PREDICTION OF MICROHARDNESS OF Al-Si ALLOY USING NEURAL NETWORK AND RESPONSE SURFACE METHODOLOGY

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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 Al-Si alloy using artificial neural network and developing a mathematical model using response surface methodology (RSM). As micro hardness mainly depend upon Ti content and aging time, the present study deals with prediction of micro hardness using neural network and response surface methodology. 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 investigation. Simulating results will show that model can effectively predict micro hardness of Al-Si alloy.

Keywords: Micro Hardness, RSM, NN.

I. INTRODUCTION

Al–Si alloy is a well-known casting alloy with high wear resistance, good corrosion resistance, and improved mechanical properties at a wide range of temperatures. These properties led to the application of Al–Si alloys in the automotive industry, especially for cylinder blocks, cylinder heads, pistons, and valve lifters. The manufacturers and designer should have update information about 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 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. [1]

Neural Networks (NNs) 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. NNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, NNs 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 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. [2]

Neural Network (NN) is simplified models of the biological nervous system. NN in general is a highly interconnected network for a large number of processing elements called neurons in an architecture inspired by the brain. They can therefore be trained with known examples of a problem to acquire knowledge about it. Learning in neural networks is highly important and is undergoing vivid research in both biological and artificial networks. Learning is not a unique process; there are different learning processes, each suitable to different process. The back-propagation algorithm is an evolved mathematical tool; however, execution of the training equations is based on iterative processes and thus is easily implementable on a computer. [3]

II. EXPERIMENTATION

High purity elements, aluminum (99.9 wt.% purity), silicon (99.95 wt.% purity), and titanium (99.99 wt.% purity) were melted in a graphite crucible at 1400°C for 30 min under argon gas atmosphere in a high-temperature programmable furnace (Nabertherm, model LHT 02/18).Three different alloys were prepared by them and chemical composition of alloy is given in table 1. The melt was poured at a cooling rate of 10^3 K/min in a steel mould to produce a casting of 14 mm in diameter and 80mm in length.

The micro hardness of as-cast and heat-treated specimens was measured using a digital Shimadzu Micro hardness Tester HMV-2000, using a load of 300 gm for 15 sec. The increase in Ti content results in an increase in the micro hardness values. This is due to the increase in the volume fraction of the relatively hard-phase Al_3Ti. This design is based on two process parameters such as Ti content, aging time with three levels each. The process parameters and their levels are shown in Table 2. All experiments have been conducted by N. Saheb. and et.al. [1]. The aim of this paper is to predict micro hardness of Al-Si alloy using RSM and NN.

Table 1 Chemical Composition of alloy

ALLOY	COMPOSITION (wt. %)		
	Al	Si	Ti
ALLOY1	Balance	11.93	1.05
ALLOY2	Balance	11.75	2.15
ALLOY3	Balance	11.46	3.96

Table 2 Process Parameters and Experimental Design levels

VARIABLES	SYMBOLS	LEVELS		
		(-1)	(0)	(1)
Ti CONTENT	Ti	1.05	2.15	3.96
AGING TIME	AGING TIME (hr.)	0	4	8

III. RESULTS AND DISCUSSIONS

3.1 Response Surface Methodology

Taking micro hardness as output and process parameters (Ti content, aging time) as input, the prediction model using response surface methodology (RSM) has been developed at 95% confidence level. Response surface methodology is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which output or response is influenced by several input variables and the objective is to find the correlation between the response and the variables investigated (Montgomery, 1997). Using least square fitting, the model is developed.

The experiments are conducted based on full factorial design, which gives a comparatively accurate prediction of micro hardness average. The first step of RSM is to find a suitable approximation for the true functional relationship between micro hardness and set of independent variables utilized. In the linear model, the micro hardness is well modeled by linear function. However, in the second order model like response surface methodology, there is a curvature in the system. The second order response surface representing the micro hardness can be expressed as a function of two process parameters such as Ti content, Aging time. It has been expressed applying regression analysis using least square method. The following second order equation (1) for quality characteristics is obtained.

