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AI-Driven Real-Time H_2S Monitoring and Risk Mitigation During Drilling in Southern Iraq Fields Using Fuzzy ART Unsupervised Learning

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ABSTRACT

Drilling in formations with hydrogen sulfide (H_2S) in southern Iraq poses environmental and safety problems. To create more sophisticated, intelligent monitoring systems, this study implemented an AI-driven, real-time methodology to monitor and mitigate the risks associated with H_2S. The system was developed using a self-learning AI agent trained using field data from 21 wells with 41 H_2S incidents.

The AI agent applies fuzzy adaptive resonance theory (ART)-based unsupervised learning to check the alert levels, predict H_2S spikes, and recommend the optimal adjustment for the mud pH to counterbalance the dissolved H_2S in the drilling fluids. Unlike static rule-based systems, this approach is based on adaptive thresholds that improve with learning and combines the alarm protocols adopted by Health, Safety, and Environment (HSE) with the proposed tresholds that reflect the formation data. This process enabled more rapid responses to fluctuations in gas levels due to earlier problem detection plus more accurate assessments of the crew's cumulative exposure.

This AI-based technology delivered a strong and adaptable approach, with several advantages. It provides an accurate estimate of the amount of H_2S in each formation, reduces the operational risk, and allows the team access to safer, data-driven decisions when drilling in H_2S bearing formations.

Keywords: AI-Driven H_2S Monitoring, Fuzzy ART Predictive Classification

INTRODUCTION

In H_2S-bearing formations, safe drilling is always a challenge and complex task [1,2]. Natural gas, crude oil, and geothermal reserves contain H_2S, which is also found in sewage as well as in decomposing animals or sediment organic matter [3]. Moreover, H_2S may be released while drilling oil wells. H_2S in the wellbore is very dangerous for operations and safety because it is poisonous, corrosive, and always present in the environment. Disasters affect people, the environment, and business because emergencies, shutdowns, and broken equipment are costly [4]. Therefore, it is vital to forecast, recognize, and regulate H_2S occurrences in order to assure well safety [5,6]. H_2S monitoring compares the responses of sensors to a set of standard responses [7] by employing analytical, statistical, and knowledge-driven methodologies to elucidate gas-inflow patterns.

The existence of H_2S in the formation fluids is critical to the economic potential value of the hydrocarbons as well as to the quality of the drilling and production processes. If H_2S enters the borehole, it can result in dangerous and expensive consequences when an inflow of H_2S is induced by drilling, completion, or testing. Besides workers being exposed to acute toxicity, this situation can cause environmental contamination and material loss to the environment due to the cracking and corrosion of drill pipes, casings, and completion equipment due to sulfide stress [8,9,10]. Additionally, the prolonged release of H_2S has widespread implications for air quality and the precipitation of acid, making H_2S management not only an occupational safety concern but an environmental one [11]. Preventive work necessitates timely and precise detection of H_2S influxes. However, conventional detection systems frequently rely heavily on static threshold-based systems or manual interpretation of sensor outputs, which are less flexible in responding to the dynamic downhole environment and are also slow in reacting during the critical early stages of incursion [3]. This negative impact on geological systems is extant in the Umm Er Radhuma and Tayarat formations,

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which are located in southern Iraq, which reveal H_2S-bearing layers that are very thin, discontinuous, and unpredictable [12]. To adress these problems, an AI-driven agent was proposed in this work using unsupervised machine learning and fuzzy ART to provide a real-time classification, clustering, prediction, and control of H_2S alerts for risk levels. The deomstrate intelligent approach includes three modules:

1. Data intelligence layer: Real field data are collected from the southern of Iraq from 21 wells containing 41 recorded H_2S enents, to generate a well-based training sets data, up-to-date, historical drilling data and mud logging. The collected data included: depth correlations, pH, gas readings, and rate of penetration.

2. AI-driven agent model using fuzzy ART core: The presented intelligent agent leveraged a fuzzy ART model [13] for unsupervised learning pattern matching and adaptive vector optimization. In comparison with traditional clustering algorithms, fuzzy ART dynamically creates and updates the alert levels based on the categories in real time mode, thereby addressing the stability-plasticity problem defined by Carpenter and Grossberg [14,15]. Which help the AI-driven agent to preserve the knowledge it gains from prior experience, while simultaneously developing and adapting to current and/or novel drilling scenarios.

3. Real-time reactance H_2S monitoring: An early indicator of H_2S intrusion can be detected throug trained agent continually checks alerts by interpreting incoming data from the mud-logging sensors. The intelligent agent, automatically cluster the readings in three groups to feed the three adaptive alert zones (i.e., green, yellow, and red), based on HSE operational thresholds. Moreover, the proposed agent suggests steps to metigate the H_2S intrusion in adequate measures, using pH or circulation to neutralize any free H_2S so that the concentration of free H_2S cannot reach hazardous levels.

