



DEVELOPING A NEURO FUZZY MODEL TO PREDICT THE PROPERTIES OF AlSi12 ALLOY

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ABSTRACT

The effects of modification and vibration during solidification of Aluminum-Silicon eutectic alloy (AlSi12) are studied and compared with unmodified alloy. Sodium and Strontium are used as modifiers. Horizontal sinusoidal vibration at different frequencies was imposed using a vibration Table. It was found that modification treatment improves properties such as ultimate tensile strength (UTS), percentage elongation, hardness, toughness, cutting force, electrical conductivity, thermal conductivity, fluidity, porosity and fatigue strength and optimum values were found for sodium and strontium weight addition of modifier. Self organized feature map (SOFM) network model is developed using Neuro Solutions package. Genetic algorithm is used to optimize the model developed. Further, neuro fuzzy model (CANFIS) is developed and compared the results with neural network model developed. Sensitivity analysis is carried out to measure the relative importance of the inputs of the model and how the model output varies in response to variation of an input. The developed models were validated experimentally.

Keywords: modification, neural networks, neuro-fuzzy, canfis, sensitivity.

1. INTRODUCTION

Among the cast aluminum alloys, Aluminum-Silicon alloy is the first and most important casting alloy primarily because of their excellent casting characteristics. Silicon is one of the few elements that may be added to aluminum, without loss of its weight advantage. Aluminum-Silicon alloys are the most important class of commercial non-ferrous alloys having wide ranging applications in the automotive and aerospace industries because of their casting characteristics, high strength-to-weight ratio, wear and corrosion resistance, pressure tightness, good weldability and good surface finish. Applications of these alloys have included automotive cylinder heads, engine blocks, aircraft components and pipe fittings. This alloy contains 10-13% by weight of silicon [1]. These are non-heat treatable and difficult to machine than Al-Cu and Al-Mg alloys [2]. The rapid cooling in pressure die casting causes, a fine structure and reduced grain size. But slower cooling rates encountered in permanent mould and sand casting, the alloy contains silicon phase in the form of large plates with sharp sides and ends, this acicular silicon plates acts as internal stress raisers in the microstructure and provide easy paths for fracture which leads to brittleness. Typical Aluminum-Silicon alloys have two major micro-structural components, namely primary aluminum and an aluminum-silicon eutectic. While nucleation and growth of the primary aluminum in the form of dendrites have been well understood, understanding of the evolution of Al-Si eutectic is still incomplete. The micro-structural changes caused by the addition of strontium to these alloys are another important phenomenon that still puzzles the scientific community. The mechanical properties of Aluminum-Silicon alloys are related to the grain size, shape, size and distribution of the discontinuous phase of the castings. Coarse grain, eutectic silicon, and cavities

reduce the tensile strength, ductility and impact strength of the alloys. If the macro and micro-structures are controlled, then the alloy will have excellent mechanical properties.

2. REVIEW OF LITERATURE

Addition of some elements like sodium or strontium in trace amounts causes a change in the solidification, morphological characteristics of silicon both in eutectic and primary form. This change (specifically the morphological change) is termed as modification. Because of its commercial importance, study of this phenomenon of modification has been the subject of intense research efforts dating back to early 1920s till today. It was found that combined additions of Sr and Na do not appear to cause improvement of the modification of the eutectic microstructure even after only a short period after addition. Na addition may promote Sr vaporization and/or oxidation kinetically, leading to a quicker loss of both modifiers, which is blamed for the rapid loss of the modification effect during melt holding [3]. Combining Sr and Na additions produced no beneficial effects on porosity and casting defects [3].

However, some recent studies have reported that modified castings are more prone to microporosity than unmodified castings [4, 5]. Excessive amounts of modifiers (over modification) results in gas porosity [6].

It is a common practice in industry to refine the microstructure through the application of post processing techniques, e.g. heat treatment, rolling, etc. Several practices are currently used during the casting process to refine the microstructure. These methods include rapid cooling, adding grain refiners, and rheocasting. All of these techniques have proved successful in producing equiaxed grains; however each has several associated disadvantages. Rapid cooling may produce cracking and it



is not suitable for thin-section castings. Adding grain refiners may be harmful to the environment, and involves problems like fading and poisoning [7]. Subjecting the solidifying melt to vibration has also proved successful in refining the microstructure. However, the lack of quantitative conclusive correlation between vibration parameters and the resulting refinement has prevented this technique from being more widely used. There are also other issues representing challenges to the application of vibration as a refinement technique. These include the applicability to large castings, effect of initial mold temperature and pouring temperature, suitability to sand molds, cost, etc.

Different methods have been used to apply vibration during casting. Electromagnetic vibration is one of the non-contact methods used to induce vibration inside the solidifying metal. The vibration is induced by applying an orthogonal static magnet and alternating electric fields. It was reported that the collapse of the cavities generated by this method was responsible for the refinement of the microstructure for Al-17%Si, A-7%Si, and gray cast iron. However, it was also reported that this method is costly and requires tremendous amount of current to be effective [8]. On the other hand, mechanical vibration is more commonly used than electromagnetic vibration due to its simplicity and low cost.

