



## **Prediction of Mechanical Properties of Steel Using Artificial Neural Network**

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**Abstract:** For product development manufacturers and designers need information about the existing materials and new material and its properties as early as possible. This paper presents a method of predicting the properties of unknown material using artificial neural network. The developed neural network model is employed for simulations of the relationship between mechanical property and the chemical composition of steel. Simulating and analyzing result shows that network model can effectively predict the mechanical properties of material. Application of the presented method enables a scientist to make free analyses of the effect of the alloying elements occurring in processing condition also using only computer simulation, without having to carry out additional and expensive experimental investigations.

**Keywords:** Artificial neural network, Steel, Radial Basis Function, Back propagation method

### **I. Introduction**

The information regarding material is very valuable to manufacturers and designer for their product development. The manufacturers and designer has to keep pace with fast changing technologies and methods. They need the information regarding new material as soon as possible. The identification of properties of unknown material in the material testing laboratory require heavy investment and also it is very time consuming. The use of simulation software in conducting experiments and prediction of properties of material will reduce the cost and time immensely. The application of neural network modeling for evaluation of the effect of the alloying elements on steels is presented. Radial basis function and Back propagation method is used to predict the properties of material. The tensile strength and hardness of selected steel is predicted using artificial neural network was pointed out, and their practical usefulness was illustrated by examples. The developed neural network model can also be employed for simulations of the relationship between mechanical property and the chemical composition of steel. This can be done in the entire range of concentrations of the main alloying elements occurring in steels taken as data set. Application of the presented method enables a scientist to make free analyses of the effect of the alloying elements occurring in processing condition also using only computer simulation, without having to carry out additional and expensive experimental investigations.

### **II. Material used for investigation**

The study of steels is important because steels represent by far the most widely used materials, and can be manufactured relatively cheaply in large quantities to precise specifications. Therefore, steel is selected as the reference group for developing a database for material identification and prediction of property using its chemical composition. Steel is an alloy that consists mostly of iron and has carbon content between 0.2% and 2.1% by weight, depending on the grade. Carbon is the most common alloying material for iron, but various other alloying elements are used, such as manganese, chromium, vanadium, and tungsten. Carbon and other elements act as a hardening agent. The amount of alloying elements and the form of their presence in the steel controls qualities such as the hardness, ductility, and tensile strength of the resulting steel with increased carbon content can be made harder and stronger than iron, but such steel is also less ductile than iron. Steel is a metallic material. Since its basic component is iron, it is included in ferrous materials group. The ferrous materials with carbon content higher than 2% are categorized as cast irons and those with carbon content less than 2% as steels. Carbon plays differing roles in affecting the constitution of the steel, as steels are heated and cooled [62, 77]. Steel also includes some other elements such as phosphorus, sulphur, silicon, nickel, etc. in proper amount according to the production purpose.

### **III Artificial neural network**

Artificial Neural Networks (ANNs) are non-linear mapping structures based on the function of the human brain. They are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. The networks imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are

imprecise and noisy [34]. Neural network has great capacity in predictive modeling. A neural network is a computational structure that is inspired by observed process in natural networks of biological neurons in the brain. It consists of simple computational units called neurons, which are highly interconnected. They are parallel computational models comprised of densely interconnected adaptive processing units. These networks are fengtine-grained parallel implementations of nonlinear static or dynamic systems. A very important feature of these networks is their adaptive nature, where “learning by example” replaces “programming” in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available [38]. Neural networks are now being increasingly recognized in the area of classification and prediction, where regression model and other related statistical techniques have traditionally been employed

