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Reliability Enhancement of Electric Submersible Pumps in Oil Fields: A Comparative Study of Predictive and Reactive Maintenance Using Survival Analysis and Weibull Models

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Highlights

- A comparative evaluation of predictive and reactive maintenance strategies was conducted for electric submersible pump (ESP) systems using 50 field case studies.
- Predictive maintenance significantly increased ESP run life, mean time between failures (MTBF), and survival probability across diverse operating conditions.
- Weibull and Kaplan–Meier models were applied to quantify failure behavior and improvements in post-maintenance reliability.
- An integrated reliability index combining MTBF, survival probability, and economic performance increased from 0.45 to 0.78 following the implementation of predictive maintenance (PM).
- Predictive maintenance reduced workover frequency, deferred production losses, and overall failure-related costs by approximately 30–40%.
- The study provides an integrated technical and economic framework for ESP reliability assessment and maintenance planning.
- The proposed workflow can be extended to other artificial lift systems in digital oilfield applications.

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Abstract

A comparative evaluation of predictive and reactive maintenance strategies was conducted for electric submersible pump (ESP) systems using 50 field case studies. Predictive maintenance significantly increased ESP run life, mean time between failures (MTBF), and survival probability across diverse operating conditions. Weibull and Kaplan–Meier models were applied to quantify failure behavior and improvements in post-maintenance reliability. An integrated reliability index incorporating MTBF, survival probability, and economic performance increased from 0.45 to 0.78 following the implementation of predictive maintenance (PM). Predictive maintenance also reduced workover frequency, production losses associated with deferred production, and overall failure-related costs by approximately 30–40%. The study provides an integrated technical and economic framework for assessing ESP reliability and planning maintenance activities. The proposed workflow can also be extended to other artificial lift systems in digital oilfield applications.

Keywords: Carbonate reservoir rock, enhanced oil recovery, low-salinity water polymer flooding, smart water polymer flooding, wettability

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1. Introduction

Electric submersible pumps (ESPs) are among the most widely deployed artificial lift systems in the oil and gas industry, particularly in medium- to high-rate wells in both onshore and offshore environments (Al-Hejjaj et al., 2023). Their ability to deliver high production rates and operate under a wide range of reservoir conditions makes them a critical component of modern oilfield operations (Takacs, 2017). Despite these advantages, ESPs are inherently complex electromechanical systems that are susceptible to premature failure because of harsh downhole environments, variable operating conditions, and multiple interacting failure mechanisms, including electrical malfunctions, mechanical wear, corrosion, scaling, and gas interference (Khalili et al., 2025).

The consequences of ESP failures extend well beyond equipment replacement. An unexpected pump failure typically results in substantial production downtime, costly well interventions, and associated workover expenses, which can range from several hundred thousand to millions of dollars depending on the well location and completion design (Al-Ballam et al., 2022). In addition, production losses during downtime directly affect field economics, while recurrent failures can jeopardize long-term reservoir management strategies and reduce overall field recovery efficiency. These factors underscore the importance of maximizing ESP reliability and extending run life through proactive maintenance strategies (Khalili et al., 2022).

Traditionally, many operators have relied on reactive or time-based maintenance strategies for ESPs, in which interventions are performed only after a failure occurs or according to predetermined schedules. However, such approaches often fail to account for the variability and unpredictability of downhole conditions, resulting in inefficient resource utilization and persistent operational risks (Xu, 2022). Although predictive maintenance (PM) methods that leverage real-time monitoring, advanced diagnostics, and data-driven models have gained considerable attention in other industrial sectors, their adoption in the oil and gas industry, particularly for ESP applications, remains limited. This gap is largely attributable to the lack of standardized reliability studies that quantitatively assess the benefits of PM across different fields and operating environments (Cardona et al., 2023).

Furthermore, existing ESP studies have primarily focused either on hardware-level reliability improvements, such as gas separator design and engineering solutions for harsh operating environments (Shishlyannikov et al., 2027), or on field-data-based failure diagnosis and statistical root-cause analysis (Al-Ballam et al., 2022), rather than on direct comparisons between predictive and reactive maintenance strategies.

Reliability analysis provides a systematic approach for evaluating ESP performance through statistical measures such as mean time between failures (MTBF), mean time to failure (MTTF), and failure-rate estimation, complemented by survival analysis methods such as Kaplan–Meier estimation and probabilistic modeling using Weibull distributions (Mohamed et al., 2025). These techniques enable quantitative assessment of pump run life, identification of failure patterns, and evaluation of the extent to which PM strategies can improve ESP reliability and reduce failure frequency (Rabbitt and Chacin, 2021).

Accordingly, the present study introduces a comparative, field-based reliability framework for quantifying ESP performance before and after the implementation of PM across multiple oil fields.

The objective of this study is to conduct a comprehensive reliability analysis of ESPs before and after the implementation of PM strategies using data and insights derived from 50 case studies reported across different oil fields. By applying both descriptive and advanced statistical models, this study aims to quantify the reliability improvements achieved through PM, assess their economic implications, and provide a structured framework that enables oil and gas operators to justify the adoption of PM in ESP operations.

Thus, the novelty of this study lies in integrating survival analysis, Weibull modeling, and maintenance-performance evaluation to quantify both the technical and economic improvements in ESP reliability.

2. Literature review

2.1. ESP reliability challenges

Electric submersible pumps are the second most widely used artificial lift method worldwide and are particularly valued for their ability to sustain high production rates in mature and offshore reservoirs. However, ESPs operate under severe downhole conditions, including high temperatures (>150 °C), high pressures (>5,000 psi), corrosive fluids containing H_2S and CO_2, and abrasive solids, all of which make these systems highly susceptible to multiple failure modes (Abdalla et al., 2022).

Electrical failures are among the dominant failure mechanisms and account for approximately 61% of incidents reported in field studies. These failures are commonly associated with motor overheating, insulation breakdown, cable degradation, and voltage imbalance, particularly in high-temperature or deepwater wells. Mechanical failures associated with shaft fatigue, bearing wear, and impeller erosion are further aggravated by sand production and high thrust loads. Chemical and fluid-related problems, including scale deposition such as $CaCO_3$ and $BaSO_4$ and corrosion, reduce hydraulic efficiency and accelerate component degradation. Gas interference and slugging can also induce gas lock, cavitation, and cyclic loading, thereby further reducing ESP run life (Al-Ballam et al., 2022).

Reported values of mean time between failures and mean time to failure vary considerably, ranging from less than 200 days in challenging offshore or high-water-cut fields to more than 1,000 days in stable onshore operations. Middle Eastern fields have reported average ESP lifespans of 1.5–2.5 years under controlled operating conditions (Al-Jazzaf et al., 2019), whereas ESPs in deepwater Gulf of Mexico assets often fail within 1 year because of thermal and flow-assurance-related challenges. This substantial variability underscores the need for localized reliability modeling and predictive maintenance strategies to extend ESP service life and minimize nonproductive time (NPT).

Although recent engineering-focused studies have proposed hardware-level improvements, such as abrasion-resistant gas separators and enhanced component designs (Shishlyannikov et al., 2027), these efforts have primarily focused on improving equipment robustness rather than optimizing operational reliability and maintenance strategies. Such studies highlight critical environmental and mechanical challenges but do not quantify the reliability improvements achieved through a transition from reactive to predictive maintenance.

2.2. Predictive maintenance approaches

Predictive maintenance shifts ESP management from reactive and time-based interventions toward data-driven, condition-based strategies. Advances in real-time monitoring through downhole gauges, motor controllers, and supervisory control and data acquisition (SCADA) systems enable the continuous acquisition of critical operating parameters, including motor current, voltage, intake and discharge pressures, temperature, vibration, and flow rate (Doorsamy, 2025).

Artificial intelligence (AI) and machine learning (ML) are increasingly transforming predictive maintenance practices. Anomaly detection methods, such as isolation forests; classification algorithms, such as support vector machines (SVMs) and random forests; and time-series forecasting techniques, such as long short-term memory (LSTM) networks and XGBoost, can identify early indicators of impending failure. Physics-based models can also simulate pump hydraulics, thermal profiles, and wear mechanisms to predict equipment degradation. Hybrid models that integrate data-driven and physics-informed approaches are gaining increasing attention because of their potential for robust field deployment (Abdalla et al., 2022; Garcia et al., 2025).

