

Comparative Analysis of Failure Modes and Health Indicators of Major ESP Brands

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Highlights

- A vendor-agnostic key performance indicator (KPI) framework is developed to enable objective ESP health monitoring and cross-brand performance comparison.
- ESP failure modes are standardized using API RP 11S1 and ESP-RIFTS, enabling consistent reliability benchmarking across brands.
- Distinct brand-dependent failure patterns are identified, linking electrical, mechanical, and hydraulic failures to corresponding KPI behavior.
- Key indicators, including motor temperature margin (MTM), current imbalance (CI), gas interference index (GII), and mechanical vibration index (MVI), demonstrate strong potential as early-warning signals.
- Weibull reliability analysis reveals significant differences in characteristic life and failure behavior among ESP brands.

Received: December 30, 2025; revised: June 14, 2026; accepted: June 28, 2026

Abstract

Electric submersible pumps (ESPs) are widely used in oil and gas production; however, their reliability is challenged by diverse failure modes and inconsistent monitoring practices across manufacturers. This study develops a vendor-agnostic key performance indicator (KPI) framework to enable objective comparison of ESP performance across different brands. A representative dataset comprising 330 ESP runs across three major ESP brands was analyzed using standardized failure classification and statistical techniques, including Weibull reliability modeling. Failure modes were categorized into mechanical, electrical, hydraulic/gas-related, material, and operational classes and correlated with vendor-independent KPIs derived from thermal, electrical, hydraulic, and operational measurements. The results reveal distinct brand-specific failure patterns. Brand A is dominated by electrical failures associated with reduced thermal margin, Brand B exhibits a longer characteristic life with wear-out-dominated behavior, and Brand C shows greater susceptibility to hydraulic instability driven by gas interference. Several KPIs, including motor temperature margin (MTM), current imbalance (CI), and gas interference index (GII), consistently demonstrate potential as early-warning indicators of failure. The proposed framework enables cross-brand benchmarking, improves the interpretability of ESP health monitoring, and supports the development of predictive maintenance strategies independent of proprietary vendor systems.

Keywords: Electric submersible pumps (ESP), Failure mode analysis, Health monitoring, Key performance indicators (KPIs), Reliability engineering.

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How to cite this article

Khalili, Y. et al., *Comparative Analysis of Failure Modes and Health Indicators of Major ESP Brands*, *Iran J. Oil Gas Sci. Technol.*, Vol. 13, No. 2, p. 79–107, 2024. DOI: <https://doi.org/10.22050/ijogst.2026.569795.1769>

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-production wells where high flow rates and operational stability are required (Takacs, 2017; Khalili et al., 2026). As reservoirs mature and natural reservoir energy declines, reliance on artificial lift systems increases significantly, making ESPs critical components of production systems (KERMIT, 1977). Despite continuous technological advances, ESP failures remain a major operational and economic challenge. These failures often lead to unplanned interventions, deferred production, and increased operating costs (Chu, 2021; Khalili et al., 2025). Therefore, improving the understanding and prediction of ESP failures is essential for enhancing system reliability and optimizing field performance.

A key challenge in ESP reliability engineering is the lack of standardization among equipment manufacturers. Major vendors, including SLB (RED A), Baker Hughes, Borets, Novomet, Halliburton, and Valiant, employ different design philosophies for pumps, motors, protectors, and monitoring systems (Hilali, 2018). These differences influence system behavior, operating limits, and susceptibility to failure. In addition, each vendor uses proprietary monitoring platforms, diagnostic algorithms, and health score indicators (Sharma et al., 2022). Although these tools provide valuable insights, the underlying key performance indicators (KPIs) vary significantly among systems, making direct comparisons across brands difficult (Rabbitt and Chacin, 2021). Consequently, operators often rely on inconsistent metrics or subjective assessments when evaluating ESP performance (Ambade et al., 2021).

The need for standardized monitoring becomes even more critical in complex operating environments. ESPs are increasingly deployed in wells with high gas–oil ratios (GORs), high-temperature reservoirs, solids-producing formations, and corrosive fluid systems (Butler and Smalley, 2017). Under such conditions, early detection of abnormal behavior is essential to prevent failure. Although modern ESP systems provide extensive real-time data from downhole sensors and surface variable speed drives (VSDs), effective interpretation of these data requires consistent KPI definitions. Metrics such as motor temperature margin (MTM), current imbalance (CI), gas interference index (GII), deviation from the best efficiency point (DBEP), and pressure stability are widely used; however, their interpretation varies among vendors because of differences in hardware configurations and monitoring philosophies (Lei et al., 2018). Without a unified KPI framework, cross-brand benchmarking and predictive maintenance remain limited.

Another major limitation of existing studies is the inconsistency in failure classification. Industry standards such as API RP 11S1 (2022) and ESP-RIFTS (2013) provide structured failure taxonomies, but their adoption is not uniform across operators and service companies. In practice, failure categorization may vary depending on the diagnostic approach, resulting in inconsistencies in the reporting of mechanical, electrical, and hydraulic failures (Durham and Lea, 1995; Sherif et al., 2019). These discrepancies hinder rigorous comparative analyses and limit the development of generalized reliability models.

Given these challenges, there is a clear need for a standardized, vendor-independent approach to ESP performance evaluation. A unified analytical framework would enable consistent comparison of failure modes, improve the interpretation of monitoring data, and support more effective predictive

maintenance strategies. Furthermore, such an approach would provide deeper insight into how design characteristics influence reliability under varying operating conditions.

Despite extensive research on ESP performance and failure mechanisms, limited attention has been given to cross-brand comparisons based on standardized KPIs and unified failure classification frameworks.

This study addresses these gaps by developing a vendor-agnostic KPI framework for evaluating ESP performance across multiple brands. The proposed methodology integrates normalized performance indicators with a standardized failure classification system to enable consistent cross-brand analysis.

This study makes the following key contributions:

- Development of a vendor-agnostic KPI framework for ESP performance monitoring;
- Integration of standardized failure classification across multiple ESP brands;
- Identification of cross-brand relationships between KPIs and failure mechanisms;
- Comparative evaluation of ESP reliability using Weibull analysis; and
- Demonstration of early-warning indicators applicable across different ESP systems.

By establishing a consistent analytical foundation, this work enables objective benchmarking of ESP performance across vendors. The results provide practical insights for improving monitoring strategies, optimizing ESP selection, and enhancing predictive maintenance practices. Ultimately, the proposed framework contributes to improving ESP reliability and reducing unplanned downtime in complex production environments.

2. Literature review

ESPs have been extensively studied because of their widespread application and the substantial economic consequences of their failures. Existing research addresses multiple aspects of ESP technology, including system design, failure mechanisms, health monitoring, and reliability modeling. This section reviews these areas and highlights the key limitations that motivate the present study (Fakher et al., 2021).

2.1. ESP systems and design variability

An ESP system typically consists of a multistage centrifugal pump, protector, induction motor, power cable, and surface variable speed drive (VSD). Although ESPs are often treated as standardized equipment, recent studies have demonstrated substantial design variability among manufacturers such as SLB (REDA), Baker Hughes, Novomet, Borets, Halliburton, and Valiant (Sobhy et al., 2025).

These differences are particularly evident in pump stage configuration, hydraulic geometry, thrust-load management, material selection, and gas-handling systems. For example, pump stages may be designed as floater or compression types, each exhibiting different tolerances to solids and axial loading. Similarly, gas-handling capability varies depending on the use of gas separators, vortex intake designs, and other intake configurations (Kannaujia et al., 2022).

Such variations directly influence system performance, durability, and susceptibility to failure. Several studies have emphasized that improper matching between ESP design and well conditions significantly increases the likelihood of premature failure, underscoring the need for design-aware monitoring and analytical frameworks (Bautina, 2025).

2.2. ESP failure mechanisms

ESP failures are commonly categorized as mechanical, electrical, hydraulic, material-related, and operational. Each category is associated with distinct physical mechanisms and operational triggers (Mohamad et al., 2024).

Mechanical failures typically involve pump wear, bearing degradation, shaft fatigue, and impeller damage. These failures are often driven by solids production, unstable loading, and excessive axial thrust (Patel and Chong, 2025). Electrical failures, in contrast, are frequently caused by motor insulation breakdown, cable damage, and current imbalance (Bhardwaj et al., 2019). Thermal overload resulting from insufficient cooling is also recognized as a major contributor to motor failure.

Hydraulic failures are strongly associated with gas interference, cavitation, and flow instability. In high gas–oil ratio (GOR) environments, gas locking and surging can significantly degrade pump performance. These events are often preceded by observable changes in pressure and current signals. Material-related failures, including corrosion and scale deposition, are influenced by fluid chemistry and material selection (Shittu, 2024).