HEALTH EFFECTS OF H_2S EXPOSURE

The health effects of hydrogen sulfide (H_2S) exposure are mainly determined by its ambient air concentrations and exposure duration. A mucous membrane irritant and asphyxiant, H_2S inhibits cellular oxygen utilization and results in other negative neurotoxic effects on the central nervous system (CNS) [3] These interacting physiological mechanisms make H_2S one of the most acutely toxic gases encountered during drilling and production. At low concentrations, H_2S primarily induces irritation in the eyes, nasal passages, throat, and respiratory tract, causing burning eyes, tearing up, coughing, and some difficulty breathing. Although these may seem to be minor issues, the onset is delayed, with effects appearing several hours or days after exposure [3]. Chronic irritation, chronic headaches, fatigue, irritability, insomnia, digestive problems, and unintentional weight loss have occurred at low levels of exposure, while the same conditions have been associated with chronic symptoms after prolonged or repeated exposure [3, 16]. When the H_2S levels are moderate, the respiratory system and eye tract irritation and pain as well as other irritation, such as dyspnea, coughing, and pulmonary edema [17]. In addition to other symptoms like dizziness, nausea, vomiting, poor coordination, and restlessness [17]. Where such that can cause systemic toxicity because the gas negatively affects oxidative metabolism and CNS functioning. H_2S at high concentrations can also rapidly become lethal. After inhalation, seizures, respiratory paralysis, loss of consciousness, coma, and fatality are common complications that can be happened within a few breaths or even following a single inhalation [17]. As such, the cumulative effects of H_2S at sublethal doses mean that any exposure (i.e., short-term or long-term) must be monitored for their duration and concentration. Therefore, time and concentration exposure must be accurately predicted and measured to better protect drilling personnel and to develop proactive strategies to minimize and counteract exposure.

OVERVIEW OF THE UMM ER RADHUMA AND TAYARAT FORMATIONS

Umm Er Radhuma and Tayarat Formations. These potential drilling sites are two adjacent carbonate successions lying in a stratigraphy pattern that appears analogous in lithology and is hydraulically linked to a limited regional aquifer system [6]. These two formations are predominantly anhydrite, argillaceous dolomite, and dolomitic limestone, intercalated with pale grey dolomitic marl, coarse crystalline dolomite, and intermittent anhydrite nodules [12]. The existence of small phosphatic grains indicates variable depositional conditions with local upwelling [18,12]. The Umm Er Radhuma and Tayarat formations are each about 500 m thick on average, ranging from around 1,000 to 1,500 m in true vertical depth (TVD) [19]. The petrographic uniformity and low permeability of the formations affect the behavior of the confined aquifer, and sulfur-containing groundwater in the pore network poses a potential

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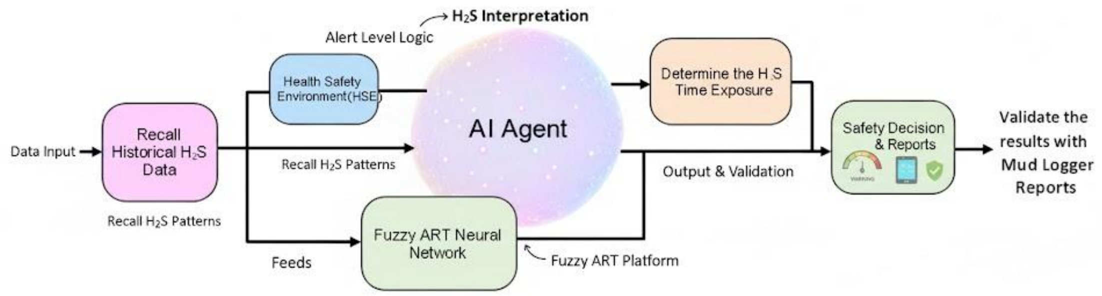
hazard during drilling. This water may be absorbed into the wellbore, causing the release of H2S due to the interaction between the reactive drilling fluid and the dissolved sulfate [19,20]. For upstream drilling operations in southern Iraq's carbonate reservoirs, it is necessary to consider the geological and hydrochemical features of the Umm Er Radhuma and Tayarat formations in order to monitor and mitigate H2S.

AI-DRIVEN, H2S AGENT FRAMEWORK

H2S agent framework in the age of AI. This stud, posited a collaborative, intelligent framework of three interconnected systems to introduce a real-time hydrogen sulfide (H2S) monitoring and risk management system (Figure 1). The system (abbreviated as the Artificial Intelligence on H2S Agent model) is intended to simulate the mud-logging equipment routine as well as human-like operations, combined with modern adaptive learning. The process started by extracting and preprocessing a historical dataset comprising 41 recorded H2S events from 21 wells corresponding to various geological and operational conditions. These data streams were analyzed sequentially, corresponding to the real-time logging trend. In the next step, the AI agent created a color-coded H2S exposure log with LED lights, where green = safe, yellow = warning, and red = critical, that interpreted and generated a continuous image of the data on the risk status for each event that occurred in the pipeline. Two alert frameworks were applied and compared: (1) a standard HSE-level policy, aligned with common industry thresholds for most drilling operations; and (2) an adaptive alert model based on a fuzzy ART unsupervised learning algorithm. The agent identified the concentration profile, exposure duration, and temporal evolution of the event that occurred at a given rate of incidence for each recorded H2S influx.

