Development of surrogate models of clamp configuration for optical glass lens centering through finite element analysis and machine learning

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Abstract
In this study, the clamping stress and force involved in the centering of optical glass lens were evaluated and quantified. On the basis of the key design parameters of the examined clamps, the finite element method was applied to predict clamping stress under various parameter combinations. Support vector regression, Gaussian process regression, and adaptive neuro fuzzy inference system algorithm of surrogate models were established using the results obtained through finite element simulation. These surrogate models, which can predict clamping stress on the basis of key parameters, can reduce the time required to perform finite element analysis while providing references for optimizing clamp configuration.

Keywords Centering process · Surrogate model · Finite element analysis · Machine learning

1 Introduction

An optical axis is defined as the line that connects the centers of the curvature of the curved surfaces on both sides of a lens. If the optical axis deviates from the lens’ geometric center axis, the imaging position of the lens will be affected and cause aberration. Centering is a key procedure in optical glass lens manufacturing because it is required to minimize the aforementioned phenomenon [1–3]. During centering, a lens is secured by a pair of bell-shaped clamps that come into contact with both of the polished surfaces of the lens. The forces between the clamps and the lens are radially balanced. Under this condition, the optical axis coincides with the geometric center line. The lens is then grounded by a grinding wheel, such that its shape becomes perfectly symmetrical with respect to the optical axis. To prevent lens clamps from scratching the polished surfaces of lens, they must be made from soft materials. Consequently, lens clamps are prone to deforming under clamping stress, which causes the central axis of a lens to become offset. With unstable clamping, a lens can be easily pushed and decentered by a grinding wheel feed. Therefore, effective methods for evaluating and analyzing clamping stress are required for the centering process.

The finite element method (FEM) is widely used to solve engineering problems, including the evaluation of stress distribution [4] and simulation of mechanical behavior [5, 6]. FEM-derived results can also be used to conduct pre-machining assessments [7, 8] and support parameter optimization [9, 10]. However, to obtain accurate simulation results, precise engineering modeling and meshing are required. Simulating and analyzing a complex finite element model are usually tasks that require substantial time and computational resources [11, 12]. Surrogate models are often applied as substitutes of complex computational models in engineering design; they are established by using simple computational models to simulate actual situations. Through complex finite element models, simulation results can be predicted by building a surrogate model with a learning algorithm. For example, António and Rasheed proposed a surrogate model by simulating the results of full-field displacement measurements using the FEM and training an artificial neural network (ANN) using the
obtained simulation results to simplify the complex operation of the FEM [13]. Tapia et al. built a surrogate model by applying Gaussian process regression (GPR) to predict the melt pool depth of the laser powder bed fusion process [14]. Numerous methods have been applied in other studies to construct surrogate models; these methods include support vector regression (SVR) [15–18], the response surface methodology [19–21], kriging [22–25], and the adaptive neuro fuzzy inference system (ANFIS) [26]. Regarding to the designation and optimization of the fixture, Hamedi used the finite element simulation conditions to pre-train an ANN model to predict the corresponding clamping force and optimize the clamping force through genetic algorithm (GA) [27]. Selvakumar et al. applied the design of experiments (DOE) method to determine the solution range and train the ANN model with FEM simulation results to predict the maximum clamping deformation according to the fixture layout [28].

In the present study, a measuring method that uses load cell and strain gauge was designed to quantify the clamping force between a lens and clamps. Through adjustments to the key structural designing parameters of clamps, data on the clamping stresses under various parameter combinations were obtained through FEM simulation. Three algorithms were applied to construct surrogate models, in which structural parameters were used to predict contact stress to optimize the configuration of clamps.

2 Methodology

2.1 Relationship between clamping and grinding

The lens centering mechanism is a form of cylindrical grinding (Fig. 1).

During grinding, the stability of a lens is dependent on the frictional force \( f \) that is applied to the contact surface by the clamping force \( F_h \); \( f \) can be expressed using the following equation:

\[
f = F_h \cdot \mu
\]  

(1)

where \( \mu \) is the friction coefficient between the lens and the clamp material. If \( f \) is less than the normal grinding force \( F_n \) or the tangential grinding force \( F_t \) induced by the grinding wheel, the lens is displaced horizontally or vertically and may also be deflected or rotated (Fig. 2). Consequently, the geometric center axis of the lens is misaligned with the clamps on both sides, resulting in an optical axis error. Grinding forces can be estimated using the following equations [29]:

\[
F_n = K_s \cdot a_e
\]  

(2)

where \( K_s \) is the wear resistance constant as defined on the basis of the workpiece and the abrasives and \( a_e \) is the effective grinding depth.

\[
F_t = \frac{P}{v_s \pm v_w}
\]  

(3)

where \( P \) is the grinding power, \( v_s \) is the linear speed of the grinding wheel, and \( v_w \) is the horizontal speed of the workpiece. The sign \( \pm \) in the denominator depends on the direction of rotation between the grinding wheel and the workpiece. It is positive when both rotate in the same direction and negative in the opposite direction.

