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Application of Artificial Neural Networks in Optimizing Polyhouse Roof Truss Design

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Abstract

Polyhouses are specialised agricultural structures developed to maintain controlled environmental conditions for crop cultivation, thereby ensuring consistent productivity even under adverse climatic circumstances. The performance of these systems largely relies on the structural stability and cost efficiency of the roof truss, which must achieve an effective balance between strength, adaptability, and economy. In this research, an Artificial Neural Network (ANN)-based modelling framework is introduced to optimise the members of polyhouse roof trusses, offering a computationally intelligent solution aligned with current advancements in innovative materials and infrastructure technologies. A total of 340 truss models, incorporating different load combinations, geometric parameters, and purlin spacings, were evaluated using STAAD.PRO software. The generated dataset was subsequently used to train and validate the ANN model for predicting the most economical pipe cross-sections of truss members under varying loading conditions. The results indicate that the ANN-based approach considerably reduces prediction errors and computational effort compared with traditional design methodologies. Overall, the proposed framework provides a structured, data-oriented strategy for optimising polyhouse roof truss systems. This method improves design precision and efficiency while supporting sustainable and technologically progressive construction practices in agricultural infrastructure.

Keywords: Artificial neural network (ANN), STAAD.PRO, polyhouse, truss, strength

INTRODUCTION

Polyhouse structures are essential to modern protected agriculture, as they enable control over temperature, humidity, ventilation, and light to support year-round crop production. Unlike open-field cultivation, polyhouses create a controlled microclimate that protects crops from adverse weather and environmental stresses. This performance depends on a stable and economical roof truss system capable of safely resisting dead, imposed, and wind loads. Consequently, the structural framework must combine strength, stiffness, durability, and cost-effectiveness, making steel pipe (circular hollow section) members well suited for polyhouse construction [1–4].

Roof truss design for polyhouses is commonly carried out using software such as STAAD.Pro, which applies finite element analysis to ensure safety and economy under multiple load combinations. Although reliable, this approach becomes time-consuming when numerous structural configurations must be assessed. Growing variation in polyhouse geometry, span, purlin spacing, and wind conditions has increased the demand for faster, scalable design methods. Traditional trial-and-error section selection with

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repeated design checks reduces efficiency and extends the overall design process [5–9].

Artificial Neural Networks (ANNs) provide a promising alternative by learning nonlinear relationships between geometric and loading parameters and the required structural sections. They can capture complex interactions and accurately predict optimal pipe cross-sections, substantially reducing computational time while achieving accuracy comparable to conventional analysis methods. Although ANNs are widely used in civil engineering applications such as damage detection, material property prediction, and structural health monitoring, their use in polyhouse roof truss design based on controlled computational datasets remains largely unexplored [10–15].

This study bridges the identified gap by developing an ANN-based framework to predict the cross-sectional area of steel pipe members in Howe-type polyhouse roof trusses. A dataset of 340 truss models generated in STAAD.Pro under varying geometric and loading conditions was used for training and validation. Comparison between ANN predictions and STAAD.Pro results demonstrates that the ANN can effectively replace repetitive computational design cycles with a rapid, data-driven approach. The findings highlight the potential of ANNs to enhance structural optimisation, reduce costs, and support design automation in polyhouse engineering [16–19].

LITERATURE REVIEW

The structural design of polyhouses and greenhouse systems has been extensively examined in the context of material optimisation, environmental loading, and overall stability. Early studies in structural optimisation developed algorithms for discrete structural improvement using Modified Rosenbrock Orthogonalisation Procedures and gradient-based methods. Their work demonstrated that the appropriate selection of steel member sections can substantially influence overall performance and cost, particularly in greenhouse frames, where lightweight yet strong sections are preferred. the importance of finite element analysis (FEA) through software such as SAP2000 for evaluating static and dynamic behaviour of truss systems. Their results highlighted the role of computational modelling in ensuring safe, durable, and material-efficient greenhouse structures, especially under diverse environmental conditions [20].

Region-specific research focused on the structural characteristics of greenhouses in the Marmara region, demonstrating the impact of configuration, geometry, and load distribution on the resulting internal forces. These studies reinforced the necessity of proper structural analysis to withstand environmental pressures such as wind. the advantages of tubular sections, citing their superior strength-to-weight ratio and economic benefits. Investigations into the behaviour of tubular members under bending stresses further validated their suitability for lightweight agricultural structures. Additionally, surveys provided insight into widespread greenhouse practices in Korea, informing the development of standardised models and safety guidelines [21]

Wind loading has been recognised as a governing factor in greenhouse design. The wind-induced pressures and load paths, demonstrating that improper assessment can lead to structural failures and significant economic losses and emphasised the importance of accurate load determination according to codal provisions such as IS:875 (Part 3), especially in regions subjected to high wind speeds. Load interactions in multiple greenhouse types, revealing the need for modifications in structural components to safely resist combined loading scenarios [22].

