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Steel Process Modeling Based on Computational Intelligence Techniques

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Abstract: This study presents computational intelligence techniques to reduce the computation error in determining the amount of alloy materials to be added during the ladle refining process to produce the specific steel grade. In this approach subtractive clustering technique is used primarily to compute the optimal cluster centers and then, the obtained optimal cluster centers are fed as input to the resilient backpropagation algorithm to reduce the computation error. The outcome indicates that the proposed method effectively ascertains the volume of alloy materials with reduced error. This technique can be used in steel making to help the operatives and also to reduce the wastage of alloy materials.

Key words: Alloy materials, ladle refining, resilient backpropagation, steel making, subtractive clustering, effectively

INTRODUCTION

Steel manufacturing is the process of making the steel from morsel and iron mineral. Different steel grades are produced in steel manufacturing by eliminating contaminants like phosphorous, surplus carbon, sulphur, silicon and nitrogen from the crude iron and adding alloying components like nickel, vanadium, chromium and manganese (Deo and Boom, 1993). The step by step procedure of steel manufacturing is shown in Fig. 1. The reused steel morsel gives the crude substance to the Electric Arc Furnaces (EAF). After stacking morsel into the electric arc furnace, electrodes are brought down through the retractable rooftop into the electric arc furnace close to the morsel metal accusation. Power exchanges from one electrode to the morsel metal accusation, after that rear to one more electrode. Warmth to soften the scrap metal charge is produced by resistance of the metal to the stream of the huge measure of power and by the warmth of the bend itself. In order to accelerate the dissolving procedure oxygen is infused into the EAF. Alloy components and fluxes might be put in to EAF toward the finish of its melt sequence or at the scoop after tapping the EAF to set up the chemistry of the warmth of steel.

The fluid steel from the electric arc furnace is transferred to ladle. After that the ladle is directed to a ladle metallurgy refining station. At the same time as the ladle is at ladle metallurgy refining station the chemistry of the warmth of the steel is checked to find out that correct alloy add-ons were done at the time of tapping of the warmth. Extra fluxes and alloy materials might be added at the ladle metallurgy refining station if needed.

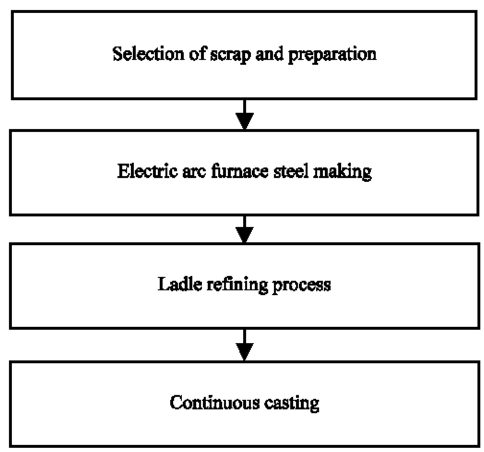

Fig. 1: Process flow of steel making

The chemistry of the warmth of steel is performed by the effervescent of inactive fumes all the way through the ladle. After the end of LMF action the ladle is then directed to the incessant cast process.

The major complication in the steel manufacturing practice is to find out the volume of alloy materials to be added at the time of ladle refining procedure to make the steel of a definite grade. In order to surmount human inaccuracy in finding out alloy add-ons, computational intelligence techniques such as fuzzy logic and Artificial Neural Network (ANN) is projected in this study.

