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RESEARCH ARTICLE

Prediction of shear strength of infilled reinforced concrete frames using efficient hybrid BR-ANN model

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Abstract
Reinforced concrete (RC) frames with infills have been widely used in conventional low-rise buildings. Due to the presence of infill walls, the shear failure as well as lateral bearing capacity of the structural system will be changed significantly compared to the bare RC frames. The purpose of this study is to predict the shear strength of masonry-infilled RC frames using hybrid neural network models, which are combined based on the Bayesian regularization (BR) algorithm and Artificial neural network (ANN). A database containing 153 test results is gathered from the literature to construct the machine learning models. The shear strength predicted by BR-ANN in this study is then compared with the conventional ANN using the Levenberg-Marquardt algorithm. Four statistical metrics, including the goodness of fit $\left(R^2\right)$, root-mean-squared error (RMSE), mean average error (MAE), and $a20-index$ are calculated to evaluate the prediction performance of the ANN models. The comparison emphasizes that the BR-ANN model accurately predicts the shear strength of infilled RC frames with a high R^2 of 0.92, a small $RMSE$ of 12 kN, and a20-index of 0.7. Moreover, the influence of input design parameters on the shear strength is assessed. Finally, a graphical user interface tool is developed for practically calculating the shear strength of infilled RC frames.

Keywords Infilled reinforced concrete frame · Shear strength · Artificial neural network · Bayesian regularization · Graphical user interface

1 Introduction

Masonry walls are often used as infills in reinforced concrete (RC) frames without considering their ability to withstand horizontal loads such as earthquakes. The infill walls contribute to the seismic capacity of the structures. Moreover, the higher lateral strength and stiffness of RC frames with infills compared to bare frames change the structural dynamic characteristics significantly. Specifically, it can reduce the fundamental period and increase the acceleration of the structure [7].

RC frames with masonry infill walls have been conventionally designed without consideration of the load-bearing capacity of infills except for its self-weight. This simplified design approach is widely accepted in various code provisions due to the complexity of the modeling process. In fact, the structural response can be significantly affected by the presence of infills when the structures subjected to earthquakes [11]. The challenge is to determine the shear strength of the infilled RC frame system during the design step. Therefore, a new approach is required to quickly calculate the shear strength of the infilled RC frame.

Peak shear strength is one of the critical values in seismic designs and structural evaluation of infilled RC frames. Numerous researchers have performed experimental and numerical studies to evaluate the seismic responses and failure mechanisms of infilled RC structures [2, 5, 6, 9, 17, 18,

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23, 26, 28, 34]. Those studies demonstrated that the shear strength of the infilled RC structure completely depends on various parameters such as infill wall properties, infill opening distribution, and RC frame dimensions properties. Therefore, it is challenged to determine a precise formulation to estimate the strength of RC frames with infill panels.

The ultimate shear strength of infilled RC frames is specified in some design codes and guidelines such as ASCE/SEI 41 – 06 [3], Canadian Concrete Masonry Producers Association [10, 27], Turkish code [40]. These models proposed shear capacity equations based on the stiffness and strength equivalent strut model. However, few studies pointed out that the code-based models showed a discrepancy in calculating the stiffness and deformation of infilled frames compared to experimental results [46]. Therefore, it is necessary to evaluate the shear strength of RC frames with infill walls using a sufficient database. To deal with this challenge, data-driven models such as artificial intelligence (AI) and machine learning (ML) techniques should be a promising solution.

AI models have been widely applied in various civil engineering predictions [19, 22, 25, 30, 41, 44, 45]. Among AI models, artificial neural network (ANN) is considered one of the efficient algorithms for capacity and performance prediction of structures [1, 4, 12, 20, 21, 32, 29, 33, 35, 39, 43]. Furthermore, typical optimization algorithms have been integrated with ANN to enhance accuracy, such as Particle Swarm Optimization [13, 31], Genetic algorithm [37], and Evolutionary optimization [36]. Another model, namely Bayesian regularization (BR), is also utilized to prevent overfitting in neural network models by incorporating Bayesian principles into the training process [8]. Specifically, an application of BR-ANN for structural prediction of RC frames with infill panels is a feasible study.

So far, some studies have employed ML techniques for infilled RC frames such as fundamental period of structures [38, 42, 43, 47], seismic performance [15], in-plane failure modes [16], and optimization of masonry [24]. However, an evaluation of the shear capacity of infilled RC frames using ML models has not been considered yet.

The purpose of this study is to predict the shear strength of masonry-infilled RC frames using hybrid neural network models, which combine the BR and ANN models. A database containing 153 experimental results is collected from the literature to construct the ML models. The shear strength predicted by BR-ANN in this study is then compared with that of the conventional ANN with the Levenberg-Marquardt algorithm. Four statistical metrics, including the goodness of fit (R^2), root-mean-squared error (RMSE), mean average error (MAE), and $a20-index$ are calculated to evaluate the prediction performance of the ANN models. Moreover, the influence of input design parameters on the shear strength is assessed. Finally, a graphical user interface tool is developed to calculate the shear strength of infilled RC frames.

2 Collected database

In this section, a dataset consisting of 153 previously conducted experimental results is collected to build predictive ML models (Blasi et al. [7]). Table 1 presents a summary of the datasets used in this study. Definitions of parameters are as follows.

