DEEP LEARNING MODEL FOR PREDICTING MOMENT CAPACITY OF COMPOSITE BEAM UTILIZING HSS GIRDER AND ECC SLAB

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Abstract: *High-strength steel (HSS) combined with engineered cementitious composites (ECC) presents a promising solution for resilient and ductile composite beams, especially in long-span and high-load applications. Experimental, numerical, and theoretical studies showed that HSS-ECC composite beams outperform HSS-concrete counterparts in terms of strength and ductility. In order to promote this type of structure to be widely applied in practice, a more accelerated, effective, and accurate approach is of great importance. Methods that use artificial intelligence (AI) to predict structural performance are gaining attention among scholars. This study explores the application of a deep learning model to predict the flexural capacity of HSS-ECC composite beams based on key material and geometric parameters (e.g., strength of ECC and HSS, dimensions of ECC slab and HSS section height, etc.). A deep learning model named Artificial Neural Network (ANN) was trained and evaluated on a compiled dataset of 132 composite beam models obtained from a numerical study and previously reported. Performance metrics, including Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), were used to evaluate the effectiveness of the employed deep learning model. The R^2 performance indicator obtained by the ANN model showed that the moment capacity prediction of HSS-ECC composite beams reaches almost 99%. All other evaluation indicators further assure the superior accuracy of this ANN model in the prediction of the moment capacity of HSS-ECC composite beams.*

Keywords: *Deep learning model; Artificial Neural Network (ANN); high-strength steel; engineered cementitious composites (ECC); composite beam; bending capacity*

Tóm tắt: *Thép cường độ cao (High-strength steel - HSS) kết hợp với vật liệu kỹ thuật gốc xi măng (Engineered Cementitious Composites - ECC) là một giải pháp đầy hứa hẹn cho các dầm liên hợp có độ bền và độ dẻo cao, đặc biệt trong các kết cấu nhịp lớn và chịu tải trọng lớn. Các nghiên cứu thực nghiệm, mô phỏng số và mô hình phân tích đã chỉ ra rằng dầm liên hợp HSS-ECC có hiệu quả vượt trội hơn so với dầm liên hợp HSS-bê tông thường về cả cường độ và độ dẻo. Để thúc đẩy loại kết cấu này được ứng dụng rộng rãi trong thực tế, việc phát triển một phương pháp nhanh hơn, hiệu quả hơn và chính xác hơn là vô cùng cần thiết. Các phương pháp ứng dụng trí tuệ nhân tạo (AI) trong dự đoán ứng xử của kết cấu đang ngày càng thu hút sự quan tâm của các nhà nghiên cứu. Nghiên cứu này tập trung vào việc ứng dụng mô hình học sâu để dự đoán khả năng chịu uốn của dầm liên hợp HSS-ECC dựa trên các tham số vật liệu và hình học của dầm liên hợp (ví dụ: cường độ của ECC và HSS, kích thước bản ECC, chiều cao tiết diện HSS,...). Mô hình học sâu Mạng nơ-ron nhân tạo (Artificial Neural Network - ANN) đã được huấn luyện và đánh giá trên bộ dữ liệu gồm 132 mô hình dầm liên hợp, được tổng hợp từ nghiên cứu số và các tài liệu đã công bố trước đó. Các chỉ số đánh giá hiệu quả gồm: Hệ số xác định (R^2), Căn bậc hai của sai số bình phương trung bình (RMSE), Sai số tuyệt đối trung bình (MAE), và Sai số phần trăm tuyệt đối trung bình (MAPE) được sử dụng để kiểm chứng độ chính xác của mô hình học sâu này. Kết quả cho thấy chỉ số R^2 của mô hình ANN đạt gần 99%, chứng tỏ khả năng dự đoán sức kháng uốn của dầm liên hợp HSS-ECC là rất chính xác. Các chỉ số đánh giá khác cũng tiếp tục khẳng định độ tin cậy vượt trội của mô hình ANN trong việc dự đoán khả năng chịu lực của dầm liên hợp HSS-ECC.*