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Fuzzy logic is an arithmetical means for managing ambiguity. Fuzzy logic way to handle complications imitates how a man would decide, merely much quicker. Fuzzy logic is fundamentally a multivalued rationale that permits in-between values to be described among usual assessments like right/wrong, yes/no and so on. Fuzzy logic offer a easy means to reach a exact finish based upon unclear, indefinite, inexact, deafening or lost data (Sivandam and Deepa, 2011; Zadeh, 1965). Grouping of statistical facts outlines the foundation of numerous categorization as well as system designing algorithms. The use of grouping is to make out innate clustering of information from a huge data collection to make a brief depiction of a system's performance (Sapna and Kumar, 2015; Chiu, 1994). The fundamental notion of fuzzy clustering is the non-distinctive separation of information in to a collection of clusters. Fuzzy clustering offers supple and sturdy technique for managing innate information with imprecision and ambiguity. ANN or Neural Networks (NN) are those information handling frameworks which are built and employed to replica the individual intelligence. The key purpose of NN study is to expand a calculation tool for replicating the intelligence to perform different computing functions at a rapid speed than the conventional method (Sivandam and Deepa, 2011).

Literature review: In the literature the numeral and content of academic studies and scientific papers related with the computational intelligence methods used in steel making for modeling ladle refinement procedure is very confined. Takagi and Sugeno (1985) presented a modeling of converter based on fuzzy technique. This model is put into practice to the converter control and the outcomes are compared with the state when an operative curbs it excluding a model. Zarandi and Ahmadpour (2009) projected multi-agent system based on fuzzy method for EAF processes of steel manufacturing. All the EAF steel making process was allotted to an agent which might work autonomously at the same time organizes and collaborate with further companion agents. The agent's know-how bases are developed using adaptive neuro-fuzzy inference method. Zarandi *et al*. (2010) presented a novel multi-agent expert scheme using adaptive neuro-fuzzy inference system for categorization of steel grades. As the proportion of components in steel manufacturing generally has an unclear nature, adaptive neuro-fuzzy systems and the fuzzy rule sets are further precise and sturdy to model this composite problem. Wieczorek and Kordos (2010) presented a system to advance the effectiveness of steel production process using computational intelligence methods. Somkuwar (2013a, b) presented ANN for envisaging the mechanical possessions of low carbon steel and hardness of high speed steel. This technique aids the expert to formulate free examination of the consequence of the alloying materials happening in dealing out situation moreover using only computer simulation, exclusive of having to perform pricey and supplementary experimental exploration.

MATERIALS AND METHODS

Subtractive clustering (Chiu, 1994) considers all data point as a prospective cluster core and delineates the gauge of the prospective of data point x_i by:

$$P_i^* = \sum_{j=1}^{n} e^{-\alpha\|x_i - x_j\|^2}$$

Where:

$$\alpha = \frac{4}{r_a^2} \quad (1)$$

and r_a is a assenting constant. Hence, the gauge of prospective for a data point is a component of its separations to every other data focuses. A data point with numerous adjacent data points will have more prospective value. The constant r_a is successfully the radius signifying vicinity, data points outer the radius has small impact on the potential. After the prospective of all data point is calculated the data point having the utmost prospective is chosen as the initial cluster center. Let x^*_1 represents the position of the initial cluster core and P^*_1 symbolize its prospective value. So, therefore the prospective of all data point x_i is amended by:

$$P_i \Leftarrow P_i - P_1^* e^{-\beta\|x_i - x_1^*\|_2} \quad (2)$$

Where:

$$\beta = \frac{4}{r_b^2}$$

and r_b is a assenting invariable. Therefore, a quantity of prospective from all data point is deducted as a function of its closeness from the primary huddle core. The data positions close to the primary clump core will possess extremely a lot abridged prospective, so are not probably to be chosen as the subsequent group core. The stable r_b is successfully the radius signifying the vicinity which will comprise quantifiable diminution in prospective. In order to evade attaining intimately separated group core the r_b value is assigned to be fairly larger than r_b value; a fine option is to have r_b = 1.5 r_a.