Mechanical vibration as a technique for grain refinement was first reported early in the last century by Sokoloff. Several other researchers have investigated the effect of vibration on the microstructure of castings. The beneficial effect of vibration was observed with several types of metals, e.g. zinc, brass, aluminum, etc. The effects include promotion of nucleation and thus reducing as-cast grain size, reducing shrinkage porosities due to improve metal feeding, and producing a more homogenous metal structure. These improved features lead to enhanced mechanical properties and lower susceptibility to cracking [9, 10].

3. RESEARCH METHODOLOGY

Experiments were conducted by adopting best melting practices and using standard test specimens to find various mechanical properties of AlSi12 alloy. Specimens were prepared using different gating systems viz, direct pouring, single gate and two gate. To find the effect of modification on the properties, modifiers like sodium and strontium were used. A vibration Table is fabricated to

apply different levels of frequency of vibration. Micro structural analysis in the three stages of experimentation is done using scanning electron beam microscope.

Best neural network model is found and genetic algorithm is used to optimize the model. Neuro fuzzy hybrid network is developed and results were compared with the neural network models developed. Neuro fuzzy model was trained optimally and graphs were drawn comparing trained data and experimental data for all the output responses. Optimally trained network is tested with production data sets and percentage error is calculated. Sensitivity analysis graphs depict the sensitivity about the mean with different input parameters.

4. EXPERIMENTATION

The experiment has been carried out in three stages by controlling the operating parameters like AlSi12 alloy composition, melting and pouring temperatures.

Stage I

In this stage, molten metal is poured into the mould boxes with direct pouring gating system (no gate). Various tests were conducted by varying sodium percentage by weight modifier and frequency of vibration. Tests were repeated with permanent modifier strontium and frequency of vibration. Percentage of modifier is added at various levels 0, 0.5, 1, 1.5, 2 and 2.5. Frequency of vibration is carried out on the mould box by bolted over the vibrating Table as shown in Figure and forced to vibrate during solidification of the molten metal in the mould box. By varying the speed of the motor the frequency of vibration has been varied. Vibration is given for 2 minutes to each casting at 0, 5, 10, 15, 20 and 25 Hz.

Stage II

In this stage, molten metal is poured into the mould box using parting gate or single gating system. Experimentation is carried as discussed in stage I

Stage III

In this stage, molten metal is poured into the mould box using step gate or two gating system. Experimentation is carried as discussed in stage I.

The values like UTS, elongation, BHN, toughness, cutting force, electrical resistivity, thermal conductivity, porosity, fatigue strength and fluidity were found in the three stages above and results were tabulated.

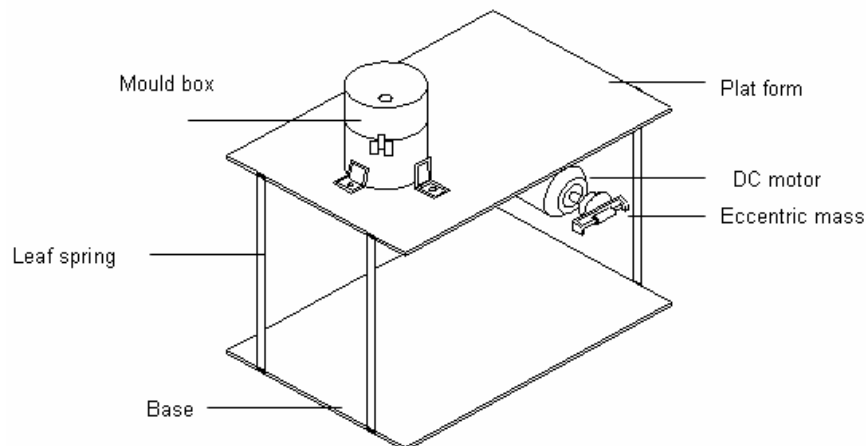


Figure-1. Line diagram of vibration table.

5. PREDICTIONS OF STRONTIUM MODIFIED ALLOY

There are 3 input parameters (no. of gates, % modifier and frequency of vibration) and 10 output parameters (UTS, % elongation, BHN, toughness, fatigue strength, cutting force, electrical resistivity, thermal conductivity, porosity and fluidity). For finding fluidity, fluidity spiral is used directly. Hence no. of gates is not an input parameter to study the Fluidity. Hence a separate model is required to develop a model to predict fluidity of the alloy. Hence for the remaining 9 output responses a single model can be developed.

Some of the most common ANN architectures considered to develop the model are: Multilayer Perceptron (MLP), Generalized Feedforward, Modular, Jordan/Elman, Principal Component Analysis (PCA), Radial Basis Function (RBF), General Regression Neural Network (GRNN), Probabilistic Neural Network (PNN), Self-Organizing Feature Map (SOFM), Time-Lag Recurrent Network (TLRN), Recurrent Network, and Support Vector Machine (SVM).