Parallel to developments in structural analysis, Artificial Neural Networks (ANNs) have gained prominence in civil engineering applications. The use of back propagation neural networks for diagnosing damage in truss joints successfully demonstrated ANN capability in recognising structural behaviour patterns even with limited measurements . ANN to fully stressed design of Pratt and Howe trusses, achieving prediction errors as low as 2.51% compared to STAAD.Pro outputs. These results confirmed the potential of ANNs as computationally efficient surrogates for structural design software.

More recent contributions expanded ANN usage into structural health monitoring and damage detection using Convolutional Neural Networks (CNNs), achieving high predictive accuracy in large-span and complex truss systems.

The literature highlights two clear trends: increased reliance on FEA-based computational tools for accurate polyhouse design and growing use of machine learning for structural prediction and optimisation. However, ANN models calibrated using large, controlled computational datasets for polyhouse roof truss design remain limited. This study addresses this gap by integrating STAAD.Pro-generated data with ANN-based modelling to develop a fast, accurate, and economical method for optimising steel pipe sections in polyhouse roof trusses.

MATERIALS AND METHODS

Steel Pipe Sections (Circular Hollow Sections)

Circular Hollow Sections (CHS) were chosen for the polyhouse roof truss because of their high strength, buckling resistance, uniform load transfer, and favourable strength-to-weight ratio. Their geometric uniformity, corrosion resistance, and ease of fabrication make them well suited for lightweight agricultural structures. All sections used comply with IS 1161:2014, ensuring consistent mechanical and dimensional properties. The section database comprises pipes with diameters from 21.3 mm to 355.6 mm in light, medium, and heavy classes, having cross-sectional areas between 1.21 cm² and 87.4 cm². These areas serve as the primary output variable for training the ANN model to predict suitable member sizes under varying load conditions.

Methods

Structural Modelling Using STAAD.Pro

A detailed computational workflow was adopted to generate the dataset required for training the ANN model. STAAD.Pro was used to perform structural analysis and design of Howe-type roof trusses under different geometrical configurations and environmental loading conditions. The methodology followed these major steps:

1. *Geometry definition:* Truss geometry was constructed using the STAAD.Pro Structure Wizard, selecting a Howe truss template and modifying member lengths, span values, purlin spacing, and chord lengths to represent realistic polyhouse configurations.The key geometric parameters that varied were length (10–20 m), width/span (5–20 m), purlin spacing (2–3 m), top chord length (4–10.5 m), and the number of panel points, resulting in the generation of 340 structurally distinct polyhouse models.
2. *Load calculations:* Load intensities were calculated in accordance with relevant IS codes. Dead load was evaluated using IS 875 (Part 1), including the self-weight of truss members, purlins, and polycarbonate roofing. Live load was determined as per IS 875 (Part 2), adjusted for roof slope and verified against IS 14462:1997 greenhouse guidelines. Wind load was computed following IS 875 (Part 3), considering terrain, topography, risk coefficients, and hill-region effects to obtain design wind speed and wind pressure using appropriate external and internal pressure coefficients. Typical results yielded a dead load of 3.809 kN, a live load of 0.924 kN, and a wind load of 3.21 kN.
3. *Assignment of section properties and boundary conditions:* Pipe sections were assigned to riser, rafter, vertical chord, incline chord, purlins, and column members. Initial trial sections were selected based on engineering judgement, after which STAAD.Pro design module (IS:800–2007) iteratively updated section sizes until all members satisfied strength and serviceability criteria. This process produced the target cross-sectional area outputs for each model, later used to train the ANN Table 1.
4. *Repeated modelling for dataset generation:* The entire design cycle was repeated across 340 polyhouse configurations, each with unique combinations of length, width, purlin spacing, chord length, purlin spacing and dead, live and wind loads. This produced a comprehensive dataset linking eight input variables to six output variables i.e. riser, rafter, vertical chord, inclined chord, purlins and column (cross-sectional area and section of each truss component) Figures 1 and 2.

Table 1. The compatible section of roof truss that passes the design calculation.

