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An Artificial Neural Network Model for the Comprehensive Study of the Solidification Defects During the Continuous Casting of Steel

Ishita Ghosh (Correspondence Author)
Department of Physics, B.A. College of Engineering and Technology, Ghutia, East Singhbhum, India
E-mail: ishi4physics@gmail.com.

Nilratan Chakraborty

University Department of Physics, Kolhan University, Chaibasa, West Singhbhum, India.

Abstract: In this study, the prediction of some of the solidification defects during the continuous casting of steel alloy is put forward by employinga data driven multilayer perceptron (MLP) based neural network model. The inputs to this neural model are the various important processing parameters such as Aluminum percent, carbon drop percent in steel production, iron oxide percent in the sand mold, carbon percent, sulphur percent, fraction solid percent and critical temperature. Efforts have been done to minimize the network training error within few training cycles by optimizing the network training architecture using the Levenberg-Marquardt (LM) training algorithm. The characterization of the behavior of the various defects during the continuous casting of the steel alloy under the influence of various processing parameters is illustrated by the parametric sensitivity analysis. It has been observed that carbon drop percent during steel production and aluminum percent in the steel alloy have significant contribution in the formation of the shrinkage defect in steel alloy castings. The regression fit between the Artificial Neural Network (ANN) predictions and the target (measured) values of the output parameters demonstrates the appreciable concurrence of the results obtained.

Keywords: Artificial Neural Network, Steelalloy, Shrinkage Volume, Burn on, Penetration Area.

1. Introduction

Steel is an important industrial alloy of high tensile strength and can resist abrasion and corrosion. In continuous casting of steel, the flow conditions have to look into many concerns such as minimizing exposure to air, evading the entrainment of slag or other foreign material, assisting the removal of inclusions into the slag layer and encouraging uniform solidification. Accomplishing these tasks successfully needs careful optimization of the process parameters during casting of steel.

1.1 Solidification defects during continuous casting of steel

Some of the defects which arise during continuous casting of steelinclude burn on, penetration, voids, cracking, hot tears, inclusions, blowholes etc. A brief review of research progress till date underlines the significance conferred to solidification defects and its alleviation. A theoretical investigation [1] has been done by Grill et.al for heat flow and gap formation in the mold of a continuous slab caster using a mathematical model with an aim to predict the casting conditions which can lead to break –outs. Harada et.al[2] examined that transverse surface cracks and the local segregation was found to be the origin of the surface cracks on the continuously cast slabs. Lin et. al [3] presented a damage based model using commercial software with a user- defined constitutive model to analyse steel castings and its tendency to form hot tears. Crowther [4] demonstrated that of the many defects in continuous casting; only transverse surface cracking is strongly influenced by the presence of micro-alloying elements such as Nb and V.BrianThomas [5] discussed about continuous casting of steel and some mathematical models which quantify and investigate the interactions between the process parameters. Camisaniet.al[6] presented an approach to eliminate the influencing variables causing surface defects using statistical hypothesis testing. Carlson et .al [7] put forward a multi-phase model that predicts melt pressure, feeding flow, and porosity formation and growth in steel castings during solidification. Naro[8] discussed the lustrous carbon defects formation in steel castings and suitable methods to eliminate defects formation.Zhang and Thomas [9] reviewed the sources of both indigenous and exogenous inclusions in continuous casting of steel. Thomas [10] put forward a computational model toinvestigate the formation of several different types of defects related to flow phenomena.

Brookset.al [11]and [12] developed a method to predict possible burn-on and penetration defect locations and performed several parametric studies to investigate the sensitivity of the predictions by a standard casting simulation. Kalandyk et.al [13] concluded from their findings that the defects are formed due to the interaction between molten metal and moulding sand constituents. Pelak et.al [14] presented the results of the analysis of surface defects of continuously cast slabs. Thomas [15] in his article discussed about some concepts which are used to model some of the solidification defects with special reference to hot tears.A model [16] was proposed which is capable of predicting levels of different combinations of the process variablesthat minimize the occurrence of shrinkage and pores.Chen and Lin[17] investigated the possible sources of these gases including hydrogen, nitrogen and oxygen causing blowholes, focusing on the preparing process that are in contact with the liquid steel during refining and casting The aim of this work by Popa and Kiss [18] presented their findings based on industrial research about the possibility of defining and cataloguing the surface defects specific to the semi- finished continuously cast products. Mukhopadhay[19] summarized the causes of porosity in steel castings. Ravi [20] put forward a collaborative system for achieving perfect castings by integrating tooling methods and process optimization.

The benchmark simulation Niyama outcomes from simulation qualificationprocedure were compared by Carlson and Beckermann[21]. Catalina and Monroe [22] proposed a simplified model for predicting shrinkage related defects in steel castings based on specific conditions and governing fluid flow conditions Tapan Roy [23] reported an in house experience of the occurrence of different types of casting defects and its scientific analysis by computerised simulation techniques.Kassie and Assfaw [24] performed a statistical analysis to optimize the process parameters to minimize major steel casting defects i.e. gas defects and shrinkage defects.Pickering [25] reviewed the developments in the understanding of the phenomena of macro-segregation. Mauderet.al[26] described an algorithm based on fuzzy logic approach used to obtain time dependant casting parameters for stabilization of the casting process and preserve high productivity. Roy [27] gave a casting simulation which aids in visualization of mould filling and casting solidification and predictionof defects like cold shut, hot spots and shrinkage.