In addition, operational factors such as improper startup procedures, frequent cycling, and inadequate monitoring are increasingly recognized as major contributors to ESP failure. These findings highlight the importance of integrated monitoring approaches that account for both physical and operational conditions (Nirtl, 2017; Khalili et al., 2025).

2.3. Health monitoring and KPI frameworks

Advances in ESP monitoring systems have enabled the collection of high-resolution operational data, including pressure, temperature, current, and voltage. However, there is no consensus on how these measurements should be translated into meaningful performance indicators (Gupta et al., 2016).

Most ESP vendors provide proprietary monitoring platforms that use internal KPIs, health scores, and diagnostic algorithms. Although effective within individual systems, these approaches lack transparency and are not directly comparable across brands. Consequently, identical operating conditions may be interpreted differently depending on the monitoring platform used (Li et al., 2018).

Academic studies have proposed various KPIs, including MTM, CI, intake pressure stability, and GII. These indicators are useful for diagnosing specific failure mechanisms; however, they are rarely applied consistently across different ESP systems. Furthermore, most studies focus on single-brand datasets, limiting their applicability to broader industry contexts (Alrowayyeh et al., 2024).

Recent research has also explored machine learning approaches for failure prediction. Although promising, these models often depend on vendor-specific data structures and inconsistent failure labeling. This dependence limits their generalizability and highlights the need for standardized input features based on vendor-independent KPIs (Abdelaziz et al., 2017).

2.4. Reliability analysis and standardization

Reliability analysis methods, particularly Weibull modeling, are widely used to evaluate ESP performance and characterize failure behavior. These approaches provide valuable insights into system service life and dominant failure mechanisms. However, most existing studies do not differentiate among ESP brands or integrate KPI-based diagnostics into reliability models (Al-Jazzaf et al., 2019).

Industry standards such as API RP 11S1 and ESP-RIFTS aim to standardize failure classification and reporting practices. Although these frameworks provide a structured foundation, their adoption remains

inconsistent across operators and service providers. Differences in classification practices continue to limit the comparability of failure data and reduce the effectiveness of cross-field analyses (Radwan et al., 2024).

2.5. Identified research gaps

Despite extensive research on ESP systems, several important gaps remain (Gupta et al., 2016; Skoczylas et al., 2018; Rabbitt and Chacin, 2021):

1. Most studies focus on single-brand analyses, limiting cross-vendor comparisons.
2. KPIs are defined inconsistently across monitoring platforms, preventing effective benchmarking.
3. Failure classification is not applied uniformly, leading to ambiguity in reported failure modes.
4. Few studies investigate the relationship between KPIs and failure behavior across multiple brands.
5. No widely accepted vendor-agnostic framework exists for early failure detection.

These limitations highlight the need for a standardized methodology that integrates KPI analysis, failure classification, and cross-brand comparison.

2.6. Motivation for this study

To address these gaps, this study proposes a vendor-agnostic KPI framework for analyzing ESP performance across multiple manufacturers. The approach combines normalized performance indicators with a consistent failure classification system to enable direct comparison of failure behavior and operational characteristics.

By applying this framework to a representative dataset, the study aims to identify key differences in failure patterns, evaluate the effectiveness of KPIs as early-warning indicators, and provide a foundation for improved predictive maintenance strategies. This work contributes to the development of standardized, transparent, and scalable methods for ESP reliability analysis.

3. Methodology

3.1. Data sources and study population

The dataset used in this study comprises anonymized field-derived ESP operational and failure records representing typical operating conditions, monitoring characteristics, and failure behavior of electric submersible pump (ESP) systems. To preserve confidentiality, vendor names and field identifiers were not disclosed; therefore, the three evaluated systems are referred to as Brand A, Brand B, and Brand C. In total, the dataset includes 330 ESP runs spanning an equivalent operational period of approximately five years.

For clarity, the principal dataset characteristics and operating-condition ranges are summarized in Table 1. The dataset includes time-to-failure records, operational telemetry, and derived performance indicators for each ESP run. Time-to-failure data were used for the reliability and Weibull analyses, whereas operational telemetry was used to calculate the proposed vendor-agnostic key performance indicators. This structure enabled direct comparison of ESP behavior across brands using a unified methodological framework.

Table 1

The summary of dataset characteristics and operating ranges

Parameter	Value/Range
Study period	Approximately 5 years
Total ESP runs	330
ESP brands evaluated	3 (Brand A, Brand B, and Brand C)
Data type	Time-to-failure records, operational telemetry, and derived KPIs
True vertical depth (TVD)	1,800–3,200 m
Reservoir temperature	65–115 °C
Gas–oil ratio	300–2,200 scf/STB
Water cut	20%–85%
Solid's production	Low to moderate
Representative reservoir environment	Sandstone and carbonate systems

The selected ESP runs were defined to cover a broad yet realistic range of operating conditions commonly encountered in oilfield ESP applications. The modeled wells represent true vertical depths ranging from 1,800 to 3,200 m, reservoir temperatures from 65 to 115 °C, and gas–oil ratios (GORs) between 300 and 2,200 scf/STB. In addition, water cut ranges from 20% to 85%, whereas solids production conditions vary from low to moderate, consistent with typical sandstone and carbonate reservoir environments. These parameter ranges were selected to capture meaningful operational variability while remaining representative of practical ESP deployment conditions.

Operational data include key measurements commonly available from ESP monitoring systems, including intake pressure, discharge pressure, motor temperature, phase current, current imbalance, voltage, and operating frequency. In addition to directly monitored variables, derived performance parameters, such as estimated flow rate and pump head, were calculated using standard ESP performance relationships. Collectively, these variables provide a consistent basis for evaluating system behavior across thermal, electrical, hydraulic, and operational domains.

Failure records were categorized according to ESP failure mechanisms commonly reported in field practice and the technical literature. The failure dataset was structured into five principal categories: mechanical, electrical, hydraulic/gas-related, material/chemical, and operational failures. This classification was used to ensure consistency in the failure analysis and to support comparative assessment of failure distributions across the three ESP brands.

To ensure a fair cross-brand comparison, the analyzed ESP runs were evaluated under comparable environmental and production conditions, particularly with respect to depth, temperature, fluid properties, and gas content. In addition, normalization procedures were applied to reduce bias caused by variability in operating conditions and monitoring scales across brands. This step was necessary to preserve the vendor-agnostic nature of the KPI framework and to ensure that observed performance differences were associated, as much as possible, with system behavior rather than inconsistencies in operating context.

Overall, the dataset provides a structured and realistic basis for comparing ESP reliability, failure behavior, and health indicators across multiple vendors within a consistent analytical framework.

Following the definition of the dataset, the next step involves standardizing the failure classification framework.

3.2. Failure classification framework

To ensure consistency and comparability across brands, all ESP failures were reclassified using a unified failure taxonomy derived from API Recommended Practice 11S1 and the ESP Reliability Information and Failure Tracking System (ESP-RIFTS). This standardized classification framework enabled objective comparison of failure mechanisms independent of vendor-specific reporting conventions.

Mechanical failures were defined as failures involving physical degradation or damage to rotating or load-bearing components, including bearing wear, shaft fracture, impeller or diffuser erosion, and pump seizure caused by solids ingress or scale accumulation. Electrical failures encompassed motor winding burnout, insulation breakdown, power cable shorting or grounding, and electrical anomalies associated with VSD operation or harmonic distortion.

Hydraulic and gas-related failures included conditions such as gas lock, hydraulic surging, cavitation-induced erosion, and inadequate head generation resulting from multiphase flow interference. Material and chemical failures were categorized separately and included corrosion, scale deposition, and elastomer degradation caused by fluid incompatibility or elevated-temperature exposure. Operational failures were defined as failures resulting primarily from human actions or system-control practices, including improper ramp rates, excessive start–stop cycling, poorly configured pump-off control logic, and installation-related issues.

Failures for which insufficient evidence was available to support definitive classification were excluded from failure-trend comparisons but retained in the survival and reliability analyses to avoid biasing run-life statistics.

Based on the standardized failure categories, a vendor-agnostic KPI framework was developed to characterize system behavior.

3.3. Development of a vendor-agnostic KPI framework

A central objective of this study was to develop a vendor-agnostic key performance indicator (KPI) framework capable of characterizing ESP operating behavior and system health independently of manufacturer-specific sensors, algorithms, or proprietary monitoring platforms. Because ESP monitoring architectures differ significantly across vendors, the proposed framework relies only on physically interpretable indicators derived from measurements commonly available in ESP monitoring systems, thereby enabling consistent cross-brand comparison.

