Functional and Failure Rate Analysis of High Integrity Pressure Protection Systems (HIPPS) for Safety Integrity Level (SIL) Determination in Oil and Gas Production Facilities

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Abstract – *Process industries rely on High Integrity Pressure Protection Systems (HIPPS) as primary safety barriers to avoid hazardous overpressure situations. Using a detailed framework of functional-performance modelling, this work investigates the suitability of HIPPS functional behavior and degradation characteristics as well as Safety Integrity Level (SIL) suitability. Continuous-time simulation was used to evaluate various performance measures, including the Functional Performance Index (FPI), System Performance Indices (SPI) and Probability of Detection (PODs). Other important metrics include false alarm rate; coverage probability; and average Probability of Failure on Demand (PFDavg). HIPPS is found to operate with high functional integrity at its inception, with FPI values nearing 1.0 and diagnostic responsiveness being the key factors. Despite this, functional performance gradually declines as undetected failures accumulate and diagnostic efficiency decreases. Over time, the SPI trend indicates an increasing divergence between projected and actual performance. A proof test interval of five years leads to a PFDavg of 0.025, which exceeds the maximum allowable PFDavg of 0.01 for SIL 2 as defined by IEC 61508, indicating that the system does not meet the required safety integrity level under this test. Ensuring compliance with SIL thresholds and verifying the impact of longer test intervals on safety standards. Robustness of the system is bolstered by low false alarm rates and strong coverage probability, but close alignment between simulated SPI values and operational data obtained from an onshore oil and gas production facility in Nigeria supports confidence in the model. The results highlight the need for shorter test intervals and improved diagnostics to sustain SIL performance.*

Keywords: *Average Probability of Failure on Demand (PFDavg), Functional Performance Index (FPI), High Integrity Pressure Protection Systems (HIPPS), Safety Integrity Level (SIL), System Performance Indices (SPI)*

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1. Introduction

Various multilayered protective measures are put in place to protect oil and gas production facilities from potential explosions, pipeline disruption or equipment failure. This ensured safety is guaranteed through these systems. The High Integrity Pressure Protection System (HIPPS) is one of the protective systems that prevent overpressure conditions that could pose a threat to personnel, the environment, and infrastructure [1]. Comparative studies have demonstrated that HIPPS provides significantly lower probability of failure on demand than conventional pressure safety valves (PSVs), making it the preferred overpressure protection solution in high-risk oil and gas facilities [2]. Independently detecting abnormal pressure and initiating system shutdowns, HIPPS functions as a barrier that meets international safety standards [3][4]. Typically, HIPPS architecture has these components: sensors, logic solvers and final control elements, configured in a two-out-of-three (2oo3) voting architecture, meaning the system initiates a protective action only when at least two of the three sensors detect an abnormal condition, thereby providing redundancy against a single sensor failure while maintaining fault tolerance [5][6]. High-pressure events are detected by sensors, the logic solver processes and validates them, and the actuators (valves) execute isolation commands. These subsystems, when taken together, determine the functional reliability and failure rate features of the system.

The most common method for evaluating the effectiveness of HIPPS is through the use of PFD and SIL classification [7]. In HIPPS, the PFD measures the probability of it failing when necessary and in SIL shows how much less risk is present. [3] designates SIL as having four levels (SIL 1–SIL 4), with a fourth level representing the highest level of [8]. Industry standards are considered to be the norm for HIPPS applications, with a minimum of SIL 3. Functional and failure rate analyses can uncover both random hardware failures and Dangerous Undetected (DU) and Dangerous Detected (DD) failure that could impact HIPPS performance [7]. Methods such as Self-Diagnostic Testing (SDT), Partial Stroke Testing (PST) and Functional Testing (FT) have helped identify and reduce DU failures while improving system reliability. The detection of localized or in-pregenital faults can be achieved through SDT and PST, but only through FT guarantees safety loop operations [5][6].

The degradation of reliability is not limited to component failures, but also encompasses testing intervals and proof test coverage. Increasing the number of tests runs over extended intervals increases the likelihood of an undetected fault, but excessive testing frequency can cause premature wear and shutdowns [7]. Therefore, to keep HIPPS within acceptable SIL ranges, it is necessary to optimize test intervals and failure rate estimation. Although previous research has emphasized reliability modelling [9] or probabilistic CCF quantification [10], only a few cases have integrated both approaches with empirical SIL evaluation.

This research addresses the existing limitations by employing reliability equations, PFD calculations, and test interval modeling to perform a functional and failure rate analysis of HIPPS. The employed methodology incorporates Fault Tree Analysis (FTA) and failure distribution functions to estimate the probabilities of component and system failures. The system's actual integrity level is ascertained by calculating the PFD-average and correlating it with SIL thresholds. The integration of functional performance analysis with SIL verification advances the use of predictive reliability management in high-risk industrial protection systems.

2. Literature Review

A. *Conceptual Basis of HIPPS*

The use of high-integrity pressure protection systems or HIPPS can provide protective measures to protect oil and gas assets from overpressure by utilizing logic-based decision loops [1]. Pressure transmitters, logic solvers and final elements (such as ESDVs) are present in each HIPPS loop, which is usually designed to use 2oo3 voting logic for improved fault tolerance [5][6]. When the pressure is unusual, the logic solver responds to it by detecting redundant sensor signals and activating the final control valves [10]. A key implementation challenge for HIPPS concerns the selection of isolation valves and actuators that can reliably achieve SIL 3 performance under demanding offshore conditions, including high-pressure and high-temperature process environments [11]. Additionally, the school's response time may affect its overall ranking. PFDs can be used by engineers to measure these failures and then determine the appropriate Safety Integrity Level (SIL) rating [3][8]. The Smart Efficiency Framework (SEF) is a systemic analytical framework developed [12], which views the performance of systems as influenced by the interdependence of sensing, predictive intelligence, and institutional or operational alignment. The authors highlight that the combination of undetected faults, a decrease in diagnostic effectiveness, and misunderstanding between modeled and actual system behavior leads to performance degradation. By emphasizing the significance of safety integrity as a dynamic system-level attribute rather than relying solely on functional performance indices (FPI), system performance metrics (SPI) and PFDavg-based evaluations in SIL determination, this perspective aligns with these standards.