- P is the axial force
- H is the story height of the frame, measured to the centerline of the beams
- L Span of the frame bay, measured to the centerline of columns
- b_b is the width of beam section
- h_b is the height of beam section
- A_{gb} is the gross area of beam cross-section
- I_{xb} is the moment of inertia about the x-axis of beam cross-section
- b_c is the width of column

Table 1 Summary of the used database

Parameter	Min	Mean	Max	SD	CoV
P	0.00	27.90	84.30	26.17	0.94
H	24.76	65.05	123.03	20.32	0.31
L	39.37	93.36	283.47	37.12	0.40
b_b	2.36	7.60	27.56	4.16	0.55
h_b	3.94	10.17	23.62	3.80	0.37
A_{gb}	9.30	92.81	325.48	80.51	0.87
I_{xb}	12.03	1421.87	15132.39	2659.83	1.87
b_c	2.36	7.80	13.78	2.53	0.32
h_c	3.94	8.46	15.75	2.88	0.34
A_{gc}	9.30	71.78	217.04	47.86	0.67
I_{xc}	12.03	692.06	4486.52	990.01	1.43
f'_c	1.407	4.277	8.040	1.518	0.355
E_c	2137.970	3648.276	5110.965	676.529	0.185
f_{yl}	31.908	67.056	89.924	12.865	0.192
f_{yt}	30.777	59.339	89.924	17.783	0.300
$\rho_{l\cdot total}$	0.0041	0.0189	0.0484	0.0114	0.6001
ρ_{tb}	0.0013	0.0046	0.0130	0.0027	0.5755
S_c	0.787	3.457	9.843	1.658	0.480
ρ_{tc}	0.0007	0.0043	0.0168	0.0029	0.6796
h_w	22.01	60.08	116.14	19.32	0.32
l_w	33.86	84.90	267.72	35.13	0.41
t_w	1.25	5.01	13.78	2.29	0.46
f'_m	0.116	1.081	3.878	0.982	0.909
E_m	15.519	632.215	2132.914	522.605	0.827
V_{max}	8.21	48.44954	264.18	37.11867	0.76613

- h_c is the height of column section
- A_{gc} is the gross area of column cross-section
- I_{xc} is the moment of inertia about the x-axis of column cross-section
- f_c' is the compressive strength of frame concrete
- E_c is the elastic modulus of frame concrete
- f_{yl} is the yield strength of longitudinal reinforcement
- f_{yt} is the yield strength of transversal reinforcement
- $\rho_{l,total}$ is the ratio of total longitudinal reinforcement to the effective beam cross-section
- ρ_{tb} is the ratio of transversal reinforcement, at the end region of beam
- ρ_{tc} is the ratio of transversal reinforcement, at the end region of column
- S_c is the spacing of transverse reinforcement, at the end region of column
- h_w is the height of masonry infill panel
- l_w is the length of masonry infill panel
- t_w is the thickness of masonry infill panel
- f_m' is the compressive strength of masonry prism
- E_m is the elastic modulus of masonry prism
- V_{max} is the maximum shear strength of the infilled RC frame

3 Machine learning model

3.1 Theoretical backgrounds

An Artificial Neural Network (ANN) is a computational model inspired by the structure and function of the human brain. It consists of interconnected nodes, called neurons, organized in layers. The three main types of layers in an ANN are the input layer, hidden layers, and output layer.

- Input layer: The input layer receives the initial data or features that are fed into the neural network for processing.
- Hidden layers: Hidden layers are intermediate layers between the input and output layers. They perform complex transformations on the input data through weighted connections and activation functions.
- Output layer: The output layer produces the final predictions or classifications based on the processed input data.

Neurons in each layer are connected to neurons in the subsequent layer through weighted connections, which are adjusted during the training process to optimize the performance of network. Activation functions introduce nonlinearity into the network, allowing it to learn complex patterns and relationships in the data. ANNs are trained using algorithms like backpropagation, where the network learns from its mistakes by adjusting the weights to minimize a predefined loss function. Once trained, an ANN can make predictions, classify data, or perform other tasks based on the patterns it has learned from the training data. Figure 1 shows the ANN structure and used activation functions.

Bayesian regularization (BR), also known as Bayesian neural networks, is a technique used in ANN models to prevent overfitting and improve generalization performance. The purpose of BR in an ANN model is to introduce a probabilistic framework that incorporates prior knowledge about the model parameters, allowing for more robust and stable predictions. BR takes a probabilistic approach by treating the weights of the neural network as random variables with prior distributions. During training, the model updates these distributions based on the data, leading to posterior distributions that capture the uncertainty in the weights.

The hybrid BR-ANN model is employed to optimize the objective function $F(w)$, expressed by Eq. (1).

$$F(w) = \beta E_D + \alpha E_w \tag{1}$$

$$E_D = \frac{1}{N}\sum_{i}^{N}\left(y_i - t_i\right)^2 = \frac{1}{N}\sum_{i}^{N} e_i^2 \tag{2}$$

$$E_w = \frac{1}{2}\sum_{i}^{m} w_i^2 \tag{3}$$

where E_D and E_w are the mean-squared error and weight, respectively; α and β denote hyper-parameters of the model; w and m represent weight and weight numbers, respectively; $D\left(x_i, t_i\right)$ is the training data; N is the number of database; y_i and t_i are the i-th prediction output and the i-th target, respectively.

It should be noted that the initiated weights of the model are random values. The density function $P(w|D, \alpha, \beta, M)$ of weights is based on Bayes' theorem, expressed by Eq. (4).

$$P(w|D, \alpha, \beta, M) = \frac{P(D|w, \beta, M)P(w|\alpha, M)}{P(D|\alpha, \beta, M)} \tag{4}$$

where M is the structure of ANN; $P(w|\alpha, M)$ and $P(D|w, \beta, M)$ represent the prior density and the likelihood functions, respectively. Noting that weights are assumed to be interference variables in the Gaussian distribution during training data sets. The probability densities of $P(w|\alpha, M)$ and $P(D|w, \beta, M)$ can be calculated by follow expressions.

$$P(D|w, \beta, M) = \frac{1}{Z_D(\beta)} exp\left(-\beta E_D\right) = \left(\frac{\pi}{\beta}\right)^{-\frac{N}{2}} exp\left(-\beta E_D\right) \tag{5}$$

$$P(w|\alpha, M) = \frac{1}{Z_w(\alpha)} exp\left(-\alpha E_w\right) = \left(\frac{\pi}{\alpha}\right)^{-\frac{m}{2}} exp\left(-\alpha E_w\right) \tag{6}$$