Từ khóa: *Mô hình học sâu; Mạng nơ-ron nhân tạo; Thép cường độ cao; Vật liệu kỹ thuật gốc xi măng (ECC); Dầm liên hợp; Khả năng chịu uốn*

1. Introduction

The continuous pursuit of safer, more efficient, and resilient structural systems has driven the evolution of construction materials and design methodologies in civil engineering. Among the recent advancements, the combination of high-strength steel (HSS) girder and engineered cementitious composites (ECC) slab in composite beams has emerged as a promising solution for modern infrastructure, particularly in applications demanding long spans and high load-bearing capacity (Nguyen and Lee, 2021). HSS offers superior yield strength and ductility, while ECC is renowned for its high compressive strain capacity (more than 0.5%), excellent strain-hardening behavior, and exceptional crack control. When being subjected to sagging moment, high strain capacity in compression of ECC slab allows HSS girder to utilize its high strength, resulting in a form of composite beam that outperforms traditional HSS-concrete composite beam in both strength and ductility (Nguyen and Lee, 2021; Nguyen and Lee, 2023; Mai et al., 2025). Despite these advantages, the widespread adoption of composite beams utilizing HSS girders and ECC slabs (hereafter referred to as *HSS-ECC composite beams*) in practice is hindered by the complexity of their structural behavior and the limitations of conventional prediction methods. Although experimental investigation is an accurate method, it is inevitably time-consuming and resource-intensive. Analytical and numerical models, though useful, often rely on simplifying assumptions that may not fully capture the intricate interactions between HSS and ECC in the composite beam subject to sagging moment. As a result, there is a growing need for more efficient, reliable, and accurate approaches to predict the bending capacity of these advanced composite beams.

In recent years, artificial intelligence (AI) and deep learning techniques have shown significant potential in addressing complex prediction problems in structural engineering (Kina et al. 2021; Moein et al. 2023). There have been dozens of studies (Tuken et al. 2021; Wakjira et al. 2022; Ge et al., 2024) exploring the use of AI models in the structural performance of composite beams. These data-driven approaches offer a promising alternative to traditional methods, especially for novel composite systems where experimental data may be limited and analytical/numerical solutions are challenging. Tuken et al. (2021) employed machine learning models to explore their prediction ability of the load-carrying capacity of ECC-RC beams. Among those models employed, Extreme Gradient Boosting (XGBoost) performed the best, achieving an accuracy rate of over 80%. Wakjira et al. (2022) predicted the load-carrying capacity of FRP bar RC beams by employing machine learning models, including Support Vector Regression (SVR), XGBoost, Random Forest (RF), Artificial Neural Networks (ANN), and CART to train the dataset consisting of 132 experimental results. The evaluation metrics obtained from these ML models show that XGBoost performed the best, as it exhibited the highest R^2 with 0.993 and the lowest values of other evaluation metrics, such as MAE, MAPE, and RMSE. Ge et al. (2024) explored the use of five machine learning models (i.e., SVR, XGBoost, ANN, ERT, RF) in predicting the flexural capacity of hybrid steel and FRP bars reinforced concrete-ECC composite beams. Recently, deep learning models, particularly Artificial Neural Networks, have become capable of learning nonlinear relationships from large datasets, enabling rapid and accurate predictions of structural performance. This study aims to develop a deep learning model for predicting the bending capacity of HSS-ECC composite beams based on key material and geometric parameters. By leveraging a comprehensive dataset and an advanced ANN architecture, the proposed model seeks to provide a practical and accurate tool for engineers and researchers. The successful implementation of such a model can accelerate the design process, optimize material usage, and promote the broader application of HSS-ECC composite beams in modern construction.

