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Application of Bayesian Logic in the Layer of Protection Analysis of Chlor-Alkali Industry

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Abstract:- Layer of protection analysis (LOPA) is an efficient tool used for evaluating the risk associated with different industries that face significant threats with severe consequences. LOPA offers a semi-quantitative outcome, leveraging information from process hazard analysis such as the frequency of initiating events, the severity of consequences, and the probability of failure upon demand. By disregarding less severe or infrequent consequences, LOPA becomes a practical and cost-effective solution suitable for real-time applications.Bayesian-LOPA methodology, an enhanced version of LOPA based on Bayes' theorem, has been recently developed. Bayesian logic utilizes prior event knowledge to predict future events, aiming to reduce uncertainty in the failure data of independent protection layers (IPLs) or events within a plant. The posterior value obtained through Bayesian estimation incorporates both historical data from prior events and real-time data from the plant, resulting in more reliable failure data for assessing risk and ensuring the safety of the plant.

In this particular study, Bayesian-LOPA was applied to assess the risk and mitigate accident scenarios in a Sodium hypochlorite plant by implementing Independent Protection Layers. The obtained risk value can be compared against risk criteria defined by the plant or government to determine if any accident scenario fails to meet the set criteria. If necessary, additional IPLs may be suggested to reduce the risk to an acceptable level. Comparatively, Bayesian-LOPA proves to be a more dependable risk assessment tool than the traditional LOPA approach. It aids in prioritizing various scenarios for maintenance and safety enhancement efforts, thereby improving the overall safety of the plant

Keywords:- *Risk assessment, Bayes' theorem, Bayesian logic, LOPA, protection layers.*

I. INTRODUCTION

The chlor-alkali industry faces significant dangers, primarily the risk of explosions and the release of harmful gases into the atmosphere, which can result in severe harm or even fatalities to both human life and property. Additionally, the presence of substances like Chromium in the process increases the workers' susceptibility to developing cancer. Considering these factors, the chlor-alkali industry falls into the category of highly hazardous industries. (Al Shanini, 2014) To effectively manage and measure the associated risks, it becomes crucial to employ a risk assessment methodology such as Layer of Protection Analysis (LOPA). By utilizing this approach, the quantification of risks and the implementation of recommended measures can be facilitated, ultimately leading to improved safety within the plant. (Summers, 2003)

When applying the LOPA methodology to the chlor-alkali industry, it is necessary to have access to failure data regarding equipment and facilities in order to quantify the associated risks. (Ravi K.S., 2016)However, due to the limited operational history of this industry, there is a scarcity of specific data on accidents and failures within chlor-alkali plants. Additionally, the collection of historical failure data has not been comprehensive thus far. Relying on this inadequate data for risk assessment may result in an inaccurate representation of the industry's actual condition. (Zheng, 2009)

As a potential solution, generic failure data from other industries such as petrochemicals and nuclear industries could be utilized to calculate risks in the chlor-alkali industry. However, it should be noted that these data may not yield accurate risk assessments due to the differences in operational conditions and environments between chlor-alkali plants and other industries. (A.S. George, 2022) The unique characteristics and processes within the chlor-alkali industry necessitate caution when extrapolating data from unrelated sectors

Hence, the significance of Bayesian logic becomes apparent. It enables the determination of more dependable risk values by leveraging both limited plant-specific data and generic data from other industries. Bayesian logic aids in generating updated failure data by incorporating prior information from the generic failure data and the likelihood information obtained from the chlor-alkali plant data. (Abimola, 2015) This updated data combines statistical failure information from the comprehensive and long-term historical database of generic data with the specific data collected from the chlor-alkali industry.

By utilizing Bayesian logic, it becomes possible to produce more reliable data as this approach is rooted in systematic logic and statistical analysis. It effectively combines the available information to derive a more accurate representation of risk, considering both the industry-specific data and broader contextual data from other relevant sectors. (Abimola, 2015)

The aim of this study is to emphasize the improved outcomes achieved by incorporating Bayesian logic into the traditional LOPA approach when calculating risk for various identified scenarios. This integration leads to statistically reliable results and enhances the layer of protection within the industry under consideration. The scope of this study is limited to a specific sodium hypochlorite plant within the chlor-alkali industry, for which plant-specific data has been collected. Generic data from sources such as OREDA and CCPS databases have been utilized. Sodium hypochlorite, with the chemical formula NaClO, consists of sodium cations and hypochlorite anions. It appears as a greenish-yellow substance with a chlorine-like sweetish odor. The molar mass of sodium hypochlorite is 74.442g/mol, and it exhibits a solubility of 29.3g/100mL in water. The compound has a melting point of 18°C and a boiling point of 101°C.

II. METHODOLOGY DESCRIPTION

The Bayesian estimation method commences by establishing a prior distribution, which should originate from sources that are unrelated to the specific plant being investigated. Suitable sources can include generic data reported in literature or utilized in previous studies. (D. Zhu, 2007) The extent of available evidence, such as plant data, plays a crucial role in determining the properties of the posterior distribution. In cases where there is insufficient data or limited prior knowledge regarding the prior distribution, or when significant uncertainty exists in the generic data sources, non-informative priors may be employed. These non-informative priors maintain the mean value of the failure rate estimate while encompassing a wide range of uncertainty to accommodate the plant-specific data.

A schematic block diagram of the plant under the analysis is shown in Figure below:

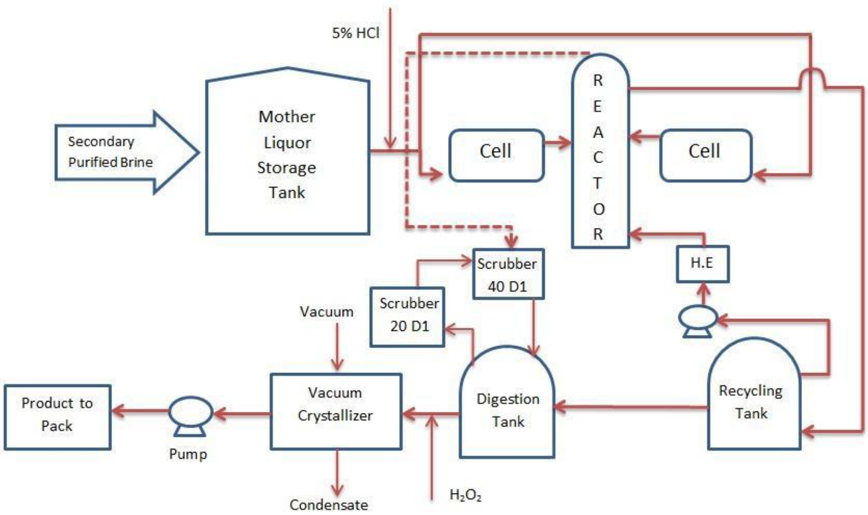

Fig. 1: Schematic block diagram of Sodium Hypochlorite plant.

