



Multiple Performance Characteristics Optimization of Cold rolling Processes Parameters Using Taguchi's Quality Loss Function

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Abstract:

Taguchi method of Optimization has successfully applied in lasts so many years in Engineering application for the improvement of product quality and process performance. Most of the Taguchi experiments are application for single characteristic optimization. Multiple characteristics Optimization in manufacturing processes has received very little attention among the Taguchi Method users. Many engineers using Taguchi methods have employed pure engineering judgment when dealing with multiple characteristics in manufacturing process optimization. This approach brings an element of uncertainty to the decision-making process. This paper presents an alternative approach for tackling such optimization problems using Taguchi's quality loss function analysis. The paper presents a case study to illustrate the potential of the proposed methodology is used to optimize Multi process performance namely thickness variation, strip flatness, production rate and Power consumption by obtaining optimal solution for control factors exit tension, entry tension, Mill speed and Roll bending pressure for cold rolling of low carbon steel in single stand reversible cold rolling mill. A L_{27} orthogonal array was selected and total 27 experiments were conducted in Single stand reversing cold rolling Mill after selecting control factors and its levels as a case study. Interaction plot shows no interaction among the control parameters. The ANOVA carried out which shows the mill speed is most significant control factor. The Prediction model has been developed at 95% confidence level. The optimal values obtained using the multi characteristics optimization Model using Taguchi loss function has been validated by confirmation experiment. Finally rolling pass schedule is optimized using optimized rolling parameters.

Keywords

Optimization, Cold rolling, Taguchi loss function, uncoiler, orthogonal array & Signal to noise ratio.

1. Introduction

1.1. Cold Rolling Process:

The purpose of a cold rolling mill is to successively reduce the thickness of the metal strip and/or impart the desired mechanical and micro structural properties[1][2]. The cold rolling of metals produces flat product like sheet, strip and foil with increase mechanical strength with close control of product dimensions and good surface finishes. Tandem type cold rolling mills used for larger scale production, whereby the strip undergoes a single pass through a train of rolling stands before being wound into coil form. The single stand type cold rolling mills are usually called as reversing mills, whereby the metal strip is successively wound and unwound in the form of coil it is repeatedly passed back and forth through the single mill stand. Reversing mills are generally used for smaller scale production of the cold rolled products.

Figure 1 show schematic representation of single stand 4HI Cold rolling mill configuration consists of two work rolls and two back up rolls. The back up rolls provides rigid support to prevent work roll bending & flexure. There are two hydraulic Jacks mounted on top of the housing on either side which provide rolling force of backup roll housing and adjust roll gap. The strip coil fed to mill via tension reel on either side of mill stand. As the strip exists the mill stand it wound tight on tension reel on other side which is and expanding mandrel that maintain contant tension during rolling process while reel on entry side maintain back tension during rolling.

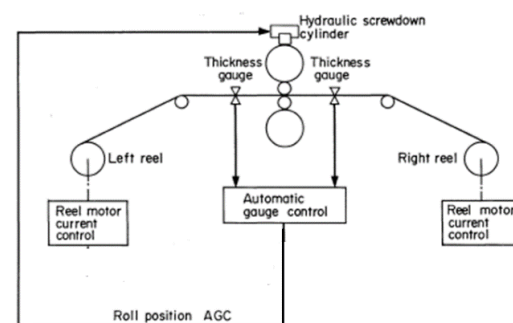


Figure 1 Schematic representation of Single stand 4 HI reversing cold rolling mil



Rolling pass schedule is the basis in the cold rolling process. It determines the stand reductions, rolling speeds, roll bending pressure and entry / exit tensions of a specified product for reversible cold rolling process mill system.

Pass schedule consists of setting of control parameters at each pass depending on various factor like input output thickness, width of the coil, material to be rolled, mill capability etc.