B. *Failure Testing and Diagnostic Techniques*

According to the literature, HIPPS reliability verification relies on three testing techniques: Self-Diagnostic (SD), Partial Stroke Testing (PST), and Functional Testing. The PFD-average model was proposed in [7] which acts as an incorporation of the intermediate partial tests and proof tests for independent DU-fails. Based on this, [6] developed the SD-PST-FT hybrid approach, which suggests that conducting diagnostic and functional tests together can lead to better detection of hidden faults and decrease maintenance downtime. The significance of CCF in determining reliability is still being recognized as significant. The use of SD and PST can identify component-level anomalies, but it may not accurately detect complex inter–system faults, making periodic FT essential for validating total system response [9]. Dynamic Bayesian network-based studies of subsea HIPPS have further demonstrated that the introduction of partial stroke testing significantly improves system reliability and availability, particularly for final control elements such as isolation valves that are most susceptible to dangerous undetected failures between full proof tests [13]. The fraction of dangerous failures detected by PST known as PST-coverage, is a critical parameter in determining the effectiveness of partial testing, and procedures for its systematic quantification have been established to guide engineers in HIPPS maintenance planning [14].

C. *Rates and Measuring Reliability Failure*

For reliability, the failure rate (λ), PFD-average and Mean Time to Failure (MTTF) are used to measure HIPPS. Incorporating different voting architectures —

such as 1oo1 (one-out-of-one, a single non-redundant channel), 2oo3 (two-out-of-three, requiring two of three channels to agree before activation), or 2oo4 (two-out-of-four, requiring two of four channels to agree) — each imposes a different trade-off between redundancy and the risk of spurious or undetected failure on the given system [7]. The fault tolerance of 2oo3 systems means that one sensor can still be operated in a different location, unlike 1oo1 systems which have no redundancy. Field data collected from Norwegian petroleum industry operations confirm that beta-factor values vary significantly between facilities and are sensitive to operational and design conditions, underscoring the need for site-specific CCF estimation rather than reliance solely on generic industry-average values [15]. The integration of MBF within Markov and FTA frameworks, as noted by [16], can enhance the prediction of functional degradation by better accounting for cumulative failures with higher accuracy. The authors [17] developed an ANN-based adaptive model which provides continuous monitoring and prediction, enabling early detection of anomalies that may translate into failure events. This enhances the estimation of failure rates, supports accurate calculation of reliability indices, and improves Safety Integrity Level (SIL) determination by offering adaptive, data-driven insights into system performance and degradation patterns. In addition, the study conducted by [10] revealed that CCFs are susceptible to different structural configurations, such as serial, parallel, and bridge, which can significantly affect system availability or safety margin in some cases but not others. A comparative reliability study on HIPPS with and without CCF considerations confirmed that neglecting CCFs leads to an overestimation of system dependability, with significant reductions in SIL rating and mean downtime when CCFs are properly accounted for using the beta-factor model combined with reliability block diagrams and fault tree analysis [18].

D. Safety Integrity Level (SIL) Determination and Standards Compliance

A structured SIL assessment is used to measure the degree of risk reduction achieved by a safety system. The SIL is verified through periodic proof testing, redundancy, and failure diagnostics as per [3]. It is established using PFD-average values. Despite the potential for optimal performance, [7][9] emphasize the necessity of reliability modeling, preventive maintenance, and adaptive fault detection strategies to realize these objectives. General formulas for PFD assessment of MooN (k-out-of-n) system architectures subject to both partial and full proof tests have been derived and validated, demonstrating that the distribution and frequency of partial tests — not merely their presence — has a measurable impact on total PFDavg across the full proof test interval [19]. Furthermore, they underscore the significance of robust modeling and failure identification methodologies.

Existing research indicates substantial advancements in comprehending HIPPS functionality and failure dynamics, but also notable limitations. Most reliability models fail to account for dynamic interactions among testing regimes, voting logic, and real-time failure dependencies [6]. Furthermore, the authors in [20] developed an advanced reliability modelling framework for High Integrity Pressure Protection Systems (HIPPS) using the Multiple Beta-Factor (MBF) approach integrated with Fault Tree Analysis (FTA) such that the model improves representation of common-cause failures, enhances prediction accuracy, reduces probability of failure on demand, and provides a more realistic and effective safety assessment for oil and gas systems. Additionally, studies relying solely on Beta-Factor or Markov analysis often neglect multi-voting system behaviour and component-specific CCF coupling. A critical area for precise SIL determination in HIPPS involves the integration of analytical frameworks, specifically the combination of Fault Tree Analysis (FTA), Markov-Based Failure (MBF) models, and empirical testing data.

3. Methodology

In this section, we consider the quantitative analysis of a high precision integrity pressure equipment which provide its functional and failure behavior to determine its reliability. This quantitative model helps in quantifying the common-cause failure (CCF) probability in systems where redundancy is used to improve reliability, such as in a HIPPS. This research utilizes various materials and components, which are: Logic Controller, Pressure Valve Controller, MATLAB/Simulink, Personal Computer, Pressure Sensor.

The method used in this research is called "multi-beta factor". The multiple beta-factor model is a reliability model that helps in quantifying the common-cause failure (CCF) probability in systems where redundancy is used to improve reliability, such as in a HIPPS. Again, multi beta factor is an advance reliability analysis approach that uses multiple beta factors to account for different common failed redundant systems, providing a more accurate system reliability. The method is used to account for common failures in redundant systems. It assumes a certain fraction of beta factor of failure in redundant components.

