**Research Paper**
https://doi.org/10.7733/jnfcwt.2021.19.1.75

# Data-Driven Modelling of Damage Prediction of Granite Using Acoustic Emission Parameters in Nuclear Waste Repository

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(Received January 11, 2021 / Revised February 15, 2021 / Approved February 18, 2021)

Evaluating the quantitative damage to rocks through acoustic emission (AE) has become a research focus. Most studies mainly used one or two AE parameters to evaluate the degree of damage, but several AE parameters have been rarely used. In this study, several data-driven models were employed to reflect the combined features of AE parameters. Through uniaxial compression tests, we obtained mechanical and AE-signal data for five granite specimens. The maximum amplitude, hits, counts, rise time, absolute energy, and initiation frequency expressed as the cumulative value were selected as input parameters. The result showed that gradient boosting (GB) was the best model among the support vector regression methods. When GB was applied to the testing data, the root-mean-square error and R between the predicted and actual values were 0.96 and 0.077, respectively. A parameter analysis was performed to capture the parameter significance. The result showed that cumulative absolute energy was the main parameter for damage prediction. Thus, AE has practical applicability in predicting rock damage without conducting mechanical tests. Based on the results, this study will be useful for monitoring the near-field rock mass of nuclear waste repository.

Keywords: Rock damage, Acoustic emission, Nuclear waste repository, Gradient boosting, Support vector regression

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## 1. Introduction

Monitoring the nuclear waste repository located in underground is required for preventing performance degradation over time. There are various factors that affect the long-term integrity of the repository, and high in-situ stress around the repository and rock damage caused by excavation are the main considerations. Rock damage creates microcracks, which propagate and bond, leading to macrocracks. Due to this, excavation damage zones are formed in the surrounding rock mass, and the stability of the repository may be decreased by deteriorating the mechanical properties of the rock mass.

Most of the rock mass damage from excavation occurs immediately after excavation, but if the in-situ stress is high, damage occurs over a long period of time, affecting the long-term stability of the repository. Therefore, to ensure the long-term integrity of the repository, it is important to understand the damage of the in-situ rock mass.

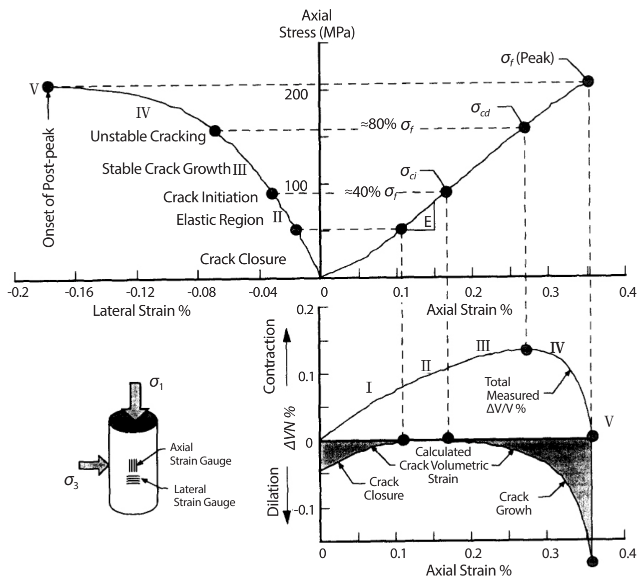
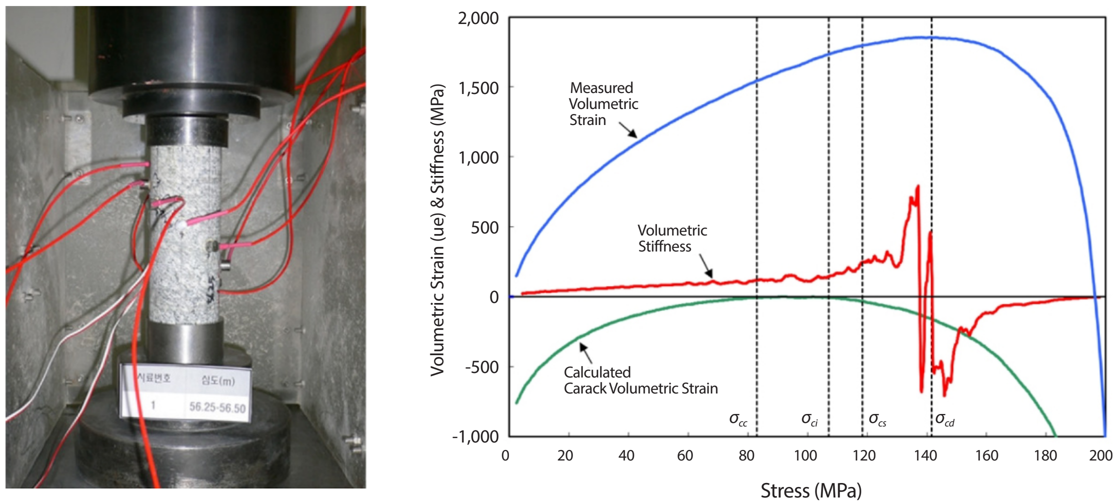



