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RELIABILITY ANALYSIS AND OPERATIONAL RISK MATRIX OF SAFETY VALVES

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ABSTRACT

This research investigates the application of reliability theory to safety valves, emphasizing fundamental concepts such as the reliability function *R(t)*, failure function *F(t)*, failure rate λ(t), Mean Time To Failure (*MTTF*), and Mean Time Between Failures (*MTBF*). A practical case study, based on data collected from a petrochemical operator, illustrates how reliability analysis can identify critical failure modes such as blockage, leaks, early opening, and corrosion, highlighting their severe consequences in safety-related applications. This research applies reliability theory to safety valves, utilizing statistical models like Exponential and Weibull distributions to analyse failure modes such as blockage, leaks, early opening, and corrosion. A key finding is that valve reliability significantly declines after approximately 3,000 operational hours, emphasizing the need for predictive maintenance strategies based on historical and real-time operational data. The study advocates for integrating reliability and maintenance analysis throughout the safety valve lifecycle, shifting from reactive to proactive maintenance to reduce unexpected failures and optimize costs. The study develops an integrated mathematical methodology for failure probability estimation. A case study from a petrochemical operator uses risk assessment tools like risk matrices to prioritize maintenance actions. Data analysis reveals an MTBF of 4250 hours, a CoV of 0.577, and reliability dropping to 49.3% at 3000 hours and 30.8% at 5000 hours. Valve blockage and leaks are critical risks, while premature opening and corrosion are medium risks.

Recommendations include using the exponential distribution for reliability analysis, implementing predictive maintenance after 3000 hours, periodic inspections and fluid filtration for valve blockages, and seal replacements and leak-tightness checks for leaks.

Keywords: safety valves, reliability, risk matrix, predictive maintenance, statistical models

INTRODUCTION

In the case of safety valves, applying reliability concepts and models is crucial to ensure their proper and safe functioning throughout their lifespan. Reliability analysis allows engineers to estimate the probability that a valve will operate effectively and avoid failures under normal operating conditions or during overpressure situations [1], [2].

Statistical models, such as the Weibull or exponential distribution, are used to evaluate how and when failures like blockage, leaks, or corrosion might develop. This enables the implementation of predictive maintenance strategies to prevent unexpected breakdowns and to develop risk mitigation measures, especially in critical applications. Moreover, these analyses help optimize the design and inspection processes, maximizing the durability and safety of the valves. As a result, the performance of safety and relief systems is improved, significantly reducing the risk of accidents and ensuring compliance with safety standards in industrial processes [3], [4].

Reliability is the measure of the likelihood that a system or a component will perform its specified functions effectively under given conditions over a particular period. It defines the probability that the system remains operational and fulfils its intended purpose without failure within the designated timeframe. In the context of industrial equipment, reliability is of utmost importance because it directly influences operational efficiency, safety, maintenance schedules, and overall cost management. Reliable systems help minimize unplanned downtimes, reduce the need for frequent repairs, and ensure that operations proceed smoothly and safely, especially in critical industrial processes where failure can lead to significant economic losses or safety hazards [5].

Fundamental concepts associated with reliability include the reliability function $R(t)$, which represents the probability that a system works without failure up to a certain time t; the failure function $F(t)$, which provides the probability that the system will have failed by time t and is mathematically expressed as $F(t) = 1 - R(t)$. The failure rate $\lambda(t)$ indicates how often failures occur over time, reflecting the frequency of breakdowns within the system as a function of time. The Mean Time To Failure (*MTTF*) measures the average operational time before a failure occurs in systems that are not repairable, serving as an important indicator of expected longevity. For systems that can be repaired after failure, the Mean Time Between Failures (*MTBF*) is used, representing the average operating time between two failures and providing insight into the system's availability and reliability. These indicators are vital for planning maintenance, designing systems with appropriate redundancy, and ensuring that operational performance meets safety and efficiency standards.

Various models are employed in reliability engineering to describe and predict how systems behave over time. These models take into account each system's failure characteristics, enabling engineers to estimate failure probabilities and plan maintenance activities effectively. The most common models include the exponential distribution, Weibull distribution, normal distribution, and lognormal distribution [6], [7]. The exponential distribution is particularly suited for systems with a constant failure rate generally applicable during the useful life phase where the likelihood of failure remains unchanged regardless of elapsed time. Its reliability function is expressed as $R(t) = e^{-\lambda t}$, where λ is the failure rate, and it is often used for electronic devices or simple systems.