This paper illustrates the use of multilayer perceptron(MLP)-based multi-input single-output (MISO) ANN model for the quantitative prediction of defect formationduring continuous casting of steel. The casting defects dealt with here are burn-on, penetration, voids and cracks. The input factorstaken into consideration for this model are carbon droppercent, aluminumpercent, iron oxide percent, critical temperature, fraction solid, sulphur percentetc.Thecombinedeffects of these processing parameters on defect formation have been highlighted by the use of this model too. The network training architecture has been optimized using the Levenberg – Marquardt(LM)algorithm to minimize the network training error within few training cycles. The characterization of influence of processing parameters (inputs) on the behaviour of defect formation during solidification of steel alloy is explained bythis sensitivity analysis of the parameters. Such an analysis pertaining to steel alloy has not been described earlier in the literature as per the inputs from the literature review by the authors. This investigation hopes to put forward abetter conception of the sensitivity of the solidification process parameters on the defect formation in steel alloy and will also help us with strategies for quality improvement to meet optimum product requirements.

2. Artificial Intelligence based modelling for the prediction of the solidification defects

The process of conversion of data into information emulating human intelligence and logical reasoning is accomplished by several modelling techniques such as ANN, Genetic algorithm, fuzzy inference systems, machine learning andprobabilistic reasoning. ANN is a computational network which can model human reasoning to decipher non-linear problems and can analyse complex problems competently where the relationships between input and output data are not very well known[28][29].

2.1 Neural Network Model

The basic constituents of an ANN structure consist of multiple inputs and outputs, hidden layers, the weights inter connecting them and the threshold values of the neurons. The MLP based ANN architecture with several nodes and layers is presented in Figure1. It is based on the multi input single output (MISO) systems requiring a single consolidated file for the model inputs for the neural simulation with a single run. A transfer function to the weighted summation of inputs is used to obtain the output from a given neural network. [28][29].They areconsecutively used as inputs to other neurons.

2.2 Analysis of the Network Training Error

The network training error is referred to the variation between the network predictions and the target values. The mean squared error (MSE) (or one of its scaled versions) is among one of the most recognised form of error function in ANN models and is utilized in our current sensitivity analysis[28][29].

2.3 Training algorithms for network optimization

Optimization of ANNs is essentially done to minimize a particular objective function with respect to certain constraints. The training of the network is necessary to minimize the errors between the predictions and the actual measured values by estimating the optimal weights. Some optimization algorithms whichefficiently improve the convergence rate of the network are back propagation (BP), Newton, conjugate gradient, Levenberg-Marqurdt (LM) and the BFGS algorithms. The LM algorithm has the advantage of combining the promptness of the Newton algorithm with the stability of the steepest descent method[28][29].

3. Formulation of the problem and methodology

This neural network model for steel alloys is developed for the study of the relative dependence of the various solidification defects during the continuous casting of steel on the various input process parameters. The variation of shrinkage volume, burn-on area, penetration area and the critical stress and strain percent have been predicted by this neural network model. The neural network tool in MATLAB software has been used for the formulation of the problem and output generation from the input parameters.

3.1 The artificial neural network model, its inputs and outputs

In this study, the neural network model is trained by using the Levenberg –Marquardt(LM) training algorithm is used to minimize the training error in a few cycles. The plots for the regression fits and mean square error are plotted to exhibit the efficiency of the model. The model inputs are Aluminum percent, carbon drop percent in steel production, iron oxide percent in the sand mold, carbon percent, sulphur percent, fraction solid percent and critical temperature. The output parameters are shrinkage volume, burn-on area, penetration area and strain percent nd critical stress for crack formation during continuous casting of steel.

3.2 Results and discussions

A schematic diagram of the artificial neural network is shown in **Figure 1.**The neural network model predictions obtained for variation of different solidification defects in steel alloy are displayed in **Figures 2 to 8**. The regression plots of the network and the mean square error relations for each of the model predictions from Figures 2 to 8 are depicted in the **Figures 9 to 15.**

Figure 2 shows the 3D visualizations for variation of shrinkage volume (cm ^{3}) as a function of both Carbon drop percent in steel production and percentAluminum in steel. It is clear from the model predictions that low Aluminumpercent and high Carbon drop percent give rise to highest shrinkage volume. Further it is predicted that low carbon drop percent and high aluminium percentwill produce minimum shrinkage volume. The other intermediate values of input variables will show average values of shrinkage volume.

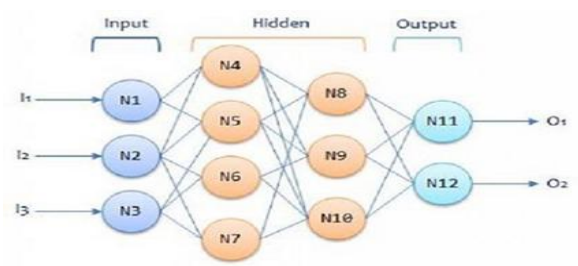

Fig.1 Illustration of an artificial neural network model.

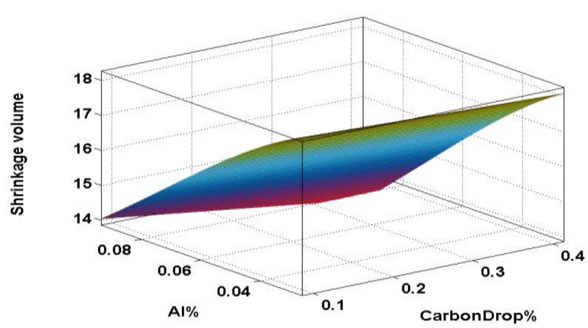

Fig.2 3D visualisation for neural predictions of variation of shrinkage volumewith carbon drop percent and Aluminumpercent as input parameters.

