PARAMETRIC STUDY OF WARREN STEEL TRUSS BRIDGE USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Steel truss bridges are a popular type of amongst several other standard bridges in Indonesia due to their light-weight yet robust and strong structure. In this study Artificial Neural Networks is used to optimize the dimensions of the steel truss bridge. The Artificial Neural Network method was chosen as it can handle complex and nonlinear problems, as well as its potential to generate accurate prediction models. Data of 319 existing constructed steel truss bridges in Indonesia were used to train the Artificial Neural Network model. The results show that the Artificial Neural Network model can predict the stress ratio of the structural elements of steel truss bridges with high accuracy ($R^2 > 0.99$). The trained ANN model was then used to optimize the dimensions of the steel truss bridges with spans range from 40 meters to 60 meters with interval of 5 meters. The optimization results showed a 5.60% weight reduction compared to previous research results and a 20% less compared to the average weight of the existing bridge. This study contributes to improving the efficiency of development steel truss bridge in Indonesia.

Keywords: truss bridge; optimization; Artificial Neural Network; design efficiency

Abstrak

Jembatan rangka baja merupakan jenis jembatan standar yang populer di Indonesia karena struktur yang ringan namun kuat dan kokoh. Pada penelitian ini, Artificial Neural Network digunakan untuk mengoptimalkan dimensi jembatan rangka baja. Metode ini dipilih karena kemampuannya menangani masalah kompleks dan nonlinier, serta potensinya untuk menghasilkan model prediksi yang akurat. Data 319 jembatan rangka baja yang ada di Indonesia digunakan untuk melatih model Artificial Neural Network. Hasilnya menunjukkan bahwa model Artificial Neural Network dapat memprediksi rasio tegangan pada elemen struktural jembatan rangka baja dengan akurasi yang tinggi. Model Artificial Neural Network yang terlatih kemudian digunakan untuk mengoptimalkan dimensi jembatan rangka baja dengan rentang bentang 40 meter hingga 60 meter dengan interval 5 meter. Hasil optimasi menunjukkan efisiensi berat sebesar 5,60% dibandingkan dengan penelitian sebelumnya dan 20% lebih efisien dibandingkan dengan jembatan yang sudah ada. Penelitian ini berkontribusi dalam meningkatkan efisiensi pengembangan jembatan rangka baja di Indonesia.

Kata-kata kunci: jembatan rangka baja; optimasi; Artificial Neural Network; efisiensi desain

INTRODUCTION

Bridges are essential infrastructure that facilitates transportation and connectivity, playing a crucial role in supporting national development (Kementerian PUPR, 2015). In Indonesia, standard bridges, are characterized by their simple structures and short spans (un-der 60 meters), constitute a significant portion of the bridge population. Among these, steel truss bridges are particularly prevalent, accounted for approximately 12% of all bridges. The demand for these bridge types is substantial and continues to grow.

However, analysis of existing bridge designs and e-catalog data reveals inconsistencies in bridge dimensions for the same span length. This suggests that current bridge designs and type selections may not be optimal in terms of steel volume, potentially leading to increased construction costs. To address this issue, this research proposes a method that can optimize dimensions of steel truss bridges, aiming to minimize construction costs in Indonesia.

In the bridge design stage, optimization is a critical step to minimize costs, enhance resource efficiency, and maximize construction benefits. The application of optimization techniques, which is continuously expanding with different type of approachs, has had a significant impact to reduce the construction cost.

In addition, as the design process of a bridge involved time-consuming and complex structural analysis and design drawings, as weel as inconsistent and ineffective design data input, resulting in a non-optimal design. The expertise of the engineers, including designed time available, can significantly influence the quality of the design products. Often, designed engineer allocates inappropriate high a safety factors, hence wasteful which is lead to inefficient and ineffective designs.

Research related to the optimization of steel structures was conducted by Tinkov and Safonov (2017), who optimized the distribution of carbon fiber in steel frame structures using a genetic algorithm. Their research results stated that the appropriate amount of carbon fiber for steel frame structures is 7.4% of the structure's weight.

Aydin (2022) conducted research on the size, layout, and tendon profile for steel truss bridges using the Jaya Algorithm. The results of Aydin's research (2022) stated that prestressing in steel truss bridges can save costs and optimize the design of steel truss bridges.

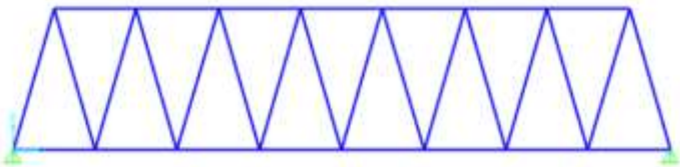
Furthermore, Serpik and Tarasova (2020) also conducted research on steel truss bridges reinforced with prestressing. The result of this research is a proposed method in the form of a multi-stage prestressing condition that can be used to analyze steel truss bridges.

Optimization of steel truss bridges was conducted using the Teaching-Learning Based Optimization (TLBO) and Biogeography-Based Optimization (BBO) methods to minimize the weight of the structure (Artar and Carbas, 2021).

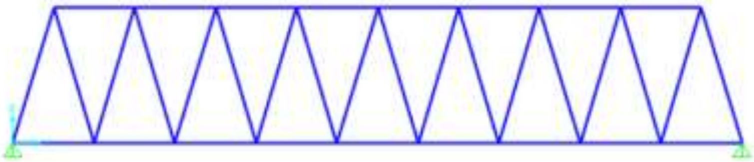
Wang et al. (2023) developed an optimization algorithm for the design of steel truss bridges with 2-layer roof braces using the Response Surface Method and Particle Swarm Optimization. The optimization results obtained include optimization in terms of superstructure work, optimization of vertical deflection, and optimization of forces in structural elements.