After the prospective of every data positions have been amended conforming to Eq. 2 the data position having the maximum residual prospective is chosen as the next group core and the prospective of all data position is decreased additionally conforming to their remoteness to the next group core. In common after attaining the kth group core the prospective of all data position is amended by:

$$P_i \Leftarrow P_i - P_k^* e^{-\beta \|x_i - x_k^*\|^2}$$

Where:

x^*_k = The position of the kt^h group core and

P^*_k = Its potential value

By Yager and Filev (1994)'s method the procedure of obtaining novel group core and amending prospective replicates:

$$P_k^* < \varepsilon P_1^*$$

where, ε is represents a miniature fraction. The option of is an imperative aspect that have an impact on the outcomes if ε value is excessively high, too little information points will be agreed to receive as group cores if ε value is excessively little, too numerous group cores will be produced. It is hard to set up a solitary ε value that toils fine for every information models and contain consequently established added norm for admitting/declining group cores (Algorithm 1):

The norm utilized:

if $P_k^* < \varepsilon P_1^*$
    Admit x^*_k as a group core and carry on
else if $P_k^* < \varepsilon P_1^*$
    Refuse x^*_k and finish the grouping procedure
else
    Let d_{min} = smallest of the remoteness among x^*_k and every formerly established group cores:

$$\text{if } \frac{d_{min}}{r_a} + \frac{P_k^*}{P_1^*} \geq 1$$

    Admit x^*_k as a group core and carry on
else
    Refuse x^*_k and assign the prospective at x^*_k to value 0. Choose the information position with the subsequent maximum prospective as the novel x^*_k and test again.
  end if
end if

At this point $\bar{\varepsilon}$ denotes a threshold meant for the prospective over which the information position is absolutely admitted as a group core; $\underline{\varepsilon}$ stipulates a threshold underneath which the information position is absolutely discarded. In general and is utilized. If the prospective descends in the gray area, it's to be ensured whether or not the information position offers a fine balance among having an adequate prospective and being amply distant on or after subsisting group cores.

Back-propagation learning: Back-propagation is that the most extensively exploited algorithmic rule for supervised learning with feed-forward net having many layers. The fundamental thought of the back-propagation erudition algorithmic rule (Rumelhart and McClelland, 1986) is that the frequent use of the progression decree to calculate the effect of all weight in the net relating to a random inaccuracy Expression E:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial s_i}\frac{\partial s_i}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} \quad (3)$$

where, w_{ij} represents the weight as of neuron j to neuroni, the outcome is mentioned as and the biased summation of the input values of neuronis denoted as net_i. When the fractional imitative for all weight is well-known the objective of reducing the inaccuracy expression is accomplished through executing an easy gradient drop:

$$w_{ij}(t+1) = w_{ij}(t) - \varepsilon\frac{\partial E}{\partial w_{ij}}(t) \quad (4)$$

Noticeably, choosing the learning rate ε value that scales the imitative has a vital result on the occasion required till convergence is achieved. If it's value is assigned too little, several steps are required to achieve the satisfactory result on the opposing a huge learning rate will perhaps direct to fluctuation, averting the inaccuracy to drop beneath a sure value. A premature method projected to get divest of the above snag is to initiate a momentum-tenure:

$$\Delta w_{ij}(t) = -\varepsilon\frac{\partial E}{\partial w_{ij}}(t) + \mu\Delta w_{ij}(t-1) \quad (5)$$

where, μ is the momentum factor that scales the effect of the preceding step on the present. The momentum tenure is supposed to make the erudition process further steady and to speed up convergence in superficial area of the inaccuracy task. Nevertheless as realistic skill has exposed, this can be not right at all times. It seems in reality that the best worth of the momentum factoris evenly drawback reliant as the erudition rate ε which no common enhancement is achieved (Riedmiller and Braun, 1993).

