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Application of Generalized Taguchi and Design of Experiment Methodology for Rebar Production at an Integrated Steel Plant

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Abstract**—**In this paper, x-ray impact of Taguchi method and design of experiment philosophy to project relationship between various factors leading to output yield strength of rebar is studied. In bar mill of an integrated steel plant, there are two production lines called as line 1 and line 2. The metallic properties e.g. yield strength of finished product of the same material is varying for a particular grade material when rolled simultaneously in both the lines. A study has been carried out to set the process parameters at optimal level for obtaining equal value of yield strength simultaneously for both lines.

Keywords**—**Bar mill, design of experiment, Taguchi, yield strength.

I. Introduction

ECONOMIC globalization and the rapid & continuous appearing of new technologies mobilized organizations to obtain the maximum degree of competitiveness, high quality products in short time in order to ensure their survival and growth in the market [1], [2]. To make higher profits, different organizations follow various procedures like market segmentation, product variation; cost reduction, customer satisfaction etc. Quality is very important to meet customer satisfaction. Thus, the quality products play significant role to the firms to survive in the market. Therefore, it is essential to produce what customer desires. In this paper, Taguchi and design of experiment methodology has been adopted to analyze rebar manufacturing process and to find out what are controllable and uncontrollable factors. The principles of experimental design first used in agriculture have been adapted successfully in industry and in military applications since 1940 [3], [4]. It also has been focused to construct a factorial design to find out substantial impacting factors and others.

II. Taguchi's Robust Design Method

Since 1960, Taguchi methods have been used for improving the quality of Japanese products with great success. It is only recently that companies all over the world began adopting Taguchi's robust design approaches in an effort to improve product quality and design robustness.

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Robust design is an "engineering methodology for improving productivity during research and development so that high-quality products can be produced quickly and at low cost" [7]. The idea behind robust design is to improve the quality of a product by minimizing the effects of variation without eliminating the causes (since they are too difficult or too expensive to control). This method is an off-line quality control method that is instituted at both the product and process design stage to improve product manufacturability and reliability by making products insensitive to environmental conditions and component variations. The end result is a robust design, a design that has minimum sensitivity to variations in uncontrollable factors. Dr. Genichi Taguchi bases his method on conventional statistical tools together with some guidelines for laying out design experiments and analyzing the results of these experiments [1].

III. Taguchi's Quality Loss Function

To measure quality, Taguchi defines a Quality Loss Function [1]. The quality loss function is a continuous function that is defined in terms of the deviation of a design parameter from an ideal or target value, see Fig. 1. Taguchi's view on the nature of the quality loss function represents a fundamental paradigm shift in the way in which manufacturers consider whether a product is good or not. The traditional approach employed by U.S. manufacturers (as evidenced by Sony-USA) has been to use a "step function" that ensures that performance fell within the upper and lower specification limits as shown in Fig. 1 (a).

Taguchi's loss function can be expressed in terms of the quadratic relationship, Fig. 1 (b).

$$L = k\,(y - m)^2 \qquad (1)$$

where y is the critical performance parameter value, L is the loss associated with a particular parameter y, m is the nominal value of the parameter specification, k is a constant that depends on the cost at the specification limits (can be determined conservatively by dividing the cost of scrap, by the square of the lower or higher tolerance values). This function penalizes the deviation of a parameter from the specification value that contributes to deteriorating the performance of the product, resulting in a loss to the customer. The loss function given in (1) is referred to as "nominal is best," but there are also expressions for cases when higher or lower values of parameters are better [7].

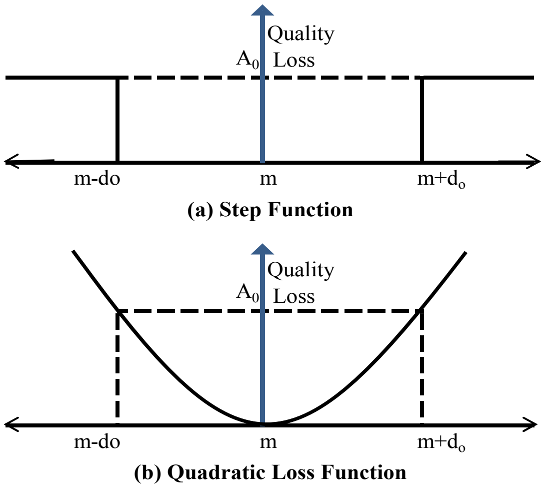

Fig. 1 Quality Loss Function

In parameter design, the system variables are experimentally analyzed to determine how the product or process reacts to uncontrollable "noise" in the system; parameter design is the main thrust of Taguchi's approach.

