International Research Journal in Global Engineering and Sciences. (IRJGES)
ISSN : 2456-172X | Vol. 5, No. 3, Sep - November, 2020
Pages 38-50 | Cosmos Impact Factor (Germany): 5.195
Received: 02.09.2020 Published: 28.11.2020

INVESTIGATION OF SQUEEZE CASTING PROCESS PARAMETERS ON SURFACE QUALITY OF ALUMINIUM ALLOY

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ABSTRACT

The casting surface finish needs to be very good for both aesthetic appearance part and proper functional part during its service life of the cast components. In the present work an attempt made to examine the effects of influencing squeeze cast process parameters such as time delay before pressurization, pressure duration, squeeze pressure, pouring temperature and die temperature on average surface roughness (Sa) of the squeeze cast components. The non-contact type, confocal microscope was used to measure the areal topography on the surface of cast specimens. Increase in time delay results in decrease in surface finish and increase in pressure duration, squeeze pressure, pouring and die temperatures resulted in improvement in the surface finish was observed. The artificial neural network model using levenberg-marquardt algorithm was developed and trained with data collected from the experimental work using Matlab software. It was found that the developed neural network reduces the mean squared error to a very small value. The accuracy of the trained network was tested with data which was not used during the training process. The results showed that the developed network predicts with an accuracy of about 3.221% mean absolute percentage error between the experimentally measured and neural network predicted values.

Keywords: Squeeze casting process, Process parameters, Surface roughness (Sa), Levenberg-Marquardt algorithm.

INTRODUCTION

In today's competitive manufacturing environment there is a great demand for the castings with more uniform smooth surface. Also the products that can be readily used in services without adding any expensive secondary processes such as plating, shot-blasting, machining, burnishing and polishing. The casting surface needs to be very good not only as an aesthetic appearance part, but also of proper functional view point during service life of the components. Good surface finish is always desirable which improves hardness, tensile strength, fatigue, corrosion and tribological properties [1]. The advanced squeeze casting process has the ability to produce smooth casting surface [2]. Vijian and Arunachalam (2007)made an attempt to optimize the squeeze cast process parameters by considering die-material (copper, stainless steel and cast iron), squeeze pressure and die temperature on

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surface finish of LM6 aluminium alloy[3]. Vijian et al (2007),investigated the surface roughness of squeeze cast LM6 alloy by considering process variablessuch as squeeze pressure, die temperature and die materials[4]. Pouring temperature considered as an influencing parameter for surface roughness during lost foam casting process of grey cast iron material by Suyitno and Sutiyoko (2012) [5]. The influence of squeeze pressure at different processing intervals were varied by keeping melt temperature, die temperature and time delay parameters at constant values and examined the resulted surface finish of squeeze cast aluminium alloy by Boschetto et al (2007) [6].Bates et al., (1968) studied the influence of mould material on the casting surface formation and reported the casting surface quality directly influences on mechanical properties such as bending and fatigue life[7].Krishna (2001) reported high quality squeeze cast products are influenced by squeeze casting process variables and till date there is no universal standard available to obtain optimal process parameters to yield high quality squeeze cast parts [8]. Artificial neural networks have potential challenges in the eve of prediction, optimization, control, monitor, identification, modelling, classification and so in the field of casting and injection moulding processes [9]. Wang et al, (2011) made an attempt to predict the temperature difference of the squeeze cast part with different squeeze cast process parameters were studied utilizing with back propagation algorithm of artificial neural networks [10]. Krimpenis et al., (2006) [11] made an attempt to predict the optimal process conditions for pressure die casting process using learning vector quantization and levenberg-marquardt (LM) algorithm of neural networks and genetic algorithm. Yarlagadda and Chiang (1999) used LM, momemtum adaptive learning and error-back propagation algorithms of neural networks to generate the process parameters for pressure die-casting process [12]. Farahnay et al., (2010) used LM algorithm to predict the liquidus temperature of the cast aluminium silicon alloys with respect to chemical compositions [13]. Mandal and Roy, (2006) used statistical design of experiments and back propagation neural network (BPNN) to predict the compression strength of the molasses of cement sand system and the guidelines for selection of hidden neurons was also illustrated [14]. Mazahery and Shabani (2012) used LM algorithm to predict porosity and mechanical properties of the commercially casting with aluminium alloy reinforced with nano-silicon carbide [15]. Zheng et al., (2009) used LM algorithm to optimize the die casting process parameters to prevent surface defects of the die cast parts [16]. Abhilash et al., (2006) predict the mechanical and micro-structure properties of casting samples of permanent mold casting process using LM algorithm [17]. From the above literatures, it is evident that the casting surface finish depends on the process variables and artificial neural networks with Levenberg-Marquardt algorithm can be used to predict the average surface roughness (Sa) for different squeeze casting conditions. So in the present experimental study an attempt is being made to explore the effects by considering the influencing process parameters such as time delay in pressure application, pressure duration, squeeze pressure, pouring temperature and die temperature on surface finish of squeeze cast LM20 aluminium alloy. An attempt was also made to develop the process model for the squeeze casting process using artificial neural