A. Modelling of HIPPS using Fault Tree Analysis (FTA)

i. Basic Event Probability

$$P_i = 1 - e^{-\lambda_i t} \quad (1)$$

The FTA is classified as one the top-down deductive method used in reliability analysis to systematically identify and assess the causes of system failures, focusing on how component failures contribute to the failure of the overall system. It is effective for High Integrity Pressure Protection Systems (HIPPS) because it models complex interactions between subsystems (e.g., sensors, logic solvers, valves) and helps quantify failure probabilities, ensuring safety and compliance in critical applications. In a HIPPS, the FTA might show that the top event (system failure) results from either sensor malfunction, logic solver errors, or valve actuation failure, breaking down these failures using logic gates like OR and AND. This equation calculates the failure probability of a basic event i over time t using the distribution exponent, where: P_i in (1) is the failure probability of a basic event i, λ_i is the failure rate of the basic event i per unit time, t is the time period during which failure is considered.

ii. Gate Probability for AND Gate and OR Gate

$$P_{AND} = \prod_{i-1}^{n} P_i \quad (2)$$

$$P_{OR} = \prod_{i-1}^{n} (1 - P_i) \quad (3)$$

(2) and (3) calculates the probability of failure for an AND and OR gates in the fault tree, where all inputs must fail for the gate to fail, such that P_{AND} is the probability that AND gate event occur, P_{OR} is the probability that OR gate event occur, n is the number to input events.

iii. Minimal Cut Sets Calculation

$$P_{cut} = \sum_{j=1}^{m} P_{AND_j} \quad (4)$$

(4) sums the probabilities of failure for all the minimal cut sets present in the fault tree, where each cut set represents a unique combination of failures leading to the top event. P_{cut} is the total probability of system failure, approximated as the sum of failure probabilities of all minimal cut sets, P_{AND_j} the probability of the j-th minimal cut set occurring, m is the total number of minimal cut sets identified in the fault tree.

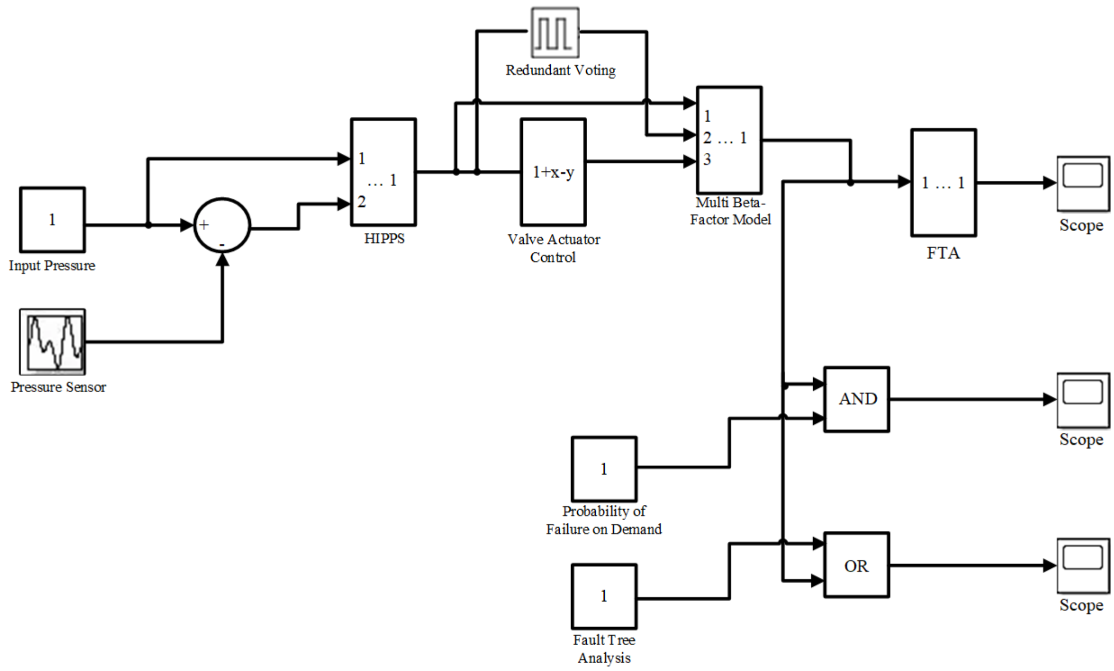

Fig. 1 Simulink Diagram of the Multi Beta Factor Model System

iv. MATLAB/Simulink Modelling

MATLAB/Simulink is used to design and model the HIPPS by utilizing the FTA method. This model has the input high pressure sensor which interfaces with the HIPPS which is connected to the control valve which lead to the multiple beta factor before going to the output on the oscilloscope, as described in (1).

B. Evaluation of the Realized Failure Rate Sequence on Common Cause Failures (CCF) with Multiple Beta-Factor (MBF) Model

i. Failure Rate of CCF with MBF

The failure rat with so many parts model is used to assess the likelihood that failures in multiple components arise due to a shared cause, impacting equipment reliability. This model accounts for the correlation between components, considering that certain failures may not be independent but rather influenced by a common underlying factor. The failure rate is calculated by applying a set of beta factors, which quality the strength of the dependency between the components in the system. By incorporating the MBF model, the system's failure behaviour can be more accurately predicted especially when the multiple components are vulnerable to similar failure modes. This methodology facilitates a more thorough comprehension of the aggregate risk, thereby contributing to the design of more robust systems through the consideration of both individual and common cause failures.

$$\lambda_{CCF} = \lambda.\beta \qquad (5)$$

(5) calculates the failure rate for a CCF using the MBF model, which adjusts the base failure rate by a beta-factor, where λ_{CCF} is the failure rate arising from the common-cause failures shared across redundant components on the system, λ is the total failure rate of an individual component, β is a dimensionless factor ($0 < \beta < 1$).