The final step in Taguchi's robust design approach is tolerance design; Tolerance design occurs when tolerances for products or process are established to minimize manufacturing and lifetime costs of the product or process.

IV. Taguchi's Parameter Design Approach

TABLE I
EXAMPLE OF NOISE AND CONTROL FACTOR [6]

	Product Design	Process Design
Outer Noise	Consumer's usage condition	Ambient Temperature
	Low Temperature	Humidity
	High Temperature	Season
	Temperature change	Input material variations
	Shock	Operators
	Vibration	Voltage Change
	Humidity	Batch to Batch Variations
Inner Noise	Deterioration of parts	Machine ageing
	Deterioration of material	Tool wear
	Oxidation/Rusting/ Decay	Deterioration
Between Product Noise	Piece to piece variation where they are supposed to be same, e.g. Young modulus, shear modulus, Allowable stress	Process to process variation where they are supposed to be same e.g. variation in feed rate.

The experimental design is widely used to optimize process parameter values in order to improve the quality properties of a product [5]. In parameter design, there are two types of factors that affect a product's functional characteristic: Control factors and noise factors. Control factors are factors which can easily be controlled such as material choice, cycle time, or mould temperature in an injection moulding process. Noise factors are factors that are difficult or impossible or too expensive to control. Hence, parameter design seeks to identify settings of the control factors which make the product insensitive to variations in the noise factors, i.e., make the product more robust, without actually eliminating the causes of variation.

Design of experiment techniques, specifically Orthogonal Arrays (OAs), is employed in Taguchi's approach to systematically vary and test the different levels of each of the control factors. Commonly used OAs includes the L4, L9, L12, L18, and L27, several of which are listed in Table II.

TABLE II (A)
SOME COMMONLY USED ORTHOGONAL $L_4(2^3)$ ARRAY

Run	Factors		
	A	B	C
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

TABLE II (B)
SOME COMMONLY USED ORTHOGONAL $L_9(3^4)$ ARRAY

Run	Factors			
	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

The product array is used to systematically test various combinations of the control factor settings over all combinations of noise factors after which the mean response and standard deviation may be approximated for each run using the following equations.

$$\text{Mean Response} = \bar{Y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

$$\text{Standard Deviation} = S = \sqrt{\sum_{i=1}^{n}\frac{(y_i-\bar{Y})^2}{n-1}}$$

where; y is response variable, $\bar{Y}$ is Average response, i= 1… n trials.

The preferred parameter settings are then determined through analysis of the "signal-to-noise" (SN) ratio where factor levels that maximize the appropriate SN ratio are optimal. There are three standard types of SN ratios depending on the desired performance response [7]:

- Smaller (S) the better (for making the system response as small as possible).

$$SN_S = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$$

- Nominal (target =T) the best (for reducing variability around a target):

$$SN_T = 10\log\left(\frac{\overline{Y}^2}{S^2}\right)$$

- Larger (L) the better (for making the system response as large as possible):

$$SN_L = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$$

These SN ratios are derived from the quadratic loss function and are expressed in a decibel scale. Once all of the SN ratios have been computed for each run of an experiment, Taguchi advocates a graphical approach to analyze the data. In the graphical approach, the SN ratios and average responses are plotted for each factor against each of its levels. The graphs are examined to "pick the winner," i.e., pick the factor level which (1) best maximize SN and (2) bring the mean on target (or maximize or minimize the mean, as the case may be).

Using this, the control factors can also be grouped as follows:

1. Factors that affect both the variation and the average performance of the product.
2. Factors that affect the variation only.
3. Factors that affect the average only.
4. Factors that do not affect either the variance or the average.

- Factors in the first and second groups can be utilized to reduce the variations in the system, making it more robust.
- Factors in the third group are then used to adjust the average to the target value. Lastly, factors in the fourth group are set to the most economical level.
- Finally, confirmation tests should be run at the "optimal" product settings to verify that the predicted performance is actually realized.