A case study was carried out on 4 Hi single stand cold rolling Mill at JSW steel coated Product limited Nagpur India carried out. Where rolling pass schedule is prepared by experience mill operator using thumb rule. As per feedback from the quality and production team finished cold rolled product is having numerous quality issues. Some of the productivity related issues reported are thickness variation and strip flatness. This happens because there no standard pass schedule available which can predict these quality parameters. As per production team cold rolling mill is fully loaded with production schedule and hence not available for doing exhaustive exercise of permutation and combination by changing of setting parameters for optimizing pass schedule. At the same time Production Manager is also concerned about power consumption and enhance production to reduce the production cost so as to increase revenues.

If the optimal values of setting parameters for pass schedule are available to the mill operator, performance of the mill can be improved and loss due to diversion of coil can be reduced substantially. Literature review [4] in this area reveals that, no theoretical model is available to arrive at the optimum setting of the single stand cold rolling Mill, satisfying multiple objectives to get desired mill performance. It is necessary to arrive at the optimum setting by planning and executing extensive experimentation. The Taguchi Approach for determining optimal settings of rolling process parameters through experiments focuses on product of single characteristic thickness variation [5]. These Optimal process parameters setting are not optimal setting for other mill performance characteristic. In solving many engineering problems on optimization, it is necessary to consider the application of Multi Response optimization, because the performance of Product is often evaluated by several characteristics / response. Antony [6] has suggested a multi-objective optimization technique using Taguchi quality loss function to simultaneously optimize the multiple quality characteristics in manufacturing processes.

The present case study is an attempt to experimentally optimize the setting parameters of pass schedule in second pass. The main objective of this paper is to show the capability of the Taguchi Quality loss function based multi response

optimization methods in increasing productivity while controlling the Quality and cost of Production.

2. Experimentation:

A series of Experiments were conducted in 4HI cold rolling Mill at JSW Steel coated Product, Kalmeshwar Nagpur, India on low carbon steel as a case study. Table 1 shows the material data for input material and output desired depend on input and output data a roll pass schedule prepared. The basic procedure for the scheduling of cold rolling mills is usually based on past experience, on trials or on rules of thumb [3]. Table 2 shows the typical pass schedule. Our experimentation was done for optimization rolling parameters for 2nd pass.

The control factors and their levels were decided for conducting the experiment, based on a “brain storming session” and by Fishbone diagram of cause and effect study that was held with a group of people and also considering the guide lines given in the operator’s manual provided by the manufacturer of the rolling mill. The input and fixed parameters used in the present study is shown in Table 3.

The control factor(Rolling parameters) identified are exit tension (TEXT), entry tension(TENT), Mill speed(MS) and Roll bending pressure(BP) to investigate their effects on the mill performance thickness variation (THKV), strip flatness (FLT), production rate (PR) and Power consumption(PC).

2.1 Levels of parameters

As per the experience and brain storming of welding operators in the industry, range for each variable (control factor) is decided. Then as per [4, 5], four levels are identified for each control factors as shown in Table 4.

2.2 Selection of Orthogonal Array (OA)

Selection of the orthogonal array is based on the calculation of the total degree of freedom of all the factors. Orthogonal arrays are special matrix in which entries are at various levels of input parameters, and each row represents individual treatment condition [8, 9]. In orthogonal array, for any pair of column all combinations for each factor level occur and they occur in equal number of times (this is called balancing property).

Degree of freedom related to a process can be calculated as [9]:

dof = (number of levels - 1) for each factor + (number of levels - 1) (number of levels - 1) for each interaction + 1.

In present case of four parameters at three different levels assuming three interaction between factors the degree of freedom is calculated as:

Dof= (3 - 1) x 4 + (3 - 1) x 2 x 3 + 1 = 21.



