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Optimization of Steel Bar Manufacturing Process Using Six Sigma

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Abstract: Optimization of a manufacturing process results in higher productivity and reduced wastes. Production parameters of a local steel bar manufacturing industry of Pakistan is optimized by using six Sigma-Define, measure, analyze, improve, and control-methodology. Production data is collected and analyzed. After analysis, experimental design result is used to identify significant factors affecting process performance. The significant factors are controlled to optimized level using two-level factorial design method. A regression model is developed that helps in the estimation of response under multi variable input values. Model is tested, verified, and validated by using industrial data collected at a local steel bar manufacturing industry of Peshawar(Khyber Pakhtunkhwa, Pakistan). The sigma level of the manufacturing process is improved to 4.01 from 3.58. The novelty of the research is the identification of the significant factors along with the optimum levels that affects the process yield, and the methodology to optimize the steel bar manufacturing process.

Keywords: **s**teel bar manufacturing industry, six sigma, yield, sigma level, design of experiments.

1 Introduction

Process optimization is essential to reduce production variation and achieve higher yield. Process optimization has ever remained a serious problem in manufacturing industries particularly steel manufacturing. Around 26% steel goes into scrap globally. If the line scrap is controlled, then 17% reduction in total energy and CO_2 emission can be achieved. Further it is stated that yield improvement through process optimization is a significant energy and CO_2 abatement strategy[1]. Steel and aluminium industries are responsible for 10% global energy and CO_2 emission. By 2050, demand for these two products is predicted to be doubled, while 50% global emission reduction is being under discussion. Failure to optimize process incurs higher production cost, generation of rework and scrap, and in turn lower profit margins for the manufacturing industries. Process optimization is the ultimate solution to cater the problem of yield loss, energy wastage and CO_2 emission of the steel industries[2].

Process optimization of steel industries is of prime importance as demand for iron and steel worldwide is at its boom[3]. Total crude steel demand has jumped from 777 million metric ton in year 1998 to 1351 million metric ton in year 2007[4]. Only in Thailand, steel consumption is raised from 12.7 million metric ton to 13.5 million metric ton from year 2005 to 2008[5]. The environmental sustainability could be threatened with the increasing demand of iron worldwide[6].

Six Sigma DMAIC cycle can be used to optimize any manufacturing process. six Sigma DMAIC cycle primarily focuses on improving the efficiency of the firm within an existing technological base. Because of its focus on process improvement plan of continuous and incremental change, it is best suited for the improvement of existing technology of the firm[7]. No additional investment is required at the start, as improvement is made within the current technological base of the firm[8]. The DMAIC cycle identifies the root causes of the problems, helps infinding solution and improves and controls the process[9]. Six Sigma has received much attention in the field of process improvement, when ever higher operational effectiveness and organizational performance is desired[10] . As a quality management philosophy[11], six Sigma has attracted academic research in recent years[12–13]. It is a process improvement approach that improves performance, enhance process capability and produce the desired results for the organizations[9, 14–15]. Six Sigma is defined as process improvement philosophy that identifies and eliminates causes of defects, reduces operation cost and cycle time, improves firm productivity, meets customer expectation more appropriately and achieves higher asset utilization, profits and returns[16].

This paper describes the optimization of the steel bar manufacturing process using six Sigma DMAIC methodology at a local industry. The findings of the paper

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can be adopted by any steel bar manufacturing industry to achieve higher yield with lower process variation. The paper is also a source of motivation for other steel bar manufacturing industries to improve the process performance under the current technological base of their organizations. The subsequent section presents a brief literature review on different process optimization strategies including six sigma, stochastic and probabilistic optimization models, application of expert systems for process improvement, engineering experimentation design and factorial design applications in the manufacturing design and process optimization.

2 Literature Review

Optimization of manufacturing process is performed in a number of different ways. The yield of the system is improved at certain investment cost by selection of weak performing manufacturing stages and increasing their probability of successfully processing items[17]. For a steel manufacturing process, quality design steel with a given specification is produced efficiently using a Just-In-Time based linear regression model. The minimization of quality variations and production cost reduction are achieved as the benefit, to a local Japanese Steel manufacturing industry using this model[18].The productivity and quality of steel billets and slabs manufacturing process is improved with the application of a developed genetic algorithm and maximum rate of casting and defect-free products is achieved by controlling the process parameters[19]. The yield of an electronics manufacturing process is improved using enhanced rolled throughput yield(ERTY) method and overall production cost is minimized by controlling scrap to minimum level[20]. In a steel industry, lean manufacturing principles are applied to enhance yield using value stream mapping and simulation of the proposed system is carried out to aid management in decision making[21].The steel manufacturing process yield and product quality is enhanced using Data Driven Quality Improvement(DDQI) method[22].