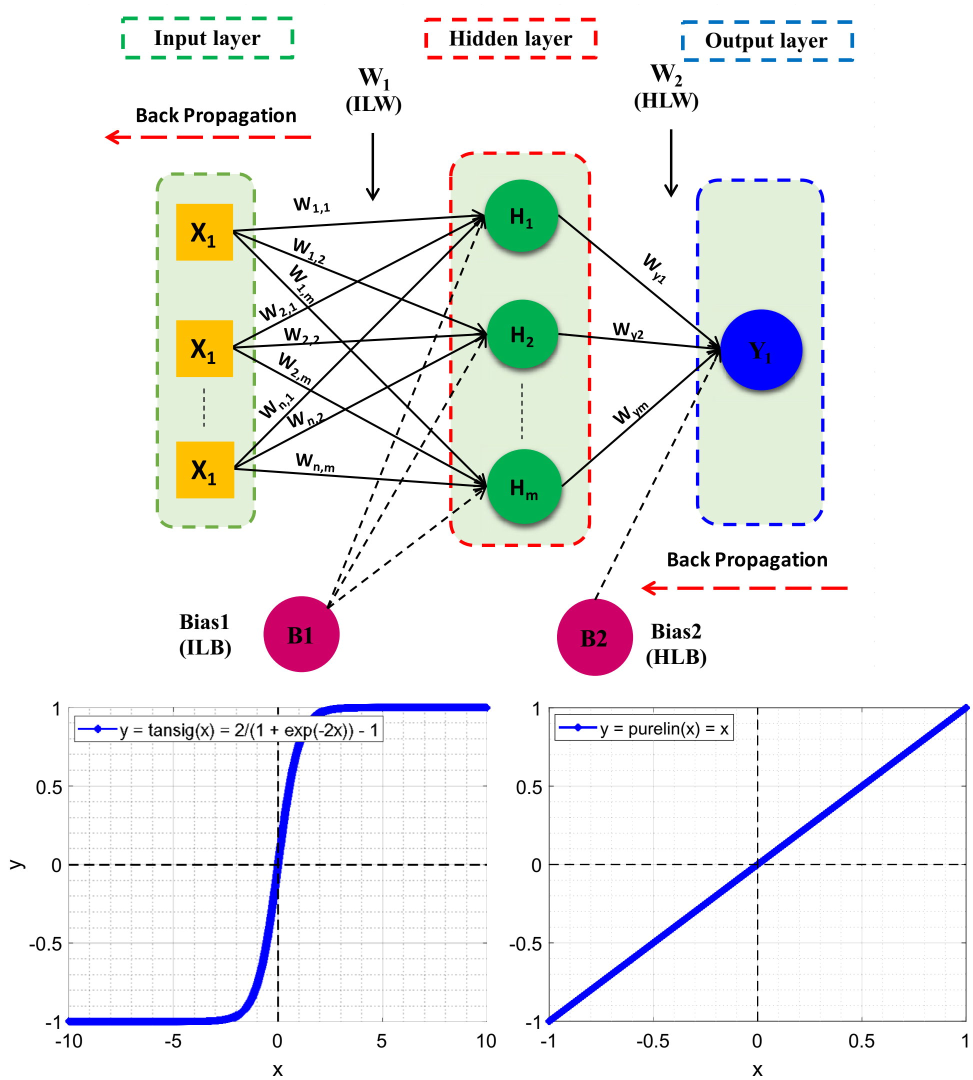


Fig. 1 Illustration of ANN model and activation functions

The probability function $P(w|D, \alpha, \beta, M)$ is re-expressed by substituting Eqs. (5) and (6) into Eq. (4), as follows.

$$P(w|D, \alpha, \beta, M) = \frac{\frac{1}{Z_D(\beta)}\cdot\frac{1}{Z_w(\alpha)}exp\left(-\left(\beta E_D + \alpha E_w\right)\right)}{P(D|\alpha, \beta, M)} = \frac{1}{Z_F(\alpha, \beta)}exp(-F(w)) \tag{7}$$

where

$$\alpha = \frac{\gamma}{2E_w};\ \alpha = \frac{N-\gamma}{2E_D};\ \gamma = N - 2\alpha\, tr(H)^{-1}$$

Foresee and Hagan [14] suggested an expression of Hessian matrix (H), which can be determined based on the Gauss-Newton approximation as follows.

$$H = \nabla^2 F(w) \approx 2\beta J^T J + 2\alpha I_N \tag{8}$$

It should be noted that weights are optimized by maximizing the function $P(w|D, \alpha, \beta, M)$ or minimizing the function $F(w)$. The iteration of training is conducted until obtaining a convergence of $F(w)$. The backpropagation process is performed to updating the weight of network to minimize the loss function, expressed by

$$w_{i+1} = w_i\left(J_i^T J_i + \mu_i I\right)^{-1} J_i^T e_i \tag{9}$$

where J denotes the Jacobian matrix.

The basic steps for performing BR-ANN model are as follows.

- *Step 1*. Data preparation:
- Collect database: Gather data sets from experimental tests, which were published in articles in journals and conference proceedings.
- Preprocess data: For this step, the data is cleaned to handle missing values and remove outliers. Addition-

ally, features of the model are normalized or standardized to ensure they are on a similar scale. Moreover, the dataset is split into training, validation, and test sets with a ratio of 70/15/15.

- *Step 2*. Choose the neural network architecture:
- Define input and output layers: Determine the number of input features and the structure of the output layer (single output for regression, multiple for classification).
- Select hidden layers and neurons: Decide on the number of hidden layers and the number of neurons in each layer based on the complexity of the data.
- *Step 3*. Initialize the BR-ANN model:

In this study, MATLAB is used for implementation. The required hyperparameters are defined for the network, including learning rate, number of epochs, batch size, and regularization parameters.

- *Step 4*. Train the model:

Before training the model, weights are randomly initialized for the network. Then, the model is training, in which the weights are updated using backpropagation and Bayesian regularization is used to minimize the loss function. This technique ensures to prevent overfitting during the training process.

- *Step 5*. Validate the model evaluate on validation set:

After training, the performance of the model is validated using the validation set. Also, to improve the model, the hyperparameters are adjusted based on validation performance.

- *Step 6*. Test the model using the test set:

Finally, the model is tested on the unseen test set to assess its generalization performance. The mean squared error (MSE) is used to check for regression problem.

- *Step 7*. Use the model for new prediction: The optimal trained model is saved for future prediction.

The flowchart of BR-ANN is shown in Fig. 2.