Sr. No.	Members	Reaction	Sections	Area of cross-section(cm^2)
1	Riser	R1	603H	5.23
2	Rafter	R2	269L	1.78
3	Vertical chord	R3	424H	4.83
4	Incline chord	R4	424L	4.83
5	Purlins	R5	213L	1.21
6	Column (eve level)	R6	889L	8.62

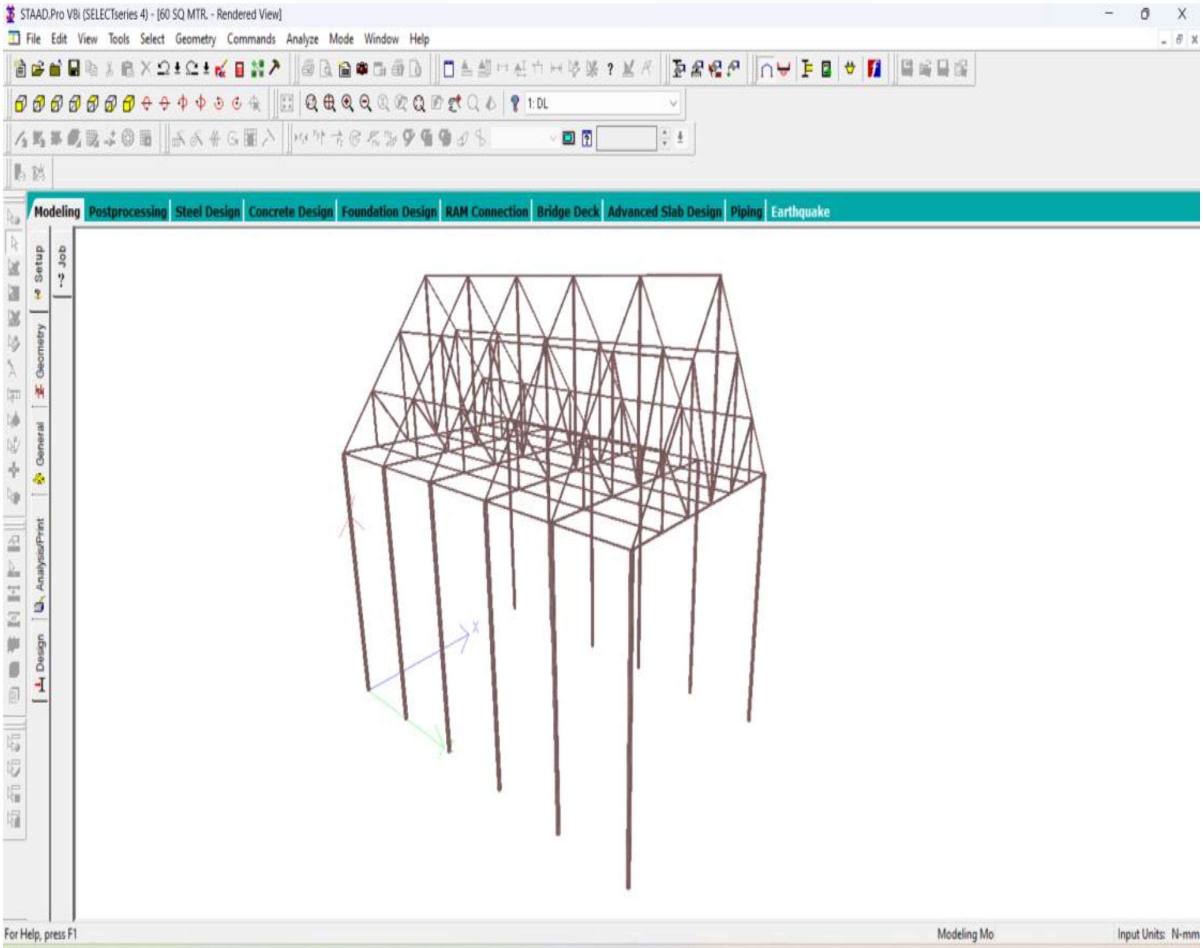

Figure 1. 3D view of polyhouse design

Artificial Neural Network Modelling

ANN Architecture

A feedforward backpropagation neural network was developed in MATLAB R2021a using the Neural Network Toolbox. The architecture consists of:

- *Input layer:* 8 neurons (Length, Width, spacing between purlins, Top chord length, Purlin spacing, DL, LL, WL).
- *Hidden layer:* 10 neurons (optimal among 1–20 tested).
- *Output layer:* 6 neurons (cross-sectional area of Riser, Rafter, Vertical chord, Incline chord, Purlins, Column).

An ANN model was developed to efficiently predict the cross-sectional areas of steel pipe members in polyhouse roof trusses. The model was trained using a dataset of 340 distinct truss configurations generated in STAAD.Pro.

