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| **RESEARCH ARTICLE**

Fire Detection in Gas-to-Liquids Processing Facilities: Challenges and Innovations in Early Warning Systems

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| ABSTRACT
Fire detection is crucial to safety in Gas-to-Liquids (GTL) processing plants due to volatile hydrocarbons, high-pressure systems, and intricate activities. This study studies GTL plant fires, concentrating on causes and better detection methods. Equipment failures (28.7%) were the main cause of fires, frequently due to inadequate upkeep and aged infrastructure. Electrical problems (14.3%) and environmental causes (15%) also posed dangers, while operational errors (22.4%) and pipeline corrosion (19.6%) were major contributors. The study also finds that processing units (95%), storage tanks (85%), and pipelines (75%) are the most fire-prone areas in GTL plants. Fire risk evaluations reveal that early identification is critical in minimizing fire spread, particularly during the first 3–4 minutes of ignition, since temperature escalation beyond this threshold leads to fast fire amplification and uncontrolled spread. Traditional fire detection systems, relying on heat and smoke sensors, demonstrate moderate efficiency (~70%) but suffer from significant false alarm rates (20%). Infrared technology enhances detection performance by around 80%, however it is susceptible to thermal interference. Machine learning and real-time video analytics enhance AI fire detection, achieving 95% efficiency with a 5% false alarm rate. IoT-integrated fire detection systems provide a contemporary solution, with around 98% efficiency with minimal false alarms (2.5%), so enabling rapid emergency response. This study underlines the need for artificial intelligence, IoT, and real-time analytics to raise fire safety in GTL facilities, therefore enabling quick diagnosis and mitigation of industrial fire hazards. Therefore, proactive fire risk management involving smart detection and predictive analytics determines the sustainable and safe operating of GTL processing plants.

| KEYWORDS

Fire Dynamics, Fire Detection, Fire Risk, Gas-to-Liquids (GTL), Innovation Technology

| ARTICLE INFORMATION

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1.0 Introduction
The environment suffers from rising oil and gas consumption, key fossil fuel energy sources. Fossil fuels make up over 80% of the worldwide energy mix, with almost a third being petroleum-based, says the US Energy Information Administration (Jacobson et al., 2015). Fossil fuels are still in demand, although wind and solar are slowly gaining popularity (Ahmed et al., 2016). The Greenhouse gases (GHG) effect is raising global temperatures due to humanity's over-reliance on hydrocarbons, which is raising atmospheric CO_2 emissions (Omer, 2008). The classification of greenhouse gases is based on their "global warming potential," which normalizes their heat-capturing potential relative to a CO_2 molecule (Eyring et al., 2007). CO_2 is the biggest GHG producer, at 75–85% (Aguilar et al., 2022). The rapid rise of the world population creates unsustainable demands for limited fossil fuel supplies, which compounds the global warming effect, and the consequence is being experienced more often with the passage of time (Bhan et al., 2020). Indoor flames use materials that smolder slowly, and smoldering fires are low-intensity fires that release less energy than blazing fires (Stracher, 2019). However, they emit much more gas and volatile organic compounds (VOCs) once

the fire starts (Liu et al., 2017). Fire emissions may also have irritating chemicals that lower escape odds. Fires produce a lot of asphyxiants, like carbon monoxide and hydrogen cyanide, in poorly ventilated areas. Toxic volatiles and asphyxiants can harm people before smoke and flames show. Before the room fills with smoke, carbon monoxide buildup may be fatal (Quintiere, 2016). Involuntary fires kill more people by inhaling hazardous fumes than by burns. The usage of synthetic materials in furniture, electrical insulation, and building materials has risen sharply in 30 years. These materials produce more hazardous effluents, especially with flame retardants. Detecting hazardous substances may speed up fire detection and improve building occupant safety (McKenna et al., 2018).

