Hybrid numerical modeling of ballistic clay under low-speed impact using artificial neural network

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Abstract Roma Plastilina No. 1 clay has been widely used as a conservative boundary condition in bulletproof vests, namely to play the role of a human body. Interestingly, the effect of this boundary condition on the ballistic performance of the vests is indiscernible. Moreover, back face deformation should be characterized by measuring the indentation in the deformed clay, which is important for determining the lethality of gunshots. Therefore, several studies have focused on modeling not only bulletproof vests but also the clay backing material. Despite various attempts to develop a suitable numerical model, determining the appropriate physical parameters that can capture the high-strain-rate behavior of clay is still challenging. In this study, we predicted indentation depth in clay using an artificial neural network (ANN) and determined the optimal material parameters required for a finite element method (FEM)-based model using an inverse tracking method. Our ANN-FEM hybrid model successfully optimized high-strain-rate material parameters without the need for any independent mechanical tests. The proposed novel model achieved a high prediction accuracy of over 98% referring impact cases.

1. Introduction

An artificial neural network (ANN) is a computational learning algorithm that is inspired by the biological neural network present in the human brain [1]. ANNs are typically composed of multiple layers of neurons such that the input data pass repeatedly through these layers before the output data are generated [2]. Owing to this distinctive learning mechanism, ANNs are expected to solve highly complex problems; however, such networks cannot distinguish between the cause and effect of the underlying problem. Therefore, “black-box” models such as ANNs are frequently arguable compared to conventional numerical approaches, such as the finite element method (FEM). Nevertheless, it is possible to incorporate ANNs into conventional methods. For example, various types of impacts, including large-scale deformations and complex failure modes, can be effectively simulated by combining these two approaches [3-11]. For example, Fernández-Fdz et al. designed a multilayer perceptron model to predict the ballistic performance of carbon fiber-reinforced polymers under high-velocity oblique impacts [3]. Ryan et al. used an ANN to predict the performance of multiwall aluminum Whipple shields against a wide range of hypervelocity impacts with a high accuracy of 92% [4]. Kılıç et al. employed a combined FEM-ANN method to predict the ballistic penetration depth of steel armors with high accuracy [5]. Ramasamy and Sampathkumar [6] evaluated the compressive strength of composites using ANNs.

ANNs require sufficient training data to make accurate predictions; otherwise, various numerical problems arise, such as overfitting. Overfitting implies that the prediction accuracy of the validation datasets is much lower than that of the training datasets [12]. This can cause a significant loss in the prediction accuracy of the model. However, it is difficult to determine the optimum number of training datasets required by ANNs. In addition, it is challenging to acquire
sufficient training data for problems such as predicting the impact of high-strain-rate deformation on different materials. Moreover, there are no set guidelines for determining the optimum number of experiments necessary, as well as the important physical outcomes for a given problem.

Roma Plastilina (RP) No. 1 clay is an oil-based backing material commonly used for evaluating the performance of body armors in ballistic tests as per the U.S. National Institute of Justice (NIJ) standards [13-17]. In such impact tests, the extent of damage to the human body by a nonpenetrating gunshot wound is determined by measuring the depth of indentation in the RP clay. RP clay provides additional support to a target and is also expected to deteriorate significantly to ballistic performance. Therefore, it is important to investigate the effectiveness of RP clay as a backing material. Moreover, RP clay backing material needs to be validated before the start of every impact test in accordance with the NIJ standards [16, 17]. To this end, several studies have been conducted to model and characterize RP clay [18-20].

FEM has been used to simulate RP clay [21]. Mates et al. obtained the material parameters of the Johnson-Cook (J-C) model by using a reference strain rate of 0.118 s\(^{-1}\) and reference temperature of 23 °C [22]. Gad and Gao compared indentation depth of between J-C model and new constitutive model [23], which can be applied in RP clay modeling based on a case where a 44.5 mm cylindrical indenter drops from 2-m height referring to Ref. [17], to confirm effect of both temperature and strain rate. Hernandez et al. used a model based on the J-C model and an inverse method to obtain the optimized set of material parameters characterizing RP clay including a test in which a 63.5 mm spherical indenter drops from 2-m height [24]. Gilson et al. analyzed the effect of Young’s modulus (in the range 2-6 MPa) on the ballistic response of RP clay by comparing the results of numerical simulations and physical experiments correspond to where a 63.5 mm spherical indenter dropped from 2-m heights [25]. Nevertheless, the previous models have only been applied to a few limited cases involving 63.5 or 44.5 mm diameter indenter from 2-m height.