Architecture is selected based on the lowest Mean Square Error (MSE) value. Once the network architecture

is selected, parameters such as the number of hidden layers, the number of epochs and the learning algorithm can be customized. Among all the above NN models studied, Self-Organizing feature map network (SOFM) gave best MSE of 0.00092 with 31000 epochs, 2 hidden layers, TanhAxon transfer function and momentum as learning rule, after many trail and error combinations. This NN model is optimized using Genetic Algorithm and MSE obtained is 0.000895, which is 2.7% less than SOFM network model.

Details of CANFIS neuro-fuzzy model data sets are given in Table-1 and various parameters selected for predicting accurate results using neuro-fuzzy network are given in Table-2. MSE of various models developed is given in Table-3.

Table-1. CANFIS model data sets.

Training data sets	Cross validation data sets	Testing data sets	Production data sets
99	3	3	3

Table-2. Parameters selected for CANFIS neuro-fuzzy model.

Input layer		Output layer	
Processing Elements (PEs)	3	Transfer function	Axon
Output PEs	9	Learning rule	Momentum
Exemplars	99	Step size	1
Hidden layers	0	Momentum	0.7
Membership function(MF)	Bell	Maximum epochs	31000
MFs per unit	3	Threshold	0.01
Fuzzy model	TSK	Weight update	Batch

**Table-3.** MSE of the models.

S. No.	Model name	No. of hidden layers	No. of epochs	Mean square error (MSE)
1	Self-organizing feature maps network(SOFM)	2	31000	0.000920
2	Self-organizing feature maps network, optimized with genetic algorithm (SOFM + GA)	2	31000	0.000895
3	Coactive neuro-fuzzy inference system (C (CANFIS))	0	30000	0.0006389

When CANFIS neuro-fuzzy model is used, MSE obtained is 0.0006389 with 30000 epochs, which is 28% less than SOFM model optimized with GA. % error of CANFIS predicted values and experimental values considered for production is calculated and shown in Table-4. From the Table-4, it is clear that fatigue strength is not best predicted as % error is more than 5%. Hence it is proposed to develop another CANFIS model by

eliminating fatigue strength from the earlier model. The new CANFIS model keeping the other parameters same as in Table-2 (except output PEs, which is 8 in new model instead of 9) with 30244 epochs, least MSE obtained is 0.000813704. This is the best model found for the prediction of AlSi12 properties except fatigue strength. A new CANFIS model is developed to predict the fatigue properties of AlSi12 alloy.

Table-4. % error of CANFIS predicted values of production data.

S. No	Property	Experimental	CANFIS predicted	% error
1	Ultimate tensile strength	73	73.12	0.16
2	Percent elongation	5	5.02	0.4
3	Brinell hardness number	44	43.61	0.88
4	Toughness	6	5.86	2.33
5	Cutting force	33	32.65	1.06
6	Electrical resistivity	0.061	0.060	1.63
7	Thermal conductivity	109	108.58	0.38
8	Porosity	1.8512	1.7872	3.45
9	Fatigue strength	98	92.67	5.43

Sensitivity values of various properties with respect to the three input process variables are given in Table-5. These values are graphically represented in Figures 1a, 1b and 1c. From the Table it is clear that, all the properties are more sensitive to % modifier. Mean square error of the network (Training) w.r.t no of epochs is shown in Figure-2. Complete error analysis of the model and best network values are given in Table-6. Hence CANFIS model at 30244 epochs is the best tool to predict

the properties of AlSi12 alloy except to predict fatigue strength. Hence with strontium modifier, total three models were developed. One is for fatigue strength; second one is for fluidity and third one for the remaining properties. Similarly three more models were developed for sodium modifier. Experimental versus CANFIS neuro-fuzzy model predicted values of UTS and percentage elongation for the entire data (108 data sets) is graphically represented in Figures 3 and 4.



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Table-5. Sensitivity values of Sr modified alloy.

S. No.	Sensitivity	No. of gates	% modifier	Frequency
1	Ultimate tensile strength	1.0512	7.4399	0.6115
2	Percent elongation	0.1220	1.1742	0.1504
3	Brinell hardness number	0.1162	0.8321	0.4350
4	Toughness	0.0695	1.3222	0.3306
5	Cutting force	0.6690	8.2953	1.5799
6	Electrical resistivity	0.0007	0.0035	0.0011
7	Thermal conductivity	0.8541	8.6216	1.1740
8	Porosity	0.2426	0.3068	0.0570

