RESEARCH ARTICLE OPEN ACCESS

Roughing Rolling Performance Improvement and Energy Optimization by ANN- DOE Modeling

Atul Modi*, D.A.Hindoliya**
**(Department of I. P. E., Shri G.S. Institute of Technology and Science, Indore, India*
Email: atul_123modi@yahoo.com
*** (Department of Mechanical Engineering, Ujjain Engineering College, Ujjain, India*
Email: dev_hindoliya@yahoo.com

ABSTRACT
The rolling manufacturing system performance and output results are controlled by shape and size obtained at different sequences at roughing mill. Roughing rolling mill plays key role for sound and forging quality grades. In presence of too many parameters, the output performance variations of the different grades in rolling are a serious problem. Influence of different rolling variables is known but parameter which affects the process most is important. Artificial neural network (ANN) was constructed to predict symptoms of rolling mill with signal to noise (S/N) ratio as performance characteristics obtained by DOE in a rolling plant. The developed ANN model is useful to predict the performance of the rolling mill by most influential variable only within the range of experimental values. The new model indicates the rolling process energy optimization with help of most energy intensive single parameter for hot rolling.

Keywords - *ANN-DOE modeling,* Roughing *rolling,, Rolling variables, S/N ratio.*

Date of Submission: 09-12-2017 Date of acceptance: 18-12-2017

I. INTRODUCTION

The steel rolling science is already developed and many improved model are working to improve the product quality but contribution of most influential parameters on different process is not known yet. In absence of clear directive rolling peoples can-not obtained the desired results. To get the desired output the different rolling sequences from roughing to finishing are performed as designed in different passes as per set variable or control factors with minimum energy losses. The economical manufacturing through saving in energy and material loss in roughing operation is a significant driving force for the development of new methodology.

In roughing rolling sequential improvement of mechanical properties and grain refinement process can be obtained by obtaining optimum reduction and densification. To obtain consistent rolling performance, a continuous deformation and reduction is required in roughing operation with minimum change in set parameters, which is also essential to obtain the desired dimensional and metallurgical results. Any deviation in rolling parameters and its setting causes variations in rolling mill output. For rolling process energy optimization is used as tool to reduce performance variations. The used rolling manufacturing system is needed to be optimized for different losses developed in different sequences. The most important elements of manufacturing system optimization is the consistency of all sequences output, so minimum shape and size variation for next processing and low energy losses are developed.

Different new models are recently developed. There has been considerable focus on neural networks in the recent past as it is widely applicable and easy to use for problems with highly non-linearity and complex data. Kim et al. [1] is develop model to adjust the roll gap for the dimensional accuracy of rod in hot rod rolling process considering roll wear using artificial neural network (ANN). It has been found that the use of ANN has got the immediate results to maintain uniform cross-sectional area constant during rod (or bar) rolling process.

Biswas S. [2] demonstrate that the high temperature rolling is performed in stable austenite region and material is completely recrystallizes after shaping. The subsequent heat treatment sequence employed result into process energy loss. Zarate and Bittencout [3] insist that the rolling forces determination is influenced by many variables and on-line-control is needed. ANN qualitative and quantitative aspects of behaviors are important and verified through simulation and sensitivity equations.

Mandal et al. [4] consider ANN is efficient quantitative tool to evaluate and predict the hot deformation. Shahani et al. [5], study the friction effect on rolling process. According to Luis and Sergio [6], ANN applications required less computational time for different system and processes of rolling plants. Zarate and Dias [7] consider, ANN applications in steel rolling are vast and trained neural network is consider as black box which is difficult to extract the useful information.

Saravanakumar et al. [8] uses ANN model to predict the mechanical properties under thermo-mechanical process parameters influences.

Bagheripoor and Bisadi, [9] consider speed, %age thickness reduction, temperature and friction coefficient as variables for rolling force prediction by ANN. They raise the need for on-line-control of parameters for consistent performance and quality results. Bambach & Seuren [10] emphasized that the performance of rolling processes is difficult to control due to the dynamic processes and new customer requirements. The rolling mill performance variations are developed by variations in rolling parameters. Unal et al. [11] use ANN to prepare fault estimating algorithm for rolling. Altinkaya et al [12] preferred ANN as, it provides a way for accurate and fast decision making and modeling. Hornik [14] described a typical multi-layer feed forwarded neural network. Deng et al. [15] explain how the output of each neuron is calculated by weight vector.

With help of this paper the rolling manufacturing complexity are tried to be reduced in routine working. The rolling people should not to worry about too many process variables but to be concentrating only on a single and most important process influencing variable. Steel plants have to improve first for the existing system in term of quality and performance variations and then go for modernization and further more investment. To obtain consistent quality with minimum rejection is the target. In steel rolling plants goal oriented consistent output performance is seemed for different grades and sizes in minimum setup.