Resilient backpropagation (Rprop) algorithm: Resilient backpropagation algorithm is a proficient novel erudition method which carries out an undeviating modification of the weight pace founded on local gradient data (Riedmiller and Braun, 1993). In key variation to formerly established alteration methods the attempt of alteration is not distorted by gradient performance whatever. In order to accomplish this, for all credence its respective renovate-value Δ_{ij} established which exclusively finds out the magnitude of the weight update. This flexible renovate-value progress all through the erudition procedure according to its confined prospect on the inaccuracy expression E in accordance with the subsequent learning canon:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} * \Delta_{ij}^{(t-1)}, \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} \rangle 0 \\ \eta^{-} * \Delta_{ij}^{(t-1)}, \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} \langle 0 \\ \Delta_{ij}^{(t-1)}, \text{ else} \end{cases} \quad (6)$$

$$\text{where, } 0 \langle \eta^{-} \langle 1 \langle \eta^{+}$$

The alteration canon toils as pursues: each instance the fractional imitative of the related weight ω_{ij} alters its sign that designates that the final renew was excessively large and the contrivance has bounded above a confined least the renovate-value Δ_{ij} is reduced by the aspect ή. If the imitative preserve its sign the renovate-value is somewhat improved consecutively to speed up convergence in low regions.

If the renovate-value for all weight is modified once then the weight-renovate itself pursues a incredibly effortless canon: if the imitative is affirmative (rising inaccuracy) the weight is reduced by its renovate-value if the imitative is negative then the renovate-value is summated:

$$\Delta\omega_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, \text{if } \frac{\partial E^{(t)}}{\partial \omega_{ij}} \rangle 0 \\ +\Delta_{ij}^{(t)}, \text{if } \frac{\partial E^{(t)}}{\partial \omega_{ij}} \langle 0 \\ 0, \text{ else} \end{cases} \quad (7)$$

$$\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta\omega_{ij}^{(t)} \quad (8)$$

But there is one exemption; if the fractional imitative alters sign that is the preceding pace was excessively huge and the least was lost the preceding weight-renovate is relapsed:

$$\Delta\omega_{ij}^{(t)} = -\Delta\omega_{ij}^{(t-1)}, \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} \langle 0 \quad (9)$$

Because of that back off weight-pace the imitative is made-up to vary its sign again in the subsequent pace. In turn to evade a dual chastisement of the renovate value, no alteration of the renovate-value be supposed to be there in the following pace. In reality it can be made by assigning $\partial E^{(t-1)}/\partial \omega_{ij}$: = 0 in the Δ_{ij} alteration rule above. The weights and also the renovate-values are altered each occasion the entire model set has been obtainable just the once to the net (erudition by eon).

Algorithm: The subsequent pseudo-code portions explain the core of the RPROP erudition and alteration procedure. The least (highest) operator is made-up to convey the least (highest) of two figures; the sign operative returns -1 if the spat is negative, +1 if the spat is affirmative and 0 or else. For every biases and weights {:

$$\text{if}\left[\frac{\partial E}{\partial \omega_{ij}}(t\text{-}1) * \frac{\partial E}{\partial \omega_{ij}}(t) > 0\right]\text{than}\{$$

$$\Delta_{ij}(t) = \text{minimum}\left(\Delta_{ij}(t\text{-}1)\right) * \eta^{+}, \Delta_{max})$$

$$\Delta\omega_{ij}(t) = -\text{sign}\left[\frac{\partial E}{\partial \omega_{ij}}(t)\right] * \Delta_{ij}(t)$$

$$\omega_{ij}(t+1) = \omega(t) + \Delta\omega_{ij}(t)$$

}

$$\text{else if}\left[\frac{\partial E}{\partial \omega_{ij}}(t\text{-}1) * \frac{\partial E}{\partial \omega_{ij}}(t) \langle 0\right]\text{than}\{$$

$$\Delta_{ij}(t) = \text{minimum}\left(\Delta_{ij}(t\text{-}1)\right) * \eta^{-}, \Delta_{min})$$

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \Delta\omega_{ij}(t\text{-}1)$$

$$\frac{\partial E}{\partial \omega_{ij}}(t) = 0$$

}

$$\text{else if}\left[\frac{\partial E}{\partial \omega_{ij}}(t\text{-}1) * \frac{\partial E}{\partial \omega_{ij}}(t) = 0\right]\text{than}$$

$$\Delta\omega_{ij}(t) = -\text{sign}\left[\frac{\partial E}{\partial \omega_{ij}}(t)\right] * \Delta_{ij}(t)$$

