

Application of Artificial Neural Networks in Optimizing Polyhouse Roof Truss Design

Deepak Kulyal^{1,*}, V.K. Verma², Aman Kumar³

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 the year-round production of crops. Unlike open-field cultivation, polyhouses create a controlled microclimate that protects crops from adverse weather and environmental stress. This performance depends on a stable and economical roof truss

system that can safely resist 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 is time-consuming when numerous structural configurations must be assessed. The growing variation in polyhouse geometry, span, purlin spacing, and wind conditions has increased the demand for faster and scalable design methods. The

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traditional trial-and-error section selection with 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 that of 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 this 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 purposes. A comparison between the ANN predictions and the 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 optimization, 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 terms of material optimization, environmental loading, and overall stability. Early studies on structural optimization developed algorithms for discrete structural improvement using modified Rosenbrock orthogonalization procedures and gradient-based methods. Their work demonstrated that the appropriate selection of steel member sections can substantially influence the 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 the static and dynamic behavior 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 has 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 reinforce 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 behavior of tubular members under bending stresses further validated their suitability for lightweight agricultural structures. Additionally, surveys provided insights into widespread greenhouse practices in Korea, informing the development of standardized models and safety guidelines [21].

Wind loading is 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 emphasized 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 the 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 the ANN capability in recognizing structural behavior patterns, even with limited measurements. ANN to the fully stressed design of Pratt and Howe trusses, achieving prediction errors as low as 2.51% compared to the STAAD.Pro outputs. These results confirm the potential of ANNs as computationally efficient surrogates for structural design software. More recent contributions have 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: an increased reliance on FEA-based computational tools for accurate polyhouse design and the growing use of machine learning for structural prediction and optimization. However, ANN models calibrated using large, controlled computational datasets for polyhouse roof truss design remain limited. This study addresses this gap by integrating the STAAD.Pro-generated data with ANN-based modelling to develop a fast, accurate, and economical method for optimizing 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 favorable strength-to-weight ratio. Their geometric uniformity, corrosion resistance, and ease of fabrication make them well-suited for lightweight agricultural structures. All sections complied 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 the light, medium, and heavy classes, with cross-sectional areas between 1.21 cm² and 87.4 cm². These areas served as the primary output variables for training the ANN model to predict suitable member sizes under varying load conditions.