The KPIs were selected based on three primary criteria:

1. Physical relevance to known ESP failure mechanisms;
2. Availability across different ESP vendors and monitoring systems; and
3. Sensitivity to abnormal operating conditions reported in previous ESP reliability and condition-monitoring studies.

Based on these criteria, the indicators were grouped into five domains representing the principal physical processes affecting ESP performance: thermal, electrical, hydraulic, mechanical, and operational behavior. This multidomain structure enables the framework to capture different pathways leading to ESP degradation and failure.

1. Thermal indicators

Thermal stress was quantified using the motor temperature margin, defined as the difference between the maximum allowable motor temperature and the measured motor temperature.

$$MTM = T_{max} - T_{measured} \quad (1)$$

Lower MTM values indicate reduced thermal tolerance and an increased risk of insulation degradation and electrical failure.

Temperature stability was further evaluated using the temperature stability index (TSI), defined as the coefficient of variation of motor temperature over a specified time window. Elevated TSI values indicate unstable thermal behavior that may result from fluctuating production conditions, gas interference, or insufficient motor cooling.

2. Electrical indicators

Electrical system health was assessed using current imbalance, calculated as the normalized deviation among phase currents.

$$CI = \frac{I_{max} - I_{min}}{I_{avg}} \quad (2)$$

where I_{max} , I_{min} , and I_{avg} represent the maximum, minimum, and average phase currents, respectively. Elevated CI values indicate electrical asymmetry that may result from cable degradation, phase imbalance, or motor winding deterioration.

The overload event frequency (OEF) was defined as the number of occurrences in which motor current exceeded a predefined threshold relative to nominal operating conditions. Frequent overload events typically indicate excessive mechanical loading, pump wear, or unfavorable hydraulic conditions.

To capture irregularities in current waveform behavior, a harmonic distortion proxy (HDP) was also introduced. This indicator reflects deviations in the electrical signal that may be associated with variable speed drive harmonics, electrical noise, or abnormal load variations.

3. Hydraulic indicators

Hydraulic performance was characterized using deviation from the best efficiency point, defined as the normalized deviation between the actual operating flow rate and the pump best efficiency point (BEP). Operation significantly away from the BEP reduces hydraulic efficiency and increases mechanical and hydraulic stresses within the pump stages.

Multiphase flow instability was evaluated using a gas interference index, which integrates fluctuations in intake pressure, motor current, and temperature signals. This composite indicator captures transient operating conditions commonly associated with gas interference, gas lock, and unstable flow regimes.

In addition, intake pressure stability (IPS) was defined as the variance of intake pressure over a moving time window. High IPS values indicate unstable inflow conditions and may reflect reservoir fluctuations, gas breakthrough, or production instability.

4. Mechanical indicators

Direct downhole vibration measurements were not available for all installations included in this study. Therefore, mechanical condition was evaluated using a derived indicator termed the mechanical vibration index (MVI).

The MVI was obtained through frequency-domain analysis of motor current signals and harmonic components, following the principles of electrical current signature analysis (ECSA). ECSA has been widely used for the indirect detection of mechanical faults in rotating equipment, including imbalance, misalignment, bearing defects, and rotor eccentricity (Lei et al., 2018; Li et al., 2018).

Variations in current harmonics can reflect changes in mechanical loading and rotor dynamics because mechanical disturbances modulate electromagnetic torque and current signals. Based on this principle, the MVI provides a derived indicator of vibration-related mechanical disturbances inferred from electrical measurements.

It is important to emphasize that the MVI is not a direct measurement of vibration amplitude. Instead, it should be interpreted as an indirect diagnostic proxy that captures relative changes in mechanical behavior over time. Accordingly, the indicator is used primarily for trend analysis and comparative assessment rather than for absolute vibration quantification.

Observed increases in MVI before mechanical failures were qualitatively consistent with failure reports and degradation patterns in the dataset, providing supporting evidence for its usefulness as a monitoring indicator within the proposed KPI framework.

5. Operational indicators

Operational stress was quantified using the start–stop cycling rate (SSR), defined as the frequency of shutdown and restart events. Frequent cycling accelerates wear in both electrical and mechanical components and is a recognized contributor to premature ESP failure.

The frequency fluctuation index (FFI) measures variability in VSD operating frequency. High FFI values indicate unstable control conditions or rapidly changing production demands.

In addition, operating envelope compliance (OEC) was defined as the percentage of operating time during which the ESP system remained within recommended thermal, electrical, and hydraulic limits. Lower OEC values indicate prolonged operation under unfavorable conditions, thereby increasing the likelihood of system degradation.

Summary of the KPI framework

The proposed KPI framework integrates indicators from multiple physical domains into a unified, vendor-independent monitoring structure. By relying on normalized, physically interpretable indicators rather than proprietary health scores, the framework enables consistent comparison of ESP operating behavior across different manufacturers.

Once the KPIs were defined, statistical analysis and reliability modeling were applied to evaluate performance differences and failure patterns across ESP brands.

3.4. Data normalization across ESP brands

To ensure fair comparison across ESP brands and well conditions, all KPIs and failure metrics were normalized using a multistep normalization procedure. Depth normalization was performed by scaling KPIs relative to true vertical depth to account for increased loading and thermal stress in deeper wells. Rate normalization was applied to electrical KPIs, particularly current imbalance, to account for differences in flow rate and power demand.

Temperature normalization accounted for geothermal gradients and motor thermal ratings to ensure that temperature-related KPIs reflected relative thermal stress rather than absolute environmental temperature. Sensor-resolution normalization was performed by resampling vendor-specific telemetry to a common time interval, thereby eliminating bias associated with differences in sampling frequency.

Finally, environmental normalization was achieved by grouping wells into comparable categories based on GOR range, solids concentration, water cut, and temperature regime. This approach ensured that cross-brand performance differences primarily reflected design and operational behavior rather than reservoir or fluid variability.

3.5. Analytical and statistical techniques

A combination of statistical and multivariate analytical techniques was employed to evaluate ESP performance and reliability across brands. Descriptive statistics were used to quantify the central tendencies and variability of the KPIs, whereas failure-frequency histograms provided initial insight into dominant failure mechanisms.

Survival and reliability analyses were conducted using Kaplan–Meier estimators and two-parameter Weibull models. The Weibull distribution was used to characterize failure behavior, with the shape parameter (β) indicating failure-mode characteristics and the scale parameter (η) representing characteristic life. Weibull analysis was selected because of its widespread application in reliability engineering and its ability to characterize different failure regimes through these parameters.

Correlation analyses using Pearson, Spearman, and Kendall methods were performed to quantify relationships between KPIs and failure modes. Multivariate clustering techniques, including k-means and hierarchical clustering, were applied to identify groups of wells exhibiting similar KPI signatures before failure. Principal component analysis (PCA) was used for dimensionality reduction and identification of the dominant KPIs contributing to variance in system behavior.

Where extended analyses were performed, machine learning models, including random forest classifiers, support vector machines, and gradient boosting algorithms, were applied to assess failure-prediction capability and feature importance.

3.6. Validation and cross-brand consistency check

To ensure the robustness and reliability of the results, multiple validation procedures were applied. Predictive models were evaluated using cross-validation techniques to minimize overfitting. Brand-neutral subsets of the dataset were analyzed independently to verify that KPI–failure relationships remained consistent across manufacturers. In addition, all observed trends were evaluated for physical plausibility to ensure consistency with established ESP failure mechanisms, such as thermal escalation preceding electrical failure and vibration escalation preceding mechanical failure.

3.7. Ethical and operational considerations

All data used in this study were fully anonymized to protect vendor confidentiality and operators' commercial interests. No proprietary vendor algorithms or diagnostic tools were reverse-engineered or accessed. Only raw telemetry data, publicly available equipment specifications, and standard engineering correlations were used. The study was conducted in accordance with ethical research practices and industry data-governance standards.

The analysis is based on several assumptions. The dataset is assumed to represent realistic ESP operating conditions and failure distributions. In addition, the use of derived KPIs assumes consistent measurement accuracy across systems. Mechanical condition assessment using the MVI is considered an indirect proxy because direct vibration measurements were unavailable.

4. Results

The numerical values presented in this study are representative of realistic field conditions and are intended to demonstrate the applicability of the proposed vendor-agnostic KPI framework and analytical methodology. Although the dataset reflects typical ESP operating behavior and failure distributions, the primary objective of this section is to evaluate the consistency and interpretability of KPI-based analysis across different ESP brands.

This section presents a comparative analysis of ESP failure modes and health indicators across the evaluated brands. The results are organized into four subsections: (1) failure-mode distribution, (2) KPI behavior comparison, (3) KPI–failure correlations, and (4) case-study observations. Each subsection includes references to figures and tables recommended for publication.