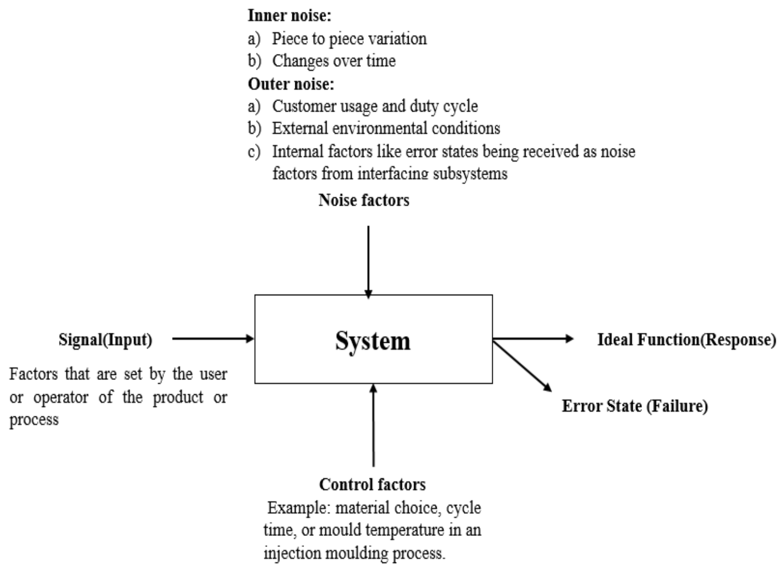

Fig. 2 Flow Diagram representing System analysis by Taguchi Approach

V. CASE STUDY

An experimental study is made using Taguchi's approach to parameter design for rebar (25R type) production at Bar Mill of an integrated steel plant.

VI. PROBLEM STATEMENT

In Bar Mill, there are two production lines i.e. Line 1 and Line 2. When particular grade material is rolled simultaneously in line 1 & 2, the metallic properties i.e. Yield Strength of finished product of the same material obtained is different for both the lines even though it is within limits. In order to maintain same value of yield strength simultaneously for both lines, it is essential to set process parameters at optimal level.

A. Objectives of the Study

- To find range of variation of controllable parameters
- To obtain 'best fit value set' from the Model to both lines.

B. About Bar Mill

It consists of Roller hearth furnace (to hold the temperature of billet for re-heating) and two lines for producing bars, channels, angles etc.

VII. PARAMETERS AND THEIR LEVEL CONSIDERED FOR ANALYSIS

TABLE III
PARAMETERS & LEVELS

Controllable Parameters/Factors	Levels	
Mill Speed	Low	High
Water Pressure	Low	High
Water Flow	Low	High

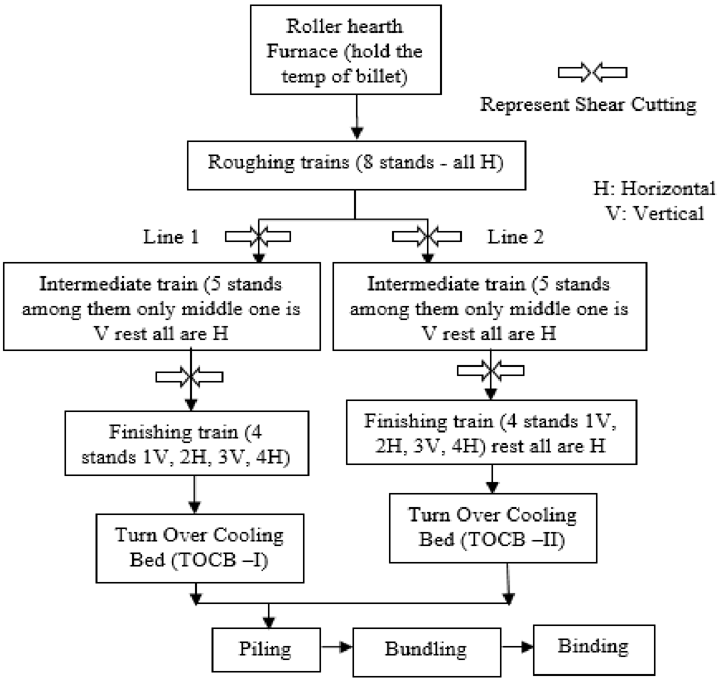

Fig. 3 Flow Diagram of Bar Mill

VIII. Assumptions/Consideration of the Study

All controlling parameters are independent of each other. Rebar production of Bar Mill products are considered for this study.

Parameters considered for this Case are limited to Three parameters (Mill speed, Water pressure and Water flow) out of eight available parameters as these parameters are controllable in nature and can set to desired level with minimum interruption in the production with the available instruments and tools The other parameters are billet temp, section weight, mill level, Carbon equivalent.