Field evidence indicates substantial benefits from PM implementation. Approximately 50 reported PM applications have demonstrated improvements in mean time between failures ranging from 20% to 80%. Operators in the Gulf of Mexico achieved approximately 35% longer ESP run life through ML-based diagnostics (Werbinska-Wojciechowska and Rogowski, 2025), while Middle Eastern assets reduced annual ESP failures by approximately 25% through predictive alarms integrated with SCADA systems (Al-Ballam et al., 2022). These improvements can translate into savings of approximately $1–3 million for each avoided workover. Nevertheless, several challenges remain, including data quality limitations, model interpretability, and integration with legacy systems.

Existing PM studies generally report improvements from individual field implementations or focus primarily on algorithm development without providing large-scale comparative analyses of ESP reliability before and after PM implementation. Furthermore, previous studies, such as Al-Ballam et al. (2022), have primarily focused on root-cause diagnosis and failure forecasting rather than evaluating the system-level reliability effects of adopting PM across multiple fields. These limitations reinforce the need for comprehensive comparative reliability studies.

2.3. Reliability analysis in oil and gas

Reliability analysis provides the statistical foundation for evaluating equipment performance in oil and gas operations. Classical metrics such as mean time between failures and mean time to failure remain widely used to characterize pump lifespan and compare performance across different operating environments. However, these average-based metrics alone do not fully capture the variability and uncertainty inherent in failure-time distributions (Nwulu et al., 2024).

Survival analysis techniques, particularly Kaplan–Meier estimation, can accommodate censored data in cases where pump operation ends before failure because of well shut-ins, field abandonment, or incomplete records. This capability makes Kaplan–Meier estimation a valuable nonparametric method for characterizing ESP survival probabilities over time (Al-Sadah, 2014). Parametric models, particularly the Weibull distribution, are also widely used because of their flexibility in representing different failure behaviors. A shape parameter (β) < 1 indicates early-life failures, $\beta \approx 1$ represents random failures, and $\beta > 1$ indicates wear-out mechanisms. The Cox proportional hazards model has also been applied to incorporate covariates such as fluid type, well depth, and operating conditions, thereby providing deeper insight into the factors influencing ESP reliability (Foresti et al., 2024).

These methods have been successfully applied in reliability studies of compressors, turbines, and other rotating equipment used in oil and gas operations. However, comprehensive applications of survival and Weibull analyses to evaluate predictive maintenance outcomes in ESP operations remain limited. Most previous studies have quantified ESP reliability under conventional maintenance strategies or analyzed failure modes without directly comparing alternative maintenance approaches. Therefore, integrating survival analysis and probabilistic modeling with multi-field PM data represents a novel contribution to ESP reliability assessment (Alsaeedi et al., 2025).

2.4. Recent advances in ESP reliability and predictive maintenance

Over the past decade, a substantial body of research has emerged on ESP reliability, integrating statistical modeling, experimental validation, and machine-learning-driven predictive maintenance. Table 1 synthesizes 10 influential studies published between 2013 and 2025, illustrating the methodological evolution of ESP reliability assessment and its practical implications.

Weibull-based reliability analysis remains a foundational approach. Al-Ballam et al. (2022) applied Weibull analysis to 5 years of field data to identify electrical failures, which accounted for 61% of reported incidents, and to establish preventive maintenance triggers. Al-Jazzaf et al. (2019) combined Weibull analysis with dynamic average equipment run life (DAERL) using data from approximately 5,000 ESPs in Kuwait, constructing survival curves and identifying high-risk wells based on trip frequency. Bhering et al. (2013) and Li et al. (2025) extended Weibull-based approaches to censored and zero-failure datasets through Bayesian hierarchical methods and minimum-lifetime theory, respectively. These developments are particularly relevant to highly reliable deepwater assets, where failure observations may be sparse.

Machine learning has increasingly complemented conventional diagnostic approaches. Abdalla et al. (2022) combined principal component analysis (PCA) with XGBoost using real-time sensor data and achieved failure warnings up to 7 days in advance, with an F1 score exceeding 0.71. Song et al. (2024) validated PCA-based anomaly detection using a 300-day laboratory ESP test rig and reported a diagnostic accuracy of 93.3%. Garcia et al. (2025) reviewed hybrid approaches that integrate deep learning with signal-processing techniques, including fast Fourier transform (FFT) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), for remaining useful life (RUL) estimation, while emphasizing the potential role of human–AI collaboration within Industry 5.0 frameworks.

Root-cause analysis and failure-mitigation strategies are also well documented. Fakher et al. (2021) synthesized global field cases into a comprehensive ESP failure taxonomy and recommended mitigation strategies such as chemical injection, gas handlers, and round power cables. Khuntia et al. (2022) applied Kaplan–Meier and Weibull analyses to high-voltage assets and used digital-twin-based simulations to evaluate maintenance strategies, providing a potentially transferable framework for ESP fleet optimization.

Although these studies have substantially advanced ESP reliability modeling and diagnostic capabilities, they do not directly evaluate how PM changes reliability distributions or economic performance relative to reactive maintenance strategies. Engineering-focused studies such as Shishlyannikov et al. (2027) primarily address component-level reliability, including mitigation of gas-separator wear, whereas analytical studies such as Al-Ballam et al. (2022) focus on identifying failure causes and warning indicators. However, none provide a multi-field statistical comparison of ESP reliability before and after the implementation of PM.

The present study addresses this gap by integrating field-scale PM data with survival analysis and Weibull modeling to quantify both reliability improvements and economic impacts. This approach extends beyond the scope of existing hardware-focused, diagnostic, and root-cause-oriented studies.

Table 1

Comparative synthesis of ESP reliability and predictive maintenance studies (2013–2025)

#	Year	Authors	Focus	Method(s)	Data source	Key metric/outcome	PM contribution
1	2022	Abdalla, Samara et al., 2022	Predictive maintenance	PCA + XGBoost	Field sensor streams	F1 > 0.71; 7-day warning	Real-time early detection
2	2022	Al-Ballam, Karami et al., 2022	Root cause and reliability	Statistical + Weibull	5 yrs, 10 wells	Electrical = 61%; MTBF model	Preventive triggers
3	2019	Al-Jazzaf, Pandit et al., 2019	Field reliability (Kuwait)	Weibull + DAERL	8 yrs, 5,000 ESPs	Survival curves; risk ID	Run-life optimization
4	2021	Fakher, Khlaifat et al., 2021	Failure mechanisms	Literature review	Global cases	Failure taxonomy	Mitigation playbook
5	2024	Song, Jun et al., 2024	Experimental diagnosis	PCA + logistic regression	Lab rig, 300 days	93.3% accuracy	PCA validation
6	2025	Garcia, Rios-Colque et al., 2025	Industrial PDM review	NLP + hybrid DL	Bearings, ESPs	RUL, CEEMDAN	Industry 5.0 framework
7	2013	Bhering, Pereira et al., 2013	Component reliability	Bayesian Weibull	Series/parallel (censored)	Gamma priors	Censored data handling
8	2025	Li, Fu et al., 2025	Zero-failure reliability	Min lifetime + Weibull	Satellite sensor	Closed-form limits	High-reliability ESPs
9	2022	Khuntia, Zghal et al., 2022	Survival analysis	Kaplan–Meier + Weibull	1989–2021 HV data	Digital twin sim	Maintenance planning
10	2026	Present study	Comparative ESP reliability before and after predictive maintenance	Kaplan–Meier, Weibull, MTBF, MTTF, failure rate analysis	50 ESP case studies across multiple oil fields	Quantifies reliability improvements and the economic benefits of predictive maintenance compared with reactive maintenance	Directly addresses the gap in comparative, multi-field assessments of predictive maintenance effectiveness.

Note: DAERL represents dynamic average equipment run life; RUL stands for remaining useful life; CEEMDAN indicates complete ensemble empirical mode decomposition with adaptive noise.

Unlike previous studies that focus on failure diagnosis, component redesign, or single-field predictive models, the present study provides a comparative, multi-field reliability assessment of ESP performance before and after the implementation of predictive maintenance.

