Comparison of Response Surface Methodology and Neural Network in Predicting Mechanical Properties of Al-Si alloy

V.M.Nangare[1*], Dr. V.M.Nandedkar[2]
[1] Research Scholar, Department of Production Engineering,SGGSIE&T, Nanded, India.
[2] Professor, Department of Production Engineering,SGGSIE&T, Nanded, India.
Corresponding author*: nangrevm@rediffmail.com

Abstract. Aluminium-Silicon alloys are sought in a large number of automotive and aerospace applications due to their low density, low cost and high wear resistance. The present study focused on Mechanical properties of the silicon based aluminium alloys. The mechanical properties of aluminium alloy castings are controlled by heat treatment variables, castings, alloy composition and melt treatment. In this paper the estimation capacities of the response surface methodology (RSM) and neural network (NN), in mechanical property estimation to determine ultimate tensile strength (UTS), hardness and wear rate in Al-Si alloy were investigated. This study aimed to investigate mechanical behavior (Ultimate tensile strength, hardness and wear rate) of Al- Si alloy against both the mould thickness and silicon content. Already available values of UTS, hardness and wear rate are used to train NN and to build mathematical model by RSM. The RSM results showed the quadratic polynomial model can be used to describe the relationship between the various factors (mould thickness and silicon content) and the response (UTS, Hardness and Wear rate). After predicting the model using RSM and NN, two methodologies were then compared for their predictive capabilities. The results showed that the RSM model is much more accurate in predicting UTS.

Keywords: RSM, NN, UTS.

1. Introduction

Aluminum-Silicon alloys are sought in a large number of automotive and aerospace applications due to their low density, low cost and high wear resistance. 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 experimentation plays an important role in Science, Engineering, and Industry. The experimentation is an application of treatments to experimental units, and then measurement of one or more responses. 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. Cast aluminum alloys are important construction materials, which are used in various fields of technology. Because of their low density, relatively low melting point, good heat and electrical conduction, low thermal expansion coefficient, good cast ability and low casting shrinkage, they are mainly used in car manufacturing as: piston castings, cylinder head castings, engine blocks, structural supporting reinforcements and elements absorbing crash impact. Aluminum alloys are also widely used in production of household goods. [1]

In an experiment, some input x's transform into an output that has one or more observable response variables y. Therefore, useful results and conclusions can be drawn by experiment. In order to obtain an objective conclusion an experimenter needs to plan and design the experiment, and analyze the results. There are many types of experiments used in real-world situations and problems. When treatments are from a continuous range of values then the true relationship between y and x's might not be known. The approximation of the response function $y = f(x1, x2,\ldots,xq) + e$ is called Response Surface Methodology (RSM).

The neural networks are used more and more widely to carry out many tasks. The advantage of the neural networks is their capability to learn and adapt to the changing condition, as well as their capability to generalize the acquired knowledge. [2]. 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. B. R. Moharana and S. K. Sahoo developed an ANN model to predict tensile strength of predicted area and results are compared with experimental result. [3] The neural technique was applied to the analysis of the ultimate tensile strength and additionally the yield strength of austempered ductile iron. [4] 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. [5]

The present study focused on Mechanical properties of the silicon based aluminum alloys. The mechanical properties of aluminium alloy castings are controlled by heat treatment variables, castings, alloy composition and melt treatment. This study aimed to investigate mechanical behavior of Al- Si alloy against both the mold thickness (10, 20 and 30 mm) and silicon content (03%, 9% and 15% Si). After predicting the model using RSM and NN, two methodologies were then compared for their predictive capabilities.

2. **Experimental Work**

These experiments were carried out by G.T. Abdel-Jaber, A. M. Omran and et.al. [6]. These results are used to predict mechanical properties. The alloys were prepared by melting the pure aluminum in an oil fired crucible furnace and the required amount of silicon was added to the molten aluminum at 800^0C in powder form with a particle size about 300 µm to 500 µm. The prepared alloys were poured in a step metal mold with different diameters of 10, 20, and 30 mm; five sets of the casting alloys were prepared with different silicon content, (3%, 9% and 15%Si). The measuring of mold temperature is performed using NiCr-Ni (DIN 43710) thermocouple that is able to measure temperature up to 1000^0C. The ultimate tensile strength and percentage elongation of the cast aluminum alloys were measured using a universal testing machine with a load capacity of 10 ton and a scale value of 0.02 ton at the lower speed of 5 mm/min.

The hardness was also measured using the macro- hardness tester. Emery paper was used to grind the surface of the specimens before testing. All the measurements were conducted on a Vickers hardness-testing device at a load of 30 kgf, for 15 seconds loading time, and 70 m/s loading speed. Tribological experiments were carried out using a wear tester; it consisted of specimen holder attached to the loading lever through two thin spring steel sheets to facilitate the measurement of friction force. The counter face, in form of bearing steel cylinder of 40 mm diameter and 11 mm height of surface roughness of 0.4 µm (Ra), was fastened to the rotating shaft of the tester. The load was applied by weights.

