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Prediction of Hardness of High Speed Steel Using Artificial Neural Network

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Abstract: ***This paper presents a method of predicting the mechanical 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 high speed steel. Simulating and analyzing result shows that network model can effectively predict the mechanical property of high speed steel. Application of this method enables a scientist or material developer to make free analyses of the effect of the alloying elements occurring in processing condition using only computer simulation, without having to carry out additional and expensive experimental investigations.***

Keywords: **Artificial Neural Network, Hardness, Radial Basis Function, Back Propagation Method.**

I. INTRODUCTION

The identification of properties of unknown material in the material testing laboratory requires 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 high speed steel is presented. Radial basis function and Back propagation method is used to identify the mechanical property of high speed steel. The 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 high speed steel is taken as data set.

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, high speed 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. 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. Steel also includes some other elements such as phosphorus, sulphur, silicon, nickel, etc. in proper amount according 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. 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

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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. 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 hardness value of high speed steel Table I data is used for prediction of hardness. All the data for hardness were processed at same condition. The input for network BP and RBF are normalized value of alloy element C, Co, Cr, V, W, Mo. While hardness is predicted based purely on these elements. Following Table II gives the value of performance index for all 33 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:

- 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.
- Average absolute error – difference between measured and predicted output values of the output variable

V. RESULT AND ANALYSIS

When the High speed steel is heated for hardening, the carbides dissolve to such a degree that the matrix acquires an alloying content that gives the hardening effect without becoming coarse grained and brittle. This means that the matrix becomes alloyed with carbon and carbide-forming elements. When the steel is heated to the hardening temperature (i.e. austenitizing temperature), the carbides are partially dissolved, results in alteration in matrix. It is transformed from ferrite to austenite. This means that the iron atoms change their position in the atomic lattice and make room for atoms of carbon and alloying elements. The carbon and alloying elements from the carbides are dissolved in the matrix if the steel is quenched sufficiently rapid in the hardening process, the carbon atoms do not have time to reposition themselves to allow the reforming of ferrite from austenite, i.e. as in annealing. Instead, they are fixed in positions where they really do not have enough room, and the result is high micro stresses that can be defined as increased hardness. This hard structure is called martensite. Thus, martensite can be seen as a forced solution of carbon in ferrite. When steel is hardened, the matrix is not completely converted into martensite. Some austenite is always left and is called "retained austenite". The amount increases with increasing alloying content, higher hardening temperature and longer soaking times. After quenching, the steel has a microstructure consisting of martensite, retained austenite and carbides. This structure contains inherent stresses that can easily cause cracking. But this can be prevented by reheating the steel to a certain temperature, reducing the stresses and transforming the retained austenite to an extent that depends upon the reheating temperature. This reheating after hardening is called tempering. Hardening of a tool steel should always be followed immediately by tempering. It should be noted that tempering at low temperatures only affects the martensite, while tempering at high temperature also affects the retained austenite. After one tempering at high temperature, the microstructure consists of tempered martensite, newly formed martensite, some retained austenite and carbides. Precipitated secondary (newly formed) carbides and newly formed martensite can increase hardness during high temperature tempering. Typical of this is the so called secondary hardening of e.g. high speed steel and high alloyed tool steels. High speed steel should always be double tempered. The second tempering takes care of the newly formed martensite formed after the first tempering. Three tempers are recommended for high speed steel with high carbon content. Carbon produces carbides and a hardenable matrix. Melting point is decrease with increase in carbon content. Low carbon content increase the impact strength but reduces the matrix hardness. Chromium reduces tendency to scaling. It is mainly present in the ferritic matrix and is largely responsible for the air hardening of High speed steel. Vanadium increases the abrasion resistance, cutting quality of the tools and the tendency to air hardening.

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Tungsten provides hot hardness by forming carbides and form-stability. Molybdenum increase hardenability, while cobalt improves hot hardness and makes the cutting tool more wear resistant. Chemical composition and hardness of high speed steel is used for prediction of hardness. All the data for hardness were processed at same condition. The input for network BP and RBF are normalized value of alloy element C, Cr, V, W, Co Mo. for prediction of hardness by these elements. Table 1 showing the maximum and minimum range of different composition of alloy elements present in the high speed steel set. The data set is divided into three set training set, validation set and testing set.