\( \mu_f \) is the grinding force ratio, that is, the ratio of the tangential and normal grinding forces; it can be obtained using the following equation:

\[
\mu_f = \frac{F_t}{F_n}
\]  

(4)

Usually, \( \mu_f \) is less than 0.5, which means that the normal grinding force is usually greater than the tangential grinding force [30].
The difficulty of centering is expressed using the coefficient $Z$, which is determined by the geometric shape of a lens; it is calculated using the following equation:

$$Z = \frac{1}{4} \times \left( \frac{D_1}{R_1} + \frac{D_2}{R_2} \right)$$

(5)

where $R$ is the radius of the curvature, which takes a positive number on the convex surface and a negative number on the concave surface; $D_1$ and $D_2$ are the diameters of the clamp that is in contact with $R_1$ and $R_2$. In general, a smaller absolute value of $Z$ indicates that the centering process is more difficult to perform. That is, the smaller the contact angle between a lens and a clamp, the lower the lateral force between the two items. Therefore, the lens is more likely to being pushed away.

2.2 Clamp design

Generally, the effective range of the polished surface of a lens is determined by its shape, and minor defects that are outside this effective range can be ignored. Therefore, a lens clamp is bell shaped, and its clamping circle must be larger than the effective range of a lens. The configuration of the contact surface between a clamp and a lens is determined by considering the morphology of the polished surface of the lens (Fig. 3). If the polished surface of the lens is concave, the clamp requires an external chamfer; if the polished surface is convex, an internal chamfer is required. A clamp must apply sufficient normal force to a lens to ensure that it is not displaced by the grinding wheel and does not become deformed. Therefore, the selection of the appropriate materials for a clamp is a key step.

2.3 Optical axis error

The area and edge difference of the contact position between the clamps and the lens are shown in Fig. 3. They affect the in-between stress that determines the deformation level of the clamps. If a clamp is deformed unevenly because of uneven force distribution or minor imperfections on its surface, the optical axis of the clamped lens deviates from the geometric center axis of the clamp on both sides, resulting in an optical axis error.

In the present study, the relationship between the peak-to-valley value of a clamp edge, the diameter of the contact area between a clamp and a lens (d), and the angle of optical axis error ($\phi$) were mathematically analyzed (Fig. 4).

If the contact diameters of a clamp on both sides of a clamped lens differ, their influence on the optical axis error of the lens also differs. If the lens has the three-dimensional space coordinates shown in Fig. 5, then the optical axis error caused by the clamp on both sides of the lens is expressed as the angles $\theta_1$ and $\theta_2$ between the offset optical axis and the Z axis. After superpositioning is performed, the overall optical axis error $\theta_3$ can be calculated using the follow equation:

$$\theta_3 = \sin^{-1}\left(\sqrt{(\sin \theta_1)^2 + 2 \sin \theta_1 \sin \theta_2 \cos \phi + (\sin \theta_2)^2}\right)$$

(6)

where $\phi$ is the phase angle between $\theta_1$ and $\theta_2$ on the XY plane that has a positive and negative value if it is less and more than 90°, respectively.

Fig. 3  Contact between clamps and lens

Fig. 4  Relationship between edge thickness difference and optical axis error

Optical axis error: $\theta = \tan^{-1}\left(\frac{x}{d}\right)$

Peak-to-valley value of surface roughness: $x$ (μm)
2.4 Experiment for evaluating clamping force

2.4.1 Experimental setup

The BE-WF-502 N centering machine (Shonan Optics) was used for the experiments performed in the present study. The grinding axis of the machine has three degrees of freedom on the X, Y, and A planes, and its clamping axis has two degrees of freedom on the X and A planes. The mechanism of centering is shown in Fig. 6. The left end of the clamp is fixed, and the clamping handle outside the machining area drives the internal gear mechanism that allows the right end of the clamp to move along the X-plane and secure the lens.