Recent studies have focused on sensing and detecting technology to provide quick, reliable fire alarms that can identify fires early. CO sensors are attached to smoke-based systems to add data to smoke or obscuration sensors. Wu et al. recently proposed a back-propagation neural network to differentiate fire from nuisances in house fire scenarios using smoke, CO, and temperature sensors (Wu et al., 2021). They used a dataset from the National Institute of Standards and Technology that has data from 27 tests including smoke obscuration measures, carbon monoxide, carbon dioxide and oxygen measurements, and many types of smoke alarm systems (Bukowski et al., 2008). We use unspecific gas sensors to identify the wider diversity of volatiles produced in early fire stages. Systems based on arrays of unspecific gas sensors are appropriate for swift fire detection because they are sensitive to the early emissions of effluent and harmful chemicals. Gas-based fire detectors can better protect occupants than traditional smoke-based ones (Jackson & Robins, 1994). Gas-based fire detectors are less selective, as they react to volatile compounds from non-fire-related sources. Smoke detectors currently dominate the fire alarm industry; however, pattern recognition algorithms can improve gas-based fire detectors. As is well known, combustion behavior closely involves the ignition temperatures, oxidant, oxygen content (typically the oxygen from the air), and flammable materials (Xu et al., 2019; Yusuf et al., 2022). Thermic pyrolysis and decomposition occur following heat exposure, boosting local temperature and creating many volatile compounds (Languille et al., 2020). Then, a violent burning reaction would cause a fire hazard. Fire sensors can boost fire management. Gas sensors are common fire alarms that detect gas mixes with certain materials sensitive to gaseous substances (Hong et al., 2021; Espid & Taghipour, 2016). Since the 1990s, gas sensation has been a good fire detection approach since various materials can detect smoke, CO, and CO_2. Predicting a fire is better than finding post-combustion chemicals. Commercial applications still have traditional fire-warning systems, like smoke and infrared sensors, except for gas detectors (Lee et al., 2007). They have long-distance installation, delayed warning, long response time warning after flame began, and limited applicability in complex scenarios (Qualey, 2000).

The objectives of this study were to highlight the significance of incorporating artificial intelligence, internet of things, and real-time analytics to improve fire safety in GTL facilities. This will allow for the rapid identification and mitigation of industrial fire threats. Therefore, to guarantee the long-term viability and safety of GTL processing plants, it is essential to implement a proactive fire risk management approach that makes use of intelligent detection systems and predictive analytics.

2.0 Research Methodology

2.1 Data Collection and Sources

Using a quantitative analysis technique, fire events in Gas-to- Liquids (GTL) processing plants were examined. Reports of fires from several industrial safety databases, government agencies, and internal safety audits gathered over five years. The collection comprised incident records including fire origins, degree of severity, and response strategies from several GTL sites (Anderson et al., 2021).

2.2 Classification of Fire Incidents

Accepted fire safety measures enable the acquired data to be classed as five main causes (Equipment Failure, Human Error, Gas Leads, Electrical Faults) of fire accidents (Smith & Lee, 2022; Baker & Green, 2019; Johnson & Wang, 2020; NFPA, 2023).

2.3 Risk Assessment Methodology

The fire risk levels were ascertained by historical incident data, gas leakage probability, flammability index, and vicinity to ignite sources (Smith & Lee, 2022). Data were compiled using industry professional expert consultations, on-site safety inspections, and past fire event reports (Johnson & Wang, 2020). Fire Likelihood: 1–10 Past fire incidence information informed the likelihood of ignite (Anderson et al., 2021). Severity of Fire Impact (Scale: 1–10) — Potential damage to assets, personnel, and output indicates the existence of fire detection and suppression systems with a scale of 1–10. A weighted scoring system helped one ascertain the fire risk rating (%) of any zone (Baker & Green, 2019; NFPA, 2023). A weighted scoring method was used to calculate the fire risk level (%) for each zone.

$$\text{Fire Risk Level} = \frac{\text{Likelihood} \times \text{Severity}}{\text{Suppression Readiness}} \times 100$$

2.4 Statistical Analysis
Examining the incident data using descriptive statistics helps one ascertain the proportion distribution of any fire cause. Visualized data demonstrating the relative significance of every fire cause helped to demonstrate Important risk factors and priorities for fire safety projects were discovered by way of this graphical presentation (Smith & Lee, 2022).