Optimal experimental design is a tool needed to reduce the amount of labor and perform cost effective experimentations. In optimal experimental design analysis, dynamic input is determined and meaningful results are obtained[23]. The applications of DOE are discussed in fields of process control, biological systems, pharmacodynamics, chemical kinetics etc. DOE helps in the extraction of quality information with less time and efficient resource consumption[24]. The quality defects in the production of asbestos roofing are analyzed in Indonesia. Sigma level is improved to 5.02 using DOE and six Sigma[25]. The mean variation in the yield strength of Thermo Mechanically Treated (TMT) steel bar is minimized using Taguchi Orthogonal Array method, DOE and optimizing quenching process[26]. DOE is used to identify the significant input factors- carbon emission, running costs and overheating risks - in the sustainable building design UK[27].The cutting parameters in milling process are optimized and trade-offs between production rate, cutting quality and sustainability are evaluated[28].For small data sets, a hybrid fuzzy regression-design of experiment model for the energy consumption estimation is made and the model is validated with small data set from 1995 to 2005 of energy consumption of Pakistan, Singapore, United States, Canada and Iran[29].

The six Sigma methodology not only helps organization to control the process improvement activities, but it also helps in the problem exploration and its understanding among all the team members of the organization[13]. The critical factors for the effective implementation of six Sigma projects include the top management commitment, mutuallyunderstood goals of overall organization, and the cultural transformation and refinement of the organization for the successful execution of the project[30]. six Sigma is applied to Hydrogen power plant and production costs are reduced[31]. six Sigma can be applied to the industries having low rate of product change and are focusing on efficiency[32].

The huge steel production yield loss, associated energy wastage, and environmental damage in the form of CO_2 emission necessitate the optimization of steel manufacturing processes. The existing research efficiently caters with the yield of steel manufacturing, process monitoring, quality control, and quality assurance by the applications of various optimization formulations, effect of inspection on yield enhancement, data driven quality improvement by collecting production data online and adjusting process parameters accordingly for process optimization, but still there is a room to identify the significant factors that have a vital effect on the process variation and yield loss of steel bar manufacturing process. An empirical research is thus required to validate that six Sigma DMAIC is a process improvement technique for steel bar manufacturing process.

3 Methodology

Six Sigma DMAIC cycle is used. Table 1 shows the approach adopted in the methodology.

3.1 Definition

Customer wants are identified by interviews and group discussions with the manager responsible for quality and the production department of the steel bar manufacturing industry, industrial estate Peshawar, Pakistan. Main problem identified in the production was yield losses. Hence the problem to be worked on is the yield enhancement, and scraps or rejects minimization. The critical-to-quality(CTQ) characteristics for the product are yield strength(YS) and ultimate tensile strength(UTS), mass per length(g/m). YS and UTS are measured in kilo pound per square inch(KSI) respectively. Mass per length is measured in grams per meter(gram/m). The product selected is the TMT steel bar of grade 60 with three different product varieties i.e. ϕ15 mm, ϕ20 mm and ϕ25 mm.

Table 1. DMAIC flow chart

Define	Voice of customer, problem statement, process map, CTQ characteristics
Measure	Key performance output variables(KPOV), current process analysis using X-Bar and R charts, standard deviation, capability analysis using Cpk, Ppk, DPMO, current Sigma Level
Analyse	Pareto analysis of yield losses, identification of Key performance input variables(KPIV) and significant levels, two-level factorial design experiment for the minimum yield loss as response, ANOVA results and discussion of results, identification of Significant Factors and Levels for the minimum yield loss using P-value, normal, and Pareto charts, main plots, interaction plots, surface response plots, cube plots, contour plots and the regression model for the factorial analysis
Improve	Production results on the optimal factors and optimum levels, improve result analysis using X-Bar and R chart results, standard deviation, improve process performance calculation using Cpk, Ppk, DPMO and Sigma level
Control	Research conclusion, the optimal process parameters declaration, one-sample Z-Test for the μ>LSL of the product

The scope of the paper includes yield enhancement. It is done by the identification and controlling of the significant factors that affect the yield of the process. The factors and their optimized settings are found using six Sigma DMAIC.

For the selected manufacturing facility, the process map is shown in the Fig. 1. Raw material in the form of billets is received by the manufacturing facility. Quality check for material composition is performed and the accepted billets are kept in stock. According to the production schedule, these billets are processed in a reheating furnace where they are heated up to 1200 ℃. The heated billets are moved to roughing mill(R.M). After R.M , steel billets of ϕ25 mm are quenched in a quenching unit(Q.U). The billets of ϕ20 mm and ϕ15 mm are further processed in intermediate mill(I.M) and finishing mill(F.M) respectively. Finally, the bars from I.M and F.M are water quenched under a water pressure of approximately 1.2 MPa and are kept in open air for cooling. A final quality check is performed here, which includes tests for Yield Strength, Ultimate Tensile Strength, and mass per length(g/m). The rejected bars are sent to scrap yard and the remaining are sent to packaging department and finally dispatched to finish good yard.

3.2 Measurement

Data is collected from the quality department of the manufacturing firm and CTQ characteristics are measured. The CTQ characteristics include yield strength, ultimate tensile strength and mass per length for the selected product variety(i.e.ϕ15 mm, ϕ20 mm, ϕ25 mm steel bars). The process performance is measured using the collected data in terms of process mean, process capability; parts per million defective and sigma level. The design specifications for the 60 grade steel bar CTQs adopted in the industry are given below in Table 2. The product made under the current process must meet these specifications.

