as 0.44, and its correlation coefficient (r) was also the most accurate as 0.85. It reveals that the random forest model outperforms other two learning programs in this study.



(a) (b)

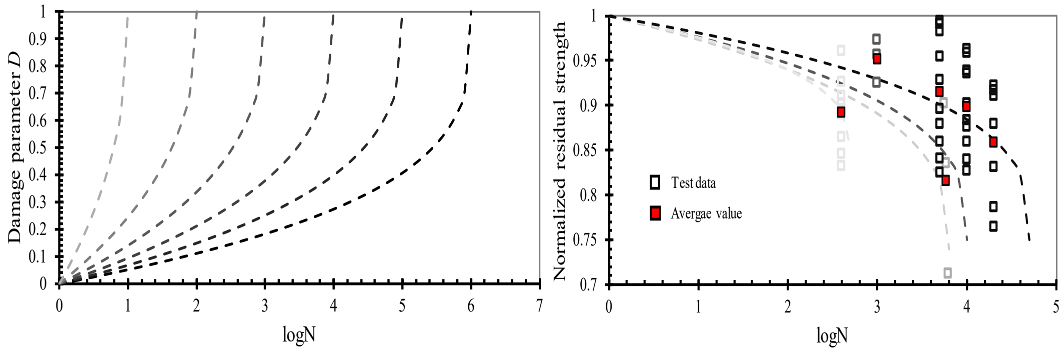
Fig. 2 Training results of machine learning models: (a) mean square error (MSE), (b) correlation coefficient (r)

4. STRENGTH DEGRADATION UNDER FATIGUE LOADING

According to the damage evolution theory of brittle materials, the damage evolution process of concrete can be expressed as shown in Fig. 3(a). On this basis, the residual strength of concrete (f_{res}) after certain cycles of fatigue loading can be derived, as follows:

$$f_{res} = f_c' - f_c'\left(1 - S_{\max}\right)D \quad (1)$$

where f_c' is the concrete compressive strength, $S_{\max}$ is the maximum stress ratio and D is the damage parameter of concrete under fatigue loading. The predicted residual strength of concrete after certain cycles of fatigue loading is compared with the experimental results, as shown in Fig. 3(b), where good prediction accuracy is found.



(a) (b)

Fig. 3 Verification of fatigue model: (a) damage evolution; (b) residual strength

5. CONCLUSIONS

Based on the machine learning results and strength degradation of concrete under fatigue loading, the following conclusions can be drawn from this study.

1. The fatigue behavior of concrete is significantly affected by key influential factors, such as compressive strength, height to width ratio, maximum stress level, minimum stress to maximum stress ratio and fatigue loading frequency. It appeared that the random forest machine learning model showed the best performance on characterizing the relationships between the experimental variables.
2. The fatigue behavior of concrete can be understood as a process of damage evolution, and it can be characterized with the strength degradation and accumulative irreversible strain. The damage parameters were quantified in this study, and it clearly correlates with strain evolution of concrete. It finally appeared that the damage of concrete under fatigue loading depends mainly on its life span (i.e., the maximum number of cycles at failure, *N*).
3. Based on the machine learning model, the maximum number of cycles at failure (*N*) was quantified, which was then utilized to estimate the damage evolution. On this basis, the strength degradation of concrete under fatigue loading can be well predicted, and those results were well coincided with the experimental results.

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