The optimization for other steel structure are also conducted, Topology-related bridge optimization was conducted to achieve bridge stability by Baandrup et al. (2020), resulting in an optimal steel weight for the girder frame on a cable-stayed bridge, which can save up to 54% of the overall steel weight. Optimization of the use of high-grade steel for bridge construction was carried out to obtain the optimum weight, cost, and environmental impact between conventional steel and high-grade steel (Skoglund et al., 2020). Optimization of steel structures for bridges was also conducted by Mohammed (2020), who examined the optimization of steel box girders using a Genetic Algorithm for volume optimization. Additionally, an analysis for the optimization of steel box girders based on fatigue performance was conducted by Zhuang et al. (2019).

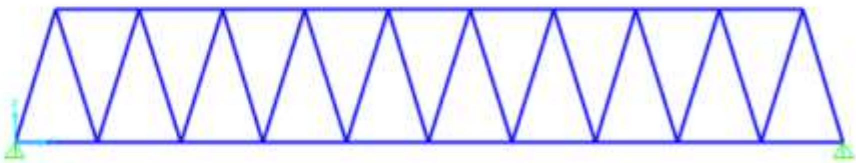
To streamline the optimization process and enhance design efficiency, this research proposes utilizing Artificial Intelligence (AI) methods, specifically Artificial Neural Networks (ANN). ANNs have shown promising results in modeling nonlinear and complex relationships, making them suitable for developing models to predict and optimize bridge dimensions. By using ANNs, an optimal bridge dimensions can be obtained, saving in time-consuming while ensuring consistent designs products.



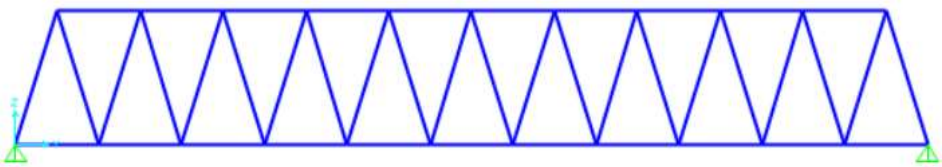
(a) Warren truss bridge of 40 m long



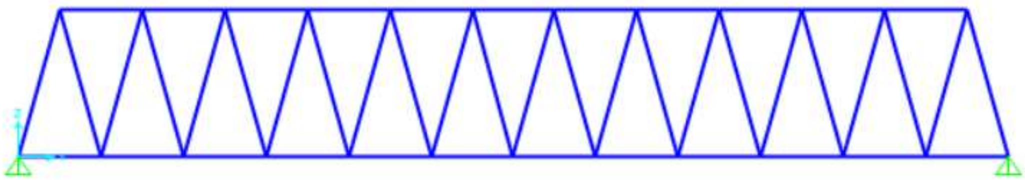
(b) Warren truss bridge of 45 m long



(c) Warren truss bridge of 50 m long



(d) Warren truss bridge of 55 m long



(e) Warren truss bridge of 60 m long

Figure 1 Warren Steel Truss Bridge Span of 40 m, 45 m, 50 m, 55 m, and 60 m

Research Limitation

The research have several limitations below:

1) Single-span simply supported class-A Warren steel truss bridge spans 40, 45, 50, 55, and 60 meters which shown in Figure 1.
2) The optimizations based on steel structure weight, concrete bridge deck is not included.
3) Bridge loading code based on SNI 1725:2016 (Badan Standardisasi Nasional, 2016), Practical Guide for Technical Bridge Planning No. 2/M/BM/2021(Direktorat Jenderal Bina Marga, 2021), and Standard Bridge Design Criteria No. 05/SE/Db/2017 (Direktorat Jenderal Bina Marga, 2017).

Research Method

The method of this research involved several key steps to achieve the optimum steel truss bridge member dimensions using ANN shown in Figure 2.