The Weibull distribution offers greater flexibility as it can model all three phases of a system’s lifecycle: early failure, random failure periods, and wear-out failure phases. Its reliability function, $R(t)= e^{-(t/\eta)^\wedge\beta}$, introduces parameters η (scale) and β (shape), which allow it to adapt to various failure behaviours. Specifically, when $\beta<1$, the model describes early failures, $\beta=1$ corresponds to constant failure rate periods like the exponential model, and $\beta>1$ captures wear-out failures typical in aging components like mechanical parts and machinery [8], [9], [10]. The normal (Gaussian) distribution is used mainly when equipment failures are dominated by wear, ageing, or accumulated damage, characterized by a predictable progression over time. It is defined by the mean (μ) and standard deviation (σ) of failure times, reflecting typical failure behaviour in many industrial components subjected to aging processes. The lognormal distribution is applicable to systems where failure times are influenced by multiplicative stress factors, such as electrical components or complex systems experiencing variable operational stresses that can multiply stress impacts and accelerate failure. The Lognormal reliability function models the probability that a component will survive up to a certain time, accounting for the multiplicative effects of stressors.

More complex systems are often modelled using Markov processes, which consider multiple operational states and transition probabilities between them. These models are especially relevant for systems with interdependent components or multiple failure modes, providing a comprehensive view of system behaviour over time. Additionally, Monte Carlo simulation methods are employed for analysing complex systems where analytical models are inadequate. These simulations run numerous iterations of potential failure scenarios, incorporating variability and uncertainty in inputs, allowing for robust estimation of reliability and failure probabilities based on stochastic behaviour [11]. In practical applications, reliability models are used in various ways in industrial equipment management. During the design phase, these models help engineers predict system performance, identify critical failure points, and incorporate redundancy or design modifications to enhance reliability. In operational phases, reliability analysis supports proactive maintenance strategies, such as predictive maintenance utilizing real-time monitoring data, guiding intervention planning before failures occur [12], [13].

Risk management also benefits from reliability data by identifying critical components whose failure could lead to safety hazards or costly downtimes, thereby prioritizing maintenance resources. Cost optimization is achieved by balancing the costs of maintenance, repairs, and downtime against the benefits of increased reliability, leading to more sustainable and economically viable operation [14], [15].

Research on reliability analysis and operational risk matrix of pressure relief valves has emerged as a critical area of inquiry due to the essential role these valves play in safeguarding pressurized equipment and ensuring process safety in various industries [16], [17]. Over the past two decades, the field has evolved from basic inspection protocols to sophisticated risk-based inspection (RBI) methodologies and probabilistic modeling approaches [18], [19]. The practical significance is underscored by statistics indicating that nearly half of pressure relief devices in industrial settings exhibit deficiencies, contributing to potential overpressure accidents with severe consequences for personnel and assets [20], [21]. Moreover, the increasing adoption of hydrogen and other alternative energy systems has introduced new challenges in valve reliability and risk assessment [22], [23].

The specific problem addressed in this review concerns the optimization of inspection intervals and the quantification of failure probabilities for pressure relief valves, which remain inadequately resolved despite extensive research [24], [25]. A critical knowledge gap exists in integrating multi-factorial influences such as design, environment, and operational conditions into failure rate evaluations and risk matrices [26], [27]. Controversies persist regarding the extension of maintenance intervals, with some studies advocating longer intervals to reduce human error and costs [28], [29], while others emphasize the increased risk of valve failure and consequent accidents [30], [31]. Failure to reconcile these perspectives may lead to suboptimal maintenance strategies, elevating the risk of catastrophic failures [32].

The aim of this research is to assess and enhance the reliability and risk management of industrial safety valves, identifying weaknesses and proposing preventive and corrective measures to ensure safe, continuous operation. The study introduces integrated modern risk and reliability analysis methods, combining qualitative and quantitative evaluations to provide a comprehensive understanding of valve behaviour. Its novelty lies in detailed risk assessment using severity and probability scales, along with concrete management strategies such as inspections, part replacements, and use of resistant materials.

