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Assessing Production Quality in Steel Manufacturing Using Statistical Control Charts and Pareto Analysis: A Case Study of the Libyan Iron and Steel Company

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Abstract

Statistical Process Control (SPC) techniques such as control charts and Pareto analysis, are widely applied in quality management to evaluate process stability and identify dominant sources of variation over time. These tools provide manufacturing industries with powerful tools to drive continuous improvement, support data-driven decision-making, and enhance customer satisfaction. The main objectives of this study are to classify and analyse the different types of defects and assess the process stability in the Hot Strip mill. This study adopts a quantitative case study at the Hot Rolling Mill of the Libyan Iron and Steel Company (LISCO). Pareto analysis and C control chart were used to identify dominant defect recourse and assess process stability respectively. Inspection reports and production data were collected and processed using spreadsheet software to assess the quality performance of tinplate production. Pareto analysis reveals that approximately 80% of defects are concentrated in four categories: Telescope (TEL), Over Thickness (OVT), Under Thickness (UNT), and Cracked Edge (CRE). Control

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chart results further indicated irregularities in the production process, with several defect occurrences falling outside statistical control limits and the variation is systematic not random. Also. the study reveals the statistical methods are not used in continuous basis on hot strip mill.

Keywords: Statistical Quality Control, Hot Rolling Mill, Pareto Chart,C- Control Charts, defects, variation.

تقييم جودة الإنتاج في تصنيع الصلب باستخدام مخططات التحكم الإحصائي وتحليل باريتو: دراسة حالة الشركة الليبية للحديد والصلب

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الملخــــــص

تُستخدم تقنيات التحكم الإحصائي في العمليات (**SPC**)، بما في ذلك مخططات التحكم وتحليل باريتو، على نطاق واسع في مراقبة الجودة لتقييم استقرار العمليات وتحديد مصادر التباين الرئيسية بمرور الوقت. تُوفر هذه الأدوات للصناعات التحويلية وسائل فعّالة لدفع عجلة التحسين المستمر، ودعم اتخاذ القرارات القائمة على البيانات، وتعزيز رضا العملاء. تعتمد هذه الدراسة منهجية كمية من خلال دراسة حالة لمصنع الدرفلة على الساخن في الشركة الليبية للحديد والصلب (**LISCO**). جُمعت تقارير التفتيش وبيانات الإنتاج وعُولجت باستخدام برنامج جداول بيانات لتقييم أداء جودة إنتاج الصفيح. تكشف النتائج أن ممارسي الجودة في المصنع لا يستخدمون باستمرار الأساليب الإحصائية المناسبة لمراقبة عمليات الإنتاج والتحكم فيها. أبرز تحليل باريتو أن حوالي 80% من العيوب تتركز في أربع فئات: التلسكوب (**TEL**)، وزيادة السُمك (**OVT**)، ونقص السُمك (**UNT**)،

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والحافة المتشققة (CRE). أشارت نتائج مخططات التحكم أيضًا إلى وجود مخالفات في عملية الإنتاج، حيث تقع العديد من حالات العيوب خارج حدود التحكم الإحصائي.
وخلصت الدراسة إلى أن دمج أدوات مراقبة الجودة بشكل أكثر منهجية في إطار إدارة الجودة من شأنه أن يعزز مراقبة العمليات، ويقلل من التباين، ويعزز ثقافة الجودة الأقوى داخل المصنع.

الكلمات الدالة: أدوات ضبط الجودة، إنتاج لفائف القصدير، مخطط باريتو، الشركة الليبية للحديد والصلب، مخططات التحكم.