#### IV Modeling

Chemical composition and ultimate tensile strength (UTS) value of Normalized steel Table I data is used for prediction of Ultimate tensile strength. All the data for Ultimate tensile strength were processed at same condition. The input for network BP and RBF are normalized value of alloy element carbon, Sulphur, Phosphorus, Manganese, Silicon, Aluminum and Niobium. While UTS is predicted based purely on these elements. Following Table II gives the value of performance index for all 128 data. The set of data was divided into three subsets. The first set contains the half of all data and was used for the modification of the neuron weights (training set). One fourth of the data was used for valuation of prediction errors by training process (validation set). Remaining data were used for the independent determination of prediction correctness, when the training process is finished. Networks were trained with use of the back propagation and radial basis function methods. For the verification of networks usability for the aims of parameters prediction the following parameters of the quality valuation were used:

- Average absolute error – difference between measured and predicted output values of the output variable.
- Standard deviation ratio – a measure of the dispersion of the numbers from their expected (mean) value. It is the most common measure of statistical dispersion, measuring how widely the values in a data set are spread,
- Pearson correlation – the standard Pearson-R correlation coefficient between measured and predicted output values of the output variable.

#### V Result and Analysis

Before modeling of the UTS profile basic statistic evaluations of predictions for whole data base were made and results are collected in Table I and Table II. In those two tables it can be seen that max percentage error is 0.216 and min percentage error is -0.210 which is very less. Results obtained from the given ranges of input data show the very good ability of the nets to predict described mechanical properties of normalized steels. The Pearson correlation coefficient is over 99% and low percentage error inform about the correct execution of the training and obtained small differences in the relation between actual and predicted measured values. The uniform distribution of vectors in every set indicates about the good ability of the networks to results generalization. The results for UTS predictions with actual data and variation with carbon, manganese and silicon are presented on fig 4, fig 5 and fig 6. The fig 4 shows that percentage increase in carbon content increases the UTS of steel. This is an agreement with results from literature [25]. Fig 5 shows the effect of manganese content and carbon content on UTS. The variation in manganese content with variation in carbon content shows that as we increase the carbon content as well as manganese content the UTS also increases. An accurate prediction of UTS of sample of steel is possible due to broad and accurate data base. Received results also have confirmed the rightness of the artificial neural networks usage as the simulating tool possible for the application in the area of material engineering for the prediction of mechanical properties. It was successfully proved that neural networks are capable to make good and focused predictions. In our case substantial amount of data base was implemented. If “necessary conditions” are fulfilled very accurate modeling of influences in chemical composition within one steel grade on UTS can be made. The “necessary conditions” are: data base must have sufficient data vectors and they have to be representative data for treated steel grade. In our case this conditions were completely fulfilled and influence of carbon content and manganese content on UTS was successfully demonstrated. Basic UTS profile was successfully modeled for all the predictions which were made during this research.

**Table 1 Analysis of data of mild steel in normalized condition**

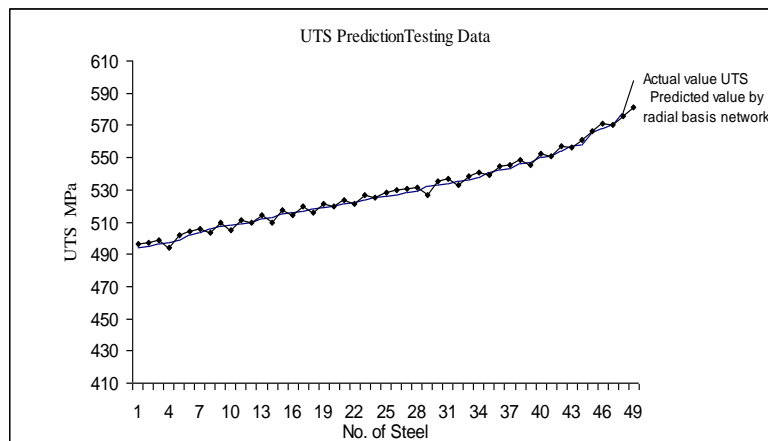
		C%	S%	P%	Mn%	Si%	Al%	Nb%	UTS
Training	max	0.19	0.029	0.04	1.50	0.39	0.030	0.071	602
	min	0.10	0.008	0.013	1.23	0.19	0.018	0.016	492
Validation	max	0.14	0.026	0.035	1.49	0.33	0.024	0.060	570
	min	0.10	0.011	0.017	1.35	0.21	0.020	0.038	497