The plant's processes rely on secondary purified brine as the input material, which is stored in the mother liquor storage tank. The pure brine may contain impurities like Calcium, Magnesium, and Sulphates, but in quantities lower than 10 g/L. The mother liquor, along with the purified brine, is transferred to Diaphragm cells. These cells consist of 12 units on each side of the reactor, totaling 24 cells. During the transfer, a 5% acidic solution (HCl) is added to the mother liquor to create a highly acidic brine solution, achieving a pH range of 5.5-6.3 within the cells.

The reactor's overflow products are directed to the Recycling tank. A portion of the contents in the Recycling tank is cooled and returned to the reactor to maintain the desired temperature. The remaining portion is transferred to the Digestion tank, where proper mixing takes place. From the Digestion tank, the mixture is further transferred to the Vacuum crystallizer. In this process, peroxide is added to the mixture to maintain the pH within the crystallizer and prevent any potential corrosion issues. A vacuum of 30mm of Hg is maintained in the vacuum crystallizer, leading to the formation of sodium hypochlorite crystals. These crystals are then pumped to a centrifuge using a progressive cavity pump. The centrifuge separates the sodium hypochlorite crystals, which are subsequently sent for packaging.The condensate from the vacuum crystallizer, known as the mother liquor, is returned to the mother liquor storage tank, and the entire process is repeated in a continuous cycle

A. Development of Bayesian-LOPA methodology

The Bayesian-LOPA methodology can be regarded as an advanced version of the LOPA method that incorporates Bayes' theorem or Bayesian logic. This term was introduced by Yun (2009) in his research. Compared to classical LOPA methods, this approach has the ability to generate statistically more reliable results. The failure data obtained from the specific facility under investigation is deemed statistically unreliable due to its limited operational history. Therefore, to enhance the reliability of the data within the facility, the Bayesian-LOPA methodology can be employed. (Qadeer, 2014) This methodology allows for the updating of plant-specific data from the chlor-alkali industry by incorporating generic data that encompasses long-term historical experience.

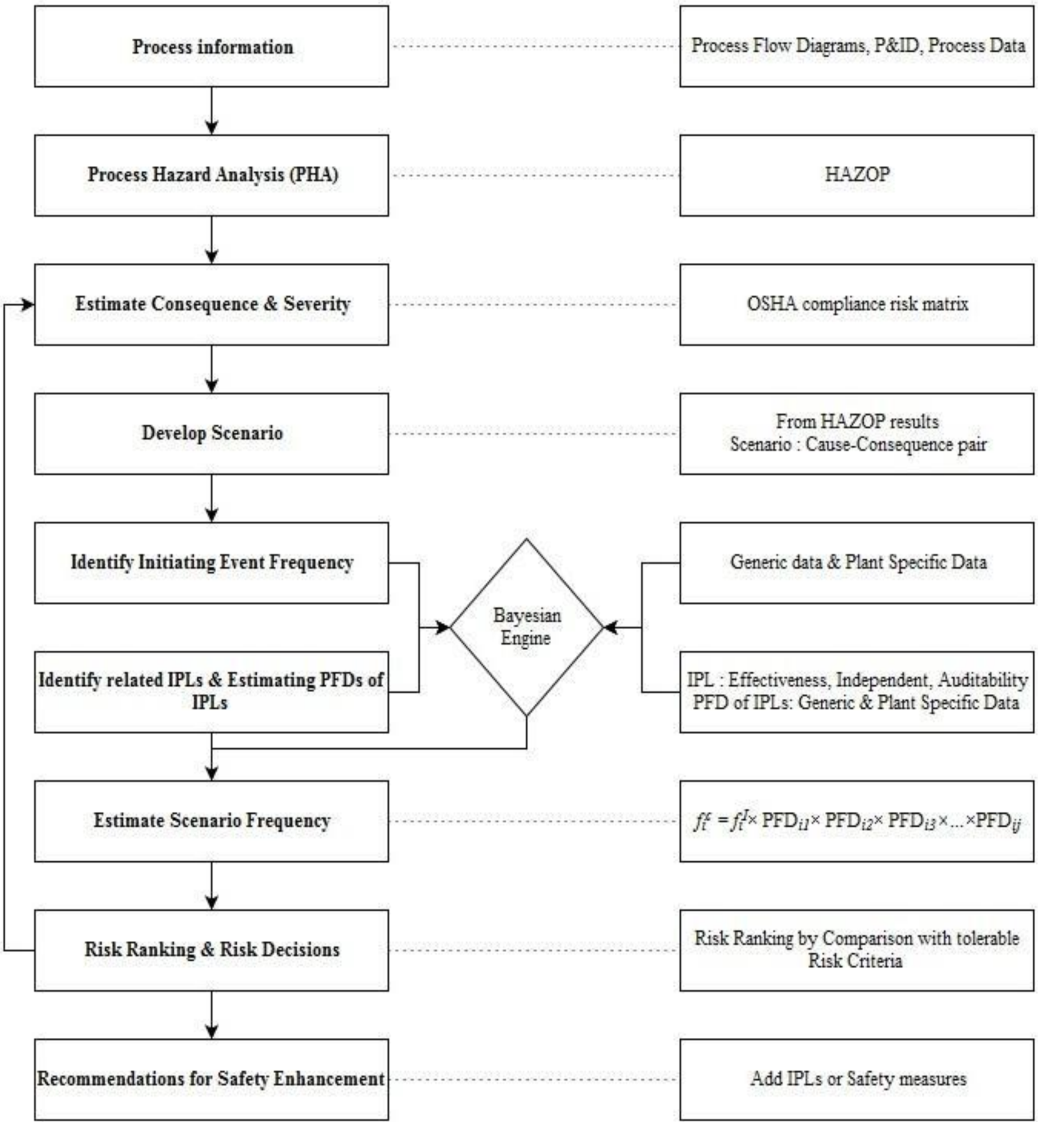

Fig. 2: Flow diagram of study. (Yun, 2009)

Once the process information is obtained, a HAZOP study needs to be conducted by a team of HAZOP analysts. The identified cause-consequence pairs from the HAZOP study are then screened for selection in the application of the LOPA method using a categorization approach. In this process, the OSHA risk matrix is utilized. The OSHA risk matrix classifies each scenario into one of four categories: A, B, C, or D, based on the combination of its frequency and severity levels. These classifications are determined through expert opinions.

