



## Maintenance Optimization in Cold Rolling Mills: A Case Study of LISCO

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### Abstract

This paper presents a comprehensive study on maintenance optimization for the cold rolling mill stands at the Libyan Iron & Steel Company (LISCO). While predictive maintenance and simulation are well-established in global steel industry literature, a significant gap exists in applying these methodologies to the specific context of aging mills in North Africa, which face compounded challenges of legacy infrastructure, spare part shortages, and supply chain instability. This study aims to bridge this gap by developing a context-specific, data-driven framework. Building on a comprehensive analysis of historical production data, internal, external, and planned stoppage records, and key reliability metrics, the study identifies major causes of downtime and evaluates their impact on mill availability and productivity. Statistical reliability analysis and discrete-event simulation modeling are employed to support data-driven maintenance planning and resource allocation. The findings highlight critical areas for targeted maintenance interventions that can significantly reduce unscheduled stoppages and enhance overall equipment effectiveness. The primary contribution lies in the integrated application of Pareto analysis, OEE assessment, and simulation to formulate a prioritized action plan tailored to LISCO's operational realities.

**Keywords:** Cold Rolling, Reliability, Simulation, Arena Software, OEE, Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), Maintenance optimization.

### 1. Introduction

The Libyan Iron & Steel Company (LISCO) is a major steel producer in North Africa, renowned for maintaining high-quality standards and operational efficiency. LISCO Cold Rolling Mill, operational since 1990, produces flat steel products with an annual capacity of around 154,000 tons, processing coils with thickness ranging from 0.4 mm to 4.0 mm and widths up to 1,270 mm, complying with international flat product norms. Ensuring continuous production and reducing downtime remain significant challenges in cold rolling operations, where maintenance plays an essential role. The steel industry's competitive environment pushes mills to adopt maintenance strategies that minimize unexpected failures, increase equipment availability, and optimize production efficiency. Recent advances in predictive maintenance, driven by IoT-based condition monitoring and intelligent diagnostics, have enhanced equipment reliability through early fault detection and process optimization. Moreover, simulation tools such as Arena Software facilitate dynamic modeling of mill operations, enabling maintenance planning without jeopardizing production. Despite these tools, aging machinery and irregular supply chains create ongoing vulnerabilities at LISCO's plant. This study integrates historical production and stoppage data with statistical reliability





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analysis and discrete-event simulation to identify key failure sources and optimize maintenance schedules, aiming to improve mill availability and throughput [1] (LISCO, 2025).

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## 2. Literature Review

In the capital-intensive steel industry, maximizing equipment uptime and reliability is paramount for maintaining productivity and profitability. Traditional time-based or reactive maintenance strategies are increasingly being supplanted by data-driven, predictive approaches that leverage advances in sensor technology and computational analytics. The research applying formal decision-making frameworks to critical systems within the sector, such as hydraulic units, has identified predictive maintenance as the prioritized modern strategy [2]. These modern frameworks aim to anticipate failures before they occur, thereby minimizing unplanned downtime and optimizing maintenance resource allocation.

Predictive maintenance (PdM) models, particularly those utilizing artificial intelligence (AI) and machine learning, represent the current vanguard of this field. By analyzing historical and real-time operational data, these models can identify subtle patterns indicative of incipient faults. For example, in the specific context of rolling mills, researchers have developed a hybrid model combining Adaptive Multivariate Variational Mode Decomposition (AMVMD) with a Multi-channel 1D Convolutional Neural Network (MC1DCNN) to diagnose faults in critical multi-row bearings, addressing the challenge of scarce real-world failure data [3]. Similarly, the integration of digital twin technology has been practically applied to rolling mills, with a defined method for creating an electromechanical system model of a horizontal stand drive to monitor elastic torque and develop control algorithms [4]. Broader surveys of the industry confirm that the transition from data collection to actionable decisions through AI is a central focus of contemporary research and development, as evidenced by comprehensive reviews analyzing its application across global sectors [5]. Overall Equipment Effectiveness (OEE) serves as a benchmark for evaluating manufacturing performance, synthesizing availability, performance, and quality into a single metric. This makes it a critical measure for quantifying the success of maintenance and operational optimization programs. Contemporary research continues to advance OEE through AI-driven predictive models and by integrating real-time operational data for dynamic efficiency assessments, making it more actionable for driving continuous improvement [6]. The effectiveness of any maintenance strategy, whether predictive or preventive, relies on a robust understanding of fundamental reliability metrics [7]. Foundational analyses of Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) remain critical for identifying failure modes and planning interventions. Comparative studies on heavy machinery have evaluated various statistical methods parametric, non-parametric, and semi-parametric for reliability evaluation, highlighting the importance of selecting the correct analytical model based on data characteristics, as demonstrated in a systematic case study of mining dump trucks [8]. Discrete-event simulation serves as a powerful complementary tool, allowing for the modeling of complex system interactions and the testing of different maintenance scenarios without disrupting physical operations, a



