

Modelling of Artificial Neural Network to control the cooling rate of a Laboratory Scale Run-Out Table

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Abstract. Run Out Tables (ROTs) have been used for long time in order to achieve different microstructure of steel in the industries. The microstructure of steel controlled by the cooling rate which in turn depends on various factors like the plate velocity, nozzle bank distance, coolant flow rate, and many others. Achieving new steel grade thus demand a proper combination setting of all such parameters. The observed data like upper nozzle distance, lower nozzle distance and mass flow rate of coolant from the laboratory scale ROTs are used to find out the cooling rate which is important parameter for achieving desired properties in steel. An Artificial Neural Network has been used here to creating an empirical relation between the observed data and thermodynamics parameter which will determine the cooling rate and validate it.

1 Introduction

Run Out Tables (ROTs) have been used for long time to achieving different microstructure of steel in the industries. The microstructure primarily depends on the cooling rate which in turn depends on various factors like the plate velocity, nozzle bank distance, coolant flow rate, and many others of Run Out Tables (ROTs). Thermo-metallurgical phase transformation taking place during the cooling process so cooling rate is the important parameter for having the desired mechanical properties of steel. In ROT high flow rates of coolants such as air, water, air water mist etc. impinged on a uniformly distributed surface area in motion is apply for Ultra-Fast Cooling (UFC).

Run Out Tables (ROTs) and cooling rate control corresponding to different properties of steel has been an important topic of discussion among researchers for a long time. Suebsomran et al. [1] study to determine the effective cooling parameters for the run-out table (ROT) of strip steel in a hot rolling process. Mukhopadhyay et al. [2] develop an on-line model for an HSM so as to obtain the appropriate cooling rates required to predict the mechanical properties of HR coil. Serajzadeh et al. [3] developed a mathematical model to prediction of temperature variations and kinetics of austenite phase change on the run-out table. Nam Han et al. [4] developed a model for deformation, temperature and phase transformation behavior of steels on run-out table in hot strip mill. Wang et al.[5] A thermal, micro structural and mechanical coupling analysis model for predicting flatness change of steel strip during the run-out table cooling process was established using ABAQUS Finite Element Software. In this model, Esaka phase transformation kinetics model was employed to

calculate the phase transformation, and coupled with temperature calculation by means of the user subroutine program HETVAL. Xiao-dong et al. [6] studied Thermal, Micro structural and Mechanical Coupling Analysis Model for Flatness Change Prediction during Run-Out Table Cooling in Hot Strip Rolling. Zhou et al. [7] Numerical analysis of residual stress in hot-rolled steel strip on the run-out table. Suwanpinij et al. [15] make fast algorithms for phase transformations in dual phase steels on a hot strip mill run-out table to study the modelling and simulation of the evolution of phases on the ROT. Weisz-Patrault et al.[16] study the evolution of residual stresses during cooling on the run out table (after hot rolling) that is a very non linear and multiphysics process. A cooling pattern is imposed to the strip on the run out table in order to obtain a specific cooling path and phase transitions.

In this work a Laboratory scale ROT with a furnace and nozzle bank has been used. Different experimental data are achieved from Laboratory scale ROT [14]. The cooling rate, which is important parameter for achieving desired properties in steel are trying to find by using the observed data. Some part of the observed data are taken as input parameter and cooling rate as an output parameter. The inverse problem is significant i.e., for a particular cooling rate as an input what will be the corresponding output parameter. The inverse problem is quite difficult because the multidimensional data are achieved from the experiment. We need apply Artificial Neural Network (ANNs) to train in order to generate more data which will enable to creating an empirical relation between the input and the output. In this present work some observed data are trained in ANNs to predict the output i.e., parameter which will determine the cooling rate and validate it.

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Table 1. Nomenclature

Symbol	Description
Q	Mass flow rate of air(m ³ /Sec)
d _u	Upper nozzle distance(m)
d _l	Lower nozzle distance(m)
T	Temperature(°C)
t	Time(Sec.)
p	Thermodynamic parameter(°C.Sec)