Following the categorization, the scenarios falling under categories A and B are chosen for the application of the Bayesian-LOPA methodology. This selection is made because these categories encompass events or scenarios that have the potential to result in fatalities or significant property damage to the facility. (Abimola, 2015)

The subsequent stage involves developing incident scenarios based on the HAZOP results from the previously selected scenarios. Once the incident scenarios are formulated, the next step is to identify the initiating events associated with each scenario. The causes identified during the HAZOP study can serve as the initiating events for the incident scenarios.

Determining the frequency of the initiating events is the next task. The frequency of initiating events can be obtained primarily from three sources. (Yun, 2009) The first source is generic data, which comprises historical data from similar industries such as offshore or petrochemical industries. (Khan F., 2009) These industries possess extensive records and a substantial sample population, providing statistical stability. However, it is important to note that these industries may not precisely reflect the operating conditions of the equipment in the specific facility under consideration.

The second source of initiating event frequency is plant-specific data, which can be acquired from the chlor-alkali industry. However, due to the limited history of collecting failure data and the short operational duration, these values may lack statistical reliability.

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Therefore, the most reliable option for assessing risk is to employ Bayesian estimation, which constitutes a third category of data sources for initiating events. Bayesian estimation leverages prior information obtained from generic data and plant-specific data from the chlor-alkali industry to generate updated posterior data. This posterior data encompasses both the long-term operational history from prior data and the specific conditions of the facility. Thus, Bayesian estimation is employed in this study to determine the frequency of initiating events.

Once the frequency of the initiating events is determined, the next step involves identifying the Independent Protection Layers (IPLs). The list of safeguards outlined in the HAZOP study for each incident scenario serves as a resource to identify potential IPLs. However, these safeguards need to be evaluated against the fundamental criteria of IPLs, which include independence, effectiveness, and auditability. (CCPS, 2008) If a safeguard satisfies all three criteria, it can be classified as an IPL. This step parallels the process of estimating the frequency of initiating events

The final stage entails making risk-related decisions by comparing the estimated frequency of the incident scenarios with the prescribed tolerable risk criteria, which may be determined by the company or government. The CCPS (2001) provides two sets of risk criteria. The first set applies when the focus is on the potential harm to humans as an outcome. In such cases, the maximum acceptable risk criteria are defined as being less than 1×10^{-5}/year, and the criteria for action required is less than 1×10^{-3}/year. The second set of risk criteria only considers harm to property resulting from incidents like fire, explosion, or releases. Here, the maximum tolerable risk criteria are less than 1×10^{-5}/year, and the criteria for action required is less than 1×10^{-4}/year.

If the estimated frequency of the incident scenario exceeds the tolerance criteria, additional Independent Protection Layers (IPLs) or safeguards must be implemented to reduce the incident frequency or mitigate the severity of the consequences.

III. RESULTS AND DISCUSSIONS

A. Results of HAZOP study and scenario making

In this study, the scenario selection process relied on a previously conducted HAZOP study of the plant. The HAZOP study encompassed a comprehensive examination of 24 nodes within the plant. From the findings of the HAZOP study, a total of 12 potential scenarios were identified for further analysis, guided by expert opinions. To refine the selection, OSHA's risk matrix was employed. The risk matrix categorized these 12 scenarios into four classes: A, B, C, and D, with each class indicating varying levels of severity.

Table 1: HAZOP nodes for chlor-alkali plant

Node	Description	Design Intention
Pure Brine feed section	Mother liquor from 10 M1 to 20 K1 and 20 K2.	To feed the right quantity and quality electrolyte to cells.
Hydrogen treatment section	Vent H_2 gas from 40D1 to 40S2 through 40T1	To vent H2 gas with maximum 2.7% O_2 and with less than 1ppm of Chlorine safely through water seal and flame arrestor.
Recycling system	Overflow from 20T1 to 20T2, Digestion, feed to 30W1 with required temp.	Electrolyte from 20K1/K2, NaClO, HClO, NaOCl allowing required time.

To prioritize the most critical scenarios, the focus was placed on classes A and B. These classes denote scenarios with the highest potential for adverse outcomes, such as fatalities or significant property damage. As a result, two scenarios were chosen for the subsequent analysis. Using the HAZOP results, each selected scenario was examined to establish a cause-consequence pair, forming the basis for the subsequent Layer of Protection Analysis (LOPA) incident scenario development.

Table 2: Incident scenarios selected for LOPA study

Scenario	Cause	Consequence	Scenario Description
1	Uncontrolled purge N_2 is coming to 20 K1, K2 through HV-201 due to malfunctioning.	Cell gas pressure increases and water seal will blow off	Water seal blow off due to increase in cell gas pressure resulting from hand valve malfunction
2	More of O_2 or Cl_2 generation due to improper HCl addition and higher current	Explosive gas mixture formation which will lead to explosion	Explosive mixture formation due to imbalance in HCl addition and current.

B. Results of Scenario 1

In the event of a malfunctioning hand valve that controls the purge of N_2 gas, there is a risk of uncontrolled purging of N_2 into the two Chlorate reactors. This uncontrolled purging can result in an elevation of the pressure within the cell. The increased pressure poses a potential danger of a water seal blow-off, which can lead to explosions and the dispersal of chemicals. Furthermore, due to the elevated working temperatures, workers in the plant may also be at risk of burns.

The occurrence rate of a malfunctioning hand valve as an initiating event can be approximated by utilizing data from OREDA and the Chlor-alkali plant. OREDA offers failure frequency information specifically for critical failures of control and safety valves. Meanwhile, the Chlor-alkali plant data provides the count of failures and the corresponding time period for these occurrences. The estimated frequency data is graphically presented in Figure 3.1, indicating that the posterior values lie between the prior information and the likelihood function. This observation suggests that the posterior values are updated by incorporating both the prior data and the likelihood information, effectively reflecting the combined influence of these two sources. Within the figure, the vertical line in the posterior column represents the 90% credible interval, ranging from 0.0292/year to 0.3897/year.