Methods

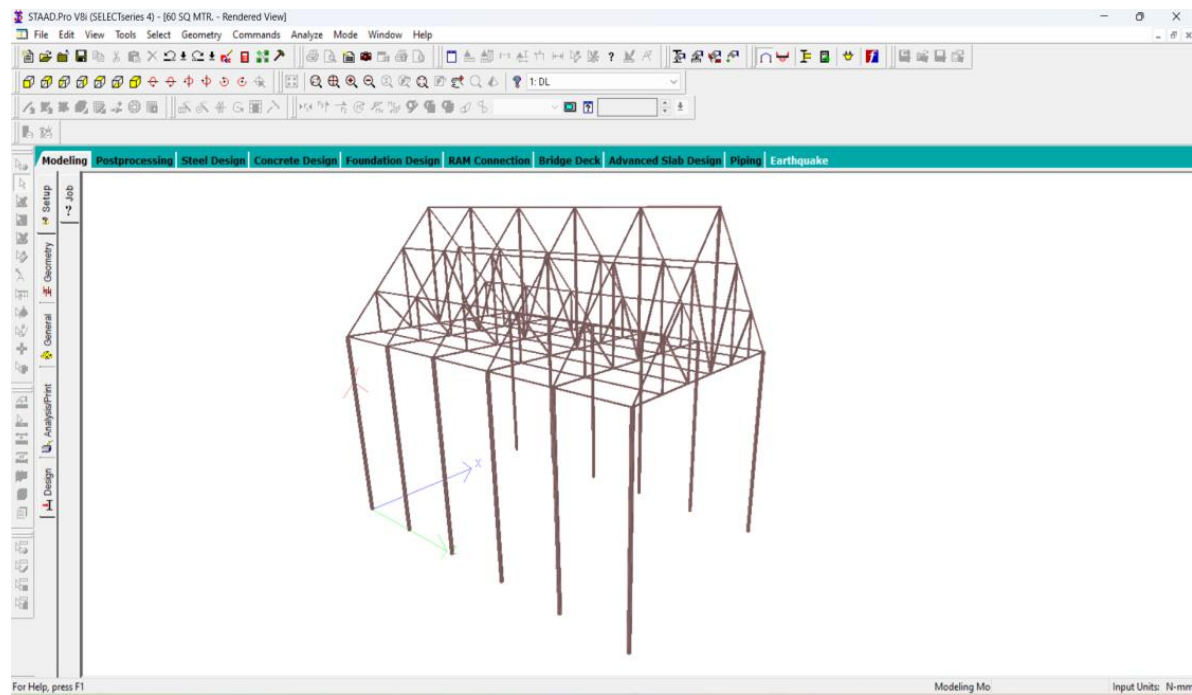
Structural Modelling Using STAAD.Pro

A detailed computational workflow was adopted to generate the dataset required to train the ANN model. STAAD.Pro was used to perform the structural analysis and design of the 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 the 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 number of panel points, resulting in the generation of 340 structurally distinct polyhouse models.
2. *Load calculations:* load intensities were calculated according to the relevant IS codes. The dead load was evaluated using IS 875 (Part 1), including the self-weight of the truss members, purlins, and polycarbonate roofing. The live load was determined according to IS 875 (Part 2), adjusted for the roof slope, and verified against IS 14462:1997 greenhouse guidelines. The wind load was computed following IS 875 (Part 3), considering the terrain, topography, risk coefficients, and hill-region effects to obtain the design wind speed and wind pressure using appropriate external and internal pressure coefficients. The typical results yielded a dead load of 3.809 kN, live load of 0.924 kN, and wind load of 3.21 kN.
3. *Assignment of section properties and boundary conditions:* Pipe sections were assigned to the riser, rafter, vertical chord, incline chord, purlins, and column members. Initial trial sections were selected based on engineering judgement, after which the STAAD.Pro design module (IS:800–2007) iteratively updated the section sizes until all members satisfied the strength and serviceability criteria. This process produced the target cross-sectional area outputs for each model, which were 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, that is, riser, rafter, vertical chord, inclined chord, purlins, and column (cross-sectional area and section of each truss component), as shown in Figures 1 and 2.

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

S.N.	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 the following:

- *Input layer:* eight neurons (Length, Width, spacing between purlins, top chord length, purlin spacing, DL, LL, and WL).
- *Hidden layer:* 10 neurons (optimal among 1–20 tested).
- *Output layer:* 6 neurons (cross-sectional areas 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.

Each configuration included eight key input parameters: length, width, purlin spacing, top chord length, dead load, live load, and wind load, which represent the primary factors governing the structural demand. These inputs were paired with the 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, as shown in Table 2.