The model may not cover practical impact conditions of various geometry of indenter and wide range of strain rates. Despite the importance of the clay, there are no practicable numerical models of the clay yet due to the difficulties of obtaining reliable material parameters in various loading conditions.

In this study, we used ANNs to determine the optimal values of the material parameters required by an FEM-based model for characterizing RP clay in accordance with the NIJ standards and their experimental results. First, we modeled the indenter and RP clay to obtain the necessary training datasets. Then, we designed three ANNs based on the results of the FEM simulations that could predict the indentation depths in RP clay due to impact by a spherical indenter with a diameter of (1) 44.5 mm at 4.47 m/s, (2) 44.5 mm at 6.26 m/s, and (3) 63.5 mm at 6.26 m/s. Next, we selected the optimal material parameters based on the predictions of our ANNs using an inverse tracking method. Finally, we implemented these optimal material parameters in our model for verification. The detailed algorithm for determining the optimal material parameters is shown in Fig. 1. We found that the accuracy of the FEM-based model was significantly improved and that the mean relative error was reduced from 17.27 % to 1.28 %.

2. Method

2.1 Finite element modeling

The parameter settings and experimental results of the different impact cases [16, 17, 26] are listed in Table 1. Case 1 corresponds to a cylindrical indenter made of 4340 steel with a spherical head of diameter 44.5±0.5 mm that was dropped from a height of 2 m [26]. Cases 2 and 3 correspond to two existing NIJ standards [16, 17]. Case 1 was introduced to facilitate high-accuracy predictions by the ANN.

2D axisymmetric FEM simulations were carried out using the Ansys Autodyn software. Kim et al. compared the indentation depth according to the effect of mesh size and boundary conditions of both clay and indenter for elaborate RP clay modeling.
The clay models have 400 mm depth and 200 mm diameter. The size of mesh in finer region is 1.0 mm, considering computation cost and mesh dependency. Moreover, both the indenter and RP clay were modeled as shell elements, as shown in Fig. 2. The duration of all the simulations was more than 10 ms, which was sufficiently long to slow the indenter. At the end of each simulation, the displacement of the indenter was recorded and compared with referred indentation depth given in Table 1. To solve a numerical impact model, computational time less than 25 min is required with a single core of Intel i5-10500 CPU.

Modeling ballistic clay in Autodyn requires an equation of state (EOS) as well as the Johnson Cook (J-C) model to account for both the hydrostatic and deviatoric components of the stress. For the indenter, the input parameters of 4340 steel were supplied from the Autodyn material library. For the RP clay, the parameters of a polynomial EOS and the J-C model were supplied based on previous results, which are listed in Table 2 [22, 23]. Note that three different EOSs were considered; however, the choice of the EOS had a negligible effect on the RP clay. The EOS we adopted can be described by the following two equations:

\[ p = A_1 \mu + A_2 \mu^2 + A_3 \mu^3 + (B_0 + B_1 \mu) p_e, \]  
\[ \mu > 0 \text{(compression)} \]  
\[ p = A_1 \mu + A_2 \mu^2 + B_1 p_e, \]  
\[ \mu < 0 \text{(tension)} \]  

where \( A_1, A_2, A_3, B_0, \) and \( B_1 \) represent the material parameters; \( \mu \) is the compressibility; \( p_e \) is the zero-pressure density; and \( e \) is the internal energy per unit mass. The J-C model is given by the following equation:

\[ \sigma = \left( A + B \varepsilon_p^\gamma \right) \left[ 1 + C \ln \left( \frac{\dot{\varepsilon}_p}{\dot{\varepsilon}_p^\gamma} \right) \right] \left[ 1 - \left( \frac{T - T_0}{T_m - T_0} \right)^n \right]^{m} \]  

where \( A, B, C, n, \) and \( m \) are the material parameters which represent the initial yield stress, hardening constant, strain rate constant, hardening exponent, and thermal softening exponent, respectively; \( \varepsilon_p \) is the effective plastic strain; \( \dot{\varepsilon}_p \) is the normalized effective plastic strain rate; \( \varepsilon_0 \) is the reference strain rate; \( T_0 \) is the reference temperature; and \( T_m \) is the melting temperature.