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \Delta\omega_{ij}(t)$$

}

}

Parameters: On the verge, every renovate-value Δ_{ij} is assigned to a primary value Δ_0. Directly find out the magnitude of the initial weight-pace for Δ_0, it is rather selected in a sensibly ratio to the magnitude of the primary weights. A fine selection is possibly. $\Delta_0 = 0.1$. But while the outcomes in the subsequent part demonstrate, the option of this factor is not decisive by any means. Yet for greatly superior or greatly lesser Δ_0 values, quick convergence is arrived.

By Spiral learning task exclusion, the assortment of the renovate-values was limited to a maximum value of $\Delta_{max} = 50.0$ and a minimum value of $\Delta_{max} = 1e^{-6}$ to evade underflow or excess tribulations of perched point variables. A soft conduct of the shrink of inaccuracy might be attained as a result of assigning the upper limit renovate-value to a noticeably lesser value $\Delta_{max} = 1.0$.

The option of the lessen part and raise part η^+ was directed by means of the subsequent thought: if a bound above a least take place, the preceding renovate-value was excessively huge. For its not recognized from gradient data what proportion the least was lost in usual it'll be a fine estimate to divide the renovate-value that is $\eta^- = 0.5$. The raise part has to be great sufficient to permit quick rise of the renovate-value in superficial areas of the inaccuracy task, on the opposite aspect the erudition method may be significantly perturbed, if a excessively great raise issue directs to unrelenting amend of the route of the weight pace. So as to induce factor option further easy, persistently fix the raise/lessen factors to $\eta^- = 0.5$ and $\eta^+ = 1.2$.

One of the most benefits of RPROP lies within the reality, that for several issues no alternative of parameters is required in any way to get best or as a minimum of almost best convergence times.

RESULTS AND DISCUSSION

For implementation the dataset of steel with 20 inputs and 6 outputs with 4190 data is taken into account for modeling. Table 1 gives the sample data for few inputs and outputs of the obtained steel dataset. The description of input and output parameters are given in Table 2.

The input parameters signify the temperature and composition of steel analyzed in EAF and LMF. The output parameters are the alloying proportions required to be calculated and added during ladle refining process according to the inputs to get the steel of preferred considerations. As the considered steel dataset have large numeral of input and output parameters the fuzzy rules and the intricacy of the system will increase. So, to acquire optimum fuzzy rules subtractive clustering technique is first applied to the steel dataset. The simulation is carried out using MATLAB R2014a. The subtractive clustering technique results with 6 cluster centers for radii 0.5 and is shown in Fig. 2 and the Root Mean Square Error (RMSE) is found to be 2.9719. The radii lies amid zero and one that denotes a cluster cores

Table 1: Sample of steel dataset

Input data (%)			Output data (kg/Mg)		
e-Mn	e-Al	l-C	Si	Mn	Al
0.0970	0.2900	0.1540	2.3726	6.9146	2.1995
0.0710	0.3040	0.1430	2.1951	5.2774	0.3594
0.0910	0.4210	0.1350	3.8953	4.8960	0.4842
0.0750	0.2730	0.1400	2.4509	6.8072	2.1916
0.0790	0.3790	0.1240	2.1695	0.0000	0.4189
0.0770	0.7620	0.1470	3.0460	5.0014	0.2761
0.0740	0.3620	0.1540	2.1764	6.7288	0.3195
0.0600	0.3120	0.1300	2.6785	6.9307	0.6231
0.0560	0.3770	0.1510	2.9650	5.5661	0.3817
0.0810	0.5000	0.1250	3.0017	5.0228	0.4120
0.1020	0.3380	0.1330	2.9366	5.0117	0.4625
0.0880	0.3040	0.1430	1.9687	6.7590	0.4242
0.0880	0.3320	0.1250	3.8318	6.3859	2.2689
0.0520	0.3380	0.1470	2.2500	6.9682	0.3947
0.0520	0.3790	0.1370	0.6634	6.6828	2.0287