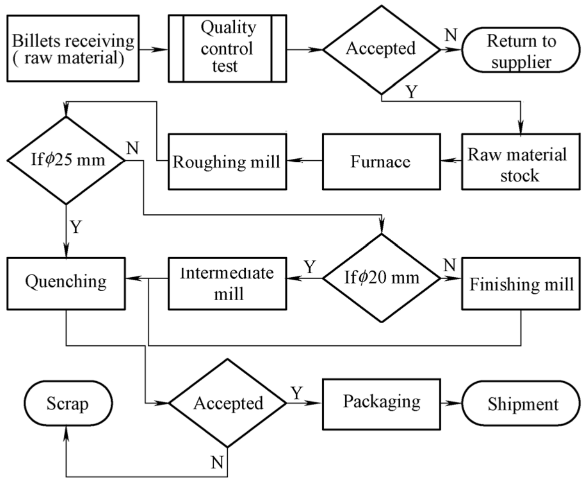


Fig. 1. Steel bar production process map of the company

Table 2. Design specifications for 60 grade steel bar

Specification limit		Lower specification limit(LSL)
Yield strength		60 kilo pound per square inch(KSI)
Ultimate tensile strength		90 KSI
Mass per length /(gm • m^{-1})	ϕ15 mm	452
	ϕ20 mm	707
	ϕ25 mm	1140

3.2.1 *Control charts*

Control charts are plotted in order to know if the process meets the design specifications. Control charts for the CTQs are made and their results are tabulated. Control chart of mass per length for 15mm steel bar is shown in Fig. 2 as an example. The LSL for it is 452 gm/m while the process mean is 471.57 gm/m. The upper and lower control limits for the process are 485.15 gm/m and 458.00 gm/m respectively. The process is in control. Similarly the control charts for the remaining CTQs are made and their parameters calculated. The obtained statistics are tabulated in Table 3. The process performance is satisfactory as mean and LCL X-bar values of all CTQs are greater than LSL. UCL R-bar and standard deviation values are greatest for mass per length of ϕ25 mm steel bar. Also the standard deviation of CTQ mass per length increases from ϕ15 mm steelbar to ϕ25 mm steel bar.

3.2.2 *Process capability*

The steel bar manufacturing process performance is measured by carrying out process capability study. The Cpk(process capability index), Ppk(process performance index) and defects per million opportunities(DPMO) are determined for each CTQ and finally the current sigma level of the process is calculated as shown in Table 4. The Cpk and Ppk are 0.72 and 0.71 respectively for the manufacturing of ϕ15 mm steel bar Gram per meter while the DPMO are 16158 as shown in Fig. 3. Similarly the process capability analysis for the remaining CTQs is made and their values are calculated. Cpk and Ppk for ϕ20 mm and ϕ25 mm steel bar are calculated as (0.64, 0.65) and (0.84, 0.85).

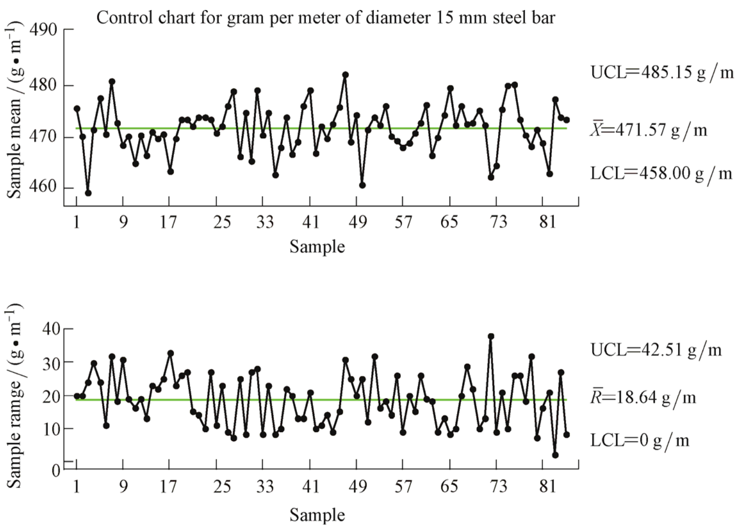


Fig. 2. Control chart of mass per length for 15mm steel bar

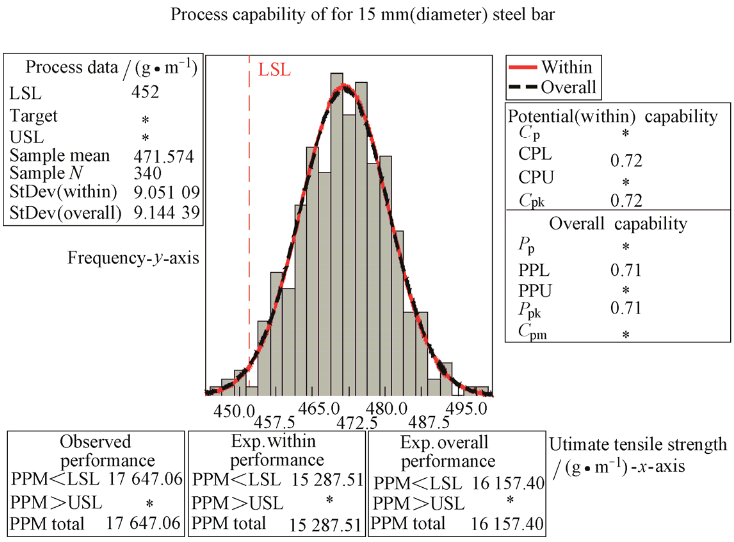


Fig. 3. Process capability of 15mm steel bar (g/m)