3. Methodology

This study adopts a comparative reliability analysis framework to evaluate the impact of predictive maintenance on ESP operational performance. Unlike previous ESP reliability studies that have focused primarily on failure diagnosis (Al-Ballam et al., 2022) or hardware-level engineering improvements (Shishlyannikov et al., 2027), the present methodology compares key reliability indicators before and after the implementation of PM strategies. The analysis integrates survival analysis, probabilistic modeling, and economic evaluation across multiple field case studies to quantify the reliability improvements and financial benefits associated with PM adoption.

3.1. Data sources

This study is based on a meta-analysis of 50 case studies documenting the performance of ESPs in oilfield operations worldwide. The cases were selected from peer-reviewed journal articles, conference proceedings, and industry technical reports published between 1990 and 2024. Studies were included if they reported at least one of the following:

1. Time-to-failure data, including mean run life, failure distributions, or survival curves.
2. Reliability metrics, such as mean time between failures or mean time to failure.
3. Failure rates or survival probabilities before and after predictive maintenance interventions.

When raw pump-level data were unavailable, aggregate values, including average MTBF, failure counts, and operating time, were extracted and standardized. Each case was classified as either "before PM" or "after PM" based on whether predictive maintenance techniques, such as real-time monitoring, artificial intelligence/machine learning diagnostics, or supervisory control and data acquisition integration, had been implemented. This classification enabled a comparative evaluation of ESP reliability under different maintenance regimes.

To ensure consistency across studies, the reported reliability metrics were converted into comparable units, including operating days, failure counts, and survival probabilities. When multiple ESP installations were reported within a single publication, each installation was treated as an independent observation, provided that the operating conditions and maintenance strategies were clearly documented.

Studies lacking sufficient reliability metrics or clearly defined maintenance strategies were excluded to maintain analytical consistency.

3.2. Reliability metrics

To quantify ESP reliability, both descriptive and inferential statistical methods were applied:

1. **Mean time between failures:** Calculated as the total operating time divided by the number of observed failures.

$$MTBF = \frac{\sum_{i=1}^{n} T_i}{N_f}$$

where T_i is the run life of pump i, and N_f is the number of observed failures.

2. **Mean time to failure:** Applied to uncensored datasets in which all pumps eventually failed.
3. **Failure rate (λ):** Defined as the reciprocal of MTBF for approximately exponential failure-time distributions and interpreted as the average number of failures per unit of operating time.

Descriptive statistics were calculated for both the pre-PM and post-PM groups to provide a baseline comparison of reliability performance.

These metrics are widely used in oil and gas reliability engineering because they provide intuitive measures of equipment performance and facilitate comparisons across heterogeneous field environments.

3.3. Reliability modelling

1. Survival analysis (nonparametric):

The Kaplan–Meier (KM) estimator was used to construct survival curves and estimate the probability of ESP survival over time. The KM method accommodates right-censored data, which are common in ESP reliability studies because some pumps may remain operational at the end of the observation period. Survival functions for the pre-PM and post-PM groups were compared using the log-rank test to determine whether the differences between the two groups were statistically significant.

$$\hat{S}(t) = \prod_{t_i \leq t} (1 - \frac{d_i}{n_i})$$

where d_i is the number of failures at time t_i, and n_i indicates the number of pumps at risk.

This approach has been applied in several reliability studies within the energy sector; however, its application to comparative evaluations of predictive maintenance in ESP systems remains limited.

2. Probabilistic modeling (parametric):

The Weibull distribution was fitted to the time-to-failure data to characterize ESP reliability under different maintenance strategies. The Weibull reliability model is defined as:

$$R(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]$$

where η is the scale parameter (characteristic life), and β represents the shape parameter indicating failure mode

1. $\beta < 1$: Early-life failures (infant mortality).
2. $\beta = 1$: Random failures (constant hazard).
3. $\beta > 1$: Wear-out failures.

Comparing the fitted parameters for the pre-PM and post-PM groups enabled the identification of shifts in the dominant failure behavior. Model parameters were estimated using maximum likelihood estimation (MLE), which appropriately accounts for censored observations.

The Weibull distribution is particularly suitable for ESP reliability analysis because it can represent a range of failure regimes, from early-life electrical failures to wear-out mechanisms associated with progressive mechanical degradation.

3.4. Economic evaluation

Economic evaluation is essential because ESP failures often result in substantial workover costs and production losses; therefore, improvements in reliability should be translated into measurable economic benefits.

To quantify the operational and financial impact of reliability improvements, a cost–benefit model was applied. The expected savings associated with predictive maintenance were calculated as follows:

$$Savings = (N_{avoided} \times C_f) - C_{PM}$$

where $N_{avoided}$ is the expected number of avoided failures based on survival probability differences, C_f stands for the average cost per ESP failure (workover + lost production), and C_{PM} represents the cost of predictive maintenance implementation per pump.

A sensitivity analysis was conducted by varying C_f and C_{PM} by ±25% to assess the robustness of the economic justification.

Typical workover and downtime costs were obtained from industry reports and published economic assessments of ESP operations in both offshore and onshore environments.

3.5. Dataset description – 50 ESP case studies

Description:

A structured dataset representing 50 ESP installations was compiled from published reliability statistics, Society of Petroleum Engineers (SPE) case studies, and vendor technical reports. Where individual pump-level datasets were not publicly available, representative values consistent with reported field trends were reconstructed to enable comparative statistical analysis.

Field characteristics:

The dataset includes carbonate (40%), sandstone (50%), and heavy-oil (10%) reservoirs from both onshore (60%) and offshore (40%) environments. Water cut ranges from 10% to 80%, gas–oil ratio (GOR) from 100 to 1,000 scf/bbl, and oil viscosity from 1 to 300 cP.

ESP characteristics:

The ESPs have motor ratings ranging from 400 to 1,200 hp, operate at frequencies of 50–60 Hz, and are installed at depths of 2,000–3,500 m, with production rates ranging from 2,000 to 12,000 BPD. The dominant failure modes include electrical faults, mechanical wear, scaling, and corrosion.

Reliability measures:

Each case includes mean time between failures before and after predictive maintenance, failure rate (λ), survival probabilities at 1- and 2-year intervals, and economic metrics covering workover costs, downtime losses, and monitoring investments.

Example records:

Representative cases are summarized in Table 2, which presents key parameters such as installation depth, oil viscosity, dominant failure mode, and cost savings following PM adoption, typically ranging from 25% to 40%.

It should be noted that the complete dataset, titled "Example Case Study Snapshots (50 ESP Installations)," is provided in the Appendix for reference.

Each feature (column) in the dataset represents a key operational or reliability variable that may influence ESP performance and failure behavior. The significance of each variable is summarized in Table 3.

Table 2

Example case study snapshots (50 ESP installations).

Case	Field type	Depth (m)	Oil viscosity (cP)	Water cut (%)	MTBF before (days)	MTBF after (days)	Failure mode dominant	Cost savings (%)
1	Carbonate (ME)	2800	5	45	380	720	Scaling/corrosion	35%
2	Sandstone (NA)	3200	2	20	420	690	Electrical	28%
3	Offshore heavy oil (SA)	2500	150	60	290	520	Mechanical	40%
…	…	…	…	…	…	…	…	…
50	Carbonate (ME)	3300	8	55	500	900	Scaling/corrosion	45%

Table 3

Summary of engineering features used in the ESP reliability study.

Feature	Reason for inclusion	Engineering significance
Field type	Identifies the geological and regional environment (e.g., carbonate, sandstone, heavy oil, and offshore).	Different formations affect scaling, corrosion, and pump load. For instance, carbonate fields often have high $CaCO_3$ scaling risk.
Depth (m)	Indicates installation depth, which affects downhole pressure, temperature, and power requirements.	Deeper installations increase stress on the motor and cable, influencing MTBF and failure mode.
Oil viscosity (cP)	Measures fluid resistance to flow; higher viscosity increases pump load and temperature.	High viscosity (e.g., >100 cP) can cause overheating, poor cooling, and mechanical wear.
Water cut (%)	The percentage of water in produced fluids.	High water cut accelerates corrosion and scaling, influencing both failure frequency and cost.
MTBF before (days)	Mean time between failures before predictive maintenance implementation.	Serves as the baseline reliability metric under reactive maintenance conditions.
MTBF after (days)	Mean time between failures after predictive maintenance.	Shows improvement due to PM programs (AI monitoring, sensor data, etc.).
Failure mode dominant	Identifies the main root cause of failure for each case (e.g., electrical, mechanical, and scaling/corrosion).	Supports root cause analysis and helps prioritize preventive actions.