It has been a good practice to apply Artificial Neural Network in research work from long time. N.Xie et al. [8] applied Artificial Neural Network (ANN) for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles. Ermis et al.[9] proposed a feed-forward back-propagation artificial neural network (ANN) algorithm for heat transfer analysis of phase change process in a finned-tube, latent heat thermal energy storage system. Islamoglu et al.[10] study presents an application of artificial neural networks (ANNs) to predict the heat transfer rate of the wire-on-tube type heat exchanger. Pacheco-Vega et al.[11] consider the problem of accuracy in heat rate estimations from artificial neural network (ANN) models of heat exchangers used for refrigeration applications. Jambunathan et al.[12] successfully applied neural networks based on the back propagation algorithm to predict heat transfer coefficients from a given set of experimentally obtained conditions. Tan et al.[13] use of artificial neural network models to simulate the thermal performance of a compact, fin-tube heat exchanger with air and water/ethylene glycol anti-freeze mixtures as the working fluids. Hassan et al. [17] study the prediction of density, porosity and hardness n aluminum–copper-based composite materials using artificial neural network. Patel G.C et al.[18] study the applications of Back propagation genetic and recurrent neural network in modelling and analysis of squeeze casting process. Junghui Chen et al.[19] monitor dynamic process fault based on neural network and PCA.

2 System Description

The laboratory scale ROTs are consist of a furnace, couple of nozzle bank which are connected with air supply line and water supply line, an electro-hydraulic actuation system for proving the reciprocating motion to the specimen plate, fixture with roller fitted rail to hold the specimen before cooling bay and mechanical handling region in between cooling table and furnace. Couples of nozzle banks, each consisting of twenty nozzle units, are on the both sides of the cooling bay so that both the upward and downward surfaces of the specimen plate can be sprayed upon at the same time. In this work only air is used for cooling. The chamber type furnace has 18 nos. of GLOBAR SD Silicon Carbide heating elements lining on the two inner side walls of the chamber. Separately installed control panel of furnace has current and voltage indicator with safety controller to

limit the maximum achievable temperature by the thermocouples which have been attached to the sample MS plate for the temperature. The operator can control the heating process with the help of an Automatic PID type programmable temperature indicating controller. Distance of the nozzle banks from the specimen plate are adjust using simple screw and nut mechanism to have the different cooling rate.

3 Modeling of Artificial Neural Network

Artificial Neural Network (ANN) is a part of Artificial Intelligence. A network or a computer system composed of artificial neurons modeled after biological nervous system, where advanced computing techniques are used to solve complex and nonlinear relationship between inputs and output variables. Through the algorithm the output signals of the neurons are expressed as the function of the input signals. Here, with our input vectors ' p_i ' respective weights ' w_i ' are multiplied and they are fed to the summing function where bias value 'b' is added to produce the net input 'n'.

$$\text{i.e., } n = \sum_{i=1}^R (p_i w_i + b), \forall i = 1(1)R$$

where, w_i = weight, b = bias value.

The net input is fed to the transfer function to generate the output.

$$\text{i.e., } a = f(n)$$

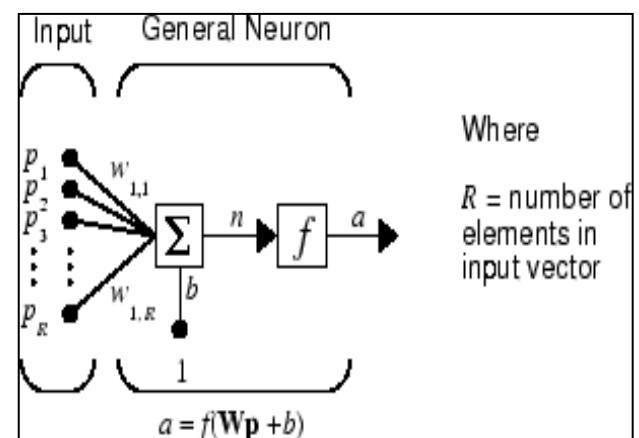


Fig. 1. A typical neuron of Artificial Neural Network

There are various types of Transfer Functions used by Artificial Neural Network where Log-Sigmoid Transfer Function ('logsig'), Tan Sigmoid Transfer Function ('tansig'), Linear Transfer Function ('purelin') are the mostly used ones. After Initialization of the bias and weights the network is become ready for training purposes which involve tuning of the values of the biases and the weights for the optimization of the network performance. There are performance functions to analyze the network performance. Mean Square Error ('mse') is used as the default performance function which is defined as below:

$$mse = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2$$

Where , e_i = error , t_i = target , a_i = output

In this paper a multilayer feed-forward neural network consisting of an input layer, single hidden layer and an output layer is proposed to fit between a numeric dataset of inputs and a dataset of outputs. Weights and biases for the inputs are updated by using standard back propagation learning algorithm. NEURAL NETWORK FITTING TOOL has been used to find the best combination of the number of hidden neurons along with the training function and transfer function. Following steps are incorporated for modeling of ANN:

Step 1. Selection of Data

A number of 29 samples of upper nozzle distance (du), lower nozzle distance(dl) and mass flow rate of air(Q) are served as the inputs where the same number of samples of $\int_0^t T dt$ i.e., a thermodynamic parameter Φ served as the target values defining the network outputs. So, input is a '29x3' matrix and the target is a '29x1' matrix.