Table 3. Control chart results of CTQs

CTQs Parameter	Mass per length /(g • m^{-1}) ϕ15 mm	ϕ20 mm	ϕ25 mm	Yield strength (KSI)	Ultimate tensile strength (KSI)
Lower specification limit	452	707	1140	60	90
Mean	472	739	1196	68	98
Lower control limit(x-bar)	458	704	1163	61	92
Upper control limit(x-bar)	485	775	1223	75	105
Upper control limit(R)	42	62	104	17	21
Standard deviation	9.1	16.7	22.2	3.8	4.4

3.2.3 *Summarized Results of Measurement Phase*

The summarized results of measurement phase are presented in Table 4.

The table includes LSL , process mean, lower bound of process, upper bound of the process, process capability index Cpk, Ppk and DPMO calculated for the respective CTQ characteristics. The summarized results help in the sigma level calculation which is the baseline quality of the current process and needs to be improved.The sigma level of the process comes out to be 3.579 as shown in Table 4. The Cpk and Ppk of mass per length of ϕ25 mm steel bar are highest among all values, i.e. 0.85 and 0.84 respectively. The line DPMO for CTQ U.T.S is 29507, which is greater than other CTQ's DPMO. In this paper an effort is made to improve the sigma level by controlling the significant factors found in the Analysis phase of the DMAIC cycle.

Table 4. Measurement phase summary

CTQs parameter	Mass per length/(g • m^{-1})			Yield strength	Ultimate tensile strength
	ϕ15 mm	ϕ20 mm	ϕ25 mm		
Process capability index(Cpk)	0.72	0.64	0.85	0.70	0.63
Process capability index(Ppk)	0.71	0.65	0.84	0.71	0.63
Defects per million opportunity (DPMO)	16 158	26 433	5 661	16 189	29 507
Per million opportunity (PMO)	10^6	10^6	10^6	10^6	10^6
Process yield	98.121 %				
Sigma level	3.579				

3.3 Analysis

The analysis phase identifies the statistically significant factors that contribute towards the rejection. Once the significant factors are identified, they can be controlled to have minimum rejection and maximum process yield. Detailed analysis is carried out using Pareto analysis, Factorial design, Plot effects and Regression model.

3.3.1 Pareto analysis

The Pareto analysis is performed for the scrap data collected from the quality engineering department and the results are shown in Fig. 4. and Table 5 The analysis revealed four major sources for process scrap are the variation in the temperature range, input material composition, cutting blades life and water pressure during quenching. These four factors contributed to a total of 92% scrap.

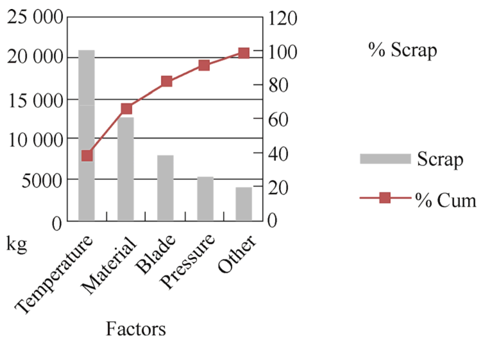


Fig. 4. Pareto chartfor scrap percentage

Table 5. Pareto analysis of scrap

Factor	Contribution/%	Scrap/kg	Cumulative/%
Temperature	0.39	21060	0.39
Material composition	0.28	15120	0.67
Cutting blades	0.15	8100	0.82
Pressure	0.10	5400	0.92
Other factors	0.08	4320	1.00
Total	1.00	54 000	

3.3.2 Factorial design

In order to confirm that the four identified factors in the Pareto analysis are statistically significant, a full factorial design is conducted. The low and high levels for the factors are set after the discussion with the production and quality experts and after overall process study. The levels are tabulated in Table 6.

Table 6. Process input factors along with respective levels

Level	Material /%(A)	Temperature /℃(B)	Cutting blades/h(C)	Water pressure/ MPa(D)
Low (–1)	0.35	900	1000	1
High (1)	0.75	1070	100	1.2

A full factorial design experiment is performed with four factors, sixteen runs for a total of 268 t of steel bar production at each run. In the experiments, the low and high levels are stated as (–1) and (1) respectively. The obtained response i.e. scrap is noted down and stated as the process response for a particular run. The complete data gathered after experimentation and P-value of the respective factors is given in Tables 7, 8. All the four factors A, B, C, and D are at low level (–1), for the first experimental run, the scrap produced is 5.32 t for a total steel bar production of 268 t. Remaining experimental runs are conducted in the same fashion. The factorial analysis revealed that the main factors A, B and C are significant with a P-value 0.00 which is less than α (0.05). Factor D is not significant as its P-value is 0.055, greater than α (0.05). 2-way Interactions are also non-significant as their P-value(0.626) is greater than α (0.05).