Fig. 1. Stress-strain curve with the four stages according to crack development (Martin and Chandler, 1994).

Acoustic emission (AE) is a kind of non-destructive test and has been used to monitor the damage of various materials including rock mass. It is a kind of elastic waves generated when accumulated deformation energy in a material releases rapidly. Utilizing the AE method, some works have been conducted for evaluating the rock damage and cracking stages [1-4]. Kim et al. [5] evaluated the degree of damage of KURT granite by identifying the relationship between AE amplitude and cumulative frequency. In addition, the damage of rock based on AE energy was evaluated and compared with the existing methods. Other researchers tried to correlate crack evolution characteristics with AE counts from uniaxial compression test [6, 7]. Wu et al. [8] evaluated the quantitative damage stress using cumulative AE count. Zhao et al. [9] analyzed the relationship between crack development and the number of AE hits for Beishan granite. The result was confirmed that the number of AE hits increased as the stress increased, and the number of hits increased sharply as the stress is close to failure. There have some works to evaluate the failure mode of rock based on AE parameters [10, 11]. They classified the failure mode into shear and tensile failure by using the relationship between the RA value obtained by dividing the AR rise time by the maximum amplitude, and the average frequency which is dividing the number of counts by the duration time.

The aforementioned works used one or two AE parameters to determine the degree of damage, damage criterion, and failure mode of rock. However, studies in consideration of several AE parameters has been rarely conducted.

In this study, we aim to propose a predictive model for the rock's damage that considers various AE parameters. For data acquisition, five granite specimens were prepared, and various AE signal data were obtained from a uniaxial compression test. By considering the AE parameters, we develop several data-driven predictive models and compare their performance. For model interpretation, relative importance between AE parameters influencing the damage prediction is analyzed.




(a) (b)

Fig. 2. (a) Uniaxial compressive test and (b) volumetric strain and stiffness on granite specimen 1.

## 2. Theoretical background

### 2.1 Quantitative damage

The reliability of quantitative damage evaluation is secured from the determination of accurate crack damage criteria. In general, the crack damage criterion for rock is determined through a laboratory experiment of stress-strain measurement. Brace et al. [12] and Bieniawski [13] determined the damage criterion for crack propagation through the relationship of axial strain according to stress for brittle materials. Martin and Chandler [14] evaluated the criterion for crack damage using inelastic volumetric strain. The propagation of crack damage of a structure can be characterized by four stages as shown in Fig. 1: crack closure, crack initiation, crack propagation, and crack damage [14-16].

Kim et al. [17] quantified the crack damage stage using inelastic volumetric strain for granite. Axial and horizontal strain depending on the increment of the load were obtained from a uniaxial compressive test, and then volumetric strain and stiffness were calculated using stress-strain relationship (Fig. 2). In this study, to quantify the degree of damage, the inelastic volumetric strain was associated with the damage degree of the rock. The inelastic volumetric strain was calculated using the eq. (1) and (2) based on the stress-strain relationship.

$$\epsilon_{\upsilon}^{ie} = \epsilon_{\upsilon} - \epsilon_{\upsilon}^{e} = \epsilon_{\upsilon} - (\epsilon^{e}_{Axial} + \epsilon^{e}_{Lateral}) \qquad (1)$$

$$\epsilon_{\upsilon}^{ie} = \epsilon_{\upsilon} - \frac{(1-2\upsilon)}{E}\sigma_{Axial} \qquad (2)$$

Where, $\epsilon_{\upsilon}$ is volumetric strain, $\epsilon_{\upsilon}^{e}$ is elastic volumetric strain, and $\epsilon_{\upsilon}^{ie}$ indicate the inelastic volumetric strain. $\epsilon^{e}_{Axial}$ and $\epsilon^{e}_{Lateral}$ means axial and horizontal strain. $E$, $\upsilon$ and $\sigma_{Axial}$ indicate the elastic modulus, poisson's ratio, and axial stress, respectively.

