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PREDICTING STRESS CONCENTRATION FACTORS IN TENSION-LOADED SHAFTS USING ARTIFICIAL NEURAL NETWORKS

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Abstract: This paper presents a novel approach to determining the stress concentration factor (K_t) for tension-loaded machine parts using artificial neural networks (ANNs). Analytical methods for calculating K_t rely heavily on empirical data and standardized charts, which are often limited to specific geometries and load conditions. To overcome these limitations, we trained an ANN model using a comprehensive dataset of empirical K_t values, covering a wide range of dimensions for tension-loaded shafts. The input parameters for the ANN model were the key geometric dimensions: the smaller diameter, the larger diameter, and the radius at the critical section of the shaft. By leveraging the ANN's capability to learn complex, non-linear relationships within the data, the model was able to accurately predict the stress concentration factor for any given set of input parameters. The results demonstrate that the ANN-based approach can serve as a reliable and efficient tool for engineers, reducing the reliance on time-consuming finite element analyses or limited empirical charts and providing quick and accurate predictions of K_t across a wide range of applications.

Key words: artificial neural networks, stress concentration factor, tension loading, training data

1 INTRODUCTION

Stress concentration factors (K_t), also labelled α_k in some literature, play a crucial role in the design and analysis of mechanical components, especially when

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dealing with parts subjected to tension loading. These factors represent the amplification of stress around geometric discontinuities such as notches, holes, or sharp transitions in cross-section, which often become critical points of failure. The precise calculation of K_t is, therefore, fundamental for ensuring the safety and durability of machine parts. Engineers have traditionally relied on empirical data and standardised charts to determine K_t values, typically derived from experiments or finite element simulations. However, such approaches are often limited to discrete datasets and are limited to specific dimension values.

In recent studies [1-3], ANN has been used to solve complex engineering problems in various fields previously solved using conventional optimisation methods. Ozden and Gokce [4] estimated the stress concentration factor using ANN in T-weld joints forced by bending. They used a data set consisting of 8500 unique data points covering a wide range of geometric structures and parameters created with the Latin Hypercube method to calculate K_t values with a parametric equation. In [5], Dabiri et al. estimated the stress concentration factors in butt and T-welded joints using artificial neural network-based models. Sivak et al. in [6] presented regression and correlation analysis and intercomparison of stress concentration factors obtained from FEM analysis with factors imported from external sources. Nagpal et al. in their research, [7], gave a critical review of stress concentration and its mitigation techniques in flat plates with singularities. The research showed that this maximum value for K_t value could be reduced either by material removal at the vicinity of the observed location by shape optimisation or by strengthening the hole by the inclusion of additional, more robust material.

Given the need for a wide range of dimensions when designing modern mechanical systems, more flexible and efficient tools for determining Kt have become increasingly evident. Recent advancements in computational techniques, particularly in artificial intelligence, have opened new avenues for addressing these challenges. Among these, artificial neural networks (ANNs) have emerged as powerful tools for modeling non-linear relationships within complex datasets, making them well-suited for applications where traditional methods may fall short.

2 PROBLEM DEFINITION

The stress concentration factor (K_t) is a dimensionless factor that quantifies how much stress is amplified at a geometric discontinuity in a material, such as a notch, hole, or sudden change in cross-section. When a component is subjected to an external load, the presence of these discontinuities causes the local stress to be significantly higher than the average stress over the rest of the part. Kt is defined as the ratio of the highest local stress to the nominal stress in the component, and it is crucial for predicting the potential points of failure in mechanical designs. By accounting for these stress concentrations, engineers can ensure that components are properly designed to withstand expected loads without failure. Figure 1 shows the empirical data for the example with a change in shaft diameter with a radius. The values are shown as relations of the smaller diameter (d), larger diameter (D), and radius (r). The curves presented as r/t use t as a short form of the relation (D-d)/2. On the vertical axis is the stress concentration factor α_k (K_t).