Introduction

The iron and steel industry is a cornerstone of global economic growth and industrialization, providing essential raw materials for infrastructure, construction, transportation, energy systems, and advanced manufacturing. In many countries, the performance of the steel sector directly reflects the pace of economic development, as it supplies critical inputs for housing, urbanization, and industrial projects. Within this context, the Libyan Iron and Steel Company (LISCO), located in Misurata, Libya, stands as one of the largest integrated steel complexes in North Africa and a key contributor to the national economy (Company Technical Reports , 2025). Equipped with significant production capacity and modern facilities, LISCO plays a vital role in meeting domestic demand and supporting regional markets. However, like many steel manufacturers worldwide, the company continues to face challenges in maintaining consistent product quality, particularly in reinforcement bars and tin rolls, where defect rates affect both competitiveness and customer satisfaction. To address these challenges, Statistical Quality Control (SQC) techniques have emerged as indispensable tools in the steel industry. By systematically analyzing production data, monitoring process performance, and identifying the root causes of variability, SQC not only reduces the occurrence of defects but also fosters a culture of continuous improvement (Montgomery & C, 2020). Prior studies have demonstrated the effectiveness of SQC in minimizing waste, optimizing resources, and ensuring compliance with international standards such as those of the British and German markets.

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Applying these methods at LISCO offers a dual opportunity: to enhance the reliability of reinforcement bar production, which is generally in line with specifications, and to significantly improve the quality of tin roll production, where higher defect rates remain a concern. The main objectives of this study are to classify and analyze the different types of defects at the Hot Rolling Mill of the Libyan Iron and Steel Company, and to apply statistical methods, specifically control charts and Pareto analysis, to evaluate and monitor the quality of the product.

Literature review

Several studies have highlighted the effectiveness of Statistical Quality Control (SQC) in monitoring production quality and detecting variability in manufacturing processes. (Banker, Chang, & Natarajan, 2014) demonstrated the use of X-bar, R, P, and C charts in pipe manufacturing to detect process variability, while (Motorcu & Güllü, 2014) applied SPC tools in machining processes to identify defect causes and enhance surface quality. More advanced approaches have been developed in recent years, such as the integration of Taguchi's loss function into economic X-bar chart design to show its impact on sensitivity and cost efficiency (S. T. A. N. , 2021). Also, the application of SQC has been strongly linked to broader quality management frameworks, with Six Sigma and Lean Six Sigma remaining widely used to systematically reduce defects and improve process performance; for example, a study in a steel galvanizing line reported an increase in process cycle efficiency from 22% to 62% after applying Lean Six Sigma (Srinivasan, Ramesh, & Sundaram, 2023). With the advancement of Industry 4.0, SQC methods, which are increasingly combined with digital technologies and artificial intelligence, where non-invasive sensors and predictive models have been employed to estimate steel properties with high accuracy (Straat, Koster, Goet, & Bunte, 2022), and multiple kernel learning has been used for early prediction of defects in thermally coated steel components (Rannetbauer, Hubmer, Hambrock, & Ramlau, 2025). Reviews of SPC applications confirm its continued relevance, but emphasize that successful implementation depends not only on tools and technology but also on operator training and the development of a

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strong quality culture within organizations (Hadiyanto & Sitepu, 2023). (Godina, Matias, & Azevedo, 2016) demonstrated the application of Statistical Process Control (SPC) in the automotive industry, showing that control charts and decision analysis can significantly improve productivity and meet increasing quality requirements.

Methodology

Although the Libyan company holds an ISO 9001 conformity certificate, it has not been updated due to the company's distance from the practical aspect in the field of quality, which greatly helped the company to realize the importance of applying quality tools in order to diagnose and analyze the causes of the production process deviation for the sheet coil product, the Hot Rolling Mill factory management provided researchers with all possible data and made it available for the purpose of the required study.
In the study, a quantitative case study approach suits the case under analysis. The study was carried out in steps:

- **Data collection**

In order to evaluate the production quality of tin rolls at the Hot Rolling Mill of the Libyan Iron and Steel Company, inspection data were collected over a three-month period (January–March 202**5**). The production was organized into three shifts (Morning, Evening, and Night), and within each shift, four operator groups (A, B, C, and D) were identified. These groups represent different operating teams responsible for running the mill during the shifts. For each group and shift, the number of inspected coils and the corresponding defects were recorded. The sample size was defined as the total number of coils produced and inspected during the study period, with defect counts expressed relative to this production volume. This allowed the calculation of defect rates rather than absolute frequencies. Sampling was performed continuously during the shifts, ensuring that the collected data reflected the actual variability of the production process.
Microsoft Excel and Minitab were used to process and analyze the data. Defect types were classified into four categories: dimensional, surface, and appearance. This structured dataset enabled meaningful comparisons across groups and shifts, and facilitated the application