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networks.

SQUEEZE CASTING PROCESS

The squeeze casting process involves the following three stages,

1. The measured quantity of the molten metal is poured into the pre-heated cylindrical die-cavity.
2. Pressure is applied through punch on the molten metal until the complete solidification takes place.
3. Punch is then retracted and the casting is ejected through ejector pins

The major factors in influencing the surface finish of the casting samples such as squeeze pressure, pressure duration, time delay before pressurization, pouring temperature and die temperatures. Good surface finish can be obtained mainly by controlling the process variables. The choice of process parameters and their respective rangesused in the current experimental study is shown in table1. The selection is done through pilot experiments and from the past literatures available.

MATERIAL AND METHODS

Excellent fluidity, pressure tightness, free from hot tearing, wear and corrosion resistance properties of LM20 alloy finds major applications in marine castings, meter cases, water jackets, street lighting, castings subjected to atmospheric conditions, automobile, office and domestic equipments [18]. In squeeze casting process the dies were exposed to severe thermo-mechanical cycles.Hence, H13 grade chromium molybdenum hot-work tool steels was heat treated to a surface hardness of 45-48 RC to with stand thermal fatigue, cracking, corrosion, erosion and indentation [19]. The quantitative chemical analysis was performed using optical emission spectrometer (OES) to determine exact chemical composition of LM20 alloy and H13 hot die steel and obtained results are shown in table 2 & 3.

EXPERIMENTAL DESIGN

A 40 tonne universal testing machine is employed for pressure application. The mica strip electrical heater is used to pre-heat the die and the punch. H13 grade chromium molybdenum based hot work die steel was used for the both die and punch.J-type thermocouple is inserted in the die of about approximately 10 mm near to the cylindrical cavity. Automatic temperature controlling capacity was incorporated to accurately maintain the die-temperature during experimentation. Electrical resistance type crucible furnace was used to melt the metal. The j-type thermocouple coupled with temperature indicator was used for measuring the melt temperature before pouring it into the cylindrical die cavity. Degassing is performed using hexachloroethane (C_2Cl_6) tablets to remove the oxides content in the melt if any. Coverflux (45 wt.% NaCl-45wt.% KCl-10 wt.% NaF) was used to clean the molten metal before pouring. The experimental set-up used for the present investigation is shown in Fig. 1.

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Fig. 1 Squeeze casting experimental set up

EXPERIMENTAL PROCEDURE:

The required quantity of the molten metal is poured into the pre-heated cylindrical die cavity after proper melt preparation using degasser and cover flux. The punch was brought in contact with the molten metal fitted at the middle of the cross-head. The entire die-setup placed on the hydraulic table. The pressure was applied by means of punch on to the metal after allowing time delay and held constant for pre-determined time until the complete solidification takes place. The punch was then withdrawn and the casting was separated from the die.