Due to a lack of method for measuring the clamping force during centering process, the position and tightness of clamping handle are generally judged according to the operator’s personal experience. Without a set of standard procedures during clamping, the processing results vary with the proficiency of operators. It is important to keep the clamping force value within a reasonable range during centering. In this study, a method involving the use of a load cell and strain gauges was developed for performing measurements on the centering machine to quantify the clamping force.

To measure the clamping force between the clamp and a lens, a load cell (JIHSENSE MT-50) was clamped using the clamp, and a strain gauge (SHOWA N11-FA-2–120-11-VSE3) was glued to the bottom of the clamping handle. A Bridge DAQ (CHIEF SI) was used to simultaneously measure the handle strain and clamping force at a sampling rate of 200 Hz. After the relevant data were obtained, the relationship between handle strain and clamping force was further analyzed.

To prevent direct contact between the load cell and the clamp, a fixture made of 6061 aluminum alloy was designed and fixed to both ends of the load cell (Fig. 7).

2.4.2 Relationship between clamping force and handle strain

For the experiments, two brass clamps, which had a diameter of 25 mm on their left sides and a diameter of 20 mm...
on their right sides, were used. The load cell was clamped in the manner depicted in Fig. 7b. The strain of the handle and the load applied to the load cell were measured during the clamping process for 30 s. The obtained signal data are plotted in Fig. 8.

During the experiment, the maximum strain on the handle was 1519.16 με, and the maximum load applied to the load cell was 380.765 N. Figure 9 reveals a significant linear relationship between handle strain and clamping load, and the correlation between the two was evaluated by calculating the coefficient of determination ($R^2$), which was determined to be 99.57%. Therefore, the handle strain could be converted into clamping force on the basis of the relationship presented in Fig. 9. By establishing the relationship, the clamping force can be determined according to the strain of the handle. This method minimizes the impact on processing and provides a quantitative standard for clamping force.

**2.4.3 Relationship between clamping force and scratches on lens surfaces**

Based on the experimental results in Sect. 2.4.2, the relationship between clamping force and scratches on lens surfaces is further investigated. A pair of brass clamps was used to hold the lenses made of HOYA FCD1. The lenses with the same geometry were clamped and ground by the grinding wheel with the same parameters to examine the clamping stability. Four loads with different magnitude were applied for clamping. Different degrees of lens surface damage were observed after centering process. In the experiment, the grinding wheel rotational speed was 2400 rpm, wheel feed rate was 0.01 mm/s, total feed was 1.0 mm, and the lens rotational speed was 2.0 rpm.

The clamping forces and the corresponding lens surface qualities are shown in Table 1. When the clamping force was greater than 294.30, scratches with different sizes could
be observed on the lens surfaces. The sizes of the scratches were larger with greater clamping forces. The surface qualities of the lenses are shown in Fig. 10. When the clamping force was 245.25 N, the lens was pushed away by the feeding of the grinding wheel. In this condition, the clamping force was unable to resist the normal grinding force. Based on the experiment, an appropriate clamping force can be determined in the finite element simulation.

2.5 Finite element method

2.5.1 Modeling and boundary conditions

During the process of centering, determining whether an applied clamping force is sufficient for resisting the grinding force of the centering process is a difficult task. Furthermore, a larger force leads to greater clamp deformation, which affects the optical axis error of a lens.

A finite element analysis can be performed to obtain detailed predictions of stress, strain, and deformation. The results of a finite element analysis can be used to evaluate optical axis error, clamp deformation, and the durability of a lens centering process. Therefore, in the present study, a finite element simulation was performed to minimize clamping stress. The amount of deformation and its effect on the optical axis of a lens can be minimized by determining the minimum amount of clamping force that is required to resist grinding force. In this study, the software ANSYS 2020 was employed to perform the finite element analysis.

Clamp and lens mechanical models were constructed for the finite element analysis conducted in the present study. Figure 11 shows how the contact points between the surfaces of a lens and the edges of a clamp were set in a face-to-face manner. A contact point usually experiences extremely high stress because of the limitation of a mesh. There should be no relative rotation between the lens and clamps, so the contact area was set as rough condition, which means no sliding on the contact area. The elements on the clamp are hexagonal. For lenses, their surfaces may be concave or convex depending on their specifications. Because the curvatures of lens surfaces are variables in a simulation, a tetrahedron is the ideal type of element for modeling the shape of a lens. Moreover, since the contact areas were the surface with curvatures, the element type was set to be second-order.