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of statistical control charts and Pareto analysis to identify dominant defect categories and assess process stability over time. Their findings highlight the importance of SPC as a systematic tool for achieving sustainable competitiveness. Overall, the literature indicates that while significant progress has been achieved in applying SQC in steel and related industries worldwide, there is still limited evidence of systematic applications in Libyan steel manufacturing contexts. This highlights a research gap, particularly in addressing the role of SQC tools combined with cultural and organizational improvements, which the present study aims to fill by evaluating production quality in LISCO. These studies underscore the value of SQC tools in early detection of process deviations, supporting informed decision-making, and minimizing production losses. This paper builds upon such findings by implementing SQC techniques in the Libyan context, specifically focusing on tin rolls.

This study addresses the persistent quality challenges in the Libyan Iron and Steel Company (LISCO), with a particular emphasis on the high defect rate in hot roll production, which adversely affects product quality, increases waste, and undermines compliance with international standards. The main objectives of this study are to classify and analyze the different types of defects in Hot roll production at the Hot Rolling Mill of the Libyan Iron and Steel Company, and to apply statistical methods specifically control charts and Pareto analysis to evaluate and monitor the quality performance of coil production. By addressing these objectives, the research seeks to provide a systematic assessment of process stability, identify the most critical sources of variability, and contribute to the development of a stronger quality culture within the company.

- Defects classifications

Dimensional defects: There are six defects related to the dimension, which are shown in table 1.

Appearance defects: There are 13 defects related to appearance are shown in Table 2.

Surface defects: There are 15 defects related to appearance are shown in Table 2.

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Table 1 Dimensional deviation defects of sheet coils.

No.	Type of Defect	The symbol
1.	Over Thickness	OVT
2.	Over Width	OVW
3.	Under Thickness	UNT
4.	Under Width	UNW
5.	Profile Variation	PRV
6.	No Graph	N.G

Table 2Appearance Defects of sheet coils

No.	Type of Defect	The symbol
1.	Bad Tail	BAT
2.	Bended Edge	BEE
3.	Cracked Edge	CRE
4.	Camber	CAM
5.	Ellipse	ELL
6.	Fish Tail	FIT
7.	Loose	LOS
8.	Telescope	TEL
9.	Toren Edge	TOE
10.	Waviness	WAV
11.	Wrinkle	WRN
12.	Zig Zag	ZZC
13.	Handing Damage	HAD

Table 3 Surface Defect of sheet coils

No.	Type of Defect	The symbol
1.	Fire Crack FIC	FIC
2.	Hot Mill Fold	HMF
3.	Hole	HOL
4.	Indentation	IND
5.	Rolled in Scale	RIS
6.	Roll Mark	ROM
7.	Rolled in Material	RIM
8.	Scratches	SCR
9.	Blister	BLR
10.	Edge Lamination	EDL
11.	Pipe Lamination	PIL
12.	Skin Lamination	SKL
13.	Sliver	SLV
14.	Grease / Dirt Pit	GDP
15.	Ruse	RUS

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- **Analytical Assessment Tools**

Data analysis employed Microsoft Excel and Minitab software, the assessment utilized two complementary analytical approaches:

- **Pareto Analysis**
  It is a tool applied to identify and prioritize the main defects categories based on frequency analysis. This approach followed the standard pareto principle to distinguish between major and minor quality problems.

- **C- control charts**
  After identifying the different types of defects by including them within four groups, we move on to applying statistical methods to control the quality of the product (coil) in the hot rolling mill, which is the second objective of this research.