RELIABILITY ANALYSIS OF A SAFETY VALVE

A safety valve is an essential component in the safety systems of industrial facilities, with the role of preventing explosions or serious failures through controlled release of excess pressure [33], [34]. The reliability of these valves is critical because a failure can led to severe consequences such as production losses, material damage, or even risks to personnel safety. Therefore, a detailed analysis of reliability and associated risks must be performed to identify weak points and implement improvement measures [35], [36], [37]. In this research, the Dn25/50-Pn40 safety valve was used, the overall drawing of which of the safety valves used in various industrial applications is presented in Figure 1, the technological line related to the valve circulates a petroleum product from the Catalytic Cracking plant.

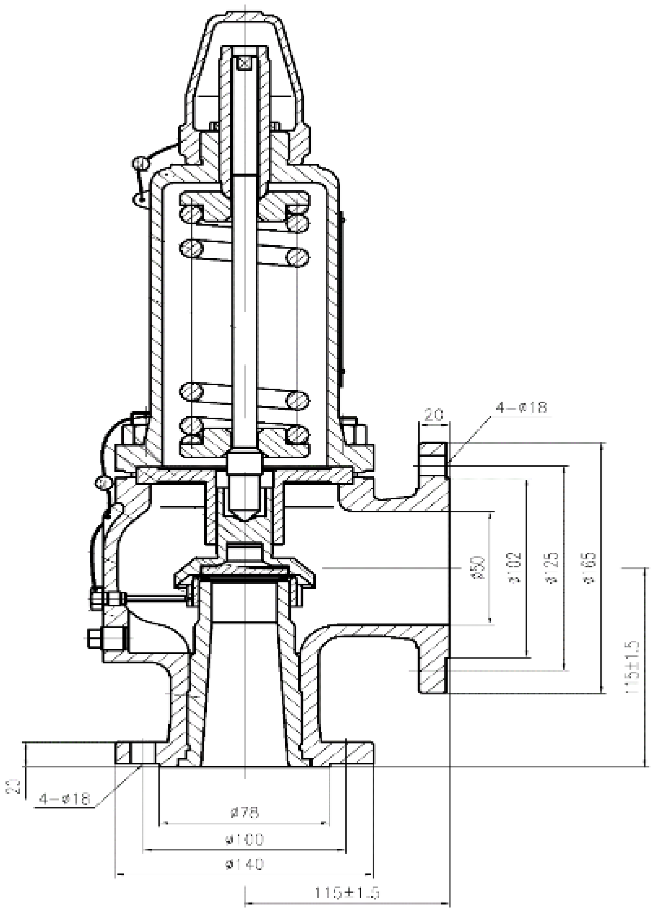

Figure 1. *General drawing of the valve type Dn25/50-Pn40*

Research on the appropriateness of the exponential distribution for reliability analysis of pressure relief valves has emerged as a critical area of inquiry due to the essential safety role these devices play in preventing overpressure incidents in industrial systems [38]. Over the past two decades, studies have evolved from basic reliability assessments using Weibull models, exponential distribution that allows the evaluation of reliability [39] to more complex analyses incorporating Bayesian methods and semi-Markov models [40], [41]. Moreover, the increasing deployment of pressure relief valves in emerging energy sectors, such as hydrogen systems, further elevates the need for accurate reliability modelling using exponential distribution [42]. The specific problem addressed is the validity of the exponential distribution assumption in modelling pressure relief valves failure times, which traditionally simplifies reliability calculations by assuming a constant failure rate [43], [44].

Input Data - *Table 1*

A. Number of tested valves: 50 identical safety valves.

B. Operating time: 5000 hours (total observation time).

C. Recorded failures (failure time in hours): 1000, 1200, 1500, 1800, 2000, 2200, 2500, 2800, 3000, 3200, 3500, 3800, 4000, 4200, 4500, 4800, 5000, 5000, ..., 5000 (the last 10 valves had no failures).