Figure 3 depicts the 3D visualization of model predictions for the variation of shrinkage volume (cm ^{3}) as a function of both carbon drop percent in steel production and percent iron oxide in the molding sand. The figure shows minimum shrinkage volume for low carbon drop percent and high iron oxide percent and a maximum shrinkage volume for low iron oxide percent and high carbon droppercent. For the rest values of input parameters, shrinkage volume shows intermediate values.

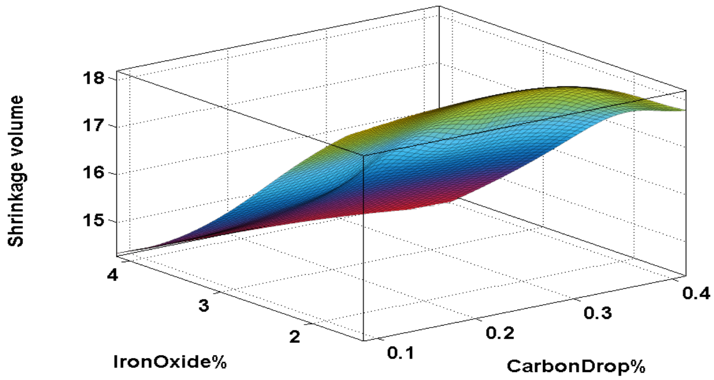

Fig.3 3D visualisation for neural predictions of variation of shrinkage volumewith carbon drop percent and Iron oxide percent as the input parameters.

Figure 4 represents the 3D visualization for neural predictions of variation of shrinkage volume (cm^3)as a function of both Aluminumpercent in steel and iron oxide percent in molding sand. The neural model predictions show that the shrinkage volume remains mostly at its intermediate values for all the values of the two input parameters. The output shows neither too high nor too low values with the variation of inputs values. The Aluminum content in steel(0.03 to 0.09%) is mainly added to deoxidize the metal which can be later reduced by carbon byforming small bubbles of CO which increases shrinkage volume[16]. The iron oxide helps to reduce the formation of defects which occurs due to expansion of silica in sand molding. The percentage of carbon drop in steel production controls the boiling of steel by the motion of the CO bubbles formed during oxygen impingement. Greater carbon drop gives lesser dissolved gases and hence lesser shrinkage volume[16]

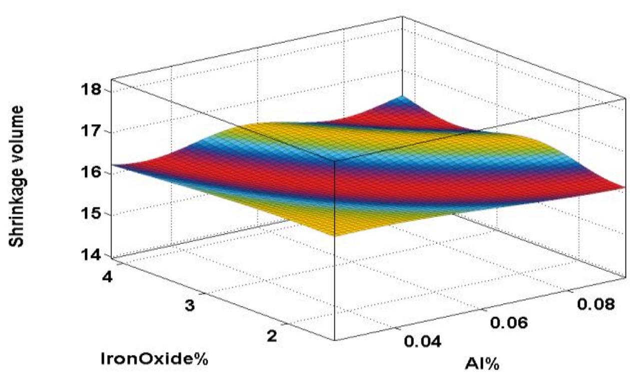

Fig.4 3D visualisation for neural predictions of variation of shrinkage volume withAluminumpercent and Iron oxide percent as the input parameters.

Figure 5 displays the 3D visualization for neural predictions of variation of burn-on area (cm^2) as a function of both fraction solid (%) and critical temperature (°C). The model predicts a minimum value of burn-on area for low values of fraction solid% at almost all values of critical temperature. The burn-on area show maximum values for high values of fraction solid% at almost all values of critical temperature. Other values of input variables predict intermediate values of the output variable.

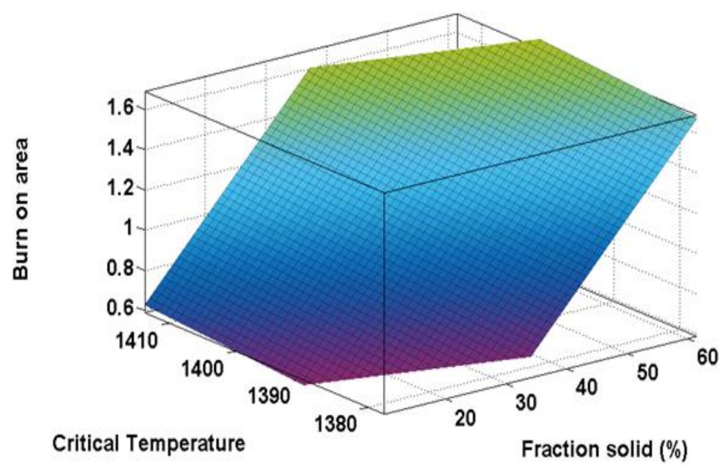

Fig.5 3D visualisation for neural predictions of variation of burn on area with fraction solid percent and critical temperature as input parameters.

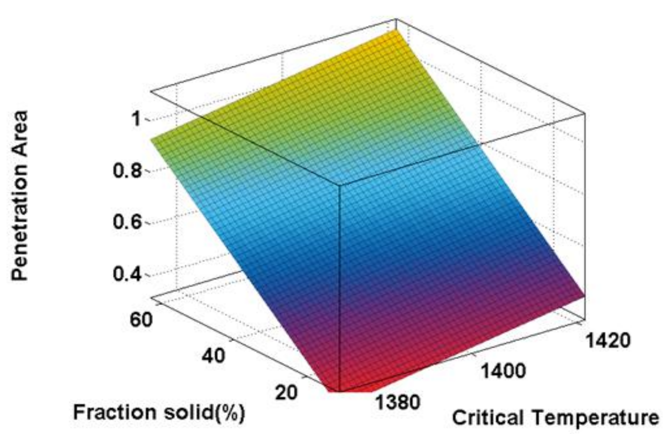

Fig.6 3D visualisation for neural predictions of variation of penetration areawith critical temperature and fraction solid percent as the input parameters.