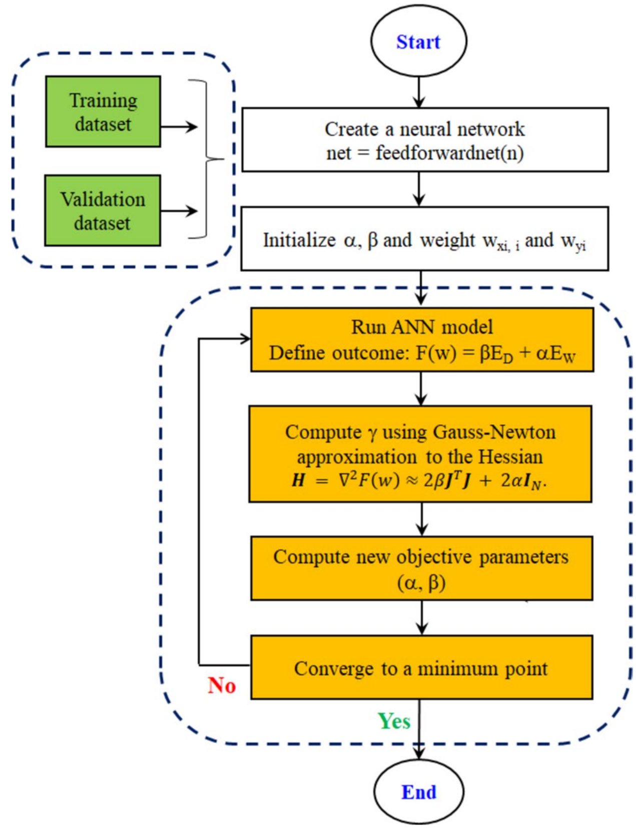


Fig. 2 Flowchart of BR-ANN

3.2 Performance indicators

In this study, we employ four statistical indicators, which are goodness of fit (R^2), root-mean-squared error (RMSE), mean average error (MAE), and $a20-index$, to evaluate the performance of predictive models. It should be noted that the R^2 represents how well a calculated set of data fits an experimental result. The higher of R^2, the better performance of the predictive model. Meanwhile, *RMSE* and *MAE* are widely used to measure the discrepancy between predicted values and experimental data. The lower the *RMSE* and *MAE*, the better the model is at estimating the output. Moreover, $a20-index$ is utilized to calculate the proportion of predicted outputs that falling ±20% over total predictions. The expressions of these metrics are as follows.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (t_i - o_i)^2}{\sum_{i=1}^{N} \left(t_i - \bar{o}\right)^2} \right) \tag{10}$$

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^{n} \left(t_i - o_i\right)^2}; \tag{11}$$

$$MAE = \frac{\sum_{i=1}^{n} |t_i - o_i|}{N} \tag{12}$$

$$a20 - index = \frac{N20}{N} \tag{13}$$

Fig. 3 Performance of BR-ANN

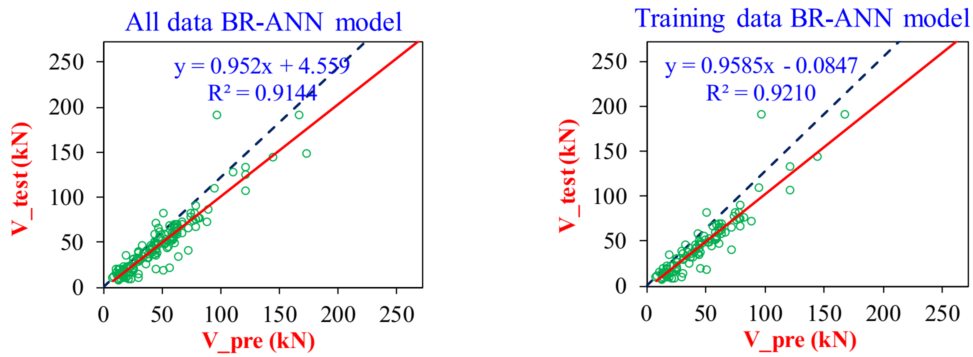
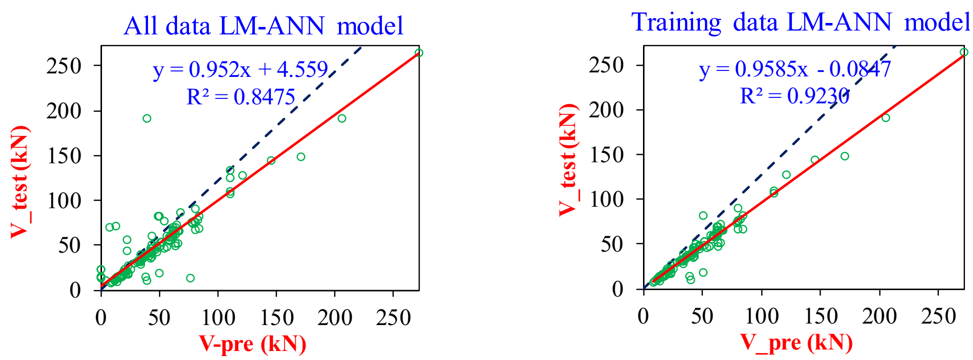


Fig. 4 Performance of LM-ANN



where t_i and o_i denote the experimental and prediction output value of i^{th} set, respectively; $\overline{o}$ is the mean of prediction outputs; N is the number of the database.

4 Results and discussion

4.1 Performance of BR-ANN model

In this study, two models BR-ANN and LM-ANN are used to predict the shear capacity of the infilled RC frames. Figures 3 and 4 show the regression results of BR-ANN and LM-ANN, respectively. It can be found that R^2 is larger than 0.92, while RMSE is smaller than 14 kN in the case of BR-ANN. Table 2 shows the training results of the two ML models with training, testing and all datasets. The statistical parameters including R^2, RMSE, MAE and a20-index are used to evaluate the forecasting performance of the models, as shown in Fig. 5. It is observed that the ANN-BR model outperforms the LM-ANN with higher values of R^2 and a20-index, smaller RMSE and MAE values. In other words, it implies that BR-ANN predicts the shear strength accurately and the hybrid BR-ANN model is superior to the traditional LM-ANN model.