Table 1 Material data

Entry thk	Exit thk	Reduction	No of pass	Material	Width	Weight of the coil
2.15mm	0.38mm	82.32%	8	ST29DC	1200 mm	20 MT

Table 2 Typical Pass schedule

Pass No.	Entry thk	Exit thk	Reduction	Exit tension	Entry tension	Rolling speed	Roll bending Pr.
	mm	mm	%	Kg	Kg	mpm	bar
1	2.150	1.735	19.302	12200	2000	300	80
2	1.735	1.400	19.302	12200	7200	500	80
3	1.400	1.130	19.302	12200	7200	600	80
4	1.130	0.912	19.302	12200	7200	600	80
5	0.912	0.736	19.302	10682	7121	600	80
6	0.736	0.594	19.302	8600	5734	600	80
7	0.594	0.479	19.302	4617	5772	600	80
8	0.479	0.387	19.302	3718	4647	600	80

Table 3: shows the control factors and fixed factors

Control factors	Abbreviation	Code	Fixed parameters
Exit Tension	TENT	A	Work roll Dia = 560 mm
Entry Tension	TEXT	B	Material Grade Low carbon steel
Mill speed	MS	C	Width = 1200 mm
Bending Pressure	BP	D	Coolant concentration = 0.5 %

Table 4 : Factors and there Levels in Design of experiment

Factor	Units	Abbreviation	Code	Levels		
				1	2	3
Exit tension	Kgs	TEXT	A	11000	11600	12200
Entry tension	Kgs	TENT	B	6000	6600	7200
Mill Speed	mpm	MS	C	400	500	600
Bending Pressure	Kg/cm2	BP	D	70	80	90

Based on these values and the required minimum number of experiments to be conducted is 21, the nearest O.A. fulfilling this condition is L27 (3⁷). Therefore, Number of trials = 27. The orthogonal arrays with actual values of input parameters are shown in Table 3.

2.3 Conduction of experiments and observations:

The work material used for the present study is Hot rolled coil (HR Coil) JSW Grade ST29DC low carbon steel (carbon 0.06 max & manganese 0.30 to 0.35). HR coil of total standard 20 tons weight. Based on Taguchi L27 orthogonal array (DOE), the proposed research has attempted to introduce practical model to measure four Mill performance characteristics namely Thickness variation, strip flatness, power consumption and production rate in cold rolling process. One of the quality characteristics of rolled strip is Thickness variation, % of total rolled strip length under specified acceptable limit (± 0.05) of the target thickness.

Target thickness in our experiment is 1.400 mm and allowable variation limit is 1.350 & 1.450 mm. There are two X- Ray Gauge at Entry and exit of Mill stand. The x ray gauge before entering mill bite measures input gauge and Gauge after mill measures output Gauge. Another quality characteristic of the rolled strip is flatness. Flatness for the strip measured in I value. The I-unit is a powerful description of the fiber length distribution in the strip width direction. Flatness is measured by shape meter roll installed in either side of the mill. Rolling Time was recorded after completion of pass weight of the coil was known hence production rate was calculated. Energy meter reading were recorded before start of the rolling and after completion of pass which provides power consumed and thus power consumed per ton was calculated. Table 6 gives the average values of all four mill performance characteristics recorded.

2.4 Computation of quality loss for each quality characteristic



In Taguchi method [10, 11], a quality loss or mean square deviation (MSD) function is used to calculate the deviation between the experimental value and the desired value. The MSD is different for different types of problems.

Table 5: Orthogonal Array (L27) with actual values

RUN	A	B	C	D
1	11000	6000	400	70
2	11600	6600	500	80
3	12200	7200	600	90
4	11600	6600	600	90
5	12200	7200	400	70
6	11000	6000	500	80
7	12200	7200	500	80
8	11000	6000	600	90
9	11600	6600	400	70
10	11600	7200	400	80
11	12200	6000	500	90
12	11000	6600	600	70
13	12200	6000	600	70
14	11000	6600	400	80
15	11600	7200	500	90
16	11000	6600	500	90
17	11600	7200	600	70
18	12200	6000	400	80
19	12200	6600	400	90
20	11000	7200	500	70
21	11600	6000	600	80
22	11000	7200	600	80
23	11600	6000	400	90
24	12200	6600	500	70
25	11600	6000	500	70
26	12200	6600	600	80
27	11000	7200	400	90

$$MSD = (y_1^2 + y_2^2 + \dots) / n \dots \dots \dots (1)$$

and for Higher-the-better type problem

$$MSD = (1/y_1^2 + 1/y_2^2 + \dots) / n \dots \dots \dots (2)$$

Where, y_1, y_2, \dots, y_n are results of the experiments (responses), and n is the number of repetitions of y_i . In present case the thickness variation in acceptable range is higher-the-better (HB) type and Strip flatness I value is smaller-the-better (SB) type. And power consumption is smaller-the-better type and Production rate is higher-the better type. The quality loss values for each Productivity characteristic

against different experimental runs are given in Table 7.

