# The Flexural Strength prediction of porous Cu-Sn-Ti Composites via Artificial Neural Networks

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**Abstract.** Porous alloy-composites have demonstrated excellent qualities with regards to grinding superalloys. Flexural strength is an important mechanical property associated with the porosity level as well as inhomogeneity in porous composites. Owing to the non-linear characteristics of the constituents of the composite material, the prediction of specific mechanical properties by means of the conventional regression model is often unsatisfactory. Therefore, the utilisation of artificial intelligence for the prediction of such properties is non-trivial. This study evaluates the efficacy of artificial neural network (ANN) in predicting the flexural strength of porous Cu-Sn-Ti composite with Molybdenum disulfide (MoS2) particles. The input parameters of the ANN model are the average carbamide particles size, the porosity volume as well as the weight fraction of the MoS2 particles. The determination of the number of hidden neurons of the single hidden layer ANN model developed is obtained via an empirical formulation. The ANN model developed is compared to a conventional multiple linear regression (MLR) model. It was demonstrated that the ANN-based model is able to predict well the flexural strength of the porous-composite investigated in comparison to the MLR model.

**Keywords:** Composite, Flexural Strength, Artificial Neural Network.

## 1 Introduction

Owing to the superior properties of porous alloy-composites, its employment in grinding tools is non-trivial, particularly to grind nickel superalloy as well as titanium alloy amongst others [1–3]. The effect of different bubble particles as pore-forming agents towards the performance Cu-Sn-Ti alloys has been investigated. Ding et al. utilised alumina ($Al_2O_3$) to fabricate porous metal-bonded cubic boron nitride (CBN) wheels. The grinding performance of the proposed composite was compared to a vitrified-bonded CBN wheel and it was shown that the former wheel exhibited better-grinding performance than that of the latter in grinding nickel superalloy owing to its lower grinding energy [4].

Chen et al. demonstrated the grinding ability of porous $Al_2O_3$ CBN wheels against vitrified CBN wheels in grinding Inconel 718 [2]. Prior to the fabrication of the porous wheel, a sensitivity test with regards to the proportion of $Al_2O_3$ weight towards the flexural strength of the composite was carried out. It was shown that $Al_2O_3$ bubbles of 15 wt% were selected as it provided reasonable corresponding flexural strength. The flexural strength which is also known as the bending strength is an important parameter that correlates the magnitude of porosity as well as the inhomogeneity of composites [1, 2, 4, 5]. The aforesaid selected composition demonstrated lower specific grinding forces, specific grinding energy, and grinding temperatures in comparison to the vitrified wheels in grinding Iconel 718.

The application of artificial intelligence in predicting mechanical properties has gained due attention owing to its ability to cater for non-linear behaviour of the constituents that yield certain properties that are cannot be provided by conventional linear regression models [6–8]. Artificial Neural Networks (ANN) has been used to predict the flexural strength and hardness resistance of ceramic particle reinforced aluminium matrix composites of varying SiC particle size with exceptional accuracy [6]. Different mechanical properties of heat-treated 30CrMoNiV5-11 steel were predicted by means of ANN [9]. The optimized number of hidden neurons was selected by varying the hidden neurons from, 5 to 20 by evaluating both standard deviation as well as the mean absolute error. It was shown that 5 hidden neurons demonstrated acceptable prediction.

Zhou et al. investigated the efficacy of ANN in predicting the flexural strength of porous Cu-Sn-Ti composite with Molybdenum disulfide ($MoS_2$) particles [7]. The authors utilised particle swarm optimisation (PSO) as well as genetic algorithm (GA) in optimising the number of hidden neurons. It was shown that the PSO-based ANN model was better than that of the GA-based ANN model with an $R^2$ of 0.9901 and 0.9235, for PSO and GA, respectively. The current investigation is aimed at evaluating the efficacy of ANN in predicting the flexural strength evaluated by Zhou et al. by employing an empirical relationship reported by Jinchuan and Xinzhe [10] in determining the optimum number of hidden neurons.

## 2 Methods

The present study utilised the data set provided by the experimental work of Zhou et al. The prediction of the flexural strength is evaluated by varying the average carbamide particles size, the porosity volume as well as the weight fraction of the $MoS_2$ particles. The ANN model is developed by obtaining the number of hidden neurons via the following equation:

$$N_h = \frac{N_{in} + \sqrt{N_p}}{L}$$

Where $N_h$ is the number of hidden neurons, $N_{in}$ is the input neurons, $N_p$ is the number of input sample whilst L is the number of hidden layers. The number of input neurons is three, the input sample is 48, whilst the number of hidden layers selected in this investigation is one. It was found that the optimum number of hidden neurons obtained via the formulation to be ten. The activation function employed in this investigation is the hyperbolic tangent sigmoid, whilst the learning algorithm selected is the Levenberg–Marquardt algorithm. The prediction ability of the ANN model developed is also compared to the conventional multiple linear regression (MLR) model.