Table 1. *Failures of safety valves*

Time interval (hours)	*Number of failed valves*	*Time interval (hours)*	*Number of failed valves*
1000	2	3200	3
1200	1	3500	2
1500	2	3800	3
1800	3	4000	3
2000	1	4200	2
2200	3	4500	2
2500	4	4800	4
2800	3	> 5000	10
3000	2		

Step 1: Calculating MTBF

MTBF (Mean Time Between Failures) is the average time between failures.

Total operating time: the 10 valves that had no failures operated each for 5000 hours.

$10 \times 5000 = 50{,}000$ hours

The 40 failed valves operated for: $1000 + 1200 + ... + 5000 = 120{,}000$ hours

Total: $50{,}000 + 120{,}000 = 170{,}000$ hours.

Number of failed valves: $n = 40$.

$$MTBF = \frac{170000\ hours}{40} = 4250\ hours$$

Interpretation: *on average, one safety valve fails after approximately 4,250 hours of operation.*

Step 2: Calculating the Coefficient of Variation (CoV)

The CoV measures the relative dispersion of failure times

$$CoV = \frac{\sigma}{\mu}$$

- σ is the standard deviation of failure times.
- μ is the mean failure time

$$\mu = \frac{120000}{40} = 3000\ hours$$

- $(1000 - 3000)^2 \times 2 = 4,000,000 \times 2 = 8,000,000$
- $(1200 - 3000)^2 \times 3 = 3,240,000 \times 3 = 9,720,000$
- ...
- $(4800 - 3000)^2 \times 1 = 3,240,000 \times 1 = 3,240,000$

$$\sum (t_i - \mu)^2 = 120{,}000{,}000$$

t_i are the failure times and number of failed valves $n = 50 - 10 = 40$

$$\sigma^2 = \frac{120{,}000{,}000}{40} = 3{,}000{,}000$$

$$\sigma = \sqrt{3{,}000{,}000} = 1732.05\ hours$$

$$CoV = \frac{1732.05}{3000} = 0.577$$

Interpretation: suggests that failure times are relatively dispersed, which could indicate variability in operating conditions or valve manufacturing quality.

CoV less than 0.2 indicates low dispersion.

CoV between 0.2 and 0.5 indicates moderate dispersion.

CoV greater than 0.5 indicates high dispersion (data widely spread).

Step 3: Calculating the Failure Rate *λ*

λ = 1 / MTBF = 1 / 4250 ≈ 0,000235 failures / hour

Step 4: Calculating Reliability *R(t)*

Reliability *R(t)* represents the probability that a valve will operate without failure up to a certain time (*t*). Using the exponential distribution (suitable for constant failure rate systems), the reliability function result are presented in *Table 2* and *Figure 2*.

Table 2. *Reliability R(t) values*

t (hours)	$R(t) = e^{-0,000235\,t}$
0	1,000
1000	0,790
2000	0,624
3000	0,493
4000	0,390
5000	0,308