ii. Effective Failure Rate

The effective likelihood of failure in a system, accounting for both individual components failed and the effects of common cause failures. This approach integrates the failure probabilities of individual elements with the likelihood of concurrent failures stemming from common causes, thereby providing a more precise depiction of system dependability. This rate is modified in accordance with the interdependencies among components, which can affect the aggregate risk when a single component malfunctions, potentially triggering the failure of additional components.

$$\lambda_{eff} = \lambda.\left(1 + \frac{n-1}{\beta}\right) \qquad (6)$$

(6) calculates the effective failure rate, incorporating the impact of multiple beta-factors on the base failure rate. λ_{eff} is the combined failure rate that accounts for both independent failures and the common-cause failures across all n redundant components.

iii. Evaluation of PFDavg to determine SIL

The evaluation of the (PFD-average) is crucial step to determine reliability of systems operating at various protective stage. PFD-average measures some safety of a system would not be successful when needed, and it is essential for assessing whether the system meets the required SIL for safety performance. The PFD-average is commonly determined by considering factors like component failure rates, redundancy, and the system's response time under fault conditions. The PFD-average is then compared to the target values defined for each SIL, which can be used by engineers to determine whether the system provides sufficient protection from potential hazards.

iv. Probability of Failure on Demand (PFD)

This is a very critical parameter when determining how good and stable a particular work or device is. Protect an equipment in circuit, particularly in protection-critical environments. It represents the its intended protection of a device should either be a function when it is made or needed, typically when answerable to a right situation. PFD design is influenced by factors such as component failure rates, system architecture, and the inclusion of redundancy. Lower PFDs are more reliable as they exhibit a lower failure risk when necessary. Engineers can use the PFD to evaluate safety systems and determine if they meet the required safety integrity standards (SIL). PFD average is used in calculating HIPPS to determine the safety integrity level (SIL). This is where the realization and calculation of the probability of failure on demand average are determine for the reliability of the high integrity pressure protection system are known for the safety integrity level. They are described in (8), (9) and (10).

$$PFD = \frac{(\lambda_{fail}.\, T_{test})}{1 + \lambda_{fail} \cdot T_{test}} \qquad (7)$$

(7) calculates the instantaneous Probability of Failure on Demand (PFD) for a single-channel system, where λfail is the dangerous undetected failure rate (per hour) and Ttest is the proof test interval (in hours). The numerator represents the cumulative failure exposure over the test interval, and the denominator normalizes for system availability.

v. Probability of failure on demand PFD-average Calculation

$$PFD_{avg} = \frac{1}{2}\,.PFD_{min} + \frac{1}{2}\,.PFD_{max} \qquad (8)$$

(8) calculates the average probability of failure on demand (PFD) by averaging the minimum and maximum PFD values.

To ensure adequate risk reduction in hazardous situations, the SLI is used to assess the protection standard across different equipment stages. Each SIL is linked to a specific set of PFD values, with the potential consequences being taken into account. By knowing some of the variables which include how difficult the equipment is, operational environment, and the potential impact of a failure, engineers can determine the appropriate SIL to achieve the desired safety performance.

$$SIL = \min\{i \mid PFD_{avg} \leq PFD_{SIL}\} \qquad (9)$$

(9) determines the Safety Integrity Level (SIL) based on the average probability of failure on demand. PFD_{avg} is the computed average probability of failure on demand for the system from (8), PFD_{SIL} is the maximum allowable PFDavg for SIL level.

vi. Influence of Testing Interval on PFD

The duration of the testing interval significantly affects the system's probability of failure on demand (PFD); longer intervals between tests can increase the likelihood of system failure when a demand is made. By reducing testing durations, safety systems are typically more reliable as they can detect potential issues before they become problematic and improve the system's reliability. A low PFD can be maintained by balancing the testing interval with operational constraints, system safety function criticality, and maintenance costs. Research has shown that partial stroke testing, when incorporated between full proof tests, can effectively extend acceptable proof test intervals by detecting a proportion of dangerous valve failures without disrupting process operations, thereby offering a practical means of balancing safety integrity with operational continuity [21].

$$PFD_{test} = \frac{\lambda_{fail -} T_{test}}{1 + \lambda_{fail} - T_{test}} \quad (10)$$

Using the same PFD formulation as (7), the effect of a varied proof test interval can be assessed by substituting different values of Ttest. (10) re-evaluates the Probability of Failure on Demand under a modified proof test interval Ttest, using the same structural form as (7). This formulation enables systematic comparison of PFD sensitivity to changes in the testing regime, consistent with IEC 61508 interval optimization requirements.

vii. Reliability Function

The reliability function is a mathematical representation of that equipment ability in delivering what was actually designed for the require period for which it was specified. By stating that the equipment can function prior to experiencing any issues, one can gain insight into the system's overall reliability. The reliability function is critical for assessing the lifespan of components and systems, helping engineers optimize maintenance schedules and design for long-term performance.

$$R(t) = e^{-\lambda t} \quad (11)$$

(11) represents the reliability function over time, showing the probability that a component will not fail up to time t, where λ is the constant failure rate of the component, t is the elapsed operating time in hours over which reliability is being evaluated.