2. Data description

A dataset comprising 132 HSS-ECC composite beam models was compiled from numerical studies and previously reported experimental results (Nguyen and Lee, 2021; Nguyen and Lee, 2023). Each data entry includes key material properties (i.e, compressive strength of ECC, yield strength of HSS) and geometric parameters (i.e, ECC slab thickness and width, HSS section height, HSS web thickness, and HSS flange thickness). The data are tabulated in the Appendix, and an explanation of the features is shown in Table 1 and Fig. 1. As indicated in Fig. 1, the moment capacity (M_u) of HSS-ECC composite beams was obtained by analysing HSS-ECC composite beam models subjected to four-point bending with shear spans of 1150 mm, using a validated finite element model reported in Nguyen and Lee (2021). Moreover, it is worth mentioning that since all ECC grades can achieve a compressive strain capacity of around 0.5%, this feature was not chosen as an input parameter for training the ANN model. Instead, according to Ref. [1], the author found that the compressive strength of ECC is an important parameter that affects the bending capacity of the HSS-ECC composite beam. This feature is thus employed as the input data for training the ANN model. The dataset was preprocessed to normalize the input features, ensuring consistent scaling and improved model convergence. The data was randomly split into training (80%) and testing (20%) sets to evaluate the model's generalization capability. The statistical distribution of parameters used in the ANN model is shown in Figure 2.

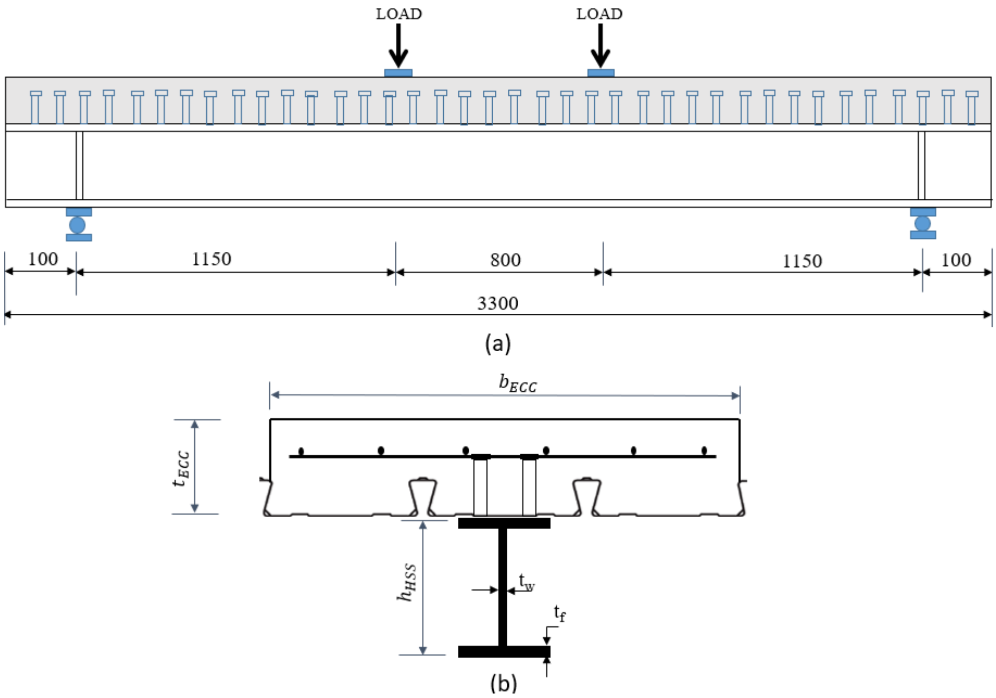

Figure 1. *HSS-ECC composite beam configuration: a) Front view, b) Side view*

3. Model development

3.1 Artificial Neural Network (ANN) model

An Artificial Neural Network (ANN), also known as a Multilayer Perceptron (MLP), is a computational model inspired by the structure of the human brain. It consists of layers of interconnected nodes (neurons), where each connection has an associated weight. The network learns by adjusting these weights to minimize the error between its predictions and the actual target values. The ANN model would typically have: i) an input layer where each neuron represents one input feature (e.g., f'_c, f_y, b_{ECC}, etc.); ii) three hidden layers where each hidden layer contains several neurons. These layers allow the network to learn complex, non-linear relationships between inputs and outputs; iii) an output layer, which is usually a single neuron that outputs the predicted value (i.e, M_u). A typical ANN model structure is shown in Figure 3. In this paper, the ANN model was designed with an input layer corresponding to the number of key parameters, multiple hidden layers with nonlinear activation functions, and an output layer representing the predicted flexural capacity. The model architecture was optimized through hyperparameter tuning, including the number of hidden layers, neurons per layer, learning rate, and activation functions. The model was trained using the backpropagation algorithm and mean squared error (MSE) as the loss function. Early stopping and dropout regularization were employed to prevent overfitting.