EXPERIMENTAL PLAN

The experiments were conducted by varying one parameter at a time from level 1-5 and keeping the rest of the process parameter as constant at the middle level-3. Twenty two different experimental conditions were conducted to examine the effects on surface roughness. Surface quality examination can be performed through both contact and non-contact type measuring instruments. There are three types of surface texture measurements namely line-profiling, areal topography and area integrator [20]. Line-profiling method is of contact type uses high-resolution probe to sense the peaks and valleys of thesurface topography and produce a quantitative profile Z(X) of the surface topography. The areal topography method uses non-contact type optical methods which extends the line-profiling method into the three dimensional images usually by raster scanning of series of series of profiles or by quantitative topographic imaging process. The non-contact type optical methods of measuring instruments have the following advantages such as non-destructive and fast because of imaging and microscopy compared to contact type stylus device [20]. Hence in the present paper non-contact type optical method using confocal microscopy measuring instrument was utilized for surface quality examination and the obtained results were tabulated in table 4.

Table 1 Process parameters and their respective levels

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Process parameters	**Units**	**Level-1**	**Level-2**	**Level-3**	**Level-4**	**Level-5**
Squeeze pressure, (S_p)	MPa	0.1	50	100	150	200
Pressure duration, (D_p)	S	10	20	30	40	50
Time delay, (T_d)	S	03	05	07	09	11
Pouring temperature, (P_t)	˚C	630	660	690	720	750
Die temperature, (D_t)	˚C	100	150	200	250	300

Table 2. Chemical Composition of LM20 Alloy

Element	Cu	Mg	Si	Fe	Mn	Ni	Zn	Pb	Sn	Ti	Al	Others
BS 1490LM20 standard (%wt)	<0.4	<0.2	10-13	<1	<0.5	<0.1	<0.2	<0.1	<0.1	<0.2	Rest	<0.2
(OES)-ASTM E1251-07	0.177	0.175	10.41	0.287	0.526	0.02	0.147	0.005	0.005	0.175	87.84	Cr-0.017

Table 3. Chemical Composition of H13 Hot die steel

Element	C	Mn	Si	Cr	P	Mo	V	Fe	S	Others
ASTM A681-08 (%wt)	0.32-0.45	0.2-0.6	0.8-1.25	4.75-5.5	<0.03	1.1-1.75	0.8-1.2	Rest	<0.03	<0.5
OES- Analysis	0.39	0.38	1.0	4.9	0.019	1.17	0.79	90.91	0.008	0.433

ARTIFICIAL NEURAL NETWORKS (ANNS) MODEL:

Neural networks works are the simplified models of our biological nervous system. Our biological nerve system consists of large number of interconnectedprocessing units termed as neurons. For example our human brain comprising of 100 billion neurons, each neurons connect up to 200000 neurons and approximately 1000-10000 connections available. The neurons were arranged to form a layer, the connection pattern formed within and between the layers though weights were termed as network architecture. Weights contain information about the input signal [21]. The neural network advantages mainly depends the network architecture and the algorithms adopted [22].

LEVENBERG–MARQUARDT ALGORITHM

The development of levenbergmarquardt algorithm was credited to Levenberg and Donald Marquardt. The LM algorithm development is to overcome the limitation of error-back propagation algorithm such as slower convergence and getting stuck with local minima. Hence it combines the features of error back propagationalgorithm and gauss newton method during the training process. LM algorithm uses error back propagation algorithm where large area of the search space and until the local minima of the error surface is reached and switches to the gauss-newton method to speed up the training process and helps to converge fast [23].