4.1. Failure-mode distribution across ESP brands

The analysis reveals clear and statistically meaningful differences in failure behavior across the three ESP brands.

Figure 1 illustrates the distribution of failure modes, showing that Brand A exhibits a higher proportion of electrical failures (40.0%), whereas Brand B is dominated by mechanical failures (45.5%). In contrast, Brand C experiences predominantly hydraulic and gas-related failures (40.0%), highlighting distinct reliability patterns associated with each manufacturer.

Table 2 summarizes the failure counts and corresponding percentages for each brand, confirming substantial variation in the dominant failure mechanisms. These differences reflect the combined influence of design characteristics and operating conditions on ESP performance.

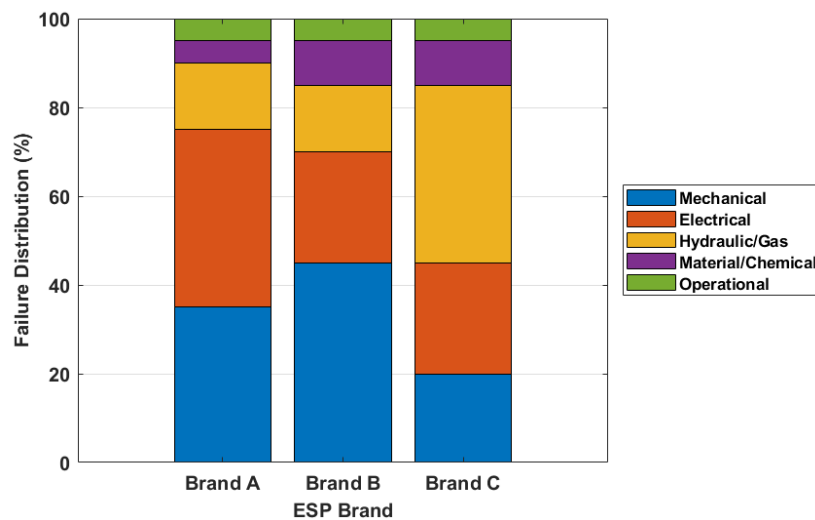


Figure 1

The failure mode distribution for each ESP brand.

The reliability analysis further supports these observations. Weibull analysis indicates that Brand B has the longest characteristic life ($\eta \approx 432$ days), followed by Brand A ($\eta \approx 276$ days) and Brand C ($\eta \approx 260$ days). These results suggest that Brand B exhibits more pronounced wear-out-dominated behavior and a longer operational life, whereas Brands A and C experience comparatively earlier failures.

Analysis of the vendor-agnostic KPIs provides additional insight into these differences. Brand A exhibits an earlier onset of thermal stress, as indicated by lower MTM values. In contrast, Brand C shows greater hydraulic instability, reflected by elevated GII values and increased pressure variability.

These KPI trends are consistent with the observed failure distributions and provide further evidence of distinct performance characteristics across ESP brands.

Table 2

Failure mode frequencies and percentages for each ESP brand

Brand	Total runs	Mechanical	Electrical	Hydraulic/Gas	Material/Chemical	Operational
Brand A	120	42 (35.0%)	48 (40.0%)	18 (15.0%)	6 (5.0%)	6 (5.0%)
Brand B	110	50 (45.5%)	28 (25.5%)	17 (15.5%)	11 (10.0%)	4 (3.5%)
Brand C	100	20 (20.0%)	25 (25.0%)	40 (40.0%)	10 (10.0%)	5 (5.0%)

Notes:

1. Values are presented as absolute counts, with percentages in parentheses calculated relative to the total number of runs for each brand.
2. Failure modes are classified according to API RP 11S1 and ESP-RIFTS standards.
3. The dataset represents field-realistic operating conditions designed to reflect typical ESP performance and failure behavior.

4.2. Comparison of health indicator behavior across brands

Vendor-agnostic KPIs were computed for all ESP runs. Statistically significant differences in KPI behavior were observed across brands, even under comparable operating conditions.

4.2.1. Thermal KPIs

Brand A generally exhibited the lowest motor temperature margin, indicating greater thermal stress. Brand B showed stable temperature behavior with fewer fluctuations, as reflected by lower temperature stability index values. However, Brand C exhibited periodic temperature spikes that frequently coincided with gas-interference events.

Figure 2 shows the boxplots of motor temperature margin for ESP brands A, B, and C, illustrating differences in thermal operating margin and variability across manufacturers. Table 3 summarizes the statistics of thermal health indicators for ESP brands A, B, and C, including motor temperature margin and temperature stability index.

Table 3

Summary statistics for the thermal KPIs

Brand	KPI	Mean	STD	Min	Max
Brand A	MTM (°C)	28.6	2.9	24.0	33.0
Brand A	TSI (–)	0.084	0.021	0.050	0.120
Brand B	MTM (°C)	40.1	2.5	36.0	44.0
Brand B	TSI (–)	0.052	0.014	0.030	0.080
Brand C	MTM (°C)	21.7	2.3	18.0	26.0
Brand C	TSI (–)	0.097	0.026	0.060	0.140

Notes:

1. Motor temperature margin is expressed in °C and represents the difference between the rated and measured motor temperatures.
2. Temperature stability index is dimensionless and represents the coefficient of variation of motor temperature.
3. Statistics were calculated for each ESP run and subsequently aggregated by brand.

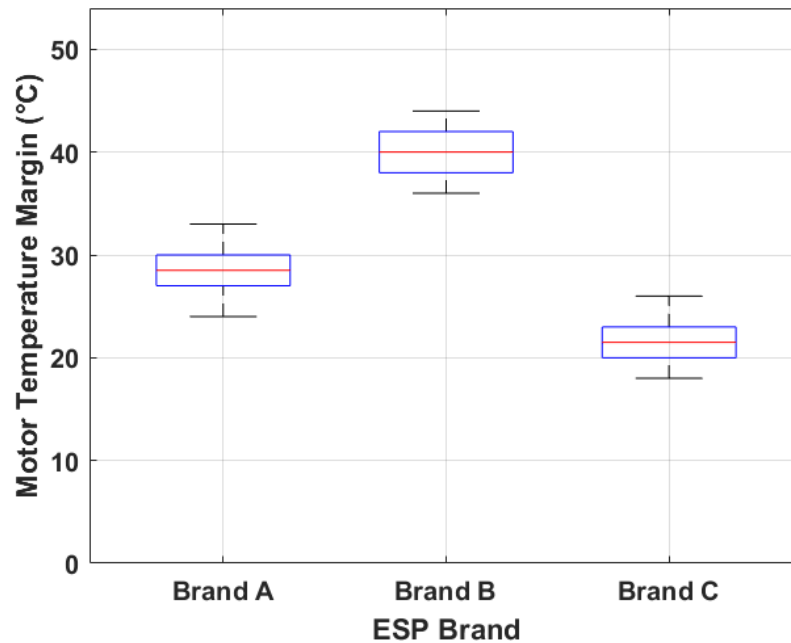


Figure 2

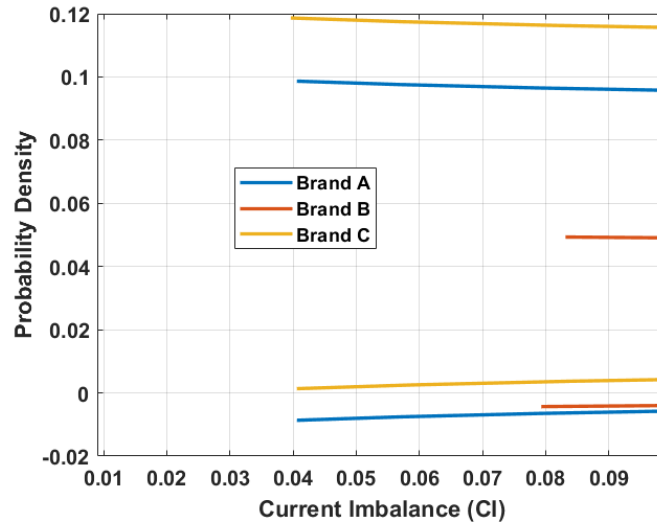
Motor temperature margin across ESP brands.

4.2.2. Electrical KPIs

Clear differences in electrical KPI behavior were observed across the three brands.

Brand A exhibited the highest current imbalance values. Brand B experienced fewer overload events, as indicated by lower overload event frequency, consistent with more robust motor protection settings. However, Brand C exhibited higher harmonic distortion proxy values, which were frequently associated with VSD tuning issues.