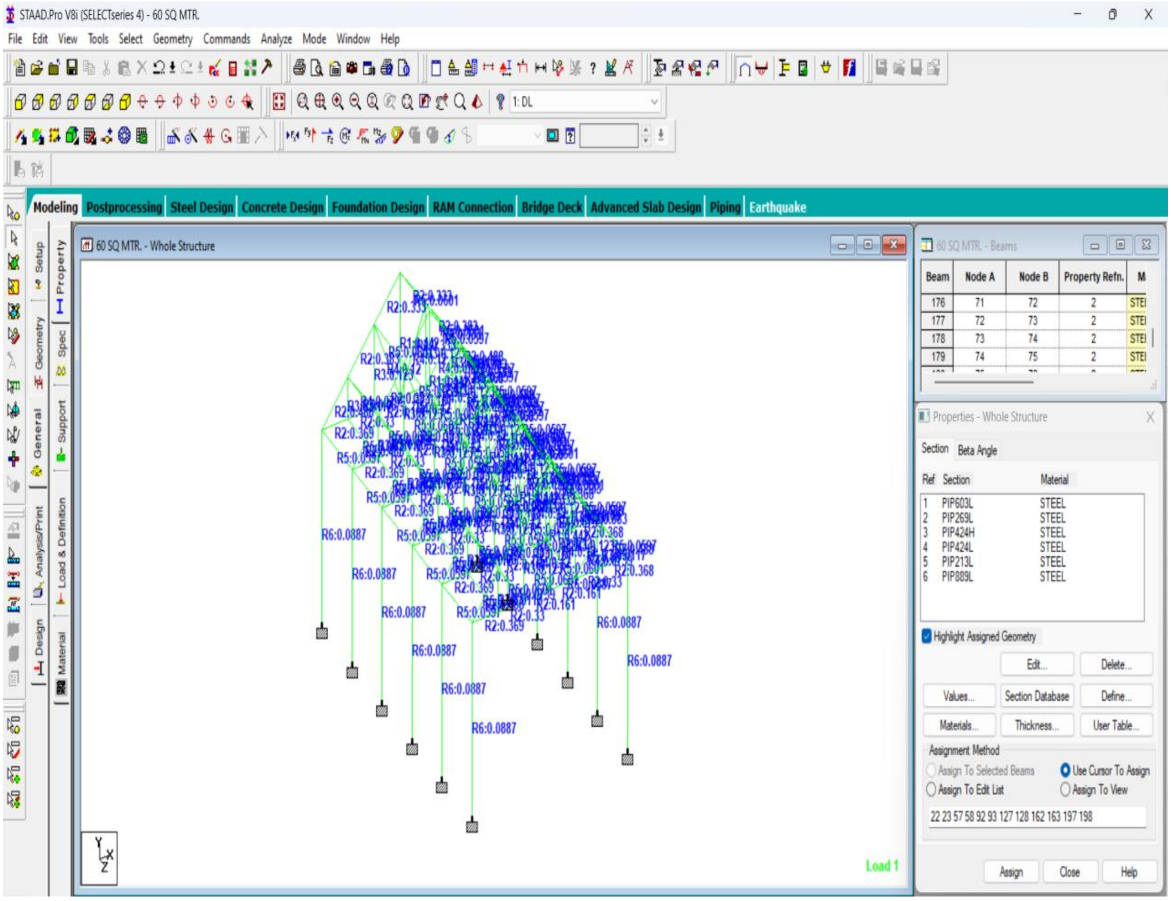

Figure 2. 3D Result showing the sections passes the design load combinations.

Table 2. Training and Testing of developed models.

Training variables	Assigned value
Neural Network	Feed-forward back propagation
Hidden Layer	10
No. of Neurons	1 to 20
Learning function	LEARNGDM (Levenberg Marquardt)
Transfer function	Tansig
Performance function	MSE (Mean squared Error)
Training function	TRAINLM
Epoch	1000

Each configuration included eight key input parameters—length, width, purlin spacing, top chord length, dead load, live load, and wind load—representing the primary factors governing structural demand. These inputs were paired with STAAD.Pro-derived cross-sectional areas for the riser, rafter, vertical chord, inclined chord, purlins, and column, forming a complete supervised dataset for ANN training Table 2.

A feedforward backpropagation ANN was adopted for its ability to model nonlinear input–output relationships. The network was developed in MATLAB using the Neural Network Toolbox and tested with varying hidden-layer sizes. A single hidden layer with ten neurons achieved the best balance between accuracy, efficiency, and generalisation. The tansig activation function was used in the hidden layer to capture nonlinear interactions, while the Levenberg–Marquardt (trainlm) algorithm was employed for training due to its fast convergence and suitability for medium-sized datasets.

To promote generalisation and prevent overfitting, the dataset was split into 70% for training, 15% for validation, and 15% for testing.