The instantaneous erosion strain (ISE) of 500 % was applied to erode elements which have excessive level of strain. The material parameters in Eqs. (1)-(3) were referred to the previous works [22, 23]. A small value for the initial yield stress \( A \) was selected (i.e., 0.01 kPa) from previous studies to model the high plasticity of RP clay. Keeping the above considerations in mind, we considered only eight material parameters (\( A_1, A_2, B_0, C, \varepsilon, m, \) and ISE) in our final model that could be determined unambiguously.

### 2.2 Artificial neural networks

An ANN typically consists of an input layer, a hidden layer, and an output layer, as shown in Fig. 4. The flow of data through the ANN can be described by the following equation [28]:

| Case number | 1 [26] | 2 [16] | 3 [17] |
|-------------|--------|--------|--------|
| Diameter (mm) | 44.5 | 44.5 | 63.5 |
| Mass (g) | 1,000 | 1,000 | 1,043 |
| Calculated impact velocity (m/s) | 4.47 | 6.26 | 6.26 |
| Indentation depth (mm) | 16.0 | 25.0 | 19.0 |

**Table 1. Referred experimental cases.**

### Table 2. Parameters of the polynomial EOS and J-C model for RP clay [22, 23].

| EOS Parameters | J-C Parameters |
|----------------|---------------|
| \( A_1 \) (GPa) | 2.804 | \( A \) (kPa) | 0.01 |
| \( A_2 \) (GPa) | 40.7 | \( B \) (kPa) | 238.0 |
| \( A_3 \) (GPa) | -36.0 | \( n \) | 0.29 |
| \( B_0 \) | 1.7 | \( C \) | 0.25 |
| \( B_1 \) | 1.7 | \( m \) | 0.502 |
| \( e \) | 0.118 |

**Fig. 2. Axisymmetric model for case 1, 2 before and after impact.**

**Fig. 3. Axisymmetric model for case 3 before and after impact.**

**Fig. 4. Structure of a simplified ANN.**
where $x_i$ is the input data, $w$ is the weight, and $b_i$ is the bias.

The hyper-parameters such as activation function, optimizer function, loss function, and learning rate, were set for our ANN models. The sum of $y_i$ was transformed using an activation function \cite{29, 30}. A rectified linear unit (ReLU) activation function was used between the input and hidden layers, as well as between the multiple hidden layers owing to advantage of efficient learning speed and implement \cite{31}. ReLU is defined as:

$$f(x) = \max(0, x).$$

A linear activation function was used between the hidden and output layers, such that

$$f(x) = ax.$$  

An ANN learns iteratively by dividing the input data into training and validation data \cite{32}. In this study, we designed ANN models using Google Colab, which is a free development environment based on Python, supplied by Google Inc. The training and validation data were split into an 80:20 ratio, and each model was trained the same number of times for 20000 epochs, which has reasonable learning speed and loss close to zero. The adaptive moment estimation algorithm (ADAM), which is based on gradient descent, was used to optimize the performance of our model \cite{33}. The mean squared error (MSE) was used as the loss function, which is given by Ref. \cite{34}. In addition, we used the backpropagation algorithm to train our model \cite{35}.

$$MSE = \frac{1}{N} \sum_{i=1}^{N}(y_i - \hat{y_i})^2.$$  

(7)

$$(y_i : \text{actual value}, \hat{y_i} : \text{predicted value}).$$

To find the ANN model with the best prediction accuracy, we first varied the total number of neurons (i.e., 25, 50, 75, and 100) based on one hidden layer. Next, we increased the number of hidden layers (i.e., 1, 2, and 3) to evaluate their effect on the performance of the ANN. Root mean square error (RMSE) and coefficient of determination ($R^2$) were used as the evaluation indices in this study, which are given by Refs. \cite{36, 37}.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N}(y_i - \hat{y_i})^2}.$$  

(8)

$$(y_i : \text{actual value}, \hat{y_i} : \text{predicted value})$$

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y_i} - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2} = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}.$$  

(9)

$$(y_i : \text{actual value}, \hat{y_i} : \text{predicted value}, \bar{y} : \text{mean value}).$$

### 3. Results and analysis

#### 3.1 Correlation analysis of material parameters and indentation depth

Although an ANN can be designed using all eight material parameters ($A_1$, $A_2$, $B$, $n$, $C$, $\epsilon$, $m$, and ISE), a large number of training datasets is required in eight dimensions. Thus, acquiring sufficient training data corresponding to eight parameters is quite challenging. To address this, we estimated the degree to which each material parameter affected the indentation depth before creating the training datasets. We termed this the absolute correlation coefficient.