Table 1. *The explanation of input features*

Component	Parameter	Explanation	Unit
ECC slab	f'_c	Compressive strength of ECC	MPa
	b_{ECC}	ECC slab width	mm
	t_{ECC}	ECC slab thickness	mm
HSS I-section	f_y	Yield strength of HSS	MPa
	h_{HSS}	HSS I-section height	mm
	t_f	HSS I-section flange thickness	mm
	t_w	HSS I-section web thickness	mm

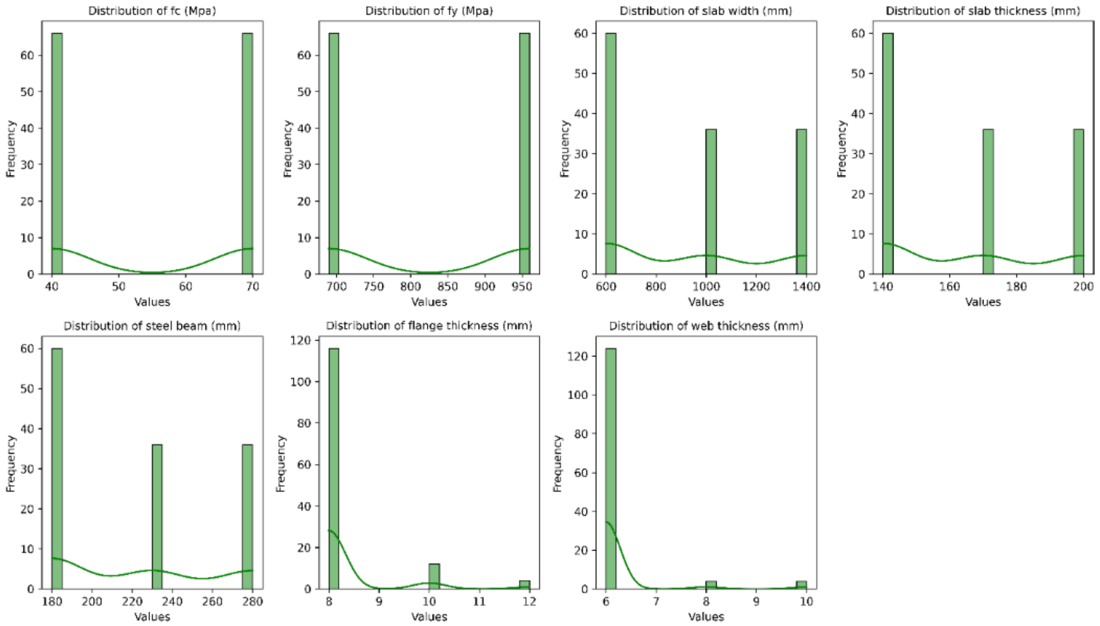

Figure 2. *Statistical distribution of parameters used in ANN model*

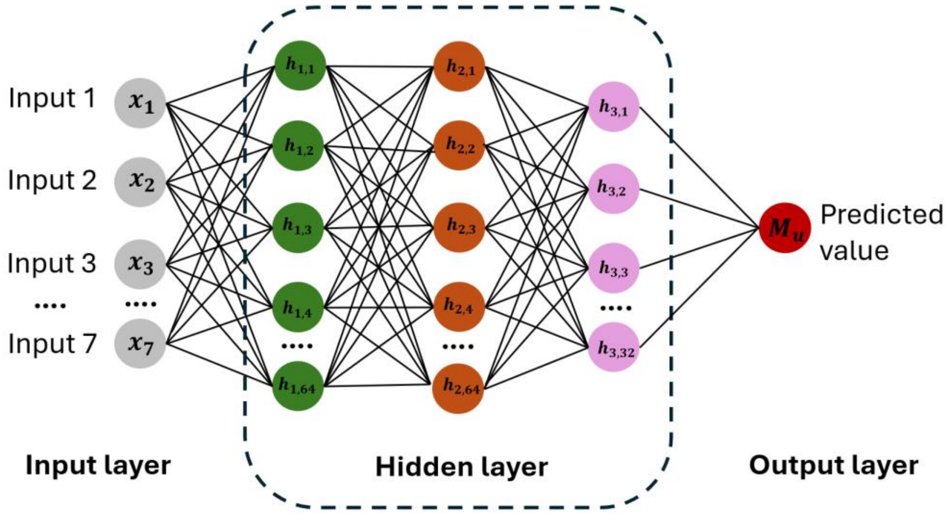

Figure 3. *The ANN model structure*

3.2 Evaluation metrics

The trained ANN model was evaluated using performance metrics, including Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide a comprehensive assessment of the model's accuracy and reliability in predicting the flexural strength of HSS-ECC composite beams. The lower values of RMSE, MAE, MAPE, the better performance of the ANN model, while an R^2 close to 1 means the well performance of the model. The formulas of the evaluation metrics are indicated in Eqs. 1 – 4. In Eqs. 1 – 4, y, y ̂, y ̅ respectively represent the actual, predicted, and mean values of data. *n* is the number of data points.

$$R^2 = 1 - \sum_{i=1}^{n} \frac{(y - y_i)^2}{(\bar{y} - y_i)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y - y_i\right| \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y}{y_i}\right| \quad (4)$$

3.3 Model parameters optimization

The purpose of model parameter optimization in an Artificial Neural Network (ANN) is to maximize the model’s performance by finding the best combination of settings. Properly tuned parameters help the model learn patterns in the data more effectively. Optimization reduces both underfitting (model too simple) and overfitting (model too complex). Parameters like learning rate, batch size, and optimizer type affect how fast and how well the model learns. Optimizing the number of layers, neurons, and activation functions ensures that the network has enough capacity to model the data, without being unnecessarily large. The values for hyperparameters are shown in Table 2.