The formula below is used to determine the root mean square error (RMSE) between the observed and anticipated values:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Qoi-Qpi)^2}{n}} \tag{1}$$

Where, “Q_{oi} is i^{th} observed values of the cross-sectional area of the steel pipes, Q_{pi} is i^{th} predicted values of the cross-sectional area of the steel pipes and n is the number of observations.”

Model performance was further assessed using regression plots, performance curves, and error histograms. The regression results showed strong agreement between predicted and target values, with correlation coefficients close to unity. Performance curves indicated an early and stable minimum in validation error, while error histograms showed errors concentrated near zero. Together, these results confirm that the ANN effectively captured the underlying structural relationships and produced predictions closely matching STAAD.Pro outcomes Figure 3.

During training, the network iteratively adjusted its internal weights and biases to minimise the root mean squared error (RMSE) between STAAD.Pro outputs and ANN predictions. The evolution of training progress, including RMSE reduction and gradient behaviour, was monitored through MATLAB’s performance visualisation tools. The network converged smoothly, with both the training and validation curves showing rapid error reduction and stable alignment.

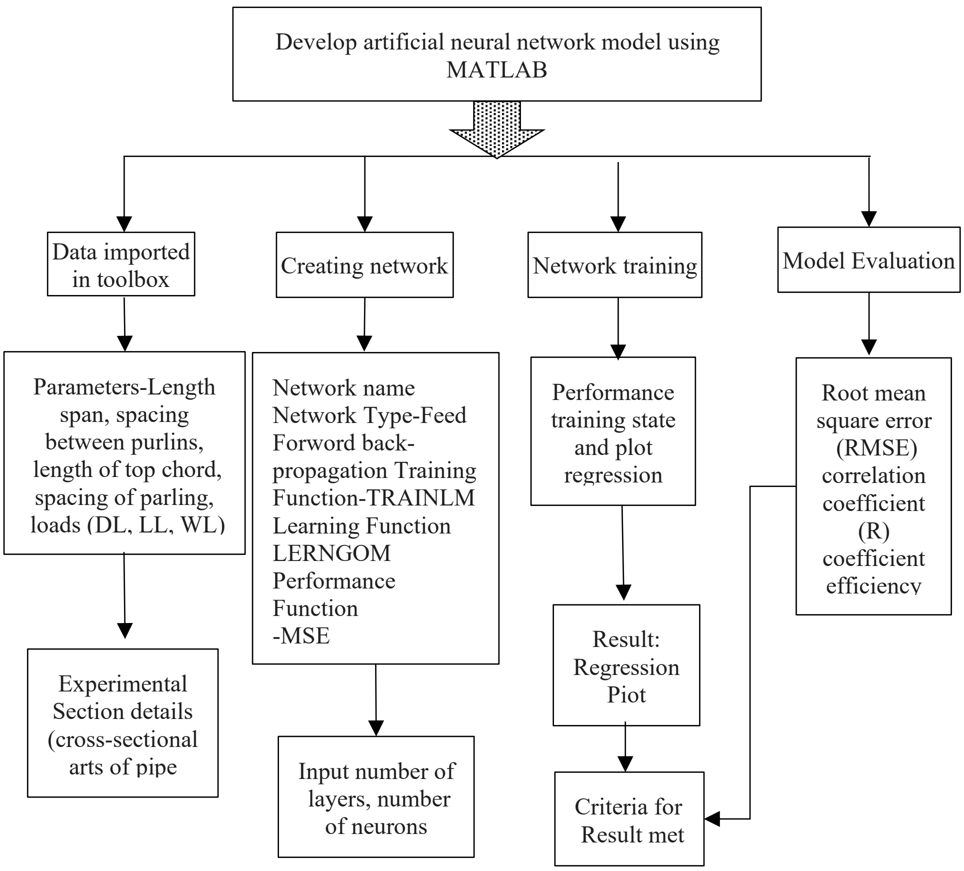

Figure 3. Flow chart of ANN methodology.

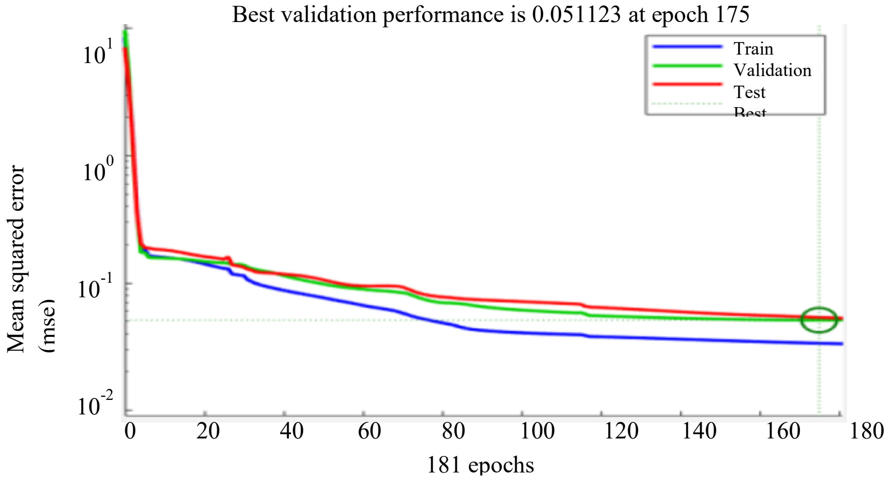

Figure 4. Performance curve of network created.