Table 2 Comparison of results obtained by BR-ANN and LM-ANN

	R^2	*RMSE*	*MAE*	$a20-index$
BR-ANN				
Training data	0.9210	13.0538	7.5093	0.6542
Validation data	0.8775	10.4745	6.6754	0.7826
All data	0.9144	12.3351	7.2586	0.6928
LM-ANN				
Training data	0.9230	11.8667	7.2753	0.6449
Validation data	0.6533	23.9566	16.9661	0.4348
All data	0.8475	16.4630	10.1889	0.5817

4.2 Effects of input parameters on the shear strength of infilled RC frames

Figure 6 shows the influence of input parameters on the predicted shear capacity of reinforced concrete frames with infill walls. It can be found that the shear capacity of the frame system is significantly improved when the width of the frame column $\left(b_c\right)$, the width of the reinforced concrete frame (L) and the elastic modulus of the infill material $\left(E_m\right)$ increase. The other parameters have a negligible influence on the shear capacity of the frame.

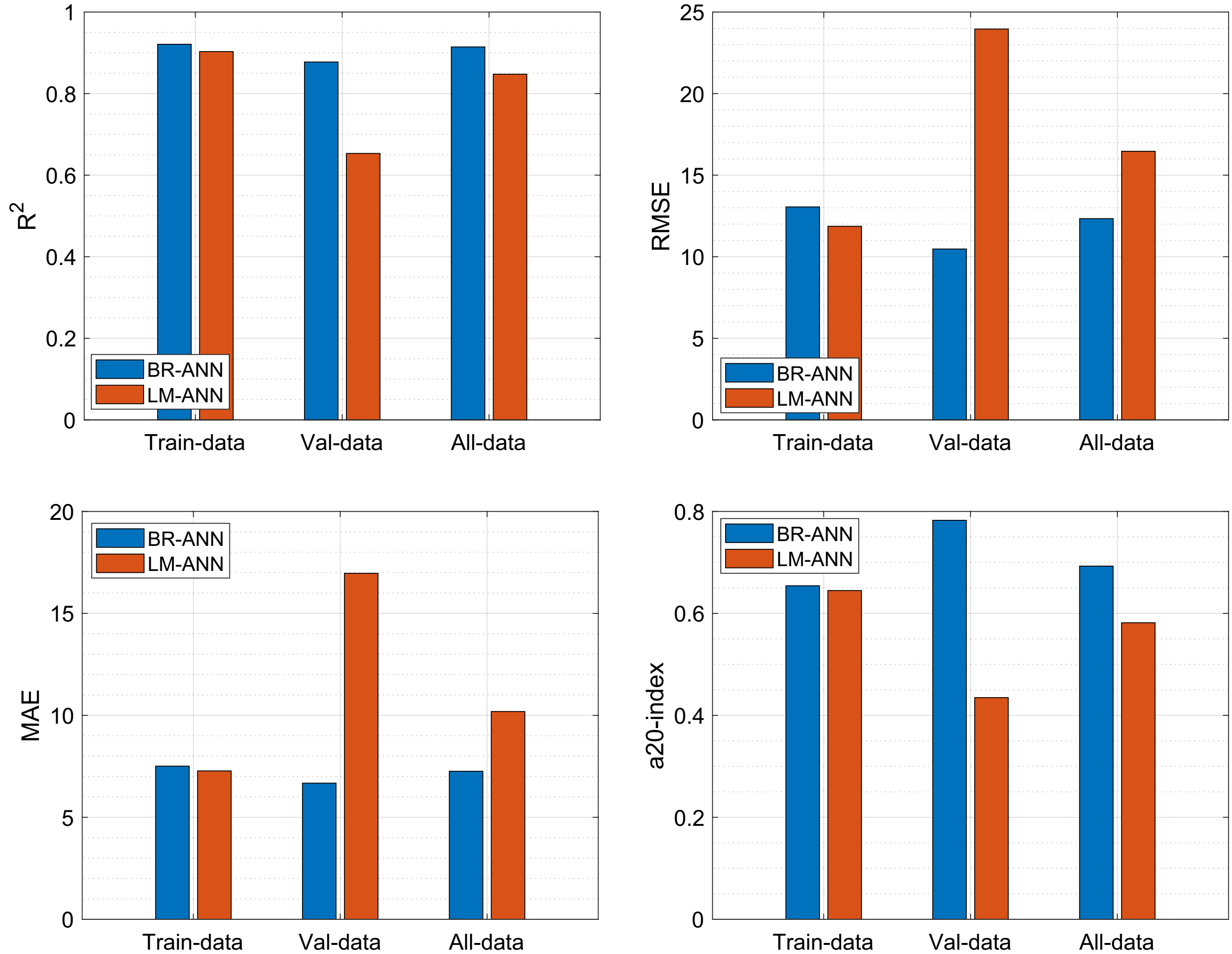


Fig. 5 Comparison of performance metrices between BR-ANN and LM-ANN

4.3 Formular for calculating the shear strength of infilled RC frames

An BR-ANN based formula for shear strength $\left(V_u\right)$ of infilled RC frames is determined by

$$V_u = 127.985 \times \left(V_N + 1\right) + 8.21 \tag{14}$$

where V_N is the normalized shear strength, calculated by

$$V_N = h_0 + \sum_{i=1}^{n} h_i H_i \tag{15}$$

where $n = 14$is the number of neurons in the hidden layer of ANN-BR; h_0 and h_i are bias and weight obtained from training ANN-BR, respectively. Those coefficients are as follows:

$$h_0 = [-0.145]$$

$$\begin{aligned} h_i = [&0.063\ -0.063\ -0.063\ -0.063 \\ &-0.063\ 0.710\ -0.063\ 0.850\ 0.515 \\ &-0.945\ 0.063\ 0.063\ -0.063\ 1.021] \end{aligned}$$

$$H_i = tanh\left(c_{i0} + c_{i1}X_1 + c_{i2}X_2 + c_{i3}X_3 + \ldots + c_{i24}X_{24}\right)$$

$$C_{i0} = \left[-0.227\ \ -0.033\ \ 0.018\ \ \ 0.237\ \ 0.122\ \ 0.016\ \ \ 0.194\ \ -0.003\ \ 0.241\ \ \ 0.244\ \ -0.860\ \ -0.022\right]^T$$

