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Prediction of Sand-Casting Defects by Artificial Neural Network

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Abstract - Sand casting defects appear unexpectedly and prediction of defects can help decide the ranges of their responsible process parameters to reduce these defects. Artificial Neural Networks (ANN) is one of the famous tools of Artificial Intelligence that can be utilised in a wide extent of problems and are getting a wider application in the foundry industries also. In this paper, a discussion about the prediction of three grey iron sand casting defects: Blow, Penetration and Erosion using ANN is presented. This is a method of assessing the suitability of sand casting process parameters by finding correlations between individual parameters and defects by means of artificial neural network systems. The implementation of ANN was performed with the application of three programs first a statistical software SPSS, second another software MATLAB and third using python programming language. The data narrating to sand casting processing parameters and relevant defects in castings is raised from a sand casting foundry. The ANN model gave better results in terms of predicted accuracy. The systems are fairly tested on real-life data acquired from the foundry, attending to a significant decrease in the rejection rate of the casting due to defects. The ANN prediction system can help foundry engineers to take decisions regarding preventing possible defects in advance.

Index Terms - Sand casting, Blow holes, Penetration, Erosion, Artificial Neural Networks.

INTRODUCTION

Artificial Neural Networks is one of the most popular algorithms in Artificial Intelligence and is the functional unit of deep Learning. ANN is a computing system that is designed to simulate the way the human brain analyses and processes information. ANN is a network of artificial neurons (or nodes) arranged in different layers and connections between the nodes. The first layer is the input layer next multiple hidden layers the last layer is known as the output layer. The input is provided to the neurons of the first layer. The output of this input layer will become the input to the next hidden layer which consists of the number of neurons with some activation functions, the output of this hidden layer will become input to the output layer frame and give the desired output (1).

The yearly casting production around the world from 2015 to 2019 has recognized remarkable growth (2), and India is the second-largest producer of castings just after china (3). Metal casting is a versatile primary manufacturing process that can produce products from a few grams to several tons from molten metal (4). The sand casting process generally means pouring molten metal into a refractory mould that contains a cavity of the required shape and allows it to solidify this final solidified object is called casting. The sand-casting process is explained stepwise in Figure 1.

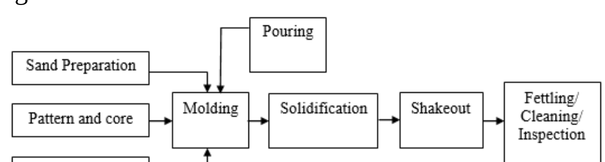


Figure 1. Sand casting process

The control of defects is an essential issue for the foundry industry and utilized several Artificial Intelligence algorithms and proven their fruitfulness for making decisions, by training AI models using past available data. The defects in foundry can be significantly decreased by predicting its occurrence and regulating the appropriate process parameters through the utilization of comprehensive domain knowledge. In work for the prediction of three grey iron sand casting defects: Blow, Penetration and Erosion the ANN is implemented using statistical softwires SPSS, MATLAB and using python programming language. The data required for training and testing of ANN model is collected from a foundry for grey cast iron component of (FG 250, Composition: C 3.3-3.7, Si 2.2-2.6, Mg 0.65-0.67, S 0.00-0.04, P 0.03-0.05, Induction furnace) overall size of 1000 × 550 × 113 mm and weighs 200 kg; its wood pattern weighs 27kg. The yield is between 70 and 75 %. The detailed drawing of the component is shown in figure 2.

Figure 2. Sand casting part considered in the study

The foundry typically carried out 4–5 heats (cycles of melting and pouring) on each working day, each heat being used to pour 4-5 castings. For each heat, 7 data items were identified for collection included Moisture percentage, Permeability, Binder Percentage, Pouring Temperature, Grain Fineness Number, Mould Hardness, Green Strength and assurance of the three defects. The data from 493 heats (approximately 1590 castings) were collected over six months. The sample dataset of 494 data entry which contains the total seven parameters for evaluation propose from that we can predict the output variables like blow, Penetration and Erosion. Each record has a class value that indicate whether the casting suffered any defect or not within six-month measurements.