Table 3. Comparison between cross-sectional area obtained through ANN predictions and STAAD.Pro outputs

Output obtained from	Riser	Rafter	Vertical chord	Inclined chord	Purlins	Column
	(cm^2)					
STAAD.Pro	5.23	1.78	4.83	4.83	1.21	8.62
ANN	5.2	1.8	4.3	4.81	1.23	8.61
Error (ANN-STAAD.Pro)	-0.03	0.02	-0.53	0.02	-0.02	-0.01

The following formula is used to get the correlation coefficient.

$$R = \frac{\sum_{i=1}^{n}(Qoi-\overline{Qo})(Qpi-\overline{Qp})}{\sqrt{\sum_{i=1}^{n}(Qoi-Qo)^2}\sqrt{\sum_{i=0}^{n}(Qpi-Qp)^2} \quad (2)$$

Once training was completed, the final network configuration was saved and subsequently evaluated using the testing dataset. Testing results confirmed that the network was able to generalise beyond the training examples, accurately predicting section sizes across configurations it had not previously encountered Figure 4.

Where, "$\overline{Qo}$ is representing the average of the cross-sectional area of the steel pipe members and $\overline{Qp}$ represent the average of the predicted cross-sectional area of the steel pipe members of the polyhouses series, whereas other symbols have the same meaning of the previous section."

Overall, the results show that a well-trained feedforward ANN can accurately replicate the behaviour of detailed computational design software. Its ability to rapidly predict cross-sectional areas without repeated structural analysis makes it an effective tool for preliminary design, optimisation, and real-time decision-making in polyhouse roof truss engineering.

RESULTS AND DISCUSSION

Structural modelling in STAAD.Pro generated a dataset of 340 polyhouse truss configurations covering varied geometric parameters and environmental loads. For each case, safe and economical cross-sectional areas were obtained for the riser, rafter, vertical chord, inclined chord, purlins, and column members. The analysis focused on determining steel pipe sections under different load combinations, including a design wind speed of 37 m/s as specified by IS codes for the Almora region of Uttarakhand, India. These STAAD.Pro outputs served as the reference dataset for evaluating ANN predictions. The dataset reflects a wide range of structural responses due to variations in span, purlin spacing, chord dimensions, and load intensities, providing a robust basis for training the predictive model Table 3.

Comparison of ANN predictions with STAAD.Pro results showed excellent accuracy for all truss members, with only minor deviations. Although the vertical chord exhibited slightly higher variation in some cases, errors remained within acceptable engineering limits. Overall results from all 340 structures showed strong agreement between ANN and STAAD.Pro values, confirming the model's ability to generalise across diverse structural conditions Table 4.

These results signify minimal absolute deviation between predicted and actual outputs and validate the suitability of the ANN for high-precision structural prediction tasks. Regression plots generated during training illustrated a tight clustering of predicted values around the best-fit line, while performance plots showed rapid error reduction and stable convergence with no signs of overfitting, as the validation error remained consistent with training error Figure 5–7.

Overall, the results confirm that ANN modelling is a powerful and efficient alternative to conventional STAAD.Pro–based design iterations for determining the cross-sectional properties of polyhouse roof truss members. The high predictive accuracy, combined with significantly reduced computation time, establishes the ANN approach as a practical tool for structural optimisation in agricultural infrastructure.

Table 4. Results obtained from ANN.