2.5 Computation of normalized quality loss for each quality characteristic

Let L_{ij} be the quality loss for the i^{th} quality characteristic at the j^{th} trial condition or run in the experimental design matrix. As each quality characteristic has different unit of measurements, it is

Table 6: Orthogonal array with Four Multiple response

RU N	THKV	FLT	PC	PR
	%	I Value	KWhr/ Ton	Tons/Hr
1	72.13	23.96	7.93	24.89
2	75.62	25.74	8.18	27.54
3	79.21	27.49	8.32	30.52
4	74.95	28.47	8.11	30.54
5	81.13	22.16	8.51	24.52
6	71.12	26.64	7.88	27.77
7	79.88	24.76	8.38	27.52
8	70.45	29.37	7.82	30.77
9	76.63	23.06	8.22	24.66
10	78.87	24.04	8.50	24.60
11	77.38	31.96	8.13	28.99
12	70.95	21.27	7.87	29.24
13	75.21	25.69	7.92	30.49
14	74.37	24.94	8.21	24.74
15	77.38	26.56	8.30	27.72
16	73.12	27.54	8.08	27.74
17	75.21	20.29	8.08	29.22
18	78.87	29.44	8.34	25.87
19	80.63	30.26	8.46	25.96
20	73.62	19.44	8.13	26.30
21	72.71	27.49	7.83	30.69
22	72.95	22.17	8.07	29.30
23	76.13	31.16	8.17	26.19
24	78.12	23.94	8.26	27.34
25	73.38	24.76	7.90	27.69
26	77.45	26.67	8.20	30.34
27	76.13	25.76	8.33	24.92

important to normalize the quality loss [3]. The normalized quality loss can be computed using:

$$y_{ij} = L_{ij} / L_{i*} \dots \dots \dots (3)$$

Where, y_{ij} = Normalized quality loss value for i^{th} experimental run and j^{th} quality characteristic, L_{i*} = maximum quality loss for the i^{th} quality characteristic among all the experimental runs. Therefore, y_{ij} varies from a minimum of zero to a maximum of 1. The computed normalized quality loss for all the performance characteristics are given in Table 7.



2.6 Computation of total normalized quality loss (TNQL)

For computing the total normalized quality loss (TL_j) corresponding to each experiment condition, we must assign a weighting factor for each quality characteristic considered in the optimization process. If w_i represents the weighting factor for the i^{th}

response, p is the number of response characteristics and N_{ij} is the loss function associated with the i^{th} quality characteristic at the j^{th} experiment condition, then TL_j can be computed using:

$$TL_j = \sum_{i=1}^p w_i N_{ij} \dots\dots\dots(4)$$

Table 7: Quality loss of Response and its normalized data

RUN	Quality Loss (dB)				Normalized Quality Loss				TNQL	MSNR (dB)
	THKV	FLT	PC	PR	THKV	FLT	PC	PR		
1	0.00019	574.0816	62.8697	0.00161	0.813	0.305	0.156	0.919	0.548	5.222
2	0.00017	662.5476	66.8333	0.00132	0.463	0.442	0.508	0.432	0.461	6.720
3	0.00016	755.8834	69.1561	0.00107	0.150	0.587	0.714	0.029	0.370	8.634
4	0.00018	810.7307	65.7477	0.00107	0.526	0.673	0.411	0.026	0.409	7.762
5	0.00015	491.0656	72.3806	0.00166	0.000	0.176	1.000	1.000	0.544	5.289
6	0.00020	709.6896	62.1582	0.00130	0.924	0.516	0.093	0.396	0.482	6.336
7	0.00016	613.0576	70.2693	0.00132	0.097	0.365	0.813	0.435	0.428	7.381
8	0.00020	862.7927	61.1114	0.00106	1.000	0.753	0.000	0.000	0.438	7.163
9	0.00017	531.7636	67.5711	0.00164	0.371	0.239	0.573	0.969	0.538	5.386
10	0.00016	577.9216	72.2528	0.00165	0.178	0.311	0.989	0.982	0.615	4.223
11	0.00017	1021.4416	66.1405	0.00119	0.304	1.000	0.446	0.220	0.493	6.148
12	0.00020	452.5547	61.8956	0.00117	0.943	0.116	0.070	0.187	0.329	9.661
13	0.00018	660.1474	62.6633	0.00108	0.502	0.439	0.138	0.032	0.277	11.136
14	0.00018	622.0036	67.3884	0.00163	0.583	0.379	0.557	0.951	0.618	4.186
15	0.00017	705.4336	68.8098	0.00130	0.304	0.509	0.683	0.404	0.475	6.463
16	0.00019	758.4516	65.3518	0.00130	0.709	0.591	0.376	0.401	0.519	5.692
17	0.00018	411.8194	65.2621	0.00117	0.502	0.053	0.368	0.190	0.278	11.117
18	0.00016	866.7136	69.5169	0.00149	0.178	0.760	0.746	0.721	0.601	4.419
19	0.00015	915.6676	71.5324	0.00148	0.038	0.836	0.925	0.704	0.626	4.073
20	0.00018	377.9136	66.1627	0.00145	0.658	0.000	0.448	0.642	0.437	7.192
21	0.00019	755.8834	61.2854	0.00106	0.751	0.587	0.015	0.009	0.341	9.351
22	0.00019	491.6567	65.0826	0.00116	0.726	0.177	0.352	0.179	0.359	8.908
23	0.00017	970.9456	66.7516	0.00146	0.416	0.922	0.500	0.661	0.625	4.084
24	0.00016	573.1236	68.2719	0.00134	0.241	0.303	0.635	0.464	0.411	7.726
25	0.00019	613.0576	62.3336	0.00130	0.682	0.365	0.108	0.408	0.391	8.155
26	0.00017	711.4667	67.1746	0.00109	0.298	0.518	0.538	0.050	0.351	9.093
27	0.00017	663.5776	69.3730	0.00161	0.416	0.444	0.733	0.913	0.626	4.062

Weightage of response characteristics
 After detailed discussion it has been assumed that the all the four response characteristics are equally important and hence equal weightage has been assigned. However, there is no constraint on weightage and it can be any value between 0 and 1 subjected to the conditions specified.
 $w_{THKV} = 0.25$ (Weightage for Thickness variation)
 $w_{FLTV} = 0.25$ (Weightage for Flatness I value)
 $w_{PC} = 0.25$ (Weightage for Power consumption)
 $w_{PR} = 0.25$ (Weightage for Production Rate)
 In present case, $p = 4$

The Total Normalized Quality Loss (TNQL) of each experiment has been calculated using the following relation:

$$TL_j = N_{1j} \times w_{THKV} + N_{2j} \times w_{FLTV} + N_{3j} \times w_{PC} + N_{4j} \times w_{PR} \dots\dots(5)$$

where:
 j – trial number, $j = 1, 2, \dots, 27$
 the total normalized quality loss in each experimental run is shown in Table7.

2.7 Computation of multiple S/N ratio (MSNR)

After the total normalized quality loss (Y_j) corresponding to each trial condition has been



calculated, the next step is to compute the multiple S/N ratio at each design point. This is given by:

$$\eta_i = -10 \log_{10} (Y_j) \dots\dots\dots(6)$$

The multiple S/N ratios along with total normalized quality losses in each trial condition are shown in Table 7.

In single quality optimization using Taguchi methodology, steps of calculating the normalized quality loss and total normalized quality loss are omitted, and in place of a multiple S/N ratio, separate S/N ratios corresponding to each quality characteristics is computed where the Y_j are the quality loss values of different quality characteristics. Other steps are same as in multi-objective optimization.