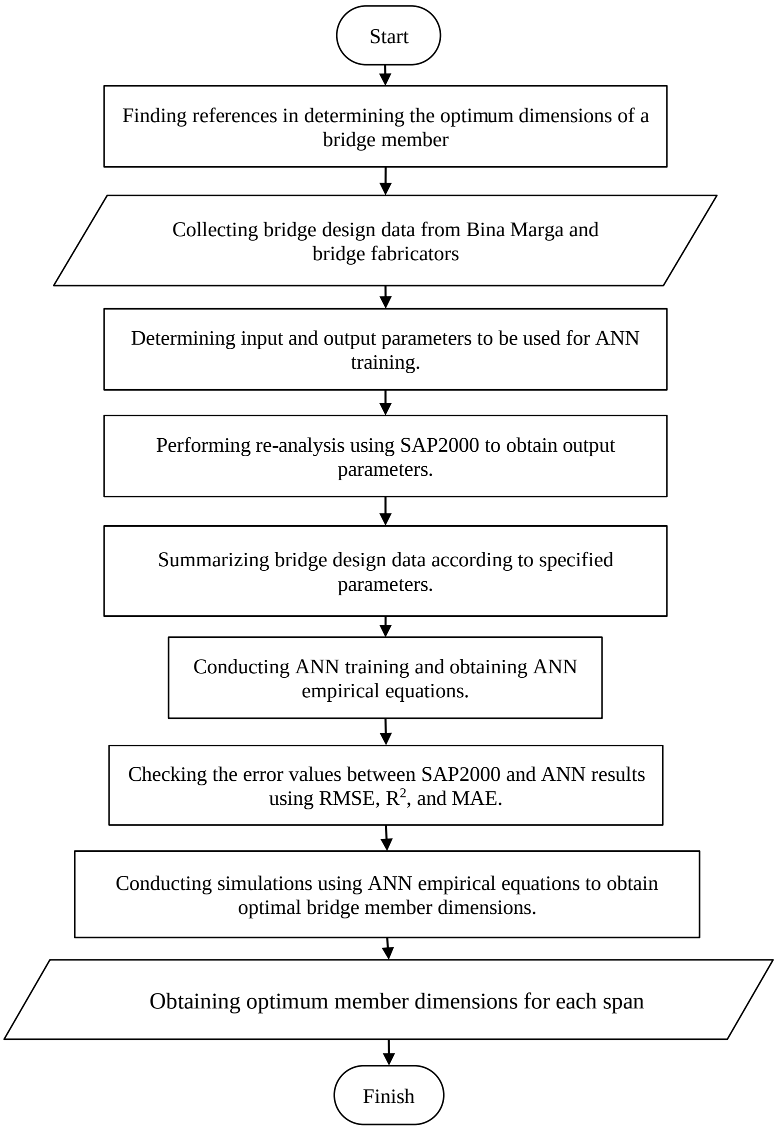


Figure 2 Research Step

DATA COLLECTION

The research began by collecting data from existing steel truss bridges in Indonesia from which is available within Directorate General of Highway (2015-2023), and from bridge fabricators, as well as from e-catalogue. This data included detailed information about the bridges, such as member profile dimensions (height, width, and thickness of various components), bridge height and width, steel grade (yield strength (F_y) and ultimate strength (F_u)), stress ratios of structural elements (top chord, bottom chord, diagonal compression, and diagonal tension), as well as deflection limitation under live-load. The design of Warren steel truss bridge are based on the typical steel truss bridge that has been used by Directorate General of Highway, i.e. Warren truss bridge with design criteria as shown in Table 1.

Table 1 General Criteria of Steel Truss Bridge

No.	General Criteria	Criteria
1	Design Life	50 years
2	Bridge Loading	SNI 1725:2016
3	Shoulders	Min 0,5 meters
4	Sidewalks	Min 0,5 meters
5	Longitudinal Slope	Max 5%
6	Vertical Clearance	Min 5,1 meters
7	Concrete Grade	Min *f'c* 30 MPa
8	Maximum Deflection	L / 800
9	Chambers	150% Dead Load + Live Load
10	Thickness of concrete deck	30 cm
11	Asphalt and Overlay	Asphalt 5 cm; Overlay 3 cm
12	Deck System Design	Non-Composite

The total population of steel truss bridges in Indonesia are 2,301 bridges. By filtering bridge data based on the research limitations such as construction year, bridge class, and span, there are only 520 bridges that govern those criterias. After screening the collected the data, only 209 bridges can be used as they have completed information. According to Al-wosheel et al. (2018), the number of data required for ANN minimum 300, therefore additional data are needed. These data are generated by simulating from the existing bridge. From these simulation, 1,282 models are generated.

Steel Member Analysis

Steel truss bridge structures have components that loaded by axial tensile and compressive forces. Tension members are reviewed based on two conditions, namely yield condition and fracture condition (Segui, 2015). The tensile member formula can be seen in equations (1) and (2).

$$\Phi_y P_{ny} = \Phi_y F_y A_g \text{, yield conditions} \tag{1}$$

$$\Phi_u P_{nu} = \Phi_u F_u A_n U \text{, fracture conditions} \tag{2}$$

Compression members are members that experience axial compression. The formula for compression members can be seen in equation (3).

$$P_r = \Phi_c P_n \tag{3}$$

P_n determined using:

1. If $\frac{P_e}{P_n} \geq 0.44$:

$$P_n = \left[0.658^{\frac{P_o}{P_e}}\right] f_y A_g \tag{4}$$

2. If $\frac{P_e}{P_n} < 0.44$:

$$P_n = 0.877 P_e \tag{5}$$

The P_e value is taken from two potential buckling modes, namely flexural buckling and torsional buckling.

Re-Analysis Data

To ensure the consistency on the application of the SNI 1725:2016 bridge loading regulations to the bridge design, the collected bridge data was re-analyzed using OAPI SAP2000 software. This re-analysis process involved re-modeling bridges and apply to the specified loading conditions. The results of the re-analysis, including internal forces, stresses, and deflections, were then compiled and used as the basis for training the ANN model. Number of data that re-analyzed are based on existing bridge data (209 models) and generated data as 1,282 models, hence total of 1,491 bridge models are than-analyzed shown in Figure 3.

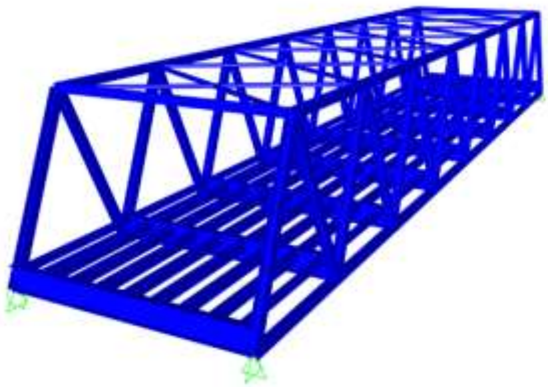


Figure 3 Steel Truss Bridge Modelling in SAP2000

From those 1,491 steel truss bridge models, 319 bridges meet the design requirements, consisting of 48 bridges with 40-meter spans, 56 bridges with 45-meter spans, 80 bridges with 50-meter spans, 110 bridges with 55-meter spans, and 25 bridges with 60-meter spans.