IX. Simulation

The experimental simulation was done using MINITAB software on intel-i5 processor with 3.2GHz and 4 GB of RAM with Operating System Window-8. Three parameters i.e. Mill Speed, Water Pressure and Water Flow are considered for analysis purpose. Minimum and maximum level for these three parameters is derived from the input raw data collected.

Consideration for simulation run,

- Nominal is the best (for reducing variability around a target Yield Strength).
- Desirable Value of Yield Strength (Target) is 570 Mega Pascal (MPa).
- Yield Strength is desired to be closer target value to optimum resource utilization.

The High-Low data set points for individual parameters are given below:

TABLE IV
DATA SET POINTS FOR PARAMETERS

Levels	Mill Speed (m/s)	Water Pressure (Kg/cm^2)	Water Flow (m^3/hr)
Low	6.80	4.30	500.00
High	12.65	7.40	721.00

- ➢ Table V represents experiment design and respective output with numeric value of variance, SN ratio and Loss function of trial runs output for production of 25R in Line-1 of Bar Mill.
- ➢ Table VI represents experiment design and respective output with numeric value of variance, SN ratio and Loss function of trial runs output for production of 25R in Line-2 of Bar Mill.

TABLE V
OUTPUT FOR PRODUCTION OF 25R IN LINE-1

Run	Mill Speed	Water Pressure	Water Flow	YS (MPa) Run-1	YS (MPa) Run-2	YS (MPa) Run-3	YS Average (MPa)	Variance	SN Ratio	Loss Function
1	Low	Low	Low	564.2	560.2	568.1	564.3	16.2	43	33.3
2	High	Low	Low	537.7	534.3	540.2	537.8	10.3	44	1046.5
3	Low	High	Low	572.6	572.0	573.1	572.7	0.3	61	6.8
4	High	High	Low	545.7	540.5	550.3	546.0	26.5	41	590.5
5	Low	Low	High	566.1	562.0	569.7	566.0	9.0	46	15.4
6	High	Low	High	541.2	538.6	545.2	541.4	12.6	44	831.4
7	Low	High	High	573.8	570.3	576.5	573.7	12.5	44	14.4
8	High	High	High	549.2	548.1	550	548.9	0.5	58	431.9

TABLE VI
OUTPUT FOR PRODUCTION OF 25R IN LINE-2

Run	Mill Speed	Water Pressure	Water Flow	YS (MPa) Run-1	YS (MPa) Run-2	YS (MPa) Run-3	YS Average (MPa)	Variance	SN Ratio	Loss Function
1	Low	Low	Low	593.9	590.2	596.1	594.0	11.4	45	571.0
2	High	Low	Low	574.5	575.3	572.2	574.7	5.5	48	20.5
3	Low	High	Low	592.3	590.5	592.1	592.5	6.3	47	498.6
4	High	High	Low	576.3	575.6	577.4	576.3	2.4	51	39.7
5	Low	Low	High	607.2	603.0	609.2	606.9	7.7	47	1382.8
6	High	Low	High	588.2	580.5	595.3	588.4	57.5	38	329.7
7	Low	High	High	605.0	602.1	605.5	605.2	8.6	46	1221.8
8	High	High	High	588.9	587.4	589.0	588.4	1.0	55	358.1

X. GRAPHICAL ANALYSIS

Parameters individual impact on Yield Strength, interaction pattern, Variance and SN ratio are being pictorially briefed in the graphs given below for both the production lines of 25R bar:

- Line-1 (25R)