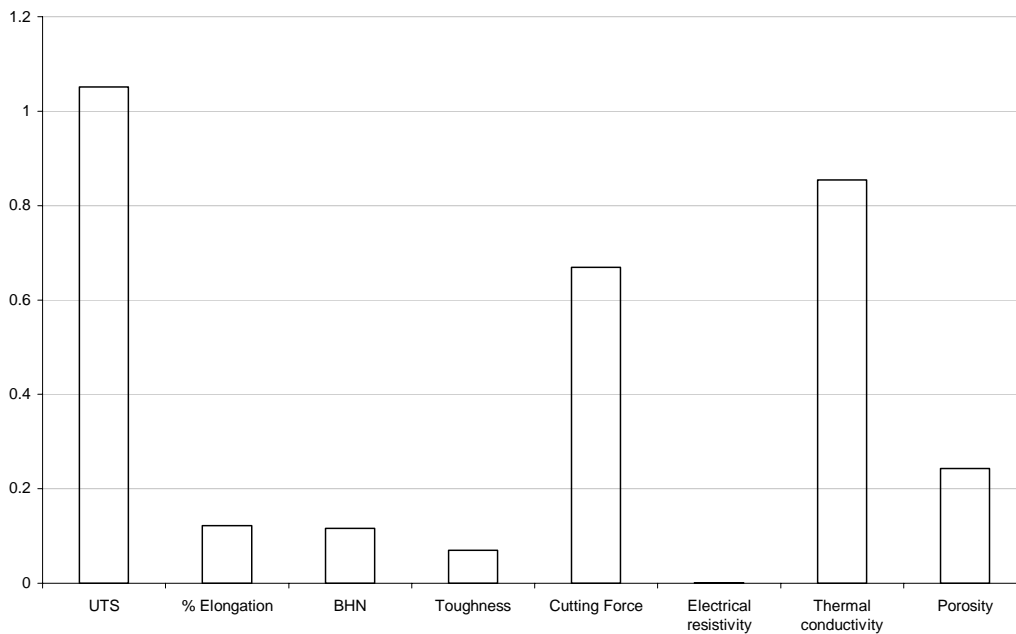


Figure-1a. Sensitivity of Sr modified AISi12 alloy with number of gates.



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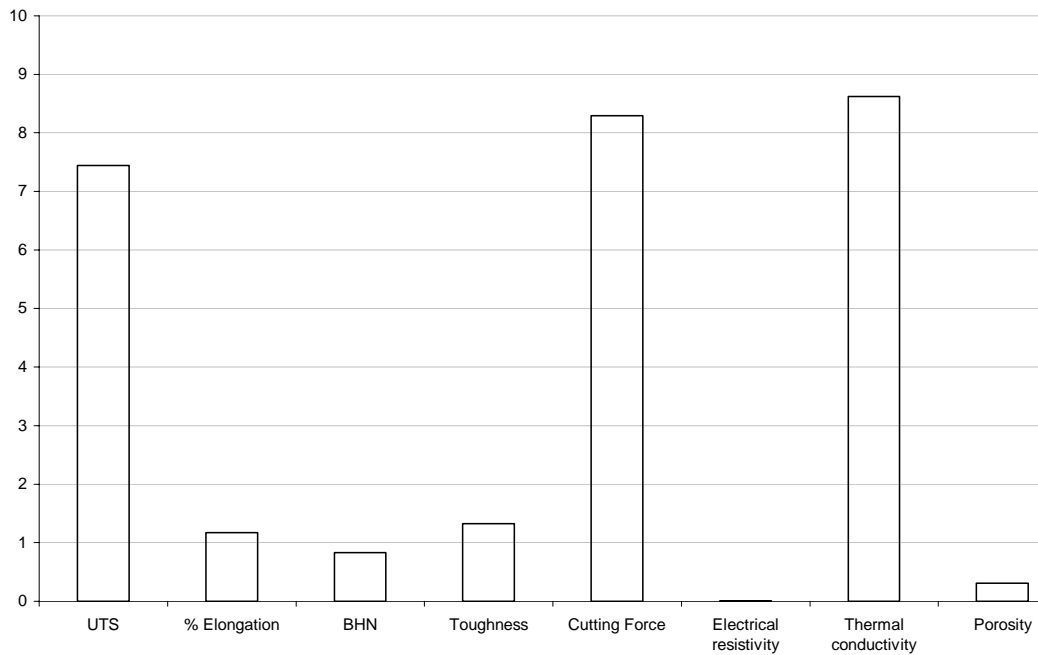


Figure-1b. Sensitivity of Sr modified AlSi12 alloy with % modifier.