The paper contents introduction and previous work done in first chapter, then discussion about rolling manufacturing system sequences and DOE in latter chapter, the chapter eight provide results and finally conclusions.

II. WHY ROLLING PROCESSES ENERGY OPTIMIZATION

The Rolling manufacturing processes, major portion of cost is developed due to different sequences energy losses, these losses are due to variations of control variables. According to Das et al. [13], energy minimum losses, wastages and uses by parameters optimization, are the only possible way to obtain the desired output. Energy intensive processes energy consumption and losses control results into energy optimization of different sequences. Final output variation chances and low mechanical properties are more in conventional rolling plants than modern system due to complex layout and old technology and equipment.

To obtain the required size of finished rolled products different pass and sequences are required from roughing to finishing. The processes are influenced by different variables which interact also. Rolling processes have needed to optimize in series or sequences of rolling to get required output in all sequences as shown in Fig.-1 in continuous manner in rolling plant at ISIM at Indore M.P.

Figure-1 Rolling manufacturing system at ISIM

The energy consumption and losses in different manufacturing system are irrespective of modern or conventional plants and its reduction can be achieved by decreasing the performance variations of different rolling sequences. Rolling process energy optimization is a tool to improve profitability, environment, sustainability and productivity. Need is developed to cut the process cost by energy optimized processes. Fig.-2 indicates the finished coil as stored after laying head in rolling plant.

Figure-2 Finished wire rod product

III. SEQUENTIAL ANN-DOE (DESIGN OF EXPERIMENTS)

DOE technique helps to study more than one factor (variables) simultaneously. Optimum or desired output needed optimum billet size and pass sequence, with desired reduction in each pass. Rolling parameters vary with different size and grades. Main objective is to obtain the stable production and to reproduce the results in each sequence. In the present work, an artificial neural network (ANN) based model has been developed for prediction and optimization of the performance of a rolling mill. The experimental observations were recorded and calculated as S/N ratio as performance index for training of the neural network.

In sequential DOE a series of small set of tests in which purposeful changes are made to the input variables of rolling process sequences for corresponding change in the output. The strategy is to vary all factors simultaneously in a planned set of experiments. The Taguchi concept is an economical method of the performance improvement to control any manufacturing losses.

The neural network understands the underlying correlations in the entered data and the same are stored as inter-neuron connection strengths or corrected weights. ANN modeling applications are versatile for rolling manufacturing system and its energy loss control. Among the networks, the best prediction performance was observed in two-hidden-layered network with minimum error.

The increased competitiveness of rolling plant requires consistent quality and excellent post processing after hot rolling.

IV. ROUGHING-PASS-SEQUENCES

Steel rolling processes are performed in various rolling passes as roughing, intermediate and finishing according to different grades and sizes. Complete rolling manufacturing operations are governed by different parameters and roll pass design are done accordingly in different pass in different mills or set of rolls. The pass designer also considers the effect of temperature during pass design as shown in Fig.-3 for roughing first box pass.

The pass designer also considers the different considerations like influence of scale, uneven heating, raw material size and shape variation etc.

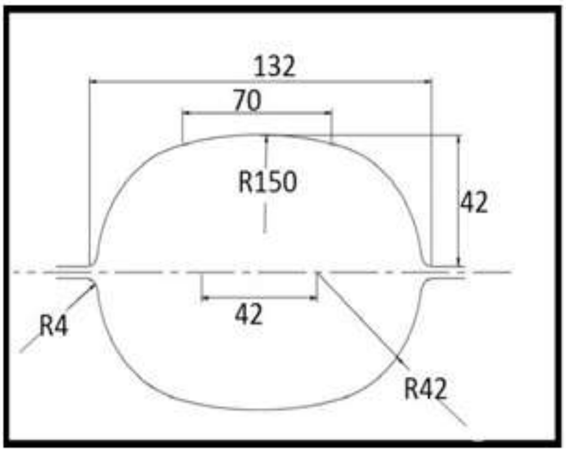

Figure-3 Roughing first box pass

The rolling people or rollers always try to achieve maximum filling of pass for best material densification, while roll pass designer have to consider the mill loading capacity also. In the conventional rolling plant the pass sequences used in roughing mill stand-I are box-oval-square-oval-square-oval-square.