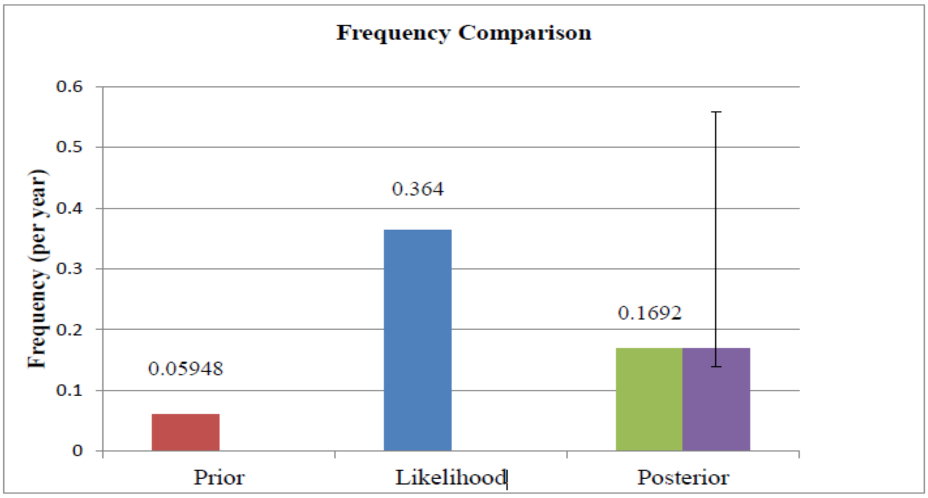

Fig. 3: Frequency of hand valve malfunctioning corresponding to Bayesian estimation

In this particular scenario, two Independent Protection Layers (IPLs) have been identified and taken into account. The first IPL is a Flow Indicator Transmitter, which is utilized to monitor and verify the flow rate. The second IPL consists of a pressure switch along with a hand valve for the purge line. It is important to note that these IPLs are assumed to be independent of each other, and it is assumed that all human interventions related to their operation are executed flawlessly.

IPL 1 refers to a Flow Indicator Transmitter. To determine the probability of failure on demand of the flow indicator, data from the OREDA database and the chlor-alkali plant are utilized. The OREDA database provides prior information on failure data for flow process sensors, which needs to be converted into Probability of Failure on Demand (PFD) data using the Frequency-PFD conversion method before incorporating it into Bayesian estimation. The converted PFD values are then employed to calculate the parameters α and β of the prior beta distribution. On the other hand, the chlor-alkali plant data supplies information regarding the number of failures and Mean Time Between Failures (MTBF) of the equipment. The test interval for the equipment can be obtained from CCPS (2001) as well. The estimated PFD for the Flow Indicator Transmitter is illustrated in Figure 3.2. The figure demonstrates that the posterior values of PFD fall within the range of the prior and likelihood values, indicating that they have been effectively updated. The vertical line in the posterior column represents the 90% Bayesian credible interval, which spans from 1.746×10^{-3}/year to 4.122×10^{-3}/year.

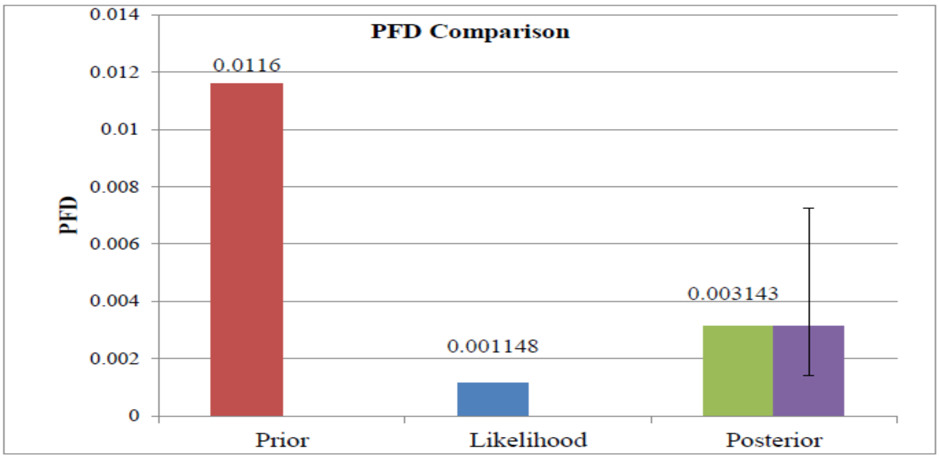

Fig. 4: PFD's of flow indicator and transmitter corresponding to Bayesian estimation

IPL 2 refers to a Pressure switch (low) with a hand valve for the purge line. To estimate the Probability of Failure on Demand (PFD) of the Pressure switch, data from the OREDA database and chlor-alkali plant are employed. The OREDA database provides the failure frequency of pressure process sensors, which needs to be converted to PFD using the Frequency-PFD conversion method. The converted PFD values are then used to calculate the parameters α and β of the prior beta distribution. Additionally, the chlor-alkali plant data provides information on the number of failures and Mean Time Between Failures (MTBF) of the Pressure switch, which are used as likelihood information. Bayesian estimation is applied to calculate the posterior values of the equipment using this data. Figure 3.3 presents a comparison of PFD values for IPL 2. The vertical line in the posterior column represents the 90% Bayesian credible interval, which spans from 5.718×10^{-4}/year to 2.903×10^{-3}/year.