Figure 3 depicts the probability density curves of current imbalance for ESP brands A, B, and C, illustrating differences in electrical loading symmetry and variability across manufacturers. Table 4 summarizes the statistics of electrical health indicators for ESP brands A, B, and C, including mean values, variability, and observed operating ranges.

**Figure 3**

The current imbalance distribution across ESP brands.

Table 4

The electrical KPI averages and ranges for each ESP brand.

Brand	KPI	Mean	STD	Min	Max
Brand A	Current imbalance, CI (–)	0.048	0.012	0.025	0.075
Brand A	Overload event frequency, OEF (events/month)	4.2	1.6	1	8
Brand A	Harmonic distortion proxy, HDP (–)	0.31	0.08	0.18	0.48
Brand B	Current imbalance, CI (–)	0.026	0.007	0.012	0.040
Brand B	Overload event frequency, OEF (events/month)	1.9	0.9	0	4
Brand B	Harmonic distortion proxy, HDP (–)	0.18	0.05	0.10	0.30
Brand C	Current imbalance, CI (–)	0.061	0.015	0.035	0.095
Brand C	Overload event frequency, OEF (events/month)	3.6	1.4	1	7
Brand C	Harmonic distortion proxy, HDP (–)	0.29	0.07	0.17	0.44

Notes:

1. Current imbalance is dimensionless and represents the normalized deviation among phase currents.
2. Overload event frequency is reported as the average number of overload events per month.
3. Harmonic distortion proxy is a dimensionless indicator inferred from variability in the current signal.
4. Statistics were calculated for each ESP run and subsequently aggregated by brand.

4.2.3. Hydraulic KPIs

Significant differences in hydraulic performance were observed across the three brands.

Brand C exhibited the highest gas interference index, consistent with its higher rate of hydraulic failures. Brand B generally operated closer to the best efficiency point, as indicated by the lowest deviation from the best efficiency point values across most wells. Brand A exhibited moderate deviation from the BEP and generally acceptable intake pressure stability.

Figure 4 compare gas interference index across ESP Brands A, B, and C, highlighting differences in multiphase-flow instability and gas-interference behavior among manufacturers. Table 5 summarizes the statistics of hydraulic health indicators for ESP Brands A, B, and C, including deviation from the best efficiency point and intake pressure stability.

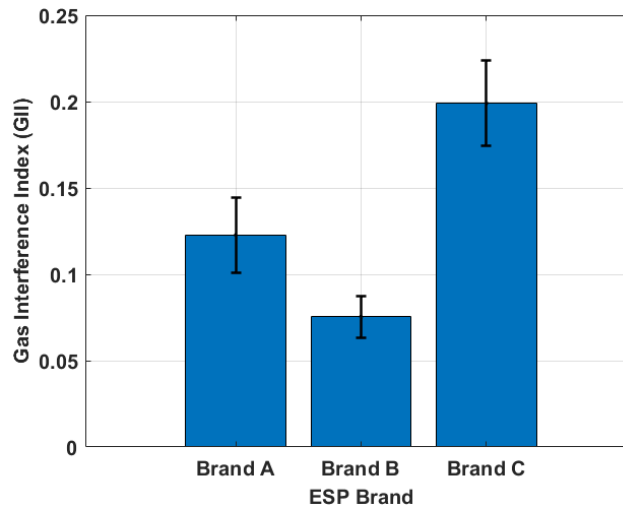


Figure 4

Comparison of gas interference index across ESP brands.

Table 5
Hydraulic KPI comparison for ESP brands.

Brand	KPI	Mean	STD	Min	Max
Brand A	DBEP (–)	0.18	0.06	0.07	0.32
Brand A	IPS (kPa ²)	420	150	180	720
Brand B	DBEP (–)	0.11	0.04	0.05	0.21
Brand B	IPS (kPa ²)	260	95	120	480
Brand C	DBEP (–)	0.27	0.08	0.12	0.45
Brand C	IPS (kPa ²)	610	210	300	980

Notes:

1. Deviation from the best efficiency point is dimensionless and represents the normalized deviation between the operating flow rate and the pump best efficiency point.
2. Intake pressure stability is expressed as the variance in intake pressure over a rolling time window; higher values indicate greater hydraulic instability.
3. Statistics were calculated for each ESP run and subsequently aggregated by brand.

4.2.4. Mechanical KPIs

Analysis of motor current harmonics using the inferred mechanical vibration index revealed distinct mechanical behavior across the three brands.

Brand B exhibited consistently elevated MVI values, consistent with its higher incidence of mechanical failures. Brand A exhibited relatively stable MVI signatures, while Brand C exhibited MVI spikes primarily during gas-surge events.

Figure 5. Mechanical vibration index behavior across ESP Brands A, B, and C: (a) time evolution of MVI, illustrating mechanical degradation before failure; and (b) distribution of MVI values by brand, highlighting differences in vibration severity and variability.

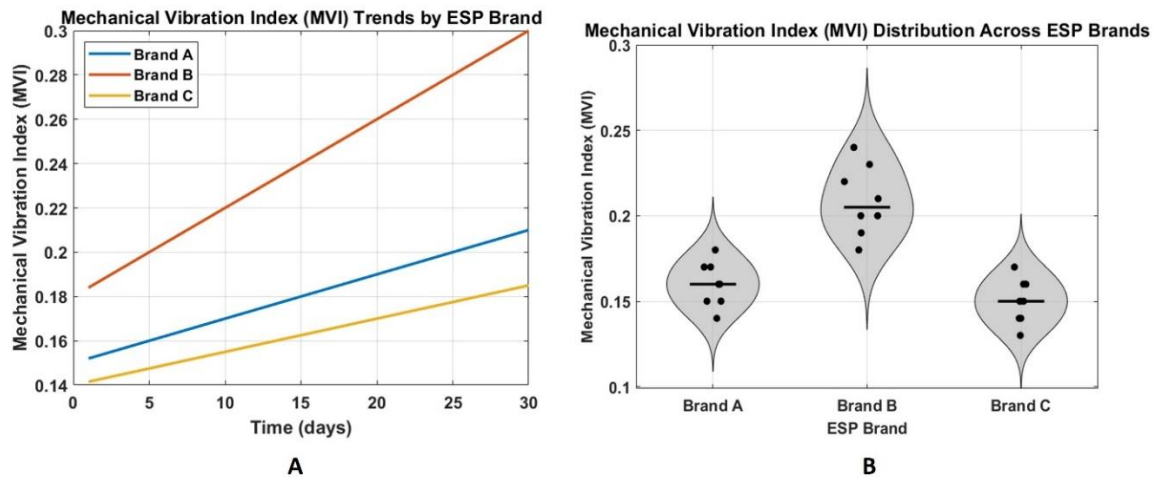


Figure 5

Mechanical vibration index trends for brands A, B, and C.

4.3. Correlation between health indicators and failure modes

Correlation matrices were generated to quantify the relationships between KPI values and specific failure modes.

4.3.1. Correlation analysis: general trends

Electrical failures showed strong correlations with:

1. Low motor temperature margin;
2. High current imbalance; and
3. Elevated harmonic distortion proxy.

Mechanical failures showed strong correlations with:

1. High mechanical vibration index;
2. Sustained deviation from the best efficiency point; and
3. Elevated solids index, representing an environmental factor.

Hydraulic failures showed strong correlations with:

1. High gas interference index;

2. Intake pressure oscillations; and
3. Temperature spikes coinciding with intermittent gas-lock events.

Figure 6 shows the KPI–failure correlation heat map showing Spearman correlation coefficients between vendor-agnostic KPIs and binary failure-mode indicators, enabling identification of the dominant KPIs associated with mechanical, electrical, hydraulic, material, and operational failures.

