Beam-column joint shear prediction using hybridized deep learning neural network with genetic algorithm

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Abstract. Scientifically evidenced that beam-column joints are a critical point in the reinforced concrete (RC) structure under the fluctuation loads effects. In this novel hybrid data-intelligence model developed to predict the joint shear behavior of exterior beam-column structure frame. The hybrid data-intelligence model is called genetic algorithm integrated with deep learning neural network model (GA-DLNN). The genetic algorithm is used as prior modelling phase for the input approximation whereas the DLNN predictive model is used for the prediction phase. To demonstrate this structural problem, experimental data is collected from the literature that defined the dimensional and specimens’ properties. The attained findings evidenced the efficitveness of the hybrid GA-DLNN in modelling beam-column joint shear problem. In addition, the accurate prediction achived with less input variables owing to the feasibility of the evolutionary phase.

1. Introduction

One of the earliest studies defined the joint shear behavior in the beam-column established by [1]. Hanson and Connor described the joint shear of a free-body diagram at the mid-height of joint panel. Followed by [2], whom proposed a qualitative joint shear resistance mechanisms. Over the last two decades, numerous attempts have been conducted on the joint shear phenomena modeling using the probabilistic methodologies and prescribed codes expression [3–10]. All the forgoing researches demonstrated a good scientific progress on the shear joint problem. However, the motivation of studying this engineering problem more comprehensively is still ongoing topic for the civil and structural scholars. This is owing to the fact, the behavior of the joint shear beam-column is highly stochastic and non-linear and it is extremely difficult to be fully understandable. Especially, when there are various variables attributes influenced the joint shear value.

The capability of deep learning neural network (DLNN) learning techniques to overcome the challenges of the traditional algorithms that depend on hand-designed features has endeared to numerous researches of science and engineering, since their proposal by [11]. Based on the latest survey conducted by Liu and his collaborators [12], DLNN exhibited its potential in various disciplines including big data analysis, solving non-linear problems, pattern recognition, decision making system. In short, the current research investigated hybrid evolutionary artificial intelligence model called GA-DLNN for predicting joint shear strength phenomena belong to RC beam-column connection. The main enthusiasm of developing the input selection algorithm is for the sake of the engineering optimization
prospective. Where the major attributes are always motivated to be abstracted and focused to be studied. Whereas, the slight influenced variables can be eliminated from the mathematical procedure. On the other hand, establishing the data-intelligence model (i.e., DLNN) is magnificently for the understanding the non-linear mechanism between the predictors and predictand which is the joint shear behavior. Further, this is highly essential for the characterizing the joint shear behavior in general. Moreover, for the the structural engineering sustainability and stability.

2. Experimental data discerption
As mentioned earlier, in this research an experimental database with total number of 98 records belong to exterior beam-column connection was observed from acknowledged researches of the literature [13]. The modeled data set covered a wide range of parameters including: concrete strength, joint reinforcement ratio, reinforcement yielding stress, column axial average stress, beam height $h_b$, columns height ($h_c$), their ratio ($h_b/h_c$), beam width ($b_b$), columns width ($b_c$), $(H)$, effective joint width ($h_j$), cylinder compressive strength of concrete ($f'_c$), $(s)$, $(f_c^{0.5})$, $(s/f_c)$, number of the influence parameters $(n)$, beam area cross section $(A_b)$, $(f_{yb})$, $(f_{yh})$, $d_b$, $A_h$, $A_v$, $f_{vy}$, and finally the horizontal joint shear $V_{jh}$. Note that the $V_{jh}$ is the targeted output for all the input combinations used in the current research.

3. Methodology overview
There have been a massive of research interest in the field of deep learning techniques and literature evidenced that a great deal of success has been achieved [14]. The neural network models have provided a powerful framework for with deep architectures for supervised learning, supported by the rapid development of computation techniques. There is a hierarchical architecture in the deep learning algorithms with several layers. Each layer constitutes a non-linear unit for information processing [15]. This paper focused mainly on the deep neural network architectures. An increase in the number of layers and units in a single layer in deep neural networks can result in functions with higher complexity since they employ deep architectures.

3.1 Deep learning neural network
Due to the amalgamation of different functions in the feedforward neural networks, they are referred to networks. The model has a directed acyclic graph which describes how real architecture of the functions [16,17]. The training data provides the non-linearity information, and the approximate example of $f^*(x)$ evaluated at different training points. Each example $x$ (input variables in the present case study) is accompanied by a label $y \approx f^*(x)$. The training examples directly points out what is expected from the output layer at each point $x$ (must generate a value that is close to $y$). The training data does not specify the behavior of the other layers; the learning algorithm is responsible for deciding how those layers must be used to produce the desired output, though the responsibility of each layer is not specified by the training data. The learning algorithm rather must decide how these layers must be used for the best implementation of an approximation of $f^*$. Since the desired output of each of these layers is not specified by the training data, they are referred to the hidden layers (i.e., the deep learning processes). Figure 1 displayed the DLNN algorithm for establishing the predictive model.
3.2 Genetic algorithm-input selection

GA is very well-known optimization technique that can classified as an evolutionary method based on biological process [18]. The effectiveness of this optimization approach discussed comprehensively in term of solving the non-linearity and stochasticity by [19]. The main processes are involved the implementation of the heuristic GA are including reproduction of chromosomes, crossover, and mutation. Note these processes are applied to satisfied the probability of the discretization of the input variables that are coded into binary strings [20–22]. The GA processes are presented in Figure 2.