Testing	max	0.14	0.026	0.035	1.50	0.34	0.029	0.061	570
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S. no	Data set	No of data	N/w type	Correlation coefficient	Max Error	Min Error	SE of estimate	Max % Error	Min % Error	% SE of estimate
1	Training data	73	RBF	0.9956	1.2914	-1.3	1.1219	0.216	-0.217	0.2099
			Back-propagati-on	0.9745	1.4311	-1.354	1.2918	0.322	-0.347	0.2116
2	Validati-on data	25	RBF	0.9899	1.2582	-1.2986	1.0745	0.2289	-0.2455	0.2039
			Back-propagati-on	0.9711	1.41	-1.971	1.084	0.2632	-0.2479	0.2091
3	Testing data	29	RBF	0.9878	1.3639	-1.3591	1.2597	0.2489	-0.2498	0.2423
			Back-propagati-on	0.9687	2.0216	-1.3911	1.2901	0.2653	-0.2589	0.2619
	min	0.11	0.011	0.017	1.36	0.21	0.020	0.032	494	

**Table II Analysis of result of Mild Steel in Normalized condition**

**Figure 1: Comparison of actual value and predicted value of UTS**



**Figure 2: Comparison of actual value and predicted value of by RBF network UTS by Back Propagation network**

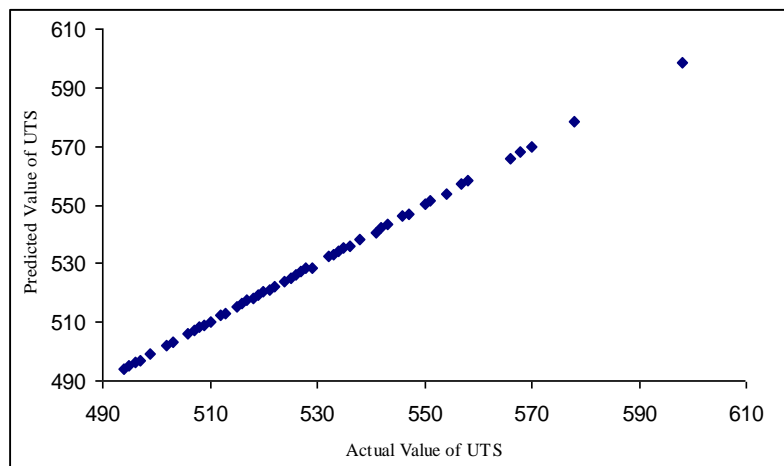
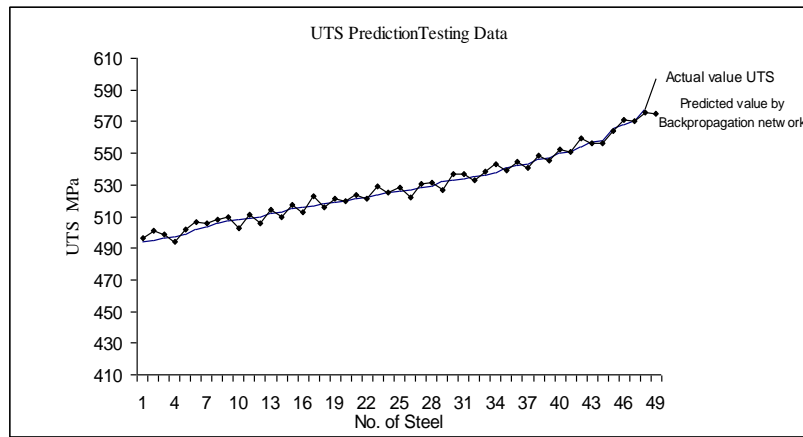


Table III shows the predicted value of tensile strength for different percentage of carbon content. The percentage of carbon content varies between the maximum and minimum range of the carbon given in the normalized steel dataset. The percentage of other alloy elements present in the steel data set is kept constant and they are also in maximum and minimum range of the percentage composition of alloy elements. The predicted UTS for different percentage of carbon content is plotted in the fig 4 which shows the effect of carbon content on UTS of steel. As the carbon content increases in the normalized steel there is increase in tensile strength also.