capability clearly evidenced in its application to optimize scheduling in steelmaking–continuous casting processes [9]. Despite these significant advancements in methodology, a distinct research gap exists concerning the tailored application of these frameworks to specific industrial contexts, particularly older mills in developing regions. Such facilities often operate with legacy equipment and face unique challenges like spare part shortages and less integrated data systems. The feasibility of modernizing such legacy infrastructure is demonstrated by the recent transformation of a tandem cold mill at Tata Steel Europe in the Netherlands. This holistic program successfully converted a plant built in 1971 from batch to continuous operation, achieving significant gains in capacity, product quality, and process efficiency through a phased upgrade that integrated new mechanical equipment with advanced digital controls and virtual commissioning [10]. This underscores the need for holistic, context-sensitive approaches that adapt general principles to local constraints and existing infrastructure. Therefore, this study addresses this gap by developing a tailored, integrated framework for LISCO. It connects foundational reliability engineering—using statistical analysis of MTBF/MTTR and discrete-event simulation—with the strategic goal of maintenance optimization. By providing a practical, data-driven case study, this research offers a replicable model for improving Overall Equipment Effectiveness (OEE) in industrial settings where the full implementation of advanced AI-driven PdM may be initially constrained.

### 3. Maintenance data collection and Synchronized Operations

#### 3.1 Production and Output Data

Historical production data from 2019 to 2024 for cold rolled coils and non-heat-treated products were compiled as shown in Table 1. Cold rolled sheets production was discontinued since 2016.

Table 1 cold rolling mill products

Year	Cold Rolled Coils (Not Heat Treated) (Tons)	Cold Rolled Coils (Tons)
2019	23,320	10,596
2020	15,591	6,891
2021	13,982	8,928
2022	24,501	11,470
2023	17,524	13,185
2024	40,122	31,040

Significant fluctuations in output were observed, with a remarkable increase recorded in 2024 reaching 71,162 tons total. These variations are attributed to operational challenges, supply chain disruptions, and fluctuating market demands.

#### 3.2 Stoppages Analysis

Detailed stoppage records were categorized into internal, planned, and external causes as presented in Table 2. Total stoppage minutes showed variability, with 2022 recording the highest at 202,106 minutes.

**Table 2** Stoppages of Cold Rolling Mill Plant

Year	Internal Stoppages	Planned Stoppages	External Stoppages	Total Stoppages
2019	80,425 (47.7%)	6,605 (3.9%)	81,630 (48.4%)	168,660
2020	38,876 (21.1%)	5,684 (3.1%)	139,400 (75.8%)	183,960
2021	24,419 (12.5%)	2,638 (1.3%)	169,083 (86.2%)	196,140
2022	51,081 (25.3%)	66,715 (33.0%)	84,310 (41.7%)	202,106
2023	54,906 (32.7%)	5,385 (3.2%)	107,700 (64.1%)	167,991
<b>Total</b>	<b>249,707 (27.9%)</b>	<b>87,027 (9.7%)</b>	<b>582,123 (65.0%)</b>	<b>918,857 (100%)</b>

To gain deeper insights into the operational challenges affecting the cold rolling mill, the internal, external and planned causes over the period from 2019 to 2023. Detailed analysis of these stoppage categories by year is summarized in tables (3-5).