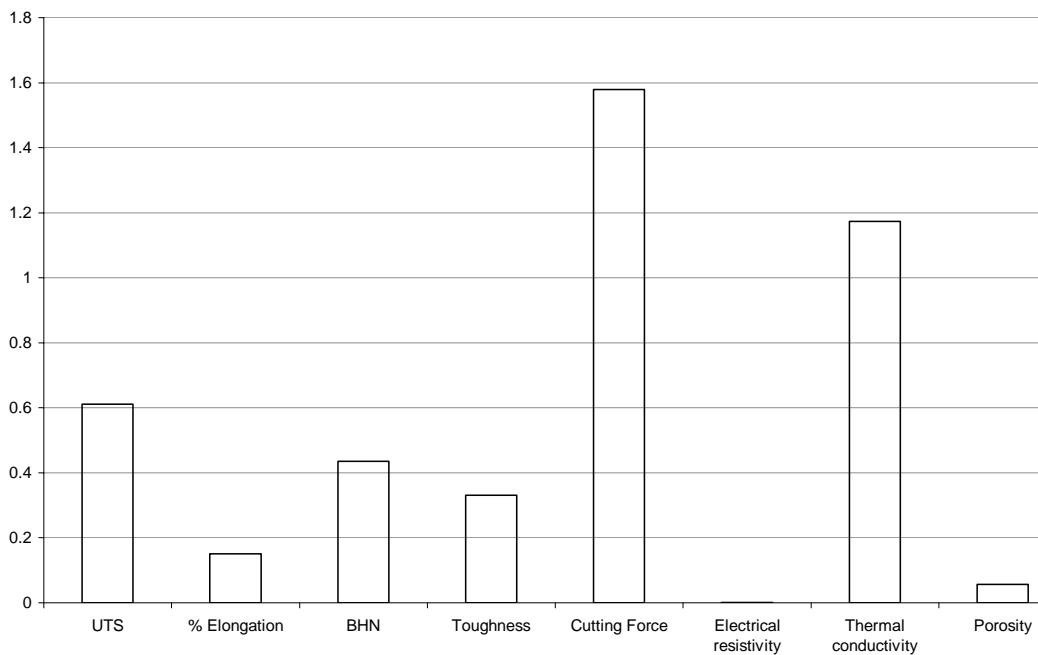


Figure-1c. Sensitivity of Sr modified AlSi12 alloy with frequency of vibration.



Training MSE

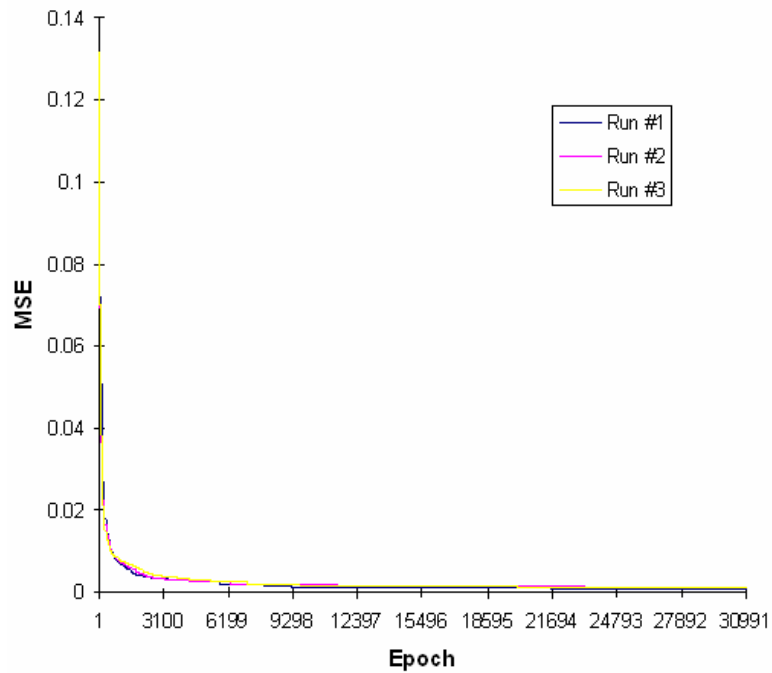


Figure-2. Mean square error of the network (Training).

Table-6. Error analysis of the model-strontium modified alloy.

(a) MSE and Std. deviation of training and cross validation network				
All runs	Training minimum	Training standard deviation	Cross validation minimum	Cross validation standard deviation
Average of minimum MSEs	0.001087476	0.000461126	0.003865431	0.00112645
Average of final MSEs	0.010460847	0.008837798	0.011532547	0.00838212
(b) Best fit values				
Best networks	Training	Cross validation		
Run #	2	3		
Epoch #	30244	22083		
Minimum MSE	0.000795124	0.002959439		
Final MSE	0.000813704	0.006708017		