Network architecture	Training		Validation		Testing		Overall	
	RMSE	R^2	***RMSE***	R^2	***RMSE***	R^2	***RMSE***	R^2
ANN	0.021	0.998	0.0067	0.997	0.036	0.997	0.022	0.997

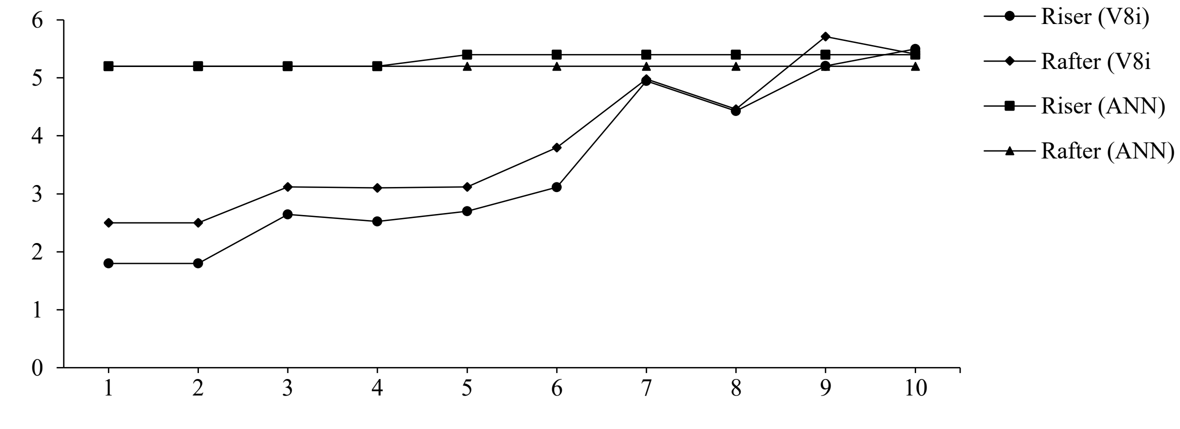

Figure 5. ANN vs Staad pro result (RISER and RAFTER).

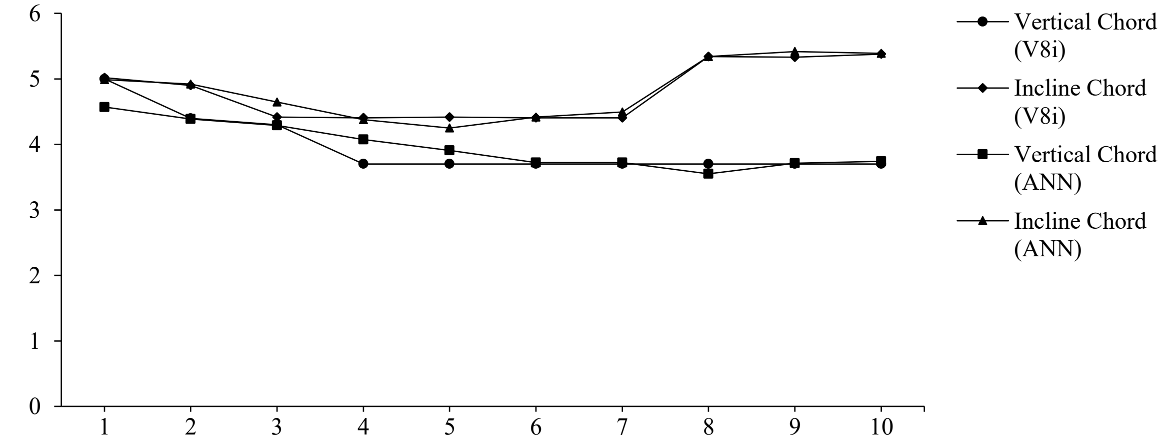

Figure 6. ANN vs Staad pro result (vertical chord and incline chord).

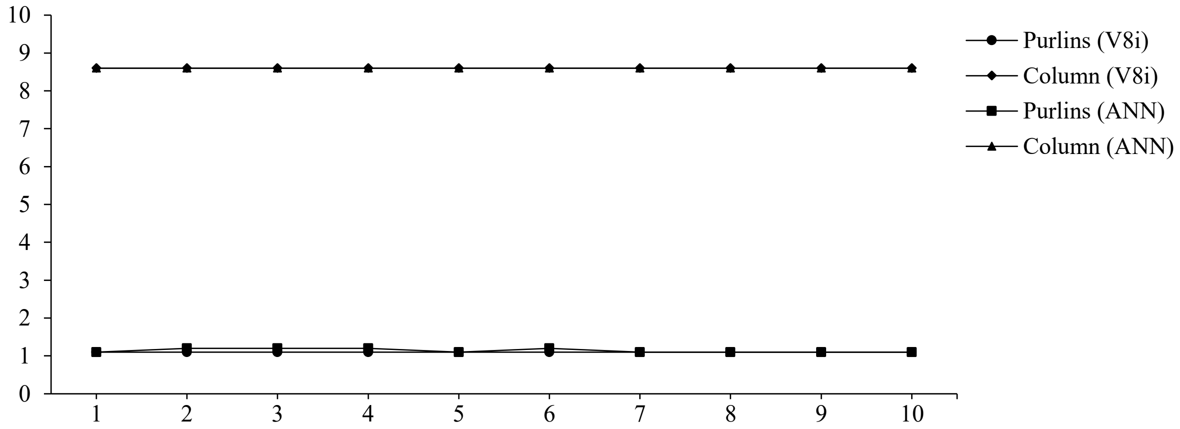

Figure 7. ANN vs Staad pro result (purlins and column).