**Figure 3:**  
actual value  
predicted  
by using RBF



**Comparison of  
of UTS with  
value of UTS  
network**

**Table III Prediction of Tensile Strength of Mild Steel with variation in Carbon Content**

C%	S%	P%	Mn%	Si%	Al%	Nb%	UTS
0.08	0.018	0.025	1.46	0.27	0.02	0.046	492
0.10	0.018	0.025	1.46	0.27	0.02	0.046	513
0.12	0.018	0.025	1.46	0.27	0.02	0.046	528
0.14	0.018	0.025	1.46	0.27	0.02	0.046	541
0.16	0.018	0.025	1.46	0.27	0.02	0.046	551
0.18	0.018	0.025	1.46	0.27	0.02	0.046	559
0.2	0.018	0.025	1.46	0.27	0.02	0.046	566

**Figure 4 Tensile Strength of Mild Steel in Normalized condition with variation in Carbon Content**

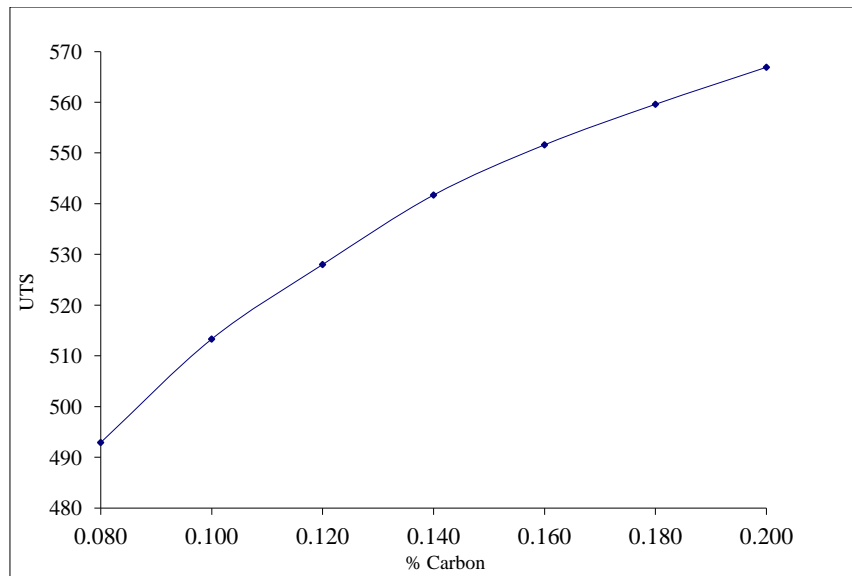


Table IV shows the predicted value of tensile strength for different percentage of carbon content and different percentage of manganese content. The percentage of carbon content and manganese content varies between the maximum and minimum range of the carbon and manganese given in the normalized steel dataset. The percentage of other alloy elements present in the steel data set is kept constant and they are also in maximum and minimum range of the percentage composition of alloy elements. The predicted UTS for different percentage of carbon and manganese content are plotted in the fig 5. The graph shows the behavior of UTS with increase in carbon percentage and manganese percentage.