### 2.2 Acoustic emission

Acoustic emission (AE) has been mainly used to evaluate the crack localization, crack condition, and crack damage criteria of the structural material through real-time monitoring. When the deformation energy is accumulated inside the material due to external load, an AE signal with a low amplitude level is generated due to microscopic cracking. After that, when the material reaches failure, the am-

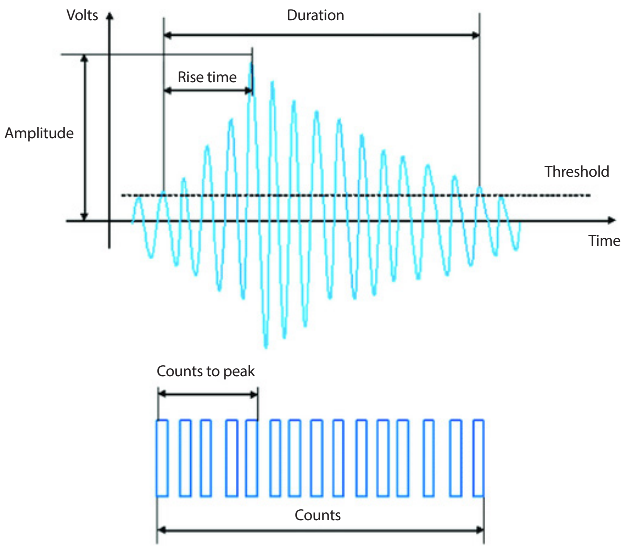



Fig. 3. Acoustic emission signal and characterized parameters (Chai et al., 2017).

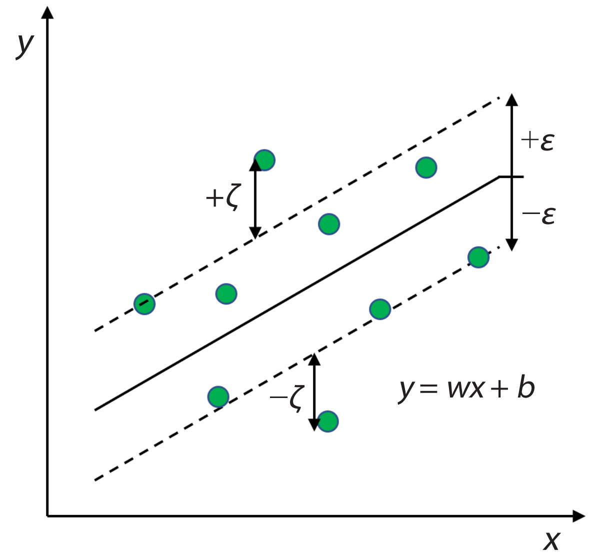



Fig. 4. Schematic representation of support vector regression.

plitude of the signal increases significantly as releasing the accumulated energy due to sliding the macroscopic crack [18]. Therefore, monitoring through AE is an efficient method to evaluate the damage history of the material according to the stress level [19].

The AE signal due to the crack in the material is collected in the form of an electrical waveform through the AE sensor (Fig. 3). AE parameters can be characterized such as maximum amplitude, the number of hits, count, rise time, and absolute energy. In addition, AE signals can be expressed as a frequency through frequency transform.

## 3. Data-driven techniques

### 3.1 Support vector regression

SVR which is a kind of supervised learning is a technique for dealing with the regression problem of support vector machine [20]. This method has a good generalization ability even in a limited number of data because it is based on the principle of minimum structural risk rather than empirical risk minimization [21].