Figure 6 exhibitsthe 3D visualizations for the neural predictions of variation of penetration area (cm^2) as a function of both critical temperature (℃) and fraction solid%. The predictions show a minimum value of penetration area at low values o fraction solid percent and at almost all values of critical temperature. Similarly maximum values of penetration area are observed at high values of fraction solid and at almost all values critical temperature. All other values of the input variables predict intermediate values of penetration area.

The steel alloy must be above the temperature at which it is fully solid for the occurrence of burn-on or penetration. The liquid metal ceases to flow if the fraction solid is quite high. This prevents metal penetration into the mold[11]. The fraction solid present in the melt is directly proportional to the temperature. These defects decrease with increase in critical temperature which is a temperature which is large enough to inhibit liquid metal flow [12]. It is observed that any critical temperature corresponding to solid fractions with values ranging from 45% to 80% produces a substantial amount of burn-on and penetration area[12].

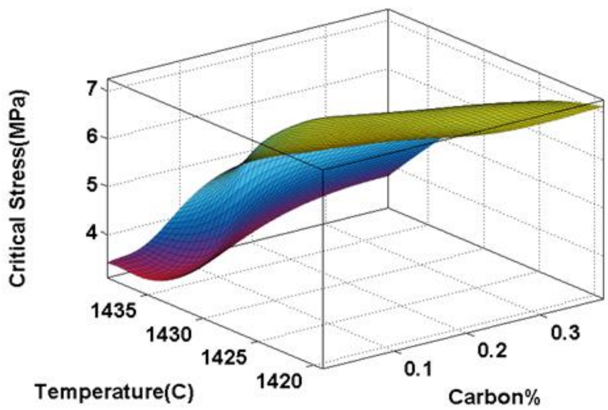

Fig.7 3D visualisation for neural predictions of variation of critical stresswith both carbonpercent and temperature as input parameters.

Figure 7 depicts the 3D visualization of the neural predictions for the variation of critical stress values for crack formation in steel alloy as a function of both carbon percent in the alloy and the temperature(℃). Low critical stress is observed at high temperature and low carbon percent in the alloy whereas high critical stress for crack is obtained for low temperature and high carbon percent in the alloy. At other values of input parameters an intermediate output is visualized.**Figure 8** illustrates the 3D visualizations of the neural predictions for variation in the strain percent in steel alloy as a function of both carbon percent and sulphur percent in the alloy. The figure portraysa maximum value of strain percent at high values of sulphur percent and low values of carbon percent and a minimum value of strain percent at low sulphur percent and high carbon percent.The rest values of input variables give rise to intermediate values of strain percent.

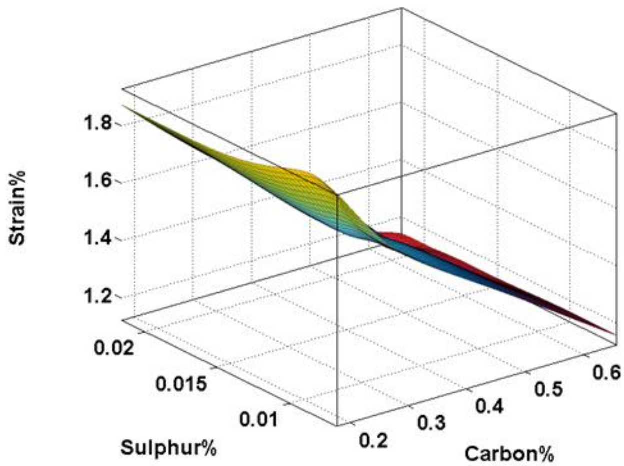

Fig.8 3D visualisation for neural predictions of variation of strain percentwith carbon percent and sulphurpercent as input parameters.

The value of either critical stress or critical strain is a parameter for crack initiation. The critical strain for internal crack formation is affected by the carbon content in the alloy. The critical strain decreases with increase in the carbon content. Further the critical strain for internal crack formation decreases largely with increase in the sulphur content. The criticalfracture stress increases with increase in carbon content [30]. This is because peritectic reaction takes place and the δ/γtransformation occurs before full solidification of the alloy. Also critical fracture stress increases with decreasing temperature due to the formation of only δ phase during the initial stage of solidification. The cracks which form during continuous casting of steel are highly dependent on the strain and tensile stress. The crack formation begins to take place when the accumulated strain is more than the critical strain and /or the applied stress is greater than the critical stress during solidification of the alloy [31].

4. Conclusion

This research paper uses a soft computing model based on Artificial Neural Network to successfully envisage the effects of some input parameters relating to the solidification and casting of steel alloy on the defects hence produced. The conclusions from these ANN predictions are matched with the literature data sets.

