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Artificial Intelligence Predictions Effect of Loading Rate, Crack Width and Crack Length Ratio on Mode I Fracture Toughness of PMMA

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Abstract. Present, artificial intelligence methods play a huge role in solving complex engineering problems such as the fracture toughness of materials, which is one of the parameters to be considered for engineering design. Fracture toughness tests can be prepared materials and test configured in a variety of ways, resulting in different fracture toughness depending on the preparation method. In this study, fracture toughness of PMMA under the effect of loading rate is one of the testing configs that can be adjusted according to the actual load characteristics of the material and the crack geometry (crack width and crack length ratio) according to crack preparation to test specimens and the effect of these factors was predicted with generalized regression neural network (GRNN) and Gaussian processes regression (GPR) models which are one of the artificial intelligence models, compared to traditional fracture toughness predictions. The results showed that artificial intelligence prediction was able to more accurately predict the effect of the factors studied on the fracture toughness of PMMA compared to the traditional fracture toughness prediction.

Introduction

Present, artificial intelligence methods play a huge role in solving complex engineering problems, such the fracture toughness of materials, which is one of the parameters to be considered for engineering design. Fracture toughness is a parameter in fracture mechanics that studies the behavior of a material where cracks or discontinuities occur and are subjected to external loads. It is commonly known that the fracture toughness values of materials depends on the type of material, loading characteristics, and geometry of the testing specimen [1]. To know how the above factors affect fracture toughness most of the general methods have to be tested on real materials which will cause quite a lot of expenses. For this reason, this study aims to create an equation that can be used to predict the effect of such factors on the fracture toughness of materials using artificial intelligence methods (AI) that are popular in the materials field today [2]. The widely used AI algorithm such as generalized regression neural network [3] and Gaussian processes regression [4] were selected to a created a prediction model based on actual fracture toughness obtained from experiments. The fracture toughness testing, AI prediction modeling, and results of AI model prediction performance compared to traditional prediction were described in the next section of this study.

Mode I Fracture Toughness Testing

In this study, the effect of loading rate and crack geometry (crack width and ratio of crack length to specimen width) on mode I fracture toughness of poly(methyl methacrylate) sheet or PMMA sheet which is widely used in lab-scale experiments was investigated. The single edge notch with a three-point bending specimen was used to tests mode I fracture toughness (Fig. 1). To determine the effect of crack geometry, the crack width of the specimen is defined as 1, 3, and 5 mm respectively, and the ratio of crack length to specimen width is defined as 0.3, 0.5, and 0.7 respectively. The specimens are prepared by laser cutting. Fracture toughness testing was performed on Lloyd universal testing machine LD series (100 kN) at loading rates 0.1, 0.5, and 1.0 mm/min. The testing sequence was generated using a general full factorial experiment design with 3 replicates for each condition. After testing the mode I fracture toughness can be calculated according to Eq. (1)

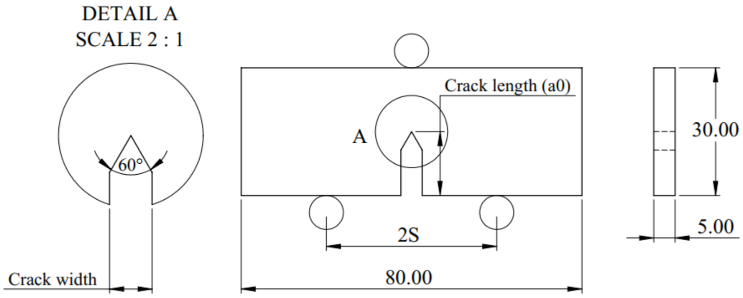


Fig. 1 Dimension of fracture toughness specimen

$$K_I = \frac{P}{Wt}\sqrt{\pi a_0} Y_I \left(\frac{a_0}{W}, \frac{S}{W}, C\right) \tag{1}$$

where K_I is the stress intensity factor that demonstrated fracture toughness of this study, P is the maximum load applied to specimen, W is the width of specimen, t is the thickness of specimen, a_0 is the initial crack length and Y_I is the mode I fracture toughness geometry factors that depended on the ratio of crack length to specimen width (a_0/W), the ratio of span length to specimen width (S/W) and crack width (C) which can be calculated using finite element analysis (FEA) which at crack width 1 mm are equal to (1.589, 2.090, 4.068), 3 mm are equal to (1.537, 1.997, 4.027), and 5 mm are equal to (1.409, 1.910, 3.968) (P.S.: number in the bracket was indicated at equal to 0.3, 0.5, and 0.7 respectively).