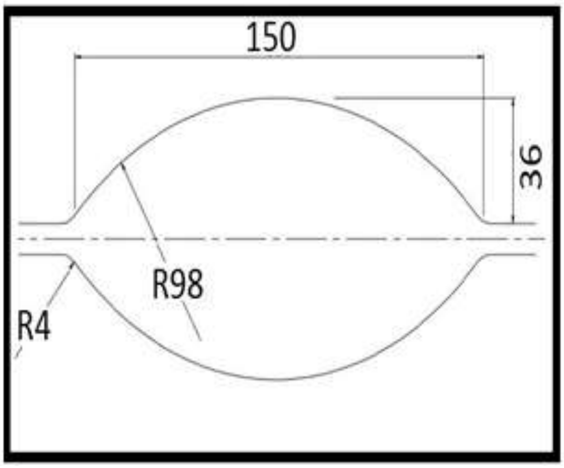

Figure-4 Roughing second oval pass

Similarly in Fig.-4 and Fig.-5 the next pass oval and square are shown. The all roughing sequence is performed at slow speed, so no difficulty in material entry. Sometime the roughing rolls are knurled also to get easy entry of billets. The pass optimum filling can be obtained by controlling rolls gap between the rolls. The dimensional shape accuracy insists for the required reduction with minimum variations in size as well as complete pass filling, so that rolling performed in each sequence as desired.

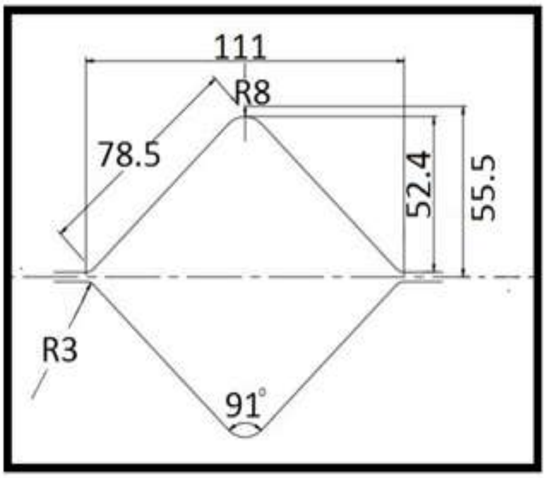

Figure-5 Roughing third square pass

The roller has to set gap so that defects may also not develop. The roughing stands generally produced semi-finished or rough surfaces, which is not useful for close sizes and tolerances but desired or target size as in the pass is essential to obtain correct tolerance of finished products. The defects such as scratches and fin are also developed. The roll pass designer considers the different pass sequences based on mill load capacity and final finished product quality.

Complex rolling process pure analytical models now requires considerable simplification in settings for routine working in the plant. Critical analysis of steel rolling process is essential to obtain the desired and perfect output in all conditions and sequences.

The roughing rolling sequence main object is to obtain heavy reduction in minimum passes, so at high temperature maximum possible reduction can obtained. It finally processed into rounds bars or wire rods with acceptable dimensional tolerance as of the rolling stands and depend on other rolling parameters. The all roughing sequence is performed at slow speed, so no difficulty in material entry. Sometime the roughing rolls are knurled also to get easy entry of billets. Normal rolling conditions and practices used by conventional wire rod plant or similar type of plant can also be represented by process diagram for conventional type of rolling.

Different experiments are performed at ISIM rolling mill for DOE modeling. Rolling is performed with different settings of control factors, generally at temperature range of around 1200-1100^0 C, selected on basis of different grades for easy bite. Three standard levels of different parameters of rolling mill are considered for modeling purpose. The selection of different level of control factors are decided on basis of type of stands and equipment.

The noise factors considered for the DOE experiment are control factor setting, other than desired in normal rolling. The solidus curve in equilibrium diagram for particular material grade indicates the maximum possible re-heat temperature for rolling at low rolling load, while the fuel energy saving view prefers low re-heat temperature. High rolling temperature is preferred due to high plasticity during deformation but limited by melting temperature of scale, furnace/ mill type, grain growth and damage to grain boundary, burning and energy consumption.

The S/N ratio as obtained is considered as performance index is mainly dependent on many factors. The rolling load can determine by the load cell fixed in the roughing stand and load can modify with the hydraulic pressure to get the desired load setting. The rolling speed can be set with help of D.C. Drives and roll gap can be measure by the filler gauge. The chances for miss-roll and other failure are increases with delayed rolling of material. Temperature drop in different pass sequences is also considered due to material lying in open.

V. ROUGHING-SEQUENTIAL-ANN-DOE

Artificial neural network (ANN) was constructed to predict symptoms of rolling mill with signal to noise (S/N) ratio as performance characteristics, obtained by DOE in ISIM plant. Total 9 experiments are performed in same mill and stand, so each treatment effect is consider. In the experiment, the information about the variation in dimensional shape in different passes of roughing sequences is determined.