The principal inferences from the research work can be summarized as follows: the proposed ANN driven computational model with the comprehensive data sets used for the quantitative description of casting defects of steel alloy is a sufficientlyprecise prediction and has an adequate concurrence with the published experimental and simulation data as given in the literature survey. The ANN approach can thus be assumed to be a proficient model for the study of casting defects in steel alloy as a function of the processing parameters during solidification. Thus theneural network approach has a winning edge over the first principle based models whenhighly non-linear relationships come into play. The LM training algorithm used here is capable of effective optimization of the neural network model and facilitates faster convergence within few training cycles. The extracts of this model hopes to enable an improved understanding of the sensitivity of the process parameters during the solidification of the steel alloy on defects formation and thus on the control of the operating factors hence involved. This will also aid in putting forward recommendations for upgrading the quality of the cast products according to the customized necessities. This work can be made further beneficial byintegrating more operating and process constraints during solidification of steel alloy with enriched experimental datasets and advanced algorithms such as machine learning algorithm or support vector machine based ANN tools.

5. References

[1] Grill, A., Sorimachi, K. and Brimacombe , J.K. June (1976), Heat flow, gap formation and break outs in continuous casting of steel slabs, *Metallurgical Transactions B*, Vol 7B, 177-189.

[2] Harada Shinzo, Tanaka Shigenori, Misumi Hideyuki, MizoguchShozo and Horiguchi Hiroshi(1990), A formation mechanism of transverse cracks, *ISIJ International*, Vol- 30 No-4, 310-316.

[3] Lin Zhiping,Monroe Charles, Huff. K. Rrichard and BeckermannChristoph, Prediction of hot tear defects in steel castings using a damage based model, *Modelling of casting and welding and solidification processes* XII, 329-336.

[4] Crowther, D.N, A comparison of the effects of microalloying on cracking during continuous casting, *Corus Research, Development and technology*, 141-174.

[5] Thomas G. Brian (2001), Continuous Casting of Steel, Chapter 15 in *Modeling for Casting and Solidification Processing*, O. Yu, editor, MarcelDekker, New York, NY, 499-540.

[6] Camisani-Calzolari. F.R., Craig, I.K., PistoriusP.C. (2002), Control structure for the reduction of defects in continuous casting, *15th Triennial World Congress*, Barcelona, Spain, Copyright IFAC.

[7] 7.. CarlsonK.D, LinZ., Hardin R.and BeckermannC.(2002), "Modeling of Porosity Formation and Feeding Flow in Steel Casting," in *Proceedings of the 56th SFSA Technical and Operating Conference*, Paper No. 4.4, Steel Founders' Society of America, Chicago, IL.

[8] NaroR. L. (2002), Formation and Control of Lustrous Carbon Surface Defects in Iron and Steel Castings, *AFS Transactions*-154, 1-20.

[9] Zhang, L. & Thomas, B.G., Nov(2003), Inclusions in continuous casting of steel, *XXIV National Steelmaking Symposium*, Morelia, Mich, Mexico, 26-28, 138-183.

[10] Thomas, Brian G. (2005)Modelling of Continuous-Casting Defects Related to Mold Fluid Flow, *3rdInternat. Congress on Science & Technology of Steelmaking*, Charlotte, NC, May 9-12, AIST, Warrendale, PA, 847-861.

[11] Brooks, B.E.and Beckermann,C.(2006), "Prediction of Burn-on and Mold Penetration in Steel Casting Using Simulation," *in Proceedings of the 60th SFSA Technical and Operating Conference*, Paper No. 5.3, Steel Founders' Society of America, Chicago, IL.

[12] BrooksB. E., Beckermann, C.and RichardsV. L.(2007), Prediction of burn-on and mould penetrationin steel casting using simulation,*International Journal of Cast Metals Research*, Vol 20, No. 4,177-190.

[13] KalandykB.,.Zapala,R.,RakowskaA.(2009), Characteristics of defects present in industrial steel castings due to metal-mould reactions,*Archives of metallurgy and materials*, Volume 54, Issue 2.

[14] PelakSlavomir, MisickoRudolf, FedakovaDagmar and BidulskaJana (2009), Between the dendrite structure quality, the casting technology and the defects in continuously cast slabs, *Materials Engineering*, Vol.16, No.4, 21-28.

[15] ThomasBrian G.,(2009) Modelling of Hot Tearing and other Defects in Casting Processes, ASM Handbook, Volume 22A: *Fundamentals of Modeling for Metals Processing*, D.U. Furrer and S.L. Semiatin, editors, 362-374.

[16] Dias AlvesLuiz Henrique, Silva MarinsFernando Augusto, AlvesArthur Guimarães, SilvaMessias Borges(2010),Process Improvement, modeling and optimization of voidsrelated to the solidification in steel casting process using the Taguchiapproach,*POMS 21st Annual Conference*, Vancouver, Canadá,May 7 to May 10.

[17] Chen Chih-Yuan and LinKuan-Ju(2011).,Forming Factors of Blowhole Defect in Continuously-Cast Beam Blank at Dragon Steel,*China Steel Technical Report*, No. 24, pp. 7-13,

[18] PopaErika Monica, KissImre(2011), Assessment of surface defects in continuously cast steel, ActaTechnicaCorviniensis,*Bulletin of Engineering* Tome IV, ISSN 2067-3809.