Prediction of mode I fracture toughness

Traditional fracture toughness prediction

Generally, when considering fracture toughness, it was found fracture toughness arises from the relationship of stress that occurred on the material. With this relationship, many researchers have come up with equations for predicting fracture toughness, known as fracture criteria. In this study, the widely used average strain energy density criterion (ASED) was employed to prediction fracture toughness. The ASED criterion was predicted based on the materials will be fractured when the average strain energy density around the crack tip over a control volume reaches critical strain energy (W_C) which depended on materials and notch properties. The prediction equation of ASED criterion was described according to Eq. (2)

$$\frac{W_1}{W_{1C}} + \frac{W_2}{W_{2C}} = 1 \tag{2}$$

where W_{1C} and W_{2C} are critical strain energy density obtained from mode I and II fracture respectively which can be calculated according to Eq. (3) W_1 and W_2 is mode I and II strain energy density generated from load applied to specimen respectively that can be calculated following Eq. (4) (When considering mode I , assumed W_2/W_{2C} which obtained from mode II is equal to 0)

$$W_{1C} = \frac{\sigma_t^2}{2E} \tag{3}$$

where σ_t is tensile strength of material (MPa) that equal to 67.05, 70.45, and 74.15 at each loading rate and E is the modulus of elasticity (GPa) that equal to 2.84, 2.95, and 3.13 at each loading rate.

$$W_1 = \frac{e_1}{E}\left[\frac{K_I^2}{R_{1C}{}^{2(1-\lambda_1)}}\right] \tag{4}$$

where e_1 is equal to 0.1186 [5], λ_1 is mode I Williams' eigenvalues equal to 0.5, and R_{1C} is mode I control volume radius[6].

Artificial intelligence method

Data preparation and model performance evaluation

Data preparation was the process that affected to prediction performance of the artificial intelligence (AI) model. The data preparation was started by reducing the different scale of input factors with normalization technique to range 0 to 1. To avoid bias occurring in train and test dataset selection process, the K-Fold cross-validation method was employed for selection. The loading rate (*R*), crack width (*C*), and crack length ratio (a_0/W) was selected as input factors of AI models, and fracture toughness (K_I) was selected as output or target of models. All AI model was generated in MATLAB programming. The model performance evaluation for both traditional and AI models has employed the common performance metric in regression problems such as coefficient of determination (R^2) and mean absolute percentage error (MAPE) which indicated the difference between prediction and actual values, both R^2 and MAPE equation described at ref [7].

Generalized regression neural network (GRNN)

The generalized regression neural network (GRNN) is one of the neural network models. The learning process of GRNN is a feedforward training type that belongs to the radial basis model. The architecture of GRNN was shown in Fig. 2 and brief was described as follows:

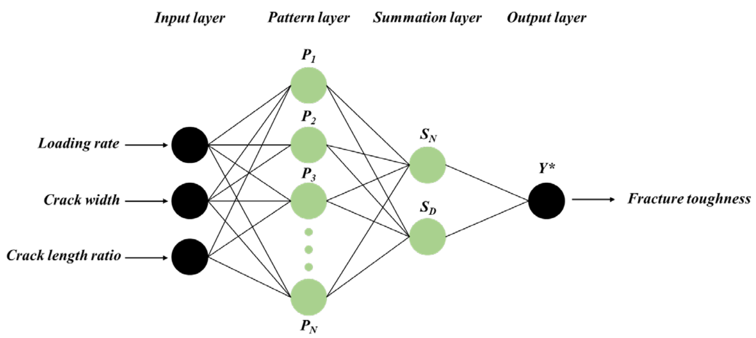


Fig. 2 Architecture of generalized regression neural network (GRNN)

Input layer: In this layer, the inputs data are introduced into the model learning process. The number of neurons in this layer is according to the dimension of the input vector.
Pattern layer: Data of the input layer were passed into this layer and transformed by the Gaussian kernel function. The number of neurons in this layer is according to the number of the training data.
Summation layer: The weight (P_i) was summarized in this layer. The S_N is neurons that officiate the summation of weight and output of training data while S_D is officiating the summation of weight only.
Output layer: The prediction results of model (Y^*) were generated in this layer which was calculated from the ratio of S_N and S_D from the previous layer. Additional information on GRNN can be found at ref. [4]