Table 7. Full factorial design experiment

Sr. No.	Material (A)	Temperature (B)	Cutting blades (C)	Pressure (D)	Scrap/t
1	–1	–1	–1	–1	5.32
2	1	–1	–1	–1	4.00
3	–1	1	–1	–1	3.85
4	1	1	–1	–1	3.00
5	–1	–1	1	–1	4.24
6	1	–1	1	–1	3.38
7	–1	1	1	–1	3.12
8	1	1	1	–1	2.72
9	–1	–1	–1	1	4.85
10	1	–1	–1	1	3.98
11	–1	1	–1	1	3.29
12	1	1	–1	1	2.92
13	–1	–1	1	1	4.18
14	1	–1	1	1	3.20
15	–1	1	1	1	3.04
16	1	1	1	1	2.02

Table 8. ANOVA results

Source	P-statistics	Conclusion
Main Effects	0.000	Significant
Material (A)	0.000	Significant
Temperature (B)	0.000	Significant
Cutting blades (C)	0.001	Significant
Pressure (D)	0.055	Non-Significant
2-Way interactions	0.626	Non-Significant

The significant factors are also shown in Fig. 5, the normal plots of the effects. The red-coloured statistically significant effect of factors A, B, and C lies away from the normal effect line. The Pareto chart of the standardized effects also shows factors A, B and C as significant ones, shown in Fig. 6. As the significant factors identified in the factorial analysis, the effects of each factor is plotted for in depth analysis and result conclusion.

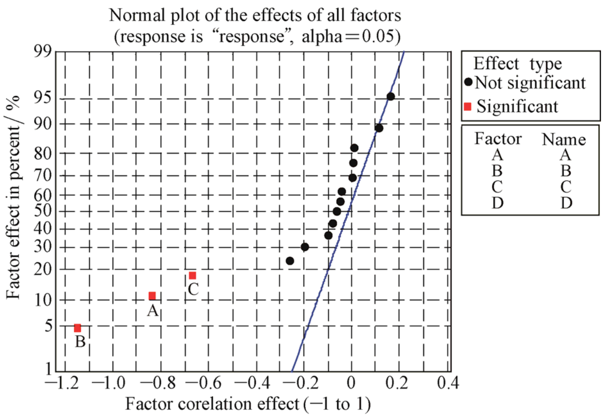


Fig. 5. Normal plot of the Factor effects

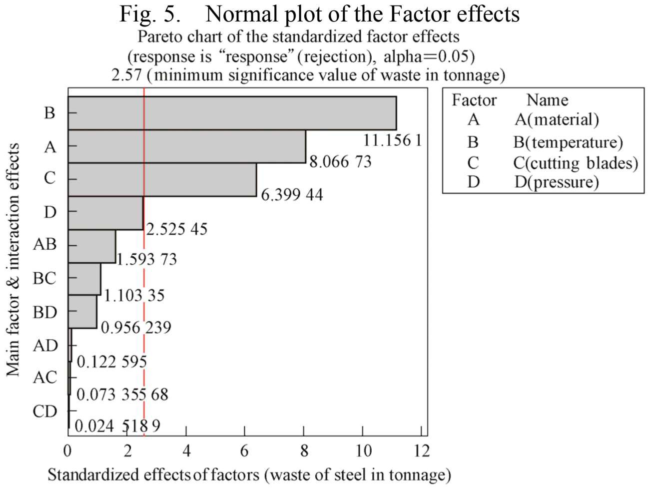


Fig. 6. Pareto chart for the standardized effects

3.3.3 *Plot Effects*

The main plots, interaction plots, surface response plots, cube plots, and contour plots are made for the factors to investigate the change in response(Rejects) with the changing level from low to high. Two important findings are made, 1. There is reduction in the scrap as the levels of the factors are moved from low to high, and 2.

No interaction among the factors is found. The main plots indicate a reduction in the rejection when the factors are moved from low level to high level. The main plots are steeper for the factors A, B and C, while the factor D does not show any significant change in response as shown in Fig. 7. Interaction is not found amongst any factor as all the interaction plots are almost parallel and no response line is crossing as shown in Fig. 8.