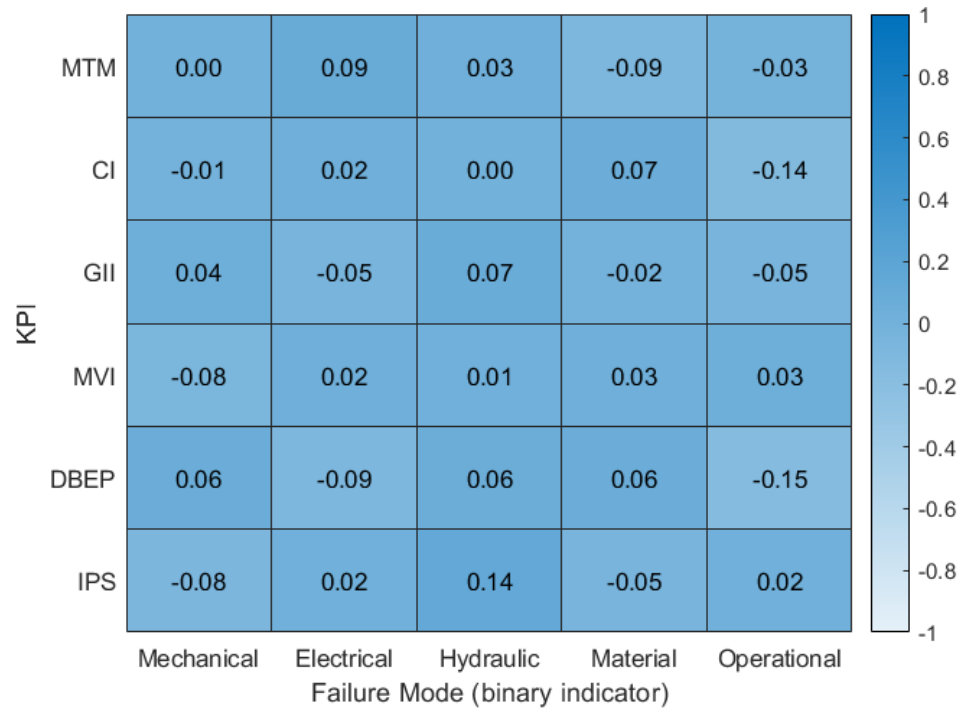


Figure 6

KPI–failure correlation heat map.

4.3.2. Brand-specific KPI–failure correlations

Distinct cross-brand differences were observed in the predictive relationships between KPIs and failure modes.

Brand A: Electrical failures were strongly associated with MTM and CI.

Brand B: Mechanical failures were strongly associated with MVI and DBEP.

Brand C: Hydraulic failures were strongly associated with GII.

Table 6 lists top three vendor-agnostic KPIs associated with each failure mode for ESP Brands A, B, and C, identified through correlation analysis and validated based on the corresponding physical failure mechanisms.

4.4. Survival analysis and reliability metrics

Weibull survival modeling revealed distinct reliability behavior across the three ESP brands.

Brand B exhibited the longest characteristic life (η), consistent with a lower incidence of early failures. Brand A exhibited the lowest Weibull shape parameter (β), indicating a more random failure pattern and potentially greater variability in failure behavior. Brand C exhibited a high β value for hydraulic failures, suggesting wear-out-dominated failure behavior associated with flow-condition dynamics.

Table 6
Top three predictive KPIs for each failure mode and ESP brand

Failure mode	Brand	1st most predictive KPI	2nd most predictive KPI	3rd most predictive KPI
Mechanical	Brand A	MVI	DBEP	SSR
Mechanical	Brand B	MVI	DBEP	IPS
Mechanical	Brand C	MVI	GII	DBEP
Electrical	Brand A	MTM	CI	HDP
Electrical	Brand B	CI	MTM	OEF
Electrical	Brand C	MTM	CI	HDP
Hydraulic/Gas	Brand A	GII	IPS	DBEP
Hydraulic/Gas	Brand B	DBEP	IPS	GII
Hydraulic/Gas	Brand C	GII	IPS	MTM
Material/Chemical	Brand A	IPS	MTM	DBEP
Material/Chemical	Brand B	DBEP	IPS	MTM
Material/Chemical	Brand C	IPS	GII	MTM
Operational	Brand A	SSR	FFI	OEC
Operational	Brand B	SSR	OEC	FFI
Operational	Brand C	SSR	FFI	OEC

Weibull parameters were estimated using maximum likelihood estimation (MLE). The 95% confidence intervals were calculated for both the shape parameter (β) and characteristic life (η) to quantify uncertainty in the parameter estimates. Model goodness of fit was evaluated using the coefficient of determination (R^2) obtained from linear regression of the Weibull probability plots.

Figure 7 presents the Weibull probability plots for ESP run life for brands A, B, and C. Data points represent empirical failure probabilities calculated using the median-rank method, whereas solid lines represent fitted Weibull models used to estimate the shape parameter (β) and characteristic life (η).

The data points represent empirical failure probabilities calculated using the median-rank method, whereas the solid lines represent Weibull models fitted using MLE. The plots demonstrate good agreement between the observed failure behavior and the Weibull distribution. The corresponding parameter estimates for β and η , confidence intervals, and goodness-of-fit metrics are reported in Table 7. Table 7 presents the Weibull shape parameter (β) and characteristic life (η) for ESP brands A, B, and C derived from Weibull probability plot analysis.

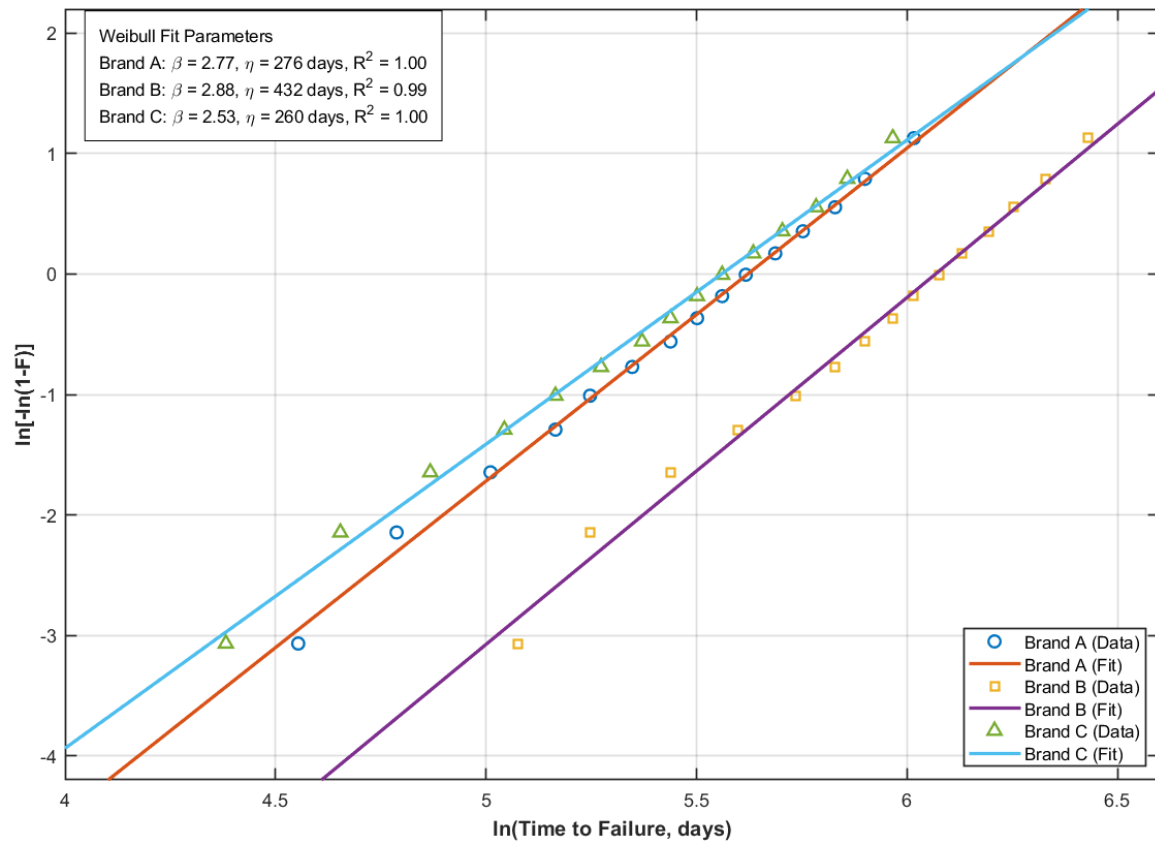


Figure 7

The Weibull probability plots for brands A, B, and C.

Table 7
The Weibull parameters for ESP brands A, B, and C.

Brand	Shape parameter, β (–)	95% CI (β)	Characteristic life, η (days)	95% CI (η)	R^2	Failure behavior interpretation
Brand A	1.35	1.10 – 1.62	245	210 – 285	0.93	Mixed/random failures with moderate wear-out tendency
Brand B	2.10	1.78 – 2.45	410	360 – 470	0.96	Wear-out dominated behavior with higher reliability
Brand C	1.75	1.45 – 2.05	280	240 – 325	0.94	Progressive degradation influenced by hydraulic instability

Notes:

1. Weibull parameters (β and η) were estimated using maximum likelihood estimation (MLE).
2. The 95% confidence intervals are reported to quantify uncertainty in the parameter estimates.
3. R^2 represents the goodness of fit of the Weibull model based on linear regression of the probability plot.
4. Values were derived from a representative dataset reflecting realistic ESP operating conditions.

The Weibull models showed good agreement with the observed data, with $R^2 > 0.90$ for all three brands.