Gaussian process regression (GPR)

Gaussian processes regression (GPR) is a generic supervised learning method designed to solve small dataset problems. The GPR models are nonparametric covariance or kernel-based probabilistic models that combine prior process and sampled training data to infer posteriori processes as interpolation results and brief was described as follows:

Applied the Gaussian Processes method (GP) into the relationship function of input (x) and output y or $f(x)$, the GP of $f(x)$ defines a priori over functions, which can be converted into a posteriori over functions once some data is obtained. The Gaussian process is indicated as follows:

$$k(x,x') = E[(f(x)-m(x))(f(x')-m(x'))^T] \tag{5}$$

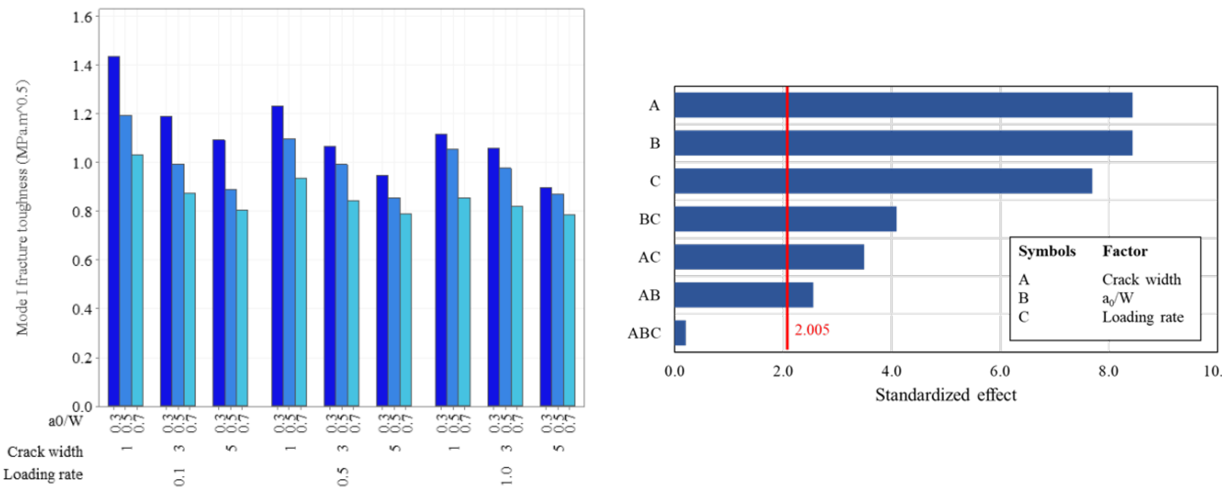
where $m(x)$ is the mean function that depicts the anticipated value of $f(x)$ at the input x and $k(x,x')$ is the covariance function or kernel function of the measured confidence level for $m(x)$. The prediction equation of GPR shown in Eq. (6)

$$p(y^*|y) = G(K^*K^{-1}y, K^{**} - K^*K^{-1}K^{*T}) \tag{6}$$

where y^* is the corresponding output of input $x*$, G is the Gaussian distribution, $K^*K^{-1}y$ is the mean of the Gaussian distribution, and $K^{**} - K^*K^{-1}K^{*T}$ is the variance of the Gaussian distribution. Then y^* known as the prediction values

Results and Discussion

The fracture toughness affected by loading rate and crack geometry of PMMA were shown in the form of average values in Fig. 3(a) which result shows a tendency for fracture toughness to decrease as the loading rate increases. When considering the effect of the crack geometry, the same behavior is observed as the loading rate at which the fracture toughness decreases when the crack geometry, both the crack width and the crack length ratio are increase. Evidence of the effect of these three factors is evident when considering the Pareto chart of standardized effect obtained from ANOVA (Fig. 3(b))