Table 1 Analysis of Data of High Speed Steel

		C	Mo	Cr	V	W	Co	Austen zing temperature °C	Tempering temperature °C	Hardness
Training	max	1.26	4.84	4.28	3.54	17.57	9.92	1280	580	68.54
	min	0.85	0.56	4.08	1.3	6.13	0.02	1150	500	60.45
Validation	max	1.26	4.84	4.28	3.54	17.57	9.92	1240	550	68.52
	min	0.85	0.56	4.08	1.3	6.13	0.02	1150	520	62.06
Testing	max	1.26	4.84	4.28	3.54	17.57	9.92	1255	580	66.87
	min	0.85	0.56	4.08	1.3	6.13	0.02	1180	500	63.64

Table II gives the value of performance index of two methods RBF and BP used for prediction of hardness of high speed steel. It shows the value of correlation coefficient, max and min error, standard error of estimate, percentage max and min error and percentage standard error of estimate for all the three set.

Table II Analysis of result of high speed steel

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	23	RBF	0.9913	0.9693	-0.9661	0.9474	1.5649	-1.5262	1.4366
			Back-propagation	0.9887	1.1751	-1.2783	1.021	1.631	-1.5 102	1.634
2	Validation data	5	RBF	0.9901	0.9691	-0.9418	1.0206	1.4683	-1.4897	1.5502
			Back-propagation	0.9732	1.2031	-1.173	1.0421	1.6193	-1.589	1.5626
3	Testing data	5	RBF	0.9893	0.9457	-0.9457	1.0202	1.4115	-1.4777	1.5466
			Back-propagation	0.9712	1.1132	-1.3031	1.032	1.5521	-1.7143	1.599

The fig 1 and 2 shows the comparison of actual value of hardness and predicted value of hardness of high speed steel by radial basis network and by back propagation method for testing data. The graph in fig 1 shows more accurate result by RBF network than BP method in graph in fig 2.

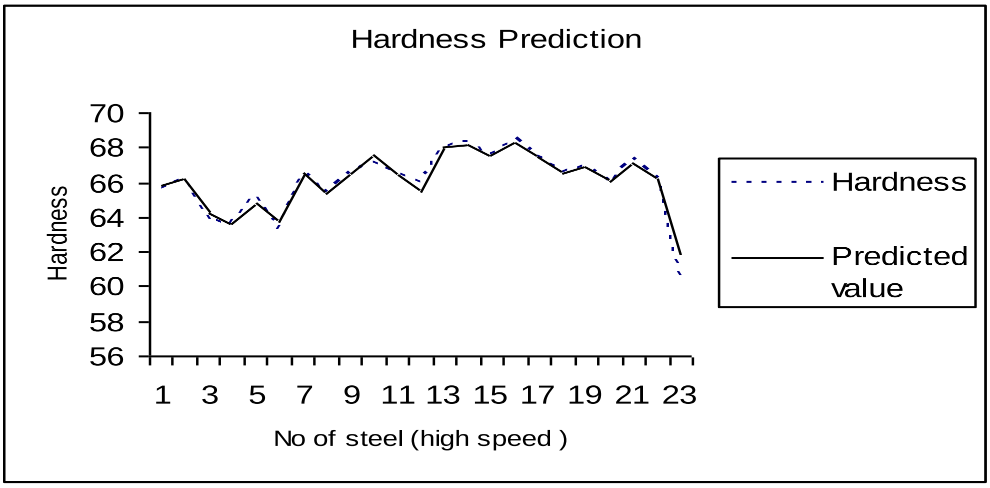

Fig 1 Comparison of actual hardness with predicted hardness of high speed steel by RBF