The most commonly used charts to monitor and continuously control the production process capability are the Attribute Control Charts .The choice of control chart depends on the type of data being analysed (Izenman, 2008), based on common scenarios for shifts and groups as shown in figure 4, in this study has been used a C chart (also known as a Count Control Chart) is used to monitor the number of defects or nonconformities in a fixed-size sample of items. It is particularly useful when each item can have multiple defects, and we interested in counting the total number of defects rather than just identifying if an item is defective. a control chart for defects or nonconformities, or c chart with three-sigma limits would be defined as follows:

$$CL=\bar{c} \tag{1}$$

$$UCL=\bar{c}+3\sqrt{\bar{c}} \tag{2}$$

$$CL=\bar{c}-3\sqrt{\bar{c}} \quad \text{(set to zero if negative)} \tag{3}$$

Assuming that a standard value for c is available. Should these calculations yield a negative value for the LCL, set LCL = 0, If no standard is given, then $\bar{c}$ may be estimated as the observed average number of nonconformities in a preliminary sample of inspection units (Ott, Schilling, & Neubauer, 2005).

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Results and Discussion

These reports work in three shifts: morning, evening, and night (M, E, N), which are divided into four groups labeled (A, B, C, D).

Table 4 shows the number of defective parts for January 2025, their weights, and their percentage of the monthly production, detailed according to the shifts and groups.The data in the table 4 shows that the highest defective type was the Telescope (TEL) with 34 defects, followed by the Excessive Thickness (OVT) with 21 defects, and the third most frequent defect was the Under Thickness (UNT) with 15 defects. It is noted that the highest number of defects was distributed across two groups, (B, D).

The study used Microsoft Office Excel to represent a Pareto chart, where the types of defects, the percentage of defective parts, and the cumulative defect were represented as shown in Table 4, on the axes of the Pareto chart, as shown in Figure 1.

Table 4 Types of Defects, Percentage of Defective Items, and Cumulative Defects for January

Defects	GROUPS				TOTAL	Cumulative Amount	Cumulative Percentage
	A	B	C	D			
OVT	3	10	3	5	21	21	21
UNT	7	2	4	2	15	36	35
OVW	2	2	0	8	12	48	47
ELL	0	0	0	0	0	48	47
UNW	1	0	0	1	2	50	49
TEL	9	3	9	13	34	84	82
ZZC	0	0	0	0	0	84	82
RIS	1	0	0	0	1	85	83
N.G	0	1	0	0	1	86	84
TOE	0	0	0	0	0	86	84
CRE	8	0	1	4	13	99	97
EDL	0	0	0	0	0	99	97
LOS	0	0	0	1	1	100	98
FIC	0	0	0	0	0	100	98
COB	0	0	0	0	0	100	98
BAT	0	0	0	0	0	100	98
BEE	0	2	0	0	2	102	100
FIT	0	0	0	0	0	102	100
HMF	0	0	0	0	0	102	100
ROM	0	0	0	0	0	102	100

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To represent the data on a Pareto chart, it is necessary to sort the defects in descending order, from highest to lowest, and then cumulatively sum the defects. After that, the cumulative percentage is calculated.

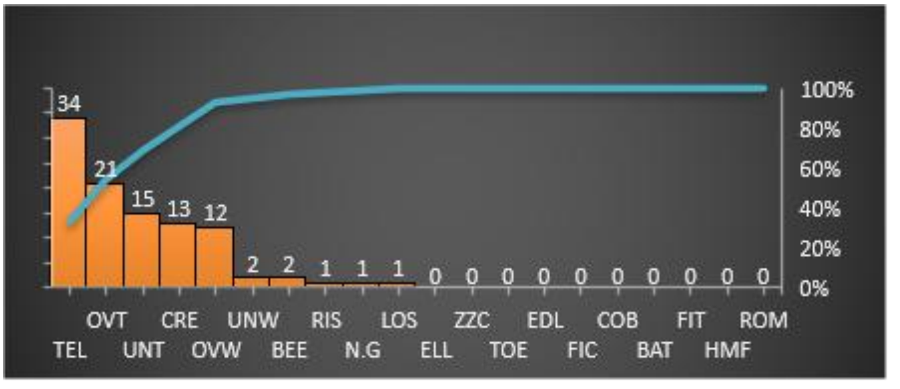

Figure 1 Pareto Chart of Defective Coils for January

From Figure 1, it can be seen that 80% of the defects are represented by the largest proportion of defects occurring in Telescope (TEL) shape, Over Thickness (OVT), Under Thickness (UNT), Cracked Edge (CRE) and Over Width (OVW). The data in Table 5 indicates that the highest defect was for the Telescope (TEL) type at 209 occurrences, followed by the Over Thickness (OVT) defect at 100 occurrences, and the third most frequent defect was the Under Thickness (UNT) type at 41 occurrences.