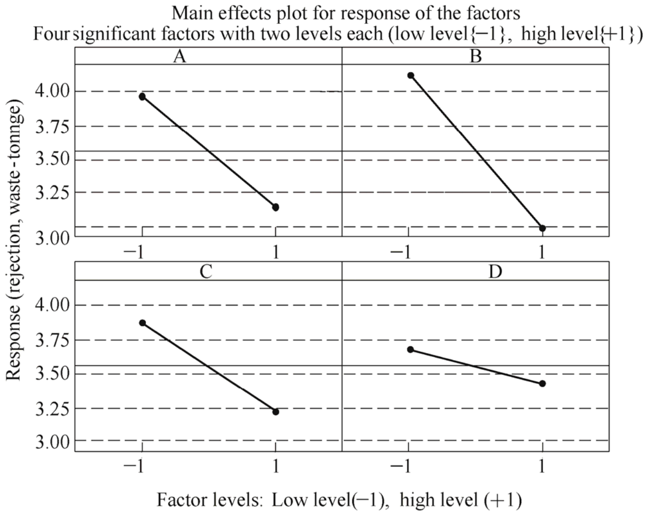


Fig. 7. Main effect response plot

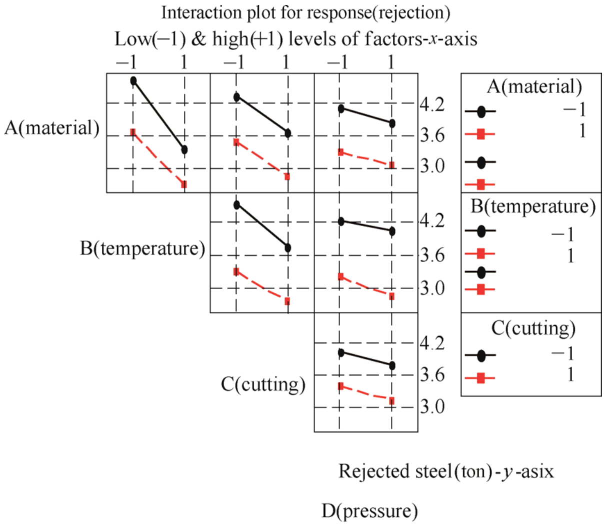


Fig. 8. Interaction plot of response for significant factors

The surface plot for factors A, C vs. Rejection is a straight surface and reveals no interaction among them as shown in Fig. 9. The cube plot for the factors A, B, C and D is plotted in the Fig. 10. It reveals that the process scrap is maximum at low level of all the factors i.e. 5.23 t and is minimum at the high level of all the factors i.e. 2.02 t. The contour plots for factor A vs. B and A vs. C is shown in the Figs. 11(a), (b). It also reveals the same result that as the factors levels are moved from low to high level, the response (rejects) reduces.

The plot effects help in the rational interpretation and conclusion of the experimentation results. It is further required to make a regression model for the performed factorial design experiment.

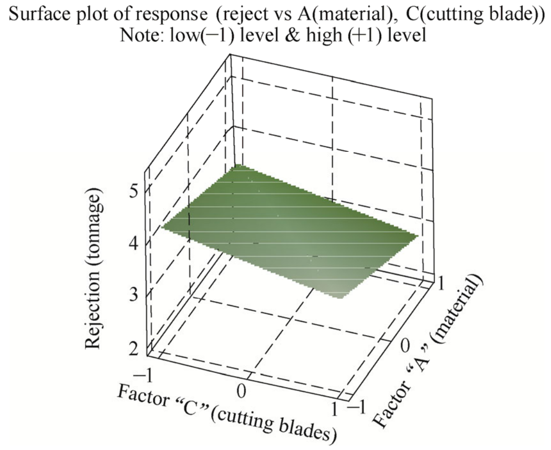


Fig. 9.　Surface plot of factors A and C vs. Response

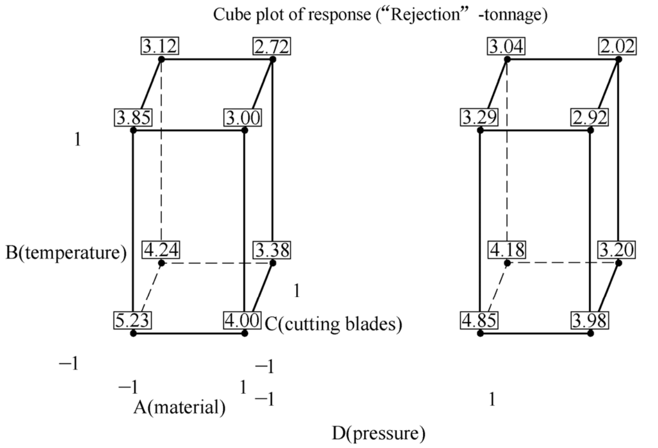
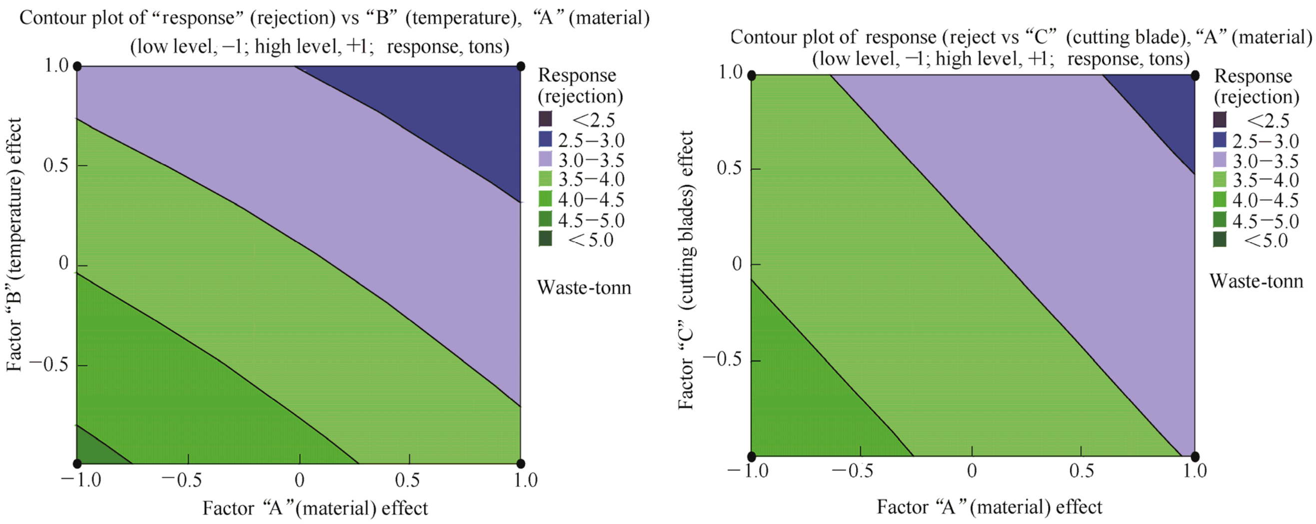