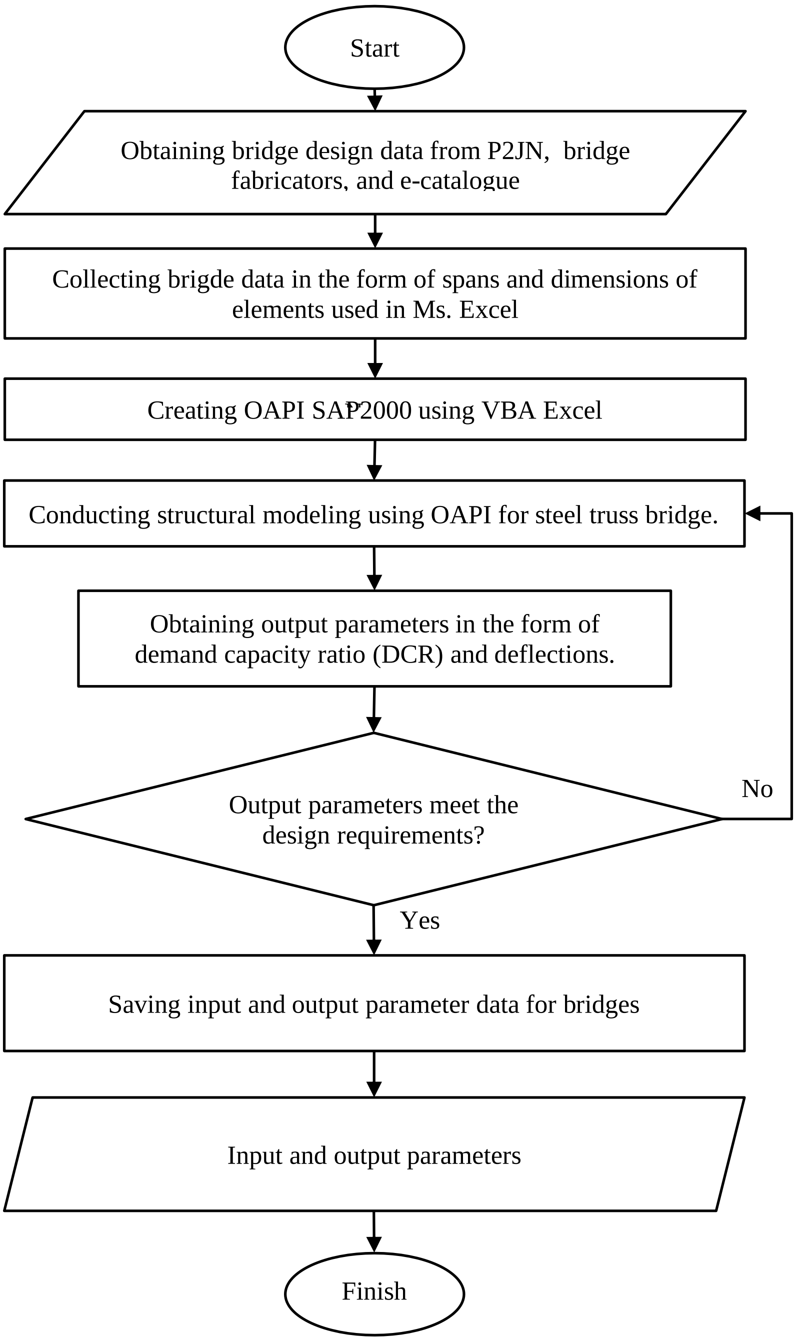


Figure 4 Re-Analysis Using OAPI SAP2000

To reduce time-consuming in preprocessing in inputing bridge data, the OAPI technigue was used. This is an application program that can implement system-to-system integration or a program that allows one application to interact with another (Dinh-Cong et al., 2020). By using this method, modeling can be done automatically by entering input in Ms. Excel, and the retrieval of bridge responds are also done automatically into MS Excel. Coding was done using Visual Basic for Application (VBA) available in MS Excel.

Open Application Programming Interface (OAPI) is a concept regarding application programming interface that integrates third-party products with SAP2000. The third-party product in this research is Microsoft Excel. Therefore, OAPI will connect SAP2000 with

Microsoft Excel to process data from structural analysis results. The re-analysis process shown in Figure 4.

ANN Model Development

The model consisted of 22 input parameters and 5 output parameters, which corresponded to the various bridge dimensions and material properties which is collected in the previous steps. The output parameters were the stress ratios of structural members and deflection, which is obtained from the OAPI-SAP re-analysis. The ANN model was than trained using the backpropagation algorithm with mode than 200,000 iterations to ensure convergence and minimize prediction errors as well. The Input parameters shown in Table 2 and output parameters shown in Table 3.