C. Evaluate Functional Performance and Validate Model Accuracy

Functional performance is typically assessed using metrics like response time, reliability indicators (e.g., mean time between failures), and failure rates; these metrics provide a window into the system's efficiency and resilience. The accuracy of predictive models is evaluated by comparing model predictions with real-world data. This is done using statistical validation methods, such as the root mean square error (RMSE) and the mean absolute error (MAE). These comparisons help identify inconsistencies, allowing for model improvements and, therefore, more accurate predictions.

i. Functional Performance Index (FPI)

$$FPI = \frac{P_{actual}}{P_{expected}} \quad (12)$$

(12) measures the functional performance of the HIPPS by comparing the actual performance to the expected performance. P_{actual} is the measured performance metric of the HIPPS at a given point, $P_{expected}$ is the theoretical or design-specification performance level that the HIPPS should achieve under normal operating conditions.

ii. Model Accuracy Validation

$$Accuracy = \frac{N_{correct}}{N_{total}} \quad (13)$$

By dividing the correct number of predictions by the predictions total number, (13) can calculate the accuracy of the model, $N_{correct}$ such that is the number of model predictions that match the actual observed data within an acceptable tolerance, N_{total} is the total number of predictions made by the model over the evaluation dataset.

iii. Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |P_{model.i} - P_{actual.i}| \quad (14)$$

(14) calculates the MAE of the model’s predictions compared to actual values, giving an average magnitude of errors, such that N is the number of data points used in the validation, $P_{model.i}$ is the value predicted by the simulation model for the i-th observation, $P_{actual.i}$ is the actual measured value for the i-th observation.

iv. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_{model.i} - P_{actual.i})^2} \quad (15)$$

(15) calculates the root mean square error of the model’s predictions, providing a measure of the average magnitude of the prediction errors.

v. System Performance Index

$$SPI = \frac{P_{required}}{P_{observed}} \quad (16)$$

(16) assesses system performance by comparing the required performance level to the observed performance.

TABLE I
PARAMETERS OF THE RESEARCH

Parameter	Sign	Value	Unit	Description
Input Pressure	P_{in}	100	Bar	The pressure entering the system
Sensed Pressure	P_{sense}	98	Bar	Pressure detected by the sensor
Failure Rate	Λ	0.001	1/hr	The failure rate of a component
Proof Test Interval	T_{test}	8760	Hours	Time interval between proof tests
Probability of Failure on Demand	PFD	Cal.Value	-	Probability that the system will fail on demand
System Response Time	T_{resp}	1.5	Seconds	Time taken by the system to respond to input
Threshold Level	T_{level}	90	Bar	Pressure threshold for triggering HIPPS
Reliability	R	0.99	-	The reliability of the system
Beta Factor	β	0.1	-	Common cause failure factor

4. Results and Discussions

A. Functional Performance Index

From Fig. 2, the functional performance index, ranging from 0.8 to 1.3 over 100 hours, reflects the varying levels of effectiveness of the system under analysis. This index quantifies a system's operational efficacy in relation to a predetermined or anticipated benchmark. A value of 1 generally signifies peak performance, implying that the system functions precisely as intended, without any deviation from its prescribed operational parameters. Conversely, values below 1, exemplified by 0.8, indicate suboptimal performance, suggesting that the system does not fully satisfy the expected functional requirements; this may be indicative of inefficiencies, partial malfunctions, or external influences impacting performance. The observed fluctuations in the functional performance index across a 100-hour period could potentially reflect the system's capacity to adjust to varying operational parameters, including changes in load, environmental factors, or the gradual onset of deterioration.

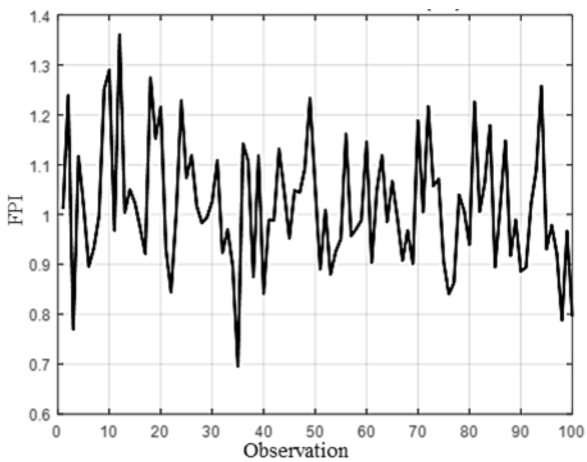

Fig. 2 Functional Performance Index

B. Model Validation

Fig. 3 illustrates the model validation procedure, revealing an MAE of 0.1% and an RMSE of 0.13%. For evaluating the model's dependability and precision, the performance indicators above are essential. The MAE of 0.1% signifies that, on average, the model's forecasts diverge from the actual values by a mere 0.1%. This minimal error rate underscores the model's considerable accuracy, implying that the predictions closely approximate the observed data, thereby demonstrating its efficacy in accurately representing the system's inherent characteristics. The root mean square error (RMSE) of 0.13%, although slightly elevated, remains quite low, suggesting that the model's predictions are generally precise, notwithstanding a few instances of minor discrepancies. The RMSE's marginal increase relative to the mean absolute error (MAE) implies that these larger errors are infrequent and do not substantially affect the model's overall efficiency.

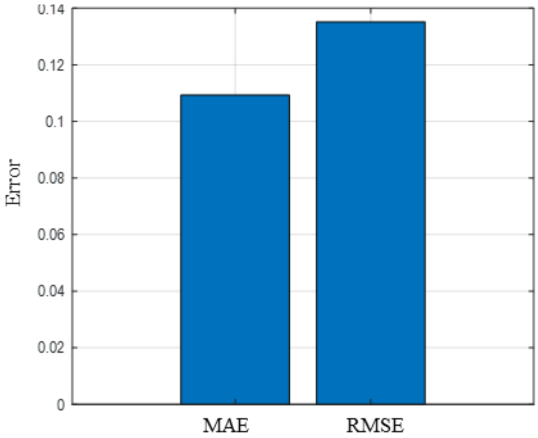

Fig. 3 Model Accuracy Validation

C. Proof Test Interval

When considering a 5-year proof test interval, the calculated PFDavg of 0.025 represents the average probability that the HIPPS will fail to perform its intended protective function upon demand within the specified test period. Since PFDavg is a probability, its value must fall strictly between 0 and 1, where 0 indicates no likelihood of failure and 1 indicates certain failure. A PFDavg of 0.025 means that, on average, the system has a 2.5% chance of failing to operate correctly when required during the 5-year proof test interval. According to IEC 61508, a PFDavg in the range of 0.01 to 0.1 corresponds to SIL 1, while SIL 2 requires PFDavg to remain below 0.01. The computed value of 0.025 therefore falls within the SIL 1 band and does not satisfy the SIL 2 or higher requirements typically expected for HIPPS in oil and gas facilities. This result underscores the need for a shorter proof test interval or improved diagnostic coverage to achieve the required SIL compliance.