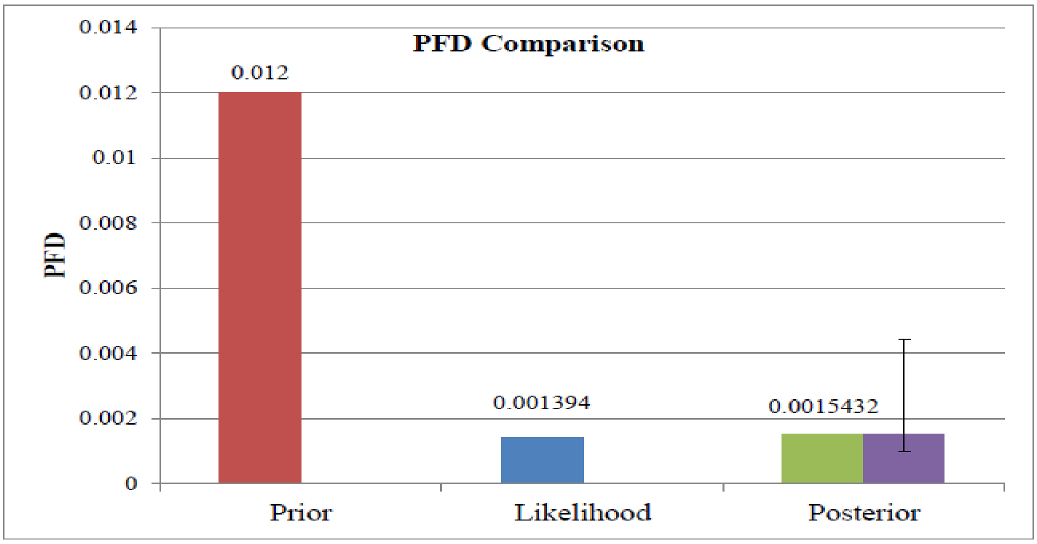

Fig. 5: PFD's of Pressure switch (low) corresponding to Bayesian estimation

Figure 3.4 presents a comparison of risk values for scenario 1, considering the prior, likelihood, and posterior information. It is observed that the posterior value of failure frequency falls between the prior and likelihood values. However, it should be noted that this pattern may not be consistent for all risk values estimated through LOPA for various incidents. The positioning of the posterior values between the prior and likelihood values depends on the use of an informative prior in Bayesian estimation. If all initiating events and IPLs exhibit the same trend (either all ascending or all descending), the final risk values estimated by LOPA will follow the same trend since they are multiplied together. However, if some initiating events or IPLs display different trends, the posterior values may or may not fall between the prior and likelihood values. This phenomenon is further explained in the subsequent section.

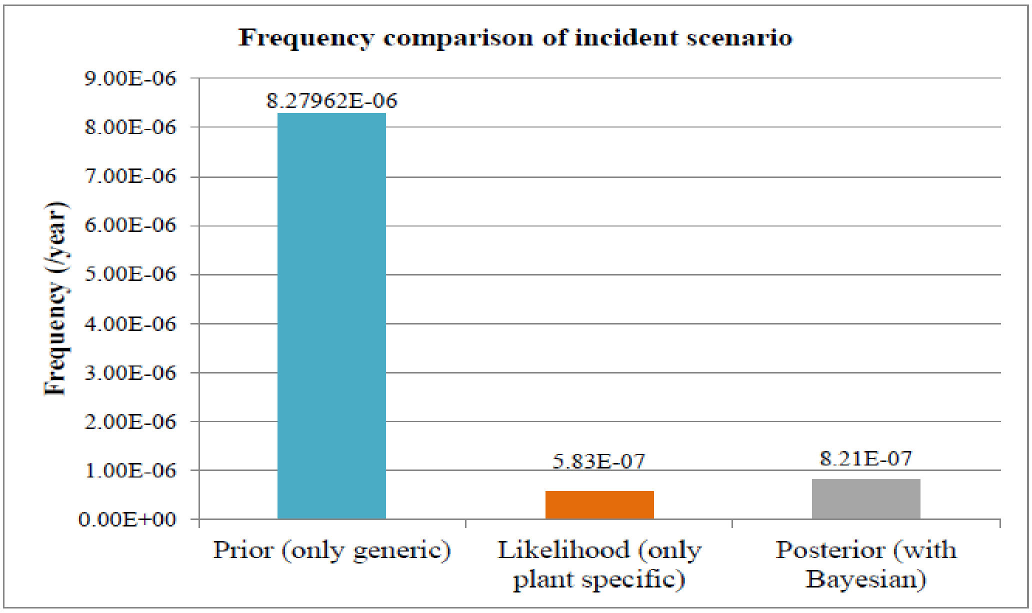

Fig. 6: Risk values of Scenario 1 by LOPA

In the case of scenario 1, the posterior risk value is determined to be 8.21×10^{-7}/year. This estimated value is then compared to the risk tolerance criteria, which specifies that the risk should be less than 1×10^{-5}/year. Based on this comparison, it can be concluded that scenario 1 is considered tolerable if the test interval and the assumptions made during the analysis are maintained.

This risk decision indicates that the level of risk associated with scenario 1 falls within an acceptable range according to the specified criteria. However, it is crucial to emphasize that this determination relies on the assumptions and conditions considered during the analysis. Any changes to these factors could potentially alter the risk assessment and subsequent decision. Therefore, it is imperative to ensure that the test interval and the assumptions are upheld to maintain the tolerable risk level for scenario 1.

C. Results of Scenario 2

The purpose of adding HCl to the mother liquor is to maintain a highly acidic solution, which in turn helps achieve a pH level of approximately 5.5-6.3 in the cell. However, in cases where there is an imbalance in the process caused by human error, an excessive amount of Oxygen or Chlorine may be generated. This can subsequently lead to the formation of an explosive mixture within the reactor, posing a significant risk of explosion.

The frequency of human errors resulting in the increased generation of O_2 or Cl_2 as an initiating event can be determined using Bayesian estimation in this particular scenario. Since the frequency of human errors is not available in generic data sources, Jeffreys non-informative prior can be employed to update the plant data. It is assumed that the prior distribution follows a gamma distribution with parameters α=0.5 and β=0. For the likelihood function, the chlor-alkali plant data provides the number of failures and the corresponding time period. The estimated frequency per year is presented in Figure 5.5. Upon updating, it can be observed from figure 3.5 that the posterior value surpasses the likelihood value. The vertical line in the posterior column represents the 90% Bayesian credible interval, ranging from 0.1041/year to 1.006/year.