2.8 Determination of factor effects and optimal settings

Next step is to determine the average effect of each factor on multiple quality characteristic at different levels. This is equal to, the sum of all S/N ratios corresponding to a factor at particular level divided by the number of repetition of factor level.

The factor levels corresponding to maximum average effect are selected as optimum level. The average factor effect has been shown in Table 8 and response plot is shown in Figure 2. The optimum setting of parameters is **A₃ B₃ C₃ D₁**.

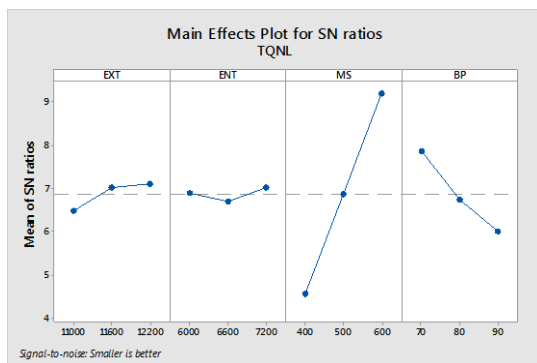


Fig 2 Main Effect Plot for S/N ratio

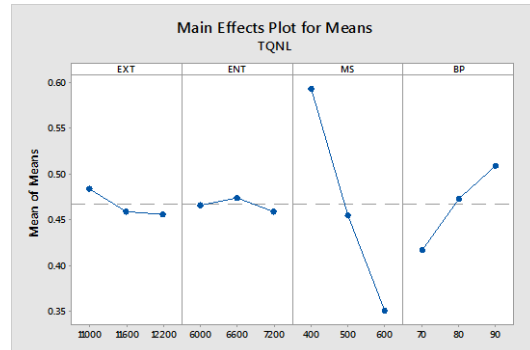


Fig 3 Main Effect Plot for Mean TNQL

Table 8 Response Table for S/N ratio of TNQL

Levels	Control factors			
	TEXT	TENT	MS	BP
	A	B	C	D
1	6.491	6.891	4.549	7.876
2	7.029	6.7	6.868	6.735
3	7.1	7.03	9.203	6.009
Delta	0.608	0.33	4.654	1.867
Rank	3	4	1	2

2.9 Analysis of variance (ANOVA)

A better feel for the relative effect of the different factors can be obtained by the decomposition of the variance, which is commonly called ANOVA. It is a computational technique to estimate quantitatively the relative significance (F-ratio), and also the percentage contribution (PC) of each factor. The sum of squares (SS) and mean sum of squares or variance (V) for each factor, and error obtained by pooling of factors C and D are computed first, to evaluate the F value and PC [6]. The degree of freedom (dof) for each factor is calculated as:

$$\text{dof} = \text{number of level} - 1.$$

The results of ANOVA for Multi Response Total Normalized Quality Loss S/N Ratio indicate that MS (Mill speed) is the most significant (81.55%) Cold rolling parameters followed by BP (13.34%) and ENT and EXT and are very less significant.

Interaction plot Fig. 4 for S/N Ratio of TNQL shows no interaction among the control factors, hence the selected delta model for experimentation is suitable for prediction of data

2.10 Confirmation Experiment

Conducting a verification experiment is a crucial final step of a robust design. Its purpose is to verify



that the optimum conditions suggested by the matrix experiment do indeed give the projected improvement. The confirmation experiment is performed by conducting a test with optimal settings of the factors and levels previously evaluated. The predicted value of multiple S/N ratio at optimum level (η_o) is calculated by following formula:

$$\eta_o = \eta_m - \sum_{i=1}^k (\eta_i - \eta_o) \dots \dots \dots (7)$$

Where, k is the no. of factors and η_m is the mean value of multiple S/N ratios in all experimental runs, η_i are the multiple S/N ratios corresponding to optimum factor levels.

The predicted value of multiple S/N ratio and that from confirmation test are shown in Table 10. The improvement in multiple S/N ratio at the optimum

level is found to be 5.01 dB. The value of thickness variation 80.57% , strip flatness I value 21.08, power consumption 7.03 KWHr/Ton and Production rate 13.52 Tons /Hr. at this optimum level are 78.35 % , 21.5 , 8.23 and 29.56 against the initial parameter setting of 73.12,24.54,8.08 and 27.74.