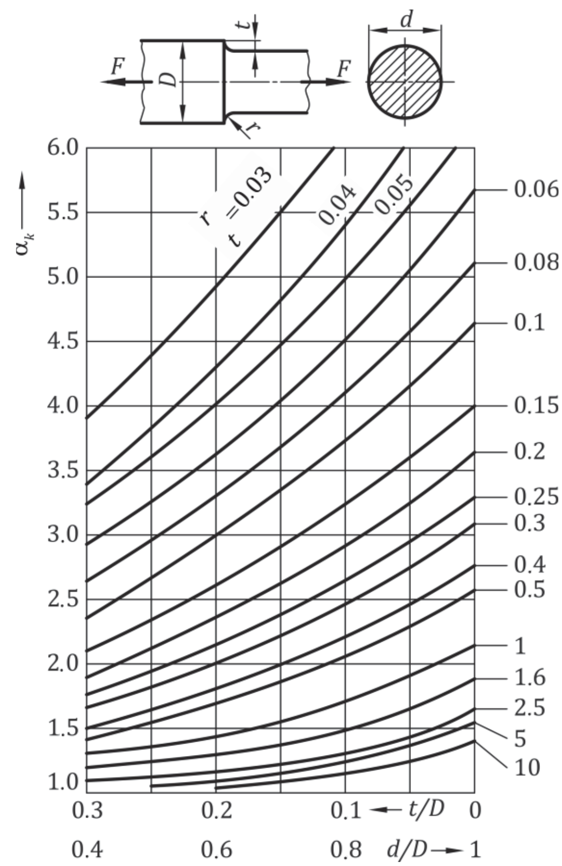

Figure 1. *The diagram for determining α_k (K_t) for a change in shaft diameter with a radius [8]*

Determining the stress concentration factor (K_t) for any combination of values for the smaller diameter, larger diameter, and radius at the stress concentration point becomes challenging when available empirical data is only presented in diagrams for specific relationships between these dimensions. These diagrams typically cover a limited range of geometric configurations, meaning engineers must rely on interpolation or extrapolation to estimate K_t for dimensions not represented in the standard charts. Such estimates can often be inaccurate, as they fail to capture the complex, non-linear relationships between the dimensions and stress concentrations, leading to potentially unreliable results and an increased risk of design errors.

This paper presents a viable approach for predicting stress concentration factors using ANNs. By training a neural network on an extensive dataset of empirical K_t values, the model developed in this study can accurately predict K_t for a wide range of geometric configurations of tension-loaded shafts. The input parameters for the ANN include the key geometric dimensions of the critical section: the smaller diameter, the larger diameter, and the radius at the stress concentration point. By leveraging the ANN's ability to capture intricate patterns and relationships in the data, this approach provides engineers with a fast, reliable, and accurate tool for predicting K_t across various scenarios, thereby reducing the reliance on traditional methods such as finite element analysis (FEA) and empirical charts.

3 ANN CONFIGURATION

In this study, an artificial neural network (ANN) was developed using the Neural Network/Data Manager (nntool) module in MATLAB to predict the stress concentration factor (Kt) for various geometric configurations. The input data matrix was composed of 2x116 values, representing the ratios r/t (radius to the relation (D-d)/2) and d/D (smaller diameter to larger diameter), extracted from diagrams in Figure 1. The corresponding value of the stress concentration factor K_t was determined for each of these input combinations. These data points were used to train a feed-forward backpropagation neural network, an architecture well-suited for capturing complex, non-linear relationships in datasets like this.

The feed-forward backpropagation method is a common neural network architecture where data flows forward through the network layers while errors are propagated backwards to adjust the weights and improve the model's performance. This iterative adjustment of weights continues during training until the error between the predicted and actual values is minimized. The training process in this network utilized the Levenberg-Marquardt (TRAINLM) algorithm, known for its fast convergence and suitability for small to medium-sized networks. This algorithm combines the advantages of the Gauss-Newton method and gradient descent, providing an efficient solution for training networks with non-linear optimisation problems.

