Bayesian Optimization Approach for Parameter Calibration of Constitutive Models in Liquefaction Analysis

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Introduction

The Finite Element (FEM) Method is a program that is widely used to analyze or predict the dynamic behaviors of the soil or structures in the geotechnical field. Especially for analyzing the dynamic behavior, the FEM analysis is evaluated as an efficient tool with high reliability and low cost.

The procedures of the FEM analysis start from the calibration work. And the only calibration work is promising work to implement the dynamic behavior of the soil in the FEM. It is usually done manually by adjusting the soil parameters to fit the simulation result into the measured data. However, manually calibrating the soil cannot quantify the data and reflect the previous knowledge robustly and may produce biased data according to the person.

Objective of the study

Therefore, this study embarked on establishing an automated parameter identification code for calibrating the dynamic behavior of the soil in the element test phase of a FEM Program using the Bayesian optimization technique. The ultimate objective of this study is to obtain the liquefaction parameter sets in the FEM program that perfectly matches with measured liquefaction resistance curve and the time history of strain data. As a first step to reach the ultimate objective, this paper attempts to match one liquefaction criteria of the liquefaction resistance curve with the measured and simulation data.

CDSS Test and FEM setup

The Cyclic Direct Simple Shear (CDSS) test that George Washington University provided during the LEAP (Liquefaction Experiment and Analysis Project) was selected for the calibration target. The CDSS test is one of the cyclic loading tests to objectively define the soil's dynamic properties. The Ottawa F-65 soil, a fine particle of sandy soil, was used for the test. $\sigma_v = 40$ kPa, $D_r = 66\%$ of soil condition was chosen for the target to optimize.

FLIPROSE and the Strain space multiple mechanism model were utilized for the FEM program platform and the constitutive model of the soil, respectively.

Bayesian optimization (BO)

Bayesian optimization is a technique widely used in data science to adjust the hyper-parameters of the coefficients in the machine learning model. The BO is based on the Gaussian Process (GP) to build the surrogate model and the acquisition function. The surrogate model is an unknown function that the GP infers by updating the surrogate model. The acquisition function is an algorithm that decides the next point to explore by comparing the exploit and the explore (trade-off).

The Botorch and AX were utilized to compose the BO loop. The Botorch is a program made for composing the BO loop, and the AX is a program that modularizes a Botorch's program to apply it with ease.

How the BO works with the FEM?

Schematic flows of how the loop works are described in Figure 1. The input & output files of the FLIPROSE consist of the text format (.txt), and the FEM calculating program is an execute file format (.exe). Therefore, a computer code was made to govern the FEM program in the framework of the BO loop.

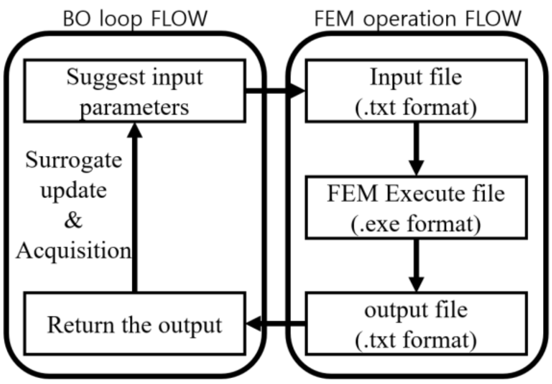

Figure 1. Interaction algorithm with BO and FEM

Optimization loop setup

Mean Squared Error (MSE) and the Mean Absolute Error (MAE) functions were used to express the discrepancy between the measured and simulated data. (Eq 1 and Eq 2.) This methodology takes advantage of making a number of values into one scalarized value for the metric to evaluate, making the problem regarding computational cost simple.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2, \qquad MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}|$$

Therefore, the objective of the BO in this metric is to minimize the metric.

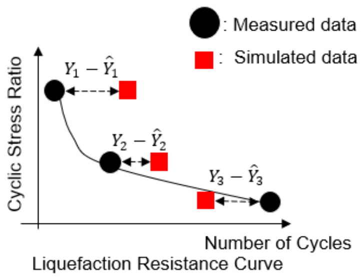

Figure 2. Interact algorithm

Besides, in order to reduce the computational cost, parameter domains (liquefaction parameters) were constrained by setting the range and the number of digits by referring to the FLIP guidelines, as shown below in Table 2. Lastly, the expected improvement method was chosen for the acquisition function. One thousand samples were generated for prior knowledge through the SOBOL algorithm, and 1000 BO were conducted.

Table 2. Designated parameter domain for BO loop

Symbol	FLIP Guideline	Set Range	Number of digits
ε_d^{cm}	0.1~0.2	0.10~0.40	2
$\gamma_{\varepsilon_d^c}$	0.5~1.0	0.01~5.00	2
r_{ε_d}	$\gamma_{\varepsilon_d^c} \times r_{\varepsilon_d} = 1.0$	0.001~5.000	3
q1	1.0~10	1.00~10.00	2
q2	0.0~2.0	0.01~2.00	2
c1	1.0~	1.00~5.00	2
ϕ_p	28°	20.00~37.99	2

Results & Discussion

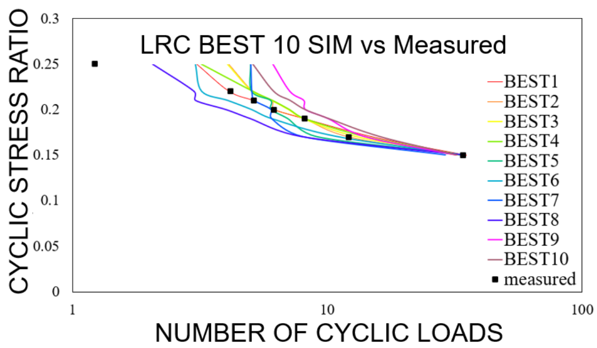

Figure 3. The best ten parameters set

Figure 3 presents the best ten parameters set with the measured data. The MSE was used for the metrics. The best match liquefaction resistance curve (LRC) data were derived from the 1818 trial, which showed 1.60 MSE with a 3.23 standard error value. However, since the time history of the strain or excess pore water pressure was not considered, the match of the strain, Excess pore water pressure ratio (E.P.W.P) showed inconsistencies between the measured and the simulated data (example: Figure 4.).

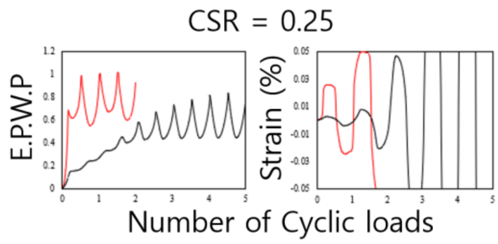

Figure 4. Example of Inconsistencies

Reference

1. Iai, S., Tobita, T., Ozutsumi, O, & Ueda, K. (2011). Dilatancy of granular materials in a strain space multiple mechanism model. *International Journal for Numerical and Analytical Methods in Geomechanics*, *35*(3), 360-392. 2. BALANDAT, Maximilian, et al. BoTorch: A framework for efficient Monte-Carlo Bayesian optimization. *Advances in neural information processing systems*, 2020, 33: 21524-21538.