

Additive versus Multiplicative Neuron Surrogates for Predicting the Structural Response of Steel Roof Trusses

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ABSTRACT: Neural network surrogates can replace repeated finite element runs in the design of steel roof trusses, but the choice of neuron model is rarely tested under controlled conditions. This study compares an additive Multilayer Perceptron (MLP) with a Multiplicative Neuron Model (MNM) at matched capacity (211 and 196 free parameters). Both were trained on a parametric STAAD.Pro database of 46,140 Fink, Howe, Pratt and Warren trusses designed to IS 800:2007, with failing designs retained. Each network predicted eight continuous responses and the binary design status from nineteen inputs. On unseen test data the MLP reached a mean coefficient of determination of 0.942–0.946 across the four profiles, against 0.700–0.775 for the MNM. Its mean absolute percentage error was 11–17 %, against 26–37 %. Total weight was predicted best ($R^2 \geq 0.964$ for the MLP) and the maximum utilisation ratio worst ($R^2 \approx 0.80$ –0.83), because the governing member changes across the design space. For design-status classification the MLP's false negative rate was 0.074–0.213, against 0.210–0.608 for the MNM. Because the MNM used a bounded geometric-mean aggregation and slightly fewer parameters, its deficit is attributed to the multiplicative form itself, which fits the near-additive structure of truss responses poorly. The MLP is recommended as the surrogate, with the utilisation ratio treated as its least certain output.

KEYWORDS: steel roof truss; surrogate model; multilayer perceptron; multiplicative neuron model; STAAD.Pro; IS 800:2007

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I. INTRODUCTION

Steel roof trusses are sized by an iterative cycle: sections are assumed, the model is analysed, code checks are read and sections are revised. Each pass requires a full finite element run. Inside an optimisation loop, where thousands of candidates must be evaluated, this cost becomes the main obstacle to practical optimum design (Salehi and Burgueño, 2018).

Artificial neural networks (ANNs) offer a way around this cost. Once trained on analysis results, a network returns structural responses almost instantly. ANN surrogates have been used for reliability analysis of steel structures (Chojaczyk et al., 2015), prediction of optimal truss member areas (Nguyen and Vu, 2021), geometrically nonlinear truss optimisation (Mai et al., 2021) and screening of candidate roof truss designs (Nguyen et al., 2021). Reviews by Thai (2022) and Dadras Eslamlou and Huang (2022) confirm that the multilayer perceptron (MLP) remains the most widely used architecture.

The multiplicative neuron model (MNM) replaces the weighted sum inside a neuron with a product of affine terms (Yadav et al., 2007). A single multiplicative unit can represent an interaction, such as span $\times$ load, that an additive unit can only approximate by combining several units. The model has performed well on time-series problems (Yadav et al., 2007; Guo et al., 2024). In an earlier study on 384 polyhouse trusses, the MNM predicted some member areas more accurately than the MLP (Kulyal et al., 2026).

Comparisons between the two neuron families usually differ in more than the neuron. A single multiplicative neuron has far fewer parameters than an MLP, and raw products of many factors can overflow numerically. Either effect can explain a performance gap. As a result, it remains unclear whether the aggregation function itself matters for structural surrogates.

This paper tests that question under controlled conditions. The contributions are:

1. A like-for-like comparison of MLP and MNM surrogates at matched capacity, with a numerically bounded multiplicative aggregation, on four truss profiles.
2. An explanation of why accuracy differs between responses, with weight predicted best and maximum utilisation worst.

3. An evaluation of design-status classification using the false negative rate, which governs safe use inside an optimiser.

The work forms part of a doctoral study (Kulyal, 2026); the use of these surrogates within a metaheuristic optimisation framework is reported separately.

II. PARAMETRIC DATABASE

The database contains 46,140 steel roof truss models across four profiles. Fink and Howe trusses cover residential spans of 6–15 m. Pratt and Warren trusses cover industrial spans of 15–40 m. Models were generated automatically by a Python script that wrote STAAD.Pro input files and ran them in batch.

For each profile, span, rise, number of panels, truss spacing and basic wind speed (33–47 m/s) were varied in a full factorial of 4,200 combinations. A buildability filter removed geometries that could not be fabricated, leaving about 55 % of combinations. Each retained geometry was analysed with five grouped-section assignments drawn from IS angle, pipe and I-sections (SP 6(1)). Loads followed IS 875 (Parts 1–3) and IS 1893, and members were checked to IS 800:2007 in Fe250 steel.

Failing designs were kept on purpose. A surrogate trained only on compliant designs never sees the other side of the limit state, which is where an optimiser searches.