The Levenberg Marquardt algorithm training includes following two parts [23],

1. Calculation of Jacobian Matrix
2. Training process design

The steps involves in calculation of Jacobian matrix includes forward and backward computations such as [23],
Forward computation involves:
1. Calculate net values, slopes, and outputs for all neurons in the first layer:

$$net_j^1 = \sum_{i=1}^{m} I_i W_{j,i}^1 + W_{j,0}^1 \qquad (1)$$

$$y_j^1 = f_j^1\left(net_j^1\right) \qquad (2)$$

$$s_j^1 = \frac{\partial f_j^1}{\partial net_j^1} \qquad (3)$$

Where,
I_i are the network inputs
Superscript "1" means the first layer
j is the index of neurons in the first layer

2. The outputs of the first layer neurons used as the inputs of all neurons in the second layer, perform similar calculation for net values, slopes, and outputs:

$$net_j^2 = \sum_{i=1}^{n_1} y_i^1 w_{j,i}^2 + w_{j,0}^2 \qquad (4)$$

$$y_j^2 = f_j^2\left(net_j^2\right) \qquad (5)$$

$$s_j^2 = \frac{\partial f_j^2}{\partial net_j^2} \qquad (6)$$

3. The outputs of the second layer neurons is used as the inputs

$$net_j^3 = \sum_{i=1}^{n_2} y_i^2 w_{j,i}^3 + w_{j,0}^3 \qquad (7)$$

$$o_j = f_j^3\left(net_j^3\right) \qquad (8)$$

$$s_j^3 = \frac{\partial f_j^3}{\partial net_j^3} \qquad (9)$$

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4. Calculate error at the output j and initial δas the slope of output j:

$$e_j = d_j - o_j \tag{10}$$

$$\delta^3_{j,j} = s^3_j \tag{11}$$

$$\delta^3_{j,k} = 0 \tag{12}$$

Where,

d_j= Target output at j^{th} neuron
o_j=Network output at j^{th} neuron from the forward calculation
e_j = Error at output j^{th}neuron
$\delta^3_{j,j}$ is the self back propagation
$\delta^3_{j,k}$ is the back propagation from other neurons in the output layer

5. Backpropagateδ from the third layer inputs to the second layer outputs

$$\delta^2_{j,k} = w^3_{j,k}\delta^3_{j,j} \tag{13}$$

Where, k is the index of the neurons in the second layer from 1 to n_2

6. Backpropagateδ from the outputs of the second layer to the inputs second layer

$$\delta^2_{j,k} = \delta^2_{j,k}s^2_k \tag{14}$$

7. Backpropagateδ from the inputs of the second layer to the first layer outputs

$$\delta^1_{j,k} = \delta^1_{j,k}s^1_k \tag{15}$$

Where$k$ is the index of neurons in the second layer, from 1 to n_1

Repeat the steps from 4-7, for the back propagation process of the other outputs

8. The whole δ and y matrix for the given inputs can be calculated using forward and backward calculation. Correspondingly the jacobian matrix can also be computed using the equation

$$\frac{\partial e_{p,m}}{\partial w_{j,i}} = -\delta_{m,j}y_{j,i} \tag{16}$$

Where,

$$\delta_{m,j} = s_j F'_{mj} \tag{17}$$

$$y_{j,i} = \frac{\partial net_j}{\partial w_{j,i}} \tag{18}$$

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$$s_j = \frac{\partial y_j}{\partial net_j} \qquad (19)$$

F'_{mj} is the derivative of the non-linear relationship between neuron j and output m.

$$\frac{\partial e_{p,m}}{\partial w_{j,i}} = \frac{\partial(d_{p,m} - o_{p,m})}{\partial w_{j,i}} = -\frac{\partial o_{p,m}}{\partial w_{j,i}} = -\frac{\partial o_{p,m}}{\partial y_j}\frac{\partial y_j}{\partial net_j}\frac{\partial net_j}{\partial w_{j,i}} \qquad (20)$$

(20)