Table 2. *Model parameters optimization*

Parameters	Values	Best values
Number of hidden layers	3 – 10	3
Neurons per layer	16 – 512	64, 32
Activation function	relu, tanh, sigmoid	relu
Optimizer	adam, RMSProp, SDG	adam
Batch size	16 -256	16

4. Results and discussion

The performance of the ANN model in predicting the flexural capacity of the HSS-ECC composite beams is evaluated by comparing the actual and predicted results, as shown in Figure 4. From Figure 4, it is indicated that the ANN model exhibits excellent prediction of the flexural capacity of HSS-ECC composite beams. To better compare the results between the prediction by the ANN model and actual results, Figure 5 plots the linear fitting line of actual and predicted values, in which the x-axis presents actual values while the y-axis indicates predicted values. The line y=x means that results that lie on this line show perfect prediction of the ANN model. In addition, the 10% error dashed lines were also plotted in this figure. The results within this range indicate the acceptable values. From Figure 5, it is said that almost all the results obtained are aligned along the perfect line (y=x). Only several results are on the above or below the perfect line; however, all the results are within the acceptable boundary. It is no doubt said that the ANN model exhibits excellent performance in predicting the flexural strength of the HSS-ECC composite beams. Moreover, the evaluation metrics, including R^2, MAPE, RMSE, and MAE, shown in Table 3, exhibit that the R^2 value reached 0.99, indicating that the model explains 99% of the variance in the flexural strength data. The RMSE, MAE, and MAPE values were all low, confirming the model's high accuracy and minimal prediction error.