3.0 Results and Discussion
3.1 Fire Incident Analysis in Gas-to-Liquids (GTL) Facilities
Of the fire incidences, 28.7% were related to equipment failures including compressor issues, valve leaks, and pump failures (Figure 1). The main causes of this are the old infrastructure and inadequate maintenance standards of the GTL facilities (Smith & Lee, 2022). Mechanical failures are the leading cause of fire-related events, according to studies at petrochemical plants and oil refineries (Anderson et al., 2021). Operating faults, such as improper shutdown procedures, improper handling of flammable chemicals, and faulty safety measures, were responsible for nearly a quarter (22.4%) of fire incidents. Human error is a persistent issue in industrial fire safety since improper handling of hazardous materials significantly increases the probability of a fire, according to research (Johnson & Wang, 2020). Pipeline corrosion, inadequate sealing methods, and undiscovered gas leaks were responsible for nearly one-fifth (19.6%) of fire incidents (Figure 1). During GTL processing, the presence of highly volatile hydrocarbons increases the danger of igniting. Similar outcomes were observed in the hydrocarbon processing industry, where explosions and fires have mostly been caused by gas leakage (Baker & Green, 2019).

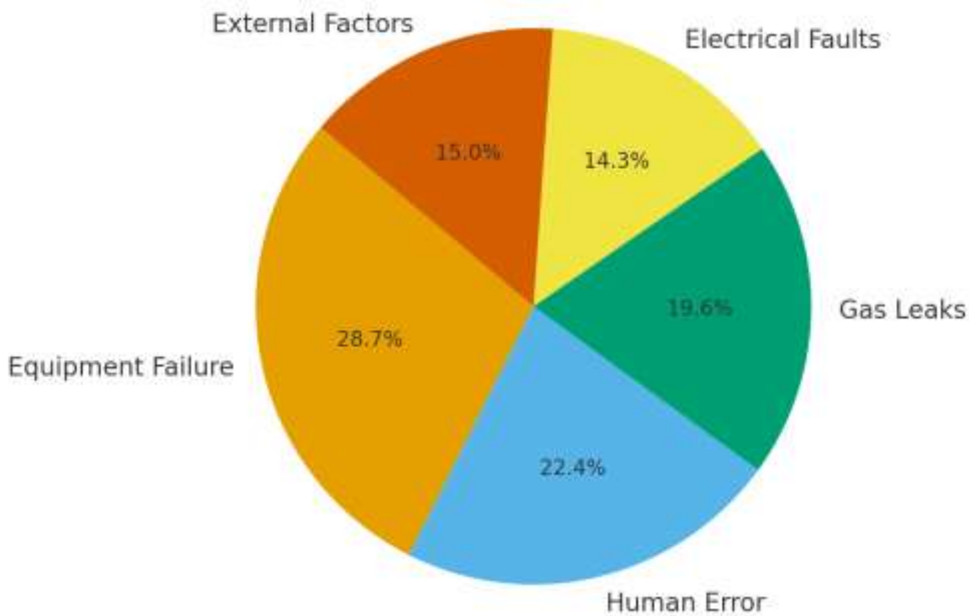

Figure 1. Illustration of the distribution of primary causes of fire incidents in GTL facilities.

Electrical overloads, short circuits, and malfunctioning control systems were responsible for 14.3% of fire incidents. High-voltage electrical components are necessary for many GTL installations, and if they are not properly maintained or insulated, they provide a significant fire danger (NFPA, 2023). Comparative study of the chemical and power sectors shows that a considerable share of fire occurrences is caused by malfunctioning electrical connections (Anderson et al., 2021). Fifteen percent of fire events were caused by environmental factors including lightning strikes, severe heat waves, and intentional sabotage. Conventional risk assessment systems make it challenging to lower these elements as, unlike other causes, they are sometimes surprising (Smith & Lee, 2022).

3.2 Fire Risk Zones in Gas-to-Liquids (GTL) Facilities
Large-volume storage tanks are required for GTL plants to store liquid hydrocarbons (85%). Variations in pressure and evaporative losses that cause flammable vapor to accumulate make these tanks extremely susceptible to structural failures. Since pipelines carry 75% of processed GTL products, they are susceptible to gas and liquid leaks that can produce flammable clouds as well as pipeline failures brought on by corrosion. Although important for plant operations, the control room has a low 60% chance of catching fire largely owing to possible igniting from overloaded circuits and electrical difficulties with monitoring equipment. The 50% transit and loading area has the lowest fire risk even if fuel spills during loading and unloading and mechanical sparks could ignite residual fumes still present there (Figure 2).