MICROHARDNESS = 68.1512+12.2306*Ti + 2.0896*AGING TIME – 1.5427*Ti*Ti – 0.0938*AGING TIME*AGING TIME– 0.1947*Ti*AGING TIME. --------------- (1)

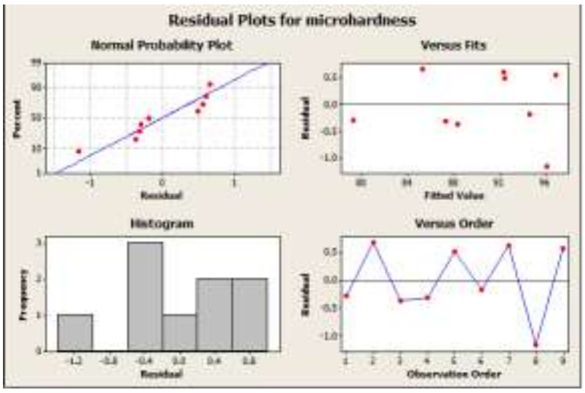

Fig.1 Residual plots for micro hardness

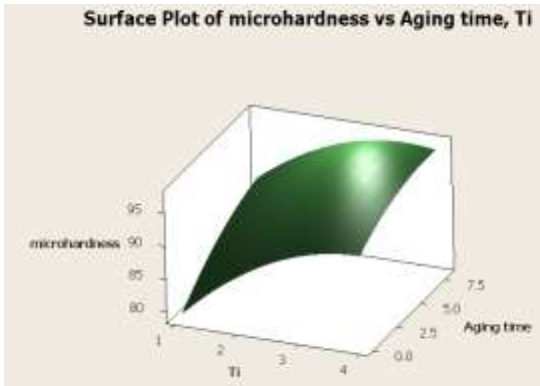

Fig. 2 Surface plot of micro hardness vs Aging time and Ti

Table 3 Estimated Regression Coefficients for micro hardness

Term	Coef	T	P
Constant	68.1512	30.762	0.000
Ti	12.2306	6.377	0.008
Aging time	2.0896	4.894	0.016
Ti*Ti	-1.5427	-4.234	0.024
Aging time*Aging time	-0.0938	-2.088	0.128
Ti*Aging time	-0.1947	-2.252	0.110

Table 4 Results for Micro Hardness By RSM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	265.403	265.403	53.0807	51.43	0.004 <0.05 SIGNIFICANT
Linear	2	237.164	61.550	30.7748	29.82	0.010
Ti	1	163.664	41.973	41.9727	40.66	0.008
Aging time	1	73.500	24.720	24.7200	23.95	0.016
Square	2	23.002	23.002	11.5011	11.14	0.041
Ti*Ti	1	18.502	18.502	18.5022	17.93	0.024
Aging time*Aging time	1	4.500	4.500	4.5000	4.36	0.128
Interaction	1	5.237	5.237	5.2368	5.07	0.110
Ti*Aging time	1	5.237	5.237	5.2368	5.07	0.110
Residual Error	3	3.097	3.097	1.0322		
Total	8	268.500				

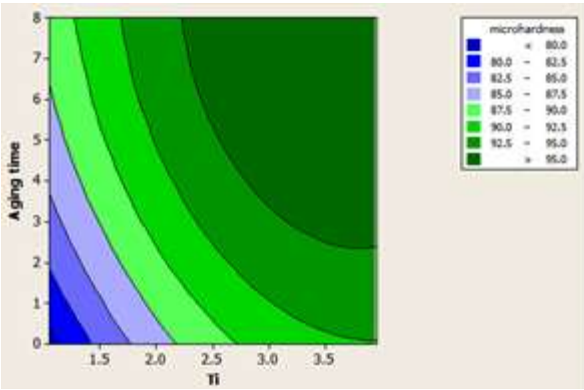

Fig.3 Effect of TI and Aging Time on Micro Hardness

Table 3 shows estimated Regression Coefficient for Micro hardness. Table 4 shows results obtained by RSM. The regression and linear terms are significant (P < 0.05). Again Table 4 shows that all linear and interaction coefficients are significant. From the square coefficients only one i.e. Ti*Ti is significant. From all significant coefficients the highest F value is obtained for P equal to 51.43, means it has highest effect on the response. The F value for the Ti is equal to 40.66, which indicates that the Ti has a relatively higher effect on the process and similarly the F value of Ti and other coefficients are very low indicate that less effect on the response.