When given the $\{(x_1,y_1),\ldots,(x_i,y_i)\} \subset R^d$ in SVR, this method has the form of the following equation, and the goal is to find the optimum $w$ and $b$.

$$y_i = w^T(x_i) + b \tag{3}$$

Where, $w$, $b$ indicates the weighted vector and bias, respectively. $(x_i)$ means the high-dimensional feature space mapped nonlinearly from $d$-dimensional input space $R^d$.

SVR is an ε-insensitvie model that is not sensitive to ε and learn to include as many samples as possible in a limited margin error (ε) tube (Fig. 4). Within the ε allowed, the error is regarded as zero value even though the training samples are added. However, if the sample is outside the ε tube, a non-zero slack variable (ζ) occurs. Hereby, the ζ represents the degree to which margins are violated.

Based on the above principle, ε-insensitvie model can be composed of the following convex optimization problem, and thus Eq. (3) can be approximated to Eq. (4).

Table 1. Several kernel functions used in SVR

| Kernel function | Formula |
|---|---|
| Linear | $K(x_i,x_j) = \langle x_i,x_j\rangle$ |
| Polynomial | $K(x_i,x_j) = (y\langle x_i,x_j\rangle + coef.)^d$ |
| RBF | $K(x_i,x_j) = exp\,(-r\lVert x_i - x_j\rVert^2)$ |

$$\underset{w,b,\zeta}{\text{minimize}}\ \frac{1}{2}\, w^T w + \mathrm{C}\sum_{i=1}^{m}(\zeta_i^+ + \zeta_i^-)$$

$$\text{subject to}\quad \begin{aligned} & y_i - (w^T\cdot\phi(x_i) + b) \le \varepsilon + \zeta_i^+ \\ & (w^T\cdot\phi(x_i) + b) - y_i \le \varepsilon + \zeta_i^- \\ & \zeta_i^+,\zeta_i^- \ge 0 \end{aligned} \tag{4}$$

Here, $C > 0$ is a regulation parameter indicating a penalty for sample error exceeding the margin $\varepsilon$. A larger $C$ value means that a smaller slack variable value is allowed, whereas a smaller $C$ value means a smaller slack variable value is allowed. $\phi$ is a function that maps the input space of the training dataset into a high-dimensional feature space.

In Hilbert's space, the result of the operation between $\phi$ can be easily calculated using the dot product of a vector without the explicit function form of $\phi$, and can be expressed as a kernel function ($K$) as in Eq. (5);

$$K(x_i,x_j) = \langle\phi(x_i),\phi(x_j)\rangle \tag{5}$$

Kernel function plays a role of expanding the input space of the training dataset into a high-dimensional space and make it possible to implement the non-linearity of complex datasets. There are various types of kernel functions established by researchers, and they are summarized in Table 1.

On the other hand, the problem solving the Eq. (4) can be easily solved by transforming it into the form of primal and dual functions based on the Lagrange multiplier method. This form of the function is a quadratic optimization problem and has a unique solution for $w$, $b$. A detailed explanation of the problem can be found in the literature [20].

### 3.2 Tree-based gradient boosting

Unlike one strong model, tree-based gradient boosting (GB) is one of the ensemble techniques that combines multiple weak models. The principle behind this method is to build a strong model by successively combining decision trees, called weak models, into an ensemble. It is suitable for complex nonlinear problems since GB has a number of tuning parameters, and mainly used for the purpose of maximizing performance.

GB is an approach to finding the ensemble model $\hat{F}$ in the weighted form of the function $h$ for the weak model (Eq. (6)).

$$\hat{F}_m\,(x) = \sum_{m=1}^{M} \alpha_m h_m(x) + C \tag{6}$$

Where, $M$ is the number of weak model, $\alpha_m$ is the coefficient of $m$ th weak model, and $C$ is a constant. $\hat{F}_m$ starts with a constant value $\hat{F}_0$ (x), and the function gradually increments according to the greedy approach (Eq. (7)).

$$\begin{aligned} &\hat{F}_m(x) = \hat{F}_{m-1}\,(x) + \underset{\alpha_m h_m}{argmin}\left[\sum_{i=1}^{n} L\big(y_i,\, F_{m\text{-}1}(x_i) + \alpha_m h_m(x_i)\big)\right] \\ &\hat{F}_0(x) = \underset{\alpha}{argmin}\sum_{i=1}^{n} L\big(y_i,\alpha\big) \end{aligned} \tag{7}$$

Calculating the function $h_m$ in Eq. (7) is a non-computable optimization problem. To solve this problem, a method of calculating $h$ using a negative slope called the pseudo residual has been proposed. For more information on this theory, it is recommended to refer to Friedman [22].