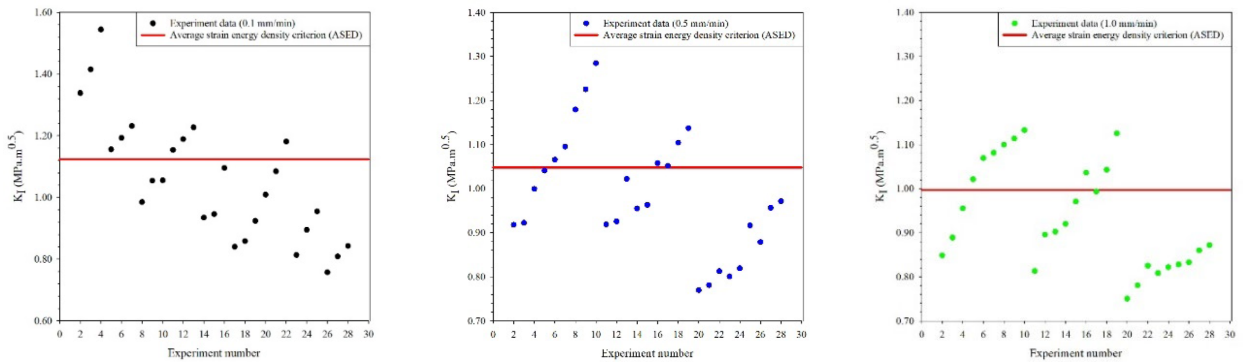


(a) (b)

Fig. 3 Fracture toughness results (a) average fracture toughness results for each condition (b) Pareto chart of standardized effects on K_I at significant level 0.05

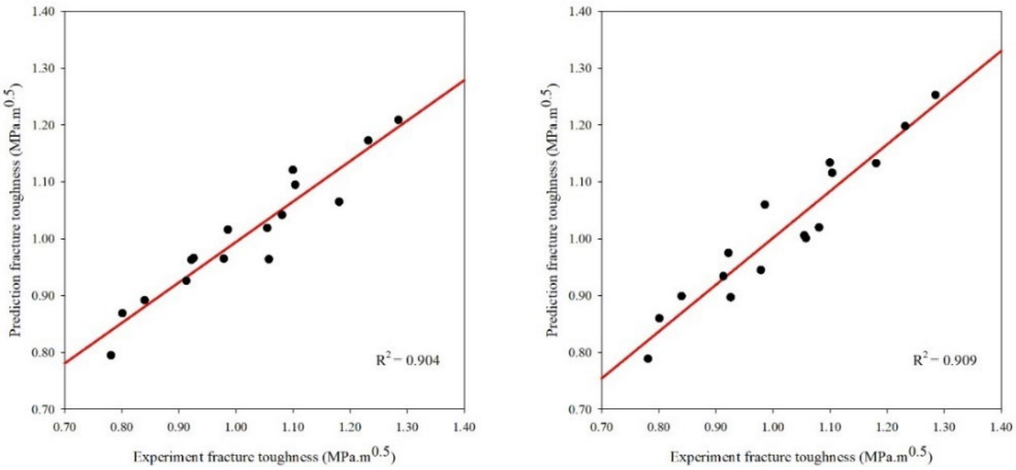
The results of the predictions with the ASED criteria separated by loading rate are shown in Fig. 4, it was found to be rather inaccurate compared to the experimental results. The ASED criteria had MAPE values is 20.20%, 15.33%, and 14.17% according to each loading rate. While compared to AI models (Fig. 5), it was found to have significantly higher predictive performance. The GRNN model had R^2 and MAPE values equal to 0.904 and 4.40% respectively and the GPR model had R^2 and MAPE values equal to 0.909 and 4.17% respectively. When considering MAPE values according to

Lewis's interpretation [8] that was found both AI models are high prediction performance (<10%) while the ASED criterion found a good or reasonable prediction (10%-50%).



(a) Loading rate 0.1 mm/min (b) Loading rate 0.5 mm/min (c) Loading rate 1.0 mm/min

Fig. 4 Prediction fracture toughness from ASED criterion at a various loading rate



(a) Testing process (GRNN) (b) Testing process (GPR)

Fig. 5 Prediction results of artificial intelligence model

Conclusion

The objective of this research was aim to prediction effect of loading rate and crack geometry on mode I fracture toughness of PMMA by generalized regression neural network (GRNN) model and Gaussian processes regression (GPR) model which not presented before. The results of the operation can be summarized as follows:

1. The loading rate and crack geometry (crack width and crack length ratio) has affected to mode I fracture toughness of PMMA, and the loading rate has the lowest affected compared to crack geometry.
2. The ASED criteria had inaccuracy in the case of the prediction effect of loading rate and crack geometry.
3. The GRNN model and GPR model was high prediction performance that had R^2 and MAPE values equal to 0.904, 4.40% and 0.909, 4.17% for each model respectively.

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