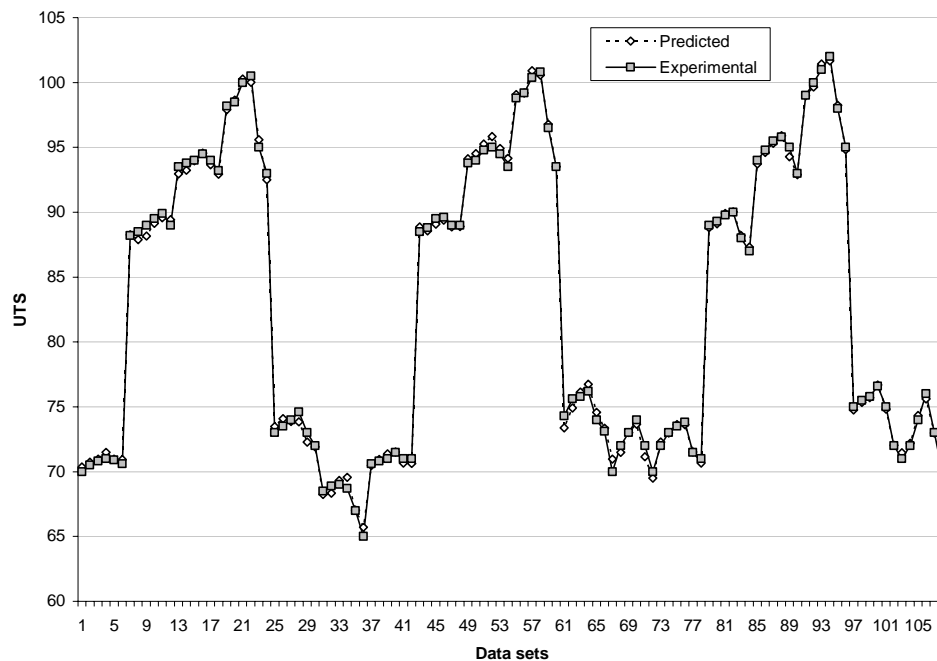


Figure-3. Experimental and network predicted values of UTS.

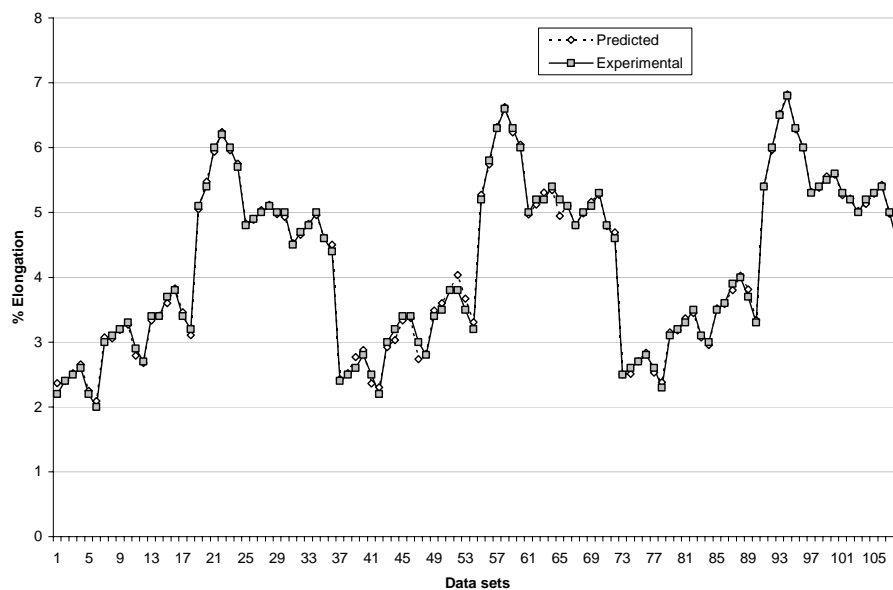


Figure-4. Experimental and network predicted values of % elongation.

6. RESULTS AND DISCUSSIONS

Surface plots for various properties with respect to % modifier and frequency of vibration of sodium modified AlSi12 alloy specimens with single gating system are shown in Figures 5 to 14. It has been found that optimum values were obtained at 1.5% by weight of modifier and vibration at 15 Hz frequency except for electrical resistance, thermal conductivity, fluidity and porosity. SEM photographs of the unmodified, modified, modified-vibrated AlSi12 alloy is shown in Figure-15. Unmodified alloy contains silicon in large flake types as shown in Figure-15a. As reported by many investigators, modification breaks up the silicon into fibrous form, which

is seen in Figure-15b. The change in silicon morphology by the use of modification and vibration during solidification is shown in the SEM micrograph of Figure-15c, and is considered to be responsible for the enhanced strength of the modified-vibrated alloy. The observed smaller fatigue striation spacing may be linked to the smaller silicon particles in the modified and modified-vibrated alloys [13]. The refinement of silicon may be due to the increased number of nuclei present, when the solidification is taking place under vibration [14].

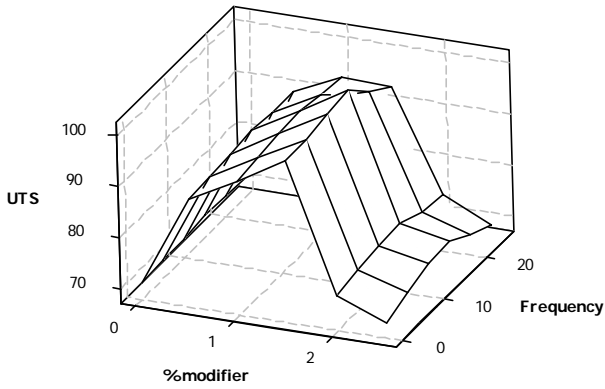


Figure-5. UTS.