Table 2 Input Parameter for ANN Model

Input Parameter	
bridge span	bottom chord flange widht
bridge height	bottom chord web thickness
lane widht	bottom chord flange thickness
sidewalk widht	compression diagonal profile height
yeild strength, F_y	compression diagonal flange width
ultimate strength, F_u	compression diagonal web thickness
top chord profile height	compression diagonal flange thickness
top chord flange width	tension diagonal profile height
top chord web thickness	tension diagonal flange width
top chord flange thickness	tension diagonal web thickness
bottom chord profile height	tension diagonal flange thickness

Table 3 Output Parameter for ANN Model

Output Parameter
Demand Capacity Ratio (DCR) of top chord
DCR of bottom chord
DCR of compression diagonal
DCR of tension diagonal
Deflection

Model Validation

The accuracy of the trained ANN model was validated by comparing its predictions with the actual results obtained from the SAP2000 re-analysis. The evaluation metrics used for validation included RMSE (Root Mean Square Error), R^2 (coefficient of determination), and MAE (Mean Absolute Error) (Chicco et al., 2021). According to Fernando (2023), the minimum value of R^2 so that the regression is good enough is 0.9.

Optimization Simulation

The validated ANN model was then used to perform optimization simulations. A range of the possible bridge dimensions was defined based on the minimum and maximum dimensions which is observed in the existing bridge data. For each span length (40-60 meters), hundreds of thousands of combinations of input parameters were simulated using the ANN model. The goal was to identify the combination of dimensions that resulted in the lowest structural weight while still satisfying the design requirements.

Table 4 Optimization Model for Steel Truss Bridge

<table>
<tr><th colspan="2">Parameter</th><th>Steel Truss Bridge</th></tr>
<tr><td colspan="2">Objective Function</td><td>Minimum weight</td></tr>
<tr><td rowspan="3">Design Variable</td><td>Bridge dimensions</td><td>Profile dimensions, bridge height, bridge width</td></tr>
<tr><td>Steel Grades</td><td>f_y and f_u</td></tr>
<tr><td>Bridge span</td><td>40, 45, 50, 55, 60</td></tr>
<tr><td rowspan="2">Constraint</td><td>Strength Limit</td><td>DCR Compression < 1, DCR Tension < 1, Deflection < L/800</td></tr>
<tr><td>Code</td><td>• SNI 1725: 2016 Pembebanan Untuk Jembatan
• Panduan Praktis Perencanaan Teknis Jembatan No. 2/M/BM/2021
• Kriteria Desain Jembatan Standar 2017 Nomor 05/SE/Db/2017</td></tr>
</table>

Verification With SAP2000

The optimal bridge dimensions obtained from the ANN simulations were verified by remodeling and re-analyzing them in SAP2000. This step ensured that the optimized designs were structurally sound and met the required safety of standards. If any of the optimized designs failed to meet the criteria, the next best alternative from the simulation results was selected and verified. This process was repeated for each span length to obtain the final optimized dimensions.

RESULT AND DISCUSSION

The optimized profiles are the top chord, bottom chord, compression diagonal, tension diagonal, and the height of the steel truss bridge. These profile parts are modified to obtain optimal dimensions for each span through trial and error. Afterward, the analysis output is obtained in the form of DCR for the top chord, bottom chord, compression diagonal, tension diagonal, and deflection. The calculation results from the Excel analysis are then used as input for calculations or learning in the ANN. The analysis results in MS Excel are explained, which shows the re-analysis results of the bridge data to obtain re-analysis output in the form of DCR for the top chord, bottom chord, compression diagonal, tension diagonal, and bridge deflection.

Based on the test results considering the number of iterations and samples, the ANN training for the steel truss bridge was conducted with 200,000 epochs and 319 samples. The ANN training results in weights in the form of input bias weights, layer bias weights, initial input weights, and initial layer weights. These weights are incorporated into the empirical equation to obtain ANN prediction values. The ANN empirical equation for steel truss bridges is as follows:

BI_{tc} : input bias weight
BL_{tc} : layer bias weight
VI_{tc} : initial input weights
WL_{tc} : initial layer weights
P_{rtc} : Prediction of DCR

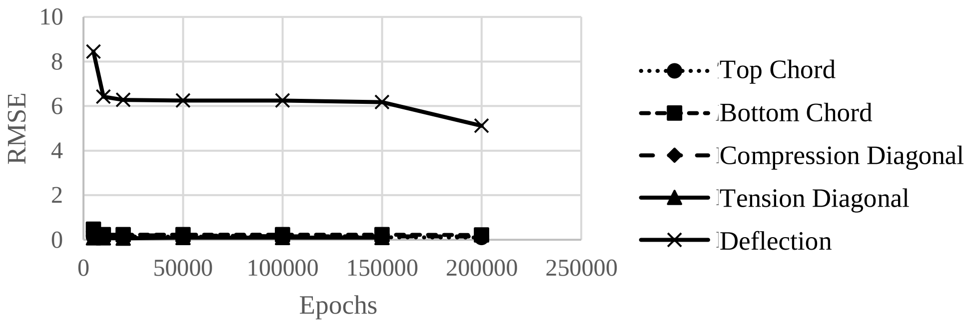
$$\begin{aligned} Z_{inj1} = {} & BI_{tc}(1) + VI_{tc}(1{,}1)\,A + VI_{tc}(2{,}1)\,B + VI_{tc}(3{,}1)\,C + VI_{tc}(4{,}1)\,D \\ & + VI_{tc}(5{,}1)\,E + VI_{tc}(6{,}1)\,F + VI_{tc}(7{,}1)\,G + VI_{tc}(8{,}1)\,H \\ & + VI_{tc}(9{,}1)\,I + VI_{tc}(10{,}1)\,J + VI_{tc}(11{,}1)\,K + VI_{tc}(12{,}1)\,L \\ & + VI_{tc}(13{,}1)\,M + VI_{tc}(14{,}1)\,N + VI_{tc}(15{,}1)\,O \\ & + VI_{tc}(16{,}1)\,P + VI_{tc}(17{,}1)\,Q + VI_{tc}(18{,}1)\,R + VI_{tc}(19{,}1)\,S \\ & + VI_{tc}(20{,}1)\,T + VI_{tc}(21{,}1)\,U + VI_{tc}(22{,}1)\,V \end{aligned} \tag{6}$$