The tuning parameters of tree-based gradient boosting can be divided into two categories: Maximum depth of the tree, maximum number of leaves as a single tree, and the number of weak models, contribution degree of the weak model as GB. These are all tuning parameters that control the complexity of the model. Since GB is based on the construction of numerous weak models with low depths of trees, the maximum depth of the tree does not exceed five in general [23].

Table 2. Descriptive statistics for the dataset used in data-driven modeling

| Index | Damage | Amplitude (dB) | Number of Hit | Number of Count | Rise Time (us) | Absolute Energy (aJ) | Initiation Frequency (kHz) |
|---|---|---|---|---|---|---|---|
| count | 3,688 | 3,688 | 3,688 | 3,688 | 3,688 | 3,688 | 3,688 |
| mean | 0.34 | 41,936 | 539 | 6,886 | 9,134 | $3.6\times10^{12}$ | 58,684 |
| std | 0.29 | 22,249 | 285 | 4,687 | 4,761 | $7.6\times10^{12}$ | 33,201 |
| min | 0.00 | 1,993 | 25 | 208 | 330 | $4.4\times10^{10}$ | 2,163 |
| 25% | 0.10 | 23,000 | 297 | 3,143 | 5,125 | $9.5\times10^{11}$ | 32,576 |
| 50% | 0.25 | 41,084 | 528 | 6,293 | 9,187 | $2.1\times10^{12}$ | 53,810 |
| 75% | 0.55 | 59,405 | 763 | 9,247 | 12,842 | $3.5\times10^{12}$ | 85,026 |
| max | 1.00 | 89,038 | 1,135 | 33,872 | 19,982 | $1.2\times10^{14}$ | 128,650 |

## 4. Data preparation

To construct a dataset to be used for supervised learning modeling, uniaxial compressive tests were conducted on five granite specimens. The crack damage criterion was obtained through the stress-strain relationship, and the degree of damage was calculated using the inelastic volumetric strain. The mechanical properties of the five specimens and the results of the experimental test can be seen from Kim et al. [5] in detail.

Eight AE sensors were attached to each specimen to obtain the AE signal according to the stress level. The AE signal can be characterized by various AE parameters, and the cumulative amplitude, hits, count, rise time, absolute energy, and initiation frequency were selected as input parameters for a prediction of damage.

In supervised learning, the entire dataset should be divided into a training set and a testing set. The training set is used for model training and hyper-parameter tuning, while the testing set is used for performance evaluation. In this study, 80% of the entire dataset was considered a training set (2,926 sets), and the remaining 20% were sampled to a testing set (732 sets). Descriptive statistics for the entire dataset is summarized in Table 2.

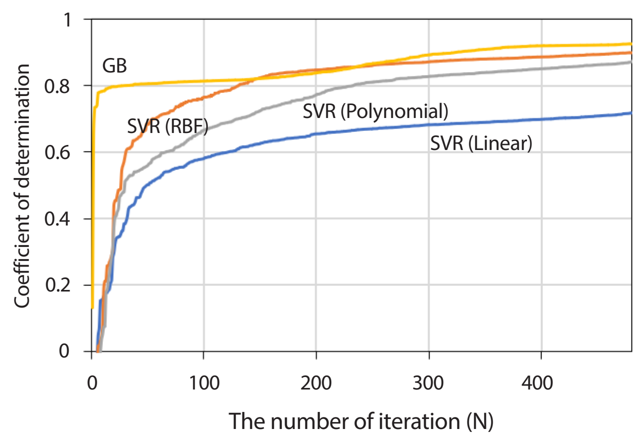



Fig. 5. Cross validated coefficient of determination versus number of iteration.