Table 5 Types of Defects, Percentage of Defective Items, and Cumulative Defect for February

Defects	GROUPS				TOTAL	Cumulative Amount	Cumulative Percentage
	A	B	C	D			
TEL	31	45	52	81	209	209	41
OVT	33	17	11	39	100	309	61
UNT	13	11	12	5	41	350	69
UNW	8	10	11	10	39	389	76
CRE	1	15	11	9	36	425	83
ELL	16	1	9	4	30	455	89
OVW	2	7	9	3	21	476	93
N.G	3	1	7	2	13	489	96
BAT	1	3	1	4	9	498	98
RIS	2	0	0	4	6	504	99
BEE	0	0	4	0	4	508	100
ZZC	0	1	0	1	2	510	100
EDL	0	0	0	0	0	510	100

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TOE	0	0	0	0	0	510	100
LOS	0	0	0	0	0	510	100
FIC	0	0	0	0	0	510	100
COB	0	0	0	0	0	510	100
FIT	0	0	0	0	0	510	100
HMF	0	0	0	0	0	510	100
ROM	0	0	0	0	0	510	100

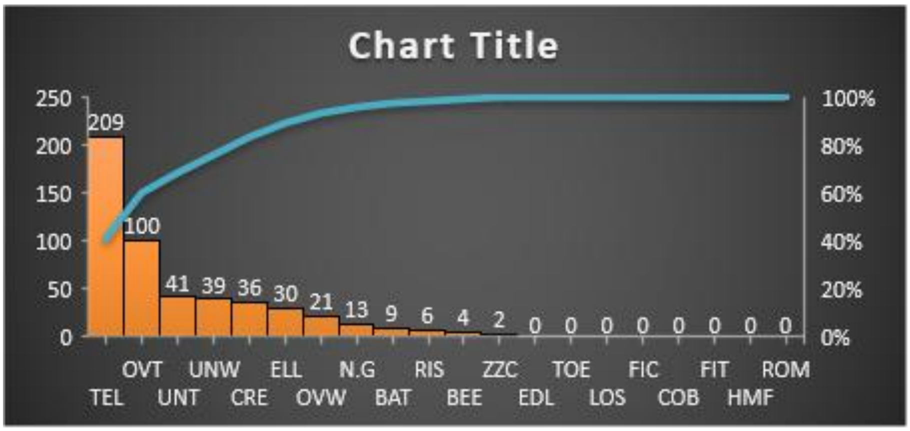

Figure 2 Pareto Chart of Defective Coils for February

From Figure 2, it can be seen that approximately 80% of the total defects are concentrated in a few dominant categories, Telescope (TEL), Over Thickness (OVT), Under Thickness (UNT), and Cracked Edge (CRE), indicating that these defect types have the most significant impact on overall product quality.

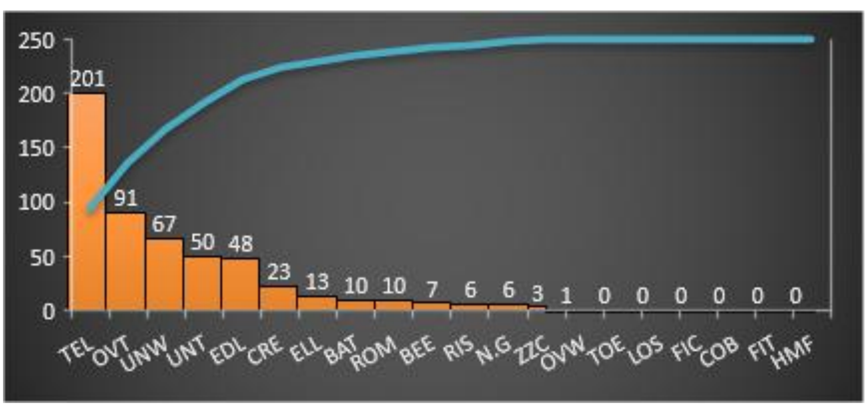

Figure 3 Pareto chart of number of defective Coils for March

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Table 6 Types of Defects, Percentage of Defective Items, and Cumulative Defects for March