$$\begin{aligned} Z_{inj2} = {} & BI_{tc}(2) + VI_{tc}(1{,}2)\,A + VI_{tc}(2{,}2)\,B + VI_{tc}(3{,}2)\,C + VI_{tc}(4{,}2)\,D \\ & + VI_{tc}(5{,}2)\,E + VI_{tc}(6{,}2)\,F + VI_{tc}(7{,}2)\,G + VI_{tc}(8{,}2)\,H \\ & + VI_{tc}(9{,}2)\,I + VI_{tc}(10{,}2)\,J + VI_{tc}(11{,}2)\,K + VI_{tc}(12{,}2)\,L \\ & + VI_{tc}(13{,}2)\,M + VI_{tc}(14{,}2)\,N + VI_{tc}(15{,}2)\,O \\ & + VI_{tc}(16{,}2)\,P + VI_{tc}(17{,}2)\,Q + VI_{tc}(18{,}2)\,R + VI_{tc}(19{,}2)\,S \\ & + VI_{tc}(20{,}2)\,T + VI_{tc}(21{,}2)\,U + VI_{tc}(22{,}2)\,V \end{aligned} \tag{7}$$

$$Z_1 = \frac{1}{1 + e^{-Zinj1}} \tag{8}$$

$$Z_2 = \frac{1}{1 + e^{-Zinj2}} \tag{9}$$

$$P_{rtc} = BL_{tc} + WL_{tc}(1)\,Z_1 + WL_{tc}(2)\,Z_2 \tag{10}$$



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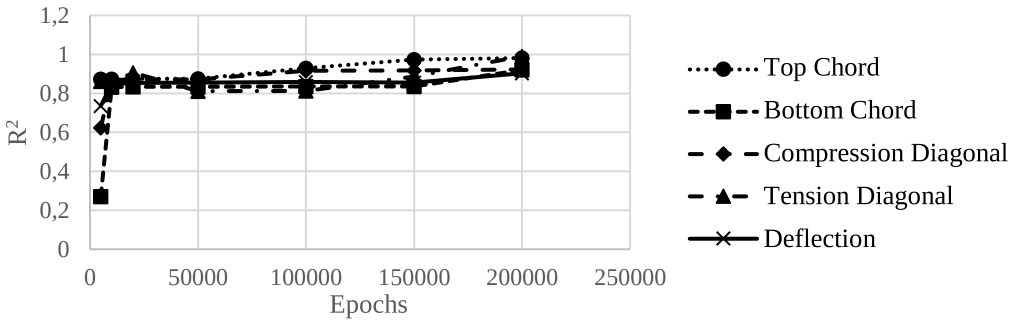

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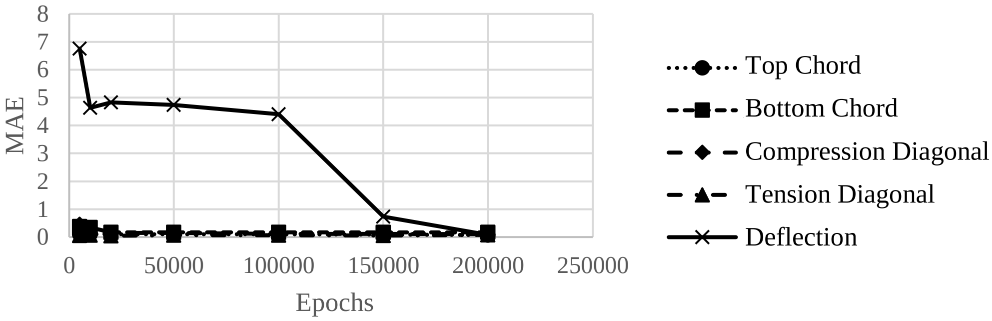
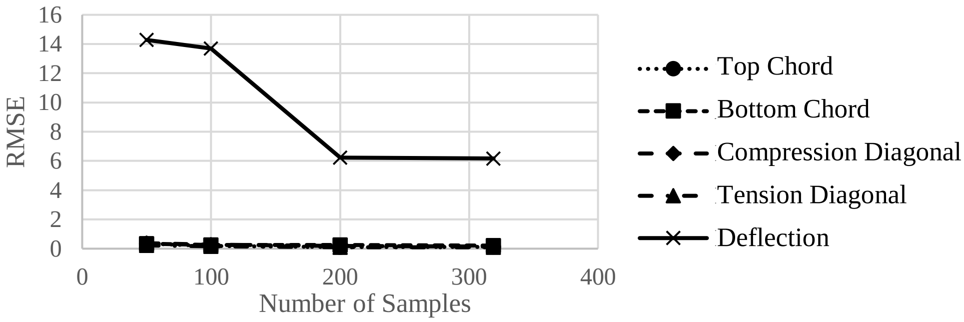


(c)

Figure 5 Error Value of Steel Truss Bridge ANN Modelling Based on Epoch
(a) RMSE (b) R^2 (c) MAE