Table 2: Description of input and output parameters

Parameter name/Units	Description
Amount of input parameters analyzed in EAF (%)	
e-C	Carbon
e-Si	Silicon
e-Mn	Manganese
e-P	Phosphorouse-S
Sulfur	
e-Cr	Chromium
e-Ni	Nickel
e-Mo	Molybdenum
e-Al	Aluminum
e-Temp	Normalized Temperature
Amount of input parameters analyzed in LMF (%)	
l-C	Carbon
l-Si	Silicon
l-Mn	Manganese
l-P	Phosphorous
l-S	Sulfur
l-Cr	Chromium
l-Ni	Nickel
l-Mo	Molybdenum
l-Al	Aluminum
l-Temp	Normalized Temperature
Output parameters (k/mg)	
C	Carbon
Si	Silicon
Mn	Manganese
P	Phosphorous
S	Sulfur
Al	Aluminum

vary of impact in all of the information proportions, guessing the information falls among a unit hyperbox. If the radii value is small it results in huge cluster cores. Amid 0.2 and 0.5 is typically being the finest value for radii (Chiu, 1994). The cluster centers and RMSE computed using subtractive clustering technique for radii values 0.2-0.5 are given in Table 3. From Table 3, the finest cluster cores are found to be 6 for radii 0.5. In fuzzy logic method the number of cluster centers is equivalent to the number of fuzzy rules and therefore, there are only 6 fuzzy rules to signify 4190 data in dataset of steel. The rule view obtained by means of subtractive clustering technique is shown in Fig. 3.

The output cluster cores of subtractive clustering technique are fed as input to the resilient backpropagation algorithm for training the net. The concert of the RPROP algorithm is assessed using Mean Square Error (MSE) and Regression (R) analysis. MSE is the average squared disparity among outputs and targets. Lesser values are better whereas zero implies no error. Regression R evaluation is carried out to appraise the rapport between outputs and targets. An R value of 1 represents a close rapport, 0 an arbitrary rapport. The recital of resilient backpropagation algorithm when trained with neural network using MATLAB R2014a is shown in Fig. 4 and its regression analysis is shown in Fig. 5.

Table 3: Cluster centers and RMSE obtained using subtractive clustering for radii values 0.2-0.5

Radii	Cluster centers	RMSE
0.2	56	2.2279
0.3	07	2.9568
0.4	11	2.9117
0.5	06	2.9719