Defects	GROUPS				TOTAL	Cumulative Amount	Cumulative Percentage
	A	B	C	D			
TEL	62	38	54	47	201	201	38
OVT	25	16	14	36	91	292	54
UNW	18	19	16	14	67	359	67
UNT	14	9	12	15	50	409	76
EDL	8	5	32	3	48	457	85
CRE	8	6	6	3	23	480	90
ELL	0	2	4	7	13	493	92
BAT	6	3	1	0	10	503	94
ROM	0	0	0	10	10	513	96
BEE	0	0	4	3	7	520	97
RIS	1	4	0	1	6	526	98
N.G	1	2	1	2	6	532	99
ZZC	0	0	1	2	3	535	100
OVW	1	0	0	0	1	536	100
TOE	0	0	0	0	0	536	100
LOS	0	0	0	0	0	536	100
FIC	0	0	0	0	0	536	100
COB	0	0	0	0	0	536	100
FIT	0	0	0	0	0	536	100
HMF	0	0	0	0	0	536	100

The Figure 3 shows that 80% of the defects represent the largest proportion of defects and occur in the Telescope (TEL) shape, Over Thickness (OVT), Under Thickness (UNT) and Cracked Edge (CRE) The control chart for the mean is drawn so that the x-axis represents the defects in the samples in the order they were taken, while the y-axis represents the mean value. Each chart has three lines: the center line, the upper control limit, and the lower control limit. A total of 20 defects were taken, each with a size of 4 observations, during the months of January, February, and March 2025. Table 7 shows the calculation of the c chart and control limits for January 2025.

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Table 7 Control limits and average calculation for January

Defects	A	B	C	D	mean value
OVT	3	10	3	5	5.25
UNT	7	2	4	2	3.75
OVW	2	2	0	8	3
WAV	0	0	0	0	0
UNW	1	0	0	1	0.5
TEL	9	3	9	13	8.5
ZZC	0	0	0	0	0
RIS	1	0	0	0	0.25
N.G	0	1	0	0	0.25
TOE	0	0	0	0	0
CRE	8	0	1	4	3.25
ELL	0	0	0	0	0
LOS	0	0	0	1	0.25
FIC	0	0	0	0	0
COB	0	0	0	0	0
BAT	0	0	0	0	0
BEE	0	2	0	0	0.5
FIT	0	0	0	0	0
HMF	0	0	0	0	0
ROM	0	0	0	0	0

The control limits for the C-chart were calculated based on the average number of defects observed during January. The center line (CL) was found to be 1.275, while the upper control limit (UCL) was 4.662, and the lower control limit (LCL) was equal to zero, reflecting the non-negative nature of defect count data. These control limits were used as statistical reference values to assess the stability of the production process and to identify any abnormal variations in defect occurrences. The following figure shows the average percentage of defects for tin rolls for January 2025.

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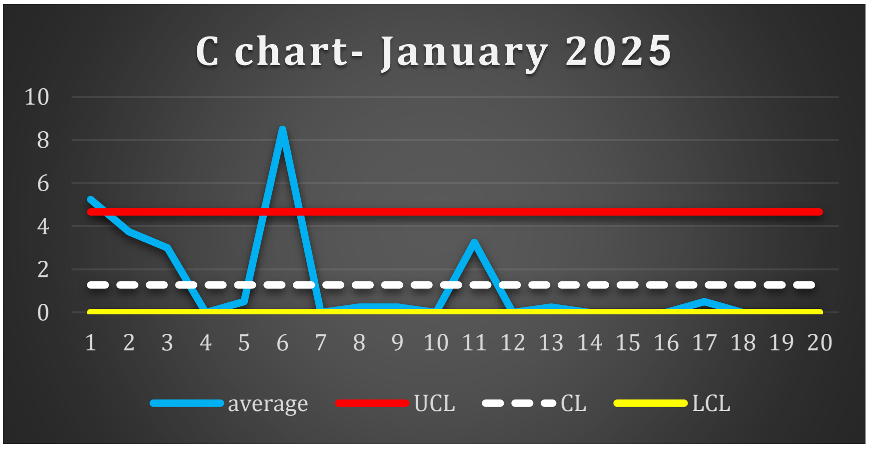