The created sand-casting data has certain characteristics that makes the analysis very challenging and attractive as well. The next Literature review about ANN in the realm of metal sand casting defect reduction is discussed.

LITERATURE REVIEW

To support sand foundry production researchers have adopted different types of Neural Networks differently. Now a review about the relevance of ANN in foundries for casting defect reduction is presented. For cause detection of gas porosity defects in sand casting (5) trained ANN using process parameters, materials used and workers involved. (6) Applied a backpropagation neural network to predict some significant defects in sand castings. For shrinkage location recognition(7) trained back propagation neural network with the results of Finite Element Methods.(8) Used artificial neural network-based methodology to the identification of flaws in the aluminium alloy castings by radio graphical image analysis. (9) Offered an Artificial Neural Network based model to foresee collapsibility of CO2 sand moulds. To assess the green compressive strength of clay bonded moulding sand (10) offered neuro-fuzzy based models and witnessed that the neuro-fuzzy model was more precise than the neural network model. (11) Indicated that the Radial Basis Function Artificial Neural Network (RBFANN) model could adequately estimate the parameter values of phosphate graphite sand. To determine the relationship between input-output parameters of cement-bonded moulding system (12) used propagation algorithm and a genetic algorithm, based neural networks and proved it can be used for both forward and reverse mapping of input and output parameters. (13) apply back-propagation neural networks and genetic neural networks for both forward and reverse modelling of input and output parameters of green sand moulding after that (14) adopted back-propagation as well as genetic neural network for determining the relationship between input-output parameters of sodium silicate bonded carbon dioxide hardened sand moulding. (15) Presented a method of selection of the proper kind of a neural network for prediction a sand moistness on the bases of certain moulding sand properties such as: permeability and friability. To analyse the influence of input variables on compressive strength of Furan No-bake mould system (16) formed ANN modal. Artificial Neural Network has also been applied in the foundry industry to control melting processes in furnaces. (17) presented Artificial Neural Network-based model to determine the active bentonite content in green moulding sand based on sand properties such as permeability, compactibility and the compressive strength, and letter (18) applied Neural Networks for controlling the quality of bentonite moulding sand. ANN has been used in the sand-casting industries for defect identification, quality assessment of the castings, prediction of possible defects, selection and control of sand mould properties and for optimization of casting input parameters.

To summaries Artificial Neural Networks have been used to carry out input-output modelling of the metal sand casting process. That Artificial Neural Networks are excellent in the sand-casting quality and mould quality predictions and for optimization of casting input parameters. Next in this work discussion about data collection from sand casting foundry is presented.

ARTIFICIAL NEURAL NETWORK AND SAND-CASTING DEFECT PREDICTION

To see whether the input parameters can predict the defects blow, penetration and erosion using the available data, an artificial neural network (ANN) is built using SPSS program (a statistical software). A Multilayer perceptron neural network is built in SPSS, with the seven input variables. The information about the network is given in the table 2.

Table 2 Network Information

Input	Covariates	1	x1

Layer		2	x2
		3	x3
		4	x4
		5	x5
		6	x6
		7	x7
	Number of Unitsa		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		8
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	Blow
		2	Penetration
		3	Erosion
	Number of Units		3
	Rescaling Method for Scale Dependents		Normalized
	Activation Function		Sigmoid
	Error Function		Sum of Squares

The network is having seven input variables in the input layer one hidden layer with eight nodes listed in the table. The network architecture is shown in figure 3. Which is having the topology of 7-8-3.