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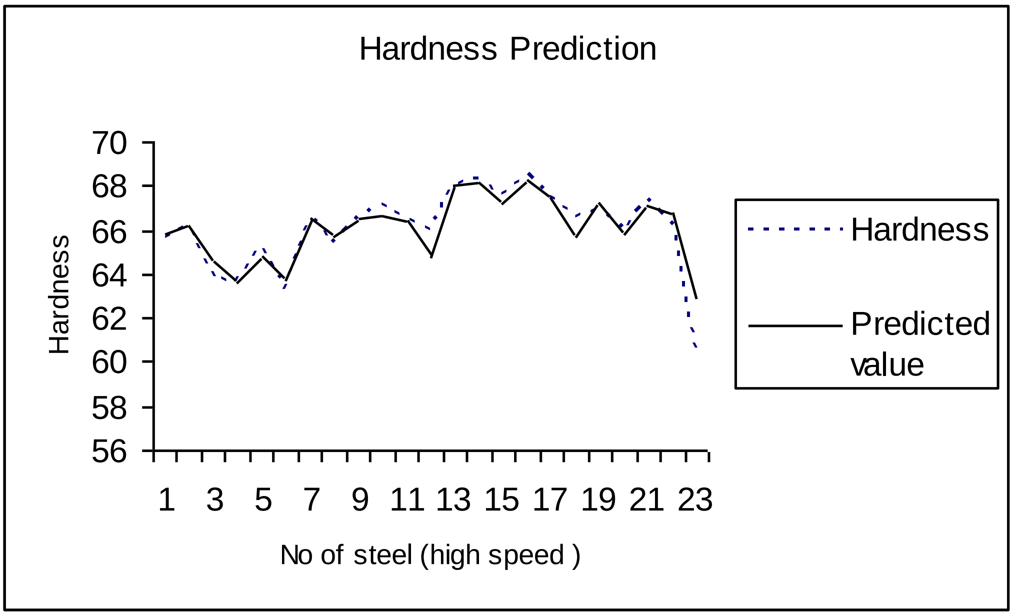

Fig 2 Comparison of actual hardness with predicted hardness of high speed steel by BP

Table III shows the predicted value of hardness for different percentage of carbon content. The percentage of carbon content varies between the maximum and minimum range of the carbon given in the high speed steel dataset. The percentage of other alloy elements present in the high speed steel data set is kept constant and they are also in maximum and minimum range of the percentage composition of alloy elements. The predicted hardness for different percentage of carbon content is plotted in the fig 3 which shows the effect of carbon content on hardness of steel. As the carbon content increases in the high speed steel there is increase in hardness also.

Table III Prediction of hardness of high speed steel with variation in carbon content

C	Mo	Cr	V	W	Co	Austenizing temp °C	Tempering temp °C	Hardness
0.8	2.7	4.08	1.3	17.6	0.07	1200	540	63.1
0.9	2.7	4.08	1.3	17.6	0.07	1200	540	64.02
1	2.7	4.08	1.3	17.6	0.07	1200	540	65.08
1.1	2.7	4.08	1.3	17.6	0.07	1200	540	66.09
1.2	2.7	4.08	1.3	17.6	0.07	1200	540	67.1
1.3	2.7	4.08	1.3	17.6	0.07	1200	540	68.11

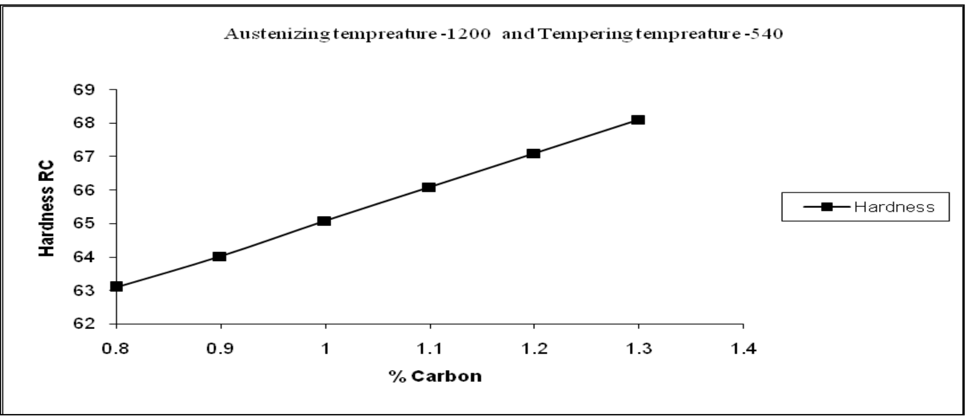

Fig 3 Hardness of high speed steel with variation in carbon content

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Table IV shows the predicted value of hardness for different percentage of carbon content and different percentage of molybdenum content. The percentage of carbon content and molybdenum content varies between the maximum and minimum range of the carbon and molybdenum given in the high speed 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 hardness for different percentage of carbon and molybdenum content are plotted in the fig 4. The graph shows the behavior of hardness with increase in carbon percentage and molybdenum e percentage.