Fig 10.　Cube plot of response of significant factors



(a) vs A, B　　(b) vs A, C

Fig. 11.　Contour plots of response

3.3.4　Regression model

The factorial design determines that A, B and C factors are significant i.e. material, temperature and cutting blades and their regression model is given in Eq. (1). The co-efficient of regression equation are β_0(grand average)=3.56, β_1(material)=0.411, β_2(temperature)= 0.569, β_3(cutting blades) = 0.326

$$Scrap = 3.62 - 0.417(A) - 0.574(B) - 0.332(C) - 0.134(D). \quad (1)$$

It implies that moving from Low to High level of Material Composition, the percentage of Scrap is expected to decrease by 0.411%, moving from Low to High level of temperature, the percentage Scrap is expected to decrease by 0.568%, and moving from Low to High level of Cutting blades, the percentage Scrap is expected to decrease by 0.327%. In the analysis phase, the reasons for low yield are investigated and Input material composition, Temperature at which input material (billets) and cutting blades (head and tail cutters of steel bar) are found to be statistically significant and are key performance input variables (KPIVs) for the steel bar manufacturing process. As the KPIVs are controlled to the desired level(all at high level), maximum yield can be obtained with minimum scrap formation.

3.4　Improvementphase

The improvement phase implements the findings of Analysis phase into the steel bar manufacturing facility and observe the improved results. The significant factors (KPIVs) found are material composition(0.75% manganese), cutting blades(100 h used) and melting temperature(1070 ℃). The plant is run on these settings and KPOVs are calculated. The results are summarized in Table 9.

The process mean and lower control limit are greater than the LSL of the product. Hence the process is under control.The process performance is also improved with a reduced standard deviation compared to the measure phase, when the plant was operating at random settings of KPIVs. The Mean, Cpk, Ppk and DPMO results of KPOVs also shown improvements compared to the measure phase and are summarized in Table 10. The DPMO for KPOVs, process yield and sigma level for the improved data is calculated and shown in Table 10. The DPMO's largest values of CTQ Ultimate Tensile Strength(UTS) & Yield Strength(YS) are 17206&1909 respectively which are still smaller than its measure phase value of 29507&16189 respectivelyas mentioned in Table 4.

Table 9. Control chart results of CTQs(KPOV)

CTQs parameter	Mass per length/(g • m^{-1})			Yield strength (KSI)	Ultimate tensile strength (KSI)
	ϕ15 mm	ϕ20 mm	ϕ25 mm		
Lower specification limit	452	707	1140	60	90
Mean	474	746	1197	69	99
Lower control limit (x-bar)	462	715	1168	64	93
Upper control limit (x-bar)	486	779	1227	74	105
Upper control limit (R)	38	56	94	15	20
Standard deviation	8.3	14.9	20.8	3.1	4.3

Table 10. Summarized results of improvement phase

CTQs parameter	Mass per length/(g • m^{-1})			Yield strength	Ultimate tensile strength
	ϕ15 mm	ϕ20 mm	ϕ25 mm		
Process capability index(Cpk)	0.72	0.87	0.96	0.94	0.72
Process capability index(Ppk)	0.87	0.89	0.92	0.96	0.71
Defects per million opportunity(DPMO)	4574	3872	2851	1909	17 206
Per million opportunity(PMO)	10^6	10^6	10^6	10^6	10^6
Process yield	99.39 %				
Sigma level	4.0073				

The process rejects are reduced while the process yield and sigma level are improved. The sigma level achieved is 4.007 3 compared to previous 3.579 at measure phase stated in Table 4.