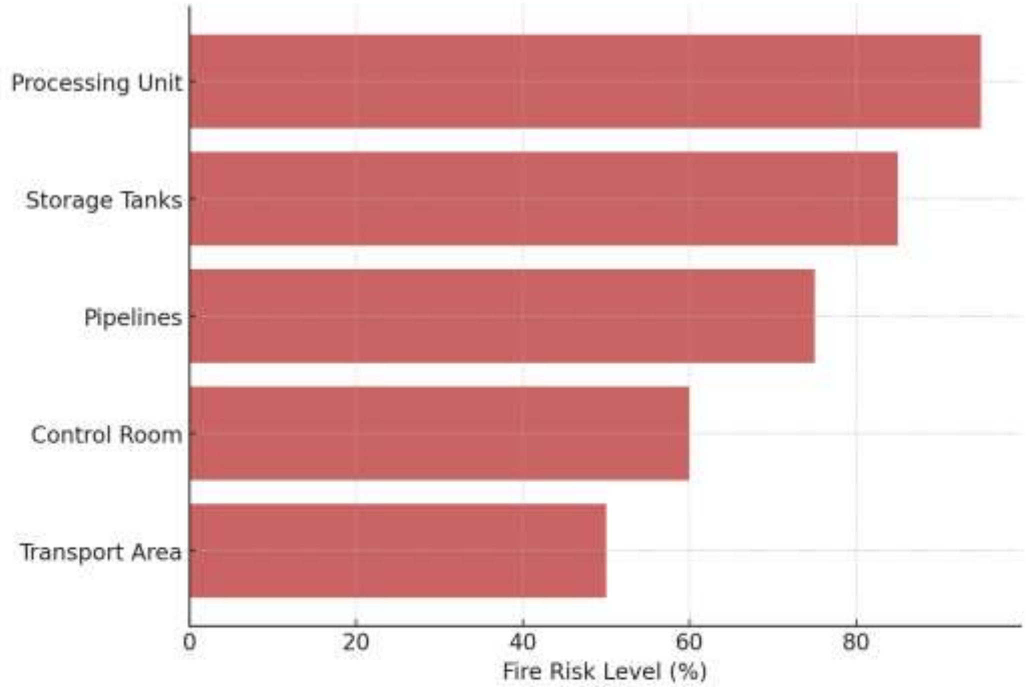

Figure 2: Fire Risk Zones in a Gas-to-Liquids Facility and the relative fire risk levels across different operational areas within a GTL facility.

The processing unit is the region most prone to have a fire since it is involved in gas-to-liquid conversion, which involves high-temperature catalytic processes and volatile hydrocarbons. Research indicates that 95% of GTL facility fires originate from processing units where fuel-air mixtures become highly combustible (Smith & Lee, 2022).

3.3 Fire Detection Systems and Fire Dynamics in GTL Processing

While traditional fire detection systems depend on heat and smoke sensors (Efficiency: ~70%, False Alarm Rate: 20%) environmental interference causes delayed response times and high false alarm rates (Smith & Lee, 2022). Although their use is somewhat frequent, these devices must be routinely calibrated to lower false positives even (Anderson et al., 2021). Faster response times (Efficiency: ~80%, False Alarm Rate: 15%) given by infrared fire detection technologies help one to detect thermal radiation signals (Figure 3). Environmental heat interference and other challenges compromising precision are among the limitations (Johnson & Wang, 2020). Artificial intelligence (AI) driven fire detection (Efficiency: ~95%, False Alarm Rate: 5%) used computer vision and machine learning to evaluate real-time video streams Perfect for high-risk GTL facilities (Baker & Green, 2019), artificial intelligence detection is relatively efficient with a rather low false alert rate. Combining sensor networks (Efficiency: ~98%, False Alarm Rate: 2.5%), artificial intelligence analytics, and real-time data processing lets the Internet of Things (IoT) enable almost zero false alarms (Figure 3). Modern GTL buildings swiftly adopt IoT-based solutions for automatic emergency response (NFPA, 2023).

