Artificial Neural Network Modelling of Moment-Resisting Bolted Steel Connections using an attribute driven approach

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Abstract.
This paper introduces a novel Artificial Neural Network (ANN) model for predicting the structural behaviour of moment-resisting bolted steel connections, with an emphasis on sustainability aligned with UN Sustainable Development Goals 9 (Industry, Innovation, and Infrastructure) and 11 (Sustainable Cities and Communities). Traditional methods like Finite Element Modelling (FEM) and Component Modelling (CM) are resource-intensive, prompting the development of a new ANN as an efficient alternative for forecasting shear stress resistance under varying load conditions and design of connection.
The ANN features a feed-forward architecture with nine normalised input variables (e.g., bolt diameter, weld fillet thickness, beam depth), a single hidden layer of five neurons, and a sigmoid activation function to capture non-linear relationships inherent in bolted steel connections. The ANN's weights and biases were initialised using the PyTorch Xavier method to launch the learning process, with updates to each neuron within a hidden layer via back-propagation, driven by Mean Square Error (MSE), gradient descent, and the chain rule, refining the model iteratively until convergence and accurate predictions on unseen data were achieved.
An ANOVA sensitivity analysis identified bolt size and weld thickness as key significant factors ($P < 0.05$), and k-fold cross-validation confirmed model generalisability without overfitting within the established boundary conditions of this study. Results demonstrate an R^2 of 0.9977 for shear stress predictions, with an average MSE of 0.9 and variance of 1.03, aligning with benchmarks from prior structural engineering research.
Complementing the ANN, the Product Optimisation Value Engineering (PROVEN) framework applies an attribute-driven methodology, using relative value indices to evaluate designs against criteria like structural integrity, weight, cost, and embodied carbon. Case studies of five connector concepts demonstrated PROVEN's ability to select optimal designs, balancing performance with sustainability.
Overall, the integrated ANN-PROVEN approach vs. traditional methods reduces design time, minimises material use, and lowers carbon emissions, advancing efficient and eco-friendly structural engineering practices.

Keywords: Artificial Neural Network, Machine Learning, Predictive Modelling, Design Efficiency, Sustainable design, embodied carbon, steel connections, structural engineering, value engineering.

1. Introduction

Steel connections play a vital role within the design of a building to ensure structural integrity is achieved within a steel framed structure. Existing analytical methods such as Finite Element Models (FEMs) and component modelling techniques are time consuming and can be costly to carry out. The use of Artificial Neural Networks (ANNs) provides a time efficient and cost-effective alternative process, capable of modelling non-linear prediction behaviour achieving a high level of accuracy. Learning from verified experimental data, ANNs have been applied to various structural elements in the construction industry demonstrating high predictive accuracy as evidenced in prior research studies.
This research discusses the development of a new evaluation tool to accurately prescribe suitable steel connection designs for a given load case using a newly defined ANN prediction model. This study specifically investigates the performance of bolted steel connections transferring shear load (kN) from a supported beam to a supporting column (as shown in figure 1). The scope encompasses boundary conditions representing shear loads of 50–400 kN and beam/column dimensions of 152–305 mm, with variations of connection parameters including flange plate thickness, plate size, weld thickness, and bolt diameter. These parameters establish the range for evaluating connection performance and training the ANN model within these limits. The model is to also allow for faster processing time and ease of use to serve the structural engineer in practice, minimising the margin of error in the selection of steel connections. To complement the design selection process of steel connections, a prioritisation of key attributes to include structural integrity, sustainability, cost and versatility was also considered serving as primary inputs to an evaluation

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trade-off tool to achieve an optimised connection design. Prioritising of attributes using an optioneering approach, Product Optimisation Value Engineering (PROVEN) refers to previous published work conducted as part of a completed PhD program by the principal author (Georgiou et.al 2015). The key objectives to advance sustainable structural engineering design were;

- A high-accuracy Artificial Neural Network (ANN) model to predict shear stress resistance in bolted steel connections, accounting for complex non-linear interactions;
- Reduction in reliance on extensive physical testing, thereby lowering material use, cost, and reducing negatively associated environmental impact;
- Minimising computational time for evaluating steel connector configurations, enabling faster and resource-efficient design processes;
- To support a more reliable and sustainable connection selection methodology that can integrate embodied carbon, cost, and structural performance into early-stage design decisions.

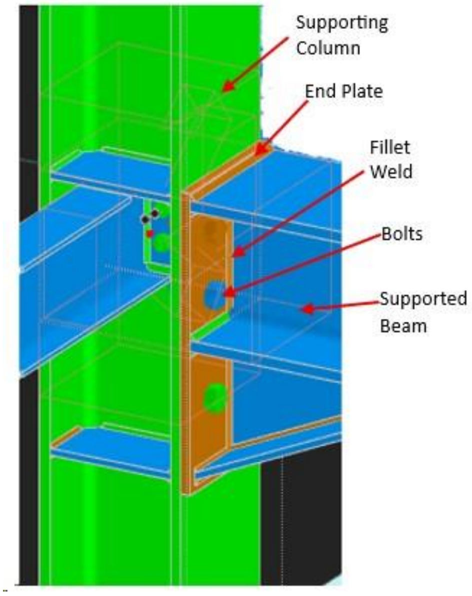

Fig. 1: Bolted end-plate beam-column Steel Connection

1.1 Artificial Neural Network Predictive Model

Artificial Neural networks are essentially a Machine Learning method inspired by the human brain comprising of a network of neurons forming the central control system (Haykin, S., 2009). In a similar way, ANNs comprise of interconnected neurons with a number of numerical inputs, multiplied by the weights on their connections with a bias added and are processed. If the result passes a certain threshold, the neuron is activated resulting in a numerical output. The neural network learns by using a continuous loop of forward propagation to generate an output through the network and backward propagation to adjust the weights and biases of the inputs to minimise the margin of error. This learning process is repeated until the desired loss function is reached, meaning an acceptable predicted ANN result has been achieved (Almeida et.al, 2020). An ANN was defined to determine the non-linear relationship between the input and output parameters for the behaviour of bolted steel connections. The research gap identified is that while prior ANN-based studies have demonstrated high predictive accuracy for various structural elements in construction (e.g., flexural strength in steel fibre-reinforced concrete [Dong Zhen et al., 2022], bond strength in fibre-reinforced polymer bars [Nadim I. Shbeeb et al., 2024], and hybrid FEM-ANN analysis of adhesive anchors [Almeida & Guner, 2020]), they do not specifically address the non-linear prediction of shear stress resistance in moment-resisting bolted steel connections. Existing ANNs lack integration with attribute-driven approaches such as PROVEN, a value engineering approach for optimised design selection, faster processing, reduced error margins, and sustainability considerations such as minimised material use and embodied carbon. This gap necessitated the development of a new feed-forward ANN with back-propagation coupled with PROVEN.