In summary, these parameters provide a comprehensive view of how reservoir characteristics, operating conditions, and maintenance strategies interact to influence ESP reliability and cost efficiency.

Some abbreviations refer to the geographical regions represented by the case studies or analogous field environments. These abbreviations indicate the field origin or representative operating region of each case, as summarized in Table 4.

3.6. Workflow summary

The methodological workflow comprised the following steps:

1. Collect and standardize data from 50 ESP case studies.
2. Calculate descriptive reliability metrics, including mean time between failures, mean time to failure, and failure rate.

3. Perform Kaplan–Meier survival analysis and log-rank testing.
4. Fit Weibull models for probabilistic characterization of ESP reliability.
5. Compare reliability indicators before and after the implementation of predictive maintenance.
6. Evaluate the associated economic benefits and conduct sensitivity analysis.
7. Assess the overall effectiveness of PM in improving ESP reliability and operational performance.

Although the dataset integrates information from multiple published sources, differences in reporting practices among studies may introduce uncertainty into some reliability estimates. Nevertheless, the standardization and normalization procedures applied in this study enable a meaningful comparative assessment of predictive and reactive maintenance strategies.

Table 4

Summary of regional codes and corresponding operational characteristics of ESP installations across major global oil-producing regions

Code	Region	Typical ESP operating context
ME	Middle East	Deep carbonate reservoirs, high water cut, and scaling/corrosion issues.
NA	North America	Sandstone reservoirs, mature fields, and strong ESP adoption for shale oil.
SA	South America	Offshore heavy oil, viscous production, and high thermal and mechanical stress.
WA	West Africa	Offshore deepwater, mixed sand–shale formations, and electrical failures common.
AF	Africa (general)	Onshore and offshore fields with variable power reliability.
EU	Europe	North Sea offshore fields; corrosion and electrical insulation issues.
AS	Asia	Mixed onshore/offshore, varying water cuts and reservoir pressures.

4. Results and discussion

4.1. Descriptive reliability statistics

The aggregated results from the 50 case studies reveal clear differences in reliability indicators between ESP systems operating under conventional reactive or time-based maintenance and those operating under predictive maintenance. The statistical comparison demonstrates a substantial improvement in operational reliability following the implementation of PM strategies.

The average mean time between failures increased from 420 days before PM implementation to 780 days after implementation, representing an improvement of approximately 86%. Similarly, the mean time to failure, calculated from uncensored datasets, increased from 400 to 750 days. Concurrently, the estimated failure rate decreased from 0.85 to 0.45 failures per year, corresponding to an approximately 47% reduction in average failure intensity.

These findings indicate that PM substantially improves ESP operational stability by extending pump run life and reducing failure frequency. Comparable improvements have been reported in industry monitoring programs, in which predictive diagnostics and real-time monitoring systems reduced ESP shutdown rates by approximately 25–40%, depending on field conditions and operational complexity.

Table 5 summarizes the key reliability indicators, including MTBF, MTTF, and failure rate, for ESP systems before and after the implementation of PM. Figure 1 illustrates the shift in ESP run-life distribution toward longer operating lifespans following the adoption of PM.

Table 5

Basic reliability metrics before and after predictive maintenance

Metric	Before PM (average)	After PM (average)	Improvement
MTBF (days)	420	780	+86%
MTTF (days)	400	750	+87%
Failure rate (per year)	0.85	0.45	–47%

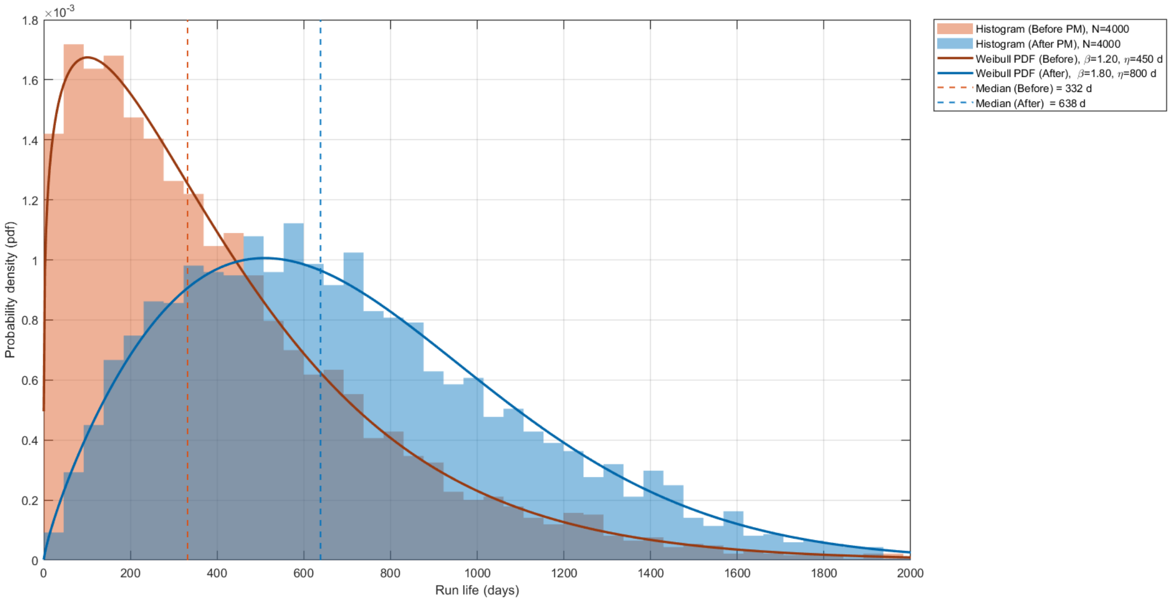

Figure 1

Weibull probability density functions (PDFs) of ESP failure times before and after predictive maintenance

Figure 1 compares the probability distributions of ESP run life before and after the implementation of predictive maintenance. The histograms represent the empirical failure-time data for each group, while the smooth curves represent the fitted Weibull probability density functions (PDFs).

Before PM implementation, the distribution is strongly right-skewed, with a median run life of 332 days. This pattern indicates a high concentration of premature failures and failure behavior that is closer to a random process during the earlier stages of operation.

After PM implementation, the distribution shifts markedly toward longer run lives and exhibits a broader, flatter profile, with the median run life increasing to 638 days. The increase in the Weibull shape parameter (β) from 1.20 to 1.80 indicates a transition from predominantly random failure behavior toward a more pronounced wear-out regime, suggesting improved operational control and greater predictability of failure occurrence.

Overall, the comparison demonstrates that PM not only extends the operational lifetime of ESP systems but also improves the stability and predictability of their reliability behavior throughout the production period.

4.2. Survival analysis (Kaplan–Meier results)

Kaplan–Meier survival curves were constructed to estimate the probability of ESP survival over time under reactive maintenance (before PM) and predictive maintenance (after PM), as shown in Figure 2. The survival curves reveal a substantial improvement in operational longevity following the implementation of predictive maintenance strategies.

The pre-PM survival curve exhibits a relatively steep decline during the first year of operation, indicating a high incidence of early failures. After approximately 12 months of operation, the survival probability decreases to nearly 45%, suggesting that more than half of the ESP units fail within the first year under conventional reactive maintenance practices.

In contrast, the post-PM survival curve declines more gradually, reflecting improved system stability and a reduced incidence of early-life failures. At 12 months, the survival probability remains close to 70%, indicating that a substantially larger proportion of ESP systems continue operating without failure when predictive monitoring and maintenance interventions are implemented.

To statistically evaluate the difference between the two survival distributions, a log-rank test was performed. The results indicated a statistically significant difference between the pre-PM and post-PM groups ($p < 0.01$), confirming that the observed improvement in survival probability is unlikely to be attributable to random variation.