To determine the actual size after rolling the sample is cut from the rolled bar after fist pass or box pass rolling. Usually in the rolling bar size and shape is checked so that the processes optimum results can be developed. The area variation is measured at five places, each is one meter apart.

The experiment objective function is the minimization of area variation from pass design and S/N ratio for lower the best type function is determined. In rolling desired dimensional results are essential so that the melting/casting defects may weld instead of opening in roughing sequences.

The furnace outlet temperature is set as DOE and is cross checked with the portable optical temperature gauge for the different pass sequences. The layout of the orthogonal array as obtained by experiments is represented in Table-1 in appendix. It indicates the rolling results with respect to area variations in various lengths for box-oval-square pass for roughing rolling sequences experiments.

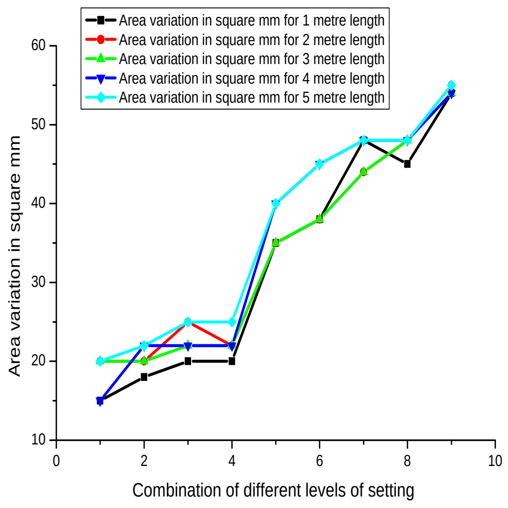

Figure-6.Variation in area for Box Pass

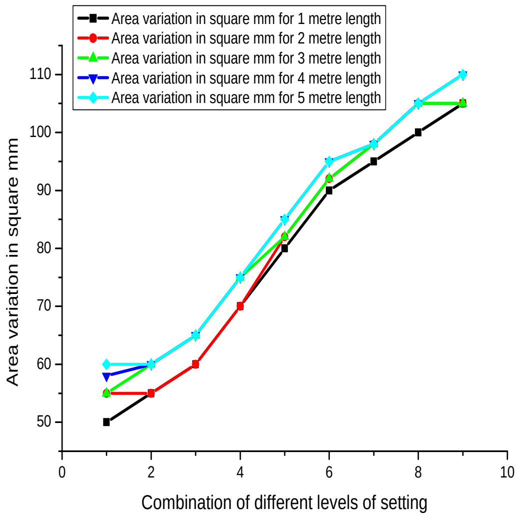

Figure-7.Variation in area for Oval Pass

Comparison of S/N ratio for different parameter settings as obtained in DOE experiments is shown in Fig.-6.Fig.-7 & Fig.-8. The variations in the areas of the work were observed is in similar pattern.

VI.NEURAL NETWORK ARCHITECTURE

The modeling of the roughing rolling was carried out with neural network toolbox of **MATLAB**®. The selected network consists of an input layer, one or more hidden layer for processing the data and one output layer. A feed forward back-propagation network type was selected for training. First, input value and target value were selected in the data manager of ANN toolbox.

The input data have been connected to the neuron with weights for correction. Input information is processed at each neuron and gives output. Information received from all the connected neuron is summed up and passed through an activation function and the activation outcome is sent out to the subsequently connected neurons. A two-layer network with 10 sigmoid neurons in the hidden layer and ten linear neurons in the output layer has been used for the present research work. Network is trained to give the desired output with minimum error using input or S/N ratio. The training data sets are group of input and corresponding desired output. Training involves the revision of the synaptic weights. The training set should be self-sufficient to train the network. The network reads and processes each set of input data and produces an output.

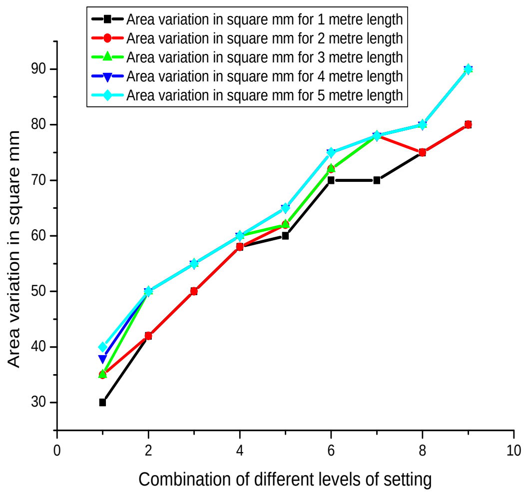

Figure-8.Variation in area for Oval Pass

The outputs from the model have been compared with the actual experimental output. Before completion of the training, there would obviously be a difference between the network's output and the target output. The weights are adjusted such that the error function is minimizes the differences between actual experimental outputs and model outputs.