The results confirm the feasibility and effectiveness of using deep learning models, specifically ANN, for predicting the flexural capacity of HSS-ECC composite beams. The high R^2 value and low error metrics demonstrate the model's capability to generalize across a diverse dataset, making it a valuable tool for preliminary design and optimization. The use of AI-driven prediction models can significantly accelerate the design process, reduce reliance on extensive experimental testing, and facilitate the adoption of advanced composite systems in practice. However, the model's accuracy is contingent on the quality and representativeness of the training data. Future work should focus on expanding the dataset, incorporating additional parameters (e.g., loading conditions, boundary effects), and exploring other deep learning architectures.

Table 3. *Performance evaluation of the ANN model*

Evaluation metrics	Training set	Testing set
R^2	1.0	0.99
RMSE	5.41 kNm	14.25 kNm
MAE	3.26 kNm	11.37 kNm
MAPE	0.58	2.01

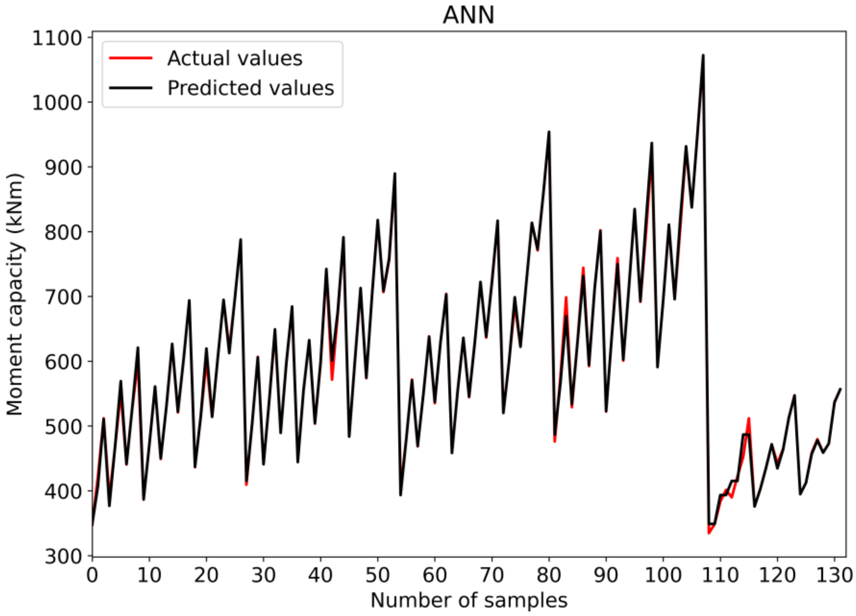

Figure 4. *Comparison of actual and predicted values of ANN model*

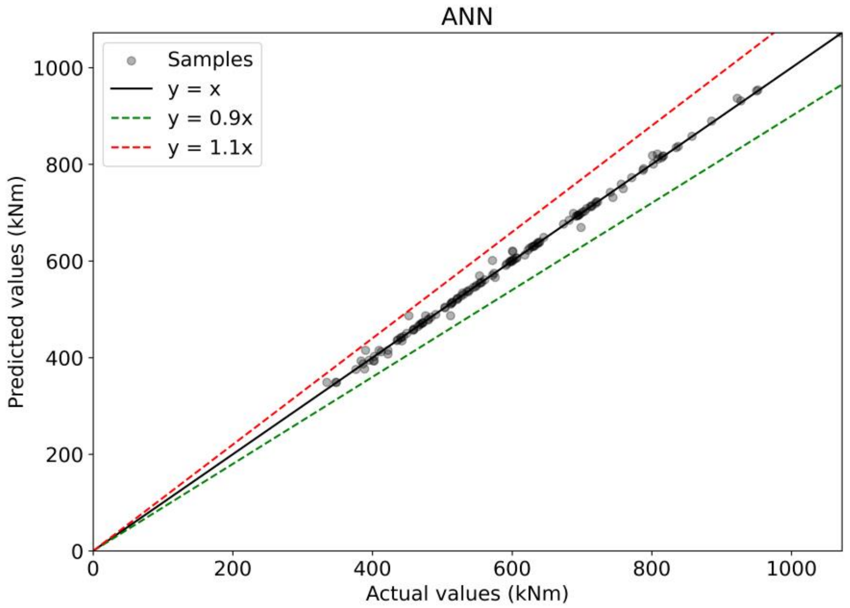

Figure 5. *The predicted versus the actual load-carrying capacity of HSS-ECC composite beams*