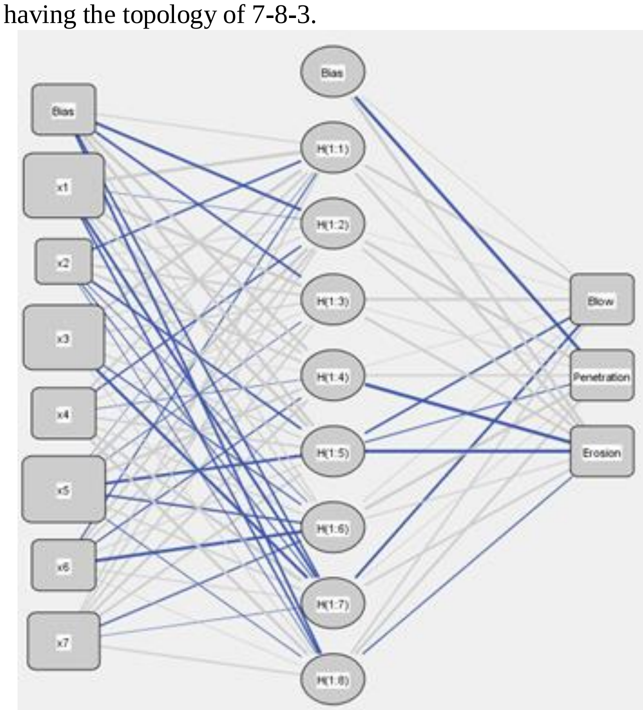


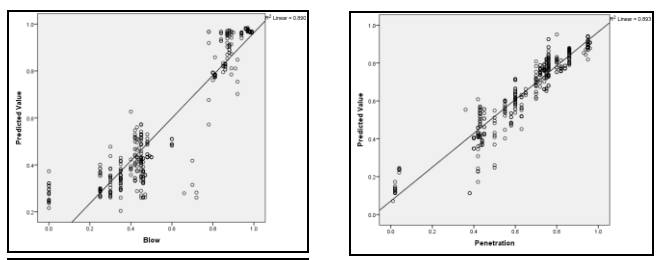
Figure 3 Network Diagram with topology 7-8-3

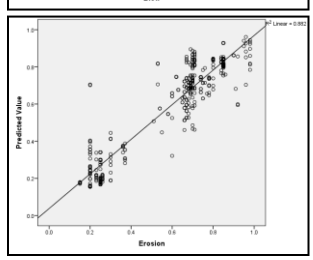
Error computations based on the training sample of the overall modal is represented in table 3. The sum of square error of the training data is 3.880 and for testing data is 1.851 which shows the Built neural network is performing well.

TABLE 3. MODEL SUMMARY

Training	Sum of Squares Error		3.880
	Average Overall Relative Error		.104
	Relative Error for Scale Dependents	Blow	.102
		Penetration	.102
		Erosion	.109
	Stopping Rule Used		1 consecutive step(s) with no decrease in errora
	Training Time		0:00:00.20
Testing	Sum of Squares Error		1.851
	Average Overall Relative Error		.141
	Relative Error for Scale Dependents	Blow	.133
		Penetration	.132
		Erosion	.152

The accuracy of the prepared ANN model is checked by R_Squared values because it is a regression model. R2 is a statistical measure of how close the data are to the filled regression line. The R2 values range from 0 to 1. From these values, one can estimate how well the model will perform while doing the predictions. The R2 value of the ANN model is shown in table 4. The R2 value of regression for the Blow prediction is 0.89, indicating 89% variance in the data was analysed and was explained by the ANN model, similarly, the R2 value of regression for the penetration prediction is .893 and R2 value of regression for the Erosion prediction is .882. So, the model can be used for the prediction of blow, penetration and erosion defects for the given input parameter values.





for blow (R^2 = 0.890)
for penetration (R^2 = 0.893)
for erosion (R^2 = 0.882)

Fig. 4 R2 values for Blow, Penetration and Erosion

Nest residual of the model is estimated. Residual is the difference between the observed value and the predicted value. The values for a good predictive model should have less residual or error. The residue charts are shown in the Figure 5. For Blow, penetration and erosion. It can be seen there is random scatter in all the data and the residue is near about zero for the predicted values of blow, penetration and erosion.