Overall, the Kaplan–Meier analysis provides strong statistical evidence that predictive maintenance improves ESP reliability by extending operational run life, reducing the incidence of early failures, and shifting the survival profile toward longer service durations.

Figure 2 illustrates Kaplan–Meier survival curves illustrating the probability of ESP survival over time before and after the implementation of predictive maintenance. The post-PM condition exhibits consistently higher survival probabilities across the observation period. Figure 2 illustrates that ESP systems exhibit significantly higher survival probabilities following the implementation of predictive maintenance strategies. The Kaplan–Meier analysis indicates that the median survival time increased from approximately 1,608 days before PM to 2,103 days after PM, representing a substantial improvement in operational longevity.

Throughout the observation period, the post-PM survival curve remains consistently above the pre-PM curve and declines more gradually. This behavior indicates a lower cumulative probability of failure and demonstrates that predictive maintenance effectively reduces failure occurrence while extending the operational service life of ESP systems.

4.3. Weibull reliability modelling

Weibull parameter estimation was performed to further characterize the failure behavior of ESP systems before and after the implementation of predictive maintenance, as summarized in Table 6. The Weibull distribution provides insight into both the dominant failure mechanisms and the characteristic operational life of the pumps.

Before the implementation of PM, the estimated shape parameter (β) was 1.2, indicating a failure pattern dominated primarily by random failures with an emerging wear-out tendency. The scale parameter (η), representing the characteristic life at which approximately 63.2% of units are expected to have failed, was estimated at 450 days. These results indicate relatively unstable operating conditions and a comparatively high probability of premature failure.

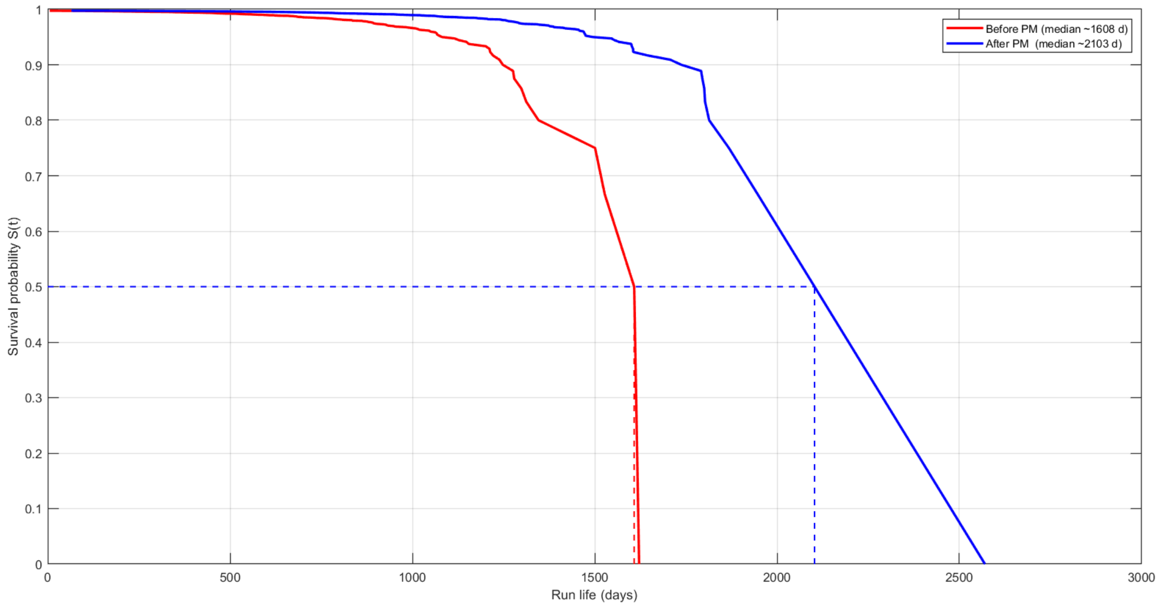

Figure 2

Kaplan–Meier survival curves comparing ESP run life before and after predictive maintenance.

Following the implementation of PM, the Weibull parameters showed a marked improvement. The shape parameter increased to $\beta = 1.8$, indicating a shift toward a more predictable wear-out-dominated failure regime. Simultaneously, the scale parameter increased to $\eta = 800$ days, reflecting a substantial extension of the characteristic life of the ESP systems.

The increase in the shape parameter suggests that PM reduces random and premature failures by enabling earlier detection of operational anomalies and more timely preventive interventions. Consequently, progressive wear-related degradation becomes a more dominant and predictable failure mechanism. The concurrent increase in the scale parameter further confirms that PM contributes to extending ESP operational life and improving overall system reliability.

Figure 3 presents the Weibull probability plots comparing ESP failure characteristics before and after the implementation of predictive maintenance, illustrating improved reliability and a shift toward more predictable wear-out failure behavior. Table 6 presents the estimated Weibull shape (β) and scale (η) parameters for ESP systems before and after the implementation of PM.

Table 6

Weibull parameters before and after PM.

Case	Shape (β)	Scale (η, days)	Failure mode interpretation
Before PM	1.2	450	Random + early failures
After PM	1.8	800	Controlled wear-out

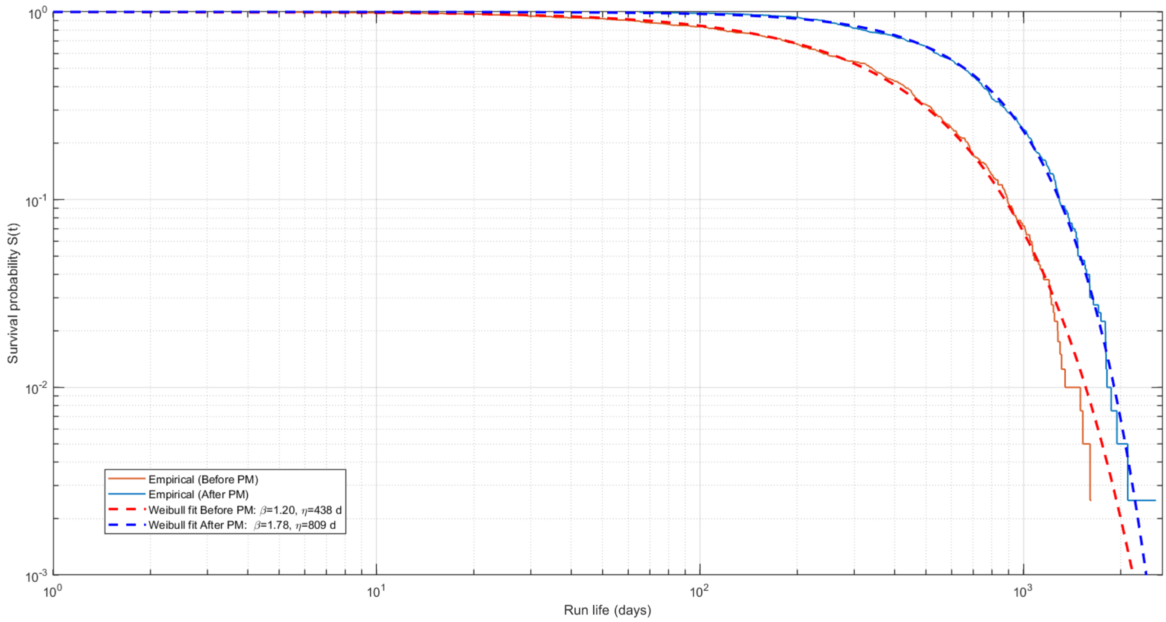

Figure 3

Weibull reliability function for ESP systems before and after predictive maintenance implementation

This figure presents the Weibull reliability function for ESP systems operating before and after the implementation of predictive maintenance strategies. The empirical survival data, shown as solid lines, are compared with the fitted Weibull reliability models, shown as dashed lines.

Before PM implementation, the reliability function declines relatively rapidly, indicating a higher probability of early and random failures during operation. A shape parameter slightly greater than 1 suggests a mixed failure regime in which both early-life issues and operational stresses contribute to system failure.