**Table IV Prediction of Tensile Strength of Mild Steel with variation in Carbon Content and Manganese Content**

Mn%	0.08%C	0.10%C	0.12%C	0.14%C	1.8%C	0.20%C
1.20	492.300	499.100	508.900	516.400	518.400	521.400
1.25	498.800	505.500	513.500	520.000	523.500	527.500
1.31	504.500	513.600	522.200	527.800	532.000	539.100
1.38	513.300	527.300	536.500	542.300	547.400	556.800
1.41	518.700	534.500	545.700	550.300	555.900	567.700
1.46	525.800	545.500	556.500	560.500	567.300	583.200
1.50	533.342	556.800	567.200	572.300	580.000	602.192
S%		P%	Si%		Al%	Nb%
0.018		0.025	0.27		0.02	0.046

**Figure 5 Tensile Strength of Mild Steel in Normalized condition with variation in Carbon Content and Manganese Content**

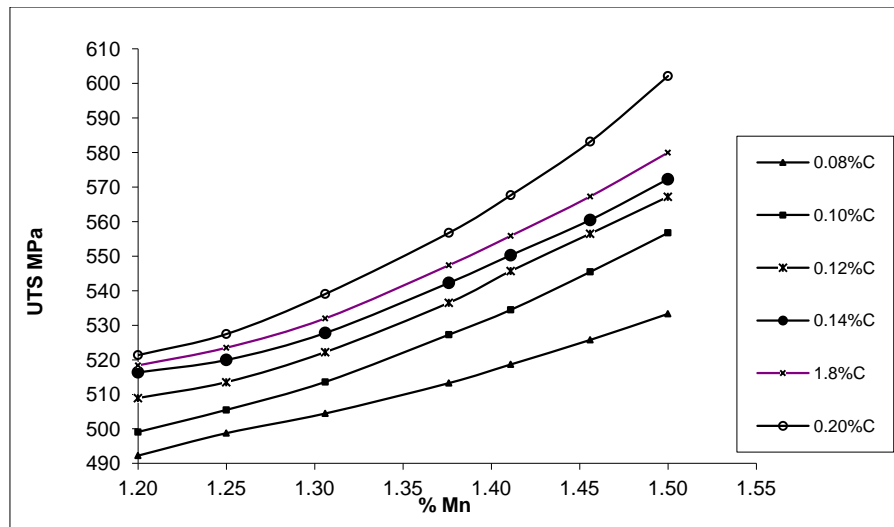
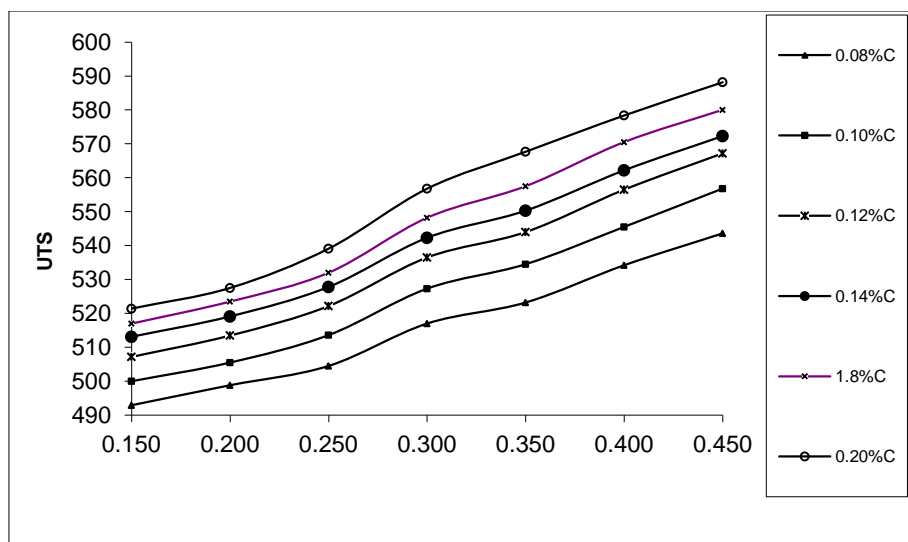


Table V shows the predicted value of tensile strength for different percentage of carbon content and different percentage of silicon content. The percentage of carbon content and manganese content varies between the maximum and minimum range of the carbon and silicon given in the normalized steel dataset. The percentage of other alloy elements present in the steel data set is kept constant and they are also in maximum and minimum range of the percentage composition of alloy elements. The predicted UTS for different percentage of carbon and silicon content are plotted in the fig 6 The graph shows the behavior of UTS with increase in carbon percentage and silicon percentage.