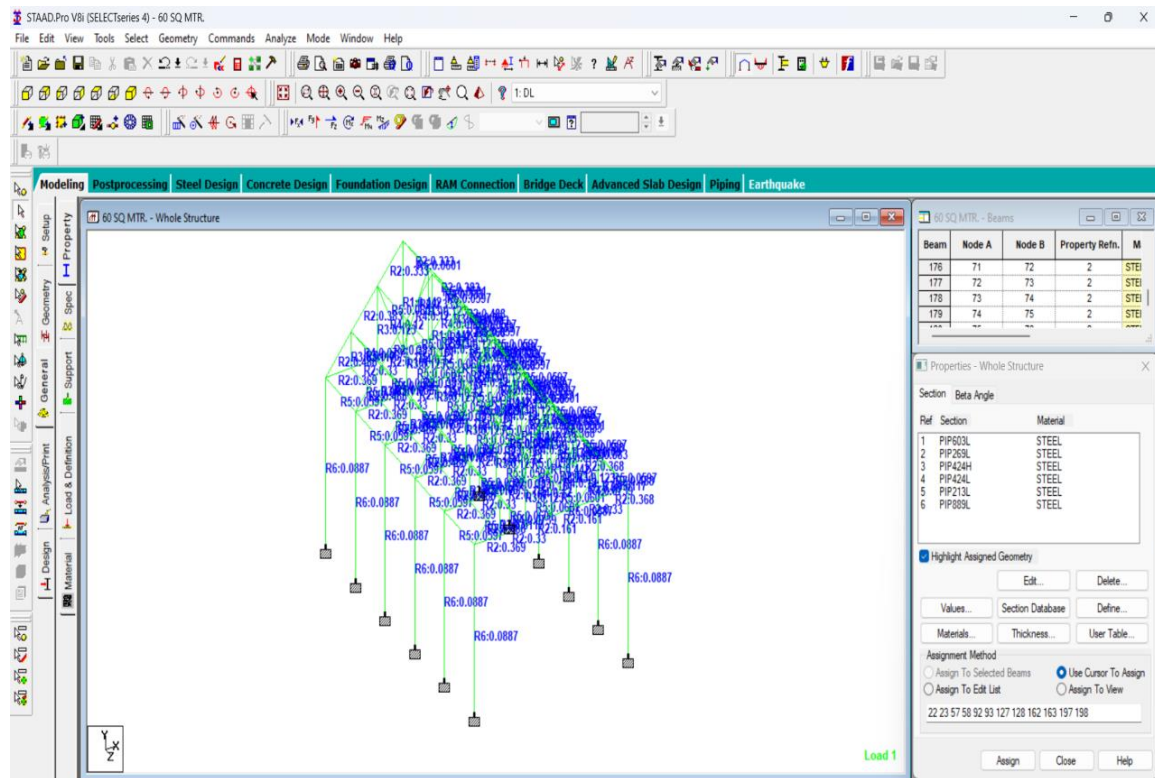


Figure 2. 3D Result showing the sections passes the design load combinations.

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

A feedforward backpropagation ANN was adopted because of 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 generalization. The tansig activation function was used in the hidden layer to capture nonlinear interactions, while the Levenberg–Marquardt (trainlm) algorithm was employed for training because of its fast convergence and suitability for medium-sized datasets.

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

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Q_{oi} - Q_{pi})^2}{n}} \quad (1)$$

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

The model performance was further assessed using regression plots, performance curves, and error histograms. The regression results showed a strong agreement between the predicted and target values, with correlation coefficients close to unity. The performance curves indicated an early and stable minimum in the validation error, whereas the 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 the STAAD.Pro outcomes Figure 3.