2. Development of the New ANN

2.1 Feed-Forward ANN Architecture with Back-Propagation Learning Algorithm

The feed-forward ANN architecture comprises of nine inputs, a single hidden layer containing five neurons whereby a transfer function and a sigmoid activation function are applied to predict the resultant shear stress (kN) within a single output, as shown in figure 2. The back-propagation involved training of the network whereby the gradient of the error was calculated and propagated back through the network, updating weights and biases for each neuron (Goodfellow et.al, 2016). This architecture was selected over alternatives for its accuracy, computational efficiency, and practicality in modelling complex structural behaviours, to achieve satisfactory structural integrity aligned with Eurocode 3.

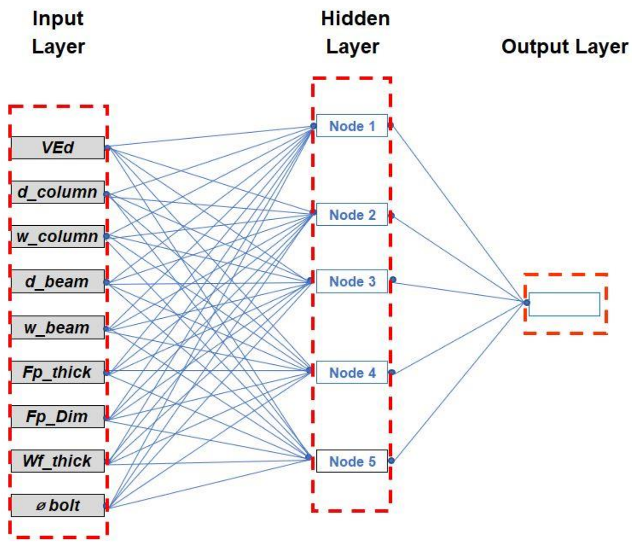

Fig.2: Schematic of ANN single-hidden layer feed-forward network

The nine inputs were identified via regression analysis and

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validated with 60 connection variations from a Design of Experiments (DoE). The input factors such as (e.g., applied force, weld fillet thickness, bolt diameter) effectively capture non-linear interactions, avoiding redundancy or omission seen in structures with fewer or excessive inputs. These factors are shown in Table 1 (Green Book, 2023; The Steel Construction Institute, 2013). The single hidden layer with five neurons was chosen to balance computational efficiency and predictive accuracy. Configurations with fewer neurons (e.g., three) led to underfitting, failing to capture intricate patterns, while more neurons (e.g., ten) caused overfitting. The chosen five neurons ensured effective convergence during back-propagation with Mean Squared Error (MSE) minimisation, maintaining an optimal balance. The single output, shear stress (kN), supports supervised learning from validated data, avoiding the complexity of multi-output models and delivers accurate predictions tailored to analysing bolted steel connection behaviour within the defined boundary conditions.

Table 1: Input Factors considered for ANN

Input Variables	Symbol	Range		unit
		Min	Max	
Applied Force	VEd	50	400	kN
Supporting Column depth	d_column	152	305	mm
Supporting Column Width	w_column	152	305	mm
Supported Beam depth	d_beam	152	305	mm
Supported Beam width	w_beam	152	305	mm
Connection Fin Plate thickness	Fp_thick	2	20	mm
Fin plate dimentions	Fp_Dim	150	500	mm
Weld Fillet thickness	Wf_thick	6	16	mm
Bolt Diameter	⌀ bolt	12	24	mm

It is essential to normalise the input factors into a single range between 0 and 1 in order for the ANN to reduce the sensitivity of the network and to improve the training and accuracy, using Eq.1 (Han et.al, 2011).

$$\frac{(x - min_{val})}{(max_{val} - min_{val})} \tag{1}$$

where; x = input value

The constituents of the ANN network comprised of a transfer function, a sigmoid activation function, learning rate and prediction error. To initiate the weights and biases for all nine inputs across five neurons within the hidden layer, a PyTorch Xavier Initialisation is used, Eq.2 (Pater et al. 2023; Glorot et.al, 2010; Paszke et al, 2019).

$$W \sim U\left(-\sqrt{\frac{6}{n_{in}+n_{out}}}, \sqrt{\frac{6}{n_{in}+n_{out}}}\right) \tag{2}$$

where; n_{in} = number of inputs, n_{out} = number of neurons gives; $W \sim U$ (-0.654, +0.654)

Figure 3 shows a visual heat map of the distribution of weight values across the range of -0.654 to +0.654 for both the inputs and neurons. This visualisation helps identify how strongly each input contributes to the network's predictions, highlights any dominant or under utilised connections, and provides insight into the overall balance and sensitivity of the model during training.