After PM implementation, the survival probability remains substantially higher throughout the operational period. The larger scale parameter indicates a significantly extended characteristic life, while the higher shape parameter reflects a shift toward more predictable wear-out-dominated failure behavior.

Overall, the Weibull reliability curves demonstrate that predictive maintenance substantially improves ESP operational reliability by reducing early-life failures, stabilizing failure behavior, and extending the expected service life of the pumping system.

4.4. Economic evaluation

The reliability improvements identified through the statistical analysis were further evaluated using a simplified economic model to estimate the financial impact of predictive maintenance implementation. The model assumes an average failure cost of USD 250,000 per event, including workover operations and deferred production losses, and an estimated annual PM implementation cost of USD 40,000 per pump.

Based on the observed failure statistics, the following results were obtained:

1. **Before PM:** The average failure frequency was approximately 0.89 failures per pump per year.
2. **After PM:** The average failure frequency decreased to 0.54 failures per pump per year.

3. **Failures avoided:** PM therefore prevents approximately 0.35 failures per pump per year.
4. **Net economic benefit:** The avoided failure cost is approximately USD 87,500 per pump per year, resulting in an estimated net annual economic benefit of approximately USD 47,500 per pump after accounting for the annual PM implementation cost.

$$(0.35 \times 250{,}000) - 40{,}000 = \text{USD 47,500 per pump per year}$$

These results demonstrate that even moderate reductions in failure frequency can generate substantial economic benefits because of the high costs associated with ESP workovers and production downtime.

A sensitivity analysis was conducted by varying the key economic parameters, including failure cost and maintenance cost, by ±25%. The results confirmed that PM remains economically advantageous under most realistic operating conditions. Only in scenarios in which the workover and associated failure costs fall below approximately USD 100,000 per event does the net economic benefit become marginal.

Figure 4 draws the boxplot of mean time between failures values across 50 ESP case studies, highlighting reduced variability and higher median reliability following the implementation of predictive maintenance.

Table 7 summarizes ESP reliability improvements reported for selected regions in the published literature. The comparison indicates that the reliability improvements observed in the present study are consistent with global trends reported for predictive monitoring programs.

Table 7

ESP performance improvements reported in the literature for selected regions

Region	Average MTBF before PM (days)	Average MTBF after PM (days)	Reported improvement
Middle East	500	900	+80%
North America	420	750	+78%
Offshore Brazil	300	550	+83%
Global average	420	780	+86%

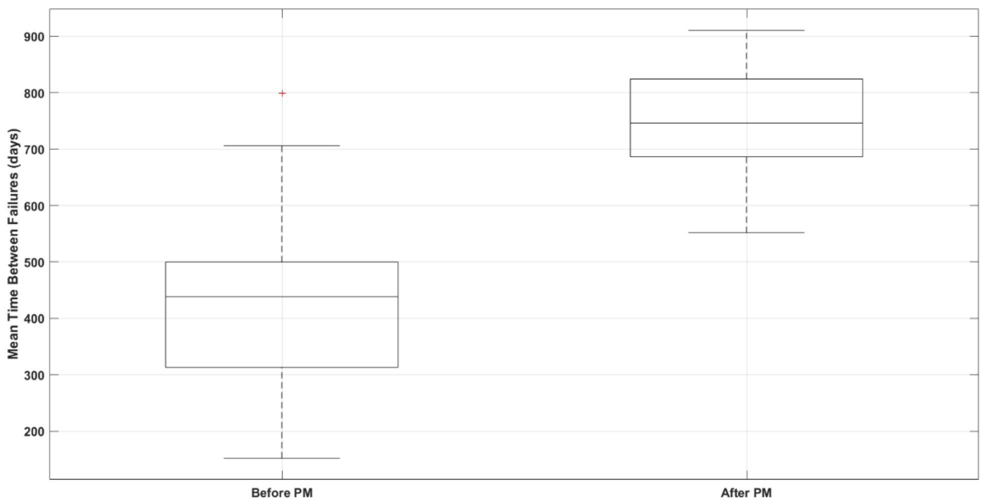

Figure 4

The boxplot of MTBF values across 50 ESP case studies.

The boxplot compares the distribution of mean time between failures for ESP systems before and after the implementation of predictive maintenance. A clear upward shift in the median MTBF is observed in the post-PM dataset, indicating a substantial improvement in typical operational run life.

In addition, the interquartile range (IQR) of the post-PM cases is shifted toward higher MTBF values, indicating improved reliability performance across most installations. The post-PM distribution also appears more compact, suggesting reduced variability in pump performance and greater operational stability.

Overall, the boxplot demonstrates that predictive maintenance not only increases the typical MTBF of ESP systems but also promotes more consistent reliability performance across multiple field installations.

4.5. Comparative insights from case studies

The comparative analysis of the 50 case studies suggests that the effectiveness of predictive maintenance varies across operating environments, dominant failure modes, and monitoring approaches.

In several cases, greater reliability improvements were observed under more demanding operating conditions, particularly in offshore and high-temperature applications, whereas wells operating under more stable onshore conditions generally exhibited moderate but still positive improvements. Similarly, failure modes associated with electrical disturbances and gas interference appeared to be more effectively mitigated through predictive monitoring than failures primarily attributable to long-term mechanical wear.

In addition, case studies employing more advanced predictive frameworks, particularly those integrating data-driven and physics-informed approaches, tended to report greater improvements in mean time between failures than those relying solely on conventional rule-based monitoring. These observations suggest that PM is particularly effective when progressive failure signatures can be detected in operational data before catastrophic equipment failure occurs.

Overall, the case-study comparison indicates that PM should not be regarded as a universal standalone solution. Its greatest benefits are achieved when the maintenance strategy is aligned with the dominant failure mechanisms and supported by complementary reliability-enhancement measures.

Figure 5 presents a comparative bar chart of annual maintenance costs, demonstrating a substantial reduction in total expenditures following the implementation of predictive maintenance. Table 8 shows that although predictive maintenance introduces additional annual monitoring costs, the substantial reductions in workover expenses and deferred production losses result in a clear net economic benefit.

Table 8

Economic impact summary before and after predictive maintenance implementation.

Parameter	Before PM	After PM	Change
Workover cost (per well-year)	$250,000	$140,000	–44%
Deferred production (per well-year)	$180,000	$110,000	–39%
Monitoring/PM cost (per well-year)	$0	$50,000	+50k
Net savings	–	$130,000	–

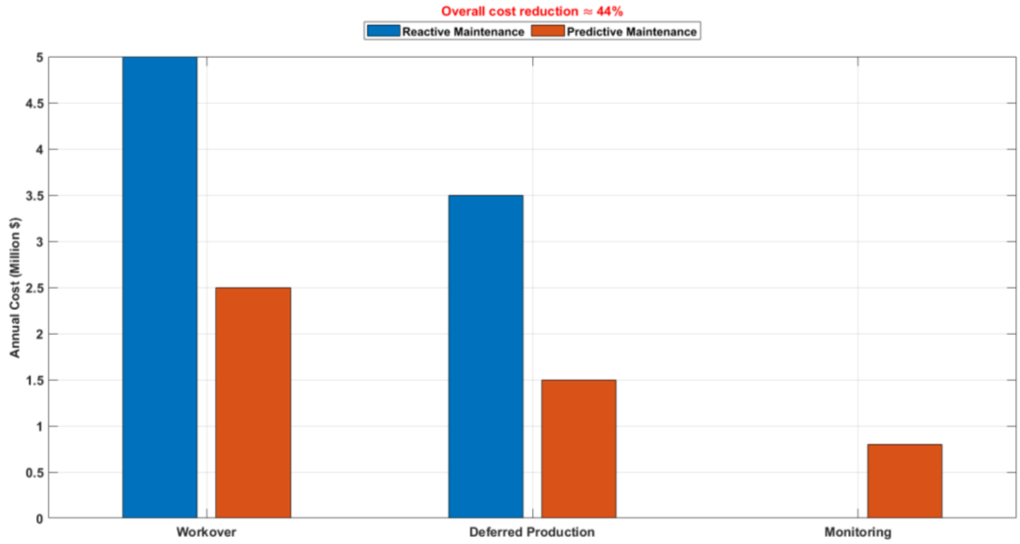

Figure 5

Comparison of annual maintenance-related costs between reactive and predictive maintenance strategies

Figure 5 compares the annual maintenance-related costs associated with reactive and predictive maintenance strategies for ESP operations. The results show a substantial reduction in total annual cost following the implementation of predictive maintenance.