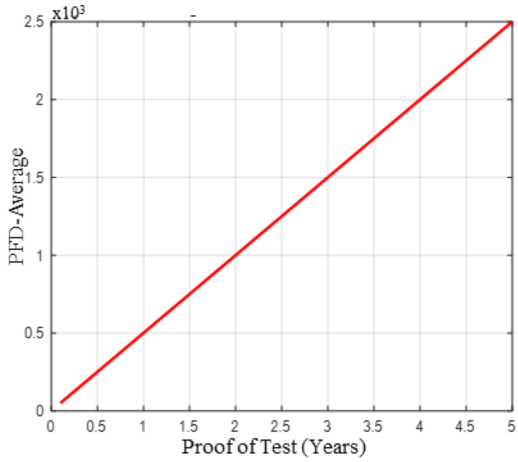

Fig. 4 PFD Average Vs Test Interval for HIPPS in SIL

D. System Performance Index Evaluation

Fig. 5 illustrates the System Performance Index (SPI) for a 100-hour period, with intervals of significance such as 0.8 at 50 hours, 1 at 80 hours and 0.9 at 100 hours. An SPI reading of 0.8 at 50 hours implies a system that is not entirely efficient, suggesting potential operational suboptimality or inefficiencies. It is observed that by 80 hours, the SPI reaches 1, thereby denoting peak performance and signifying that the system is operating at its maximum efficiency. The observed enhancement implies that the system has attained a stable and optimal condition, potentially attributable to maintenance interventions, recalibration procedures, or other modifications that have improved its operational efficacy. It is further observed that at the 100-hour mark, the SPI experiences a slight reduction to 0.9; although this still signifies satisfactory performance, it represents a minor decrease from the zenith observed at the 80-hour interval.

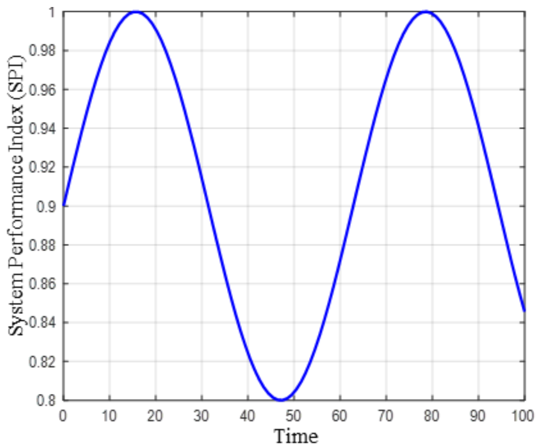

Fig. 5 System Performance Index

E. Probability of Detection

Fig. 6 presents the correlation between the Probability of Detection (Pd) and the Noise Ratio (NR). A Pd of 1, coupled with a Noise Ratio (NR) of 20 dB, denotes an optimal scenario for precise detection. Specifically, a Pd of 1 suggests the system's flawless signal detection, with no instances of missed signals, thereby representing a 100% detection rate. This degree of accuracy is paramount in contexts where the omission of a signal result in substantial repercussions. The 20dB noise ratio serves as further evidence that a higher noise usually indicates better clarity, and thus more clearly distinguishes the signal from the background noise. Increasing the strength of signals to 20 to 1 dB improves the detection system's ability to identify them with greater accuracy.

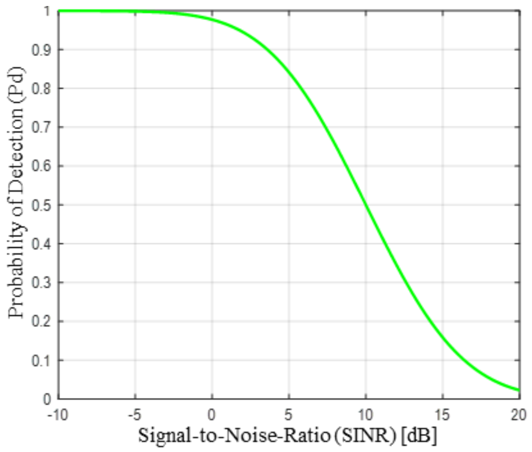

Fig. 6 Probability of Detection

F. False Alarm Rate

In Fig. 7, the false alarm rate shows a considerable reduction, dropping from 1 to 0.01, when the threshold level is set to 5. At the outset, with a false alarm rate of 1, the system exhibits a high incidence of erroneous detections, incorrectly categorizing normal operating conditions as faults. This increased rate indicates that the system's sensitivity is insufficiently calibrated, resulting in a substantial number of false positives. As the threshold level is raised to 5, the system's detection process becomes more selective. Consequently, this increased threshold requires more robust or well-defined signals to trigger an alarm, thereby reducing the likelihood of false positives. At a level of 5, the false alarm rate is substantially reduced to 0.01. Thus, the system's reliability has been considerably improved, given that false positives occur infrequently. Consequently, false alarms are reduced and the overall system performance is improved, while also improving the accuracy of an individual's false flag.