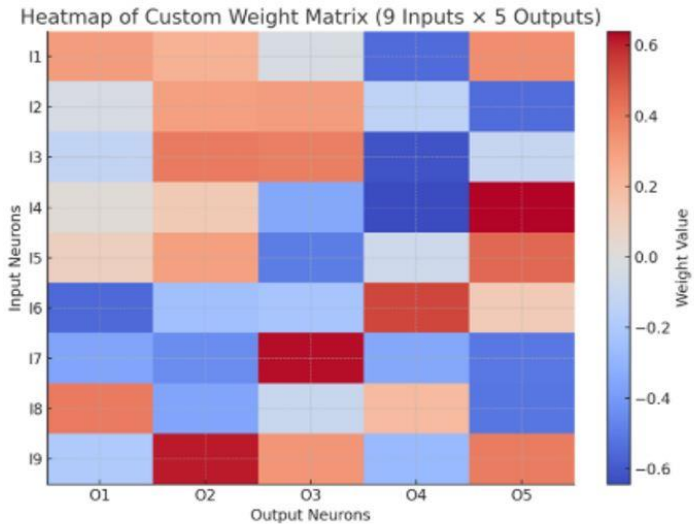

Fig. 3: Xavier Initialised Heat Map

The calculated input to each neuron is performed using Eq.3 (Debney, P, 2020) before a sigmoid activation function is applied, Eq.4 (Goodfellow et.al, 2016).

$$\sum_{i=1}^{m} Wi * Xi + b \tag{3}$$

where, w_i = weighted value of input, x_i = input value, b = bias

$$\frac{1}{1+ e^{-x}} \tag{4}$$

The primary purpose of the sigmoid activation function is to introduce non-linearity into the network to effectively map input values to a predicted output. The sigmoid function was chosen as it generates binary outputs as either zero or one, suitable for binary classification problems. As the input values are normalised to a value between (0 – 1) the sigmoid function lends itself well as a compatible activation function. The sigmoid function also has a smooth and continuously differentiable nature across its entire domain, as well as its demonstrated effectiveness in prior studies (Haykin, S, 2009). The final generated output of the ANN will also be between (0 – 1) and the translated shear stress (kN) is obtained using equation 5 (Haykin, S, 2009).

$$y * (t_{max} - t_{min}) + t_{min} \tag{5}$$

The predicted output of the ANN is treated with the mean squared error (MSE) to determine the error of margin between the predicted results vs. actual validated result, using Eq.6 (Haykin, S, 2009).

$$\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y})^2 \tag{6}$$

where; y_i = actual value, $\hat{y}$ = predicted value, n = number of data points.

2.2 Back-Propagation

A back-propagation is then performed through the network to update the weights and biases of each input for every associated neuron within the hidden layer to minimise the MSE through a number of iterations. This is performed using a gradient of loss Eq.7, derivative of sigmoid function Eq.8 and chain rule Eq.9 (Haykin, S, 2009).

$$\frac{dL}{d\hat{y}} = \hat{y} - y \tag{7}$$

$$\sigma'(z) = \hat{y}(1 - \hat{y}) \tag{8}$$

$$\delta = \frac{dL}{dz} = \frac{dL}{d\hat{y}} \text{ x } \sigma'(z) \tag{9}$$

The weights are updated using Eq.10, Eq.11 and biases using Eq.12 (Haykin, S, 2009).

$$\frac{\partial L}{\partial w_1} = \delta \text{ x } \chi_1 \tag{10}$$

$$W_1^{new} = W_1 - \text{n x } \frac{\partial L}{\partial w_1} \tag{11}$$

$$b^{new} = b_1 - \text{n x } \frac{\partial L}{\partial b} \tag{12}$$

3. Experimental Design Methodology

The application of Design of Experiments (DoEs) in this study was critical for the development of a robust and representative dataset used as part of the training of the new ANN model to account for the interactions of all input design variables to learn the non-linear relationships of bolted steel connectors. The DoE framework supports both statistical validation and the iterative process required by the ANN to generate accurate results (Montgomery, D.C., 2006).

In this study, a stratified sampling technique and custom fractional factorial was used as part of a DoE approach to support the scope of this research. A total of 60 tests were defined to account for variations in input parameters within the defined boundary conditions of this study (Ahmed, S, 2024). This approach allows for the main effects of the range and combination of the input interactions to be analysed and supports the development and prove out of the non-linear ANN predictive model. The defined test schedule specified, provides a good grounding for the statistical analysis of results and machine learning-based modelling.

In contrast, a full factorial design would have produced in excess of 8000 tests which is not practical and unnecessary and so the custom fractional factorial design was chosen in order to reduce the number of tests to 60 runs while maintaining the key interactions between inputs to achieve meaningful results. This reduction was made after a preliminary review of the design matrix had revealed some test combinations were too similar with each other yielding repetitive results with minimal contribution to the ANN training. The strategic approach used in the reduction of tests was deemed sufficient and at the same time optimised the available time and resources. The custom factorial design feature was used within Minitab statistical software in order to create a test schedule with a total of 60 runs.

The defined DoE schedule was run using a validated component software programme 'Smart Engineer' to serve as the target response data for shear stress (kN), shear strain (g), moment (kNm) and rotation (˚). The Smart Engineer software uses a component model method referencing the EC3 procedure.

Furthermore, a sensitivity analysis using Analysis of Variance (ANOVA) within Minitab software was carried out on the actual data obtained from the Smart Engineer software of all 60 tests. The ANOVA had shown that the regression model created to evaluate shear stress resistance was statistically significant, with a model P-value of 0.000. The main factors that were statistically significant with a p value < 0.05 were; bolt size, weld fillet thickness, beam depth and applied load and the combination of these factors explains the variation in shear stress resistance, shown in table 2. The lack-of-fit test with a P value of 0.119 indicates no significant deviation in the data, and so the number of tests was appropriate to capture the complexity of the system (Choi et.al, 2024).

Therefore, the 60 DoE tests are justified as they provide the required resolution to differentiate significant input factor effects from insignificant ones and to ensure reliable interpretation of interaction effects.

Table 2: ANOVA Sensitivity Analysis

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	36	752783	20910.7	137.51	0.000
Linear	23	712970	30998.7	203.86	0.000
Bolt Size	7	4027	575.3	3.78	0.007
d_beam	3	1577	525.7	3.46	0.033
Wf_thick	3	3655	1218.5	8.01	0.001
Fp_Dim	1	35	35.3	0.23	0.635
d_column	5	113	22.6	0.15	0.978
VEd	4	1908	476.9	3.14	0.034
2-Way Interactions	13	248	19.1	0.13	1.000
Bolt Size*Fp_Dim	7	168	24.0	0.16	0.991
d_beam*Fp_Dim	3	38	12.5	0.08	0.969
Wf_thick*Fp_Dim	3	73	24.4	0.16	0.922
Error	23	3497	152.1		
Lack-of-Fit	12	2425	202.1	2.07	0.119
Pure Error	11	1072	97.5		
Total	59	756281			

The final step within the test phase involved running the 60 tests through the newly developed fully trained ANN model and carrying out data analysis. To statistically analyse the final results obtained from the new ANN, a k-fold split cross validation technique was adopted to assess the performance and generalisability of the model without requiring excessive data. The use of 60 runs is justified as it enables a robust 5-fold cross-validation process, providing a balanced trade-off between training and validation. With 12 runs per fold, the ANN is repeatedly trained on a substantial 80% of the data (48 runs) and validated on the remaining 20% (12 runs), which it had not seen during the training phase.