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

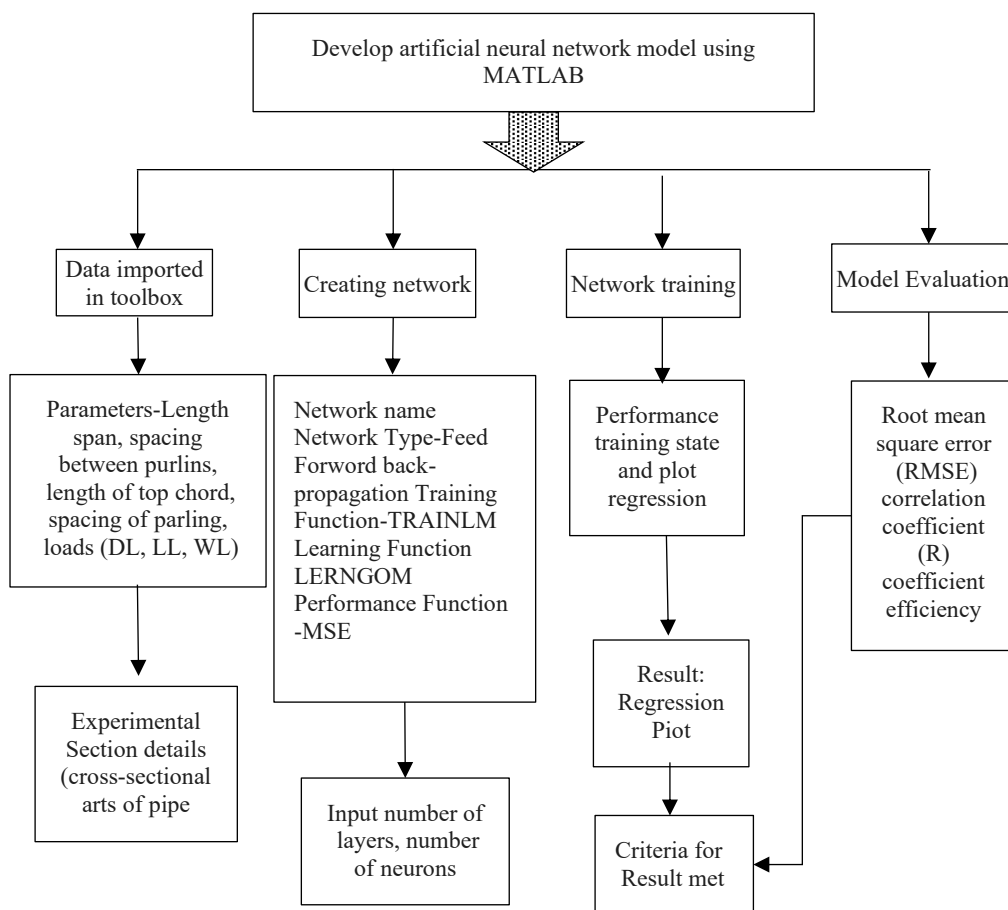


Figure 3. Flow chart of ANN methodology.

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

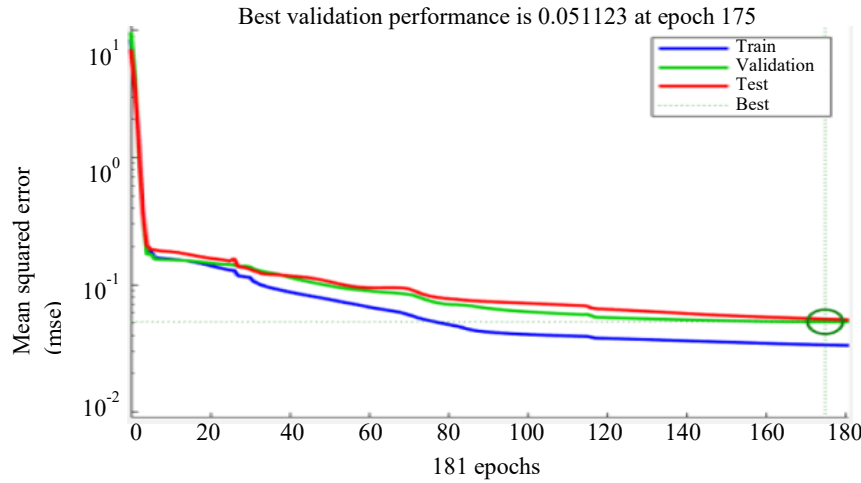


Figure 4. Performance curve of network created.

The following formula is used to get the correlation coefficient.

$$R = \frac{\sum_{i=1}^n (Q_{oi} - \overline{Q_o})(Q_{pi} - \overline{Q_p})}{\sqrt{\sum_{i=1}^n (Q_{oi} - \overline{Q_o})^2} \sqrt{\sum_{i=1}^n (Q_{pi} - \overline{Q_p})^2}} \quad (2)$$

Once the training was completed, the final network configuration was saved and subsequently evaluated using the testing dataset. The testing results confirmed that the network could generalize beyond the training examples, accurately predicting section sizes across configurations that it had not previously encountered (Figure 4).

where , “ $\overline{Q_o}$ represents the average of the cross-sectional area of the steel pipe members, $\overline{Q_p}$ represents the average of the predicted cross-sectional area of the steel pipe members of the polyhouse series, and the other symbols have the same meaning as in the previous section.”