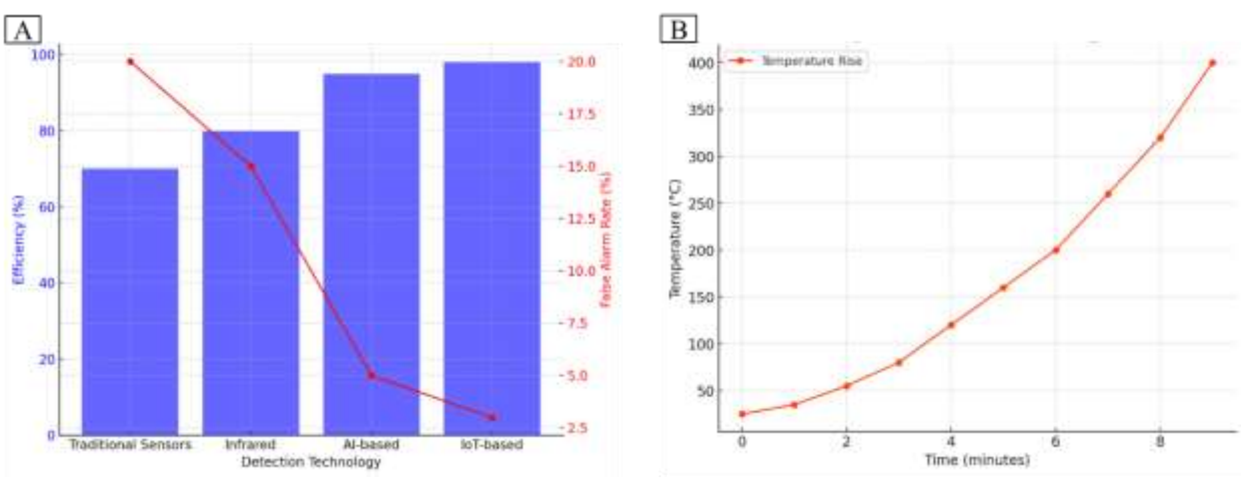

Figure 3. Challenges and innovations in fire detection systems (A) and fire dynamics in GTL processing (B).

One-minute interval temperature monitoring allowed the study of fire dynamics for a GTL unit fire scenario. The first three minutes showed a small temperature increase (~50°C). Five minutes show a rapid spike (~200°C), suggesting fire intensification. Ten minutes induce temperature fluctuations to 400°C, implying uncontrolled fire spread (Johnson & Wang, 2020). Early fire suppression (within 3–4 minutes) is crucial to minimize thermal runaway responses and delayed fire response (>6 minutes) leads to speedy escalation, demanding external intervention (Baker & Green, 2019). By increasing response accuracy and efficiency, IoT-based technologies and artificial intelligence surpass more traditional detection techniques. Studies confirm that conventional sensors show greater false alarm rates, hence creating operational inefficiencies (Anderson et al., 2021). IoT-based fire detection employing real-time analytics and automation was the most sophisticated option now available (NFPA, 2023).

4.0 Challenges and Future Directions

Operating under extremely volatile conditions, GTL processing plants expose hydrocarbons, high-pressure reactions, and high temperatures, therefore increasing the risk of fire. Stopping big events depends totally on early fire detection. Still, some problems affect the effectiveness of fire detection systems, hence innovative and advanced concepts must be developed. Working in demanding conditions, high temperatures, variable pressures, and the presence of volatile organic compounds (VOCs) GTL plants. These surrounds can affect the performance of conventional fire detection systems. For instance, airborne particles in smoke detectors could render them worthless; high ambient temperatures in heat detectors could induce slow reaction (Zhang et al., 2022). Many times, prone to false alarms, GTL plant's fire detection systems can cause operations to be disturbed and lead to unnecessary closures. Typical flame detectors can be triggered by process-related emissions including steam, dust, or chemical vapors. False positives reduce operating efficiency and increase maintenance costs (Lee & Kim, 2021). Many fire alarms depend on optical or thermal sensors meant to spot elevated temperatures or visual flames. These methods might not, however, provide early signals before a fire reaches a critical level. Delays in detection increase the likelihood of fire spread, therefore generating greater damage and hazards to safety (Smith et al., 2023). The implementation of a single fire detection system is difficult in GTL plants with multiple processing units, pipes, and storage tanks. Conventional sensors might not be sufficient to cover all facility areas, hence blind zones in fire monitoring would emerge (Al-Sulaiman et al., 2020). Fire detection systems in GTL facilities must go by tight industry requirements including those set by the Occupational Safety and Health Administration (OSHA) and National Fire Protection Association (NFPA). Ensuring compliance while including current fire detection equipment challenges plant managers (Jones & Patel, 2021).