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4. Analysis of Results of the ANN

After training the Artificial Neural Network (ANN) through multiple iterations of backpropagation, an average Mean Squared Error (MSE) of 0.90 with a variance of 1.03 was achieved compared to actual reference results, as presented in Table 3. These results demonstrate that the ANN effectively captured the non-linear relationships between input variables and corresponding structural responses, closely aligning with real-world data. The model's robustness was further validated by its reliable and accurate predictions across all 60 Design of Experiments (DoE) tests, benchmarked against data from the Smart Engineer software.

The ANN demonstrated a high prediction accuracy for the primary output, shear stress (kN), with an R^2 value of 0.9977, indicating excellent correlation with actual test data. In addition, the ANN achieved a similar level of accuracy for secondary outputs, including moment (kN), rotation (°), and shear strain (γ), as shown in figure 4, where high R^2 values were consistently observed. These results align with findings from prior research on similar complex structural engineering problems (Shbeeb et al., 2024; Zhen et al., 2022), reinforcing the ANN's predictive capability for bolted steel connector applications.

By training and validating on different subsets, the k-fold split prevented the ANN from overfitting to the training data. This ensured strong generalisation to unseen configurations within the defined boundary conditions of this study, such as varying bolt diameters and end plate fillet weld thickness. In effect, this had proven statistical reliability of the ANN in processing unseen data, providing greater confidence in the usability of the predictive model for the specific load cases used in this research investigation.

The limited dataset size may however restrict the model's ability to generalise across diverse load cases or unique connection designs outside the study's boundary conditions. To mitigate these limitations, further research can explore alternative strategies to mitigate overfitting, such as enhanced cross-validation techniques beyond the mentioned k-fold split, and to explore the dataset's representativeness to ensure robustness. Sensitivity studies and collecting larger datasets can be carried out to validate the model's reliability across a broader range of boundary conditions and configurations of connection designs.

The reliance on limited data underscores the need for supplementary validation, such as Finite Element Modelling (FEM), for novel cases, ensuring the ANN's reliability in real-world applications.

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Table 3: MSE & Variance Results of ANN Predicted Results

										ACTUAL Smart Engineer Results	ANN Predicted 8th Iteration	Mean Square Error
	VEd	*d_column*	*w_column*	*d_beam*	*w_beam*	*Fp_thick*	*Fp_Dim*	*Wf_thick*	*⌀ bolt*	*Connection Capacity*	*Connection Capacity*	(MSE)
	KN	mm	mm	mm	mm	mm	mm	mm	mm	(kN)	(kN)	
Test No.												
1	50	152	152	152	152	4	200	6	12	103.59	104.11	0.27
2	100	152	152	152	152	16	250	20	12	103.59	104.11	0.27
3	150	152	152	152	152	4	200	6	16	192.92	193.88	0.93
4	200	152	152	152	152	16	250	20	16	192.92	193.88	0.93
5	250	152	152	152	152	4	200	6	20	180.22	181.12	0.81
6	300	152	152	152	152	20	250	16	20	227.81	228.95	1.30
...	...	...	...	...	...	...	...	...	...	...	...	...
60	400	305	305	305	305	20	250	16	24	433.77	434.64	0.75