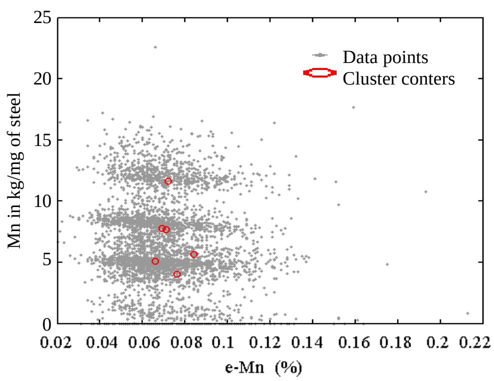

Fig. 2: Subtractive clustering output with 6 cluster centers

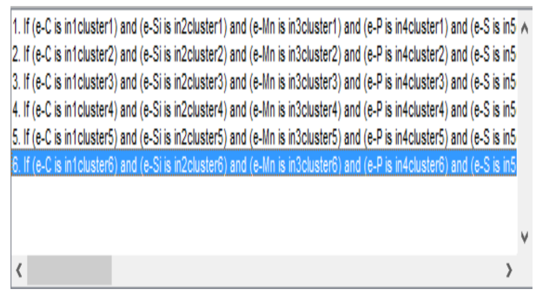

Fig. 3: Fuzzy rules obtained using subtractive clustering technique

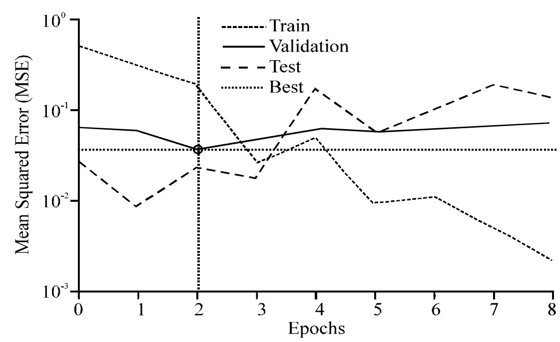

Fig. 4: Performance of resilient backpropagation algorithm

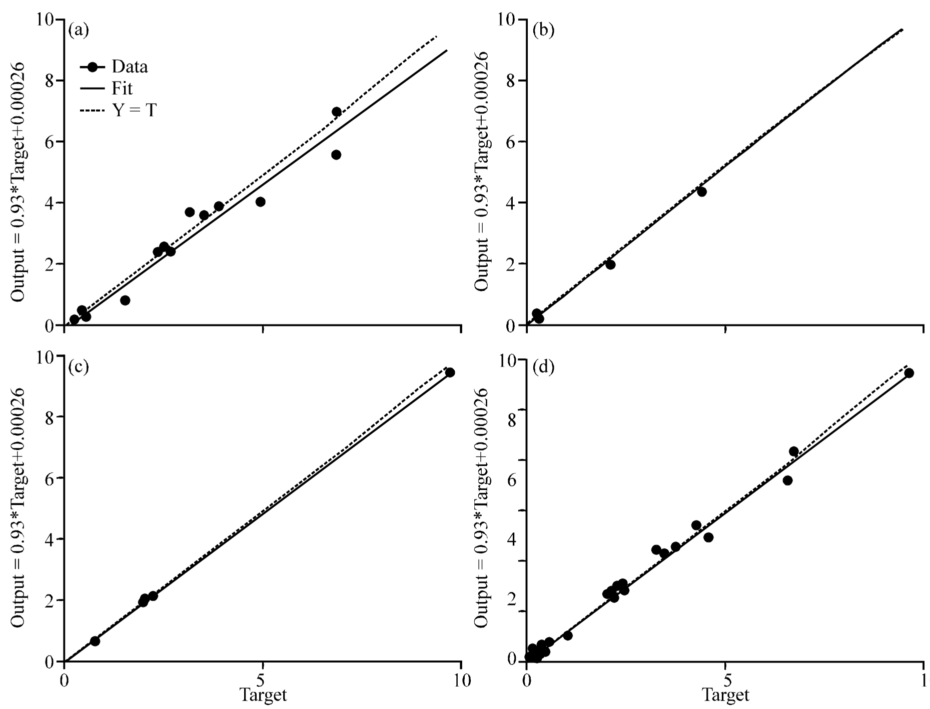

Fig. 5: Regression analysis plot obtained using resilient backpropagation algorithm

The recital of the network is computed in terms of MSE and hence, the MSE for the proposed network when trained using resilient backpropagation algorithm is found to be 0.034397 at epoch 2. The root mean square which means the square root of MSE is found to be 0.1854. From Fig. 5, it is observed that the value of regression R is close to 1 indicating the perfect correlation between the outputs and the targets. The simulation outcomes of the proposed system specifies that the RMSE obtained using Resilient backpropagation algorithm 0.1854 is found to be least when compared to RMSE obtained using subtractive clustering 2.9719.

CONCLUSION

This study proposed the computational intelligence techniques for modeling of ladle refining process in steel making. Using a fuzzy subtractive clustering technique the optimal cluster centers are computed first and then it is given as input to the resilient backpropagation algorithm to compute alloy proportions required to make desired steel with reduced error. The outcomes indicate that the integration of fuzzy clustering with neural network in determining needed alloy proportions resulted with reduced error rate. This developed model can be employed in steel making to aid the operator for effective production of preferred steel.

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