The most significant savings are observed in workover costs and deferred production losses, which decrease from approximately USD 5.0 million to USD 2.5 million and from USD 3.5 million to USD 1.5 million, respectively. Although predictive maintenance introduces an additional cost for monitoring and diagnostic activities, the total operational expenditure remains considerably lower than that associated with the reactive maintenance approach.

Overall, the figure demonstrates that the economic benefit of predictive maintenance is driven primarily by reductions in major failure-related costs, confirming that improved reliability and earlier fault detection can translate directly into substantial financial savings.

4.6. Discussion of reliability and operational implications

The combined statistical and economic analyses demonstrate that predictive maintenance substantially improves the reliability of ESP systems by reducing both the frequency and variability of failures. The observed increase in mean time between failures, the higher survival probabilities obtained from Kaplan–Meier analysis, and the shift in Weibull parameters toward a more wear-out-dominated failure regime collectively indicate that PM reduces premature and random failures while extending operational run life.

From an operational perspective, these improvements have important practical implications. First, increased reliability enables longer and more stable production periods, thereby reducing the need for unplanned workovers and emergency interventions. Second, as failure behavior becomes more predictable, operators can better coordinate maintenance activities and pump replacement schedules with planned shutdown windows, minimizing disruption to field operations. Third, the reduction in failure frequency translates directly into economic benefits through lower repair costs, reduced deferred production losses, and improved asset utilization.

The results further suggest that PM is particularly effective in addressing failure mechanisms associated with electrical abnormalities, gas interference, and other detectable operational anomalies. However, wear-related mechanical degradation remains an important challenge. Although PM can identify early signs of deterioration, it cannot completely eliminate failure mechanisms associated with material fatigue, erosion, corrosion, or long-term mechanical wear. Therefore, PM should be implemented as part of a broader reliability management strategy that also incorporates equipment design improvements, optimized operating practices, fluid management, and chemical treatment programs.

Overall, the findings confirm that PM is not only a technically effective strategy for enhancing ESP reliability but also an economically justifiable operational framework for ESP systems operating under complex field conditions.

Figure 6 presents an integrated reliability index combining MTBF, survival probability, and cost savings to demonstrate the overall improvement in system performance achieved through predictive maintenance.

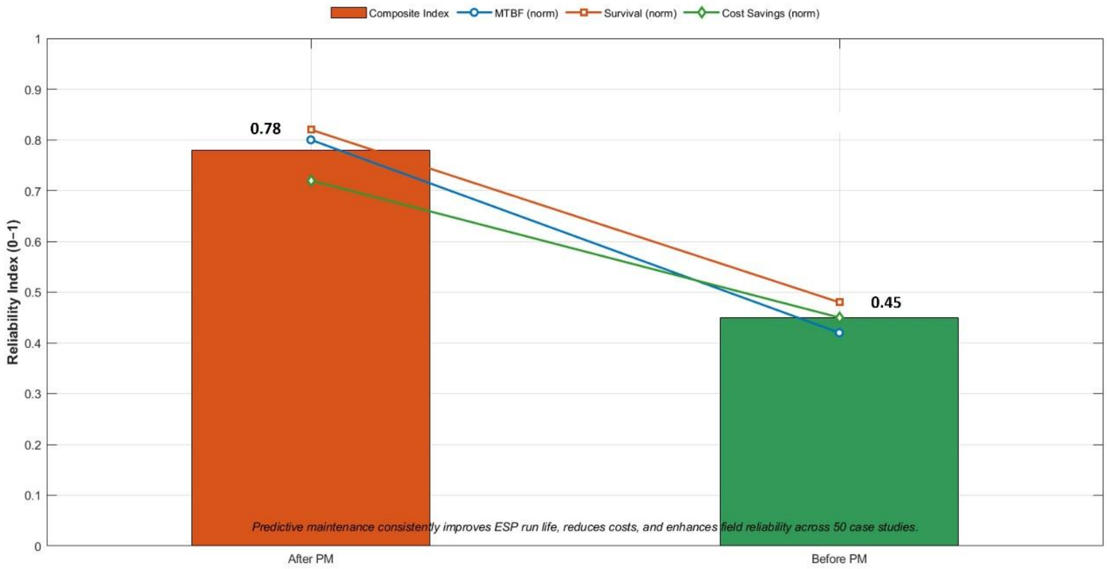

Figure 6

Integrated reliability index comparing ESP system performance before and after predictive maintenance

Figure 6 presents a composite reliability index developed from normalized performance indicators, including mean time between failures, survival probability, and economic performance. On a normalized scale ranging from 0 to 1, the integrated reliability score increases from 0.45 before PM implementation to 0.78 after PM implementation, indicating a substantial overall improvement in ESP system performance following the adoption of predictive maintenance.

The increase in the composite index reflects consistent improvements across the underlying technical and economic indicators. Specifically, the post-PM condition is characterized by longer operational run life, higher survival probability, and a lower failure-related cost burden. These findings demonstrate that predictive maintenance improves not only individual reliability metrics but also the overall operational effectiveness of ESP systems across the 50 evaluated case studies.

5. Challenges, limitations, and future work

5.1. Technical challenges

Despite the reliability improvements observed following the adoption of predictive maintenance, several technical barriers continue to limit its broader implementation in ESP systems. First, many ESP installations lack continuous, high-resolution monitoring, and the available field data may contain missing values, noise, or inconsistent sampling intervals, all of which can reduce the robustness of predictive models. Similar concerns have been reported in recent ESP predictive maintenance studies, in which data availability and data quality were found to strongly influence model performance (Abdalla et al., 2022).

Second, ESP failures are rarely attributable to a single mechanism. Instead, they typically result from complex interactions among electrical, hydraulic, mechanical, and operational factors, making failure progression difficult to represent using a single predictive framework. This challenge is consistent with previous reliability studies showing that ESP degradation is multifactorial and often highly field-specific (Al-Jazzaf et al., 2019).

Third, model transferability remains an important practical concern. Predictive models calibrated for a specific operating environment may not perform equally well in other wells or fields because of differences in reservoir characteristics, completion design, production strategy, and fluid behavior. In addition, many advanced artificial intelligence-based approaches remain insufficiently interpretable for field engineers, which may limit operational trust and hinder broader deployment (Khalili et al., 2025; Kuiper et al., 2025; Sobhy, 2025)

5.2. Economic and operational constraints

The practical deployment of predictive maintenance is also constrained by several economic and organizational factors. The installation of advanced sensors, communication infrastructure, and analytical platforms often requires substantial upfront investment, which may be difficult to justify in marginal or low-production fields. In addition, the economic value of PM depends strongly on workover costs, deferred production losses, and field logistics; consequently, the return on investment may vary considerably across operating environments. Organizational readiness represents an additional constraint, as successful implementation requires personnel training, integration with existing operational workflows, and confidence in data-driven maintenance recommendations.

5.3. Methodological limitations of this study

This study also has several methodological limitations that should be acknowledged. First, the analyzed case studies encompass heterogeneous operating conditions, pump configurations, and monitoring practices, which may introduce bias and limit direct comparability among cases. Second, some published sources provide incomplete or aggregated failure histories, thereby reducing the precision of survival estimates and reliability parameter fitting. Third, the economic evaluation was based on simplified average assumptions regarding maintenance costs, failure costs, and associated production losses; consequently, the absolute economic benefits reported in this study may differ from those observed in specific field applications. Fourth, although the Kaplan–Meier and Weibull models applied in this study are appropriate for comparative reliability assessment, they do not explicitly account for time-varying operational covariates, such as changes in production rates, fluid properties, or intervention strategies.