The boundary conditions of the simulation performed in the present study included the clamping force and fixed support. The fixed support, which fixes the geometry with a zero displacement, was positioned at the bottom of clamp 1 (left side of the clamp in Fig. 11). A clamping force was applied to clamp 2 (right side of the clamp in Fig. 11).

2.5.2 Mesh convergence analysis

The simulation results could be unreliable because the FEM is a numerical method that uses discrete data points. To ensure the reliability of the FEM results, an analysis of convergence was conducted. Theoretically, the result obtained from a discrete data point should be close to the actual value because the elements are highly intensive. In the analysis of convergence, element size was used as the independent variable. When element size was smaller,
The number of elements increased, and the meshed elements become more intensive. The average stresses experienced by the clamps with a decreasing element size were recorded. The error of the $j$th iteration $e_{ij}$ in a convergence was obtained using the following equation:

$$e_{ij} = \frac{\sigma_{ij} - \sigma_{ij-1}}{\sigma_{ij-1}} \times 100\%$$ (7)

where $\sigma_{ij}$ is the stress $\sigma_i$ of the $j$th iteration. The outputs comprised $\sigma_{n1}$ (i.e., average surface normal stress of clamp 1), $\sigma_{n2}$ (i.e., average surface normal stress of clamp 2), $\sigma_{eqv1}$ (i.e., average surface equivalent stress of clamp 1), and $\sigma_{eqv2}$ (i.e., average surface equivalent stress of clamp 2).

Convergence analyses were performed for the meniscus and biconcave and biconvex lenses. Tables 2, 3 and 4 and Fig. 12 reveal that the errors of the third iteration, and the sixth to eighth iterations were generally less than 10% for the three types of lenses. The error value increased in the iteration that followed the third iteration. However, the sixth to eight iterations produced more reliable results because smaller element sizes were used; thus, the corresponding simulation results are expected to be more accurate. Moreover, a simulation with fewer elements requires less time to complete and generate results. The analyses of convergence indicated that the sixth simulation, in which an element size of 0.8 mm was used, provided the optimal balance between accuracy and simulation time.

Multiple FEM analyses were conducted, during which changes were made to clamp configuration parameters such as outer diameter, thickness (difference between the inner and outer diameters), Young’s modulus of material, and contact curvature. The simulation results were recorded, and the
3 Surrogate model and regression analysis

3.1 SVR

SVR is a regression analysis that is based on support vector machines (SVMs). SVR and SVM algorithms are highly similar, and both are useful for classifying and predicting data with high-dimensional features. The difference between them is that an SVM model uses a hyperplane to maximize the separation between different groups of data to achieve classification, whereas an SVR model minimizes the distance of all data points to a hyperplane. In an SVR model, support vectors are used to represent data points outside a hyperplane. For the hyperplane, a $\varepsilon$ value must be defined, and the boundary line is formed by $\pm \varepsilon$. The distance from a support vector to a boundary is the residual $\zeta$, and the $\zeta$ inside the hyperplane has a zero value. SVR is performed to identify the optimal $\varepsilon$ value for minimizing residual error (Fig. 13). With the kernel function providing various options, SVR can be applied to both linear and nonlinear classification. In the present study, a radial basis function (RBF) kernel was used for SVR modeling to accommodate the nonlinearity of prediction results.

3.2 GPR

GPR is a nonparametric probabilistic model that is based on the Bayesian inference method; it can also be applied in both classification and regression analyses to perform accurate predictions for data with a small number of samples and features [31]. The model learns the exact values for each parameter in a function and evaluates the probability distribution of all possible values. Therefore, GPR is not limited by the form of functions. The Gaussian process can be interpreted as follows: When $x = [x_1, x_2, x_3 \ldots x_n]$, and $g(x) = [g(x_1), g(x_2), g(x_3) \ldots g(x_n)]$ has a multivariate Gaussian distribution, then $g$ is a Gaussian random process that can be expressed using the following equation:

$$g(x) = N(\mu(x), k(x, x'))$$

(8)

where $\mu(x)$ is the mean function and $k(x, x')$ is the covariance function.