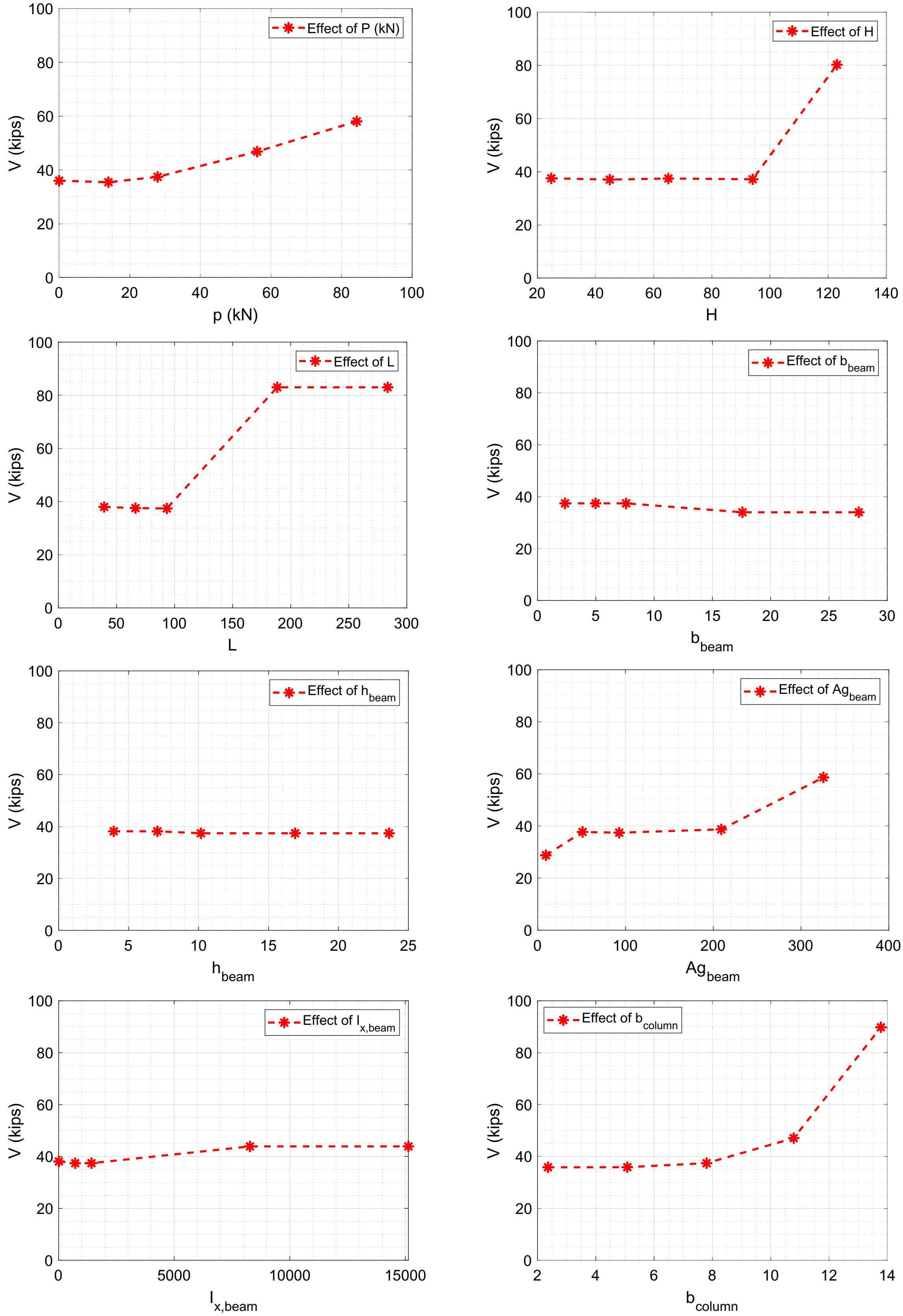


Fig. 6 Effects of input parameters on the output prediction