The ability of the ANN to replicate STAAD.Pro behaviour with near-perfect consistency underscores its potential to support rapid design cycles, parameter studies, and automated decision-making in polyhouse engineering.

In addition to accuracy, the study assessed the economic performance of different section types. STAAD.Pro analyses comparing I-, T-, channel, and pipe sections showed that pipe sections are the most cost-efficient for polyhouse structures due to lower material use, simpler fabrication, lighter weight, and easier installation. Although I- and T-sections provide higher strength, their greater material demand and fabrication complexity make them less suitable for lightweight agricultural applications, while channel sections offer only moderate savings. The close agreement between ANN predictions and STAAD.Pro results further confirms that pipe sections can be safely and effectively optimised using machine learning Figure 8.

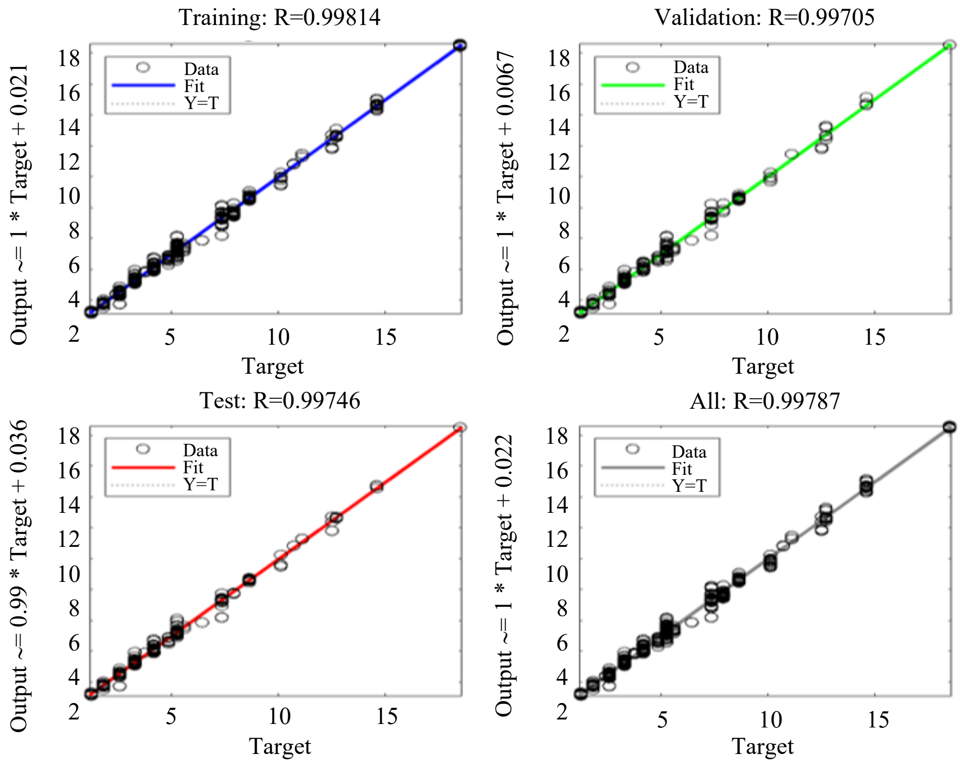

Figure 8. Graph between experimental (target) cross-section area of pipe and predicted (output) cross-section area of pipe.

CONCLUSION

This study demonstrates the effectiveness of Artificial Neural Networks (ANNs) in optimising the cross-sectional design of steel pipe members for polyhouse roof trusses. A dataset of 340 truss configurations generated through STAAD.Pro analysis enabled the ANN to learn nonlinear relationships between geometry, loads, and structural demand. Trained using the Levenberg–Marquardt algorithm and rigorously validated, the model achieved high predictive accuracy (correlation coefficient ≈ 0.997) with minimal errors, closely replicating STAAD.Pro results while eliminating repetitive computational design iterations.

Beyond accuracy, the ANN provides clear practical benefits by enabling rapid member-size prediction, reducing computational effort, and supporting efficient evaluation of multiple design alternatives. The study also confirms that pipe sections are the most economical choice for lightweight polyhouse structures compared to I-, T-, and channel sections, and shows that their optimal sizing can be reliably predicted using ANN across varied conditions. Overall, ANN-based modelling emerges as an efficient, accurate, and scalable tool for polyhouse truss design, with strong potential for integration into automated and AI-driven structural optimisation frameworks.

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