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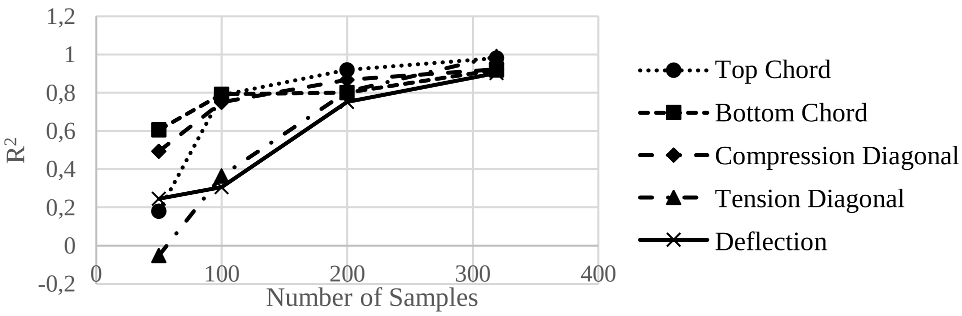

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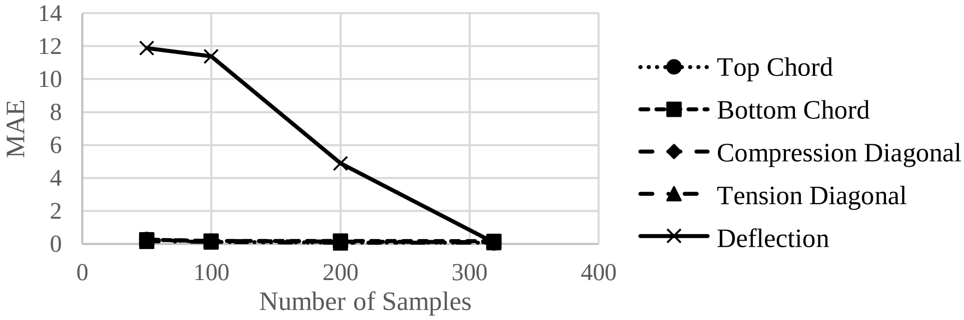

(c)

Figure 6 Error Value of Steel Truss Bridge ANN Modelling Based on Number of Sample
(a) RMSE (b) R^2 (c) MAE

After the ANN program is trained using steel truss bridge input data, an empirical equation is obtained that describes the relationship between input and output. This training process continues until the ANN output and the expected target reach a point of convergence, meaning that the resulting empirical equation has a very small error rate for each data point.

The ANN empirical equation are then evaluated using RMSE (Root Mean Square Error), R^2 (Coefficient of Determination), and MAE (Mean Absolute Error). The smaller the RMSE and MAE values, the better the ANN prediction. The higher the R^2 value, the better the ANN prediction as well. The results of the error value evaluation are shown in Table 5.

Table 5 ANN model validation based on RMSE, R^2, and MAE

Variabel *Output*	RMSE	R^2	MAE
DCR *Top Chord*	0.048	0.997	0.039
DCR *Bottom Chord*	0.054	0.996	0.049
DCR Diagonal Tekan	0.106	0.991	0.081
DCR Diagonal Tarik	0.032	0.998	0.031
Lendutan	0.749	0.999	0.011

From the above error value evaluation results, it was found that the RMSE and MAE values are acceptable, and the R^2 values are good (greater than 0.9), thus the ANN empirical equation is acceptable and can be used for the optimization process.

Simulations were carried out by changing the dimensions of the steel truss bridge using the empirical ANN equation that had been obtained. The simulation is carried out by creating a table of bridge profile dimension ranges based on the minimum and maximum dimensions of the existing bridge. Simulations are carried out for each span, simulating a steel truss bridge with a span of 40 meters requires 196,608 data combinations.

Trial and error simulations are carried out to obtain profile dimensions that meet the design requirements and have the lowest structural weight. The same optimization process is carried out for spans of 40-60 meters for steel truss bridges. The optimum dimensions of each span resulting from optimization using the ANN method for steel truss bridges are shown in Table 6 and the comparison with other researchers and existing bridges is shown in Figure 7. The steel weight shown are based on the weight of all steel structure component, including the connections.

Table 6 Table of Optimum Dimensions of Steel Truss Bridges for Each Span Resulting from the ANN Optimization Method

Parameter	40	45	50	55	60
Bridge Height (*m*)	8.5	8.364	8	8	9
Lane Widht (*m*)	7	7	7	7	7
Pedestrian Width (*m*)	1	1	1	1	1
Yield Strength of Steel F_y (*MPa*)	345	345	345	345	345
Ultimate Strength of Steel F_u (*MPa*)	450	450	450	450	450
Height of Top Chord (*mm*)	300	400	350	350	400
Width of Top Chord Flange (*mm*)	300	300	350	350	400
Thickness of Top Chord Web (*mm*)	8	12	14	12	10
Thickness of Top Chord Flange (*mm*)	12	18	22	14	18

Table 6 Table of Optimum Dimensions of Steel Truss Bridges for Each Span Resulting from the ANN Optimization Method (Continue)

Parameter	40	45	50	55	60
Height of Bottom Chord Profile (*mm*)	300	300	350	350	350
Width of Bottom Chord Flange (*mm*)	300	300	350	350	350
Thickness of Bottom Chord Web (*mm*)	8	8	10	10	12
Thickness of Bottom Chord Flange (*mm*)	10	12	12	16	16
Height of Compression Diagonal (*mm*)	300	400	400	400	350
Width of Compression Diagonal Flange (*mm*)	300	300	400	350	400
Thickness of Compression Diagonal Web (*mm*)	8	12	12	10	10
Thickness of Compression Diagonal Flange (*mm*)	10	18	12	14	14
Height of Tension Diagonal Profile (*mm*)	300	300	400	350	400
Width of Tension Diagonal Flange (*mm*)	300	300	350	350	350
Thickness of Tension Diagonal Web (*mm*)	8	8	10	10	10
Thickness of Tension Diagonal Flange (*mm*)	10	12	12	14	14
Steel Volume (m^3)	8.892	11.335	13.287	14.348	17.268
Steel Weight (*kg*)	69,802	88,980	104,303	112,629	135,554

The optimization results of steel truss bridges in this study than compare to the weight of the steel truss bridge optimization from other studies and from existing steel truss bridges. Figure 7 shows that the optimization results are more efficient in terms of structural steel weight compared to other studies and existing bridges. The value of the optimization results in this study compared to Hasançebi (2007) proved to be more efficient by 5.60%.