TRAINING PROCESS DESIGN FOR LM ALGORITHM

The training process using levenberg–marquardt algorithm includes the following steps [23]:

1. Initialize weights with random generation, forward computation to determine the network output and evaluate error.
2. The objective of training process is minimize the error, Hence weights need to update using Eq. (21) to adjust weights to achieve best results

$$w_{k+1} = w_k - (j_K^T j_k + \mu I)^{-1} j_k e_k \qquad (21)$$

The combination of two algorithms such as gauss-newton and steepest descent method, LM algorithm switches to gauss newton method during the training phase, when the μ (combination co-efficient) is very small from Eq. (21) to Eq. (22).

$$w_{k+1} = w_k - (j_K^T j_k)^{-1} j_k e_k \qquad (22)$$

When μ is very large equation the LM algorithm switches to error back propagation method and changes the update rule from Eq.(21) to Eq. (23). Wherein α =1/μ is used.

$$w_{k+1} = w_k - \alpha g_k \qquad (23)$$

$$g_k = \left[\frac{\partial E}{\partial w_1}\frac{\partial E}{\partial w_2} - - - - \frac{\partial E}{\partial w_N}\right]^T \qquad (24)$$

Where g_k is the gradient vector, α is the learning rate parameter, e_k is the error vector, j is the jacobian matrix. W is the weight vector, *p* is the index of patterns, from 1 to *P*, where *P* is the number of patterns. *m* is the index of outputs, from 1 to *M*, where *M* is the number of outputs, *i*and *j* are the indices of weights, from 1 to *N*, where *N* is the number of weights and *k* is the index of iterations.

3. Calculate the total error with new updated weights.

4. If the present total error is increased as a result of new update weights, then retract the step (such as reset the weight vector to the precious value) and increase combination coefficient μ by a factor of 10 or by some other factors. Then go to step 2 and try an update again.

5. If the current total error is decreased as a result of new updated weights, then accept the step (such as keep the new weight vector as the current one) and decrease thecombination coefficient μ by a factor of 10 or by the same factor as step 4.

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6. Go to step 2 with the new weights until the current total error is smaller than the desired value

The feed forward multi-layer perceptron neural network with single hidden layer was used. Tan sigmoid activation function used in the hidden layer to train the neural network with LM algorithm. The total 21 surface roughness values obtained at different experimental conditions was used to train and test the accuracy of the network. 18 experimental data was chosen at random to train the network and remaining 3 data which was not used during training is used to test the prediction accuracy of the developed network as shown in table 4. Squeeze casting process parameters were expressed as the input neurons in the input layer and surface roughness is expressed as the output neuron in the output layer of the developed network. There is no perfect procedure for the choice of hidden neurons used in the hidden layer till date. In the present work the choice based on the minimum mean squared error obtained as shown in the Fig 2

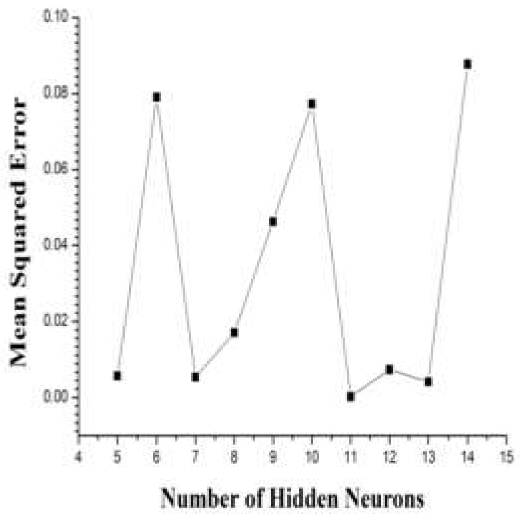

Fig. 2 Selection of hidden neurons

The best architecture with minimum mean squared error was obtained at eleven hidden neurons; 5-11-1 gives minimum mean squared error as shown in Fig. 3. In present work, network training completed with the prediction accuracy of 2.4314% MAPE. Once the network training was completed, the weights are optimized and the network was ready for prediction. The trained network was used to predict the test cases as shown in table 4 and the network predicted with the 3.221% MAPE for four test cases