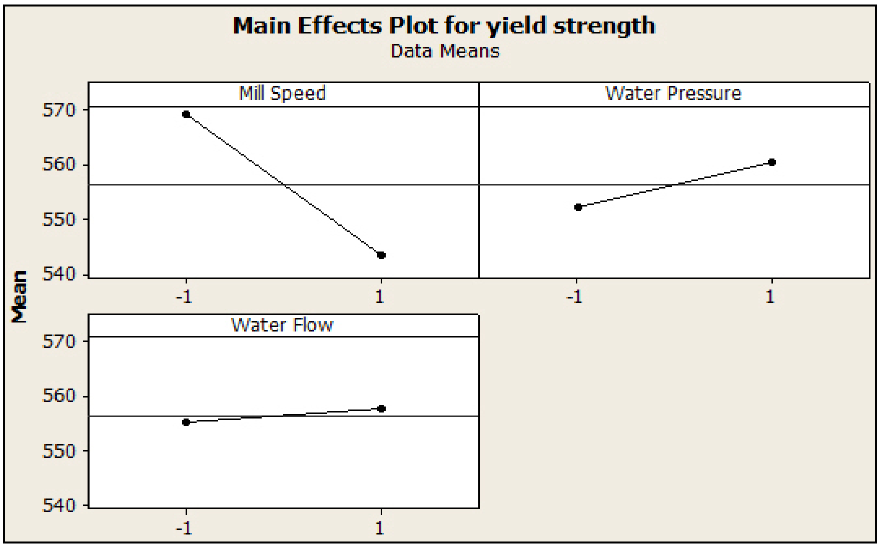

Fig. 4 Parameter impact on Yield Strength (YS). Note: It shows that there is high variability in YS w.r.t. mill speed and negatively correlated

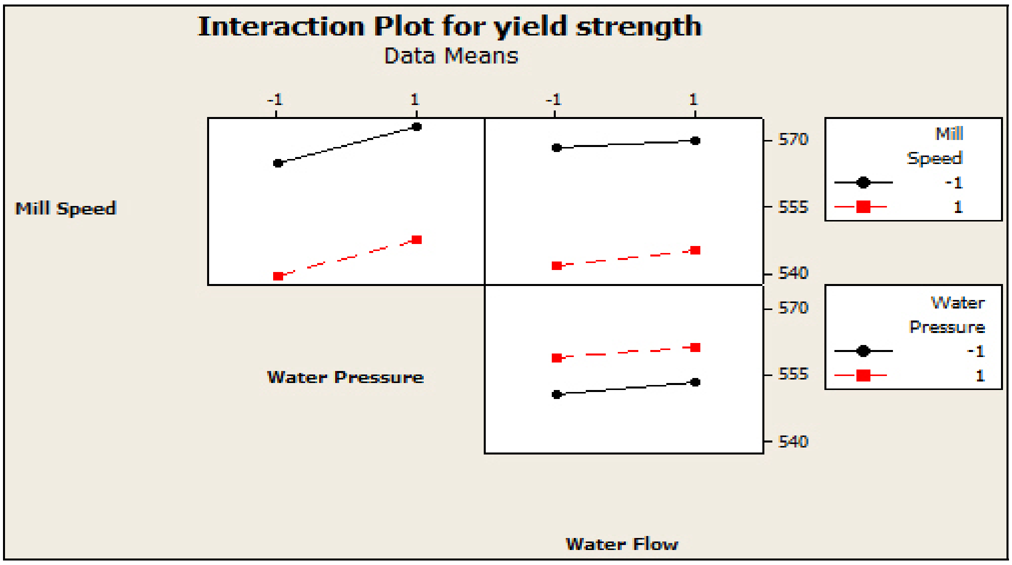

Fig. 5 Interaction pattern of Parameters. Note: Since plots are almost parallel in graphical pattern it shows that there is almost no interaction between parameters