Step 2. Division of Data

Input vectors and target vectors are divided into three data sets as follow- (i)Training: These data will be used for purpose of training of the network. (ii)Validation: These data will be used to validate Network generalization. (iii)Testing: These data will be used for completely independent test of network generalization. Different combination of this division has been tried out and 60%-20%-20% division is found to give the most accurate result respectively.

Step 3. Creation of Network

In building the network structure different combinations of number of hidden neurons, different transfer function has been used. It was found that sigmoid transfer function ('tansig') in the hidden layer and linear transfer function ('purelin') in the output layer give the most suitable result when the hidden layer size is 20.

Step 4. Training Network

Several algorithms are tested, out of which Levenberg-Marquardt training algorithm of MATLAB ('trainlm') is found to be the most accurate when Mean Squared Error (MSE) is considered to be the performance function. The training stopped when validation error is increased six iterations.

Step 5. Evaluation

Mean Squared Error (MSE) is used as the performance function. There are various tools like performance plot, regression plot, histogram plot which are used to validate and analysis the network performance.

4 Results & Discussion

The number of neurons in the hidden layer is varied to find out the optimal size of the hidden layer. MSE and correlation coefficient(R) are chosen as the performance index. Table 2 shows the values of MSE and correlation coefficient(R) for different sizes of hidden layer.

Table 2. Comparison of Different Network Structure

ANN Structure	3-15-1	3-20-1	3-25-1	3-30-1
MSE	4.89×10^{-16}	9.97×10^{-23}	9.97×10^{-23}	9.97×10^{-23}
Overall Correlation Coefficient	0.1455	0.7929	0.5829	0.3256

It can be concluded from table 2 that the optimal structure of the neural network is 3-20-1 which is shown in figure 2.

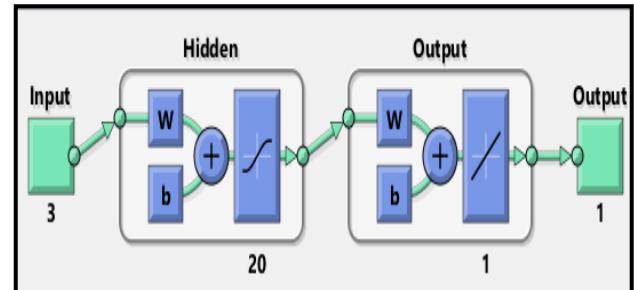


Fig. 2. Neural Network Architecture

When the network was trained in this structure using Levenberg-Marquardt training function of MATLAB, we obtain respective output for each input. Training is stopped at iteration 6 when the MSE is 9.97×10^{-23} . Figure 3 showing a plot of training error, validation error and test error which signify that the result is reasonable since (i) the final Mean Square Error is very small (ii) training error and Validation error have similar nature & characteristics (iii) no significant over fitting is occurred by iteration 3 where the best validation performance is occurred.