Gradient Descent with Momentum (LEARNGDM) was the adaptation learning function, which enhances the primary gradient descent method by adding momentum. This helps the network avoid local minima during training by maintaining the direction of previous weight updates, leading to faster convergence.

The network's performance was evaluated using the Mean Squared Error (MSE) function, which measures the average squared difference between the network's predictions and the actual data. Lower MSE values indicate better model performance, reflecting more minor network prediction errors. The neural network training results in the nntraintool are shown in Figure 2.

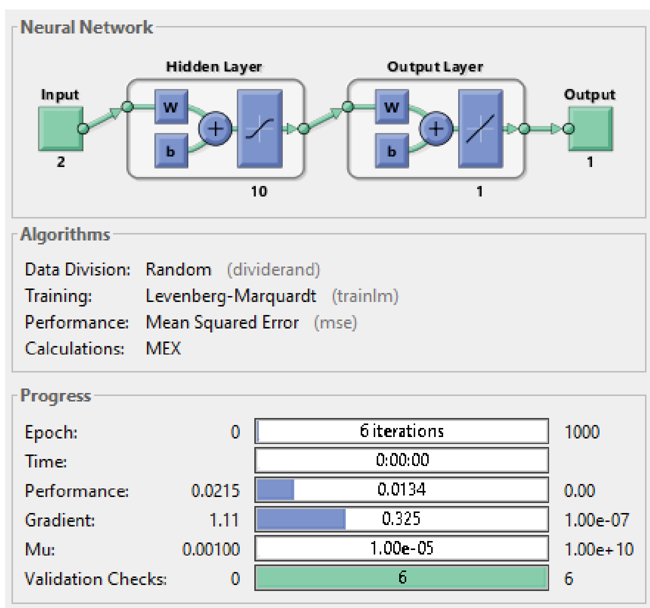

Figure 2. *Neural network training results in the nntraintool*

The network had two layers. The first layer consisted of 10 neurons, with the transfer function TANSIG (a hyperbolic tangent sigmoid function) mapping input data into a range between -1 and 1, helping the network learn complex patterns. The second layer, which produced the final output, used the PURELIN transfer function, a linear function ideal for regression tasks, where continuous values like K_t must be predicted. This combination of layers and functions allowed the ANN to accurately capture the relationship between the geometric inputs and the stress concentration factor, offering a robust tool for engineering design applications.

4 RESULTS

Neural network training for regression involves adjusting the network weights based on the errors between predicted outputs and actual target values, allowing the model to learn the underlying relationships in the data. During this process, optimization algorithms, such as gradient descent, minimize errors using performance metrics like Mean Squared Error (MSE) to guide the adjustments. Successful training results in a model capable of accurately predicting continuous output values for new, unseen input data. The neural network training regression (plotregression) results (Figure 3) show that training, validation, testing, and overall results converge.