3. Optimization of Pass schedule

Above experiment was carried out in second pass only, refer table 2, similar experimentation can be carried out for remaining passes up to 4th pass. Optimal setting parameters at each pass to be obtained. Final Optimized pass schedule has been obtained with optimal setting of Process parameters.

Table 9 ANOVA for S/N Ratio of TNQL

Factors	DOF	SS	MS	F- Value	P-Value	% Contribution
TEXT(A)	2	1.993	0.9965	3.28	0.109	1.67
TENT (B)	2	0.494	0.2468	0.81	0.487	0.41
MS (C)	2	97.456	48.73	160.45	0	81.55
BP (D)	2	15.94	7.9698	26.24	0.001	13.34
A * B	4	0.715	0.1786	0.59	0.684	0.60
A * C	4	0.81	0.2026	0.67	0.638	0.68
A * D	4	0.282	0.0705	0.23	0.911	0.24
Error	6	1.822	0.3037			1.52
Total	26	119.511				

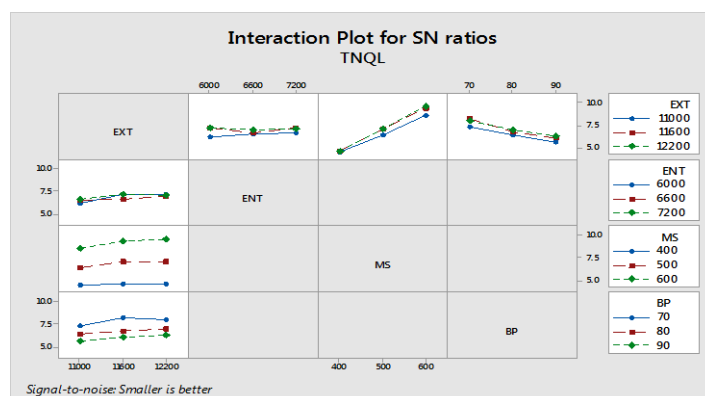


Figure 4 : Interaction Plot for S/N Ratio TNQL

Table 10: Results of Confirmatory Experiment

	Unit	Initial setting	Predicted Result	Actual Results	Improvement	Error in Prediction
Factor Level		A1B2C2D3	A3B3C3D1	A3B3C3D1		
Thickness variation	%	73.12	78.35	80.57	10.19%	
Flatness I value	I	27.54	21.5	21.08	23.46%	



Power consumption	KWhr/Ton	8.08	8.23	7.03	4.33%	
Production Rate	Tons / Hr	27.74	29.56	31.49	13.52%	
TQNLS/N Ratio		5.57	10.5885	10.896	95.62%	4.42%

Table 11 : Optimized Pass schedule

Pass No.	Entry thk	Exit thk	Reduction	Exit tension	Entry tension	Rolling speed	Roll bending Pr.
	mm	mm	%	Kg	Kg	mpm	bar
1	2.15	1.735	19.302	11000	2000	300	80
2	1.735	1.4	19.302	12200	7200	600	70
3	1.4	1.13	19.302	12200	7200	600	70
4	1.13	0.912	19.302	12200	7200	600	70
5	0.912	0.736	19.302	10600	7000	600	80
6	0.736	0.594	19.302	8600	5700	600	80
7	0.594	0.479	19.302	4600	5700	600	80
8	0.479	0.387	19.302	3800	4600	600	80

Table 11: Improvement after optimized pass schedule

Response Characteristics	Unit	Target	Initial	Optimized Result	Improvement
Thickness variation	%	95.00	82.45	91.88	11.44 %
Flatness	I Value	10.00	20.74	13.47	35.05 %
Power consumption	KWhr/ ton	62.00	75.58	71.00	6.06 %
Production rate	Ton/Hr	28.00	22.55	22.97	1.86 %

3 CONCLUSIONS

The conclusions drawn from above results are summarized as:

1. The Taguchi's quality loss function can be used to optimize the multiple performance characteristics. A significant increase in S/N ratio (5.01 dB) has been registered at optimum parameter setting in the present experimental investigation. Also, all four performance characteristics (Strip thickness variation, strip flatness, power consumption and production rate) have been considerably improved as compared to initial parameter settings of the experiment.
2. The optimum parameter values in the present operating conditions are: Exit tension = 17200 Kg, Entry tension = 7200 Kg, Mill speed 600 = mpm and Bending Pressure = 40 Kg/cm².