When the network has run through all the input pattern, mean square error greater than the maximum desired tolerance, a new 'Epoch' (a run through all training input-output sets) is started after completion of the current one and the synaptic weights are further adjusted towards reducing the error function. This process continued until the error function comes under the desired tolerance zone. This repetition process of the training and correction of the weights is known as back propagation algorithm. The mean square error (MSE) was selected as the typical performance function for training of feed forward neural networks as shown in equation (3).

MSE $= \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - t_a)^2$ **(3)**

Learning rate is also an important function for training of the network. During the training of the network, a learning rate of 0.5 and 100 numbers of epochs have been used. Several training algorithms and network types are available in MATLAB® [14].

VII. GENERALIZATION OF MODEL

By sequential DOE for box-oval-square rolling sequence, rolling temperature is determined as most influential parameter to obtained consistent output. The importance of most influential and energy intensive parameter on different rolling sequences are obtained and by in-line-control of temperature, process energy losses are also minimized and different requirement are easily developed. The experimental results have been used to construct a simple network for making the correlations between the input and output parameters with the help of training and transfer function of the network. **Fig.**-9 represents the performance or S/N ratio comparison of the rolling mill in box-oval-square sequences as in **appendix**.

The research work introduces an artificial neural network (ANN) application to a conventional wire rod hot rolling mill to improve the roller's prediction ability for dimensional tolerance of rolled products, as a function of most influential process parameters and to improve output results. Energy intensive processes energy consumption and losses control by in-line-control of energy intensive parameter temperature, results into energy optimization of complete cycle. New improved P-Diagram indicates that energy optimized rolling operations are be performed at target temperature only by in-line-control for different grades at higher speed, %age reduction for desired dimensional and metallurgical requirements.

New P-Model is applicable to modern plant also as they shows performance variation in absence of in-line-control of parameters. Improved model removed this limitation with the help of guide rings in roller table, so material enters with extra thrust. Results of rolled bars performance and quality characteristics 'Y', mathematically are represented P-Model as-

Old Y= F (Control factors, Noise factors)
New Y= F (Temperature)

Main difference in both models is that in energy optimized model rolling sequences or process energy losses are minimized by in-line-control of most influential variable e.g. temperature. The rollers have to consider only rolling temperature during complete rolling sequences. Energy intensive rolling process is energy optimized by the parameter which controls the process energy consumption as well as energy losses. Temperature is an energy intensive parameter which can optimize the complete rolling processes by its in-line-control, energy consumption, material efficiency, mechanical properties, output performance and losses, delays, miss-rolls are minimized.

VIII. RESULTS AND DISCUSSIONS

Optimum performance is the target in presence of all types of undesirable factors in routine rolling conditions. Experiments determined rolling temperature as most influential parameter. With help of proper monitoring of most influential parameters the complete process is energy optimized and different losses are minimized.

The S/N ratio variation indicates the change in rolling performance as size variation in the experiment. Error indicates the difference in actual S/N ratio with the obtained by trained network. **Fig.-**10 represents the performance comparison of the rolling mill trained network *trainlm* with experimental output and network's modeled output, which is also very close and similar. After training of the network, the following results were observed as in Table: 4.

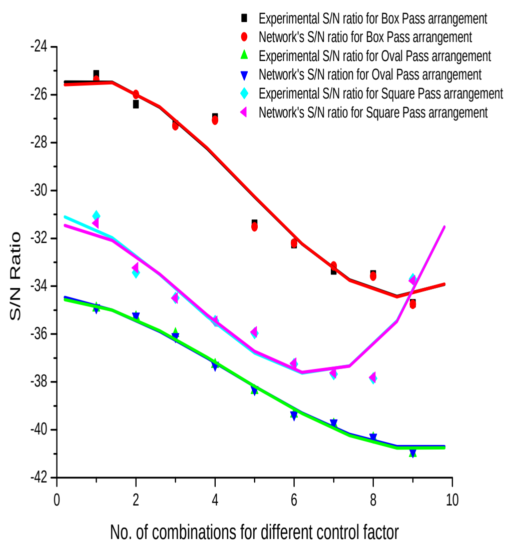

Figure-9 Comparison of S/N ratio ANN-DOE

The larger value of S/N ratio is preferred. The lower value with minus sign is preferred for S/N ratio at which higher rolling temperature are used, so for process optimization maximum possible (4) rolling temperature at roughing mill is preferred as on it maximum S/N ratio is obtained. The experimental results of a rolling mill may be presented by following mathematical expressions as Network's output –

$$\frac{S}{N_{(Box\ Pass)}} = -25.5946 + 0.3772\,x - 0.51488\,x^2 + 0.03602\,x^3$$

$$\frac{S}{N_{(Oval\ Pass)}} = -31.05381 - 0.16353\,x - 0.414\,x^2 + 0.04348\,x^3$$

$$\frac{S}{N_{(Square\ Pass)}} = -34.42159 - 0.17944\,x - 0.18544\,x^2 + 0.01412\,x^3$$

The in-line-control of temperature variable is essential to minimize the effects of different process other factors, which cause variations in the reproduction of dimensional and metallurgical results in each pass in rolling. The error variation is also both negative and positive and similar pattern for different rolling sequences indicates trueness of experiment.