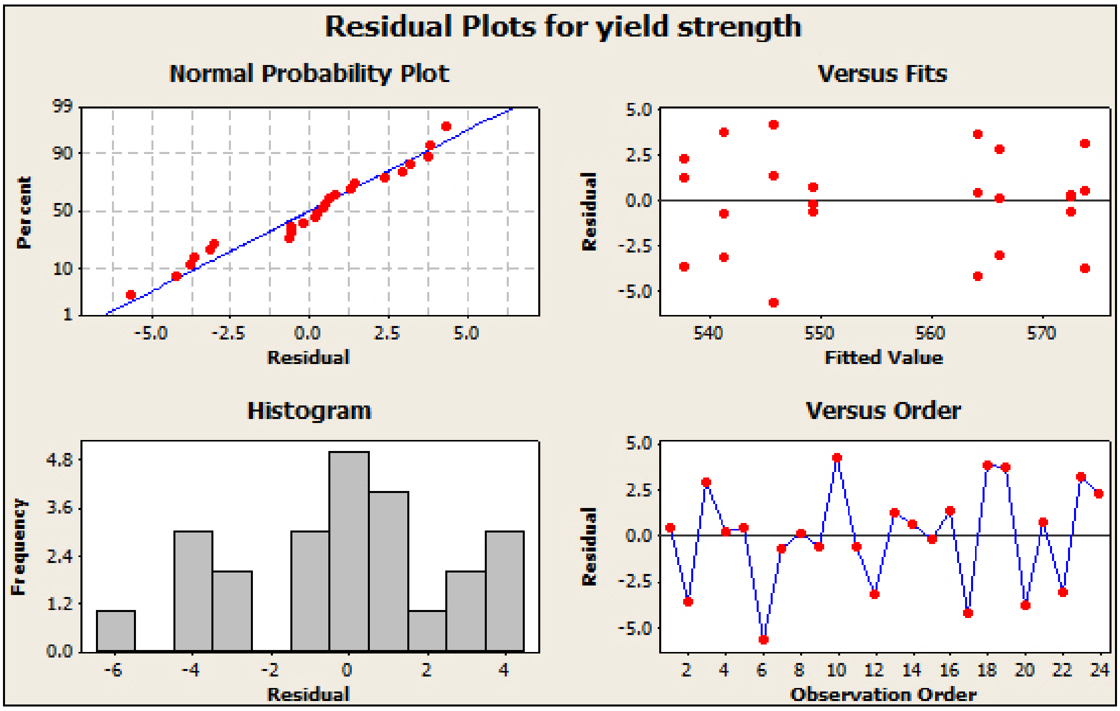

Fig. 6 Data points and residual plots and variability. Note: Normal plot shows good fit and residual plots shows variability of observed and projected data points

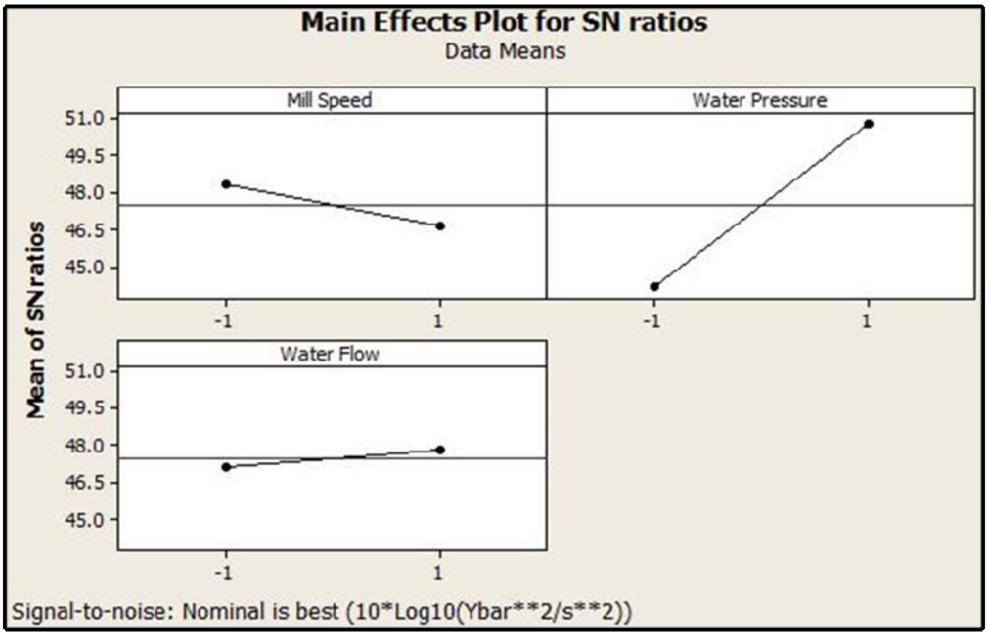

Fig. 7 Main effect Vs SN ratio. Note: High variability in water pressure, SN ratio show that there might be more inherent noise factors

o Line-2 (25R)