## 3 Results and Discussion

The prediction ability of the developed ANN against the conventional MLR model with regards to the flexural strength of the investigated composite is illustrated in Fig. 1. It is apparent from the figure that the MLR model does not provide a desirable prediction of the aforesaid property in comparison to the developed ANN model. Table 1 indicates the summary of the evaluation metrics carried out in the present investigation, namely, R2, RMSE and MAE. It could be observed from the table that the R2, RMSE and MAE for the ANN and MLR models are 0.9932, 4.2587, 1.4679 and 0.9762, 7.4658, 5.9226, respectively. The table suggests that the impeccable correlation, R2, and the lower RMSE and MAE provided by the ANN model indicate its efficacy in predicting the flexural strength of Cu-Sn-Ti composite in comparison to the MLR model.

It is worth noting that although the MLR model provided a reasonably good $R^2$ of 0.9762, nonetheless, it is unable to predict well mainly sample number 3,4,8 and 9, respectively with a magnitude of approximately 10 MPa. In view of the flexural strength of the composite, such order of magnitude is non-trivial. Conversely, the ANN model developed, particularly the selection of the hidden neurons via the equation suggested by Jinchuan and Xinzhe, is able to provide an excellent prediction of the flexural strength of the composite samples. Moreover, the proposed method is able to provide yield a better prediction ability in comparison to the more sophisticated genetic algorithm and particle swarm optimisation-based method in determining the suitable number of hidden neurons as reported in [7].

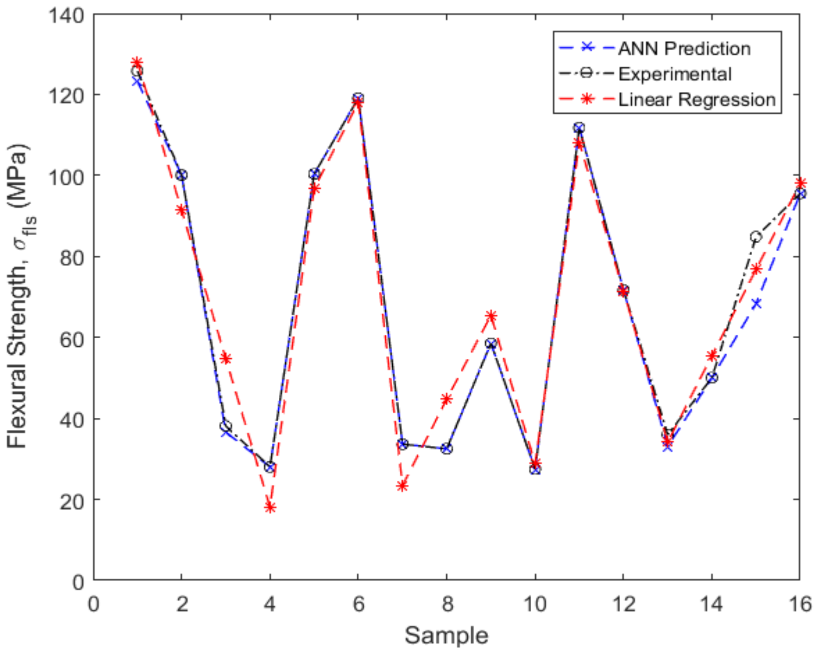

**Fig. 1.** Flexural strength predictions

**Table 1.** Model evaluation

| | Models | |
|---|---|---|
| Evaluation Metrics | ANN | MLR |
| $R^2$ | 0.9932 | 0.9762 |
| RMSE | 4.2587 | 7.4658 |
| MAE | 1.4679 | 5.9226 |

## 4 Conclusion

The present investigation evaluates the prediction of the flexural strength of Cu-Sn-Ti composite through the employment of ANN. The selection of the hidden neuron that yields noteworthy prediction results was based on a simple equation. It was demonstrated that the proposed ANN model is more superior in comparison to the conventional MLR model owing to its ability to cater for the non-linear behaviour of the parameters that determine the flexural strength of the composite. Future investigation shall explore the significance of the individual parameters' contribution towards the evaluated property, i.e., flexural strength as well as the influence of different activation functions, learning algorithms and the influence of multiple hidden layers towards the prediction of the aforesaid Cu-Sn-Ti composite property.

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