The ANN modeling also indicates that selection of optimum rolling parameter to optimize the complete rolling process is useful and applicable to different rolling condition. Goal oriented consistent output performance is developed for different grades and sizes in minimum setup time. Energy intensive rolling process is energy optimized by the energy intensive parameter which controls the process energy consumption as well as energy losses. Rolling temperature in-line-control is only solution to obtain desired results reproducibility each time for different grade and size.

The energy consumption and losses in different manufacturing system are irrespective of modern or conventional plants and its reduction can be achieved by decreasing the performance variations of different rolling sequences.

Table-5 Expected change in rolling problems

S.N.	Rolling problems	Commonly used techniques	Possible solution by the research work
1	High energy intensity	Energy audit	Energy optimization of processes
2	Multivariable processes	S.Q.C.\ Control charts	Single variable optimization
3	Too many sequences	Reduction in used sequences	Sequential optimization
4	Pass design problems	Heavy reduction	Mill based pass design
5	Quality problems	Product Inspection	Processes sequential optimization
6	Raw material problems	Material Inspection	Con-cast-sequential optimization
7	Roller problems	Incentive scheme	Energy sequential optimization

The most important elements of rolling manufacturing system optimization is the consistency of all sequences output, so minimum shape and size variation from material to material, absence of grain variation, reduced alloying cost and low energy losses are developed. The plant all delays and miss-roll is also be minimized and processes are performed in optimum manner to get better yields.

Table-5 indicates the expected change in rolling problems possible solution. The new model has advantage of target oriented setting of temperature throughout different rolling sequences. In roughing rolling, finishing or all rolling sequences the temperature role is an essential element for process energy optimization by minimum losses and control output / performance. The model can be used for wide range of ambient condition for prediction of output from Rolling mill with single parameter. This study can be used to assess the performance and make comparison of rolling sequences in any plant.

IX. CONCLUSIONS

An artificial neural network (ANN) model for roughing rolling mill is proposed in this work to reduce rolling complexity. Modeling method is very useful to generalize the improve model of Rolling mill with most influential parameter which is energy intensive also. A close agreement between network output and experimental output was observed.

Rolling process complexity reduced and target result are easily obtained. ANN modeling of S/N ratio is not only useful to obtain the desired results but motivate the rollers to develop optimize rolling results in different situations. Control on rolling noise factors is obtained to develop the set targets.

Roll pass design is also made according to rolling temperature and any variation of temperature causes rolling defects. The proposed method for obtaining ANN model and optimized weights for an artificial neural network has been found to be useful for rolling process energy loss control by optimum temperature setting. The proposed ANN model can be used to predict the performance of the rolling mill within the range of experimental values. The research work can reduce rolling processes energy losses to obtained better results.

ACKNOWLEDGEMENTS

We are thankful to **M\S Indore Steel & Iron mills Ltd. Indore** for support and facility for experiments**.**