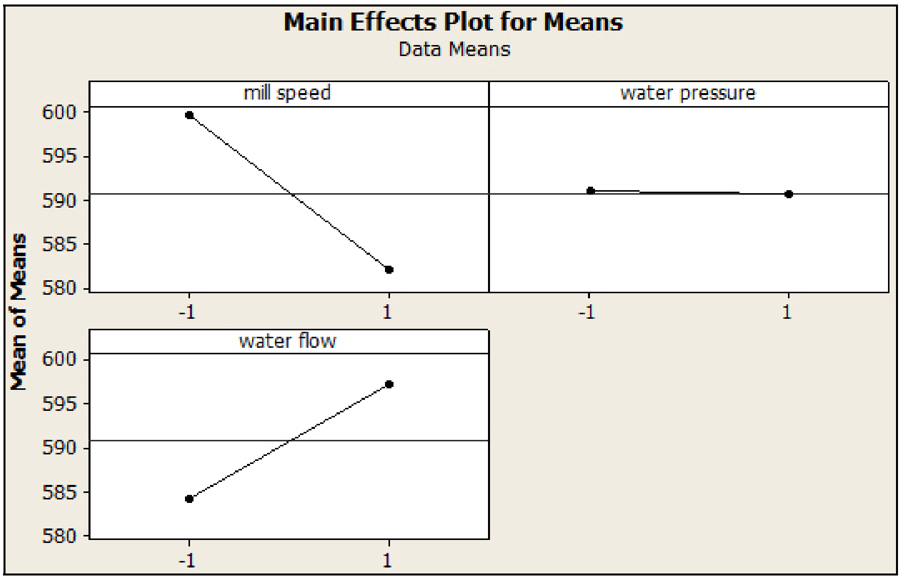

Fig. 8 Parameters' impact on Yield Strength (YS). Note: It shows that there is high variability w.r.t. mill speed and negatively correlated, water pressure have lesser impact whereas water flow having substantial impact positively correlated

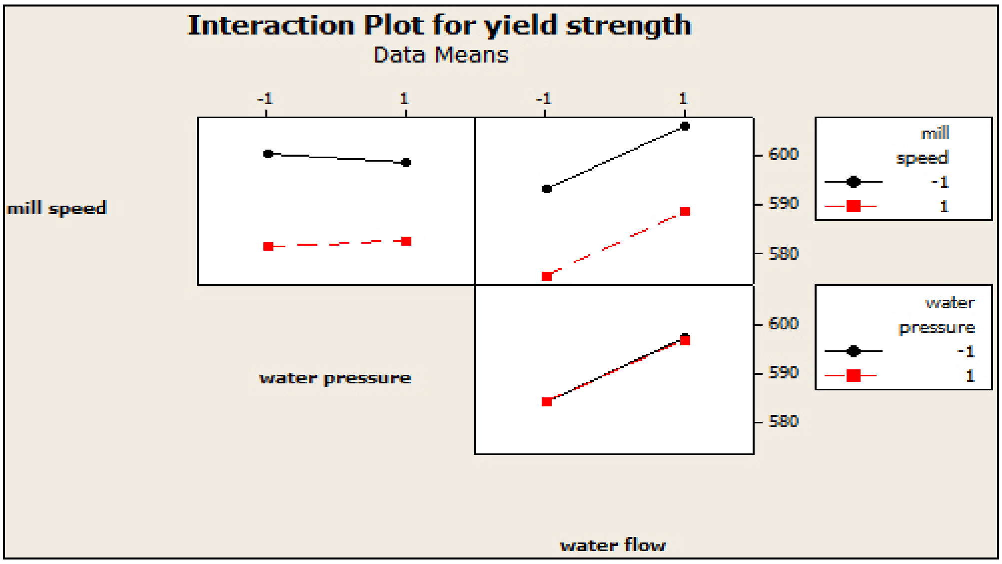

Fig. 9 Interaction pattern of Parameters. Note: Since plots are almost parallel in graphical pattern it shows that there is no interaction between parameters