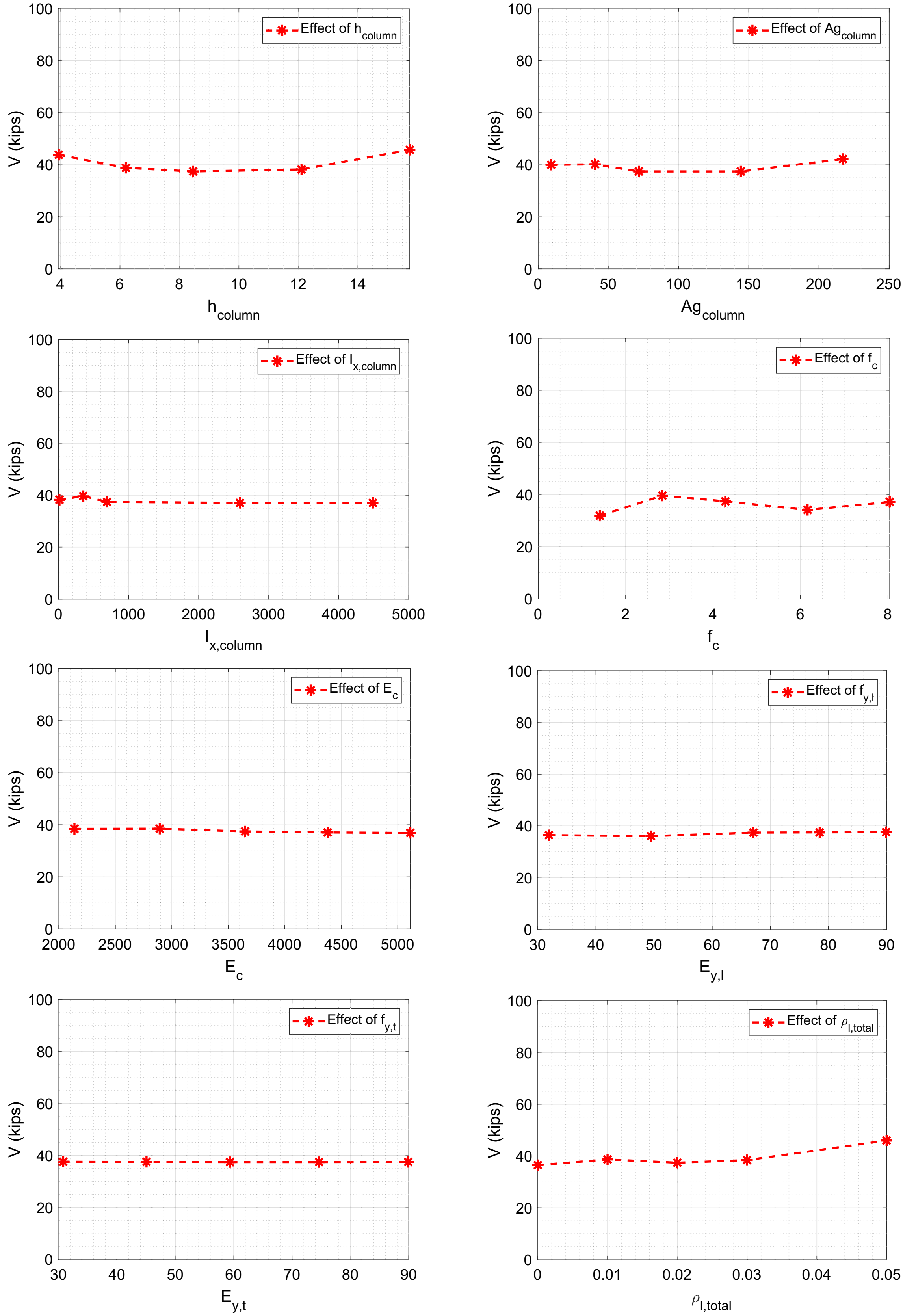


Fig. 6 (continued)

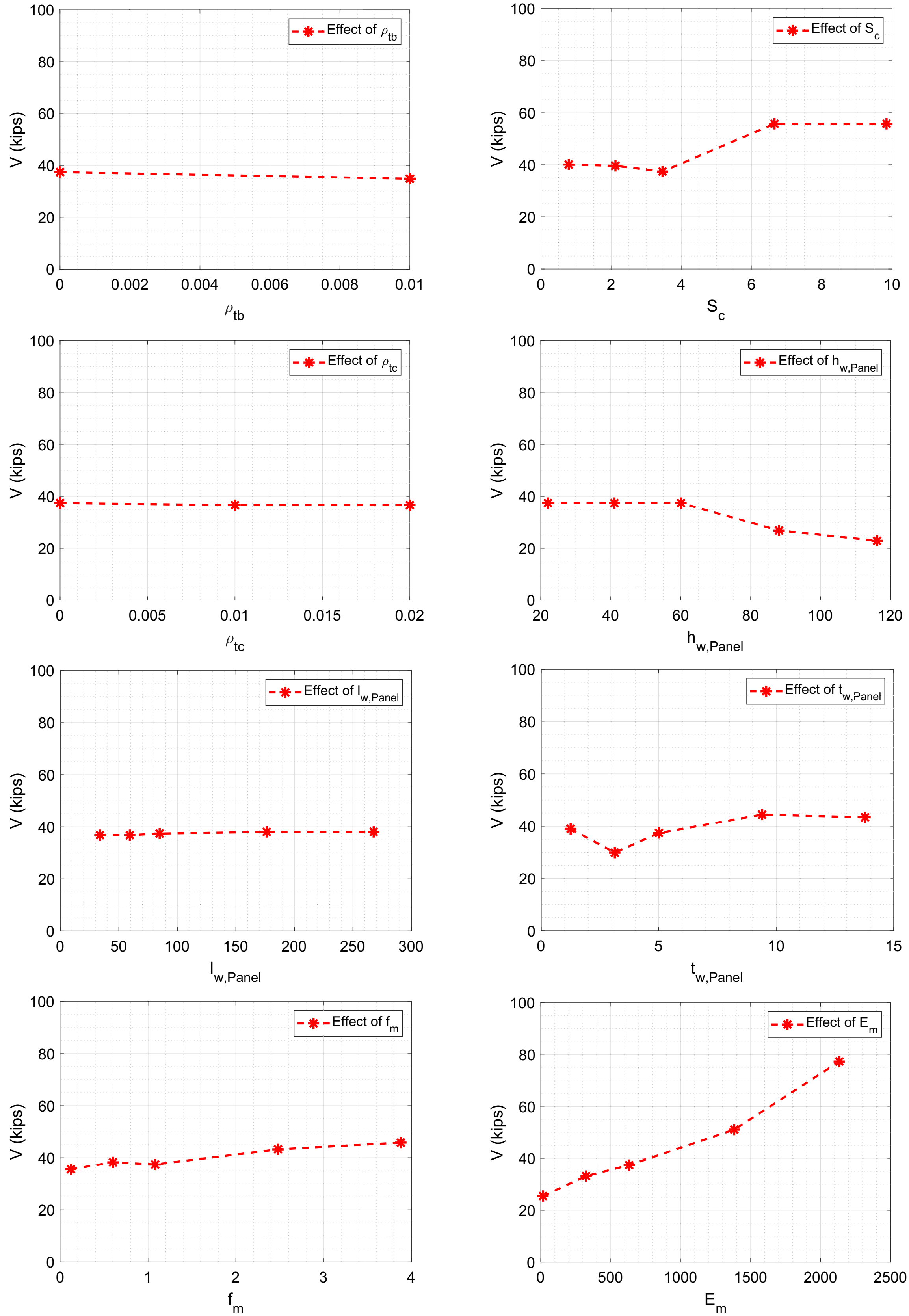


Fig. 6 (continued)