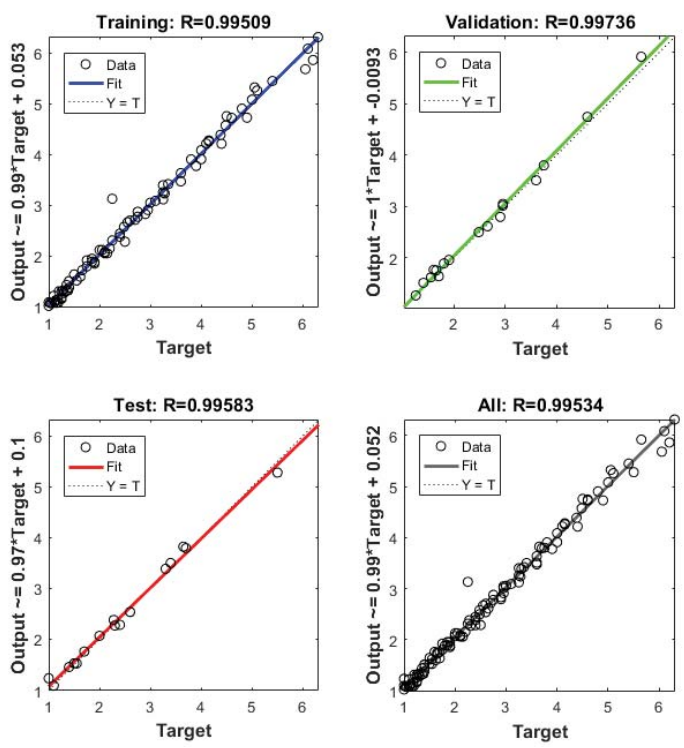

Figure 3. *Neural network training regression*

Table 1 shows the expected results from the diagram shown in Figure 1 and ANN results for 25 cases of various dimension ratios. Figure 4 shows a graphic representation of the stress concentration factor results from Figure 1 compared to ANN results.

Table 1. *Expected and ANN results for 25 cases of various dimension ratios.*

d/D	**r/t**	**Expected values (Figure 1)**	**ANN results**
0.8	5	1.25	1.1449
0.93	2.5	1.5	1.5501
0.95	1.6	1.75	1.765
0.94	1	2	2.0468
0.65	0.5	1.75	1.9704
0.78	0.5	2	2.1696
0.55	0.4	1.75	1.8211
0.7	0.4	2	2.1428
0.45	0.3	1.75	1.7465
0.6	0.3	2	2.0461
0.65	0.25	2.25	2.2725
0.85	0.25	2.75	2.6702
0.55	0.2	2.25	2.1702
0.75	0.2	2.75	2.6272
0.65	0.15	2.75	2.7656
0.95	0.15	3.75	3.7002
0.55	0.1	2.8	2.9651
0.75	0.1	3.58	3.6366
0.65	0.08	3.5	3.6871
0.89	0.08	4.5	4.6966
0.57	0.06	3.5	3.7395
0.89	0.06	5	5.2631
0.65	0.05	4.25	4.367
0.75	0.04	5.15	5.0989
0.75	0.03	5.8	5.4461

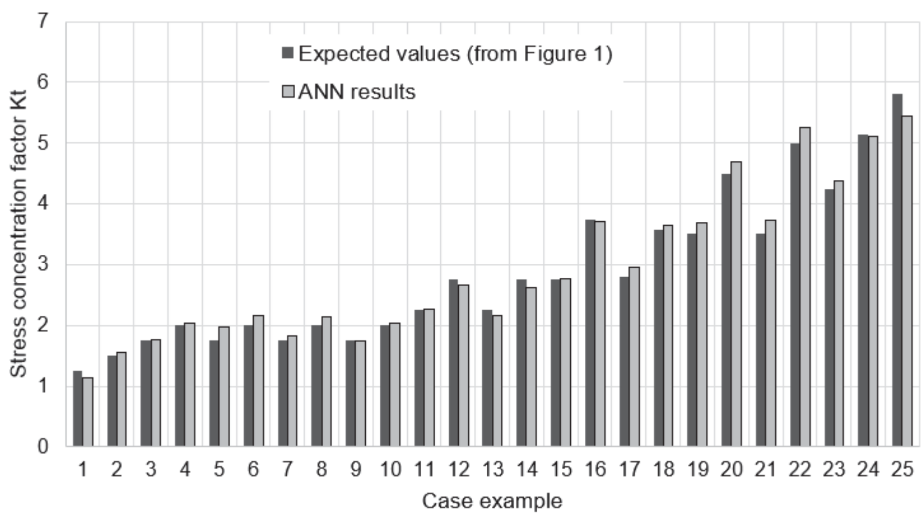

Figure 4. *Graphical representation of expected and ANN results for 25 case examples of various dimension ratios.*

There are some discrepancies between the values derived from the diagram in Figure 1 and the ANN results, but the results are usable. This validates that the approach presented in this research can be used for practical applications.