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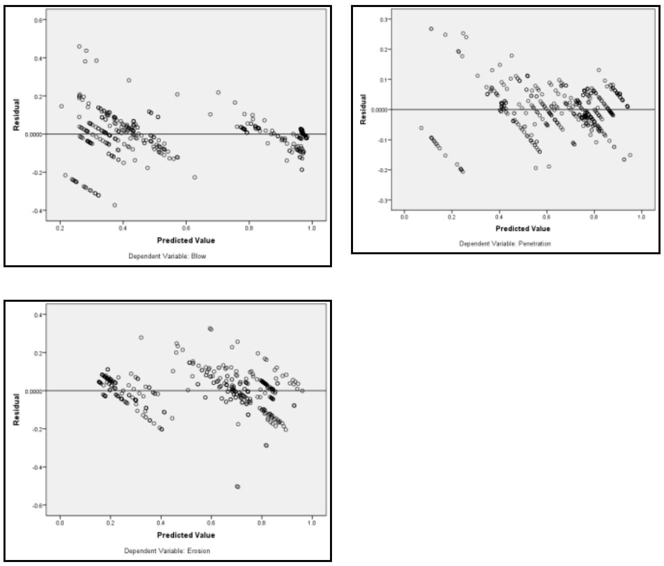


Figure 5. Regression for prediction of Blow, Penetration and Erosion

SAND-CASTING DEFECT PREDICTION USING ARTIFICIAL NEURAL NETWORK

Here MATLAB is used to create an ANN model and to see whether the input parameters can predict the defects blow, penetration and erosion using the available data. The procedure of developing the ANN model is discussed here.

First, the dataset is loaded into MATLAB. The total size of the data is 493*10, as it is having 493 observations and seven independent variables (moisture%, permeability, Binder%, Pouring temperature, GFN, Mould Hardness and Green strength) and three independent variables (Blow, Penetration and Erosion). Then data is separated into training and testing datasets. 70% of data is divided for testing and 15% of data is used as the validation data set. The remaining 15% of the data will be used for testing the developed model. The network architecture of the build ANN model is shown in figure 6. It has 7 neurons as there are 7 input variables in the dataset, and 3 neurons in the output layer. And there are 10 neurons in the hidden layer, so the network topology is 7-10-3.

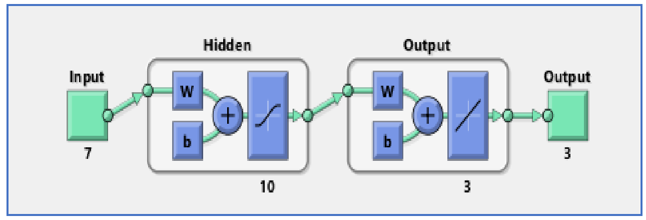


Figure 6. Network topology

For training of the ANN Levenberg Marquard Training algorithm is used. The validation performance of the neural network is displayed in figure 7 the error was changing for different iterations starting from zeroth iteration, the best validation performance is 0.0061801 at the tenth epoch.

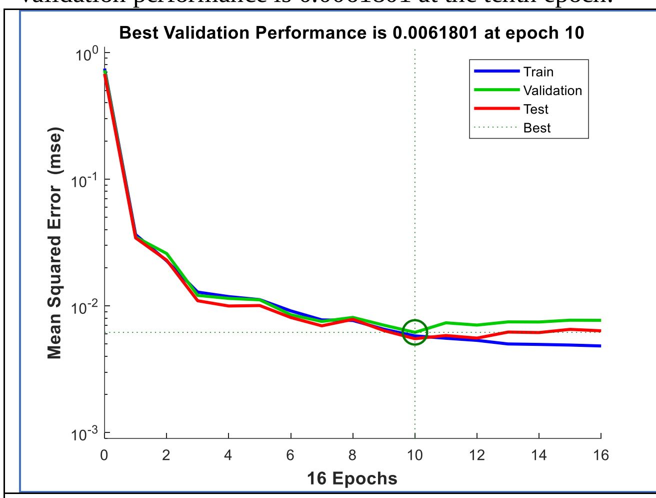


Figure 7 Validation performance of ANN Model

The validation check is shown in figure 8. Here validation check is at 16 epochs. It menaces at 16th epoch it has a better performance.