Experiments were carried out using a constant load of 60 N and a sliding velocity of 2 m/s for a sliding distance of 1200 m for each test which provide to be sufficient for highlighting reliable differences among the specimens. The test specimen was prepared in a cylindrical shape of 20 mm diameter and 15 mm height. Wear of the test specimens was determined by weight loss. Tests were conducted at room temperature whenever the contact zone is drip-feed lubricated with lubricating oil (SAE: 80W-90). [6]

Table 1 Process Parameters and Experimental Design levels

VARIABLES	SYMBOLS	LEVELS		
		(-1)	(0)	(1)
Si CONTENT	Si	3	9	15
MOLD THICKNESS	MOLD THICKNESS	10	20	30

This design is based on two process parameters such as Si content, mold thickness with three levels each. The process parameters and their levels are shown in Table 1.

3. RESULT AND DISCUSSION

3.1 RESPONSE SURFACE METHODOLOGY

Taking UTS, Hardness and Wear rate as output and process parameters (Si content, mold thickness) 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 UTS, Hardness and Wear rate average. The first step of RSM is to find a suitable approximation for the true functional relationship between UTS, Hardness, Wear rate and set of independent variables utilized. In the linear model, the UTS, Hardness and Wear rate 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 UTS, Hardness and Wear rate can be expressed as a function of two process parameters such as Si content, mold thickness. It has been expressed applying regression analysis using least square method. The following second order equations (1) for quality characteristics are obtained.

UTS = 127.097 + 4.056 * Si + 0.492 * MOLD THICKNESS - 0.079 *Si*Si - 0.018* MOLD THICKNESS*MOLD THICKNESS -0.042*Si*MOLD THICKNESS

HARDNESS=8.63889+6.58333*Si+2.39583*MOLDTHICKNES-0.25926*Si*Si-0.05333*MOLDTHICKNESS*MOLDTHICKNESS0.02917*Si*MOLDTHICKNES

WEAR RATE = 32.8333 - 3.0833* Si - 0.2125* MOLD THCIKNESS + 0.1389*Si*Si +0.0125*Si*MOLD THICKNESS ----------- (1)

Table 2 Estimated Regression Coefficients for UTS

Term	Coef	SE Coef	T	P
Constant	127.097	9.18379	13.839	0.001
Si	4.056	1.14021	3.557	0.038
Mold thickness	0.492	0.84910	0.579	0.603
Si*Si	-0.079	0.05645	-1.394	0.258
Mold t*Mold thi	-0.018	0.02032	-0.902	0.433
Si*Mold thickness	-0.042	0.02395	-1.740	0.180

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	980.11	980.111	196.022	23.73	0.013
Linear	2	932.33	104.824	52.412	6.35	0.084
Si	1	704.17	104.490	104.490	12.65	0.038
Mold thi	1	228.17	2.769	2.769	0.34	0.603
Square	2	22.78	22.778	11.389	1.38	0.376
Si*Si	1	16.06	16.056	16.056	1.94	0.258
Mold*Mold	1	6.72	6.722	6.722	0.81	0.433
Interact	1	25.00	25.000	25.000	3.03	0.180
Si*Mold	1	25.00	25.000	25.000	3.03	0.180
Residual Error	3	24.78	24.778	8.259		
Total	8	1004.89				

Table 3 Estimated Regression Coefficients for Hardness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	627.361	627.361	125.472	34.66	0.007
Linear	2	384.000	315.991	157.995	43.64	0.006
Si	1	384.000	275.338	275.338	76.05	0.003
Mold thickne	1	0.000	65.757	65.757	18.16	0.024
Square	2	231.111	231.111	115.556	31.92	0.010
Si*Si	1	174.222	174.222	174.222	48.12	0.006
Mold*Mold t	1	56.889	56.889	56.889	15.71	0.029
Interaction	1	12.250	12.250	12.250	3.38	0.163
Si*Mold thi	1	12.250	12.250	12.250	3.38	0.163
Residual Error	3	10.861	10.861	3.620		
Total	8	638.222				

Term	Coef	SE Coef	T	P
Constant	8.63889	6.08034	1.421	0.250
Si	6.58333	0.75490	8.721	0.003
Mold thickness	2.39583	0.56216	4.262	0.024
Si*Si	-0.25926	0.03737	-6.937	0.006
Mold thickness*Mold thic	-0.05333	0.01345	-3.964	0.029
Si*Mold thickness	-0.02917	0.01586	-1.839	0.163

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Table 4 Estimated Regression Coefficients for Wear Rate

Term	Coef	SE Coef	T	P
Constant	32.8333	2.44067	13.453	0.001
Si	-3.0833	0.30302	-10.175	0.002
Mold thickness	-0.2125	0.22565	-0.942	0.416
Si*Si	0.1389	0.01500	9.258	0.003
Mold thickness*Mold thickness	-0.0000	0.00540	-0.000	1.000
Si*Mold thickness	0.0125	0.00636	1.964	0.144