**Table 3** Internal Stoppages of Cold Rolling Mill Plant

Year	Operation	Mechanical	Electrical	Rollers Workshop	Labor	Cranes	Other	Total
2019	2,145 (2.7%)	45,040 (56.0%)	31,384 (39.0%)	195 (0.2%)	0	395 (0.5%)	1,266 (1.6%)	80,425
2020	2,791 (7.2%)	17,510 (45.0%)	15,709 (40.4%)	775 (2.0%)	900 (2.3%)	105 (0.3%)	1,086 (2.8%)	38,876
2021	620 (2.5%)	10,890 (44.6%)	12,169 (49.8%)	170 (0.7%)	0	0	570 (2.3%)	24,419
2022	3,031 (5.9%)	30,438 (59.6%)	17,173 (33.6%)	30 (0.1%)	0	0	410 (0.8%)	51,081
2023	3,031 (5.5%)	25,674 (46.7%)	25,976 (47.3%)	170 (0.3%)	0	0	56 (0.1%)	54,906
<b>Total</b>	<b>11,618 (4.7%)</b>	<b>129,552 (51.9%)</b>	<b>102,411 (41.1%)</b>	<b>1,340 (0.5%)</b>	<b>900 (0.4%)</b>	<b>500 (0.2%)</b>	<b>3,388 (1.4%)</b>	<b>249,707</b>

**Table 4** External Stoppages of Cold Rolling Mill Plant

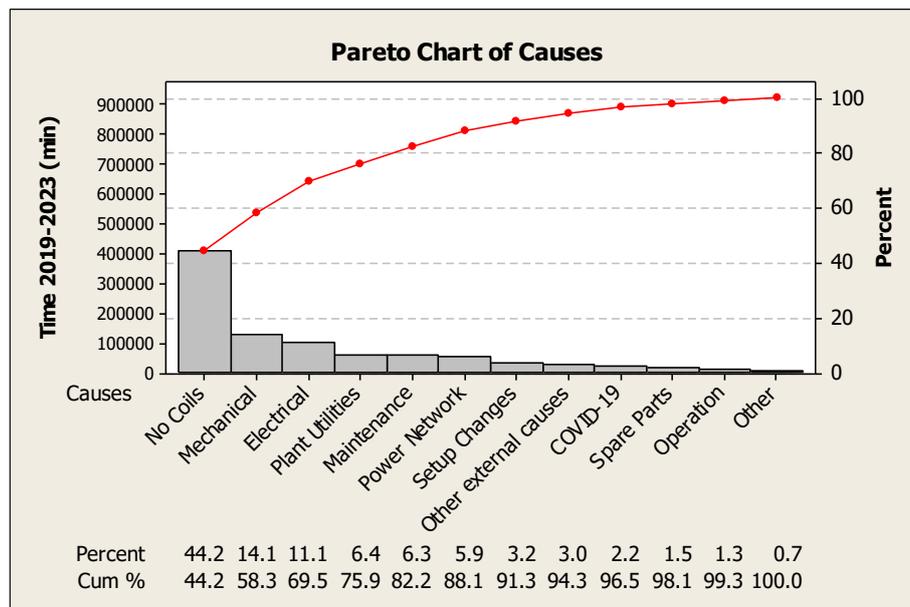
Year	No Coils	Spare Parts	Power Network	Plant Utilities	Other	COVID-19	Total External
2019	60,870 (74.6%)	10,800 (13.2%)	0	9,960 (12.2%)	0	0	81,630
2020	103,150 (74.0%)	0	15,040 (10.8%)	1,110 (0.8%)	0	20,100 (14.4%)	139,400
2021	129,483 (76.6%)	0	39,600 (23.4%)	0	0	0	169,083
2022	52,985 (62.8%)	3,295 (3.9%)	0	130 (0.2%)	27,900 (33.1%)	0	84,310
2023	60,000 (55.7%)	0	0	47,700 (44.3%)	0	0	107,700
<b>Total</b>	<b>406,488 (44.3%)</b>	<b>14,095 (1.5%)</b>	<b>54,640 (6.0%)</b>	<b>58,900 (6.4%)</b>	<b>27,900 (3.0%)</b>	<b>20,100 (2.2%)</b>	<b>582,123</b>

**Table 5** Planned Stoppages of Cold Rolling Mill Plant

Year	Setup Changes	Maintenance	Total Planned
2019	6,605	0	6,605
2020	0	5,684	5,684
2021	2,638	0	2,638
2022	9,115 (13.7%)	57,600 (86.3%)	66,715
2023	5,385	0	5,385
<b>Total</b>	<b>23,743 (27.3%)</b>	<b>63,284 (72.7%)</b>	<b>87,027</b>