5. Conclusions

This study presents a deep learning-based approach for predicting the flexural capacity of HSS-ECC composite beams. The developed ANN model was trained and evaluated on a compiled dataset of 132 composite beam models obtained from a numerical study and previously reported. Performance metrics, including Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), were used to evaluate the effectiveness of the employed deep learning model. By comparing the predicted results obtained from the ANN model with the actual results, it is shown that the ANN model is able to achieve superior accuracy, with an R^2 value of 0.99 and low other evaluation metrics. The findings highlight the potential of AI-driven methods, particularly the ANN model, in enhancing the design and application of advanced composite structures in civil engineering.

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Appendix

No.	f'_c (MPa)	f_y (MPa)	b_{ECC} (mm)	t_{ECC} (mm)	h_{HSS} (mm)	t_f (mm)	t_w (mm)	M_u (kNm)
1	40	690	600	140	180	8	6	347.3
2	40	690	600	140	230	8	6	422.1
3	40	690	600	140	280	8	6	511.8
4	40	690	600	170	180	8	6	388.7
5	40	690	600	170	230	8	6	467.5
6	40	690	600	170	280	8	6	553.2
7	40	690	600	200	180	8	6	440.6
8	40	690	600	200	230	8	6	526.7
9	40	690	600	200	280	8	6	600.3
10	40	690	1000	140	180	8	6	386.4
11	40	690	1000	140	230	8	6	470.9
12	40	690	1000	140	280	8	6	560.6
13	40	690	1000	170	180	8	6	449.1
14	40	690	1000	170	230	8	6	530.7
15	40	690	1000	170	280	8	6	625
16	40	690	1000	200	180	8	6	521
17	40	690	1000	200	230	8	6	602.6
18	40	690	1000	200	280	8	6	692.9
19	40	690	1400	140	180	8	6	436.4
20	40	690	1400	140	230	8	6	514.1
21	40	690	1400	140	280	8	6	600.9
22	40	690	1400	170	180	8	6	514.1
23	40	690	1400	170	230	8	6	606.1
24	40	690	1400	170	280	8	6	694.6
25	40	690	1400	200	180	8	6	618.1