Figure 4 Average of defects percentage for tin rolls for January

It is clear from Figure 5 that the number of defects for samples No. 1 and 6 falls outside the upper limit of control, and this indicates irregularity in the production process, which requires identifying the causes. Table 8 shows the calculation of the c chart and control limits for February 2025.The control limits of the C-chart were determined based on the average number of observed defects. The center line (CL) was calculated as 6.375 defects, while the upper control limit (UCL) reached 13.9496, and the lower control limit (LCL) remained at zero, due to the non-negative nature of defect data. These control limits served as reference thresholds for monitoring process stability and detecting any unusual variations in defect occurrence during the February production period.

Table 8 Control limits and average calculation for

Defects	A	B	C	D	mean value
OVT	33	17	11	39	25
UNT	13	11	12	5	10.25
OVW	2	7	9	3	5.25
WAV	0	0	0	0	0
UNW	8	10	11	10	9.75
TEL	31	45	52	81	52.25
ZZC	0	1	0	1	0.5
RIS	2	0	0	4	1.5
N.G	3	1	7	2	3.25
TOE	0	0	0	0	0
CRE	1	15	11	9	9
ELL	16	1	9	4	7.5

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LOS	0	0	0	0	0
FIC	0	0	0	0	0
COB	0	0	0	0	0
BAT	1	3	1	4	2.25
BEE	0	0	4	0	1
FIT	0	0	0	0	0
HMF	0	0	0	0	0
ROM	0	0	0	0	0

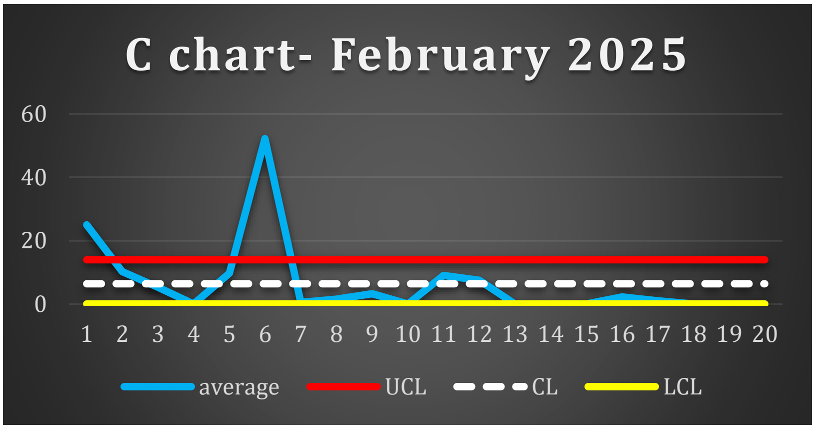

Figure 5 Average of defects percentage for tin rolls for February

It is clear from Figure 6 that the number of defects for samples No. 1 and 6 falls outside the upper limit of control, and this indicates irregularity in the production process, which requires identifying the causes. Table 9 shows the calculation of the c chart and control limits for March 2025. The C-chart control limits indicated a center line (CL) of 6.7, an upper control limit (UCL) of 14.4653, and a lower control limit (LCL) of 0, supporting the evaluation of process stability**.**

Table 9 Control limits and average calculation for March

Defects	A	B	C	D	mean value
OVT	25	16	14	36	22.75
UNT	14	9	12	15	12.5
OVW	1	0	0	0	0.25
EDL	8	5	32	3	12
UNW	18	19	16	14	16.75
TEL	62	38	54	47	50.25
ZZC	0	0	1	2	0.75
RIS	1	4	0	1	1.5

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N.G	1	2	1	2	1.5
TOE	0	0	0	0	0
CRE	8	6	6	3	5.75
ELL	0	2	4	7	3.25
LOS	0	0	0	0	0
FIC	0	0	0	0	0
COB	0	0	0	0	0
BAT	6	3	1	0	2.5
BEE	0	0	4	3	1.75
FIT	0	0	0	0	0
HMF	0	0	0	0	0
ROM	0	0	0	10	2.5