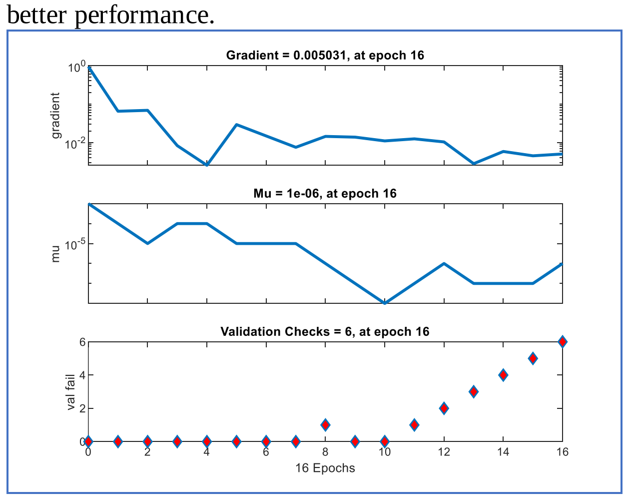


Figure 8. Validation check

The amount of error is shown in the output error histogram figure 9.

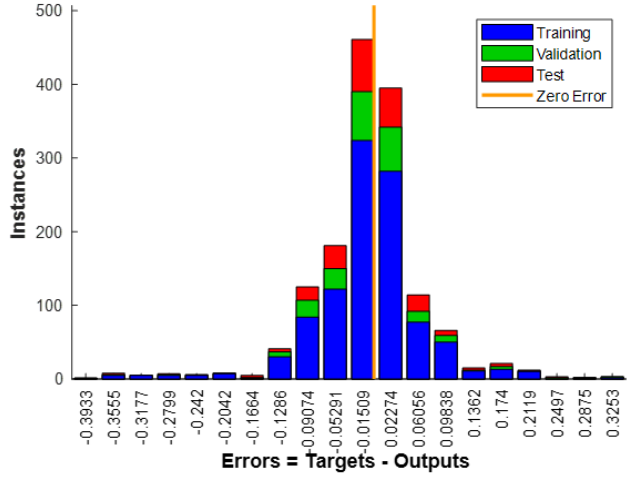


Figure 9. Error histogram

To check the performance of the ANN model the regression plots of the model is shown in figure 10. For training data set R=0.95429, for the validation dataset, the performance of the model is 0.95077 and for the testing dataset the performance of the model is 0.95747 and for all datasets, the performance of the model is 0.95417.

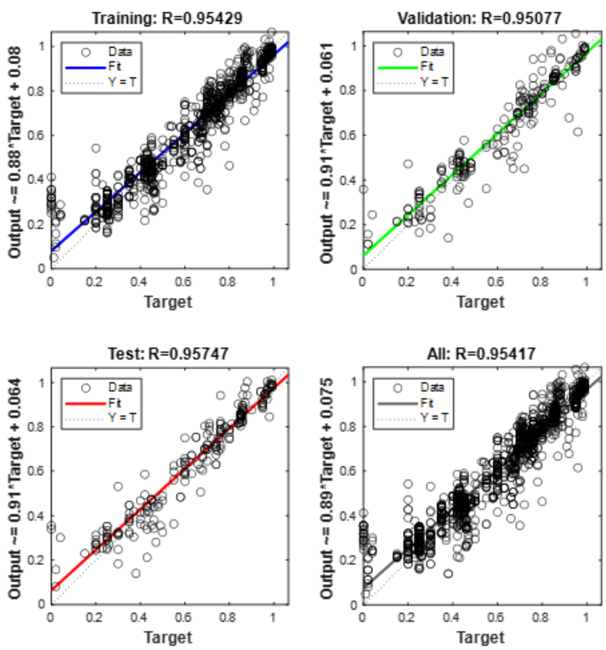
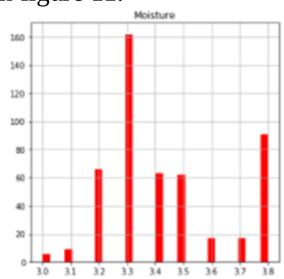