Overall, the results show that a well-trained feedforward ANN can accurately replicate the behavior 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, optimization, 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 various geometric parameters and environmental loads. For each case, safe and economical cross-sectional areas were obtained for the riser, rafter, vertical chord, inclined chord, purlin, and column members. The analysis focused on determining the steel pipe sections under different load combinations, including a design wind speed of 37 m/s, as specified by the IS codes for the Almora region of Uttarakhand, India. The STAAD.Pro outputs served as the reference dataset for evaluating the ANN predictions. The dataset reflects a wide range of structural responses owing to variations in the span, purlin spacing, chord dimensions, and load intensities, providing a robust basis for training the predictive model, as shown in Table 3.

A comparison of the ANN predictions with the STAAD.Pro results showed excellent accuracy for all truss members, with only minor deviations. Although the vertical chord exhibited slightly higher variations in some cases, the 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 generalize across diverse structural conditions (Table 4).

These results indicate a minimal absolute deviation between the predicted and actual outputs and validate the suitability of ANN for high-precision structural prediction tasks. The regression plots generated during training illustrated a tight clustering of predicted values around the best-fit line, while the performance plots showed rapid error reduction and stable convergence with no signs of overfitting, as the validation error remained consistent with the training error (Figures 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 a significantly reduced computation time, establishes the ANN approach as a practical tool for structural optimization in agricultural infrastructure.

Table 4. Results obtained from ANN.

Network architecture	Training		Validation		Testing		Overall	
	<i>RMSE</i>	R^2	<i>RMSE</i>	R^2	<i>RMSE</i>	R^2	<i>RMSE</i>	R^2
ANN	0.021	0.998	0.0067	0.997	0.036	0.997	0.022	0.997

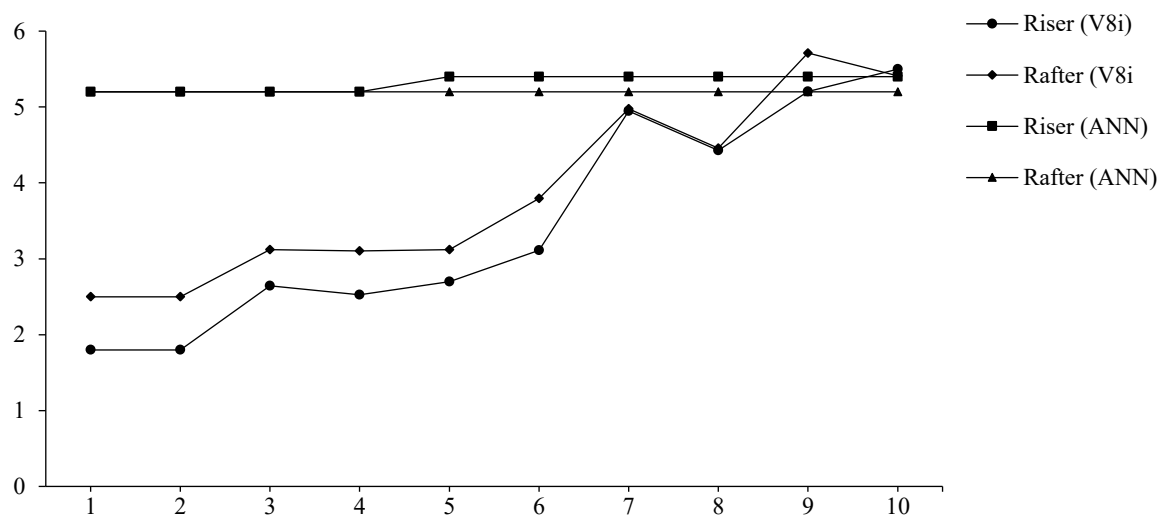


Figure 5. ANN versus Staad pro result (RISER and RAFTER).