Mechanical failures dominate internal downtime at 51.9% (129,552 min) followed closely by electrical issues at 41.1% (102,411 min), together accounting for 93% of all internal stoppages., No Coils availability remains the critical vulnerability at 44.3% (406,488 min) of external downtime, confirming supply chain as the primary production bottleneck. Power network failures peaked dramatically in 2021 (39,600 min, 23.4% of external), exposing infrastructure dependency. 2022 major overhaul (66,715 min) with maintenance dominating at 86.3% (57,600 min) represents industry-standard annual intervention. Other years show critically low planned activity (avg 4,900 min/year), averaging 9.7% of total stoppages.

A Pareto analysis was conducted on the cold rolling mill stoppage data (2019-2023) to identify the vital few causes responsible for 80% of total downtime. The combined dataset of 918,857 minutes was analyzed using Minitab software, with results presented in Figure 1. This approach prioritizes maintenance interventions by ranking causes by total minutes lost, enabling targeted strategies for maximum impact.



**Figure 1:** Pareto Chart of Stoppages Causes for All Years

Coils unavailability emerges as the dominant factor, representing 44.2% of 5-year total, underscoring chronic supply chain vulnerability as the primary production bottleneck. Mechanical and Electrical failures form a consistent 25-45% equipment reliability cluster, peaking in 2019 baseline (45.3% combined). Addressing top-5 causes (No Coils, Mechanical, Electrical, Plant Utilities, Planned Maintenance) yields 82.3% downtime reduction potential, representing optimal resource allocation for cold rolling mill optimization.

### 3.3 Stand Performance Data

Time performance metrics for rolling, hardening/annealing, and slitting/recoiling stands were analyzed, including shift time, production time, stoppage time, machine down time, and operational down time (Tables 6-8). The rolling stand showed machine down time percentages ranging from 55.8% to 83.6%, while recoiling stand exhibited extreme variability with 89% operational down time in 2024. These patterns indicate significant maintenance intervention opportunities.

**Table 6** Rolling Stand Performance Data

Year	Shift time (min)	Prod. Time (min)	Stop. Time (min)	Machine Down Time (min)	Op. Down Time (min)
2019	151,950	47,850	104,100	87,075 (83.6%)	17,025 (16.4%)
2020	52,500	24,290	28,210	15,755 (55.8%)	12,455 (44.2%)
2021	81,300	29,250	52,050	35,480 (68.2%)	16,570 (31.8%)
2022	118,500	48,365	70,135	55,125 (78.6%)	15,010 (21.4%)
2023	63,000	28,845	34,155	28,130 (82.7%)	6,025 (17.3%)
2024	154,800	78,630	76,170	55,925 (73.5%)	20,245 (26.5%)

**Table 7** Hardening/Annealing Stand Performance Data

Year	Shift time (min)	Prod. Time (min)	Stop. Time (min)	Machine Down Time (min)	Other Down Time (min)
2022	36,300	13,005	23,295	10,230 (43.9%)	13,065 (56.1%)
2023	20,400	5,355	15,045	4,750 (31.6%)	10,295 (68.4%)
2024	42,000	17,615	24,385	12,255 (50.3%)	12,130 (49.7%)

**Table 8** Slitting and Recoiling Stand Performance Data

Year	Shift time (min)	Prod. Time (min)	Stop. Time (min)	Machine Down Time (min)	Other Down Time (min)
2022	45,000	30,540	14,460	7,975 (55%)	6,485 (45%)
2023	40,200	21,170	19,030	13,105 (69%)	5,925 (31%)
2024	52,800	21,375	31,425	3,470 (11%)	27,955 (89%)

### 3.4 Overall Equipment Effectiveness (OEE) Estimation

OEE was calculated for 2019-2023, combining availability, performance, and quality metrics (Table 9). Values ranged from 5.1% to 11.3%, with availability and performance consistently below 50%. High quality rates above 97% indicate effective quality control, while low availability underscores the need for maintenance optimization targeting frequent downtimes.