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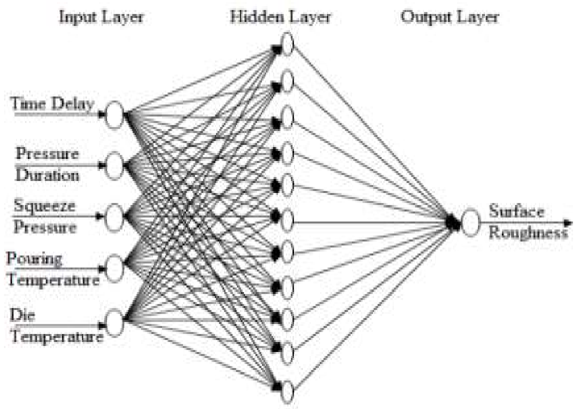

Fig. 3 Structure of artificial neural network

RESULTS AND DISCUSSION

The surface quality examination performed using non-contact-type, confocal microscope on squeeze casting samples. For each process parameter five levels were considered to examine the individual effects on Surface roughness (S_a). The experiments performed by varying one parameter at a time from level (1-5) by keeping the rest of the parameters at the middle level. The results show that increase in the time delay parameter increases the surface roughness was observed. This is because as time delay time increases the metal starts solidifying, solid thin film forms at the outer surface due to loss of fluidity of the melt and the applied pressure at that instant does not helps the metal to have close contact with the die surface results in increase in surface roughness values. The higher pressure duration results in improved surface roughness, because as pressure duration increases the metal is in contact with the die surface for a longer duration and not allowing the metal to pull away from the die surface results in improved surface finish value. However pressure duration after 40 seconds finds negligible effect in improving surface finish was observed. Increase in pressure level improves the surface finish of the casted samples. As squeeze pressure increases improvement in the metal contact with the die surface also improves, applied pressure forces molten metal very close to the die surface and applied pressure also increases the melting point of the alloy as per Clausius–Clapeyron equation. An improved surface finish was observed at 200 MPa pressure compared to 0.1 (atmospheric) MPa. Higher die at 300˚C and pouring temperature at 750˚ C, result in improved surface finishbecause generally aluminium alloys improves fluidity at higher die and pouring temperature. The metal remains fluidity for a longer time compared to low die and pouring temperatures coupled with the applied pressure results in improved surface finish. The best surface finish of about 1.028 µm was obtained when the time delay was at 3 s, pressure duration of 30 s, squeeze pressure at 100 MPa, pouring temperature at 690˚C and Die temperature at 200˚C and the corresponding obtained 3-dimension surface texture is shown in Fig 4. (a). Rough surface roughness value of about 2.951 µm was obtained at 0.1 MPa (no load) condition and the corresponding surface texture obtained is shown in Fig. 4 (b).

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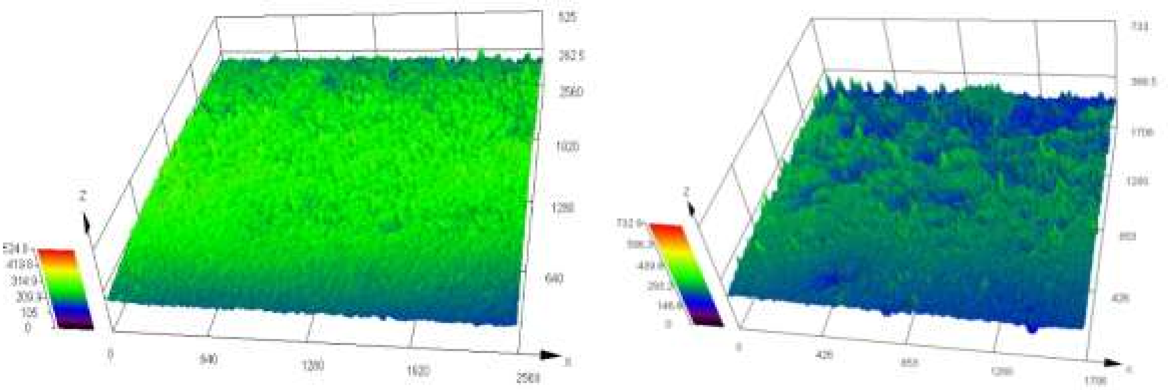