MSE 0.9

Variance 1.03

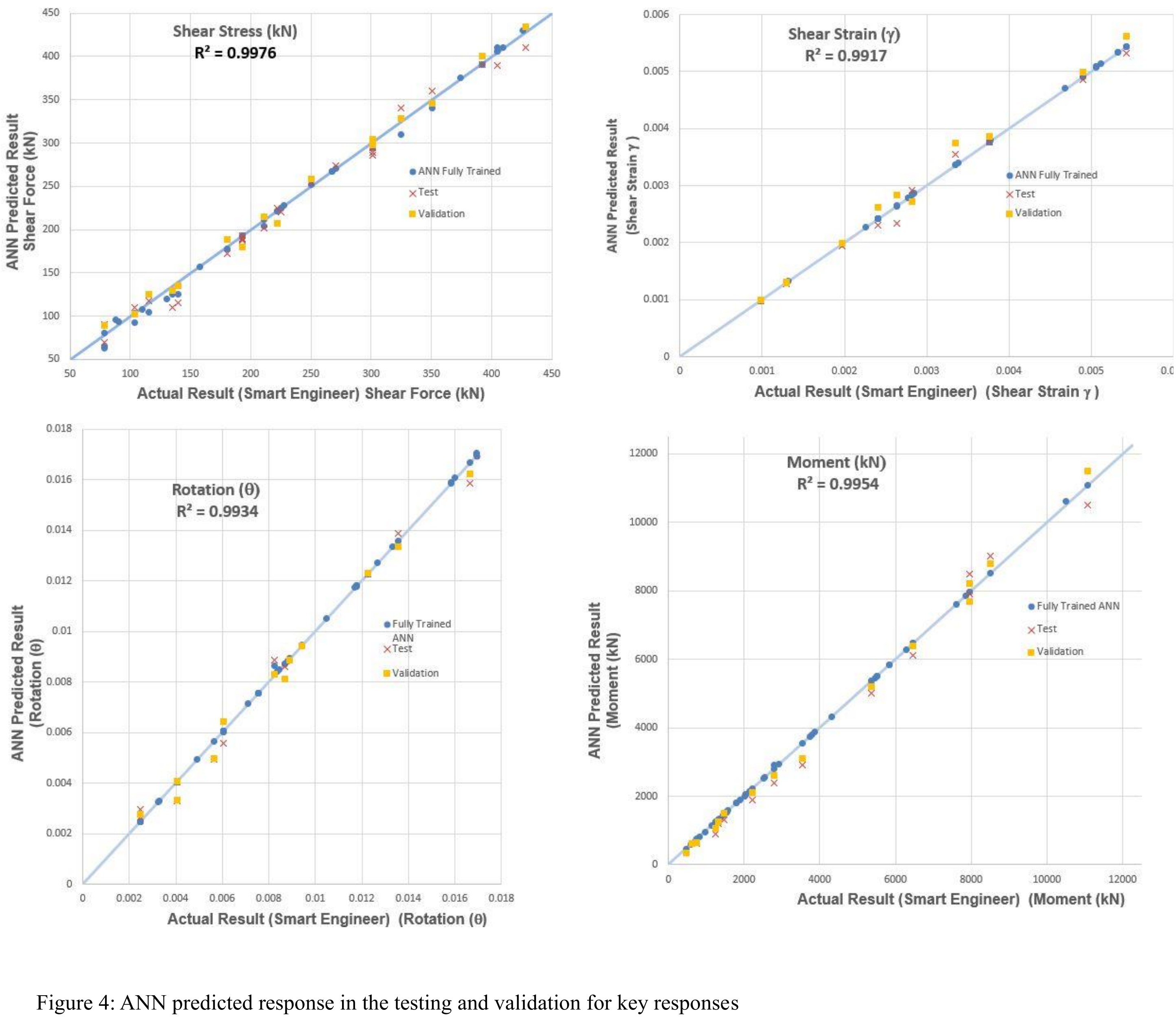

Figure 4: ANN predicted response in the testing and validation for key responses

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4.1 Response Surface Model

It is useful to identify the inputs that had the largest influence upon the final shear stress (kN) output.
A regression analysis of the key inputs had revealed the weld fillet thickness and bolt diameter inputs had the largest influence on the resultant shear stress with the largest R^2 value of 1.0 and 0.99 respectively.
A Response Surface Model (RSM) was employed to model the performance relationship between weld fillet thickness of the end plate and bolt diameter, enabling the optimisation of these design parameters to achieve optimal outcomes in terms of structural performance, weight efficiency, cost, and embodied carbon (CO_2), shown in figure 5.

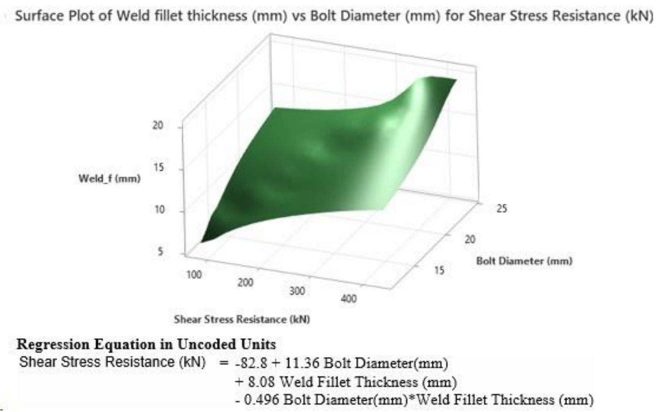

Fig.5 Response Surface Model (Weld Fillet thickness & Bolt Diameter)

5. Concept Design Selection using PROVEN tool

Previous research carried out by the author (Georgiou. A, 2015) developed a mathematical tool 'PROVEN' (Product Optimisation Value Engineering) as part of a completed PhD, to aid the concept design selection process using an attribute driven approach. The findings of the PhD were presented at several global sustainability conferences with published work featuring in two published journals. The PROVEN tool was tried and tested within the Automotive and Construction industries for the identification and selection of an optimised concept design that proved to be very useful.

The PROVEN approach complements the application of the new ANN, as the predicted outputs for bolted steel connector designs were assessed against other alternative designs to determine the most optimal design in meeting key performance attributes. This involved a prioritisation of key attributes to include structural integrity, sustainability, cost and versatility for the selection of steel connections, considered as part of this research study. The following theoretical steps of the PROVEN framework were applied to determine an optimal design for a bolted steel connector.

5.1 Value Equation

The relative value of a product as a result of a single attribute at level **g** located between $\boldsymbol{g_C}$ (critical) and $\boldsymbol{g_I}$ (ideal) is given by Cook's adapted value equation 13

$$\boldsymbol{v(g) = \left[\frac{(g_C - g_I)^2 - (g - g_I)^2}{(g_C - g_I)^2 - (g_0 - g_I)^2}\right] \gamma} \qquad (13)$$

where:

- $v(g)$ is the customer perceived value of a product attribute with performance g;
- g_I and g_C are the ideal and critical value of the S-model curve for a performance measure;
- g_0 is the performance of the baseline vehicle;
- γ is a weighting factor representing the importance of the product attribute to the customer.

As attributes tend to have different units of measure, equation 13 normalises all values to 1.0 allowing for an easier comparison to be made particularly with a rather complex system. 'The ideal point '$\boldsymbol{g_I}$' of the value curve is defined as the performance level at which the derivative of the value curve reaches zero. This means that any further improvement in this performance measure does not improve the customer-perceived value of a product attribute. The critical point '$\boldsymbol{g_C}$' is defined as the performance level at which the value curve crosses the performance axis, meaning that at this point or beyond the performance of the product is so poor that the customer perceives the product to have absolutely no value' shown in figure 6 (Cook, 1997).

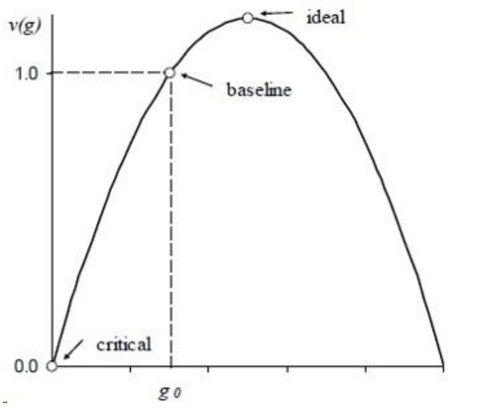

Figure 6: Relative Value Attribute (Cook, 1997)

5.2 Relative Value Index Model (RVI)

The Relative Value Index (RVI) is a mathematical model based on the Taguchi's loss function, adapted from statistical process control methods. The RVI is more meaningful as actual data is derived from each of the attribute performance parameters to generate a value index that can be used to compare between various attributes where units of measure maybe different (Downen et.al., 2005).
The total value of a product taking into account as many attributes as required can be calculated using a Relative Value Index (RVI) based on Taguchi's adapted loss function, equation 14.