Figure 10. R Values of Training, Validation, and Testing and for All data set.

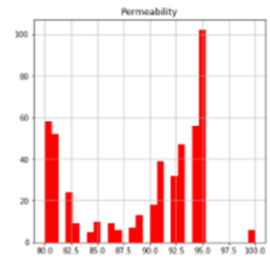
As the performance the model is very good and can be used for prediction of sand-casting defects for the given input parameter values. Hance both the models prepared by SPSS and MATLAB can be used to predict the sand casting defects: Bow, penetration and erosion. ANN can also be implemented using python, next discussion about implementation of ANN sand casting defect prediction using the same data is presented.

SAND-CASTING DEFECT PREDICTION

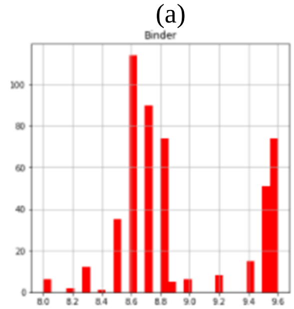
Using the same data one more ANN model is implemented using python and its in-built packages. The implementation process is discussed next stepwise. First all the required libraries like pandas, numpy, sklearn along with keras is imported. Keras is basically a frame work in python that allows to implement ANN models. Next the data is visualised to see the target and impacting variables, shown in figure 11.



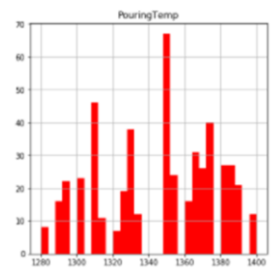
(a)



(b)



(c)



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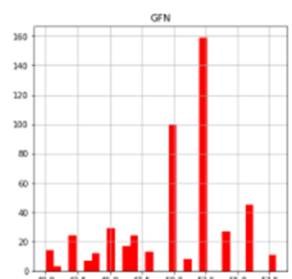
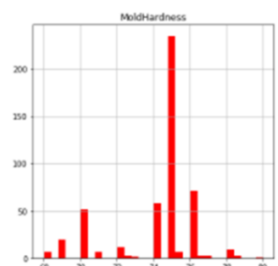
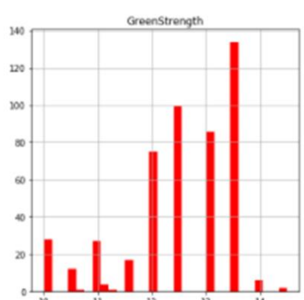


(e)



(f)



(g)

Figure 11. Relative frequency distribution of variables, (a) moisture, (b) permeability, (c) binder, (d) pouring temperature, (e) grain finesse number, (f) mould hardness, (g) green strength

After visualising the data, it is prepared for modelling the whole data is spited into the ratio of 80:20 for training and testing the model. After that the model is trained and build the input, hidden and output layer activation function, weights and bias are defined in block of cods. Keras is used to build the model sequentially layer by layer. Next step is to compile the mode means to keep the model ready to consume the data. After compiling the model run it is up to 100 epochs in the batch size of 20. In every epoch the weights and bises get adjusted and model accuracy improves. The model accuracy started from 0.624 and after the weights adjustment and going back and forth the model gave 95% accuracy. Here we defined keras model and then called the keras and got 95% accuracy in test data. Hance ANN easily implemented using python also in a very simple way and the performance of the model is very good.