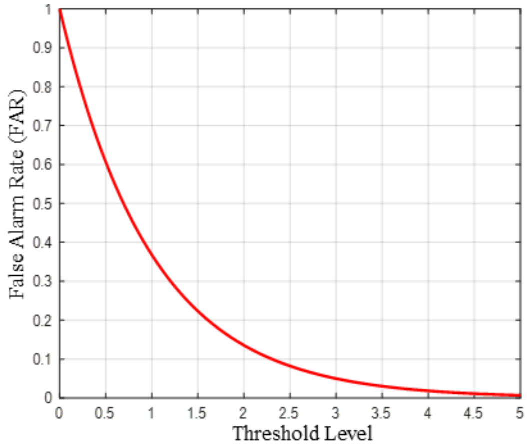

Fig. 7 False Alarm Rate

G. Coverage Probability Evaluation

Fig. 8 presents the diagnostic coverage probability of the HIPPS as a function of the spatial extent of the monitored pipeline segment, expressed in meters. Diagnostic coverage probability refers to the likelihood that the HIPPS sensor network and logic architecture will successfully detect a dangerous failure condition anywhere within the monitored segment. At shorter pipeline distances, the coverage probability reaches its peak value of 1.0, indicating complete detection capability within the near-field instrumentation zone of the facility. As the monitored distance increases — for instance, across longer intra-facility pipeline runs up to a maximum of 100 meters — the effective coverage probability declines due to increasing signal propagation delay, sensor spacing, and communication latency between field devices and the logic solver. This behavior underscores the importance of optimizing sensor placement density and communication architecture within the HIPPS installation to maintain adequate fault detection across the full extent of the protected segment.

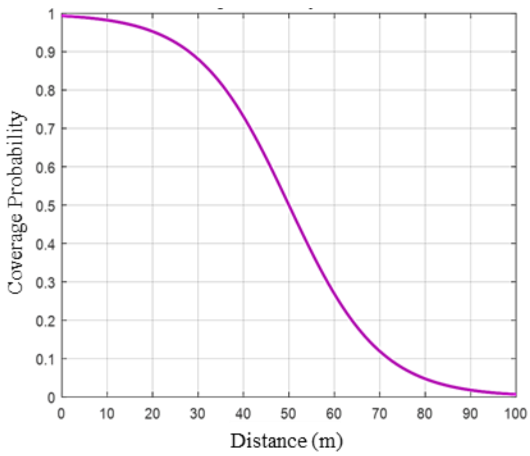

Fig. 8 Coverage Probability vs Distance

H. SPI Model vs Real World Data

To validate the simulation model, the computed SPI values were compared against operational performance data recorded from an instrumented HIPPS unit at an onshore oil and gas production facility in Rivers State, Nigeria, over a continuous 100-hour monitoring period. This dataset was obtained during routine operational logging and captures real sensor, logic solver, and valve actuation performance under normal production conditions. Significant differences in performance over time can be observed by comparing the simulated System Performance Index (SPI) with this real-world data, as shown in Fig. 9. The system's SPI at the 50-hour point is 0.8, whereas the real-world SPI is 0.9. Initially, this suggests that the real-world system outperforms the model, which could indicate a conservative bias in its early predictions. Furthermore, as the observation period reaches 80 hours, the system's SPI peaks at 1.0, aligning with the model's optimal performance forecast. The empirical data reveals a modest reduction to 0.89, suggesting that although the system maintains satisfactory functionality, it falls short of the model's projected optimal performance. By the 100-hour interval, the real-world SPI further diminishes to 0.86, whereas the system's SPI exhibits a slight decrease to 0.9.

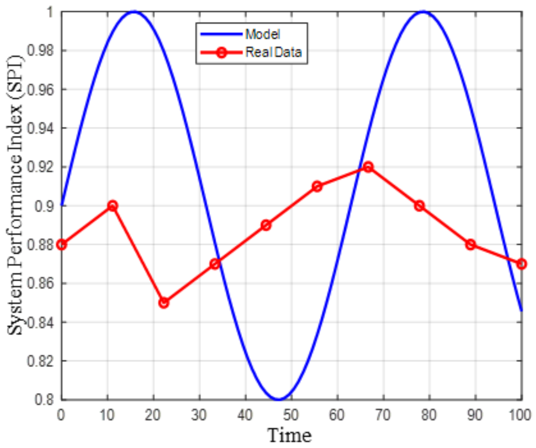

Fig. 9 System Performance Index (SPI) Model vs Real World Data

5. Conclusion

By utilizing an elaborate functional analysis framework, this study examined the Functional behavior, failure rate performance and Safety Integrity Level (SIL) suitability of high-integrity pressure protection systems (HIPPS). Functional metrics such as the Functional Performance Index (FPI), System Predictor (SPI) and Probability of Detection (POD), false alarm rates, and coverage probability were included in the study. The Probability of Failure on Demand (PFDavg) was also examined at realistic proof test intervals. HIPPS is known to have high functional integrity at the beginning of its service, with FPI values near 1.0 and high POD values. Over time, the performance indices gradually decline as a result of an increase in dangerous undetected failures and progressively decreasing diagnostic coverage. A growing gap between required and achieved performance was confirmed by the SPI trend as operational hours increased. A proof test interval of five years yielded a PFDavg of 0.025, which places the system within the SIL 1 band ($0.01 \leq$ PFDavg < 0.1) and does not satisfy the SIL 2 or higher requirements mandated by IEC 61508 for HIPPS applications in high-risk oil and gas facilities. This was noteworthy. If HIPPS does not meet the SIL compliance requirements at extended test intervals, the system falls outside the acceptable SIL 1–4 classification band a defined by IEC 61508, meaning it provides insufficient risk reduction for use as a safety-critical protective function. Additionally, even with a proof test interval that exceeded acceptable thresholds, dangerous failures could still occur due to the strong coverage probability, low false alarm rates, and good early operational performance. The functional model used was validated by demonstrating the close alignment between simulated and real-world SPI data during the functional validation. This is noteworthy. Collectively, these results indicate that functional reliability and SIL compliance are highly affected by proof test intervals, diagnostic efficiency, as well as patterns of component degradation.

Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

Author Contributions

All authors contributed to the completion of the article as there were no distinct contributions. All contributions were made for all the sections of this article.