[19] MukhopadhyayM.K.(2011),Porosity in Steel Casting, *Indian Foundry Journal*, Vol 57,No. 4,April, 44-47.
[20] Dr. RaviB.(2011), A Holistic Approach to Zero Defect Castings,Technical Paper for *59th,INDIAN FOUNDRY CONGRESS*, Chandigarh.
[21] CarlsonK.D., and BeckermannC.(2012), "Sensitivity of Steel Casting Simulation Results to Alloy Property Datasets," in *Proceedings of the 66th SFSA Technical and Operating Conference*, Paper No. 5.3, Steel Founders' Society of America, Chicago, IL.
[22] CatalinaA. V and MonroeC. A. (2012), Simplified pressure model for quantitative shrinkage porosity prediction in steel castings,*IOP Conf. Series: Materials Science and Engineering* 33, 012067.
[23] RoyTapan, (2013), Analysis of Casting Defects in Foundry by Computerised Simulations (CAE) - A New Approach along with Some Industrial Case Studies,*Transactions of 61st Indian foundry congress.*
[24] KassieAchamyeleh Aand AssfawSamuel B.(May. 2013),Minimization of Casting Defects,*IOSR Journal of Engineering* (IOSRJEN)Vol. 3, Issue 5, 31-38.
[25] PickeringEdward John (2013), Macro-segregation in Steel Ingots: The Applicability of Modelling and Characterisation Techniques, *ISIJ International*, Vol. 53 No. 6, 935–949.
[26] 26.MauderTomáš,StetinaJosef , MasarikMiloš(2013), On-line fuzzy regulator for continuous casting process , *Metal 2013*, 15. - 17. 5., Brno, Czech Republic, EU.
[27] Roy,T. May (2014), Analysis of casting defects in steel foundry by computerizeds new approach along with some industrial case studies, *71st World Foundry Congress, Advanced Sustainable Foundry*, Bilbao, 19-21 May.
[28] Pratihar,D.K. (2008),*Soft Computing*, Narosa Publishing House, Daryaganj, New Delhi.
[29] Rajasekaran, S. and PaiG.A. Vijayalakhsmi(2003),*Neural networks, fuzzy logic and Genetic algorithm, Synthesis and applications*, PHI learning private limited, New Delhi,1-439.
[30] Kon,Y.M , Yeo, T.J, Seol, D.J. andOh, K.H.(2000), A new criterion for internal crackformation in continuously cast steels,*Metallurgical and materials transactions B*, Vol.31B, 779-794.
[31] Brimacombe, J. K. and Sorimachi, K.(1977), Crack formation in the continuous casting of steel, *Metalurgical Transactions B*, Vol. 8B, 489-505.

Figures:

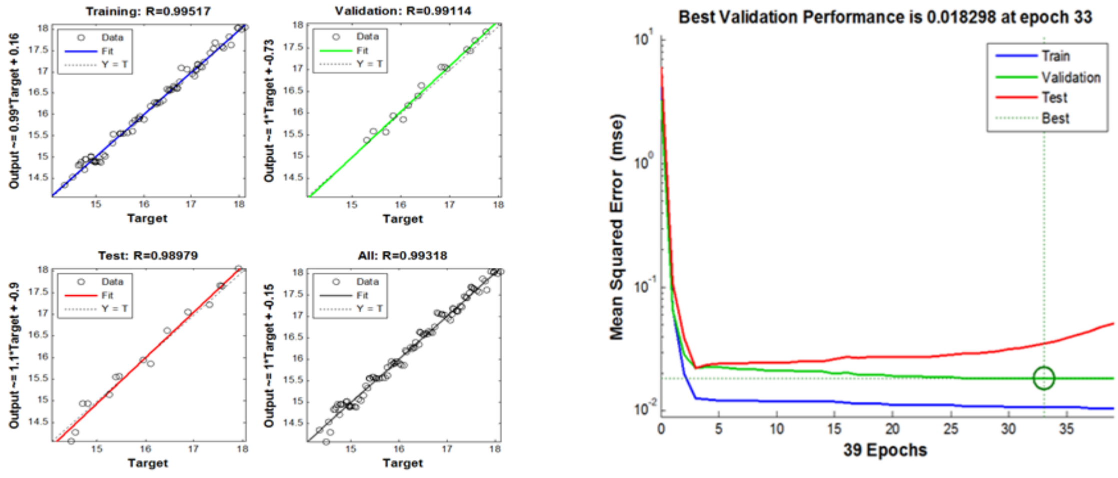

Figure9: Regression and error plots for Fig-2.

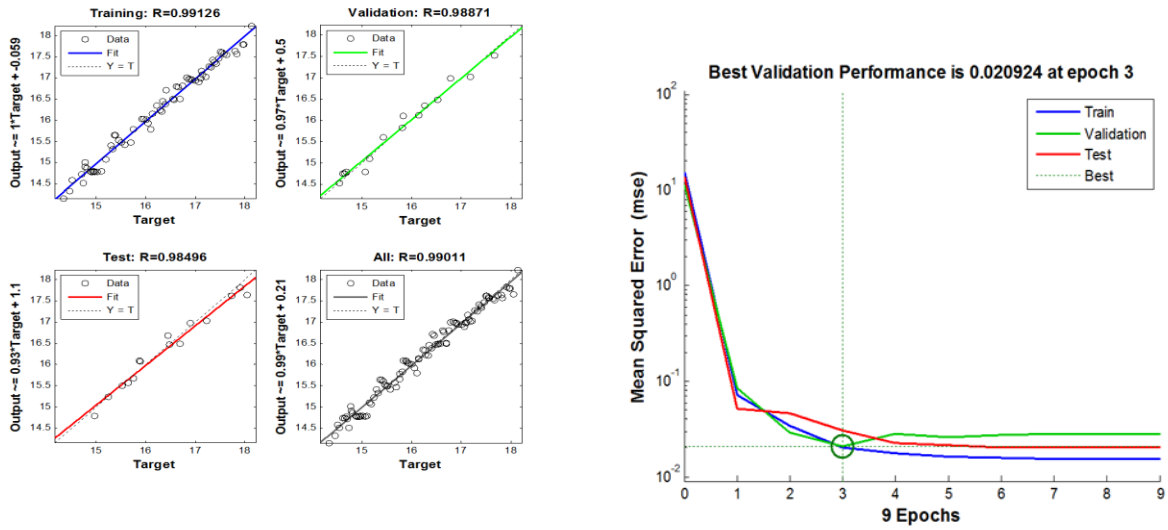

Figure 10:Regression and error plots for Fig-3.