REFERENCES

[1]. Kim, D.H., Lee, Y. and Kim, B.M. Application of ANN for the dimensional

accuracy of work piece in hot rod rolling process. *Journal of Materials Processing Technology*, 2002 , 214–218.
[2]. Biswas S., *Simulation of thermo-mechanical deformation in high speed rolling of long steel products*, M.E. Thesis, Worcester Polytechnic Institute, 2003.
[3]. Zarate, L.E. and Bittencout, F.R. Representation and control of the cold rolling process through artificial neural networks via sensitivity factors. *Journal of materials processing technology*, 197, 2008, 344–362.
[4]. Mondal, S., Sivaprasad P.V., Venugopal S. and Murthy K P N., Artificial neural network modeling to evaluate and predict the deformation behavior of stainless steel type AISL 304 L during hot torsion. *Applied Soft computing, 9*, 2009, 237-244.
[5]. A.R. Shahani, S. Setayeshi, S.A. Nodamaie, M.A. Asadi, S. Rezaie, Prediction of influence parameters on the hot rolling process using finite element method and neural network, *J. Mater. Process. Technol.* 209, 2009, 1920–1935.
[6]. Luis E . Z. Ã, Se´rgio M .D., Qualitative behavior rules for the cold rolling process extracted from trained ANN via the FCANN method, *Engineering Applications of Artificial Intelligence* 22, 2009, 718–731.
[7]. Zarate, L.E. and Dias, S.M., Qualitative behavior rules for the cold rolling process extracted from trained ANN via the FCANN method. *Engineering Applications of Artificial Intelligence* 22, 2009, 718–731.
[8]. Saravanakumar, P., Jothimani, V., Sureshbabu, L., Ayyappans, S., Noorullah, D. and Venkatakrishnan, P.h., Prediction of Mechanical Properties of Low Carbon Steel in Hot Rolling Process Using Artificial Neural Network Model. *Procedia Engineering*, 38, 2012, 3418-3425.
[9]. Bagheripoor, M., Bisadi, H., Application of artificial neural networks for the prediction of roll force and roll torque in hot strip rolling process. Applied Mathematical Modelling Vol.-37, *Elsevier* 2013, 4593-4607.
[10]. Bambach, M., Seuren, S., On instabilities of force and grain size predictions in the simulation of multi-pass hot rolling processes. *Journal of Materials Processing Technology* 216, 2014, Pages 95-113.
[11]. Unal, M., Onat, M., Demetgul, M. and kucuk, H., Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network. Measurement, 58, 2014, 187-196.
[12]. Altinkaya, H., Orak, I.M. and Esen, I., Artificial neural network application for modeling the rail rolling process. *Expert Systems with Applications*, 41, 2014, 7135-7146.
[13]. Das S., Mathur, J., Bhattacharyya, T., Bhattacharyya, S., Failure Analysis of Re-Bars during Bending Operations , Case Studies in Engineering Failure Analysis, 2, 2014, 51–53.
[14]. Hornik K., "Approximation capability of multi-layer feed forward networks as universal approximations". *Neural networks*, (1991), 4:251-7.
[15]. J. Deng, D. Gu, X. Li, Z.Q. Yue, Structural reliability analysis for implicit performance functions using artificial neural network, *Struct. Saf.* 27, 2005, 25–48.
[16]. R. Kazan, M. Firat, A.E. Tiryaki, Prediction of spring back in wipe-bending process of sheet metal using neural network, *Mater. Des.* 30, 2009, 418–423.
[17]. Matlab, Version 7, *neural network tool box*, Inc; 2004.

APPENDIXES-

Roughing Rolling Sequential DOE

Table 1: The orthogonal array for DOE for Box pass sequence of roughing stand-1

Ex. No	Temp. °C	Rolling Pressure Tons	% age Red. Sq.mm	Speed m/s	Area Variation in Sq.mm 1M-L	Area Variation in Sq.mm 2M-L	Area Variation in Sq.mm 3M-L	Area Variation in Sq.mm 4M-L	Area Variation in Sq.mm 5M-L	S/N Ratio 'n'
1	1	1	1	1	15	20	20	15	20	-25.15
2	1	2	2	2	18	20	20	22	22	-26.40
3	1	3	3	3	20	25	22	22	25	-27.25
4	2	1	2	3	20	22	22	22	25	-26.95
5	2	2	3	1	35	35	35	40	40	-31.40
6	2	3	1	2	38	38	38	45	45	-32.25
7	3	1	3	2	48	44	44	48	48	-33.35
8	3	2	1	3	45	48	48	48	48	-33.51
9	3	3	2	1	54	55	54	54	55	-34.72

Table 2: The orthogonal array for DOE for Oval pass sequence of roughing stand-1

Ex. No	Temp °C	Rolling Press. Ton.	% Red. Sq.mm	Speed m/s	Area Variation in Sq.mm In 1M	Area Variation in Sq.mm In 2M	Area Variation in Sq.mm In 3M	Area Variation in Sq.mm In 4M	Area Variation in Sq.mm In 5M	S/N Ratio
1	1	1	1	1	50	55	55	58	60	-34.92
2	1	2	2	2	55	55	60	60	60	-35.28
3	1	3	3	3	60	60	65	65	65	-35.99
4	2	1	2	3	70	70	75	75	75	-37.27
5	2	2	3	1	80	82	82	85	85	-38.36
6	2	3	1	2	90	02	92	95	95	-39.35
7	3	1	3	2	95	98	98	98	98	-39.77
8	3	2	1	3	100	105	105	105	105	-40.34
9	3	3	2	1	105	105	105	110	110	-40.99

Table 3: The orthogonal array for DOE for Square pass sequence of roughing stand-1