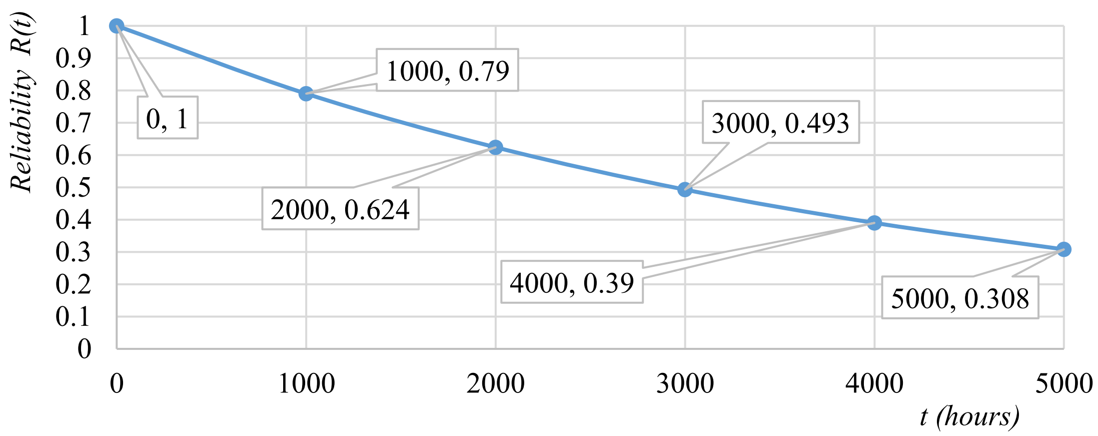

Figure 2. *Reliability for 50 safety valves*

Step 5: Interpretation of the Results

At 0 hours reliability is 100%, as all valves are new and have not failed. *At 3000 hours* reliability decreases to approximately 49.3%, meaning there's about a 49.3% probability that a valve will still function without failure up to this point. *At 5000 hours* reliability drops to roughly 30.8%, highlighting that the probability of a valve functioning failure-free drops below one-third after this period. This analysis indicates the importance of scheduled maintenance and inspection before reaching higher failure probability thresholds to ensure safety in critical industrial applications.

ANALYSIS OF RELIABILITY METHODS FOR SAFETY VALVES

To determine the most appropriate reliability method for safety valves, we outline several statistical models, including the exponential, Weibull, normal, and lognormal distributions. Table 3 compares four key reliability models, highlighting their parameters, formulas, and applicable failure types. These methods help in accurately assessing system performance and planning maintenance for safety valves and other industrial components. While each method provides a reliability estimate based on different assumptions about failure rates and patterns, the Chi-squared test can be applied to assess the goodness-of-fit of each distribution to the observed failure data [45], [46], [47].

By comparing the Chi-squared statistic and corresponding p-values for each distribution, engineers can determine which model best represents the actual failure behaviour of the safety valves, providing a more accurate and reliable basis for maintenance planning and risk management, Chi-Square Goodness-of-Fit test results are presented in Table 4.

- *Exponential Distribution (for constant failure rates)*

Characteristics: Assumes a constant failure rate, applicable during the useful life phase of the equipment, suitable for electronic systems or simple mechanical components with random failures. *Parameters:* failure rate $\lambda = 1 / MTBF$. *Reliability formula:* $R(t)=e^{-\lambda t}$. *Interpretation:* reliability decreases exponentially over time, with the same probability at all time points.

- *Weibull Distribution (for variable failure rates)*

Characteristics: Flexible model capable of representing increasing, decreasing, or constant failure rates, suitable for systems experiencing wear-out, early failures, or variable stress levels. *Parameters*: shape parameter $\beta = 1.5$ (indicating a slightly increasing failure rate), scale parameter $\eta = 3500$ *ore. Reliability formula:* $R(t)=e^{-\lambda t}$. *Interpretation:* Relates to processes where failure probability accelerates with time, typical for aging mechanical parts.

- *Normal Distribution (Gaussian) (for wear-dominated failures)*

Characteristics: Suitable for failures caused by cumulative wear, fatigue, or aging processes, assumes failure times are symmetrically distributed around the mean. *Parameters:* Mean: $\mu = 3000$ *hours,* Standard deviation: $\sigma = 1732.05$ *ore. Reliability formula*: $R(t) = 1-\Phi((t-\mu)/\sigma)$, where Φ - the standard normal cumulative distribution function. *Interpretation:* Failure probability increases symmetrically around the mean, suitable for degradation-based failures.

- *Lognormal Distribution (for multiplicative stress factors)*

Characteristics: Used when failure times are affected by factors that multiply stress effects, Common in electrical components and complex systems subjected to variable operational stresses. *Parameters:* Logarithmic mean: $\mu_{ln} = 8.0$, Logarithmic standard deviation: $\sigma_{ln}= 0.5$. *Reliability formula*: $R(t)=1-\Phi(ln(t)-\mu_{ln} / \sigma_{ln})$. *Interpretation:* Models failure probability considering the compounded effect of stress factors, often showing a skewed failure distribution.