RESULT AND DISCUSSION

To see the performance of the ANN model for the prediction of Blow all the 493 predictions and actual data are tabulated and compared to determine the accuracy of the model on the bases of its correct predictions shown in Table 4. The model predicted 264 times blow can occur at given level of input parameters. And actually, the number of times the blow occurred were 276.

TABLE 4. PERFORMANCE OF THE ANN MODEL FOR BLOW

Heat No	**Prediction for Blow**	**Actual Blow**	**Performance of the model**
DM006	No Blow	No Blow	1.00
DM067	Blow	Blow	1.00
DM106	No Blow	No Blow	1.00
DM121	No Blow	No Blow	1.00
DM374	No Blow	No Blow	1.00
DM409	No Blow	No Blow	1.00
DM410	No Blow	No Blow	1.00
DM432	No Blow	Blow	0.00
DM462	Blow	Blow	1.00
-	-	-	-
DM493	Blow	Blow	1.00
Total	264	276	416.00

To see the performance of the ANN mode for the prediction of penetration all the 493 predictions and actual data are tabulated and compared to determine the accuracy of the model on the bases of its correct predictions shown in Table 5. The model predicted 413 times prediction can occur at given level of input parameters. And actually, the number of times the penetration occurred were 387.

TABLE 5. PERFORMANCE OF THE ANN MODEL FOR PENETRATION

Heat No	Prediction for penetration	Actual penetration	Performance of the model
DM001	Penetration	Penetration	0
DM070	Penetration	No penetration	1.00
DM111	Penetration	Penetration	1.00
DM231	Penetration	Penetration	1.00
DM284	Penetration	Penetration	1.00
DM401	No penetration	No penetration	1.00
DM434	Penetration	Penetration	1.00
-	-	-	-
DM493	No penetration	No Penetration	0.00
Total	413	387	453.00

To see the performance of the ANN mode for the prediction of erosion all the 493 predictions and actual data are tabulated and compared to determine the accuracy of the model on the bases of its correct predictions shown in Table 6. The model predicted 335 times erosion can occur at given level of input parameters. And actually, the number of times the erosion occurred were 331.

TABLE 6. PERFORMANCE OF THE ANN MODEL FOR EROSION

Heat No	**Prediction for erosion**	**Actual erosion**	**Performance of the model**
DM053	No erosion	No erosion	1
DM195	No erosion	No erosion	1
DM200	Erosion	No erosion	0
DM253	No erosion	No erosion	1
DM297	Erosion	Erosion	1
DM340	Erosion	Erosion	1
DM369	Erosion	Erosion	1
DM412	erosion	Erosion	1
-	-	-	-
DM493	No erosion	No erosion	1
Total	335	331	488.00

The computed accuracy of the model for blow, penetration and erosion is summarized in table 6. As the performance of the ANN model for all three defects is quite satisfactory. Model prediction for erosion is best with the accuracy of 98.99% followed by prediction of prediction and then blow is 83.16%.

TABLE 6 PERFORMANCE OF BAYESIAN-BASED SAND-CASTING PREDICTION SYSTEM

	Blow	Penetration	Erosion
Actual no of	276	387	331

defects in Data			
Predictions by the model	265	413	335
Accuracy	84.38%	91.89%	98.99%

Hance ANN easily implemented using python also in a very simple way and the performance of the model is very good so the model can be used for prediction of blow, penetration and erosion defects for the given input parameter values.

CONCLUSION

ANN models have been used to carry out input-output modelling of the metal sand casting process. Nowadays different ways are available to build the ANN models and use them in the wared range of problem domains. It can be used for defect prediction and quality assurance for the grey iron sand casting using different statistical software like SPSS and MATLAB. And it can be implemented using python also in very simple steps. All the ANN models presented in this work gave better results in terms of the predicted accuracy of the defects. This type of prediction system can help foundry engineers to take decisions regarding preventing possible defects in advance. conclusion section is usually required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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