For our correlation analysis, the eight material parameters were either multiplied or divided by a constant factor (i.e., 2 and 4) to generate 33 analytical datasets. Simulations were performed using these 33 datasets and the absolute correlation coefficients for each material parameter corresponding to different indentation depths were calculated, as shown in Table 3.

A larger absolute correlation coefficient for a given material parameter indicates that it has a greater effect on the indentation depth. We selected only those material parameters with an absolute correlation coefficient greater than 0.1. Based on this selection criterion, only the material parameters $B$, $n$, and $C$ of the J-C model qualified for all three impact cases. Consequently, the number of input variables in the ANN was reduced from eight to three. The proper range of variables was considered by referring to other studies \cite{20, 22-24}. These three vari-

### Table 3. Absolute correlation coefficients for different indentation depths.

| Material parameters | Case 1 | Case 2 | Case 3 |
|---------------------|--------|--------|--------|
| $A_1$ (GPa)         | 0.029  | 0.031  | 0.030  |
| $A_2$ (GPa)         | 0.029  | 0.031  | 0.030  |
| $B$ (KPa)           | 0.522  | 0.500  | 0.470  |
| $n$                 | 0.600  | 0.490  | 0.636  |
| $\epsilon$ ($s^{-1}$) | 0.025  | 0.026  | 0.024  |
| $m$                 | 0.070  | 0.078  | 0.074  |
| ISE                 | 0.029  | 0.034  | 0.030  |

### Table 4. Material parameters for training datasets.

| Material parameters | Min | Default | Max |
|---------------------|-----|---------|-----|
| $A_1$ (GPa)         | 2.804 (fixed) |
| $A_2$ (GPa)         | 40.7 (fixed) |
| $A$ (KPa)           | 0.01 (fixed) |
| $B$ (KPa)           | 59.5 | 238.0 | 952.0 |
| $n$                 | 0.0725 | 0.29 | 1.16 |
| $\epsilon$ ($s^{-1}$) | 0.007813 | 0.25 | 1.00 |
| $m$                 | 0.502 (fixed) |
| ISE                 | 5.0 (fixed) |
ables were multiplied and divided by factors of 2 and 4 to generate 145 training datasets for the ANN. Table 4 shows the parameter settings for these training datasets. Among parameter settings, simulation results with B of parameter settings of 59.5 and C of 0.007813 do not apply to training datasets, because the current mesh models with the small values produced excessively deep indentation depth, much deeper than the refined zone.

3.2 Design and selection of the optimal ANN

The three material parameters, B, n, and C, which had the most influence on the indentation depth, formed the input layer of our ANN, whereas the indentation depth formed the output layer. The details of the activation functions, learning rate, and epoch used in our model have already been discussed in Sec. 2.2. We named our models A, B, and C corresponding to impact cases 1-3, respectively. To increase the prediction accuracy of the ANN having a single hidden layer, the total number of neurons was increased. These models were named A1, A2, A3, and A4 corresponding to 25, 50, 75, and 100 neurons, respectively.

Fig. 5 shows the RMSE and $R^2$ as functions of the number of neurons and number of hidden layers for different ANN models. The smaller the value of RMSE and closer the value of $R^2$ to 1.0, the higher is the accuracy of the model. We observed that for a single hidden layer, the accuracy of the ANN was enhanced when the number of neurons was increased to 100 for all three impact cases.

In addition, we varied the number of hidden layers (i.e., 1, 2, 3) of the ANN while keeping the total number of neurons fixed at 100. For example, model A4-2 represents impact case 1 and an ANN composed of 100 neurons and 2 hidden layers. Based on our evaluation, models A4-3, B4-3, and C4-2 were found to have the best prediction accuracy. This implies that increasing the number of hidden layers does not necessarily guarantee better results. Although the prediction accuracy improved as the number of hidden layers was increased in model B4, this was not the case for model C4. For example, the RMSE of model C4-2 increased from 0.3474 to 0.4136 for model C4-3 while $R^2$ remained constant at 0.999. The selected optimal ANN models took less than 10 min each to predict the indentation depth.

3.3 Prediction of optimal material parameters

To find the optimal material parameters within the range of our training datasets, the maximum and minimum values of the three parameters, B, n, and C were divided by a constant factor. The maximum and minimum values of these parameters are listed in Table 4. Subsequently, one million target datasets were generated from 145 variations of these three input parameters.