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$$\boldsymbol{RVI}_{\,i} = \frac{v(g_{i1})\gamma + v(g_{i2})\gamma + v(g_{i3})\gamma + \cdots v(g_{in})\gamma}{\boldsymbol{n}} \qquad (14)$$

The exponential weighting factor '$\boldsymbol{\gamma}$' reflects the relative importance of each attribute to the overall product RVI of the attributes $\boldsymbol{g_i}$ and $\boldsymbol{n}$ represents the number of concept designs to be evaluated. The multiplicative relationship between the attributes means that a specific product attribute depends not only upon its own level but also on the levels of the other attributes (Downen et.al., 2005). The RVI is useful for the assessment of concept designs as it uses a data-driven approach.

5.6 ANN and PROVEN Integration

The new ANN developed as part of this research study complements the PROVEN methodology by providing rapid, accurate shear stress (kN) predictions of bolted connections, which PROVEN uses to evaluate and rank design options using a multi-attribute performance driven process, including cost and embodied carbon emissions.
This synergy enables the selection of an optimised bolted steel connection design that minimises embodied carbon, through reduced material weight and cost while maintaining structural integrity under load conditions. The ANN calculates the non-linear predictive modelling, while PROVEN applies a data-driven, multi-attribute framework for holistic optimisation, aligning with sustainability goals, UN SDGs 9 and 11.
The workflow diagram shown in figure 7 displays the integration of the ANN output (shear stress kN) with PROVEN.

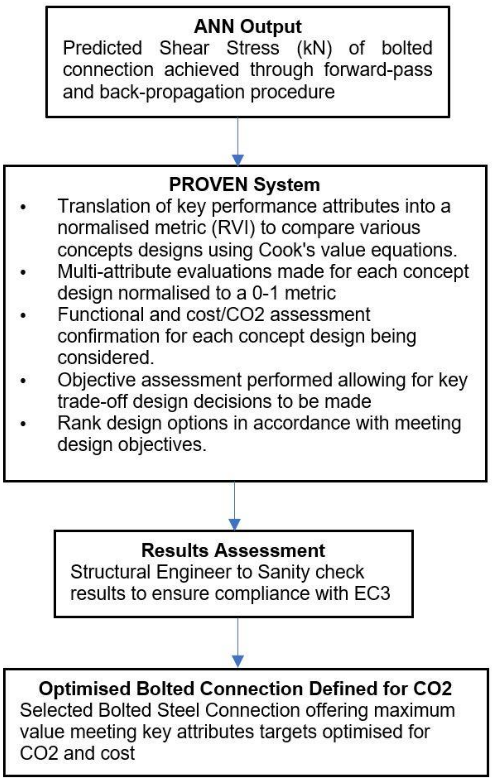

Fig. 7: ANN-PROVEN Integration

5.3 Design Selection using PROVEN

The application of PROVEN was used to assist in the selection of five competing bolted steel connector designs, in identifying the most optimal design, shown in table 6.
Using Cook's adapted value Equation 13, and the adapted RVI Equation 14; by substituting in the performance attribute values for each concept design, provides the overall assessment for each design, normalised to a value of 1.0.
The first step of PROVEN was to define the range of each attribute bound relevant for bolted steel connections in terms of the critical value, a target value and an ideal value. The following attribute bound settings were defined through the DoE test runs performed, shown in table 4.

Table 4; Attribute Bounds defined for Bolted Steel connections derived from DoE's

	Attribute Bounds			
Attribute (g)	Critical_c	Target_0	Ideal_i	Weighted (γ)
Shear Stress (kN)	400	225	175	0.9949
Shear Strain (g)	0.005	0.003	0.0012	0.9917
Moment (kNm)	215	100	80	0.9343
Rotation (q)	0.038	0.0025	0.001	0.9456
Weight (kg)	4	1.8	1.2	1
Cost (£)	9	6	5	1
CO2 (kgCO2e/kg)	4	2	1	1

The weighted values (γ) featured in table 4 are derived from regression analysis, apart from the weight, cost and CO2 attributes which have all been set to a maximum of 1, as these attributes are inter-related, as lowering the overall weight would reduce the cost and lower embodied carbon CO2 emissions (IStructE, 2025). As an example, regression analysis for shear strain (γ) has been carried out as shown in figure 8. It must be noted; the bolt size and number of bolts were chosen as prime parameters with the largest influence on the shear stress of a steel connector. Other factors such as end plate thickness and the size of the plate all play a role and fixed assumptions have been made as part of the regression analysis which includes a total of four bolts (2 rows of two bolts), end plate thickness of 8mm and plate size of 200mm

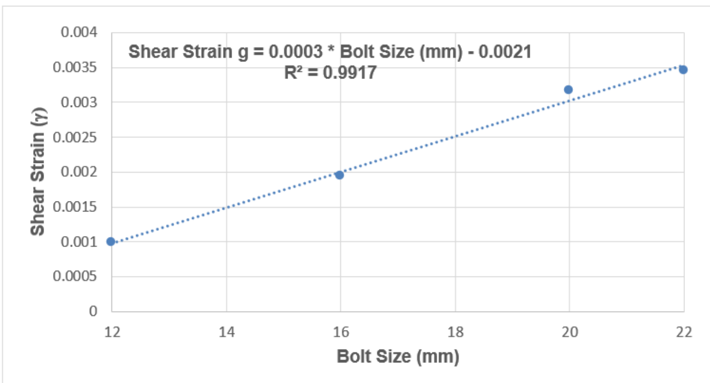

Fig. 8; Regression Analysis for Shear Strain (γ) vs. Bolt size (mm)

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5.4 Case Study using PROVEN

As a demonstrative case, Concept Design 1 (table 6) will be evaluated against the moment capacity (kNm) using the PROVEN methodology. The same procedure is subsequently applied to all other attributes and concept designs.