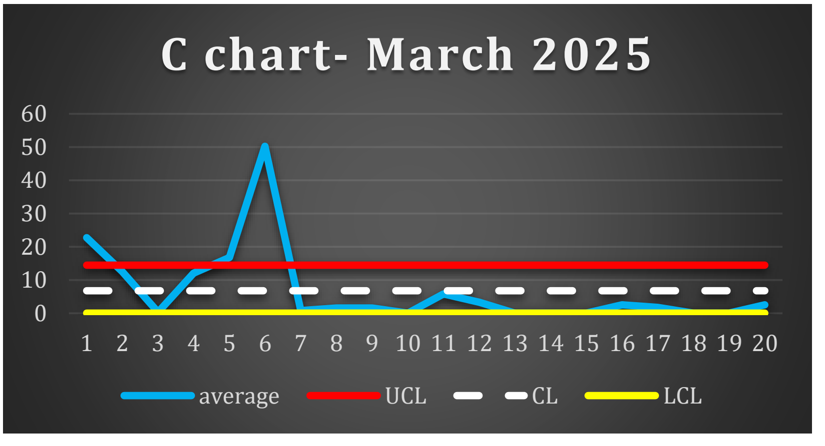

Figure 6 Average of defects percentage for tin rolls for March

It is clear from Figure 7 that the number of defects for samples No. 1, 5 and 6 falls outside the upper limit of control, and this indicates irregularity in the production process, which requires identifying the causes.

Conclusion and Recommendations

This study applied Statistical Quality Control (SQC) techniques including control charts and Pareto analysis to evaluate and monitor the production quality at the Libyan Iron and Steel Company (LISCO), with a particular focus on tin roll manufacturing. The results indicated tin roll production exhibits a high frequency of defects that compromise product quality and process stability.

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Pareto analysis revealed that four dominant defect types Telescope (TEL), Over Thickness (OVT), Under Thickness (UNT), and Cracked Edge (CRE) account for over 80% of the total recorded defects. Control charts further confirmed process instability, with several sample points falling outside the statistical control limits. These out-of-control conditions suggest the presence of assignable causes, such as equipment misalignment, inconsistent raw material properties, or operator-related variations.

The control charts revealed several out-of-control points, particularly in samples 6 and 11 (OVT and TEL respectably) across the three-month period. These deviations may be attributed to irregularities in raw material input, operator handling inconsistencies, or equipment calibration issues. To address these anomalies, corrective actions such as recalibrating rolling equipment, enhancing operator training, and implementing stricter input material checks are recommended.

The observed process instability highlights underlying challenges faced by the company, including limited use of statistical tools, insufficient documentation of defect sources, and lack of real-time monitoring. Compared to similar studies in steel manufacturing. LISCO's current practices show a gap in systematic quality control. While other facilities have successfully reduced defect rates through integrated SPC and Six Sigma frameworks, LISCO still relies on manual inspection and reactive measures. This underscores the need for a proactive, data-driven quality strategy.

Based on the identified out-of-control points and recurring defect categories, the following targeted recommendations are proposed:

1-Prioritize corrective actions on the dominant defect types (TEL, OVT, UNT, CRE), which together account for more than 80% of total defects, by investigating equipment calibration, raw material consistency, and operator practices.

2-Enhance operator and quality staff training with a focus on practical application of SPC tools, root cause analysis, and defect prevention, addressing the lack of systematic statistical methods currently observed at LISCO.

3-Establish preventive maintenance programs for rolling equipment to reduce mechanical deviations that contribute to thickness and edge defects.

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4-Adopt structured root cause analysis methods (e.g., 5 Whys, Fishbone Diagram) specifically for recurring out-of-control conditions, linking corrective actions directly to identified causes.
5-Introduce digital, real-time quality monitoring systems (such as SCADA, Minitab, Power BI) to improve traceability, accelerate decision-making, and reduce reliance on manual inspection.
6-Strengthen and update the ISO 9001 quality management system, embedding continuous improvement and risk-based thinking to address organizational gaps and foster a proactive quality culture.

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