Based on our evaluation, models A4-3, B4-3, and C4-2 were tested on the one million target datasets to predict the indentation depth for each impact case. Next, the function $f$ was calculated as the sum of the differences between the indentation depth predicted by the ANN models and the reference indentation depth, which is experimental impact results [16, 17, 26], such that

$$f = \sum_{i} \left[ \left| 16 - K_i \right| + \left| 25 - K_i \right| + \left| 19 - K_i \right| / 3 \right]. \quad (10)$$

Finally, the optimal material parameters were selected using the inverse tracking method ($f^{-1}$).

Fig. 6 shows the geometric distribution of the material parameters predicted by the ANN models and inverse tracking method with the following characteristics. In Fig. 6, 3000 sets of material parameters, which induce low level of error less than 0.3 % between the indentation depths predicted by our algorithm and the corresponding reference indentation depths, are shown for each impact case. The data highlighted in red corre-
spond to 30 sets of material parameters that are common to all three impact cases with an averaged error below 2.5%.

In Fig. 6, we observe that the geometric distribution of the material parameters corresponding to impact cases 1 and 3 is almost indistinguishable; however, the geometric distribution corresponding to impact case 2 is distinctly different. Three separate intersection regions are also seen to form, which consist of 30 sets of material parameters.

### 3.4 Data validation

The ten best sets of material parameters that are applicable to all three impact cases were selected from among the 50 sets of material parameters discussed in Sec. 3.3. Note that the average error between the indentation depths calculated using these ten sets of material parameters and the corresponding reference indentation depths is expected to be less than 1.52%; nevertheless, these material parameters need to be validated. Therefore, we conducted FEM simulations using these ten sets of material parameters to verify that the numerical indentation depths were in agreement with those predicted by the ANN models.

Following data validation, the optimal material parameters for modeling RP clay were selected, as listed in Table 5. The parameters B, n, and C were determined using our ANN models, while the remaining parameters were adopted from previous studies. We compared the indentation depths that were numerically estimated using the optimal material parameters (predicted by our ANN models) with those that were estimated using the default material parameters, as shown in Fig. 8. Fig. 8 displays the percentage relative error with respect to the reference indentation depth for the cases presented in Fig. 8. We observe that the use of optimal material parameters signifi-

| Parameter | Value  |
|-----------|--------|
| B (kPa)   | 86.5454|
| n         | 0.1493 |
| C         | 0.4387 |

Table 5. Optimal material parameters of the Johnson-Cook model for RP clay.
of training datasets, the reliability of a single result is difficult to
previously generated datasets. 

sets (i.e., 75 %, 50 %, 25 %, 10 %, and 5 %) from a set of 145 
model was trained using a randomly reduced number of data-
examine its effect on the prediction accuracy of the ANN. Our 
ANN. Therefore, we varied the number of training datasets to 

termine the exact number of training datasets required by an 
required to ensure that the ANN has good prediction accuracy. 

However, because of its black-box nature, it is difficult to de-

3.5 Effect of the number of training datasets

As mentioned, a sufficient number of training datasets is re-
quired to ensure that the ANN has good prediction accuracy. 
However, because of its black-box nature, it is difficult to de-
terminate the exact number of training datasets required by an 
ANN. Therefore, we varied the number of training datasets to 
examine its effect on the prediction accuracy of the ANN. Our 
model was trained using a randomly reduced number of data-
sets (i.e., 75 %, 50 %, 25 %, 10 %, and 5 %) from a set of 145 
previously generated datasets.

When ANNs are trained using a randomly extracted number 

training datasets, the reliability of a single result is difficult to 
guarantee. Therefore, we designed ten models using the re-
duced training dataset for each impact case. For example, first, 
we trained an ANN model using 75 % of the original 145 train-
ing datasets for impact case 1; next, this process was repeated 
ten times to generate ten ANN models for impact case 1.

The ANN models trained on a reduced number of datasets 

were used to predict the indentation depths corresponding to 
the input parameters B, n, and C. The reference indentation 

depth was compared with the indentation depth predicted us-
ing ten sets of material parameters having the lowest error that 
were selected using the inverse tracking method. The detailed 
process is illustrated in Fig. 1. FEM simulations were per-
formed using the optimal material parameters, and the indenta-
tion depths predicted by the ANN models were compared with 
the simulation results. Figs. 9 and 10 show the percentage 
relative error between the FEM and ANN results as well as the 
average prediction accuracy of the ANN models for a reduced 
number of training datasets.