**Table V Prediction of Tensile Strength of Mild Steel with variation in Carbon Content and Silicon Content**

Si%	0.08%C	0.10%C	0.12%C	0.14%C	1.8%C	0.20%C
0.15	492.900	500.000	507.200	513.100	517.000	521.400
0.20	498.800	505.500	513.500	519.100	523.500	527.500
0.25	504.500	513.600	522.200	527.800	532.000	539.100
0.30	517.000	527.300	536.500	542.300	548.200	556.800
0.35	523.200	534.500	544.000	550.300	557.500	567.700
0.40	534.200	545.500	556.500	562.200	570.500	578.400
0.45	543.600	556.800	567.200	572.300	580.000	588.200
S%		P%	Mn%	Al%		Nb%
0.018		0.025	1.46	0.02		0.046

**Figure 6 Tensile Strength of Mild Steel in Normalized condition with variation in Carbon Content and Silicon Content**



## Conclusion

Simulating and analyzing result shows that network model can effectively predict the mechanical properties of material. The predicted tensile strength of steel, by Back propagation correlation coefficient equals to 0.9687, The tensile strength prediction max error 3.21, minimum error -3.011, standard estimation of error 0.2101, % error 0.653 Maximum, % error -0.589 Minimum, and standard estimation of error is 0.0219 is obtained. The Radial basis network gives better approximation, by using RBF the correlation coefficient equals to 0.9956. Which show the closeness of true value of the required property is achieved by the RBF neural network and radial basis method selection is best amongst the two. The maximum error is 2.99, minimum error -2.47, standard error of estimation is 0.1181, % maximum error 0.50, % Minimum error 0.413 and standard error of estimate 0.0219 is achieved. Application of the presented method enables a scientist to make free analyses of the effect of the alloying elements occurring in processing condition also using only computer simulation, without having to carry out additional and expensive experimental investigations.

## References

1. Ashby, M. F., "Materials selection in mechanical design", second edition, 1999, Butterworth Heinemann, Oxford.
2. Feldman, J. A., "Neural networks, artificial intelligence and computational reality", Computers in Industry 14, 1990, pp 145-148.
3. Kadir Cicek A, Metin Celik A.Y. and Ilker Topcu B, "Short communication on integrated decision aid extension to material selection problem", Materials and Design 31, 2010, pp 4398-4402.
4. Feigenbaum E A, "The art of artificial intelligence: Themes and case studies of knowledge engineering", Proc. Fifth Int. Joint Conf on Artificial Intelligence, Morgan Kaufmann, CA, 1977, pp. 1014-1029.
5. Ferrante M., Santo S.F. and Castro J.F.R., "Material selection as a interdisciplinary technical activity: basic methodology and case studies", Material Research, 2000, Vol.3, No. 2, pp.1-9.
6. Mahmoud M. A. A. and AL-Hammad A., "An expert system for evaluating and selection of floor finishing materials. Expert Systems with Applications", 10, 1996, pp 281-303.
7. Sestito S. and Dillon T, "Knowledge acquisition of conjunctive rules using multilayered neural networks", International Journal of Intelligent System 8, 1993, pp 779-805.
8. Jia-li Tang, Qiu-ru Cai and Yi-jun Liu, "Prediction of Material Mechanical Properties with Support Vector Machine," mvhi, International Conference on Machine Vision and Human-machine Interface, 2010, pp.592-595.
9. Donald R Askeland and Phule P. P., "The science and engineering of material fourth edition", Thomson Asian Pvt. Ltd. Singapore, 2003, ISBN no. 981-243-855-6.