3. The percentage contribution of factors in increasing order is: MS (Mill speed) is the most significant (81.55%)

Cold rolling parameters followed by BP (13.34%) and ENT (and EXT and are very less significant.

4. The loss of quality is always possible during optimization of multiple quality characteristics at a time. The deviation of quality from its optimum value depends mainly on the weight assigned to it. Therefore, a careful selection of weights for different quality values plays a crucial role in multi-objective optimization.

5. The optimal values obtained using the multi-response optimization models have been validated by confirmation experiments.

6. Results of optimized Pass schedule obtained using optimal process parameter shows improvement in all



the four responses thickness variation reduced by 11.44%, strip flatness improved by 35.05%, power consumption reduced by 6.06% and production rate increased by 1.86%

References :

- [i] Roberts, W., *Cold Rolling of Steel*, Marcel Dekker, 1978, Chpt. 9
- [ii] Vaidya V.A. "Optimization of cold rolling mill process to improve productivity and Product Quality of steel - an overview" 2015 IJEDR | Volume 3, Issue 4 | ISSN: 2321-9939 V.
- [iii] Wang, D. D., Tieu, A. K., DeBoer, F. G., Ma, B. & Yuen, W. Y. D. (2000). Toward a heuristic optimum design of rolling schedules for tandem cold rolling mills. *Engineering Applications of Artificial Intelligence*, 13 (4), 397-406.
- [iv] Bland, D. R. and Ford, H., "The calculation of roll force and torque in cold strip rolling with tensions," *Proc. Inst. Mech. Eng.*, 1948, Vol. 159, pp. 144-153.
- [v] Vivek.V, "Taguchi approach for optimization of process parameters in improving Quality of steel strip in single stand cold rolling Mill". *American Journal of Engineering Research (AJER)*, e-ISSN : 2320-0847 p-ISSN : 2320-0936, Volume-6, Issue-3.
- [vi] Antony, J., "Simultaneous optimisation of multiple quality characteristics in manufacturing processes using Taguchi's quality loss function," *International Journal of Advance Manufacturing Technology*, Vol. 17, pp. 134-138, 2001.
- [vii] Taguchi G, Konishi S "Taguchi Methods, orthogonal arrays and linear graphs, tools for quality American upplier institute, *American Supplier Institute; 1987 [p. 8-35]*
- [viii] Phadke, M. S., "Quality Engineering using Robust Design," Prentice-Hall, pp. 41-65, 1989.
- [ix] Hong, D. K., et.al, "Robust optimization design of overhead crane with constration using the characteristic functions," *International Journal of precision Engineering and Manufacturing*, Vol. 7, No. 2, pp. 12-17, 2006.
- [x] Chen, et.al, "Application of Taguchi method in the optimization of laser micro-engraving of photomasks," *International Journal of Materials & Product Technology*, Vol. 11, No. 3/4, pp. 333-344, 1996.
- [xi] Han, S. R., et.al, "Effects of process variables on the gas enetrated part in gas-assisted injection molding," *International Journal of Precision Engineering and Manufacturing*, Vol. 7, No. 2, pp. 8-11, 2006.
- [xii] Antony, J., "Simultaneous optimisation of multiple quality characteristics in manufacturing processes using Taguchi's quality loss function," *International Journal of Advance Manufacturing Technology*, Vol. 17, pp. 134-138, 2001.
- [xiii] Derek, W.B. (1982). *Analysis for optimal decisions*, John Wiley and Sons, New York.
- [xiv] Gupta, V., Murthy, P.N. (1980). *An introduction to engineering design methods*, Tata McGraw-Hill, New Delhi.