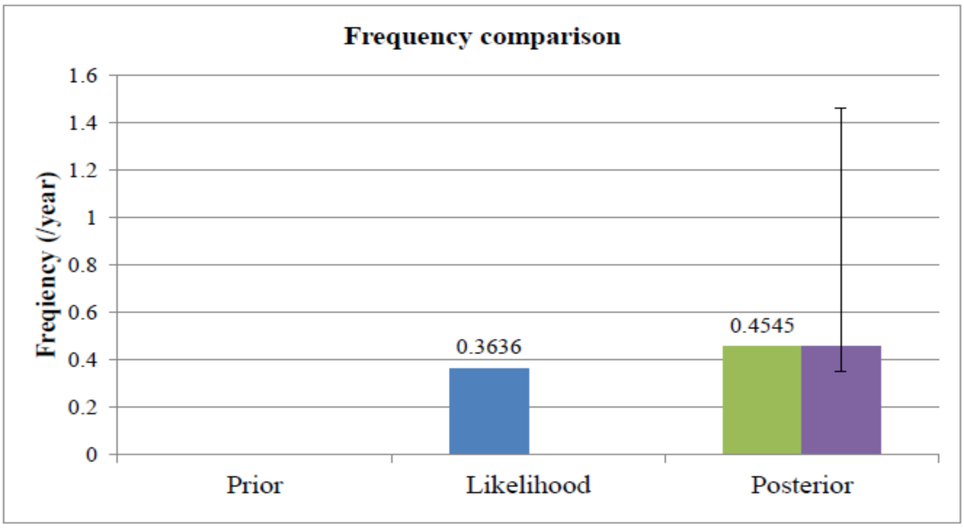

Fig. 7: Frequency of human errors corresponding to Bayesian estimation

In this particular scenario, three Independent Protection Layers (IPLs) have been taken into account. The first IPL is an Automated Immunoassay Analyzer equipped with a flow indicator and control alarm. The second IPL is an oxygen analyzer that triggers the electrolyzer shutdown at an oxygen concentration of 2.7% and initiates acid feed. Lastly, the third IPL considered for this scenario is a pressure indicator and transmitter. It is assumed that all IPLs operate independently of each other, and any necessary human interventions are carried out flawlessly.

IPL 1 refers to the Automated Immunoassay Analyzer (AIA-202,203) with HCl addition and pH measurement, as well as the inclusion of a Flow Indicating and Control Alarm (FICA-203). The Probability of Failure on Demand (PFD) for this specific IPL can be estimated by utilizing both the OREDA database and the chlor-alkali plant data. The OREDA database provides failure frequency data concerning flow process sensors, which serves as the prior information for the estimation. However, before using this data, it must be converted into PFD data through the frequency-PFD conversion method. On the other hand, the plant-specific data provides information regarding the number of failures and the Mean Time Between Failures (MTBF) of the instrument. The test interval for this equipment is determined using the CCPS database, establishing the likelihood data required for the Bayesian estimation. Figure 3.6 visually represents the results obtained from the Bayesian estimation, displaying the PFD values for the IPL. The vertical line within the posterior column indicates the 90% Bayesian credible interval, ranging from 2.927×10^{-3}/year to 6.902×10^{-3}/year.

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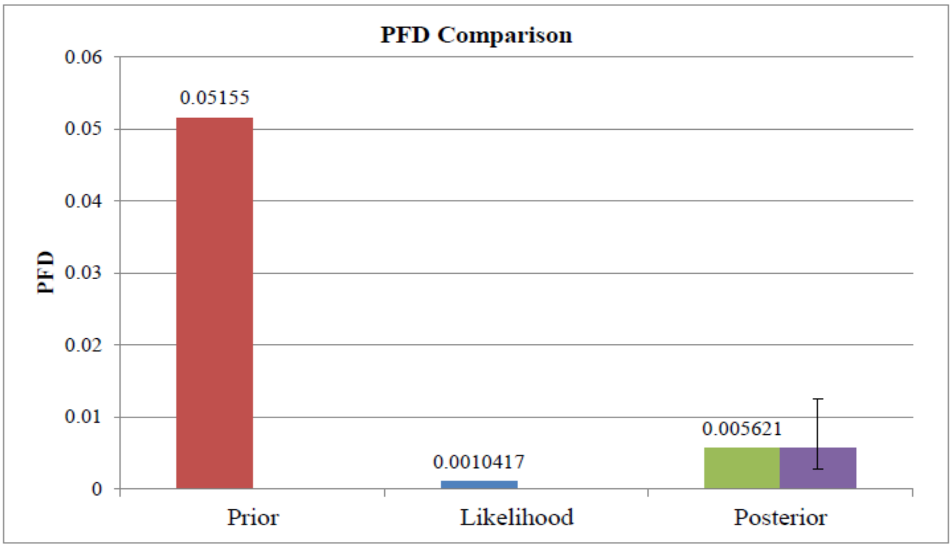

Fig. 8: PFD’s of AIA corresponding to Bayesian estimation

IPL 2 refers to the Oxygen analyzer (AIA-401) with the capability of tripping the electrolyzer at 2.7% Oxygen and acid feed. The Probability of Failure on Demand (PFD) for this instrument can be estimated by utilizing both the OREDA database and the plant-specific data. The OREDA database provides failure data specifically related to Level process sensors, which serves as historical information about the equipment and acts as prior data for the estimation. However, before incorporating this data into the Bayesian estimation, it needs to be converted into PFD values using the frequency-PFD conversion method. On the other hand, the plant-specific data contains information regarding the number of failures and Mean Time Between Failures (MTBF) of the instrument, along with the test interval derived from the CCPS. These data form the likelihood function for the Bayesian estimation. The estimated PFD values are depicted in figure 3.7, with the vertical line within the posterior column indicating the 90% Bayesian credible limit, ranging from 1.0304×10^{-3}/year to 2.60×10^{-3}/year