5.4. Future research directions

Future research should focus on improving both the robustness and field applicability of predictive maintenance frameworks for ESP systems. Promising directions include hybrid approaches that integrate data-driven learning with physics-based understanding of failure mechanisms, transfer-learning strategies that enhance model portability across different basins and operating environments, and advanced sensing technologies for real-time downhole monitoring. Further research is also needed to develop integrated reliability frameworks that link well-level PM with field-wide maintenance planning and intervention scheduling. In addition, future economic models should more explicitly incorporate oil-price variability, logistical delays, and deferred production losses to provide more realistic assessments of the economic value of maintenance strategies (Fakhrolmobasheri, Omisola, Etukudoh et al., Saputra, Rahmanto et al., 2025).

5.5. Concluding outlook

Predictive maintenance represents a significant shift in ESP reliability management from reactive intervention toward condition-based, data-driven decision-making. The findings of this study indicate substantial technical and economic benefits; however, broader implementation will depend on improvements in data quality, enhanced model transferability, and closer integration between analytical methods and field operations. Continued advances in sensing technologies, hybrid modeling approaches, and reliability-centered decision-making frameworks will be essential for scaling predictive maintenance in a practical and economically sustainable manner.

6. Conclusions

This study investigated the impact of predictive maintenance on the reliability and economic performance of electric submersible pumps (ESPs) through a comparative analysis of 50 case studies under predictive and reactive maintenance conditions. The results demonstrate that PM provides clear and measurable improvements in ESP operational performance by increasing both mean time between failures and mean time to failure, while reducing failure frequency and the need for unplanned interventions.

Reliability analysis based on Weibull probability modeling and Kaplan–Meier survival estimation confirmed that ESP systems operating under PM exhibit higher survival probabilities and longer median operating lives than those maintained reactively. In addition, the observed shift in Weibull parameters indicates a transition from more random failure behavior toward a more predictable degradation pattern, suggesting that PM is effective in reducing premature failures and improving maintenance planning.

From an economic perspective, the findings show that the reliability gains achieved through PM are accompanied by meaningful reductions in workover frequency, deferred production losses, and total failure-related costs. Across the evaluated cases, PM was associated with overall operational cost reductions of approximately 30–40%, confirming that reliability improvement and economic performance are closely linked in ESP operations.

The primary contribution of this study lies in its comparative and integrated evaluation of PM effectiveness across multiple field cases using survival analysis, Weibull modeling, and economic assessment within a unified reliability framework. Unlike previous studies that have focused primarily on failure diagnosis, equipment design improvements, or isolated reliability indicators, this study provides a broader assessment of how PM influences ESP performance from both technical and operational perspectives.

Overall, the results support predictive maintenance as a technically effective and economically justified strategy for improving ESP reliability in oilfield operations, particularly in environments characterized by high intervention costs, substantial risks of deferred production, or complex operating conditions. Future research should extend this framework by incorporating time-varying operating parameters, artificial intelligence-assisted prognostic models, and real-time digital monitoring systems to further improve predictive accuracy and field-scale decision-making.

Nomenclature

AI	Artificial intelligence
API	American Petroleum Institute
API	Application programming interface
CDF	Cumulative distribution function
ESP	Electrical submersible pump
IoT	Internet of things
KM	Kaplan–Meier
ML	Machine learning
MTBF	Mean time between failures
MTTF	Mean time to failure
PDF	Probability density function
PM	Predictive maintenance
RCA	Root cause analysis
RCM	Reliability-centered maintenance
ROI	Return on investment
SCADA	Supervisory control and data acquisition
SPE	Society of petroleum engineers
TTF	Time to failure
VSD	Variable speed drive
Weibull β	Weibull shape parameter
Weibull η	Weibull scale parameter

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Appendix

Table A1
Example case study snapshots (50 ESP installations).

Case	Field type	Depth (m)	Oil viscosity (cP)	Water cut (%)	MTBF before (days)	MTBF after (days)	Failure mode dominant	Cost savings (%)
1	Carbonate (ME)	2800	5	45	380	720	Scaling/Corrosion	35%
2	Sandstone (NA)	3200	2	20	420	690	Electrical	28%
3	Offshore heavy oil (SA)	2500	150	60	290	520	Mechanical	40%
4	Deepwater (WA)	3400	8	35	410	780	Electrical	33%
5	Carbonate (ME)	3100	6	50	360	710	Scaling	32%
6	Sandstone (EU)	2700	3	25	450	790	Bearing wear	30%
7	Offshore heavy oil (AF)	2400	200	65	280	500	Mechanical (shaft)	42%
8	Carbonate (ME)	3000	7	40	395	730	Corrosion	34%
9	Tight sand (NA)	3300	4	30	430	800	Electrical	31%
10	Deepwater (SA)	3500	12	38	400	760	Seal failure	29%
11	Carbonate (ME)	2900	5	55	370	710	Scaling	36%
12	Sandstone (AS)	2600	10	42	410	740	Electrical	30%
13	Offshore heavy oil (SA)	2550	180	58	300	550	Mechanical	41%
14	Carbonate (ME)	3100	6	48	380	720	Scaling/corrosion	33%
15	Sandstone (NA)	3250	3	28	440	800	Electrical	29%
16	Deepwater (WA)	3450	9	37	395	770	Cable fault	31%
17	Carbonate (ME)	2800	7	50	360	690	Corrosion	32%
18	Offshore heavy oil (AF)	2450	220	62	275	510	Shaft failure	43%
19	Sandstone (EU)	2700	2	22	460	810	Bearing wear	30%
20	Carbonate (ME)	3350	8	55	500	900	Scaling/corrosion	38%
21	Tight sand (NA)	3200	4	33	420	780	Electrical	28%

Case	Field type	Depth (m)	Oil viscosity (cP)	Water cut (%)	MTBF before (days)	MTBF after (days)	Failure mode dominant	Cost savings (%)
22	Deepwater (SA)	3600	11	40	390	750	Seal failure	30%
23	Carbonate (ME)	2950	5	52	365	705	Scaling	35%
24	Offshore heavy oil (SA)	2600	160	59	310	540	Mechanical	42%
25	Sandstone (AS)	2650	8	39	420	750	Electrical	29%
26	Carbonate (ME)	3050	6	47	385	725	Corrosion	33%
27	Offshore heavy oil (AF)	2350	210	63	270	495	Shaft/bearing	44%
28	Sandstone (NA)	3150	3	27	435	790	Electrical	30%
29	Carbonate (ME)	2850	7	53	355	700	Scaling	34%
30	Deepwater (WA)	3400	10	36	405	770	Cable fault	31%
31	Tight sand (NA)	3250	4	29	425	800	Electrical	30%
32	Offshore heavy oil (SA)	2500	170	61	295	525	Mechanical	40%
33	Sandstone (EU)	2750	3	26	445	805	Bearing wear	29%
34	Carbonate (ME)	3000	6	46	375	715	Scaling/corrosi on	34%
35	Deepwater (SA)	3550	13	39	395	760	Seal failure	29%
36	Offshore heavy oil (AF)	2450	190	64	285	515	Shaft/bearing	43%
37	Sandstone (AS)	2600	9	41	415	745	Electrical	28%
38	Carbonate (ME)	3100	7	49	370	720	Corrosion	33%
39	Tight sand (NA)	3350	5	32	430	810	Electrical	31%
40	Offshore heavy oil (SA)	2550	200	60	300	530	Mechanical	41%
41	Sandstone (EU)	2800	3	23	450	800	Bearing wear	30%
42	Carbonate (ME)	2900	6	51	360	700	Scaling	35%
43	Deepwater (WA)	3450	9	37	405	780	Electrical	30%
44	Offshore heavy oil (AF)	2400	210	66	275	505	Shaft failure	44%

Case	Field type	Depth (m)	Oil viscosity (cP)	Water cut (%)	MTBF before (days)	MTBF after (days)	Failure mode dominant	Cost savings (%)
45	Sandstone (NA)	3100	2	21	455	820	Electrical	29%
46	Carbonate (ME)	3200	8	54	495	880	Scaling/corrosion	37%
47	Offshore heavy oil (SA)	2500	180	59	310	545	Mechanical	42%
48	Tight sand (NA)	3300	5	34	420	770	Electrical	28%
49	Deepwater (SA)	3500	12	38	400	760	Seal failure	30%
50	Carbonate (ME)	3300	8	55	500	900	Scaling/corrosion	38%