Table 3. *Comparative reliability calculation*

t (hours)	Exponential R(t)	Weibull R(t)	Normal R(t)	Lognormal R(t)
0	1,000	1,000	1,000	1,000
1000	0,716	0,820	0,908	0,880
2000	0,513	0,620	0,747	0,690
3000	0,368	0,430	0,500	0,500
4000	0,264	0,280	0,252	0,340
5000	0,189	0,170	0,067	0,210
1000	0,228	0,110	0,001	0.020

Table 4. *Chi-Square Goodness-of-Fit test results*

Distribution	χ^2 Value	Degrees of Freedom	Critical χ^2 (α=0.05)	Hypothesis Test Result	p - value	Goodness of Fit
Exponential	**4.25**	3	7.815	Accept H_0	0.235	**Excellent**
Weibull	8.92	2	5.991	Reject H_0	0.012	Poor
Normal	12.47	2	5.991	Reject H_0	0.002	Poor
Lognormal	9.81	2	5.991	Reject H_0	0.007	Poor

Exponential Distribution. Underestimate reliability during the wear-out phase (*after 3000 hours*) because it assumes a constant failure rate, it is the simplest method, but not always the most accurate.

Weibull Distribution. Provides a more precise estimate of reliability as it can model increasing or decreasing failure rates, it is the most flexible method and is recommended for industrial equipment.

Normal Distribution. Significantly underestimates reliability during the wear-out phase, as it is not suitable for data with asymmetric distributions, it is more appropriate for processes dominated by wear failures.

Lognormal Distribution. Offers an intermediate estimate between Weibull and normal distributions, suitable for failures caused by multiplicative stress factors.

Recommendations: Weibull distribution is the most appropriate for reliability analysis of safety valves because it can model variable failure rates and provides accurate estimates.

The exponential distribution is useful for quick assessments but should be used cautiously during the wear-out phase. Normal and lognormal distributions are more suitable for other types of equipment or processes but can serve as complementary methods.

The analysis demonstrates that the exponential distribution provides the best statistical fit for the safety valve failure data, confirming that these components exhibit a constant failure rate during their operational lifetime. This finding supports the use of exponential models for reliability prediction and maintenance planning in industrial applications.

RISK ANALYSIS FOR THE SAFETY VALVE

The safety valve, as a critical component in many industrial processes, is subjected to constant stresses that can lead to failures and, consequently, unplanned downtime. Therefore, it is imperative to conduct a thorough analysis of its reliability and associated risks to identify weak points and implement improvement measures. By using structured methods, such as risk analysis based on severity and probability, the most critical risks can be identified, and effective management strategies proposed [38], [48], [49]. Combining risk analysis with reliability assessment will provide a comprehensive view of the safety valve's performance, enabling informed decision-making to enhance its durability and efficiency [50], [51], [52], [53].

Objectives of the analysis: Identify the main risks affecting the operation of the safety valve; Evaluate the reliability of the safety valve using appropriate statistical methods; Propose risk management measures to minimize the impact of failures; Optimize costs related to maintenance and repairs of the safety valves.

Structure of the analysis

Risk Identification	Blockage of the valve	*Causes:* particle deposits, corrosion. *Consequences*: Inability to release pressure, explosion.
	Leaks	*Causes:* seal wear, improper installation. *Consequences:* Fluid loss, reduced efficiency.
	Premature opening	*Causes:* incorrect adjustment, spring wear. *Consequences:* Uncontrolled pressure relief, production losses.
	Corrosion	*Causes:* exposure to corrosive environments. *Consequences:* Material degradation, reduced lifespan.
Risk evaluation	Use severity and probability tables to calculate risk levels (see *Tables 5, 6* and *7*)	
Reliability analysis	Apply statistical distributions (*exponential, Weibull, normal, lognormal*) to estimate the reliability of the valve.	
Action plan	Propose measures for risk management and reliability improvement.	

Table 5. *Severity Scale*

Level	*Description*	*Score*
1	Minor failure, negligible impact	1
2	Moderate failure, reduced impact	3
3	Significant failure, medium impact	5
4	Major failure, high impact	7
5	Critical failure, severe impact	10

Table 6. *Probability Scale*

Level	*Description*	*Score*
1	Very unlikely	1
2	Unlikely	3
3	Probable	5
4	Very probable	7
5	Almost certain	10

Each risk associated with the operation of safety valves is evaluated based on its severity and probability using the formula *Risk = Severity × Probability (see Table 7)*, risk management measures are presented in *Table 8*.