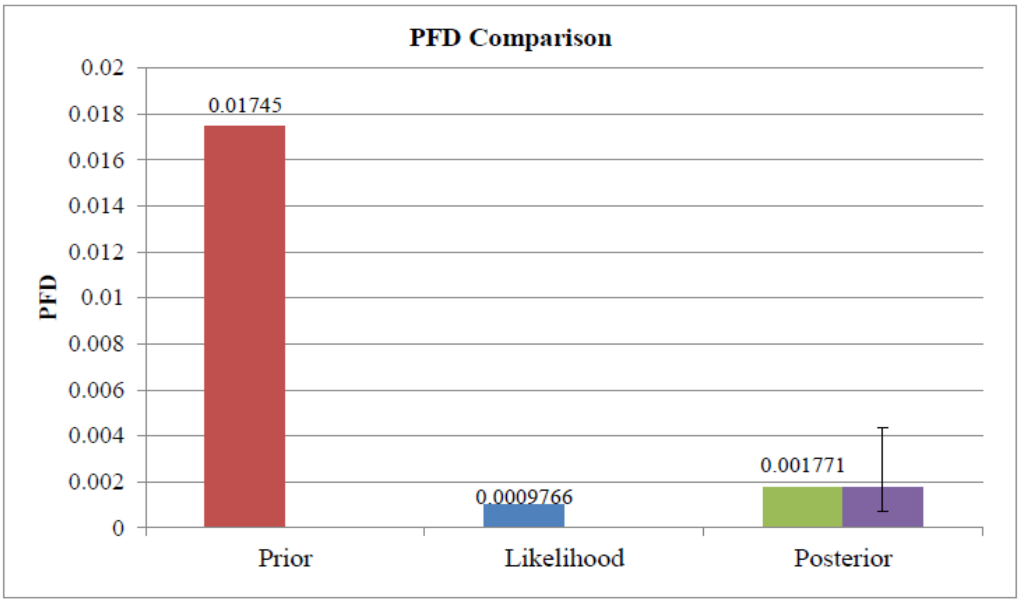

Fig. 9: PFD’s of oxygen analyzer corresponding to Bayesian estimation

IPL 3 refers to the inclusion of a Pressure Indicator Transmitter (PIT-403). The Probability of Failure on Demand (PFD) for this IPL can be refined by incorporating data from the CCPS and the chlor-alkali plant data. The CCPS database contains relevant failure data specifically related to pneumatic pressure transmitters, which can be utilized as prior information. To utilize this data as prior information, it needs to be converted into PFD values through the frequency-PFD conversion method. Additionally, the chlor-alkali plant data provides the number of failures and Mean Time Between Failures (MTBF), while the CCPS provides the test interval for the equipment. These elements complete the likelihood function. The estimated PFD values for the IPL are depicted in Figure 3.8, with the vertical line in the posterior column denoting the 90% Bayesian credible interval, ranging from 5.631×10^{-4}/year to 1.512×10^{-3}/year

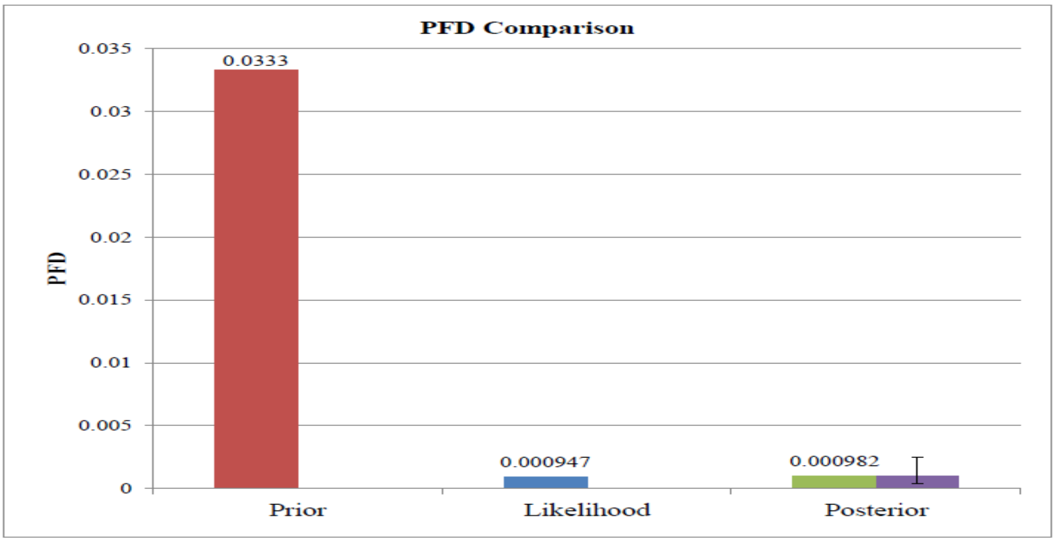

Fig. 10: PFD's of pressure indicator transmitter corresponding to Bayesian estimation.

The comparison of risk values for scenario 2 is shown in Figure 3.9.

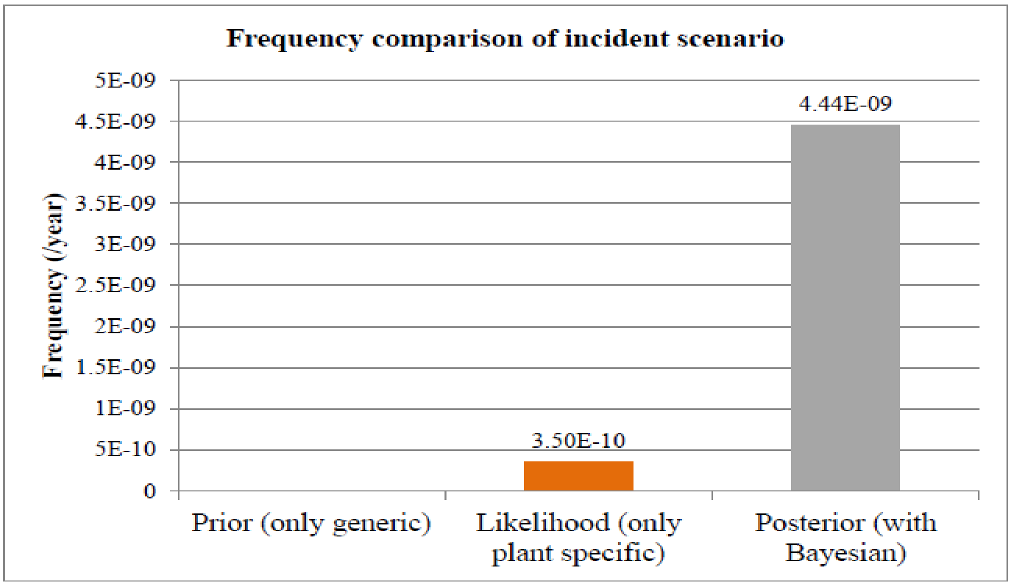

Fig. 11: Risk values of scenario 2 by LOPA

In the case of scenario 2, the calculated posterior risk value is determined to be 4.44×10^{-9}/year. This value can be evaluated by comparing it to the predefined tolerable risk criteria, which states that the risk should be less than 1×10^{-5}/year. Based on this assessment, it can be concluded that scenario 2 falls within the acceptable risk range, given that the test intervals and assumptions of independence made during the analysis are upheld.

This conclusion implies that, according to the available data and analysis, scenario 2 poses a level of risk that is considered tolerable within the established guidelines. It suggests that the existing safety measures and control mechanisms, along with the specified test intervals, are adequate in mitigating the potential risks associated with scenario 2. However, it is crucial to ensure that the recommended safety protocols, monitoring procedures, and assumptions are consistently adhered to in order to maintain this acceptable level of risk.