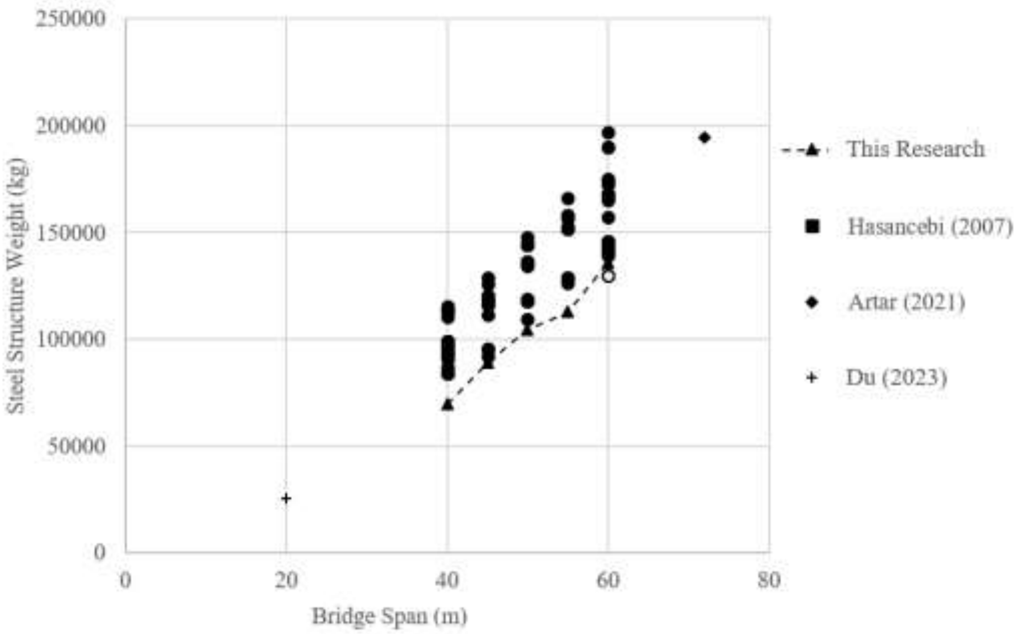

Figure 7 Span vs Optimum Steel Weight of Steel Truss Bridge

Artar (2021) conducted an optimization study for a 72 meters span steel truss bridge, while Du et al. (2023) conducted an optimization study for a 20 meters span steel truss bridge. Although Artar and Du's research cannot be directly compared with the optimization results in this study due to differing spans, it can be seen in Figure 7 that the results of this study approach the findings of both Artar and Du. Meanwhile, if it compared with the existing bridge (174,168 kg) the difference in weight between the existing steel truss bridge and the steel truss bridge as result of this research is about 20%.

The results of the optimization of steel truss bridge dimensions using the ANN method are as follows:

1) Structural analysis modeling was performed on 1,282 steel truss bridges with spans of 40, 45, 50, 55, and 60 meters. The results of this modeling are in the form of internal forces in bridge elements and deflection, which are used as output parameters for ANN analysis. The number of models that fulfil the design criteria are 319 model. These models are used for ANN training.
2) The number of input parameters used is 22 parameters, and the number of output parameters is 5. The ANN training was carried out using 319 models and 200,000 iterations using the results of the bridge structural analysis.
3) The RMSE value for the steel truss bridge is 0.032-0.105 for the stress ratio of structural elements and 0.749 mm for deflection. This value is good enough so that the predicted value can be used for optimization.
4) The R^2 value for the prediction of steel truss bridges is above 0.99 for all variables. This value is excellent so that the predicted value can be used for optimization.
5) The MAE value for the prediction of steel truss bridges is 0.03-0.08 for the stress ratio of structural elements and 0.011 for deflection. This value is excellent so that the predicted value can be used for optimization.
6) From the results of the ANN prediction of the steel truss bridge, the empirical equation is close to the analysis results so that optimization can be done using the ANN empirical equation.
7) Optimization is carried out by trial and error of input parameters and processing them with the output parameters of the ANN prediction results. The optimum dimensions from a span of 40 meters to 60 meters are obtained.
8) The research results are compared with other studies. The optimization results in this study are more efficient than other researchers by 5.60%. Meanwhile, compared to the average weight of the existing bridges, the results of this study are more efficient by 20%.

CONCLUSION

This study successfully developed an accurate ANN model to predict the steel truss bridges behavior. The ANN model was then used to optimize the dimensions of steel truss bridges with spans of 40 meters up to 60 meters. The optimization results in this study are more efficient than other researchers by 5.60% and compared to the average weight of existing bridges, the results of this study are more efficient by 20%. This research contributes to improving the efficiency of steel truss bridge design in Indonesia.

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