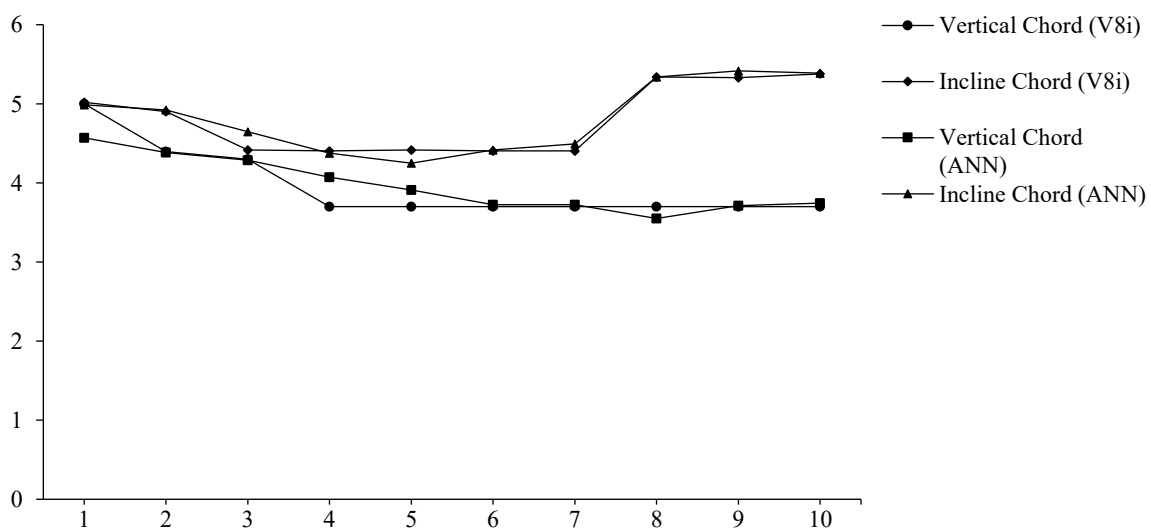


Figure 6. ANN versus Staad pro result (vertical chord and incline chord).

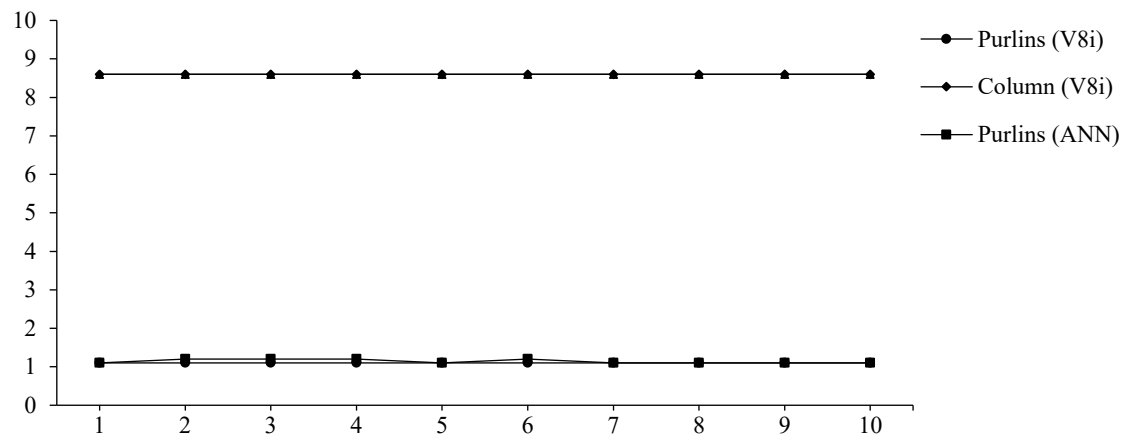


Figure 7. ANN versus Staad pro result (purlins and column).