The residual plot for micro hardness is shown in Fig.1. This residual plot in the graph for normal probability plot indicates the data are normally distributed and variables are influencing the response. And the Residuals versus fitted value indicate the variation is almost constant. According to the histogram, data are not skewed and not outline exist approximately. Residual versus order of the data indicates that there are systematic effects in the data due to time or data collection order. Fig. 2 shows surface plot for micro hardness. Figure 3 show effect of Ti and aging time on micro hardness.

3.2 Neural Network

NNs are computational models, which replicate the function of a biological network, composed neurons are used to solve complex functions various applications. The NN used here consists of three layers named as input layer, hidden layer and output layer as shown in Fig.3. The Input layer consists of different number of inputs variables/process parameters as described before. The Back Propagation Algorithm (BPA) is essentially stochastic approximation to nonlinear regression. [4, 5] .Several researchers are used BPA to model micro hardness and predict mechanical properties using neural network. [6]

In this work, MATLAB 7.9 is used for training the network model for micro hardness prediction. The designed neural networks structure used here is 2-1-1, with 2 corresponding to the input layer neurons, 1 to hidden layer neurons and 1 to output layer neurons. The numerical optimization technique used for this work is called Levenberg-Marquardt (LM). The developed NN architecture is trained with help of back propagation algorithm using 9 data sets. The neural network described in this work, after successful training, is used to predict the micro hardness of alloy. The % errors listed in Table 5 are calculated between the experimental and predicted value ranging between ± 2.01624. This result elucidated that, the developed neural network model have high accuracy for the micro hardness prediction.

3.3 Comparision Between RSM and NN

Comparison of RSM and NN showed in table 5. The maximum % error in case of RSM is 1.2281 and maximum % error in case of NN is 2.01624. Both RSM and NN can be used to predict micro hardness of Al-Si alloy. Table 6 shows comparison between RSM, NN and experimental values of micro hardness. The result show good agreement with experimental micro hardness.

Table 5 Comparison between RSM and NN

Ti	Aging time	Micro hardness (HV)	RSM	% ERROR	NN	% ERROR
1.05	0	79.0	79.2925	0.3703	79.4135	0.52342
1.05	4	86.0	85.3333	0.7752	84.5434	1.693721
1.05	8	88.0	88.3742	0.4252	88.9419	1.07034
2.15	0	87.0	87.3157	0.3629	87.4896	0.56276
2.15	4	93.0	92.5000	0.5376	91.1667	1.97129
2.15	8	94.5	94.6843	0.1950	93.6855	0.861905
3.96	0	93.0	92.3918	0.6540	94.8751	2.01624
3.96	4	95.0	96.1667	1.2281	95.9763	1.02768
3.96	8	97.5	96.9415	0.5728	96.6131	0.909641

Table 6 Comparison between Experimental and Predicted Micro Hardness Values By RSM and NN

SR.NO.	Ti	AGING TIME	MICROHARDNESS	RSM	NN
1	1.05	2	85	83.3131	84.84
2	1.05	6	87	87.522	86.987
3	2.15	2	90	90.386	90.1535
4	2.15	6	94	93.847	94.273
5	3.96	2	95	94.7026	94.501

IV. CONCLUSION

From the above discussion following important conclusions are derived

1. Ti content (%wt.) has strong influence on micro hardness. By changing the Ti value the response will be changed dramatically, so the Ti value should be carefully selected.
2. The aging time has also strongly affected the micro hardness but less than Ti content. But we cannot ignore this parameter.

3. Both RSM and NN show good agreement with experimental results. The results obtained by RSM and NN shows small % error (< 2.01624 %) while predicting micro hardness.
4. Therefore both methods can be effectively used to predict micro hardness of Al-Si alloy.

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