IV. SUMMARY

To summarize, the Bayesian-LOPA methodology has proven to be highly effective in conducting risk assessments for chlor-alkali plants with limited operational history. This approach can also be successfully applied to other industries that face similar challenges, such as nuclear power plants, refineries, and space industries, where the availability of failure data is scarce.The key advantage of the Bayesian-LOPA methodology lies in its ability to overcome the limitations of traditional risk assessment methods when data is limited. By incorporating prior information, such as generic failure data from relevant databases, and combining it with plant-specific data, Bayesian estimation provides a robust framework for estimating failure frequencies and evaluating risk.

Furthermore, the Bayesian-LOPA methodology is versatile and can be complemented with other analysis techniques such as Fault Tree Analysis (FTA) and Event Tree Analysis (ETA). This integration allows for a comprehensive and multidimensional approach to risk assessment, enhancing the overall accuracy and reliability of the results.By utilizing the Bayesian-LOPA methodology, industries can make informed decisions regarding risk management strategies, prioritize safety measures, and allocate resources effectively. This methodology serves as a valuable tool in enhancing safety practices and mitigating potential risks in complex industrial settings with limited available data.

V. CONCLUSION

Based on the findings of this study, it can be inferred that the selected chlor-alkali plant demonstrates commendable safety measures in place to prevent hazardous incidents. However, certain areas within the plant were identified as having inadequate safeguards. Therefore, it is strongly recommended to implement additional safety measures in these specific areas to further enhance overall plant safety.It is important to acknowledge that the estimated results and recommendations presented in this study are solely based on publicly available information. Consequently, while the study provides valuable insights, it is crucial to recognize that the findings may not entirely encompass the complexities and unique characteristics of a real-world chlor-alkali plant. Therefore, caution must be exercised in applying these results to legal activities or decision-making processes without considering site-specific conditions and expert consultation.

To ensure the highest level of safety and adherence to regulations, it is essential to conduct thorough and comprehensive evaluations tailored to the specific operational context of the chlor-alkali plant. This entails considering additional factors, such as proprietary information, internal plant assessments, and expert opinions, to validate and refine the results obtained from this study. By adopting a holistic approach and engaging relevant stakeholders, plant operators and safety professionals can effectively address any identified gaps and further improve the plant's safety performance.

REFERENCES

[1.] Abimola M., Khan F., Khakzad N., Butt S. (2015), “Safety and risk analysis of managed pressure drilling operations using Bayesian Network” Safety Science, 76, 133-144
[2.] AIChE (2000). Guidelines for Chemical Process Quantitative Risk Analysis, Second Edition, New York, AIChE
[3.] Al-Shanini A., Ahmed A., Khan F. (2014), “Accident modelling and analysis in process industries” Journal of loss prevention in process industries, 32, 319-334.
[4.] S. George, Nyzal Moideen, Sivi Varghese, Anoop Warrier, M. S. Khan (2022), “Accidents in the chemical industry: An analysis of the HFACS-PEFE model to examine the role of human factors” International Journal of Research Publication and Reviews, Volume 3, Issue, 6, pp. 3701-3708. DOI: https://doi.org/10.55248/gengpi.2022.3.6.40
[5.] S. George, V. R. Renjith (2017), “Layer of Protection Analysis of Sodium Hypochlorite Plant in a Chlor-Alkai Industry: A Fuzzy LOPA Approach”, Open Access International Journal of Science and Engineering, Volume 2, pp.22-32.
[6.] CCPS, (2008). Guidelines for Hazard Evaluation Procedures, Third ed. John Wiley & Sons, Inc., Hoboken, NJ.
[7.] D. Zhu et al., (2007). A framework to integrate software behavior into dynamic probabilistic risk assessment. Reliability Engineering and System Safety, vol. 92, pp.1733–1755
[8.] Kalantarnia, M., Khan, F.I. and Hawboldt, K., (2009), Risk assessment and management using accident precursors modeling in offshore process operation, In 28th International Conference on Ocean, Offshore and Arctic Engineering May, Hawaii
[9.] Khan, F.I, Kelly, Maryam K, (2009) Dynamic risk assessment using failure assessment and Bayesian theory. J. Loss Prev. Process Industries, vol. 22, pp.600-606
[10.] M. Abimbola et al., (2014). Dynamic safety risk analysis of offshore drilling. Journal of Loss Prevention in the Process Industries, vol. 30, pp.74-85
[11.] M. Panchal, P. P. Mithun, A. S. George, (2023), Ä study on the application of dynamic risk assessment in chemical process industries”, International journal of research publication and reviews, 4(1), 2298-2307
[12.] N. Khakzad et al., (2012). Dynamic risk analysis using bow-tie approach. Reliability Engineering and System Safety, vol.104, pp.36–44
[13.] Rathnayaka, S., et al., (2012). Accident modeling and risk assessment framework for safety critical decision making: application to deep water drilling operation, journal of risk and reliability.
[14.] Ravi K Sharma, V.R. Renjith, Amal S George, Meenu Vijayan (2016), “Post – Accident Analysis of Vapour Cloud Explosions in Fuel Storage Terminal”, Proceeding of the International Conference on Recent Advances in Civil Engineering (ICRACE’ 16), CUSAT, Kochi, pp.283-289.
[15.] Qadeer, A., Khan, F. and Ahmed, S. (2014), “Improving safety and availability ofcomplex systems using a risk-based failure assessment approach”, Journal of LossPrevention in the Process Industries, 32, 218-229.
[16.] Summers A, (2003), “Introduction to layer of protection analysis” Journal of Hazardous Materials, 104(1-3), 163-168.
[17.] S. Varghese, Amal S. George, Anoop Warrier, M Shahnawaz Khan (2022), “Pre-Analysis of Fire and Smoke Propagation in a Multi-Storied Building by Using FDS Software” International Journal for Research Trends and Innovation, Volume 7, Issue 6, pp. 1284-1291. DOI Number: 10.6084/m9.doione.IJRTI2206193

ISSN No:-2456-2165

[18.] Woodward, J. L., & Pitalado, R. M. (2010). LNG risk based safety: Modeling and Consequences analysis. New Jersey: John Wiley and Sons publication.
[19.] Yun, G., Rogers,W. and Mannan, S.,(2009), Risk Assessment of LNG importation Terminals using the Bayesian-LOPA Methodology. Journal of Loss Prevention in the Process Industries, vol. 22, pp. 91–96.
[20.] Zheng, X., Liu, M., (2009). An overview of accident forecasting methodologies. Journal of Loss Prevention in the Process Industries, vol.22, pp.484–491.