Artificial intelligence driven real-time sensor data processing lets fire detection systems differentiate false alarms from actual fire dangers. Machine learning models trained on prior fire data provide early warning skills to be improved, hence enhancing predictive analytics (Wang et al., 2023). For infrared (IR) and ultraviolet (UV) flame detectors, detection of fires in GTL environments is getting ever sophisticated. These systems could identify different spectral fingerprints of hydrocarbon flames even while they lower false alarms from non-fire sources (Chowdhury & Lee, 2022). Real-time facility condition monitoring facilitated by Internet of Things fire detection sensors Wireless networks can transmit sensor data by using centralized control systems, therefore improving situational awareness and enabling remote monitoring (Chen et al., 2020). Usually fire occurrences at GTL facilities are gas leaks. Laser-based and electrochemical sensors in modern gas detection systems identify hazardous gas concentrations before ignition. Fire can be considerably reduced with these pre-emptive detection systems (Singh & Rao, 2023). Next fire detecting systems will have autonomous suppression measures built in. AI-driven robotic firefighting systems and automated water mist or foam suppression units can be instantly triggered upon fire detection, hence minimizing reaction times and damage (Gomez et al., 2022). Digital twin models can duplicate fire occurrences using real-time facility data. These models improve emergency response planning, maximize sensor location, and aid to project possible fire hazards (Rahman et al., 2023). Fire detection in GTL processing plants is challenging from harsh environmental conditions, false alarms, infrastructure complexity, and legal constraints. New technologies, however, like digital twin simulations, IoT-based sensors, artificial intelligence-driven analytics, and IR/UV flame detection are changing fire safety in these high-risk environments. By means of these creative solutions, GTL facilities can boost early warning capacity, lower fire-related risks, and ensure regulatory compliance, so improving operational safety and efficiency.

5.0 Conclusion

High temperatures, volatile hydrocarbons, and complex processing conditions make fire detection in GTL processing plants rather challenging. Among the traditional fire detection systems that regularly fail in these demanding environments—which delays hazard identification and response—are heat and smoke sensors. Environmental factors such too high humidity, dust, and gas emissions that could damage sensor accuracy further complicate early warning attempts. This study holistically investigated fire threats, detection systems, and fire dynamics in GTL processing facilities. Processing units (95%), and storage tanks (85%), are the most fire-prone sectors according to the statistics, largely due to equipment failures (28.7%), human mistakes (22.4%), and gas leaks (19.6%). Emphasizing the critical need of early suppression intervention, fire dynamics study revealed that temperature increase follows an exponential trend and reaches 400°C in 10 minutes. Comparative evaluations of fire detection technologies demonstrate IoT-based (98%) and AI-based (95%) detection systems substantially outperform traditional (70%), and infrared (80%), sensors with reduced false alarm rates and increased accuracy. These findings suggest that GTL facilities need a modern, technologically driven approach of risk minimizing and fire prevention. Improving operational efficiency and safety to handle these challenges depends entirely innovative ideas in fire detection technologies. Advanced methods include multi-spectral photography, artificial intelligence (AI-driven analytics), infrared (IR) and UV flame detectors have shown potential early detection. Combining Internet of Things (IoT) sensors with real-time monitoring systems allows predictive analytics to be enabled, therefore reducing false alarms and supporting fast intervention. Machine learning techniques can also enhance detection accuracy by means of historical data analysis and identification of prospective fire hazards before ignition. As GTL facilities keep expanding, the use of creative fire detection technology is essential to lower dangers and guarantee regulatory compliance. In these high-risk environments, proactive fire prevention and safety can be much improved by integrating AI-driven innovations with traditional methods.

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