## 5. Result and discussion

### 5.1 Model optimization

Hyper-parameters must be pre-trained before building the model. Hyper-parameter selection is an essential process because performance varies greatly depending on the combination of hyper-parameter set. Therefore, we tried to search for the hyper-parameter set that has the best

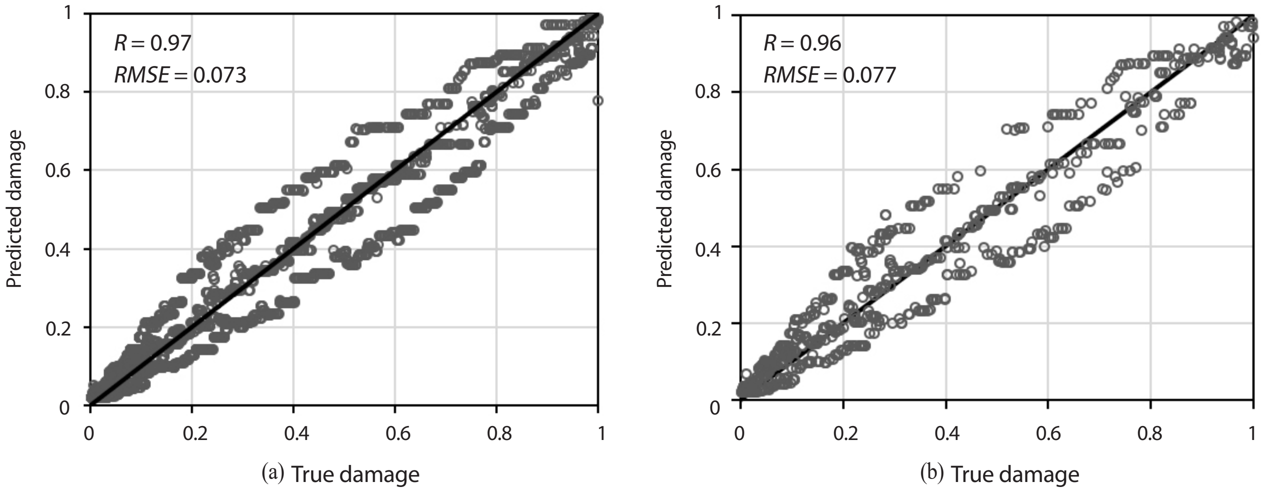



Fig. 6. Performance of the optimum GB model on (a) training set and (b) testing set.

performance.

For hyper-parameter tuning, random sampling was used. The grid search reflects all combinations of sets, thus it's obvious, but it takes quite a while. To reduce the temporal cost, random sampling was used in this study, and it is known that it shows good performance as a result of simulation [24].

Fig. 5 shows $R^2$ in ascending order according to 500 random samplings for each model. Regardless of the data-based method, $R^2$ increased rapidly and then showed a tendency to converge. All the SVRs generally showed a pattern to converge after 80 times, but the model GB represented a gradually increasing trend after 10 times. Most of the increase was achieved at 84.6%, 82.8%, 71.2%, and 77.2% of the whole increase for GB, $SVR_{RBF}$, $SVR_{polynomial}$, and SVRlinear. In the final stage, the maximum $R^2$ was recorded as 0.93, 0.90, 0.87, and 0.72 for GB, $SVR_{RBF}$, $SVR_{polynomial}$, and $SVR_{linear}$. The nonlinear functions showed higher $R^2$ compared with the $SVR_{linear}$. The results indicate that the relationship between the AE parameters and the degree of damage has a non-linear relation. The GB model was finally selected in this study because GB has the highest global performance in the final stage.

## 5.2 Results of the optimum models

The selected GB model was evaluated for the training set and the testing set using the indices *R* and *RMSE*. The performance results for the training set indicate the goodness of learning, while the performance for the testing set describes the generalization ability of the model [25].

Fig. 6(a) shows the comparison result of the observed and predicted damage of the optimum GB model for the training set. The correlation *R* between the observed and the predicted value of the GB model with the optimum hyper-parameter was 0.97, which can be seen as a high learning performance for the training set with nonlinearity. The *RMSE* was 0.073, and it can be explained that it shows an error rate of 7.3% for the normalized damage.

The GB model trained with optimum hyper-parameters was verified as testing set for generalization performance, and the results can be seen in Fig. 6(b). The *R* and *RMSE* of the GB model for the testing set were 0.96 and 0.077, respectively, which were almost similar to the results for the training set. This finding can be explained as showing good learning ability without over-fitting for the training set and simultaneously high generalized prediction performance.