Step 1: Using Eq.13, and substituting the Moment (kNm) attribute bounds $\boldsymbol{g_C = 215}$, $\boldsymbol{g_I = 80}$, $\boldsymbol{g_0 = 100}$ from table 4 and using the achieved Moment (kNm) performance value from table 5 for Concept design 1 ($\boldsymbol{g}$ = 83.6 kNm), ($\boldsymbol{\gamma = 0.9343}$) gives;

$$\left[\frac{(215-80)^2-(83.6-80)^2}{(215-80)^2-(100-80)^2}\right]0.9343 = 0.95 \text{ (RVI)}$$

The calculated 0.95 relative value index corresponds to the RVI as shown in table 6 circled in red. As Cook's RVI equation normalises all calculated values to 1.0, in the case of the Moment attribute for Concept design 1, it is 95% efficient in meeting the moment performance target.

Step 2: To assess all attributes for all designs with a normalised value to 1.0, the Relative Value Index (RVI) equation 14, is used to calculate the overall rating of each design.

The RVI equation effectively adds all individual attribute relative value index's and the resultant RVI is divided by the total number of attributes assessed. For concept design 1, the RVI equation is as follows;

0.94+1.28+0.95+0.87+0.86+0.34+-0.16 / 7 = 0.73

The same procedure is then carried out assessing each concept design against the performance attributes. The results as indicated in table 6, revealed concept design 2 scored the highest total RVI for all assessed attributes scoring **0.98**, mainly attributed to achieving the lightest weight design, most cost effective and best in class for CO2 sustainability. Concept design 5 scored the lowest RVI of **0.5,** making this design the worse performing in meeting the overall required attribute targets.

Table 5: Inputs & Outputs of five concept designs of bolted steel connections

	Input Variables									Outputs						
Concept Design	VEd (kN)	d_column (mm)	w_column (mm)	d_beam (mm)	w_beam (mm)	Fp_thick (mm)	Fp_Dim (mm)	Wf_thick (mm)	ø bolt (mm)	Shear Stress (kN)	Shear Strain (γ)	Moment (kNm)	Rotation (°)	Weight (kg)	Cost (£)	CO2 (kgCO2e/kg)
1	100	152	152	152	152	16	250	20	12	103.59	0.0013	83.6	0.0021	2.37	8.30	4.13
2	150	152	152	203	203	4	200	6	16	192.92	0.0024	91.2	0.0024	1.80	6.30	3.13
3	200	203	203	305	305	6	250	6	16	211.00	0.0026	132.0	0.0015	2.21	7.75	3.85
4	250	305	305	254	254	20	200	16	20	301.06	0.0037	184.3	0.0029	2.04	7.13	3.55
5	350	305	305	305	305	9	200	16	24	392.10	0.0049	205.9	0.0032	1.98	6.94	3.45

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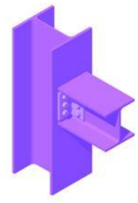
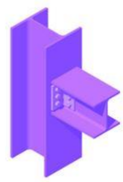
Table 6: Bolted Steel Connection Design Appraisal using PROVEN

			Concept Design 1		Concept Design 2		Concept Design 3		Concept Design 4		Concept Design 5	
												
Design Criteria	Design Criteria Targets	Weighting	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI
Shear Stress (kN)	225	0.9949	103.59	0.94	192	1.0	211	1.0	301	0.7	392	0.1
Shear Strain (γ)	0.003	0.9917	0.00128	1.28	0.0024	1.2	0.0026	1.1	0.003	0.7	0.0048	0.1
Moment (kNm)	100	0.9917	83.6	0.95	91.2	1.0	132	0.8	184	0.4	205	0.1
Rotation (θ)	0.0025	0.8661	0.00211	0.87	0.0023	0.9	0.0015	0.9	0.0029	0.9	0.003	0.9
Weight (kg)	1.8	1	2.37	0.86	1.79	1.0	2.21	0.9	2.03	1.0	1.98	1.0
Cost (£)	6	1	8.3	0.34	6.29	1.0	7.74	0.6	7.13	0.8	6.93	0.8
CO2 (kgCO2e/kg)	2	1	4.12	-0.16	3.13	0.9	3.85	0.2	3.54	0.5	3.44	0.6
Total Relative Value Index (RVI)				0.73		0.98		0.78		0.70		0.50
Ranking				3		1		2		4		5

5.5 Design Optimisation

To identify the concept design for achieving the highest performance targets in terms of; shear stress, shear-strain,moment and rotation, new attribute bounds are defined shown in table 7. This scenario may suit a specific application where extreme boundary conditions require high shear stress resistance, leaving minimal opportunity to optimise weight,cost, and CO_2 emissions.

Table 7: Updated Attribute Bounds for Maximum Steel Connector Performance

	Attribute Bounds			
Attribute (g)	Critical_c	Target_0	Ideal_i	Weighted (γ)
Shear Stress (kN)	400	300	250	0.9949
Shear Strain (g)	0.005	0.003	0.0012	0.9917
Moment (kNm)	40	130	140	0.9343
Rotation (q)	0.03	0.0021	0.001	0.9456
Weight (kg)	4	2	0.5	1
Cost (£)	9	7	4	1
CO2 (kgCO2e/kg)	4	3.8	1	1

Steps 1 & 2 of the PROVEN methodology were run again with results presented in table 8. Concept design 3 scored the highest total RVI of 0.77 and concept design 2 was the next favourable design alternative with an RVI of 0.74. As the aim was to identify a design to deliver high structural performance attribute values, this did come at an increase in cost, weight and CO2 even though these values are lower for concept design 2. This is due to requiring more material such as larger bolt diameters, thicker weld fillet and end plate thickness that all add to the weight, cost and CO2 attributes.(Regan, C. 2018; Sabatka et al. 2015; Stark, J. 2023).

The results presented as part of the PROVEN application in the selection of steel connection design proved to be very useful in identifying the most optimal design using an attribute driven approach.

This creates a substantially optimised product offering to the market, minimising cost and component weight with associated sustainability advantages in lowering embodied carbon emissions.