26	40	690	1400	200	230	8	6	698.1
27	40	690	1400	200	280	8	6	787.2
28	40	960	600	140	180	8	6	409.4
29	40	960	600	140	230	8	6	503.7
30	40	960	600	140	280	8	6	606.6
31	40	960	600	170	180	8	6	441
32	40	960	600	170	230	8	6	538.8
33	40	960	600	170	280	8	6	645.2
34	40	960	600	200	180	8	6	490.5
35	40	960	600	200	230	8	6	596.9
36	40	960	600	200	280	8	6	681.4
37	40	960	1000	140	180	8	6	444.5
38	40	960	1000	140	230	8	6	554.9
39	40	960	1000	140	280	8	6	632.5
40	40	960	1000	170	180	8	6	503.7
41	40	960	1000	170	230	8	6	596.9
42	40	960	1000	170	280	8	6	740.6
43	40	960	1000	200	180	8	6	571.6
44	40	960	1000	200	230	8	6	673.3
45	40	960	1000	200	280	8	6	788.3
46	40	960	1400	140	180	8	6	483.6
47	40	960	1400	140	230	8	6	599.2
48	40	960	1400	140	280	8	6	711.9
49	40	960	1400	170	180	8	6	573.9
50	40	960	1400	170	230	8	6	700.9
51	40	960	1400	170	280	8	6	816.5
52	40	960	1400	200	180	8	6	706.7
53	40	960	1400	200	230	8	6	756.1
54	40	960	1400	200	280	8	6	885.5
55	70	690	600	140	180	8	6	402.5
56	70	690	600	140	230	8	6	480.1
57	70	690	600	140	280	8	6	571.6
58	70	690	600	170	180	8	6	468.6
59	70	690	600	170	230	8	6	549.1
60	70	690	600	170	280	8	6	638.3
61	70	690	600	200	180	8	6	535.3
62	70	690	600	200	230	8	6	629.6
63	70	690	600	200	280	8	6	703.8
64	70	690	1000	140	180	8	6	459
65	70	690	1000	140	230	8	6	553.7
66	70	690	1000	140	280	8	6	636
67	70	690	1000	170	180	8	6	544.5
68	70	690	1000	170	230	8	6	628.5
69	70	690	1000	170	280	8	6	722.2
70	70	690	1000	200	180	8	6	636.5
71	70	690	1000	200	230	8	6	720.5
72	70	690	1000	200	280	8	6	815.4
73	70	690	1400	140	180	8	6	521
74	70	690	1400	140	230	8	6	599.7
75	70	690	1400	140	280	8	6	687.7
76	70	690	1400	170	180	8	6	622.7
77	70	690	1400	170	230	8	6	719.3
78	70	690	1400	170	280	8	6	813.6
79	70	690	1400	200	180	8	6	771.1
80	70	690	1400	200	230	8	6	857.3
81	70	690	1400	200	280	8	6	951.6
82	70	960	600	140	180	8	6	476.1
83	70	960	600	140	230	8	6	575.6
84	70	960	600	140	280	8	6	698.6
85	70	960	600	170	180	8	6	529

86	70	960	600	170	230	8	6	631.4
87	70	960	600	170	280	8	6	744.1
88	70	960	600	200	180	8	6	592.4
89	70	960	600	200	230	8	6	713.6
90	70	960	600	200	280	8	6	802.1
91	70	960	1000	140	180	8	6	522.3
92	70	960	1000	140	230	8	6	639.4
93	70	960	1000	140	280	8	6	759
94	70	960	1000	170	180	8	6	600.9
95	70	960	1000	170	230	8	6	714.2
96	70	960	1000	170	280	8	6	834.9
97	70	960	1000	200	180	8	6	691.7
98	70	960	1000	200	230	8	6	801
99	70	960	1000	200	280	8	6	922.3
100	70	960	1400	140	180	8	6	591.1
101	70	960	1400	140	230	8	6	694.6
102	70	960	1400	140	280	8	6	808.5
103	70	960	1400	170	180	8	6	695.8
104	70	960	1400	170	230	8	6	807.9
105	70	960	1400	170	280	8	6	927.5
106	70	960	1400	200	180	8	6	837.8
107	70	960	1400	200	230	8	6	949.9
108	70	960	1400	200	280	8	6	1070.1
109	40	690	600	140	180	8	6	334.7
110	40	690	600	140	180	8	6	348.5
111	70	690	600	140	180	8	6	383.5
112	70	690	600	140	180	8	6	401.4
113	40	960	600	140	180	8	6	389.9
114	40	960	600	140	180	8	6	422.1
115	70	960	600	140	180	8	6	452
116	70	960	600	140	180	8	6	511.8
117	40	690	600	140	180	10	6	376.1
118	40	690	600	140	180	12	6	402.5
119	70	690	600	140	180	10	6	435.3
120	70	690	600	140	180	12	6	471.5
121	40	960	600	140	180	10	6	442.2
122	40	960	600	140	180	12	6	464.6
123	70	960	600	140	180	10	6	512.9
124	70	960	600	140	180	12	6	547.4
125	40	690	600	140	180	10	8	395
126	40	690	600	140	180	10	10	412.3
127	70	690	600	140	180	10	8	458.3
128	70	690	600	140	180	10	10	479.6
129	40	960	600	140	180	10	8	458.9
130	40	960	600	140	180	10	10	472.7
131	70	960	600	140	180	10	8	537.1
132	70	960	600	140	180	10	10	556.6