Table IV Prediction of hardness of high speed steel with variation in carbon content and molybdenum content

% Mo	0.8% C	0.9% C	1.0% C	1.1% C	1.2% C	1.3% C
0.5	63.67	63.57	64.26	64.81	65.09	65.36
1.2	65.97	65.81	66.21	66.21	66.45	66.6
1.6	66.69	66.45	66.78	66.78	67	67.08
2	66.74	66.78	66.87	67.08	66.99	67.23
2.4	66.62	66.87	66.87	67.05	66.72	67.14
3	66.8	66.6	66.39	66.33	66.2	66.67
3.7	66.23	65.95	65.82	65.64	66.04	66.43
4.1	65.88	65.45	65.25	65.03	65.61	66.11
4.4	65.7	65.3	65.05	64.89	65.43	66.02
Value of Other alloying element during						

Cr	V	W	Co	Austenizing temp°C	Tempering temp°C
4.08	**1.3**	**17.6**	**0.07**	1200	540

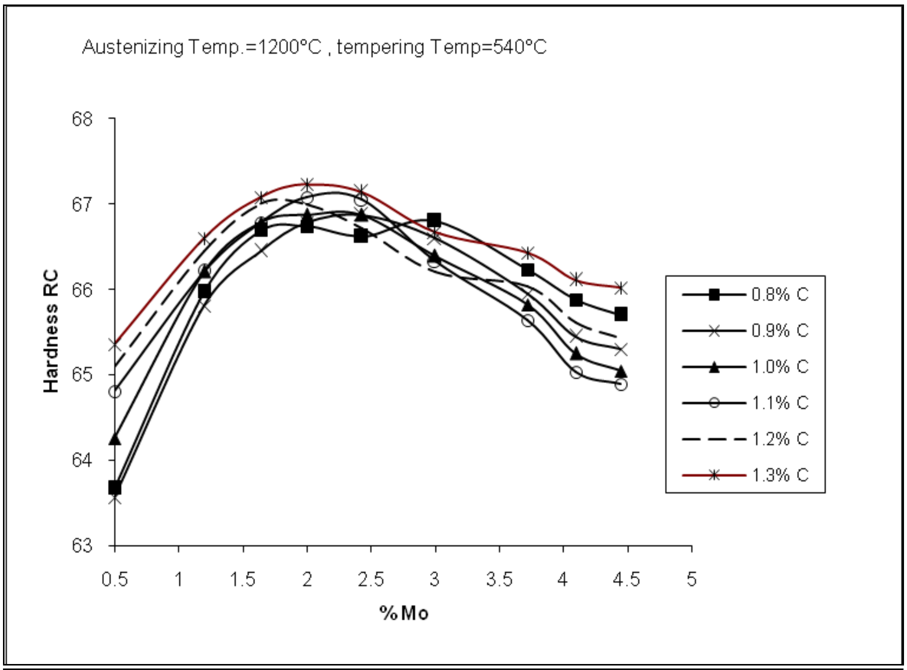

Fig 4 Hardness of high speed steel with variation in carbon content and molybdenum content

VI. CONCLUSION

Results obtained from the given ranges of input data show the very good ability of the nets to predict hardness of high speed steel. The results for hardness predictions with two most important chemical elements carbon and molybdenum is done, with percentage increase in carbon content increases the hardness of high speed steel. The predicted hardness for High speed steel by radial basis network, the correlations coefficient 0.9913, max error

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0.9457, minimum error -0.9457, standard estimation of error 1.0202, % error 1.4115 Maximum, % error-1.4777 Minimum, and standard estimation of error is 1.5466 is obtained. The BP network gives the correlations coefficient 0.9712, max error 1.1132, minimum error -1.3031, standard estimation of error 1.032, % error Maximum 1.5521, % error-1.7143 Minimum, and standard estimation of error is 1.599 is obtained. Simulating and analyzing result shows that network model can effectively predict the mechanical properties of material.

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