**Table 9** OEE estimates of Cold Rolling Mill

Year	Availability (%)	Performance (%)	Quality (%)	OEE (%)
2019	22.1	52.30	97.7	11.30
2020	15.3	50.20	97.7	7.50
2021	12.0	56.00	97.9	6.60
2022	19.3	54.30	97.9	10.30
2023	21.6	40.60	97.7	8.60

### 3.5 Reliability Analysis

The Time Between Failures (TBF) and Time to Repair (TTR) data were derived from comprehensive failure and maintenance logs obtained from the LISCO Cold Rolling Mill maintenance department for the period 2019-2023. Raw data included daily shift reports, maintenance work orders, and equipment downtime records. These records were compiled, cleaned, and processed to calculate consecutive operational and downtime periods for each mill stand. TTR was calculated as the elapsed time from failure onset to operational restoration, while TBF was calculated as the operational time between the end of one repair and the start of the next failure. Table (10) provides a sample of the processed data for the Rolling stand.

**Table 10** Sample Processed Data for Rolling Stand TBF & TTR Calculation

Date	Shift Time (min)	Planned Maintenance (min)	Machine Down Time (min)	Operation Time (min)	TTR (min)	TBF (min)
01/01/2019	900	0	40	860	-	-
02/01/2019	900	0	150	750	150	805
03/01/2019	900	0	60	840	60	795
06/01/2019	900	0	900	0	20700	420
06/02/2019	900	0	525	375	525	187.5
07/02/2019	900	0	720	180	720	277.5

An example of the descriptive statistics and formal goodness-of-fit test results from Minitab for Recoiling machine TBF is presented in table (11)

**Table 11** Descriptive Statistics and Goodness-of-Fit Tests for Recoiling Stand TBF

Statistic	Value	Distribution	AD Statistic**	p-value	LRT p-value***
N	72	Normal	3.781	<0.005	-
Mean	1528.8 min	Lognormal	1.469	<0.005	-
StDev	1420.49 min	3-Parameter Lognormal	0.489	*	0.003
Median	1048.2 min	Exponential	<b>0.545</b>	<b>0.436</b>	-
Min	15 min	2-Parameter Exponential	0.562	> <b>0.250</b>	1.000
Max	7020 min	Weibull	<b>0.482</b>	<b>0.232</b>	-
Skewness	1.60	3-Parameter Weibull	0.487	0.234	1.000
Kurtosis	2.68	Gamma	<b>0.478</b>	> <b>0.250</b>	-
		3-Parameter Gamma	0.478	*	1.000

Notes: \* Indicates the test is not valid for this distribution.

\*\* AD test stands for Anderson-Darling goodness-of-fit test

\*\*\* LRT p value stands for The Likelihood Ratio Test for three-parameter distributions

Time Between Failures (TBF) and Time to Repair (TTR) statistics were determined for each stand (Table 12). Recoiling stand demonstrated superior reliability with 1528.8 min average TBF, while rolling stand had the lowest TBF (613 min) but longest TTR (461.7 min).

**Table 12** Statistical Metrics of Cold Rolling Machines

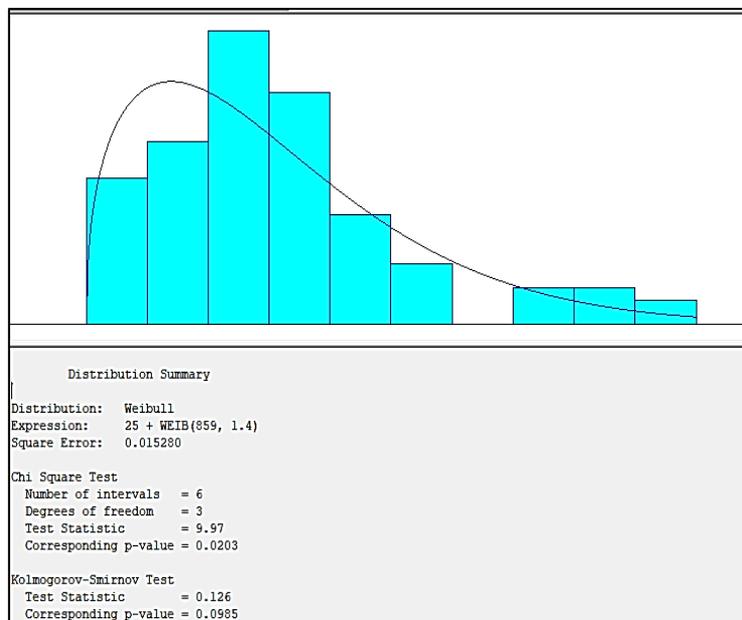
Metric	Rolling Machine	Hardening Machine	Recoiling Machine
N	602	92	72
Avg TBF	613 min	819 min	1528.8 min
Avg TTR	461.7 min	296 min	336.3 min