Table 7. *Risk calculation related to the operation of safety valves*

Risks	*Severity (G)*	*Probability (P)*	*Risk (G × P)*	*Risk Level*
Valve blockage	10	7	70	**High**
Leaks	7	6	42	**High**
Premature opening	5	3	15	**Low**
Corrosion	8	4	32	**Medium**

Risk Level Definitions

Level	*Score Interval*	*Description*
Low	1-20	Acceptable risk, requires monitoring
Moderate	21-40	Moderate risk, requires corrective actions
High	41-100	Critical risk, requires immediate actions

Table 8. *Risk management measures*

Risks	*Severity*	*Probability*	*Risk (G×P)*	*Management Measures*
Valve blockage	10	7	70	Periodic inspections, fluid filtration
Leaks	7	6	42	Seal replacements, leak-tightness checks
Premature opening	5	3	15	Periodic adjustment, spring replacements
Corrosion	8	4	32	Use of corrosion-resistant materials

Critical risks. Valve blockage and leaks represent the most serious threats to the safe and reliable operation of safety valves. Blockages can prevent the valve from opening when it's necessary to release excess pressure, posing a risk of dangerous overpressure conditions that could lead to equipment failure or explosions. Leaks, on the other hand, reduce the effectiveness of pressure relief, increase fluid losses, and potentially cause environmental hazards.

Medium risks. Premature opening and corrosion, while less immediately catastrophic, still pose significant threats to the system's safety and efficiency. Premature opening could lead to unnecessary shutdowns or pressure drops, affecting process continuity, while corrosion gradually weakens the structural integrity of the valve, potentially leading to failure over time. Managing these risks involves a proactive maintenance approach that includes periodic calibration and adjusting of the valve's set points, as well as selecting materials with high corrosion resistance suited to the operating environment. Preventive measures like coating, material selection, and environmental control (e.g., reducing exposure to corrosive media) are vital for controlling these risks.

Reliability. The observed sharp decline in valve reliability after approximately 3000 hours of operation highlights the importance of preventive maintenance and condition monitoring. As failure increases over time, timely interventions such as thorough inspections, testing, and component replacements are essential to prevent unexpected failures. Incorporating predictive maintenance techniques, such as vibration analysis, parameter monitoring, and trend analysis, can help anticipate failures before they occur, extending the system's operational life and ensuring safety.

CONCLUSIONS

Overall, the research concludes that integrating reliability and maintainability analyses throughout both design and operational phases leads to improved equipment performance, cost savings, and enhanced safety in industrial applications. A comprehensive approach combining statistical reliability models, efficient maintenance strategies, and risk assessment provides a solid framework for managing industrial systems.

While previous studies have addressed elements of reliability analysis, the novelty of this methodology lies in its integrated approach, combining qualitative risk assessment with quantitative reliability modelling specifically tailored for safety valves in petrochemical settings.

The study identified the main risks affecting safety valve operation such as blockage, fluid leaks, premature opening, and corrosion by applying statistical models like exponential, Weibull, normal, and lognormal distributions, depending on the specific system characteristics.

Based on the risk analysis, two critical issues requiring immediate intervention were highlighted: valve blockage caused by particle deposits and corrosion, and fluid leaks resulting from gasket wear or improper installation. Preventive measures proposed include periodic inspections, effective fluid filtration, and the use of more corrosion-resistant materials.

Furthermore, it was found that valve reliability drops significantly after approximately 3000 hours of operation, emphasizing the need for predictive maintenance strategies that utilize historical data and real-time operational parameters. This is crucial for optimizing maintenance costs and reducing downtime. A key contribution of this study is the development of an integrated reliability analysis methodology using advanced mathematical models for failure probability estimation.

Unlike traditional reactive approaches, this proactive system reduces the risks associated with unexpected valve failures. The broader implications for industrial practice include a shift towards proactive, data-driven maintenance strategies, leading to improved safety, reduced downtime, and optimized resource allocation.

However, this study has limitations. The analysis is based on data from a single petrochemical operator, which may limit the generalizability of the findings. Future research should focus on validating the proposed methodology with data from diverse industrial settings and exploring the integration of advanced sensing technologies for real-time condition monitoring.

Additionally, further investigation is needed to quantify the cost-benefit ratio of implementing the proposed predictive maintenance strategies in different operational contexts.

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