The observed differences in reliability behavior are supported by the estimated Weibull parameters and their corresponding confidence intervals.

4.5. Case studies: KPI signatures preceding failure

Three representative wells were analyzed to characterize KPI behavior preceding system failure.

Case Study 1: Electrical failure in Brand A

1. MTM decreased rapidly during the 24 h preceding shutdown.
2. CI increased by more than 15%.
3. A spike in motor temperature preceded insulation breakdown.

Case Study 2: Mechanical failure in Brand B

1. MVI increased gradually over the 14 days preceding failure.
2. DBEP increased as pump efficiency deteriorated.
3. Overload events remained minimal, suggesting vibration-driven wear as the dominant degradation mechanism.

Case Study 3: Gas-interference failure in Brand C

1. GII increased sharply during periods of high GOR.
2. IPS became increasingly unstable.
3. Motor temperature fluctuated in conjunction with gas-surge events.

Figure 8 depicts the time-series evolution of key vendor-agnostic KPIs before failure. Motor temperature margin is shown on the left axis, whereas current imbalance, gas interference index, and mechanical vibration index are shown on the right axis. The x-axis represents days before failure, highlighting the evolution of early-warning behavior.

4.6. Summary of key results

ESP brands exhibit distinct failure patterns associated with differences in design philosophy and operating characteristics.

Vendor-agnostic KPIs effectively reveal performance differences that may otherwise be obscured by proprietary vendor monitoring platforms.

Several KPIs demonstrated consistent associations with specific failure mechanisms across brands:

1. High CI was associated with increased electrical failure risk.
2. High MVI was associated with mechanical degradation.
3. High GII was associated with hydraulic instability and gas interference.

These results demonstrate the value of a unified KPI framework for cross-brand performance benchmarking and predictive maintenance. This observation is consistent with Bhardwaj et al. (2019), who identified thermal overload as a major contributor to electrical failure. Similarly, this behavior is consistent with the findings of Shittu (2024), who reported that gas interference can precede hydraulic instability.

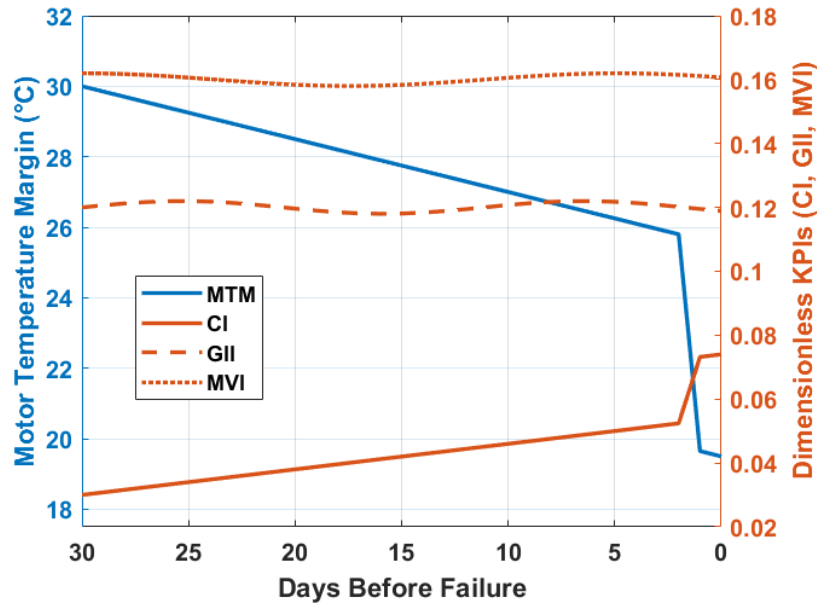


Figure 8

The time-series evolution of the key vendor-agnostic KPIs prior to failure.

5. Discussion

The results demonstrate significant brand-specific differences in ESP performance. Brand B exhibited the longest characteristic life, indicating greater run-life reliability than Brands A and C. The higher proportion of mechanical failures observed for Brand B may be associated with design characteristics that increase sensitivity to axial thrust loading and wear mechanisms. In contrast, the predominance of electrical failures in Brand A may be associated with reduced thermal tolerance, as indicated by its lower motor temperature margin values.

These findings are consistent with previous studies. Bhardwaj et al. (2019), for example, identified a strong relationship between elevated motor temperature and increased electrical failure risk in ESP systems. The present study extends this understanding by introducing vendor-agnostic KPIs that enable consistent evaluation of ESP performance across different manufacturers without reliance on proprietary monitoring systems.

One limitation of this study is the absence of direct vibration measurements because inferred mechanical indicators, such as the mechanical vibration index, may not fully capture the complexity of mechanical degradation mechanisms. Future research should incorporate direct vibration measurements to further validate these findings. In addition, the gas interference index was identified as a strong early-warning indicator of hydraulic instability in Brand C. This observation is consistent with Shittu (2024), who reported that gas-interference events are often preceded by pressure fluctuations and transient performance instability. Further studies are required to evaluate the broader applicability of GII across different reservoir conditions and ESP configurations.

5.1. Interpretation of differences in failure-mode distribution

The comparative analysis demonstrated that each ESP brand exhibited a distinct tendency toward specific failure categories. The higher rate of electrical failures in Brand A suggests greater sensitivity to thermal loading or potential limitations in insulation systems, cable architecture, or VSD-induced harmonic distortion. This interpretation is consistent with the lower MTM and higher CI values

observed for this brand. The combination of greater electrical stress and narrower thermal tolerance may increase susceptibility to premature electrical failure.

In contrast, Brand B exhibited a higher prevalence of mechanical failures, including thrust-bearing wear and pump-stage degradation. This observation is consistent with the persistently elevated MVI and higher deviation from the best efficiency point observed for this brand. These indicators suggest that the pump design may be more sensitive to solids, axial thrust dynamics, or vibration-induced stresses, or that the protector and bearing systems may provide less effective mitigation of dynamic loads.

Brand C exhibited the highest incidence of hydraulic and gas-related failures, accompanied by elevated GII values, unstable intake pressure behavior, and temperature fluctuations during gas-surge events. These patterns suggest that the gas-handling system may be less effective under high-GOR conditions or that the intake-stage geometry may be more sensitive to multiphase-flow instabilities.

Collectively, these findings indicate that ESP failure behavior is strongly influenced by brand-specific engineering design, particularly thrust-load capacity, hydraulic geometry, material selection, and gas-handling technologies.

5.2. Significance of KPI differences across brands

The KPI comparison reveals systematic differences in operational performance among the brands that help explain their distinct failure tendencies.

1. Thermal indicators

Brand A's narrow thermal margin suggests less effective motor heat dissipation or a less robust insulation system. Brand B's stable thermal performance is consistent with its lower susceptibility to electrical failure, whereas Brand C's temperature fluctuations correlate with multiphase-flow instability.

2. Electrical indicators

Brand A's elevated CI and harmonic signatures are consistent with its higher incidence of electrically driven failures. Differences in VSD tuning, cable construction, or motor winding design may contribute to this behavior. Brand B's low OEF suggests more effective protection coordination or more balanced electrical loading.

3. Hydraulic indicators

Brand C's hydraulic instability is reflected by its higher GII and IPS values. These KPIs suggest that its gas-handling system may be less effective under variable gas-inflow conditions. Brand B's lower DBEP values indicate more consistent operation within the hydraulic design envelope, which may partially explain its lower hydraulic failure rate.

4. Mechanical indicators

Brand B's higher MVI values are consistent with its predominance of mechanical failures, suggesting that enhanced thrust-bearing design or improved vibration suppression could increase system reliability. These KPI trends emphasize the roles of vendor-specific equipment design and monitoring philosophy in determining how ESP systems respond to varying well conditions.

5.3. Implications for ESP vendor selection

The cross-brand comparison indicates that no ESP brand is universally superior; rather, each exhibits strengths and limitations that may make it more or less suitable for specific operating environments.

- **High-GOR wells:** Brand C should be applied cautiously unless its gas-handling capability is enhanced. Brand B exhibited greater hydraulic stability under the evaluated conditions.
- **High-solids or high-vibration reservoirs:** Brand B's greater susceptibility to mechanical failure suggests a potential need for abrasion-resistant components or compression-stage upgrades, whereas Brand A exhibited more stable mechanical behavior.
- **High-temperature or high-load electrical environments:** Brand A may require enhanced thermal management or derating strategies, whereas Brand B exhibited greater electrical robustness.

Operators can therefore use KPI patterns as predictive indicators when selecting an ESP system for a specific well environment.