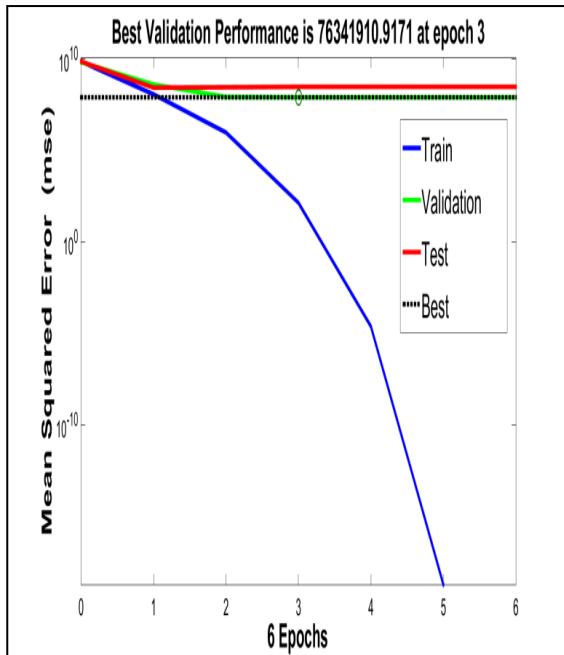
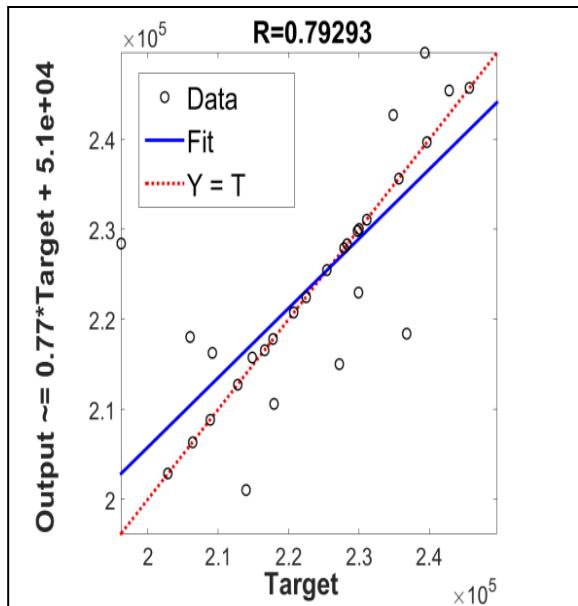
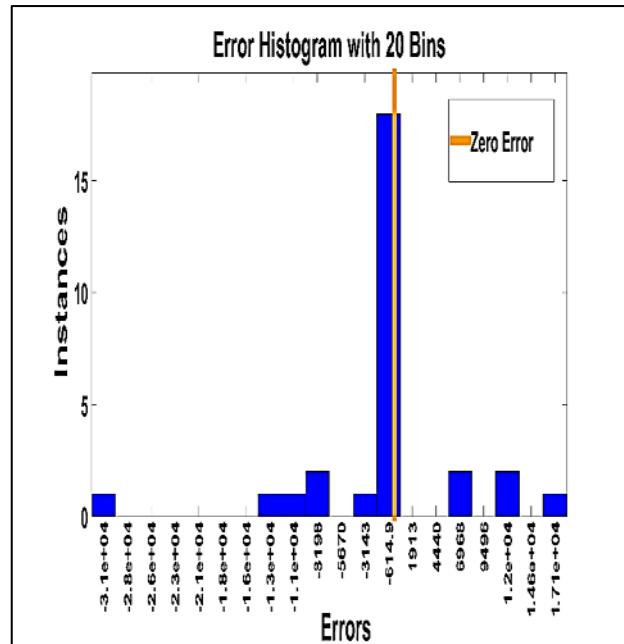
**Fig. 3.** Performance Plots

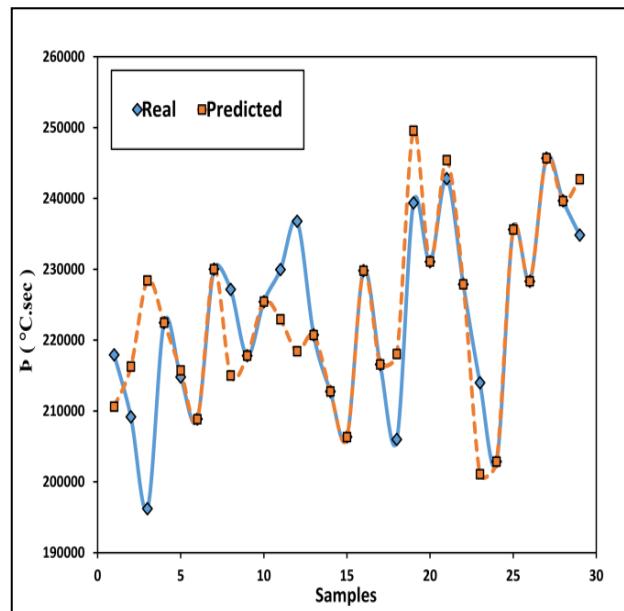
Figure 4 shows the regression analysis between the network outputs and the corresponding targets. Overall Coefficient of Correlation is found to be $R = 0.79293$.

**Fig. 4.** Regression Analysis between outputs & Targets

Additional verification of the Network performance is obtained from Error Histogram which shows the outliers where the fit is significantly worse than the majority of the other datas . Error Histogram is shown in Figure 5.

**Fig. 5.** Error Histogram

A relative comparison is done between the predicted outputs and real measured targets which are shown graphically in Figure 6. Where the curve is significantly overlapping which indicates the accuracy of the performance of the Artificial Neural Network.

**Fig. 6.** Predicted outputs Vs Real Measured Targets

5 Conclusion

Heat transfer from a heated MS plate in a laboratory scale ROT under different cooling conditions has been experimentally observed. An empirical relation between the thermodynamic parameter defining the overall heat transfer rate with the affecting cooling condition parameters have been obtained by Artificial Neural

Network mapping. Satisfactory matching has been observed in the predicted and actual data.

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