A statistical analysis was conducted using both Minitab statistical software and Arena's Input Analyzer (template within Arena Software) to determine the optimal probability distributions for Time Between Failures (TBF) and Time to Repair (TTR) for each machine as shown in table (13). Minitab's distribution identification and Anderson-Darling (AD) goodness-of-fit tests were cross-validated with Arena Input Analyzer's suite of tests (Sum of Squared Errors/SSE, Chi-Square, and Kolmogorov-Smirnov/K-S). This approach ensured robustness in distribution selection for the discrete-event simulation model.

**Table 13** Validated Distribution Selection for Simulation Modeling

Machine Parameter	Selected Distribution	Minitab Validation	Input Analyzer Validation	Final Expression for Arena
Rolling TBF	Empirical	No adequate parametric fit	Empirical distribution fitted to 24 intervals.	CONT (0.000, 8, 0.173, 214, ..., 0.998, 4952)
Rolling TTR	Empirical	No adequate parametric fit	Empirical distribution fitted to 20 intervals.	CONT (0.000, 10, 0.957, 1044.5, ..., 0.998, 20700)
HardeningTBF	Weibull	WeibullAD=2.472, LRT P=0.962	Weibull. SSE=0.0153; K-S p=0.0985.	25 + WEIB (859, 1.4)
Hardening TTR	Weibull	Weibull. AD=0.747, LRT P=0.054	Weibull. SSE=0.0040; Chi-Sq p=0.409; K-S p>0.15.	10 + WEIB (254, 0.819)
RecoilingTBF	Exponential	Exponential AD=0.545, p=0.436.	Exponential. SSE=0.00199; Chi-Sq p=0.56; K-S p>0.15.	5 + EXPO (1520)
Recoiling TTR	Weibull	Weibull. AD=0.562, LRT P=0.151	Weibull. SSE=0.00381; Chi-Sq p=0.593; K-S p>0.15.	10 + WEIB (210, 0.618)

Figure 2 shows the Input Analyzer output showing the Weibull distribution fit for the hardening machine's TBF data, while Figure 3 displays the corresponding Minitab probability plot, both confirming the statistical adequacy of the selected Weibull distribution for simulation modeling.



**Figure 2:** TBF best-fit distributions using Input analyzer of Hardening Machine

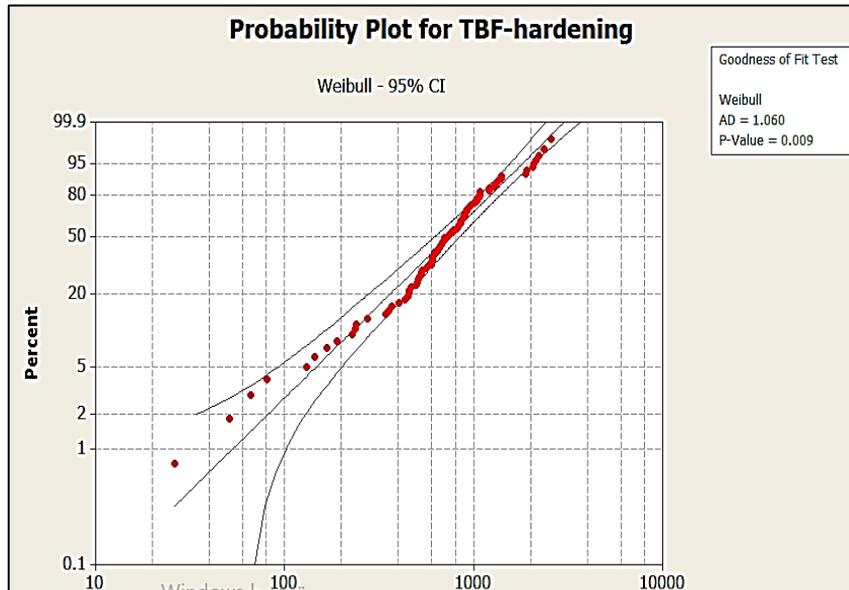


Figure 3: TBF Probability Plot of the Hardening machine using Minitab Software.