We observed that the average prediction accuracy of the 
ANN models declined as the number of training datasets was 
reduced. For example, the average accuracy was more than 
90 % when more than 25 % of the training datasets were used; 
however, it dropped sharply when less than 10 % of the train-
ing datasets were used. In addition, the relative error remained 
similar when more than 25 % of the training datasets were 
used. Thus, at least 36 training datasets are required to ensure 
a prediction accuracy of 90 % or more for our ANN models.

Furthermore, a larger number of training datasets does not 
necessarily guarantee a higher prediction accuracy for differ-
ent impact cases. For example, for impact case 3, the relative 
error of the model designed using 75 % of the training data-
sets was 0.3 % higher than that of the model designed using 
only 50 % of the training dataset. This may be the result of a 
significant loss in specific training datasets during the random 

3. Discussions

In this study, we used ANNs as a tool to determine the opti-
material parameters required to model RP clay for three 
different impact cases. In this section, here are some of the 
implications of our findings.

First, the parameters B, n, and C, which are directly related 
to the strain rate, were most influential among the eight mate-
rial parameters of the RP clay model. This was confirmed by 
the correlation analysis performed for all three impact cases 
presented in Sec. 3.1. Considering the relatively low impact 
velocities of the cases and the correlation analysis result, it is 
mandatory to include the effect of strain rate to obtain more 
accurate numerical models.

Second, impact case 2 is the key to determining the optimal 
material parameters that are applicable to all three impact 
cases. The geometric distributions of the material parameters, 
which were selected within a certain error, were similar for the 
different impact cases except for impact case 2, represented 
as a blue plane in Fig. 6. This difference is responsible for the 
formation of complex intersection key regions between the 
material parameters of the three impact cases in Fig. 6. This 
distinctive geometric difference in Fig. 6 appears to be caused 
by different strain rate in between the cases. The ratio between 
impact velocity and diameter of indenter was almost identical in 
impact cases 1 and 3. However, the ratio of impact case 2 was 
about 1.4 times higher. The higher ratio provides higher range 
of strain rate during deformation. This implies that the ANN 
models which dealt with strain rate effect need to have various 
impact cases having wide range of strain rate. The selection of 
a comparable target dataset is crucial for determining the opti-
mal material parameters. If there were no different strain rates 
in impact cases, the optimal material parameters or intersecting 
key region would be hardly determined.

Third, only 36 training datasets were sufficient to ensure a 
prediction accuracy of more than 90 % for our ANN models. It 
is important to determine the optimal number of training data-
sets required to make accurate predictions using ANNs. We 
found that the prediction accuracy of our ANN models re-
remained above 90% even when only 25% of the original number (145) of training datasets were used. However, when the data loss exceeded 75%, the prediction accuracy of the models decreased sharply. A high prediction accuracy of 90% even for a significantly reduced training dataset is probably because our ANNs consist of a large number of neurons and multiple hidden layers.

It is notable to observe that the level of accuracy improved dramatically from 17.27% to 1.28% by incorporating FEM and ANN models. Our research work implies that the selection of appropriate cases covering different strain rate is important as discussed with Fig. 6. On the other hand, the proposed simulation models considered only frictionless condition and indentation depth as comparable data. Any more informative series of comparable data, for example, geometric deformation contour near indentation, velocity profile of the indenter from experiment, frictional effect, and microfracture in the contacting layer, may be helpful to understand and improve the numerical model. The result shows that the hybrid method can also easily be used to simulate other impact cases with considering necessary type of data and key cases containing physical phenomenon, similarly to strain rate effect. The proposed method would relieve the burden of building numerical models, which is to get input parameters from tons of various experiments.

5. Conclusions

We determined the optimal values of the material parameters required to model RP clay, which is commonly used to evaluate bulletproof armors, using ANNs and the inverse tracking method. Among the eight material parameters (i.e., A1, A2, B, n, C, ε, m, and ISE) typically used to model RP clay, we selected only the strain-rate-dependent material parameters of the J-C model: B, n, and C. The optimal B, n, and C values returned by our ANN models were 86.5454 kPa, 0.1493 kPa, and 0.4387, respectively. We found that the mean relative error between the referred indentation depth and the indentation depth numerically estimated using the default parameter values was significantly reduced from 17.27% to 1.28% when the optimal parameter values were used. The geometric distribution with the parameter inputs emphasized that the range target dataset must be desirably selected to provide an interesting case containing physical phenomena. Our proposed method could be used to create an accurate clay model, which in turn can improve the effectiveness of bulletproof vests.

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