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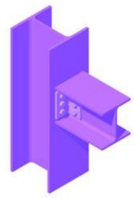
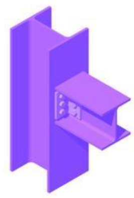
Table 8; Bolted Steel Connection using PROVEN for Shear Stress, Shear Strain, Moment and Rotation Prioritisation

			Concept Design 1		Concept Design 2		Concept Design 3		Concept Design 4		Concept Design 5	
												
Design Criteria	Design Criteria Targets	Weighting	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI	Achieved Attribute Performance	RVI
Shear Stress (kN)	300	0.9949	103.59	0.94	192	1.0	211	1.0	301	0.7	392	0.1
Shear Strain (γ)	0.003	0.9917	0.00128	1.28	0.0024	1.2	0.0026	1.1	0.003	0.7	0.0048	0.1
Moment (kNm)	130	0.9917	83.6	0.95	91.2	1.0	132	0.8	184	0.4	205	0.1
Rotation (θ)	0.0021	0.8661	0.00211	0.87	0.0023	0.9	0.0015	0.9	0.0029	0.9	0.003	0.9
Weight (kg)	2	1	2.37	0.86	1.79	1.0	2.21	0.9	2.03	1.0	1.98	1.0
Cost (£)	7	1	8.3	0.34	6.29	1.0	7.74	0.6	7.13	0.8	6.93	0.8
CO2 (kgCO2e/kg)	3.8	1	4.12	-0.16	3.13	0.9	3.85	0.2	3.54	0.5	3.44	0.6
Total Relative Value Index (RVI)				0.61		0.74		0.77		0.69		0.44
Ranking				4		2		1		3		5

6. Comparative Case Study: ANN-PROVEN vs. Component Modelling for Bolted Steel Connection Design

To demonstrate the sustainability advantages for carbon reductions achieved with the ANN-PROVEN approach vs. traditional Component Modelling (CM), a comparative case study has been carried out for a bolted end-plate beam-column connection under shear load.

The load condition entailed a beam-column bolted connection under a 200 kN shear force within a multi-storey office building. The load scenario considers steel beams and columns of identical dimensions, each connection secured with four bolts. The results of the ANN-PROVEN methodology vs. CM can be seen in table 9.

The analysis indicates that the CM method resulted in a bolt diameter of 20mm paired with a fillet weld of 16mm, whereas the ANN-PROVEN method had chosen a thicker weld of 20mm and a reduced 16mm bolt diameter. This adjustment accounted for a net reduction in embodied carbon and weight of approximately 15% and a 16% cost reduction.

For a building featuring 200 bolted steel connections, with four bolts per connection, this translates to a cumulative net weight reduction of 47.2 kg and a total embodied net carbon saving of 87.32 $kgCO_2e/kg$ without compromising structural integrity and safety.

The ANN's rapid processing capability enables the assessment of thousands of design iterations, while PROVEN's attribute driven assessment method identifies trade-offs with slightly thicker welds in exchange for smaller diameter bolts to meet the structural integrity requirements. Alternatively, re-executing the CM to explore these trade-offs is feasible but would be highly time-intensive to identify an acceptable optimisation.

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Table 9; Quantitative Comparison (Component Modelling vs. ANN-PROVEN)

	Input Variables				Attributes Efficiency		
	Bolt Size (mm)	Fillet Weld (mm)	Fin-Plate Thickness (mm)	Fin-Plate Dimension (mm)	Steel Weight (kg)	*Embodied Carbon (kgCO2e/kg)	**Cost (£)
Component Modelling	20	16	16	250	0.40	0.74	0.48
ANN-PROVEN Method	16	20	16	250	0.34	0.63	0.40
Savings/Reduction					15%	15%	16%

* IStructE (2025) provides guidance on embodied carbon for mild steel of; 1.77 $kgCO_2/kg$
** Jozepa (2025) cites a structural steel cost of £1,200 per ton for UK

6. Conclusions

The integration of the ANN with the PROVEN methodology establishes a systematic, evidence-based approach to optimise bolted steel connection designs. This framework enhances performance, reduces material consumption, and promotes sustainability through efficient and data-driven design decisions.

The ANN significantly shortens processing time compared with conventional methods, where structural engineers manually adjust parameters in FEM or component-based models, a process that is both time-intensive and impractical. The ANN output feeds directly into the PROVEN methodology to evaluate and rank design options using a multi-attribute performance driven process, that considers cost and embodied carbon emissions, enabling the selection of lightweight, cost-effective, and structurally sound connector configurations.

The ANN's deep learning phase successfully mapped non-linear input relationships, reducing error margins to an acceptable level. Statistical analysis confirmed the ANN's accuracy against component modelling software, with an MSE of 0.9 and variance of 1.03, demonstrating its ability to learn real-world non-linear patterns. The PROVEN approach prioritised attributes through regression analysis, aiding sustainable design optimisation and selection, though a limitation is the ANN's challenge with unique load cases, requiring FEM and physical testing for validation.

The ANN delivered consistent and precise outcomes across 60 DoE tests, achieving a robust R^2 of 0.9977 for shear stress (kN) predictions, within the defined boundary conditions of the specific load case of this study. Overfitting risks were mitigated through k-fold cross-validation, while the DoE framework and stratified sampling ensured statistical robustness and representativeness. However, the small dataset size could limit the model's ability to generalise across diverse load cases outside the boundary conditions of the study or unique connection designs. Further research can explore collecting larger datasets via experiments, sensitivity analysis and enhanced k-fold validation to evaluate input impact and improve model robustness. Expanding the dataset through these methods will strengthen the ANN's generalisability beyond the defined boundary conditions and ensure greater reliability across diverse structural applications.

In conclusion, the combined ANN and PROVEN approach offer a reliable method to optimise bolted steel connector designs during the conceptual phase, minimising processing time. This research offers a substantial contribution to the field, with practical implications for design decisions, as evidenced by the experimental testing phase.

Future research could expand to hybrid connections (e.g., timber-steel or concrete-steel) and automate the process with a Python script and Gradio interface for broader applicability across varied boundary conditions.

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