#### 4. Results and Discussion

The analysis reveals that LISCO's cold rolling mill is constrained by chronic supply chain disruptions and equipment unreliability. Coils unavailability accounts for 44.2% of total downtime (2019-2023), followed by Mechanical (14.1%), Electrical (11.1%), Plant Utilities (6.4%), and Planned Maintenance (6.3%) stoppages. These five causes meet the Pareto threshold, directly linking to production volatility. Stand-level analysis identifies the Rolling stand as the critical bottleneck (MTBF: 748.70 min), validating equipment priorities and explaining the low OEE availability (<50%) despite high quality. Simulation modeling corroborates this, with results closely matching historical data and confirming the Rolling stand's disproportionate impact. The integrated Pareto-OEE-simulation framework reduces complexity to five actionable priorities, capturing 82.3% of improvement potential. This dictates that the Rolling stand warrants immediate focus, while Recoiling's reliability may allow capacity assessment. External factors like utilities require root-cause analysis beyond direct plant control.

#### 5. Conclusion

This study analyzed LISCO's cold rolling mill, identifying five causes for 82.3% of downtime and the Rolling stand as the critical bottleneck. The primary contribution is a diagnostic framework that integrates Pareto analysis, OEE, and simulation to prioritize maintenance in legacy settings, offering a replicable model for targeting availability losses. This foundation enables logical extensions, such as implementing condition monitoring tools on prioritized



equipment to validate predictions, and developing real-time data dashboards to transform analytical insights into dynamic, actionable operational intelligence.

## References

- [1] LISCO. (2025). Cold rolling mill operational and maintenance records (2019–2024) [Unpublished raw data]. Libyan Iron and Steel Company.
- [2] Torre, N. M., Salomon, V. A., & Marins, F. A. (2025). Maintenance Strategy Selection of Hydraulic Systems In The Steel Industry: A Design Science Research
- [3] Zhao, C., Sun, J., Lin, S., & Peng, Y. (2021). Fault diagnosis method for rolling mill multi-row bearings based on AMVMD and MC1DCNN under variable working conditions. *Sensors*, \*21\*(16), 5494. <https://doi.org/10.3390/s21165494>
- [4] Gasiyarov, V. R., Radionov, A. A., Loginov, B. M., Zinchenko, M. A., Gasiyarova, O. A., Karandaev, A. S., & Khrumshin, V. R. (2023). Method for defining parameters of electromechanical system model as part of digital twin of rolling mill. *Journal of Manufacturing and Materials Processing*, 7(5), 183. <https://doi.org/10.3390/jmmp7050183>
- [5] Rashid, A. B., & Kausik, M. A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, 7, 100277. <https://doi.org/10.1016/j.hybadv.2024.100277>
- [6] Zhou, D., Wang, J., Pan, E., Chen, H., & Chen, Z. (2025). Multi-dimensional fusion prediction and sensitivity analysis for overall equipment effectiveness based on temporal hybrid perception network. *Computers & Industrial Engineering*, 111369. <https://doi.org/10.1016/j.cie.2025.111369>
- [7] Nyman, D., & Mountjoy, B. (2021). *Maintenance and operational reliability: 24 essential building blocks*. Industrial Press.
- [8] Moniri-Morad, A., & Sattarvand, J. (2023). A comparative study between the system reliability evaluation methods: case study of mining dump trucks. *Journal of Engineering and Applied Science*, 70(1), 103. <https://doi.org/10.1186/s44147-023-00272-y>
- [9] Shao, X., Fang, W., Wang, J., Zhang, Q., & Chen, Z. (2024). Simulation Model of a Steelmaking–Continuous Casting Process Based on Dynamic-Operation Rules. *Materials*, 17(17), 4352. <https://doi.org/10.3390/ma17174352>
- [10] SMS group. (2025, July 10). Modernization of Tata Steel's tandem cold mill: From batch operation to high-productivity continuous rolling in two shutdowns. <https://www.sms-group.com/insights/all-insights/from-batch-operation-to-high-productivity-continuous-rolling-in-two-shutdowns>