Fig. 4 Surface texture of the cast samples, (a) Smooth surface and (b) Rough surface.

Table 4. Summary results of experimentally measured surface roughness and ANN simulation results

Exp. No	Squeeze Cast Process Parameters					Experimentally Measured Surface Roughness, (µm)	ANN Prediction	Residual	Mean Absolute Percentage Error (MAPE)
	T_d	D_p	S_p	P_t	D_t	Sa			
1	3	30	100	690	200	**1.028**	1.1116	8.138	
2	5	30	100	690	200	2.099	2.0896	0.448	
3	9	30	100	690	200	2.614	2.5928	0.811	
4	11	30	100	690	200	2.851	2.7613	3.146	
5	7	10	100	690	200	2.612	2.6261	0.539	
6	7	20	100	690	200	2.432	2.3861	1.887	Training Subset (2.4314%)
7	7	40	100	690	200	1.779	2.013	13.153	
8	7	50	100	690	200	1.810	1.7848	1.392	
9	7	30	50	690	200	2.457	2.3035	6.247	
10	7	30	150	690	200	2.088	2.0583	1.422	
11	7	30	200	690	200	1.810	1.7845	1.409	
12	7	30	100	630	200	2.714	2.7029	0.409	

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13	7	30	100	720	200	1.810	1.8734	3.503	
14	7	30	100	750	200	1.669	1.6698	0.048	
15	7	30	100	690	100	2.561	2.5538	0.281	
16	7	30	100	690	200	2.177	2.1801	0.133	
17	7	30	100	690	250	2.129	2.1196	0.442	
18	7	30	100	690	300	2.091	2.0836	0.354	
19	7	20	100	690	200	2.432	2.3861	1.887	Testing Subset (3.221%)
20	7	30	100	660	200	2.550	2.4763	2.891	
21	7	30	100	690	150	2.436	2.317	4.885	
22	--	---	0.1	690	200	2.951			

CONCLUSION

Following conclusion can be drawn from the current study,

1.Time delay at 3 s, pressure duration at 30 s, squeeze pressure at 100 MPa, pouring temperature at 690˚C and die temperature at 200˚C yields smooth uniform surface. The rough surface obtained at (0.1 MPa) without pressure application.

2. Increase in time delay results in increase in rough surface, this is because the metal loses its fluidity and the applied pressure is not sufficient enough to make close contact with the die surface.

3. Increase in pressure level and pressure duration contributes towards improvement in surface finish. This is because applied pressure increases the melting point of the alloy and forces the metal close to die surface walls and higher pressure duration holds the metal close enough to the die surface and not allowing the metal to pull away from the die surface walls results in improvement in the surface finish values.

4. The artificial neural network developed for squeeze casting process based on the experimental results obtained at different squeeze casting conditions. 5-11-1 finds the best network architecture for the present application. The trained neural network as great forecasting ability, when presented with totally new squeeze cast conditions and predicted with overall accuracy of 3.221% MAPE between the experimental and the network predicted values. The developed network can be used for the selection of process parameters by any novice user without having prior background knowledge of the squeeze casting process.

ACKNOWLEDGEMENT

The authors would like to thank Department of applied mechanics and hydraulics,National Institute of Technology Karnataka-Surathkal for providing research facilities

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