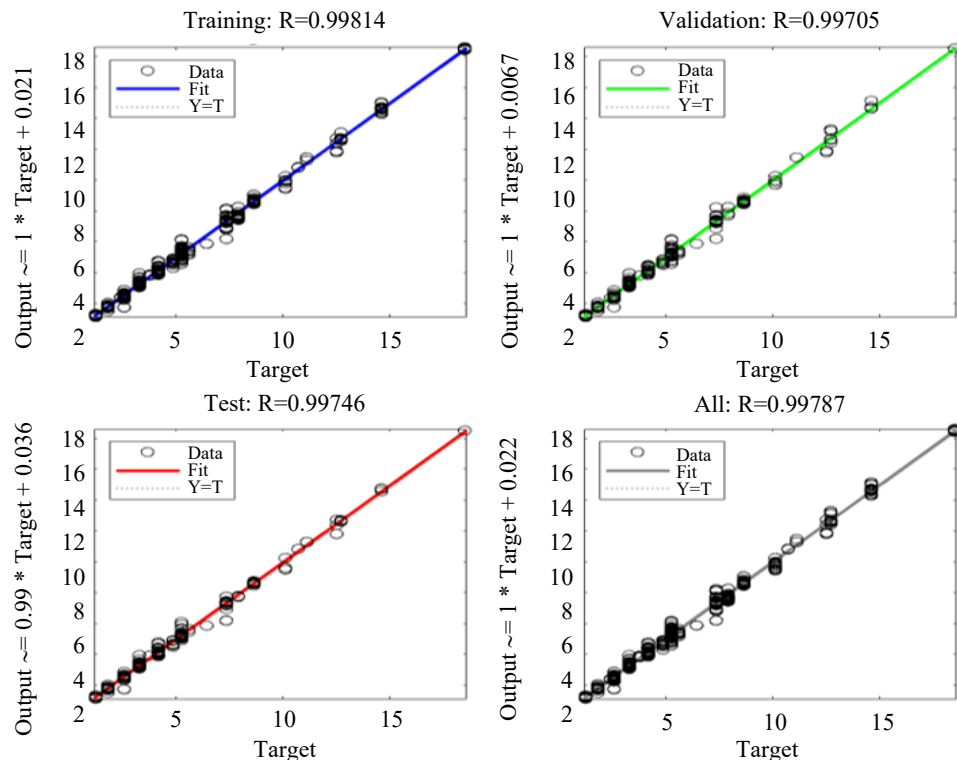


Figure 8. Graph between experimental (target) and predicted (output) cross-sectional areas of the pipe.

The ability of the ANN to replicate the STAAD.Pro behavior 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, this 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 because of 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, whereas channel sections offer only moderate savings. The close agreement between the ANN predictions and STAAD.Pro results further confirms that pipe sections can be safely and effectively optimized using machine learning, as shown in Figure 8.

CONCLUSION

This study demonstrates the effectiveness of Artificial Neural Networks (ANNs) in optimizing 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 the 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 the STAAD.Pro results while eliminating repetitive computational design iterations.

Beyond accuracy, 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 confirmed that pipe sections are the most economical choice for lightweight polyhouse structures compared to I-, T-, and channel sections, and showed that their optimal sizing can be reliably predicted using ANN across varied conditions. Overall, ANN-based modelling has emerged as an efficient, accurate, and scalable tool for polyhouse truss design, with strong potential for integration into automated and AI-driven structural optimization frameworks.