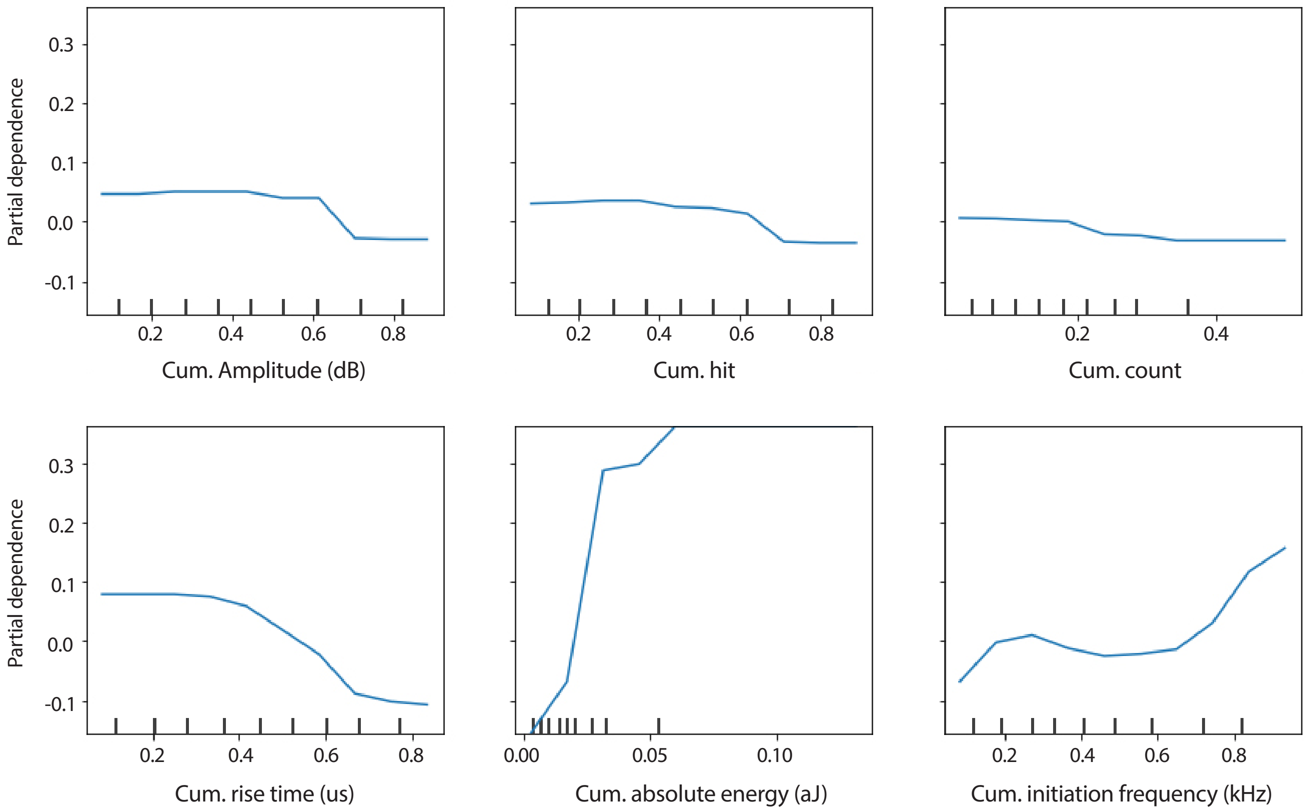



Fig. 7. Partial dependence plots of AE parameters in optimum GB model for prediction of damage.

## 5.3 Importance analysis for cumulative AE parameters

For a better understanding model, not only model prediction but also model analysis should be performed in parallel. The partial dependence proposed by Freidman [22] means the margin effect of the influence parameter on the prediction result of the data-driven model. In other words, it evaluates whether the relationship of each influence parameter to the target parameter is linear, nonlinear, or has little relationship. The parameter importance proposed by Breiman et al. [26] is a value representing the importance of the influence parameter in the decision tree. In GB, parameter importance is calculated using the average value derived from multiple decision trees [22], and express the contribution of the influence parameter to the prediction of the target.