5 CONCLUSION

The trained neural network in this paper demonstrated its practical applicability by obtaining results for specific, known cases of dimension ratios. By utilising the input data derived from a matrix of geometric configurations, the ANN created in MATLAB could predict the stress concentration factor (Kt) accurately. This approach capitalises on the strengths of artificial intelligence, allowing for the effective modeling of complex, non-linear relationships that traditional methods may struggle to capture. The successful application of the ANN model showcases the potential for more efficient assessments in mechanical design.

The predicted K_t values were compared with those obtained from established empirical diagrams to validate the neural network's performance. A total of 25 samples were evaluated in this process, which provided a comprehensive basis for assessing the model's accuracy. While some discrepancies were noted between the predicted and actual values, the results were considered satisfactory, indicating that the ANN can effectively serve as a reliable alternative to traditional methods. The flexibility of the ANN allows for rapid predictions across a broader range of geometric configurations, which is particularly advantageous in scenarios with limited time and resources.

The evaluation of the ANN's performance revealed a mean error of -0.04717 and a mean absolute error of 0.114832 among the tested samples. These metrics highlight the model's capability to produce accurate predictions while demonstrating a relatively low deviation from empirical values. Such results affirm the potential of using artificial neural networks to predict stress concentration factors and suggest avenues for further research and refinement of the model. As engineers seek more efficient and reliable methods for analysing complex mechanical systems, integrating ANN technology into standard practices represents a significant advancement in the field.

REFERENCES

[1] Stojanovic, B., Gajevic, S., Kostic, N., Miladinovic, S., Vencl, A. (2022). Optimization of parameters that affect wear of A356/Al_2O_3 nanocomposites using RSM, ANN, GA and PSO methods, *Industrial Lubrication and Tribology*, 74/3, p.p. 350-359.

[2] Saddam Husain, Bagylan Kadirbay, Anwar Jarndal, Mohammad Hashmi (2023). Comprehensive Investigation of ANN Algorithms Implemented in MATLAB, Python and R for Small-Signal Behavioral Modeling of GaN HEMTs, IEEE Journal of the Electron Devices Society, p.p. 1-13.

[3] D. Vasavi Krishna, D., Surya Kalavathi, M., Ganesh Babu, B. (2024). A Novel NR-DA-Based ANN for SHEPWM in Cascaded Multilevel Inverters for Renewable Energy Applications, *International Transactions on Electrical Engineering and Computer Science*, 3/4, p.p. 135-143.

[4] Osman Bahadır ÖZDEN, Barış GÖKÇE (2024). Estimation of Stress Concentration Factor Using Artificial Neural Networks in T-Weld Joints Forced by Bending, *Technical Gazette*, 31/5, p.p. 1478-1484.

[5] Mohammad Dabiri, Mehran Ghafouri, Timo Björk (2017). Estimation of stress concentration factor in butt and T-welded joints utilizing artificial neural network-based models, *Rakenteiden Mekaniikka (Journal of Structural Mechanics)*, 50/3, p.p. 362-367.
[6] Peter Sivák, Ingrid Delyová, Jozef Bocko (2023). Comparison of Stress Concentration Factors Obtained by Different Methods, *Applied Sciences*, 13/13328, p.p. 1-20
[7] Shubhrata Nagpal, Nitin Jain, Shubhashish Sanyal (2011). Stress Concentration and its Mitigation Techniques in Flat Plate with Singularities—A Critical Review, *Engineering Journal*, 16/1, p.p. 1-15.
[8] Jovičić, S., Mrjanović, N. (2023). *Osnovi konstruisanja – treće izdanje*, Fakultet inženjerskih nauka Univerziteta u Kragujevcu, Kragujevac.