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	82.2500	82.2500	16.4500	28.20	0.010
Linear	2	30.0000	60.4092	30.2046	51.78	0.005
Si	1	24.0000	60.3971	60.3971	103.54	0.002
Mold thi	1	6.0000	0.5173	0.5173	0.89	0.416
Square	2	50.0000	50.0000	25.0000	42.86	0.006
Si*Si	1	50.0000	50.0000	50.0000	85.71	0.003
Mold *Mold	1	0.0000	0.0000	0.0000	0.00	1.000
Interaction	1	2.2500	2.2500	2.2500	3.86	0.144
Si*Mold thi	1	2.2500	2.2500	2.2500	3.86	0.144
Residual Error	3	1.7500	1.7500	0.5833		
Total	8	84.0000				

Table 2, 3, 4 shows estimated Regression Coefficient for UTS, Hardness and Wear rate respectively. The regression and linear terms are significant ($P < 0.05$). Again Table 2, 3, 4 shows that all linear and interaction coefficients are significant. From the square coefficients only one i.e. Si*Si is significant. From all significant coefficients the highest F value is obtained for P equal to 12.65, 76.05, and 103.54 means it has highest effect on the response. Si has a relatively higher effect on the process than mold thickness.

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. 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. Several researchers are used BPA to model UTS, Hardness and Wear rate and predict mechanical properties using neural network.

In this work, MATLAB 7.9 is used for training the network model for UTS, Hardness and wear rate 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 UTS, Hardness and wear rate of alloy. The % errors listed in Table 5, 6, 7 are calculated between the experimental and predicted value ranging between ± 7.19326. This result elucidated that, the developed neural network model have high accuracy for UTS, Hardness, Wear rate prediction.

3.3 COMPARISION BETWEEN RSM and NN

Comparison of RSM and NN showed in table 5, 6, 7 for UTS, Hardness and Wear rate. The maximum % error in case of RSM is 4.16687 and maximum % error in case of NN is 7.664. Both RSM and NN can be used to predict UTS, Hardness and Wear rate of Al-Si alloy. Table 5, 6, 7 shows comparison between RSM, NN and experimental values of UTS, Hardness and Wear rate. The result show good agreement with experimental UTS, Hardness and Wear rate.

Table 5 Prediction of UTS by RSM and NN.

Si	Mold thickness	UTS	RSM	%ERROR	NN	%ERROR
3	10	140	140.389	0.27785714	140.1701	0.1215
3	20	137	138.556	1.13576642	137.132	0.09635
3	30	135	133.056	1.44	135.54	0.4
9	10	159	156.556	1.537106918	158.021	0.615723
9	20	152	152.222	0.14605263	149.81	1.440789
9	30	142	144.222	1.56478873	139.2208	1.957183
15	10	165	167.056	1.24606061	165.92	0.55758
15	20	162	160.222	1.097530864	162.62	0.38272
15	30	150	149.722	0.185333333	149.47	0.353333

Table 6 Prediction of Hardness by RSM and NN.

Si	Mold thickness	Hardness	RSM	%ERROR	NN	%ERROR
3	10	43	43.806	1.87442	43	0
3	20	53	50.889	3.983019	53	0
3	30	46	47.306	2.83913	49.3089	7.193261
9	10	63	62.889	0.17619	63.2823	0.448095
9	20	67	68.222	1.82388	65.1721	2.72821
9	30	64	62.889	1.735938	63.4721	0.82484
15	10	64	63.306	1.084375	64	0
15	20	66	66.889	1.34697	66	0
15	30	60	59.806	0.323333	60	0

Table 7 Prediction of Wear rate by RSM and NN.

Si	Mold thickness	Wear Rate	RSM	%ERROR	NN	%ERROR
3	10	23	23.0833	0.36217391	22.999	0.004348
3	20	21	21.3333	1.58714286	20.9978	0.010476
3	30	20	19.5833	2.0835	18.4673	7.664
9	10	16	15.3333	4.166875	16.5515	3.44688
9	20	14	14.3333	2.38071429	14.0149	0.10643
9	30	13	13.3333	2.56384615	13.8733	6.71769
15	10	17	17.5833	3.43117647	17.5078	2.98706
15	20	18	17.3333	3.703888889	17.5036	2.757778
15	30	17	17.0833	0.49	17.2359	1.38765

4. Conclusion

From the above discussion following important conclusions are derived

1. Si content (%wt.) has strong influence on UTS, Hardness and Wear rate. By changing the Si value the response will be changed dramatically, so the Si value should be carefully selected.
2. The mold thickness has also strongly affected the UTS, Hardness and Wear rate but less than Si 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 (< 7.01624 %) while predicting hardness.
4. Therefore both methods can be effectively used to predict UTS, Hardness and Wear rate of Al-Si alloy.

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