Fig. 7 shows the results of partial dependence on each influence parameter. In general, the higher the change in partial dependence depending on the change of the influence parameter, the higher the importance of the influence parameter. The partial dependence of the cumulative absolute AE energy showed a strong positive correlation. The AE energy is known to be due to the energy released by the crack growth of the rock [27], and thus is directly proportional to the actual energy of the rock [5]. This evidence can be considered to be consistent with the result of the positive correlation between the damage degree and the cumulative AE energy.

Fig. 8 describes the importance of each input parameter to the degree of damage. The importance of the cumulative absolute energy was found to be 0.78 and considered as

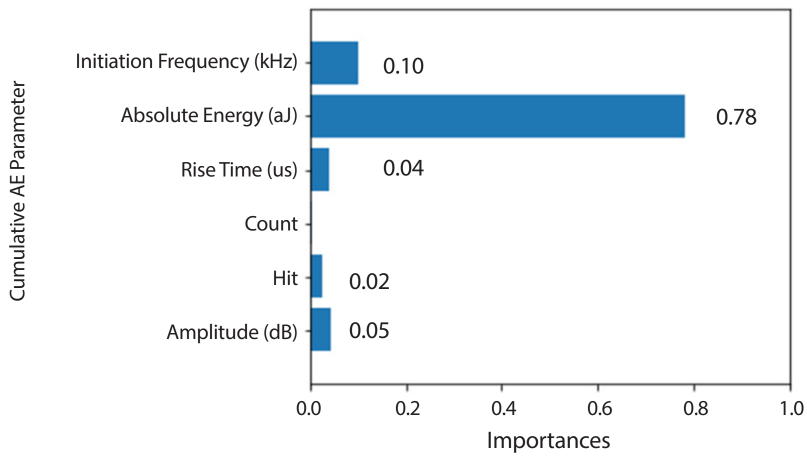



Fig. 8. Importance of AE parameters in optimum GB model for damage prediction.

the dominant parameter affecting the prediction of damage. Among AE parameters, Kim [28] correlated quantitative damage to AE energy including an in-situ test. These results also support the results of several other studies [5, 18].

The frequency characteristics showed the importance of 0.1 for the prediction of damage. The frequency distribution is known to be related to the stress level including rock type and degree of fracturing [29]. In light of this, the AE frequency is definitely associated with the damage degree, but it is not proper to use alone due to the low importance. In addition, since the value varies with the type of AE sensor used for measurement and the adhesion condition to rock [30], and thus must be considered together with several AE parameters.

## 6. Conclusion

Various data-driven predictive models for the damage evaluation on five granite rocks were introduced and compared in this study. To increase the reliability of the model, several AE parameters characterized from the AE signal were considered. For a better understanding for the model, parameter analysis was conducted for the prediction of damage. The conclusion derived from the results can be summarized as follows;

1. As a result of cross-validation for optimum hyper-parameter selection, the maximum $R^2$ of 0.93, 0.90, 0.87, and 0.72 were derived by GB, $SVR_{RBF}$, $SVR_{polynomial}$, and $SVR_{linear}$ models in the final convergence stage. The nonlinear models showed higher $R^2$ compared to the linear model $SVR_{linear}$. This shows that there is a nonlinear relationship between the AE parameter and the degree of damage;
2. Among the nonlinear models, the GB model showed the highest cross-validated $R^2$. It can be seen that the GB model expresses the nonlinearity between the damage and AE parameters of the rock better than the nonlinear SVR;
3. As a result of applying the optimum GB model to testing set. The $R$ value between predicted and true damage showed high scores of 0.96, which is similar with the result ($R$ = 0.97) for training set. The small difference between these results indicates the goodness of both learning degree and generalization performance without over-fitting;
4. The partial dependence of the cumulative absolute AE energy on damage degree represented a strong positive increase. This shows that as the absolute AE energy increases, the degree of damage increas-

es proportionally, and it can be seen that there is a strong positive correlation. In addition, the cumulative absolute energy showed the highest importance of 0.78, which means that the cumulative absolute energy is the most important parameter to the damage prediction in the GB model;

from the study, we confirmed that this finding gives insights that AE has possibility in predicting the quantitative damage of the rock without the mechanical test. It is expected to be useful works as a basic study for monitoring the rock mass near the nuclear waste repository.

## Acknowledgment

This research was supported by the Nuclear Research and Development Program of the National Research Foundation of Korea (NRF-2021M2c9A1062949) funded by the Minister of Science and ICT.

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