Table 1: Composition of the database

Profile	Category	Span (m)	Records	Failing designs (%)
Fink	Residential	6–15	11,550	13.8
Howe	Residential	6–15	11,550	32.6
Pratt	Industrial	15–40	11,520	40.4
Warren	Industrial	15–40	11,520	39.7
Total	—	6–40	46,140	31.6

Each record has nineteen inputs: span, rise, spacing and number of panels; dead, imposed and wind load; cross-sectional areas of six member groups (top chord, bottom chord, verticals, diagonals, columns, purlins); rise-to-span ratio; roof slope; and lengths of four member groups. The nine outputs are maximum utilisation ratio (UTIL_MAX), maximum nodal displacement, total weight (WEIGHT), maximum compression, maximum tension, column axial force, column utilisation, purlin utilisation and the binary design status (DESIGN_FAIL). A design fails if its utilisation exceeds 1.0 or its deflection exceeds the permitted limit.

III. SURROGATE MODELS AND TRAINING

3.1 Multilayer perceptron

The MLP has one hidden layer of ten logistic units and a logistic output unit. Each hidden unit forms a weighted sum of the inputs:

$$h_j = \sigma \left(\sum_{i=1}^{19} w_{ji} x_i + b_j \right), \quad y = \sigma \left(\sum_{j=1}^{10} v_j h_j + c \right)$$

where σ is the logistic function. The network has 211 free parameters.

3.2 Multiplicative neuron model

The MNM uses five multiplicative units feeding a linear read-out and a logistic output. A raw product of nineteen factors can overflow or vanish. Each unit therefore forms the signed geometric mean of its affine terms, which stays bounded for any number of inputs:

$$u_k = \text{sgn} \left(\prod_{i=1}^{19} z_{ki} \right) \exp \left(\frac{1}{19} \sum_{i=1}^{19} \ln |z_{ki}| \right), \quad z_{ki} = w_{ki} x_i + b_{ki}$$

$$y = \sigma \left(\sum_{k=1}^5 v_k u_k + c \right)$$

The MNM has 196 free parameters, slightly fewer than the MLP. Any gap in accuracy therefore cannot be explained by the MNM being larger, or by numerical overflow.

3.3 Training protocol

Each profile's database was split 70:15:15 into training, validation and testing subsets, stratified on design status. All variables were scaled to 0.1–0.9 using the minimum and maximum of the training subset only, so no information from unseen records leaked into training.

One network was trained per output, giving nine networks per model and profile. Both models used identical settings: mini-batch backpropagation (batch 256) with momentum 0.9, a decaying learning rate from 0.5, up to 300 epochs, and early stopping after 45 epochs without validation improvement. Each fit was repeated from three fixed random seeds and the run with the best validation performance was kept. The code was written from first principles in MATLAB so that the two models differ only in the aggregation function.

3.4 Performance measures

Regression accuracy was measured by the coefficient of determination (R^2), root mean square error, mean absolute error and mean absolute percentage error (MAPE), all computed in engineering units after reversing the scaling. Classification was measured by accuracy, area under the receiver operating characteristic curve (AUC) and false negative rate (FNR), defined as the share of failing designs predicted to pass. All results refer to the testing subset, which was not used in training or model selection.

IV. RESULTS

4.1 Overall accuracy

The MLP was more accurate than the MNM on every profile, by about 0.2 in mean R^2 and 15–20 percentage points in MAPE (Table 2). The ranking was the same for the root mean square and mean absolute errors, so it does not depend on the measure chosen. Results were consistent across the four profiles, indicating that the ranking depends on the neuron model rather than the truss configuration.

Table 2: Mean testing accuracy over the eight continuous responses

Profile	MLP R^2	MNM R^2	MLP MAPE (%)	MNM MAPE (%)
Fink	0.9419	0.7557	11.75	26.38
Howe	0.9458	0.7504	11.22	26.60
Pratt	0.9451	0.7748	17.30	35.47
Warren	0.9419	0.7002	16.63	37.03

Errors were lower on residential profiles than on industrial ones. The industrial span range is wider and more of its records lie near the limit state, where responses change fastest.

4.2 Accuracy by response

Total weight was the best-predicted response and maximum utilisation the worst, for both models on every profile (Table 3). The MLP's utilisation R^2 of 0.80–0.83 is well below its weight R^2 of 0.96–0.97. The MNM's utilisation R^2 fell to 0.48–0.60.