Ex. No	Temp. *c	Rolling Pressure Ton	% Reduc. Sq.mm	Speed m/s	Area Variation in Sq.mm In 1MLg	Area Variation in Sq.mm In 2MLg	Area Variation in Sq.mm In 3MLg	Area Variation in Sq.mm In 4MLg	Area Variation in Sq.mm In 5MLg	S/N Ratio
1	1	1	1	1	30	35	35	38	40	-31.07
2	1	2	2	2	42	42	50	50	50	-33.43
3	1	3	3	3	50	50	55	55	55	-34.49
4	2	1	2	3	58	58	60	60	60	-35.45
5	2	2	3	1	60	62	62	65	65	-35.96
6	2	3	1	2	70	72	72	75	75	-37.25
7	3	1	3	2	70	78	78	78	78	-37.67
8	3	2	1	3	75	75	80	80	80	-37.85
9	3	3	2	1	80	80	90	90	90	-33.70

Table 4: Experimental and network's S/N ratio for different Pass of the rolling mill.

S.N.	For Box Pass			For Oval Pass			For Square Pass		
	Experi-mental S/N ratio	Network's S/N ratio	Error	Experi-mental S/N ratio	Network's S/N ratio	Error	Experi-mental S/N ratio	Network's S/N ratio	Error
1.	-25.15	-25.389	0.23921	-34.92	-34.901	-0.019	-31.07	-31.3629	0.2929
2.	-26.4	-25.991	-0.40882	-35.28	-35.241	-0.039	-33.43	-33.229	-0.201
3.	-27.25	-27.301	0.050559	-35.99	-36.101	0.111	-34.49	-34.501	0.011
4.	-26.95	-27.069	0.11918	-37.27	-37.291	0.021	-35.45	-35.469	0.019
5.	-31.4	-31.522	0.12215	-38.36	-38.313	-0.047	-35.96	-35.908	-0.052
6.	-32.25	-32.2	-0.04968	-39.35	-39.368	0.018	-37.25	-37.2196	-0.0304
7.	-33.35	-33.159	-0.19149	-39.77	-39.702	-0.068	-37.67	-37.618	-0.052
8.	-33.51	-33.585	0.07499	-40.34	-40.301	-0.039	-37.85	-37.8088	-0.0412
9.	-34.72	-34.764	0.043911	-40.99	-40.912	-0.078	-33.7	-37.902	0.072

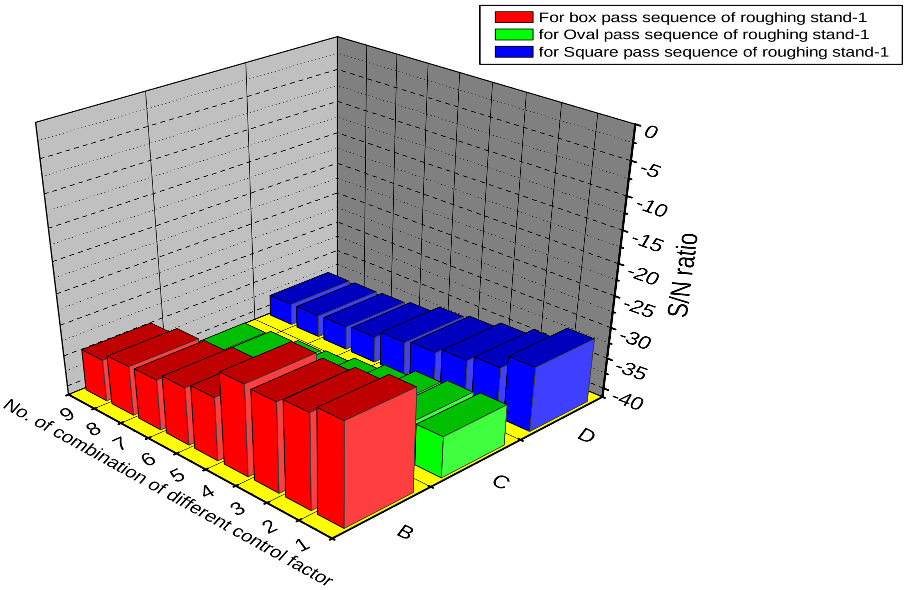

Figure-9.Variation in S/N ratio for Box-Oval-Square Pass.

International Journal of Engineering Research and Applications (IJERA) is **UGC approved** Journal with Sl. No. 4525, Journal no. 47088. Indexed in Cross Ref, Index Copernicus (ICV 80.82), NASA, Ads, Researcher Id Thomson Reuters, DOAJ.

Atul Modi "Roughing Rolling Performance Improvement and Energy Optimization by ANN-DOE Modeling." International Journal of Engineering Research and Applications (IJERA) , vol. 7, no. 12, 2017, pp. 01-10.