References

[1] E. M. Marszal, and E. W. Scharpf, “Safety Integrity Level Selection: Systematic Methods Including Layer of Protection Analysis,” *International Society of Automation*, 2009. ISBN: 978-1-945541-50-6.

[2] K. Sotoodeh, "High integrity pressure protection system (HIPPS) usage justification from safety and reliability point of views," *Safety in Extreme Environments*, vol. 3, pp. 113–123, 2021. https://doi.org/10.1007/s42797-021-00033-1.

[3] IEC 61508, “Functional Safety of Electrical/Electronic/Programmable Electronic Safety-Related Systems,” *International Electrotechnical Commission*, https://standards.globalspec.com/std/1250318/iec-61508-1

[4] IEC 61511, “Functional Safety – Safety Instrumented Systems for the Process Industry Sector,” *International Electrotechnical Commission,* https://26164953.s21i.faiusr.com/61/ABUIABA9GAAg5fmIjQYo1tntGA.pdf.

[5] M. Tanjin Amin, F. Khan, and S. Imtiaz, "Dynamic availability assessment of safety critical systems using a dynamic Bayesian network," *Reliability Engineering & System Safety*, vol. 178, pp. 108-117, 2018, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2018.05.017.

[6] Y. Yu, Y. Liang, S. Wu, B. Cai, Y. Pan, R. Gao, S. Cheng, Y. Cui, Y. Yang, and H. Guo, "Safety performance evaluation of offshore high integrity pressure protection system using multiphase dynamic Bayesian network methodology," *Ocean Engineering*, vol. 310, no. 2, 2024, ISSN 0029-8018, https://doi.org/10.1016/j.oceaneng.2024.118620.

[7] H. Jin, and M. Rausand, "Reliability of safety-instrumented systems subject to partial testing and common-cause failures," *Reliability Engineering & System Safety*, vol. 121, pp. 146-151, 2014, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2013.08.006.

[8] M. Cheraghi, and S. Taghipour, "Safety Integrity Level (SIL) evaluation of safety instrumented systems considering competing failure modes and subsystem priorities," *Reliability Engineering & System Safety*, vol. 260, 2025. ISSN 0951-8320, https://doi.org/10.1016/j.ress.2025.111025.

[9] S. Alizadeh, and S. Sriramula, "Reliability modelling of redundant safety systems without automatic diagnostics incorporating common cause failures and process demand," *ISA Trans*, pp. 599-614, https://doi.org/10.1016/j.isatra.2017.09.007.

[10] S. B. Govardhan Rao, J. P. Castellanos-Ardila and S. Punnekkat, "A Systematic Review of β-factor Models in the Quantification of Common Cause Failures," *2023 49th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, Durres, Albania, pp. 262-269, 2023, https://doi.org/10.1109/SEAA60479.2023.00048.

[11] K. Sotoodeh, "A review of high integrity pressure protection systems (HIPPSs) and challenges related to valve selection for HIPPS application for a flare line in an offshore project," *Safety in Extreme Environments*, vol. 4, pp. 47–58, 2022. https://doi.org/10.1007/s42797-022-00051-7.

[12] P. I. Onu and R. O. Okeke, "Towards Systematic Energy Efficiency: The Smart Efficiency Framework for Sustainable Transitions in Nigeria and West Africa," *Journal of Alternative and Renewable Energy Sources*, vol. 11, no. 3, pp. 14-26, Oct. 2025.

[13] C. Wang, Y. Liu, W. Hou, C. Yu, G. Wang, and Y. Zheng, "Reliability and availability modeling of Subsea Autonomous High Integrity Pressure Protection System with partial stroke test by Dynamic Bayesian," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 235, no. 2, pp. 268–281, 2021. https://doi.org/10.1177/1748006X20947851.

[14] M. A. Lundteigen and M. Rausand, "Partial stroke testing of process shutdown valves: How to determine the test coverage," *Journal of Loss Prevention in the Process Industries*, vol. 21, no. 6, pp. 579–588, 2008. https://doi.org/10.1016/j.jlp.2008.04.007.

[15] S. Hauge, P. Hokstad, S. Håbrekke, and M. A. Lundteigen, "Common cause failures in safety-instrumented systems: Using field experience from the petroleum industry," *Reliability Engineering & System Safety*, vol. 151, pp. 34–45, 2016. https://doi.org/10.1016/j.ress.2015.09.018.

[16] E. Zio, "Reliability engineering: Old problems and new challenges," *Reliability Engineering & System Safety*, vol. 94, no. 2, pp. 125-141, 2009, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2008.06.002.

[17] P. I. Onu, and R. O. Okeke. "Energy-Efficient Internet of Things (IoT) Device Communication With Artificial Neural Networks (ANN)". *Asian Journal of Engineering and Applied Technology*, vol. 15, no. 1, Apr. 2026, pp. 25-36, https://doi:10.70112/ajeat-2026.15.1.4338.

[18] H. Metatla and M. Rouainia, "Functional and dysfunctional analysis of a safety instrumented system (SIS) through the common cause failures (CCFs) assessment. Case of high integrity protection pressure system (HIPPS)," *International Journal of System Assurance Engineering and Management*, vol. 13, no. 4, pp. 1932–1954, 2022. https://doi.org/10.1007/s13198-021-01608-8.

[19] F. Brissaud, A. Barros, and C. Bérenguer. "Probability of failure of safety-critical systems subject to partial tests." *2010 Proceedings - Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1-6, 2010.

[20] R. O. Okeke and P. I. Onu. "Reliability Modelling of a High Integrity Pressure Protection System (HIPPS) Using the Multiple Beta-Factor Approach for Enhanced Safety in Oil and Gas," *Asian Journal of Engineering and Applied Technology*, vol. 15, no. 1, pp. 37-49, 2026. https://doi.org/10.70112/ajeat-2026.15.1.4339.

[21] M. A. Lundteigen and R. Marvin. "The effect of partial stroke testing on the reliability of safety valves." 2007.