3.3 Modeling development

The modeling procedure of the current research conducted based on two phases: (i) the evolutionary phase, and (ii) the predictive model phase. The first phase was developed to identify the most correlated input attribute for the predictive model matrix in which presented as followed:
Model 1
\[ V_{jh} = f(b_c, A_v) \]  
(1-1)
Model 2
\[ V_{jh} = f(b_b, s, A_v) \]  
(1-2)
Model 3
\[ V_{jh} = f(b_c, s, h_c, A_v) \]  
(1-3)
Model 4
\[ V_{jh} = f(b_c, H, f'_c, s/f_c, A_v) \]  
(1-4)
Model 5
\[ V_{jh} = f(b_c, s, A_v, A_h, A_v, f_{yy}) \]  
(1-5)
Model 6
\[ V_{jh} = f(b_c, b_b, H, f'_c, s/f_c, n, A_v) \]  
(1-6)
Model 7
\[ V_{jh} = f(b_c, s, h_b, h_b/h_c, b_b, A_b, d_b, f_{yy}) \]  
(1-7)
Model 8
\[ V_{jh} = f(h_c, s, H, f'_c, b_b, n, A_p, f_{yy}, A_v) \]  
(1-8)
Model 9
\[ V_{jh} = f(b_c, s, h_b, b_b, h_b/h_c, s/f_c, d_b, A_h, A_v, f_{yy}) \]  
(1-9)
Model 10
\[ V_{jh} = f(b_c, h_c, b_b, h_b/h_c, f_0, s/f_c, n, A_b, A_h, A_v) \]  
(1-10)
Model 11
\[ V_{jh} = f(b_c, s, h_b, h_b/h_c, f_0, b_b, n, A_b, d_b, f_{yy}, A_v, f_{yy}) \]  
(1-11)
Model 12
\[ V_{jh} = f(h_c, h_b, b_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, d_b, A_h, A_v) \]  
(1-12)
Model 13
\[ V_{jh} = f(h_c, h_b, h_b, b_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, d_b, A_h, A_v, f_{yy}) \]  
(1-13)
Model 14
\[ V_{jh} = f(h_c, h_b, b_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, A_h, f_{yy}, A_v, f_{yy}) \]  
(1-14)
Model 15
\[ V_{jh} = f(h_c, b_b, h_b, H, b_j, h_b/h_c, f_0, s/f_c, A_p, f_{yy}, d_b, A_h, f_{yy}, A_v) \]  
(1-15)
Model 16
\[ V_{jh} = f(h_c, h_b, b_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, f_{yy}, d_b, A_h, f_{yy}, A_v, f_{yy}) \]  
(1-16)
Model 17
\[ V_{jh} = f(b_c, h_c, b_b, h_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, f_{yy}, d_b, A_h, A_v, f_{yy}) \]  
(1-17)
Model 18
\[ V_{jh} = f(b_c, h_c, b_b, h_b, H, b_j, h_b/h_c, f_0, s/f_c, n, A_b, f_{yy}, d_b, A_h, f_{yy}, A_v, f_{yy}) \]  
(1-18)

Note that all these input combinations are function to the predicted value of the joint shear strength \( V_{jh} \). The prediction skills are evaluated in the current modeling using mean absolute error (MAE), root mean square error (RMSE), mean relative error (RE\%), and correlation coefficient \( R^2 \) [23,24]. The evaluation metric can be explained as follow:

\[
MAE = \frac{1}{N} \sum_{n=1}^{n} |V_{jh(\text{obs})} - V_{jh(\text{pre})}| \tag{1-19}
\]
\[
RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{n} (V_{jh(\text{obs})} - V_{jh(\text{pre})})^2} \tag{1-20}
\]
\[
RE = \frac{\sum_{n=1}^{n}[V_{jh(\text{obs})} - V_{jh(\text{pre})}] - \sum_{n=1}^{n}[V_{jh(\text{obs})} - V_{jh(\text{Mobs})}]}{\sum_{n=1}^{n}[V_{jh(\text{obs})} - V_{jh(\text{Mobs})}] - 100} \tag{1-22}
\]
\[
R^2 = \frac{\sum_{n=1}^{n} (V_{jh(\text{obs})} - V_{jh(\text{Mobs})}) (V_{jh(\text{pre})} - V_{jh(\text{Mpre})})}{\sqrt{\sum_{n=1}^{n} (V_{jh(\text{obs})} - V_{jh(\text{Mobs})})^2} - \sum_{n=1}^{n} (V_{jh(\text{pre})} - V_{jh(\text{Mpre})})^2} \tag{1-23}
\]

where \( V_{jh(\text{obs})}, V_{jh(\text{pre})} \), and \( V_{jh(\text{Mobs}), V_{jh(\text{Mpre})}} \) are the observed and predicted joint shear, (and the mean observed and predicted joint shear).