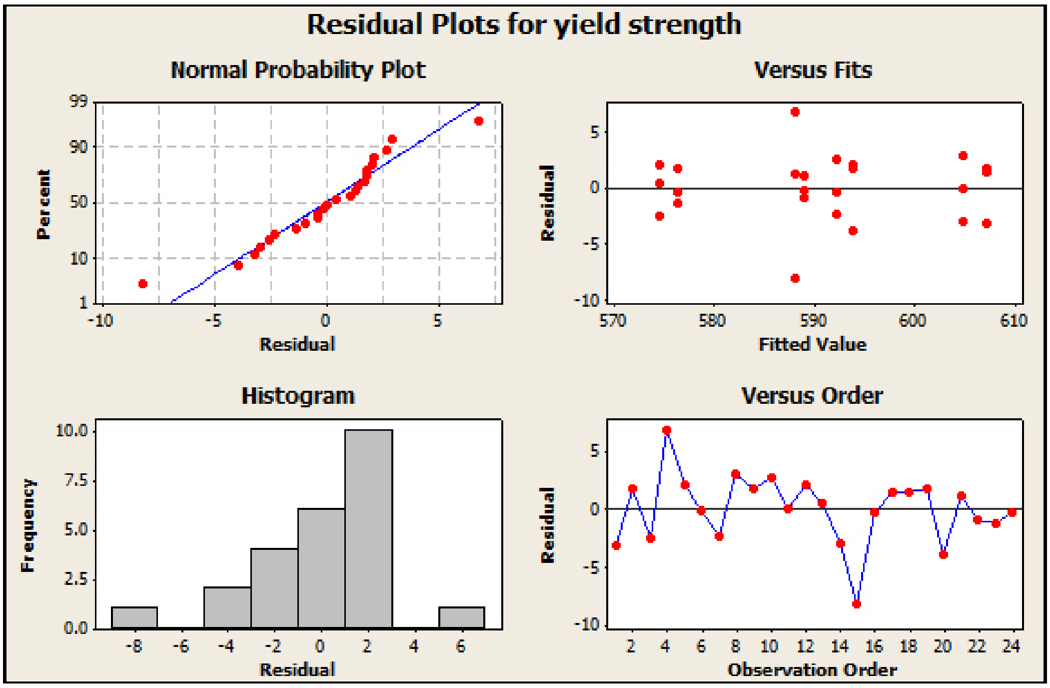

Fig. 10 Data points and residual plots and variability. Note: Normal plot shows good fit and residual plots show variability of observed and projected data points

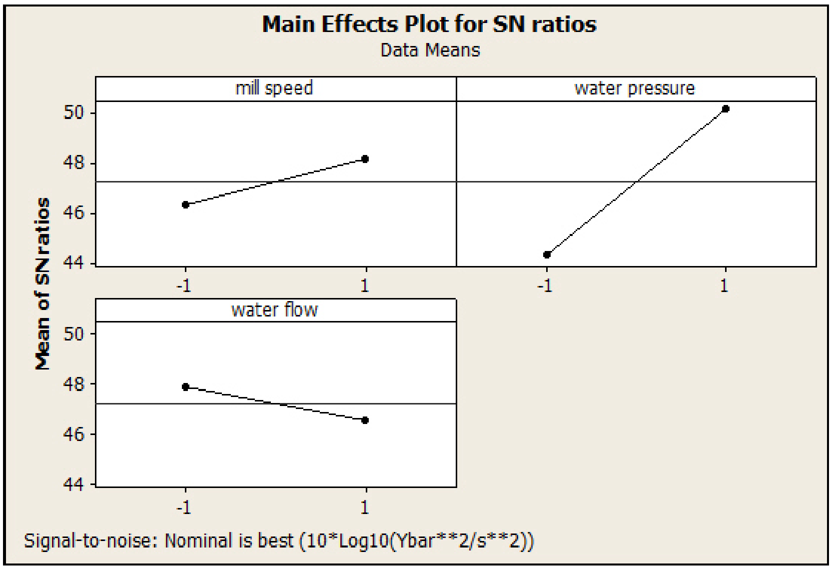

Fig. 11 Main effect Vs SN ratio. Note: High variability in water pressure SN ratio show that there might be more inherent noise factors

XI. Results

A. Manufacturing of 25R in Line 1

From the graphical analysis (Figs. 4-7) as mentioned above and the experimental run Table V for Line-1, it is found that parameter having following combination of mill speed @6.8 m/s, water pressure @7.4 kg/cm^2, water flow @ 500 m^3/hr having 'minimum loss function value' and 'maximum SN ratio' regarding Yield Strength. Hence, it can be considered to be optimal parameter setting for the desired output at Line-1.

B. Manufacturing of 25R in Line 2

From the graphical analysis (Figs. 8-11) as mentioned above and the experimental run Table VI for Line-2, It is found that parameter having following combination of mill speed @12.63 m/s, water pressure @7.4 kg/cm^2, water flow @ 500 m^3/hr having '2nd minimum value of loss function' and '2nd maximum SN ratio' regarding Yield Strength. Here, 2nd maximum SN ratio and 2nd minimum loss function parameters values have been selected to make it near optimal in both the functions value.

XII. CONCLUSION

The findings from this study are:

- The parameters considered for this model are not unique for same sections rolled in both the lines simultaneously, since the behavior is indifferent w.r.t yield strength.
- The parameter values are set based on the data analysis, such that optimal value of yield strength is obtained.
- It can be concluded that line 1 and 2 have different inherent noise related to Mill Speed that to be studied further.
- On further physical observation, it has been noted that manufacturing line-2 is having more wear and tear of copper cooling plates leading to more variations and same is matching from DOE variation output table.

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