3.5 Control

The results are communicated to the team and the production department is directed to run the production process under the desired factors settings as shown in the Table 11. As the production system is run under the stated settings, the maximum yield is achieved with the improved process performance.

Table 11. Significant factors and optimum process level

Level	Factor A (manganese)	Factor B (temperature)	Factor C (cutting blades)
High	0.75%	1070 ℃	100 h

The one-sample Z-Test is performed on the improved data in order to know if the mean of the process is greater than the given product LSL. The test is performed with a 95% confidence level and the results are summarized in Table 12.

Table 12. One-sample Z-test results for the results

CTQs parameter		Standard deviation	Alternate hypothesis	*P*-value	Results (alternate hypothesis testing)
Mass per length /(g • m^{-1})	ϕ15 mm	8.36	$\mu>452$	0	Accept
	ϕ20 mm	14.94	$\mu>707$	0	Accept
	ϕ25 mm	20.8	$\mu>1140$	0	Accept
Yield strength		3.144	$\mu>60$	0	Accept
Ultimate tensile strength		4.311	$\mu>90$	0	Accept

The one sided tail test for $\mu>$LSL is performed. The p-value less than α(0.05) indicate the rejection of Null Hypothesis, $H_o=\mu\leqslant$LSL and hence the Null Hypothesis is rejected and Alternate Hypothesis, Ha$=\mu>$LSL is accepted. Hence it is concluded that the mean value CTQ’s i.e. (KPOVs) are greater than LSL as desired.

4 Result and Discussion

For all the CTQ characteristics, Cpk and Ppk are improved, and DPMO and standard deviation are minimized as the steel bar manufacturing is conducted on the optimized levels of identified factors as shown in Tables 13, 14.

Table 13. Measuring vs. improvement phase results

CTQs parameter	Mass per length/(g • m^{-1})			Yield strength	Ultimate tensile strength
	ϕ15 mm	ϕ20 mm	ϕ25 mm		
Process capability index(Cpk) of measure phase	0.72	0.64	0.85	0.70	0.63
Process capability index(Cpk) of improvement phase	0.72	0.87	0.96	0.94	0.72
Process capability index(Ppk) of measure phase	0.71	0.65	0.84	0.71	0.63
Process capability index(Ppk) of improvement phase	0.87	0.89	0.92	0.96	0.71

For the steel bar manufacturing process of the selected facility, the highest improved Cpk 0.96 is of CTQ mass per length of ϕ25 mm steel bar while the highest Ppk 0.96 is of

CTQ Y.S.

Table 14. Measuring vs. improvement phase results

CTQs parameter	Mass per length/(g • m^{-1})			Yield strength	Ultimate tensile strength
	ϕ15 mm	ϕ20 mm	ϕ25 mm		
Defects per million opportunity (DPMO) of measure phase	0.72	0.64	0.85	0.70	0.63
Defects per million opportunity (DPMO) of improvement phase	0.72	0.87	0.96	0.94	0.72
Standard deviation of measure phase	0.71	0.65	0.84	0.71	0.63
Standard deviation of improvement phase	0.87	0.89	0.92	0.96	0.71

As the Ppk is improved, the DPMO for all the CTQ characteristics are drastically decreased which shows the inversely proportion between the parameters. It is also noticed that when the process achieves 4σ process performance level and there is a shift in the process mean, then the long term Cpk and Ppk of the process lies in between the range of 0.71 to 0.96 as shown in Table 13. Process variation is also minimized which is evident from the reduced standard deviation of the process.

The improvement is also evident in process yield and sigma level as shown in Table 15. Hence the objective process optimization through yield enhancement, process performance and sigma level improvement is achieved.

Table 15. Improved yield & sigma level

Process yield (measure phase)	Process yield (improvement phase)	Sigma level (measure phase)	Sigma level (improvement phase)
0.98	0.99	3.58	4.01

5 Conclusions

(1) The KPOVs are defined and KPIVs are identified that significantly affect the process yield. The process performance is measured in terms of Cpk, Ppk, DPMO and Sigma Level.

(2) The process yield calculated is 98.121% from the DPMO and sigma level was 3.579 for the process.

(3) To improve the process performance, in depth process analysis is carried out and a factorial design experiment is performed.

(4) The statistically significant factors along with the optimum level settings are found.

(5) The factors include material composition, temperature and cutting blades.

(6) The production line was operated on the optimum settings and improved results are presented.

(7) The process yield is improved to 99.39% of the total production and the sigma level is improved to 4.007 3.

6 Future Recommendations

A detailed six sigma DMAIC methodology is conducted to identify the significant factors and their impact on the yield. Four factors which include material composition, melting temperature, cutting blades sharpness, and water pressure during quenching with respective two levels are considered for the experimentation. Revolution per minute(RPM) of the conveyor of the line, can also be considered as fifth factor in the experimentation. The two levels of each of the factors can be extended to multi levels. For material composition factor, only two levels of the manganese are considered that can be extended to multi-levels. Also sulphur and carbon can be considered to check the effect different materials on the yield of the manufacturing facility. Similarly, multi levels of temperature, water pressure during quenching can also be tested and explored.

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