4. Joint shear prediction analysis
By recalling the main aim of the present study, this section is discussed the implementation of the employment of the hybrid GA-DLNN on the beam-column joint shear prediction. Indeed, the main inspiration of devoting this approach in the field of structural engineering in order to provide an easy and intelligent model that can be applied for real engineering practice. Based on the numerical statistical evaluation metrics tabulated in Table 1, it can be observed that the joint shear investigated in accordance of wide range of input combination. However, the attained results demonstrated variance outcomes. The best prediction results identified for Model 6 and Model 14 with correlation regression values 0.88 and 0.92, respectively. Model 14 could eliminated four variables that exhibited less influence to the targeted variable \( V_{jh} \), in which provided a reasonable solution. The other excellent input combination,
Model 6 that indicated its prediction skills with including seven variables (i.e., $b_c$, $b_b$, $H$, $f'_c$, $s/f_c$, $n$, $A_v$) only, that gave a perfect solution with engineering optimization prospective.

| Models    | MAE   | RMSE  | RE%  | $R^2$  |
|-----------|-------|-------|------|--------|
| Model 1   | 209.1439 | 244.2575 | 11.8619 | 0.6031 |
| Model 2   | 159.0401 | 210.7275 | -10.4181 | 0.7459 |
| Model 3   | 152.7922 | 202.9763 | 3.02179 | 0.7069 |
| Model 4   | 166.6005 | 205.4624 | -11.5576 | 0.7763 |
| Model 5   | 161.4492 | 220.0787 | -10.8532 | 0.7303 |
| Model 6   | **134.6139** | **158.0685** | **-11.4712** | **0.8823** |
| Model 7   | 206.8392 | 272.3324 | -0.63218 | 0.4917 |
| Model 8   | 181.7253 | 236.3841 | -13.4925 | 0.7139 |
| Model 9   | 163.7863 | 218.6789 | -13.2947 | 0.7704 |
| Model 10  | 147.7235 | 209.9443 | -12.0954 | 0.7734 |
| Model 11  | 193.5223 | 243.2407 | -18.3117 | 0.7405 |
| Model 12  | 159.4951 | 218.3748 | -11.9957 | 0.7488 |
| Model 13  | 205.3932 | 250.5302 | -19.6313 | 0.7388 |
| Model 14  | **115.0746** | **141.4397** | **-12.2096** | **0.9238** |
| Model 15  | 217.8899 | 283.4964 | -23.6467 | 0.7226 |
| Model 16  | 201.3741 | 250.3991 | -20.5874 | 0.7743 |
| Model 17  | 173.5161 | 230.1902 | -15.6410 | 0.7603 |
| Model 18  | 209.3070 | 255.6957 | -23.6298 | 0.8017 |

In more presentable vision, Figure 3 illustrated the scatter plots of the best prediction input combinations (Model 6 and Model 14). The figure visualized an acceptable agreement between the observed and predicted values around the 45° ideal line. Also, it can be observed, the prediction for the low, medium and high shear presented almost the same variance with slight diversion.

**Figure 3.** The scatter plots graphical presentation between the observed and predicted values of the joint shear over the testing phase.

Figure 4 displayed the relative error ($RE\%$) distribution percentage graph over the testing phase period. The $RE$ percentage pattern for Model 6 limited between -25% and +20% for the majority of the observation. Except, couple observation exceeded the -55% and +39%. Although Model 14 indicated higher $R^2$ than Model 6; yet, the $RE$ pattern revealed higher under predicting percentages that exceeded the -20% for 50% of the testing phase. This is best can be explained due to the influence of the correlation coefficient to the high records. Whereas, the $RE$ denoted error percentage for each record individually. In summary, the investigated model showed an optimistic finding that give a promising possibility for engineering implementation.
5. Conclusions
In this research, new hybrid data-intelligence model called GA-DLNN is proposed to predict the joint shear strength of exterior beam-column structure frame. The modeling established using published experimental work by various scholar over the last two decades. A full details of these data summarized by [13]. The predictive DLNN model advanced with an input optimization method to select the most correlated input attributes to predict the joint shear strength. This is owing to conceptual fact, engineers always seek for optimal solution for any problem with minimum available information. The optimal input attribute combinations that attained the best prediction skill are Model 6 and Model 14 in which denoted seven and fifteen variables, respectively. Overall, the proposed integrated model showed an acceptable agreement between the observed experimental joint shear and the predicted value. In quantitative terms, the best models achieved with (MAE-RMSE) values (134.6-158.0) and (115.0-141.4) for Model 6 and Model 14, respectively. In general, the motivation of the applied methodology provided a robust and simple method for the structural engineering prospective.

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