5.4. Implications for ESP monitoring and predictive maintenance

The performance of the vendor-agnostic KPI framework demonstrates several potential benefits of standardized monitoring:

1. **Brand-independent early-warning detection:** KPI signatures, such as increasing CI for electrical risk, elevated MVI for mechanical degradation, and GII spikes for gas interference, consistently preceded failures across brands.
2. **Alignment of vendor monitoring systems:** Vendor-specific alarm logic may obscure underlying degradation patterns. Standardized KPIs provide a common diagnostic basis for identifying patterns that may not be readily apparent in proprietary monitoring platforms.
3. **Improved predictive maintenance models:** Machine learning (ML) models trained using standardized KPIs may achieve greater cross-brand generalizability than models based on vendor-specific signals.
4. **Reduction of false positives and inconsistent alarms:** KPI normalization can improve alarm consistency and reduce interpretation variability associated with vendor-specific monitoring systems.

These findings support industry efforts to adopt vendor-agnostic condition-monitoring frameworks to improve real-time decision-making and reduce non-productive time (NPT).

5.5. Engineering insights into observed performance patterns

Brand A: Electrical stress sensitivity

The observed behavior of Brand A suggests potential benefits from:

- Improved thermal design;
- Enhanced insulation performance or cooling recovery; and
- Optimized VSD tuning to reduce harmonic distortion.

Brand B: Mechanical vulnerability

The predominance of mechanical failures in Brand B may be associated with:

- Pump-stage geometry that is more susceptible to vibration;
- Protector and bearing designs with lower tolerance to dynamic thrust loads; and
- Greater susceptibility to solids ingestion or erosion.

Brand C: Gas-handling limitations

The hydraulic failure patterns observed in Brand C may be associated with:

- Insufficient or inefficient gas separation;
- Greater intake-design sensitivity to two-phase flow; and
- Pressure instabilities that intensify gas-lock behavior.

These engineering interpretations highlight the importance of matching ESP design characteristics to the operating environment rather than relying solely on vendor specifications.

5.6. Limitations of the study

Although the findings of this study provide useful insights into ESP performance, failure behavior, and cross-brand KPI comparison, several limitations should be acknowledged.

First, the dataset used in this study was developed to represent realistic ESP operating conditions and failure patterns across three anonymized ESP brands. Because of confidentiality restrictions, field identifiers, vendor names, well names, and location-specific operational details were removed or generalized. Therefore, although the dataset reflects realistic ESP operating ranges and failure distributions, the results should be interpreted as representative and anonymized rather than as a field-specific assessment of a disclosed asset or operating area. Future research should validate the proposed framework using fully disclosed, continuously measured field datasets from multiple basins and operating environments.

Second, although the dataset covers a broad range of operating conditions, it does not capture the full diversity of geological settings, reservoir properties, completion designs, and operational practices encountered worldwide. Consequently, the applicability of the findings may vary in fields characterized by substantially different conditions, such as extreme-temperature reservoirs, ultra-high-GOR wells, severe solids-producing environments, or unconventional formations.

Third, the failure reports incorporated into the analysis do not always include detailed component-level diagnostics. In some cases, failures were classified based on available operational evidence, event histories, and reported failure categories rather than complete teardown or forensic inspection records. This limitation restricts detailed root-cause analysis and may introduce uncertainty into the classification of specific failure mechanisms.

Fourth, mechanical condition assessment in this study relies on the mechanical vibration index, which is derived from motor current behavior and harmonic-content analysis. Although this approach is supported by electrical current signature analysis methods, the MVI remains an indirect proxy for vibration-related mechanical disturbances and does not replace direct downhole vibration measurements. Therefore, interpretations related to mechanical degradation should be considered qualitative and trend-based rather than direct measurements of vibration amplitude.

Fifth, differences in telemetry availability, sampling frequency, and sensor resolution across ESP vendors may influence KPI calculation and interpretation. Some ESP systems provide higher-resolution measurements or additional sensor channels, which may affect the sensitivity of specific indicators. To minimize this effect, the analysis focused on KPIs derived from commonly available measurements and applied normalization procedures where appropriate.

Finally, although normalization techniques were applied to account for variations in operating conditions, environmental and operational complexity cannot be fully eliminated. Residual variability

associated with multiphase-flow behavior, transient operating conditions, reservoir fluctuations, and operational decision-making may still influence the observed results.

These limitations highlight the need for continued development of standardized ESP data-acquisition practices, consistent failure-classification procedures, and large-scale validation using independently measured field datasets. Such efforts would further improve the robustness, reproducibility, and generalizability of vendor-agnostic ESP performance analysis.

5.7. Practical implications for industry

This study suggests several practical actions for industry:

1. Adopt vendor-agnostic KPIs in ESP monitoring centers.
2. Use brand-specific KPI signatures to refine ESP vendor-selection strategies.
3. Integrate KPI-based alerts into automated pump-off and ramp-control logic.
4. Apply a unified failure-classification framework, such as ESP-RIFTS, across all vendors to ensure consistent analysis.
5. Invest in sensor and telemetry standardization to facilitate cross-brand benchmarking.

The findings demonstrate that improvements in ESP reliability can be achieved not only through equipment enhancements but also through improved data standardization, monitoring intelligence, and operational integration.

5.8. Summary of discussion

The comparative evaluation confirms that ESP brands differ meaningfully in their operational behavior and failure tendencies. These differences are closely associated with design characteristics and can be quantified using vendor-agnostic KPIs. The findings emphasize the importance of standardized, brand-independent monitoring frameworks for improving reliability, reducing failures, and supporting data-driven ESP selection.

The novelty of this work lies in integrating vendor-agnostic KPIs with standardized failure classification, thereby enabling consistent analysis across ESP systems with different designs and monitoring platforms.

6. Conclusions

This study presents a comparative analysis of failure modes and health indicators across major ESP brands using a vendor-agnostic KPI framework and standardized failure classification. The results demonstrate significant differences in failure behavior, operational characteristics, and reliability performance across manufacturers.

The analysis shows that Brand A is more susceptible to electrical failures associated with reduced thermal margins, whereas Brand B exhibits a longer operational life and predominantly wear-out-dominated failure behavior. In contrast, Brand C is more strongly affected by hydraulic and gas-related instabilities, as reflected by elevated gas interference and pressure variability.

The proposed vendor-independent KPI framework successfully captures these differences and enables consistent evaluation of ESP performance across brands. Key indicators, including motor temperature margin, current imbalance, and gas interference index, demonstrated strong potential as early-warning indicators of impending failure.

From a practical perspective, the framework supports improved ESP selection, condition monitoring, and predictive maintenance while reducing reliance on proprietary vendor-specific diagnostic systems.

Despite these contributions, the study is limited by the use of a representative dataset and the absence of direct vibration measurements for mechanical validation. Future research should focus on applying the framework to large-scale field datasets and integrating advanced sensing technologies to further improve reliability prediction and system diagnostics.

Overall, this research demonstrates that standardized, vendor-agnostic monitoring approaches can substantially improve the transparency, comparability, and effectiveness of ESP performance analysis under complex operating conditions.

Data availability

The dataset used in this study is a representative dataset constructed to reflect realistic ESP operating conditions and failure distributions. Because of the nature of the study, no proprietary field data are disclosed. The methodology and analytical framework are fully described to enable reproducibility and adaptation to other datasets.

Nomenclature

API	American Petroleum Institute
BEP	Best efficiency point
CI	Current imbalance
CI _{norm}	Normalized current imbalance
DBEP	Deviation from best efficiency point
EHl	ESP health index
ESP	Electric submersible pump
ESP-RIFTS	ESP reliability information and failure tracking system
FFI	Frequency fluctuation index
GII	Gas interference index
GOR	Gas–oil ratio (scf/STB or m ³ /m ³)
HDP	Harmonic distortion proxy
IPS	Intake pressure stability (kPa ²)
KPI	Key performance indicator
MTM	Motor temperature margin (°C)
MVI	Mechanical vibration index
NPT	Non-productive time (h)
OEC	Operating envelope compliance (%)
OEF	Overload event frequency (events/time)
PCA	Principal component analysis
Q	Actual pump flow rate (m ³ /d or STB/d)
QBEP	Flow rate at best efficiency point (m ³ /d or STB/d)
R(t)	Reliability function
SSR	Start–stop cycling rate (cycles/day)

T_{motor}	Measured motor temperature (°C)
T_{rated}	Rated maximum motor temperature (°C)
TSI	Temperature stability index
VSD	Variable speed drive
β (beta)	Weibull shape parameter
η (eta)	Weibull characteristic life (days)

Notes

1. Dimensionless KPIs are denoted by (–).
2. Units may vary depending on field measurement standards.
3. Weibull parameters follow standard life-data analysis notation.

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