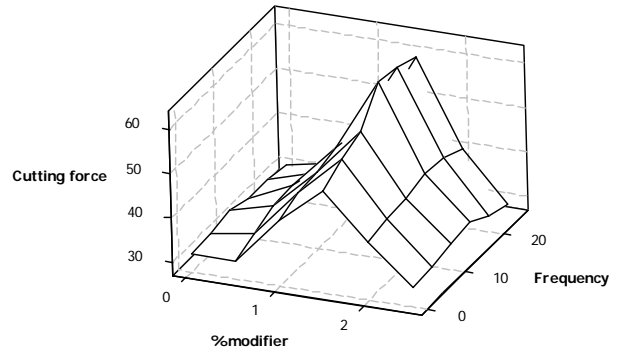


Figure-9. Cutting force.

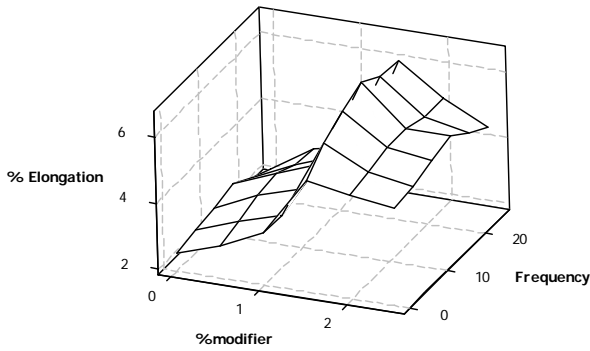


Figure-6. % Elongation.

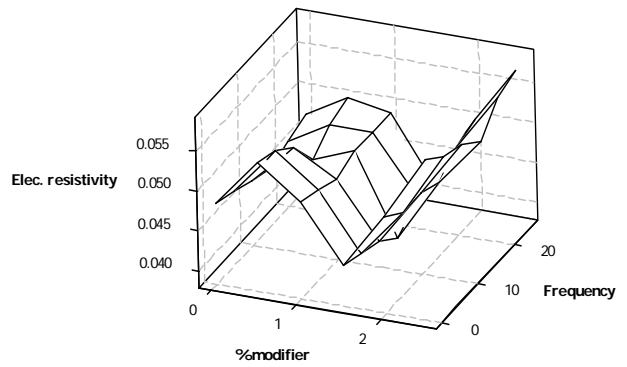


Figure-10. Elec. resistivity.

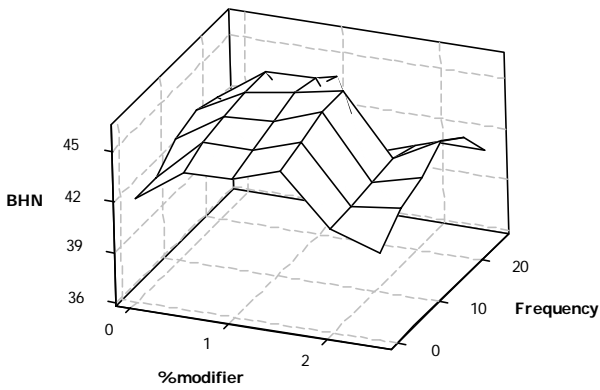


Figure-7. BHN.

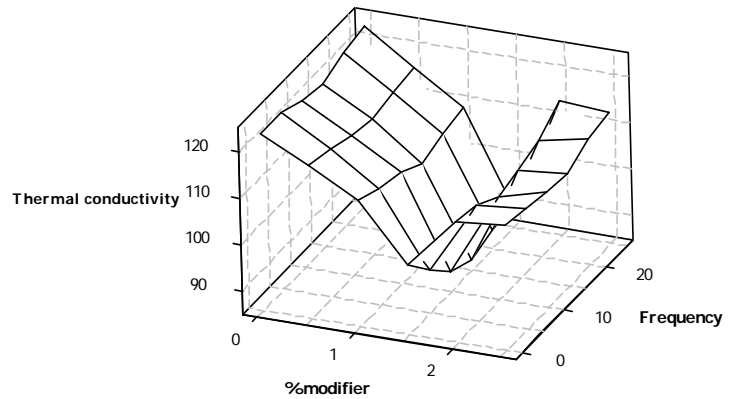


Figure-11. Thermal conductivity.

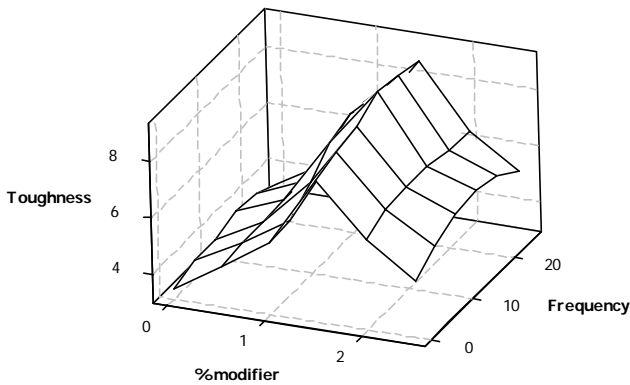


Figure-8. Toughness.