3.3 ANFIS

An ANFIS is a feed-forward ANN that is based on the Takagi–Sugeno model, which integrates fuzzy logic rules into the architecture of a neural network and thus combines the advantages of fuzzy logic networks and neural networks [32, 33]. As illustrated in Fig. 14, the structure of an ANFIS can be divided into five layers in accordance with the following sequence: fuzzification layer, product layer, normalized layer, defuzzification layer, and output layer. In the first layer, each node is a labeled adaptive node with a membership function, and each input value (E, Z, and T) is translated into linguistic variables that represent the degree to which it conforms to a label (A, B,

| Table 2 | Convergence analysis of meniscus lens |
| Simulation order | Element size (mm) | $\sigma_{x1}$ | $\sigma_{x2}$ | $\sigma_{eq1}$ | $\sigma_{eq2}$ |
|-------------------|-------------------|-------------|-------------|-------------|-------------|
| 1                 | 5                 | X           | X           | X           | X           |
| 2                 | 4                 | 61.84       | 203.12      | 0.65        | -0.54       |
| 3                 | 3                 | 2.99        | 2.53        | 0.02        | 3.75        |
| 4                 | 2                 | 33.50       | 32.13       | 3.28        | 3.13        |
| 5                 | 1                 | 27.64       | 29.37       | -1.55       | 0.47        |
| 6                 | 0.8               | 7.25        | 8.77        | 0.45        | -3.40       |
| 7                 | 0.6               | 8.17        | 8.10        | -0.25       | -2.58       |
| 8                 | 0.5               | 2.18        | 3.90        | -0.26       | 0.17        |

| Table 3 | Convergence analysis of biconcave lens |
| Simulation order | Element size (mm) | $\sigma_{x1}$ | $\sigma_{x2}$ | $\sigma_{eq1}$ | $\sigma_{eq2}$ |
|-------------------|-------------------|-------------|-------------|-------------|-------------|
| 1                 | 5                 | X           | X           | X           | X           |
| 2                 | 4                 | 100.51      | 44.02       | -2.70       | 0.30        |
| 3                 | 3                 | -3.99       | -4.12       | 2.01        | 2.07        |
| 4                 | 2                 | 43.54       | 35.46       | 3.35        | 4.90        |
| 5                 | 1                 | 46.96       | 47.08       | -1.73       | 1.69        |
| 6                 | 0.8               | 3.49        | 3.34        | -1.05       | -1.08       |
| 7                 | 0.6               | 8.48        | 8.36        | -0.95       | -0.97       |
| 8                 | 0.5               | 3.49        | 3.34        | -1.05       | -1.08       |

Table 4 Convergence analysis of biconvex lens

| Simulation order | Element size (mm) | $\sigma_{x1}$ | $\sigma_{x2}$ | $\sigma_{eq1}$ | $\sigma_{eq2}$ |
|-------------------|-------------------|-------------|-------------|-------------|-------------|
| 1                 | 5                 | X           | X           | X           | X           |
| 2                 | 4                 | 5.47        | 3.26        | -0.12       | -0.11       |
| 3                 | 3                 | 8.32        | 6.35        | 2.35        | 1.29        |
| 4                 | 2                 | 32.56       | 53.54       | 3.43        | 7.61        |
| 5                 | 1                 | 45.29       | 38.76       | -0.32       | -2.59       |
| 6                 | 0.8               | 0.66        | -5.46       | -1.30       | -1.36       |
| 7                 | 0.6               | 8.51        | 11.70       | -0.76       | -0.49       |
| 8                 | 0.5               | 3.42        | 5.01        | -1.69       | -0.72       |
and C). Various types of member functions can be used, including linear, polynomial, and Gaussian functions. On the basis of the nonlinearity of the predicted clamping stress, Gaussian membership functions were applied in the present study. In the second layer, each node follows a specific fuzzy rule and generates an output that is the algebraic product of all input signals to represent the weight of the rule. The weights are then normalized in the third layer. In the fourth layer, each node is an adaptive node that provides a crisp output value on the basis of the normalized weights. The signals are then summed in the fifth layer to produce the final output value.

### 3.4 Modeling

Since the normal grinding force $F_n$ is the main result that pushes the lens from the original location and scratches the polished surfaces, it was concerned in the FEM and the following model. The resistance against normal grinding force is the stress that can resist the normal grinding force $F_n$ from pushing the lens away. The resistance against normal grinding force was the sum of $\sigma_{n1}$ and $\sigma_{n2}$, which were obtained from the FEM results.