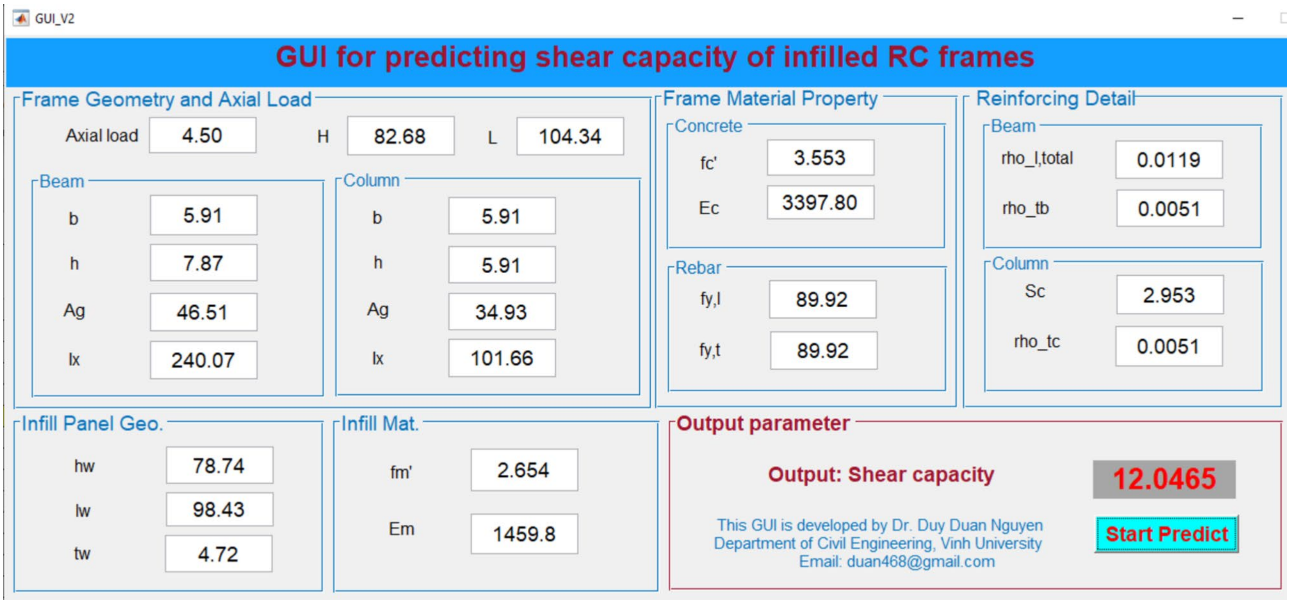


Fig. 7 GUI for predicting shear strength of infilled RC frames

-0.459	-0.351	0.136	-0.137	-0.046	0.487	0.363	-0.472	0.681	0.272	-0.612	-0.223	-0.547	0.385	0.472
0.248	0.015	-0.454	0.249	-0.375	-0.259	0.486	0.723	0.262	0.491	0.457	0.327	0.253	0.248	-0.516
0.013	0.069	0.019	0.000	0.028	0.064	0.008	-0.030	0.042	0.037	-0.017	-0.006	0.017	-0.056	-0.019
-0.450	-0.427	-0.253	0.050	0.119	0.289	-0.437	-0.318	-0.156	-1.604	0.390	0.041	0.808	-0.260	-0.011
0.054	0.430	-0.087	-0.141	-0.337	0.022	0.158	0.279	0.458	-0.606	-0.139	0.164	0.028	-0.115	-0.026
-0.121	-0.072	0.049	-0.089	0.036	-0.565	0.765	-0.039	-0.924	-0.415	0.500	0.415	0.337	0.375	0.110
-0.206	-0.843	0.273	0.240	0.013	0.144	1.139	-0.226	0.090	-0.564	-0.076	-0.291	0.018	-0.022	-0.299
0.263	0.451	-0.476	-0.206	-0.075	0.903	0.536	-0.150	0.141	-0.452	0.244	0.060	0.051	-0.014	0.724
-0.076	-0.289	0.061	0.406	0.379	0.444	0.145	-0.118	0.048	0.126	0.033	-0.276	0.013	-0.977	-0.698
-0.161	-0.437	-0.459	-0.130	0.236	-0.670	0.044	-0.601	-0.285	-0.091	0.296	0.132	-0.331	0.562	0.143
-0.016	-0.718	-0.471	0.742	-0.085	-0.390	-0.488	-0.858	-0.278	0.050	-0.444	-0.614	0.090	0.632	-0.117
-0.015	-0.086	-0.024	0.000	-0.036	-0.082	-0.012	0.041	-0.053	-0.045	0.021	0.009	-0.024	0.071	0.025

4.4 GUI tool

To apply the ML model to the practice of predicting the shear capacity of infilled RC frames, a GUI tool has been built based on the developed ANN-BR model. The GUI tool is to help engineers conveniently calculate the shear capacity of RC frames with infill walls. Figure 7 describes the GUI tool, in which users only need to enter the input parameters and receive the output quickly. Note that the prediction model is limited to the scope of the data set provided in Table 1. Users can download this GUI tool completely free of charge at https://github.com/duyduan1304/GUI_SS_InfilledRCFrames.

5 Conclusions

This study proposed the hybrid Bayesian regularization – Artificial neural network (BR-ANN) model for calculating the shear strength of infilled reinforced concrete (RC) frames. A set of 153 data samples was gathered and used to develop the machine learning model. The shear strength predicted by BR-ANN in this study is then compared with that of the conventional Levenberg-Marquardt ANN algorithm. Four statistical metrices including the goodness of fit $\left(R^2\right)$, root-mean-squared error (RMSE), mean average error (MAE), and $a20-index$ are calculated to evaluate the prediction performance of the ANN models. The following conclusions are drawn.

- The hybrid BR-ANN model predicts the shear strength of infilled RC frames accurately with a high R^2 of 0.92, a small *RMSE* of 12 kN, and a20-index of 0.7.
- The effects of input design parameters on the shear strength are evaluated. The width of the frame column $\left(b_c\right)$, the width of the RC frame (L), and the elastic modulus of the infill material $\left(E_m\right)$ are significantly influential parameters on the output.
- A graphical user interface tool is developed for practical calculation of the shear strength of infilled RC frames.
- It should be noted that the BR-ANN model can only predict the shear strength of infilled RC frames within the range of datasets provided in Table 1. A re-training process of the model is required if the values of input parameters stay outside of the range. Moreover, a wide range of datasets should be employed to extend the applied boundaries of the BR-ANN model.

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Declarations

Conflict of interest The authors declare no conflict interest.

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