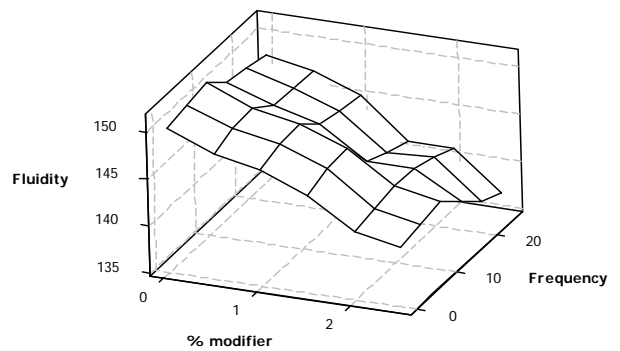


Figure-12. Fluidity.

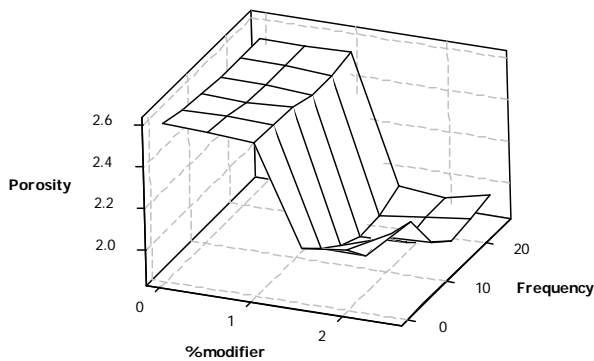


Figure-13. Porosity.

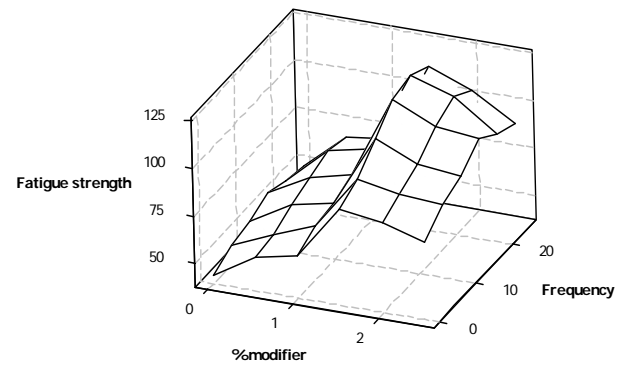


Figure-14. Fatigue strength.

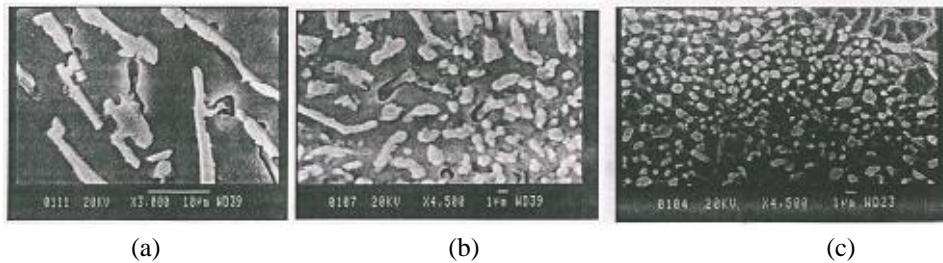


Figure-15. SEM micrographs in three stages (X4500).

7. SUMMARY

Neuro fuzzy models are developed to predict the output responses for varied input process parameters of AlSi12 alloy. The output obtained from neuro fuzzy model for training and cross validation are compared with desired response values and found that they are in good agreement. The network is also tested by using a new set of input variables for verifying the prediction from the network and found that satisfactory results are obtained. It is found that neuro-fuzzy network is the best tool to predict the properties of AlSi12 alloy with different weight percentages of modifiers and different levels of frequency of vibration applied.

8. CONCLUSIONS

Modification treatment on AlSi12 alloy using Sodium/ Strontium modifiers, improves the properties such as ultimate tensile strength, percentage elongation, hardness, toughness, cutting force, electrical conductivity and thermal conductivity. Optimum values are obtained at 1.5% by weight addition of Strontium/Sodium modifier. Modification with vibration further improves the mechanical properties of AlSi12 alloy. At 15 Hz frequency optimum values are obtained. Modified-vibrated alloy has changed the silicon morphology better compared to the modified alloy. It is found that fatigue strength of modified-vibrated Al-Si eutectic alloy is higher than that of the unmodified and modified alloys. It is also found that vibration during solidification reduces the porosity in modified Al12Si alloy. Fluidity decreases with increasing the weight percent of strontium modifier. Modification with vibration increases the fluidity slightly.

From neuro-fuzzy network model, it is found that fatigue strength is more sensitive to number of gates and fatigue strength and thermal conductivity are more sensitive to % modifier and electrical resistivity is least sensitive to %modifier. Sensitivity values of thermal conductivity and fluidity are next to fatigue strength than all other properties with respect to frequency of vibration. Porosity and electrical resistivity are least sensitive to frequency of vibration. Porosity decreases with increase in % modifier up to 1.8% by weight of sodium. Porosity is maximum at 0.5 % by weight of sodium as per neuro fuzzy hybrid model predictions.

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