REFERENCES

1. Amir, H. M., & Hasegawa, T. 1988. Greenhouse structure design optimization. *J. Irrig. Eng. Rural Plan.*, (14): 33–52.
2. Choi, Yun, and Yoon. 2014. Survey Analysis of the Characteristics of Greenhouses in Korea– *Int. J. Environ. Rural Dev.*, 5–1.
3. Farooq, F., Amin, N. M., Khan, K., Sadiq, R. M., Javed, M. F., Aslam, F. and Alyousef, R. 2020. A comparative study of random forest and genetic engineering programming for the prediction of compressive strength of high strength concrete (HSC). *Appl. Sci.*, 10(20): 1–18.
4. Gao, Y., & Yang, X. 2021. Research on Deep Convolutional Neural Network in Damage Identification of Truss Structure. ‘In: *IOP Conference Series: Earth and Environmental Science*, (LIMIT-2021 in June). pp. 12–33.
5. Ghani, S., Bakochristou, F., ElBialy, E. M. A. A., Gamaledin, S. M. A., Rashwan, M. M., Abdelhalim, A. M., & Ismail, S. M. (2019). Design challenges of agricultural greenhouses in hot and arid environments A review. *EAEF*, 12(1), 48–70.
6. Gupta, D., Santosh, D. T., Debnath, S., Maitra, S., & Gaikwad, D. 2020. Modeling and simulation application for greenhouse microclimatic studies and structural analysis. *PCSA*, 300–312.
7. IS:1161. 1998. “Steel tubes for structural purposes”, New Delhi, India.
8. IS:14462. 1997. “Recommendations for stack sampling for particulate matter determination including safety requirements”, New Delhi, India.
9. IS:800. 2007. General construction in steel - Code of practice. New Delhi: Bureau of Indian Standards, New Delhi, India.
10. IS:875, Part 1. 2015. Indian Standard Code of Practice for Design Dead Load on Buildings and Structures, Second Revision, New Delhi, India.
11. IS:875, Part 2. 2015. Indian Standard Code of Practice for Design Live Load on Buildings and Structures, Second Revision, New Delhi, India.
12. IS:875, Part 3. 2015. Indian Standard Code of Practice for Design Wind Load on Buildings and Structures, Second Revision, New Delhi, India.
13. Kalyanshetti, M. G., & Mirajkar, G. S. 2012. Comparison between conventional steel structures and tubular steel structures. *Int. J. Eng. Res. Appl.*, 2(6), 1460–1464.
14. Kendirli, B. 2006. Structural analysis of greenhouses: A case study in Turkey. *Build. Environ.*, 41(7), 864–871.
15. Krishna, D. A., Priyadarsini, R. S. and Narayanan, S. 2021. High temperature effects on different grades of concrete. *Sadhana*, 46(1): 1–12.
16. Liu, Z., Jiang, A., Shao, W., Zhang, A., & Du, X. 2021. Artificial-neural-network-based mechanical simulation prediction method for wheel-spoke cable truss construction. *International Journal of Steel Structures*, 21(3), 1032–1052.

17. Mehrjoo, M. & Khaji, N. & Moharrami, Hamid & Bahreinineja, Ardeshir. 2008. Damage detection of truss bridge joints using Artificial Neural Network. Expert system with application. 35. 1122-1131. 10.1016/j.eswa.2007.08.008.
18. Patrikar, A., & Pathak, K. K. 2016. Fully stressed design of Fink truss using STAAD. Pro software. Open J. Civ. Eng., 6(4), 631–642.
19. Saltuk, B. 2019. Structural analysis example of steel construction greenhouses. ABTD, (16), 61–68.
20. Satpaise, W. B., & Lande, S. P. 2005. Optimization of different types of steel trusses using fully stressed design concept, IETIR (1): pp. 1–17.
21. Saxena, S., & Pathak, K. K. 2015. Application of artificial neural networks for fully stressed design of Pratt and Howe Truss. New Technologies Sci. Eng, (2): 94–103.
22. Singh, L., Kaushal, A. and Digra, A., 2021. A review on stability of polyhouse structures. International Journal of Agricultural Sciences, 17, pp.285–291.