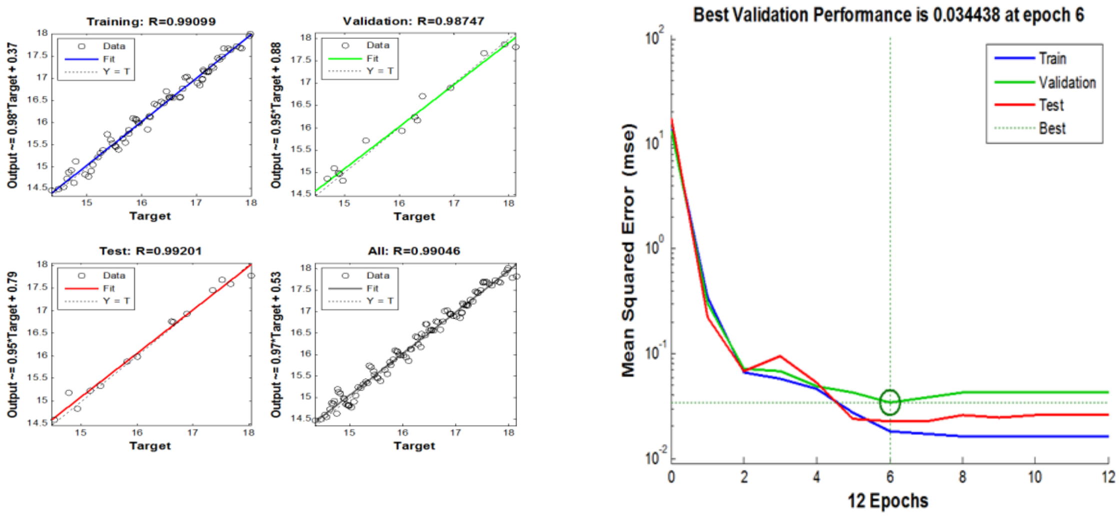

Figure 11: Regression and error plots for Fig-4.

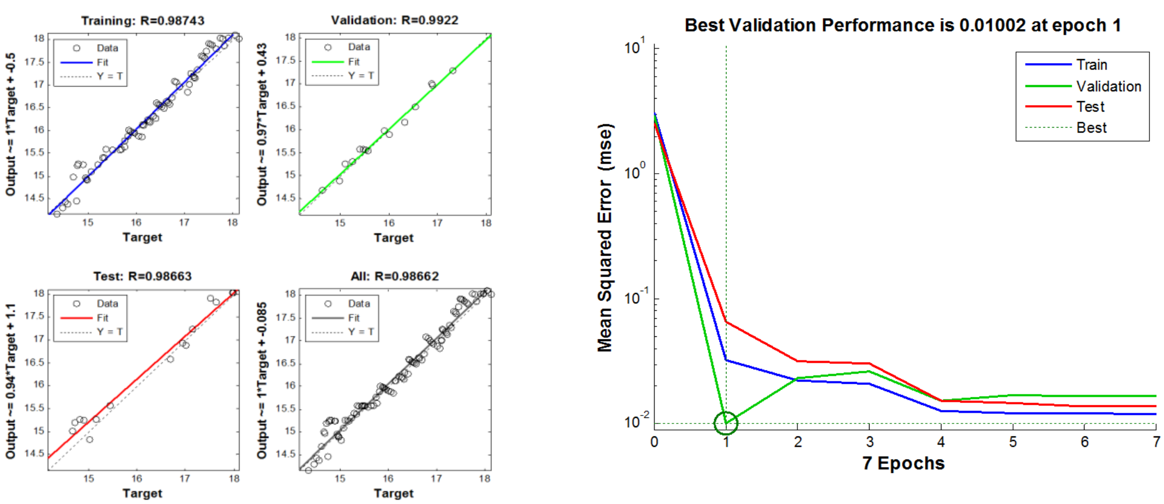

Figure 12:Regression and error plots for Fig-5.

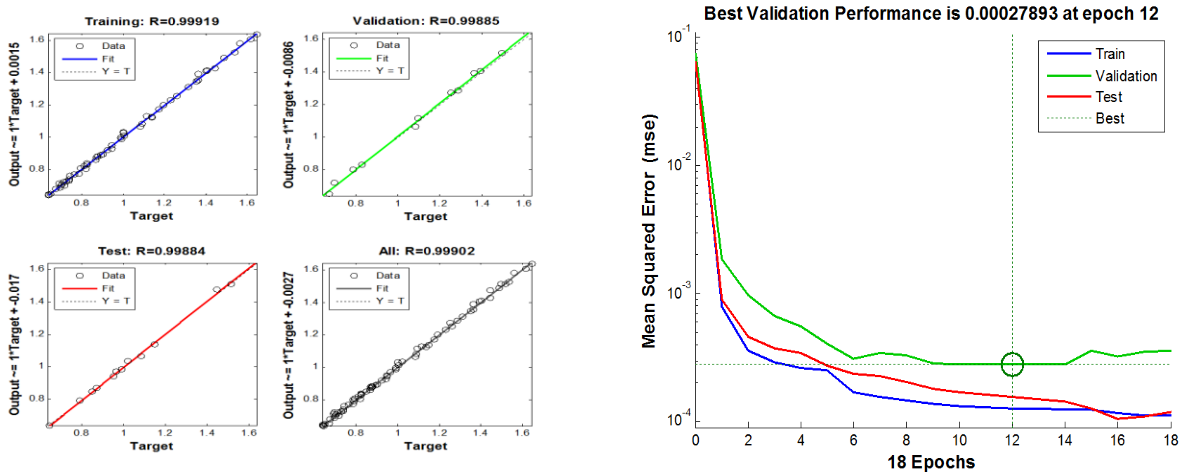

Figure 13:Regression and error plots for Fig-6.