Table 5 reveals that 590 sets of test data on three input parameters were used to train and test the aforementioned models, and the resistance-against-normal-grinding-force (MPa) data obtained from each group of parameters after the completion of a finite element simulation were used as responses in an algorithm. In addition, 80% and 20% of the data were used for training and testing, respectively. The hyperparameters of SVR and GPR were optimized through cross-validation, and the convergence of the model was also verified. The optimal parameters of the ANFIS used in the present study were obtained using the least squares method.

The accuracy of the model was evaluated using the coefficient of $R^2$ and root mean square error (RMSE), which are
calculated using the residual sum of squares (RSS) and total sum of squares (TSS); the following equations are used:

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$  \hspace{1cm} (9)

$$TSS = \sum_{i=1}^{n} (y_i - \bar{y})^2$$  \hspace{1cm} (10)

$$RMSE = \sqrt{\frac{1}{n} RSS}$$  \hspace{1cm} (11)

$$R^2 = 1 - \frac{RSS}{TSS}$$  \hspace{1cm} (12)

where $y_i$ is the actual data point, $\hat{y}_i$ is the predicted data point, and $n$ is the total number of data points. Generally, a smaller RMSE results in a more accurate model prediction. The closer an $R^2$ value is to 1, the more favorable is the interpretability of the model. To eliminate the effect of sample size on $R^2$, the adjusted $R^2$ is calculated using the following equation:

$$AdjustedR^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1}$$  \hspace{1cm} (13)

where $n$ is the sample size and $p$ is the number of features.

4 Results and discussion

Figure 15 compares the results of the FEM simulation and the prediction results obtained using the SVR, GPR, and ANFIS algorithms.

As shown in Table 6, The adjusted $R^2$ values of all algorithms were revealed to be greater than 0.95, indicating that the three trained surrogate models can appropriately interpret the simulation results. The comparison of the RMSE results revealed that the SVR model produced the smallest error, followed by the ANFIS model. Compared with the SVR and ANFIS models, the GPR model produced the largest RMSE. This could be due to the relationship between how GPR was predicted and the sample size, that is, the randomness of the dataset was positively correlated with the number of samples. As a result, with the sample size of the present study, the RMSE results of the GPR model were slightly inferior to those of the other two models. Figure 15 reveals that the GPR model produced extreme prediction values at specific points. Overall, under the data conditions of the present study, the three prediction models all produced favorable prediction results, and the SVR model achieved the best performance.
In the present study, a machine learning-based regression model is established to predict the clamping resistance against normal grinding force during optical glass lens centering; with this model, continuous finite element analyses can be conducted in a more time- and computing-efficient manner. In total, 590 sets of clamping parameters are used as training and testing samples for three regression algorithm models (i.e., SVR, GPR, and ANFIS). Among the three models, the SVR model has the most favorable performance with an adjusted \( R^2 \) of 0.9580 and an RMSE of 0.0012. The applicability and robustness of the SVR model can be further enhanced through field verification and optimization algorithms.

### Table 6 Evaluation of accuracy of each algorithm

| Model                                | Adjusted \( R^2 \) | Root mean square error |
|--------------------------------------|--------------------|------------------------|
| Support vector regression            | 0.9580             | 0.0012                 |
| Gaussian processes regression        | 0.9713             | 0.0259                 |
| Adaptive neuro fuzzy inference system| 0.9688             | 0.0020                 |

### 5 Conclusion

In the present study, a machine learning-based regression model is established to predict the clamping resistance against normal grinding force during optical glass lens centering; with this model, continuous finite element analyses can be conducted in a more time- and computing-efficient manner. In total, 590 sets of clamping parameters are used as training and testing samples for three regression algorithm models (i.e., SVR, GPR, and ANFIS). Among the three models, the SVR model has the most favorable performance with an adjusted \( R^2 \) of 0.9580 and an RMSE of 0.0012. The applicability and robustness of the SVR model can be further enhanced through field verification and optimization algorithms.

### Author contribution

Chun-Wei Liu: Conceptualization, supervision
Shiau-Cheng Shiu: Finite element simulation, convergence analysis
Kai-Hung Yu: Experiment design, writing, algorithmic modeling.

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### Data availability

Not applicable.

### Code availability

Not applicable.

### Declarations

#### Ethics approval

Not applicable.

#### Consent to participate

All authors were fully involved in the study and preparation of the manuscript; each of the authors has read and concurs with the content in the final manuscript.

#### Consent for publication

All authors consent to publish the content in the final manuscript.

#### Conflict of interest

The authors declare no competing interests.

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