Table 3: Testing R^2 for the easiest and hardest responses

Profile	WEIGHT, MLP	WEIGHT, MNM	UTIL MAX, MLP	UTIL MAX, MNM
Fink	0.9684	0.9373	0.8094	0.5981
Howe	0.9718	0.9340	0.8347	0.5131
Pratt	0.9645	0.9219	0.8105	0.5577
Warren	0.9651	0.9195	0.8046	0.4840

In predicted-versus-actual plots, the MNM flattened at the upper end of the utilisation range and under-predicted the highest ratios. This is the unsafe direction, because an overstressed design then appears to be within capacity.

4.3 Design-status classification

The MLP classified design status well and the MNM did not (Table 4). The MLP's AUC was 0.965–0.989, showing that it ranks designs correctly. The MNM missed up to 61 % of failing Fink designs.

Table 4: Testing classification performance for DESIGN FAIL

Profile	Acc., MLP	Acc., MNM	AUC, MLP	AUC, MNM	FNR, MLP	FNR, MNM
Fink	0.9561	0.9031	0.9647	0.9246	0.2125	0.6083
Howe	0.9602	0.8164	0.9891	0.8852	0.0743	0.2885
Pratt	0.9358	0.8200	0.9850	0.8992	0.0873	0.3319
Warren	0.9265	0.8287	0.9833	0.8946	0.1050	0.2099

The Fink profile had the highest MLP accuracy but also its highest FNR. Only 13.8 % of Fink records fail, so accuracy is dominated by the passing majority while the minority class is handled less well. Accuracy alone is therefore a misleading measure for this task.

V. DISCUSSION

5.1 Why the multiplicative model falls short

The MNM's weakness is often attributed to numerical overflow of long products, or to its small size. Neither explanation applies here. The geometric-mean aggregation is bounded for any number of inputs, and the MNM had 196 parameters against the MLP's 211.

What remains is the form of the aggregation. A multiplicative unit couples its inputs: changing one input rescales the contribution of every other. Truss responses in this database are close to additive. Total weight is a sum of member contributions (area $\times$ length $\times$ count), and member forces are sums of load effects. Approximating an additive relation with products is possible but inefficient, and adding more multiplicative units does not help because every unit has the same form.

This also explains why the MNM did comparatively well on some members in the earlier polyhouse study (Kulyal et al., 2026). That dataset had only two effective design variables, and the members the MNM predicted better were those that study linked to span $\times$ load interactions.

5.2 Why utilisation is hardest to predict

Weight changes smoothly and in one direction as any input changes, so a single-hidden-layer network fits it well. Maximum utilisation is a maximum over all members. As geometry or sections change, the governing member can switch, for example from top chord to a web diagonal, producing a step in the response surface. A smooth network averages across the step and loses accuracy exactly at the design boundary.

5.3 Implications for design use

Weight is the usual objective of truss optimisation and is predicted well. Utilisation is a constraint and is predicted less well. When the surrogate is used inside an optimiser, the utilisation limit should be applied with a margin that absorbs this error, and every design returned should be checked in the analysis software before use.

For the classifier, FNR matters more than accuracy. A false negative is a failing design accepted as safe, and an optimiser searching for the lightest passing design is drawn towards exactly the region where such errors occur. The MLP's high AUC shows that its remaining false negatives can be reduced by lowering the decision threshold below 0.5, at the cost of rejecting more sound designs. That threshold should be chosen explicitly for the level of conservatism required.

5.4 Limitations

The database covers Fe250 steel and the stated span ranges only. Each result is the best of three training runs, which is too few for a formal estimate of run-to-run spread. Several inputs are derived from others, which should be considered in any sensitivity study built on these models.

VI. CONCLUSIONS

MLP and MNM surrogates were compared at matched capacity on 46,140 STAAD.Pro truss models covering four profiles. The main conclusions are:

1. The MLP is an adequate surrogate for steel roof truss responses, with mean testing R^2 of 0.942–0.946 on all four profiles.
2. The MNM is not, with mean R^2 of 0.700–0.775 and MAPE above 26 %. Because size and numerical overflow were controlled, the gap is attributed to the multiplicative aggregation, which fits near-additive structural responses poorly.
3. Weight is the easiest response and maximum utilisation the hardest, because the governing member changes across the design space. Utilisation constraints should be applied with a margin.

4. For design-status classification, the MLP's FNR was 0.074–0.213 against 0.210–0.608 for the MNM. FNR, not accuracy, should govern the choice of classifier and decision threshold.

The MLP is therefore recommended as the surrogate for optimisation of steel roof trusses. Extending the database to other steel grades and testing architectures that can represent step changes in utilisation are suggested for future work.

DECLARATIONS

Source of the work. This article is derived from the doctoral thesis of the first author (Kulyal, 2026). Results are reported from that study and are not published elsewhere in journal form.

Data availability. The parametric database is available from the corresponding author on reasonable request.

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