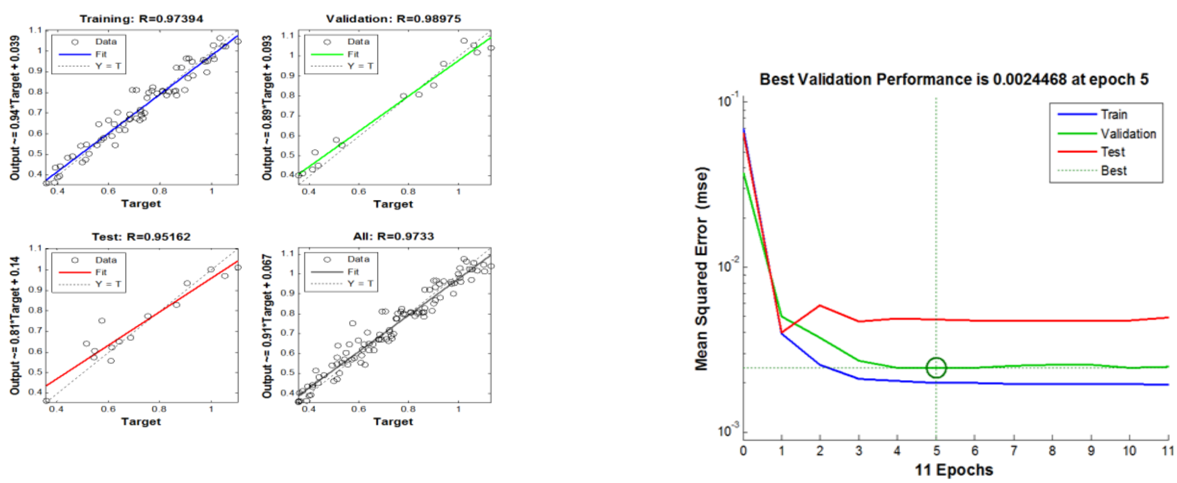

Figure 14: Regression and error plots for Fig-7.

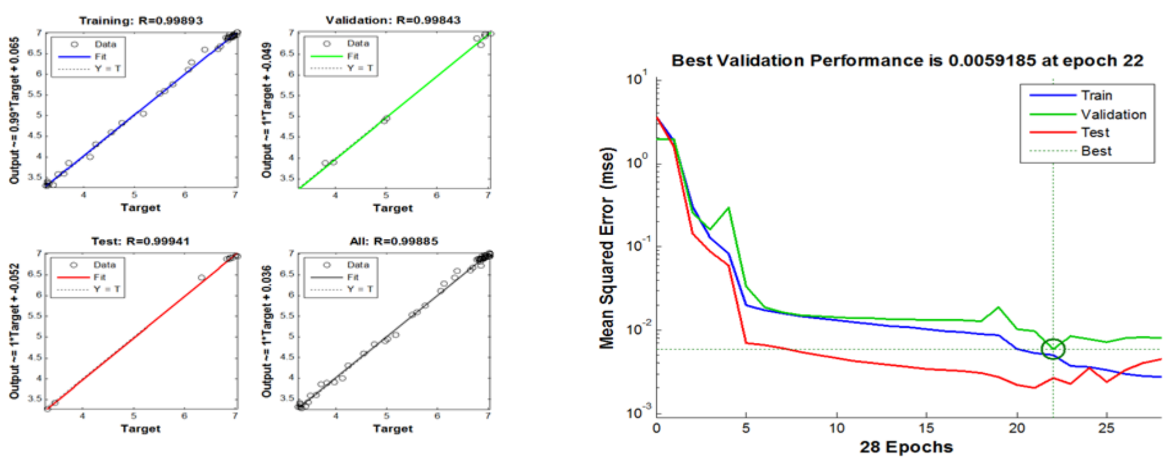

Figure 15: Regression and error plots for Fig-8.

Table- 5.1 Input data for the neural network model.

Sl.No of input parameters	Name of the input parameters and their inputs.	Data range used for the ANN	Output parameters
1	Carbon (%)	0.200-0.635	Strain % (for crack)
2	Sulphur (%)	0.0075-0.0209	
3	Temperature(℃)	1437.69-1420.05	Critical Stress (MPa) (for crack)
4	Carbon (%)	0.01944-0.3685	
5	Critical Temperature(℃)	1377.28-1419.5	Penetration Area (10^{-10} m^2)
6	Fraction solid(%)	60.75-13.68	
7	Critical Temperature (℃)	1377.77-1419.7	Burn –on area (10^{-10} m^2)
8	Fraction Solid(%)	11.2538-59.3769	
9	Aluminum (%)	0.029-0.090	Shrinkage Volume (10^{-4} m^3)
10	Iron oxide (%)	1.560-4.032	
11	Carbon drop (%)	0.399-0.101	

Table 5.2 Chemical composition of steel

C	Mn	Si	P	S	Al	Ni	Cr	Mo	Fe
0.26-0.32	0.65-0.85	0.30-0.60	<0.03	<0.03	0.02-0.09	<0.30	<0.30	<0.20	Balance