The fuzzy ART neural network provides self-sufficient clustering and ranking of events based on similarity patterns and severity, repeatedly training on historical well data and improving its decision boundaries with the addition of new data. Based on this experience learning approach, this AI H2S agent iteratively changes its alert thresholds, leading to enhanced sensitivity and specificity of hazard recognition. Running the simulated model, the trained agent can analyze H2S streams as the condition unfolds and conduct an event-triggering action to activate the setting of an appropriate warning level and suggest mitigation actions. This adaptive data-driven architecture converts the most traditional, fixed threshold-monitoring method into a self-learning intelligent system that can be adapted for diverse field conditions and can improve predictive performance [6].



Figure

1—AI agent to monitor H_2S using fuzzy ART.

Figure 2 shows real-time data from H2S detectors at rig locations (i.e., floor, shale shaker, and mud processing units) that identify atypical gas concentrations. The AI-driven fuzzy ART model proposed in this study collected data from 21 wells that had 41 H2S incursions. The unsupervised learning using the fuzzy ART algorithm first labeled the data with three alarm levels in relation to the H2S concentration indicating safe, transitional, or critical exposure. This automatic detection facilitates receiving more accurate detection of H2S dangers in real time by enhancing the predictive and preventative abilities of normal monitoring systems.

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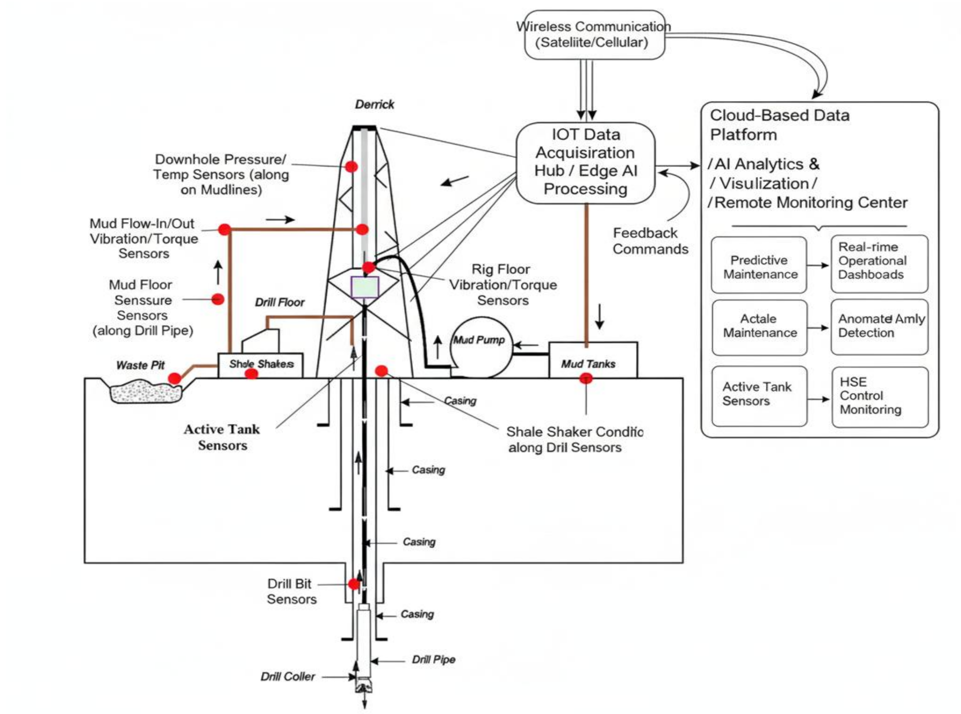

Figure 2—Internet of Things (IoT) system architecture of the drilling rig.

AI-DRIVEN AGENT TO LEARN H_2S ALERT LEVELS BASED ON A FUZZY ART MODEL

The current investigation advances the seminal research of [21], which employed H_2S detection data from only 12 drilled wells in two Iraqi formations (i.e., Umm Er Radhuma and Tayarat), whereas this paper is based on data from 21 wells with 41 observations of H_2S. This expanded dataset supported the creation and validation of an AI-based H_2S agent capable of learning, classifying, and adapting under real-time alert thresholds using a fuzzy ART model. The unsupervised learning process adopted couple of key stages for data preprocessing, classification, and adaptive clustering that are crucial to ensure that AI-driven agent is correctly interprets the changing patterns on site. The learned workflow adopted, shown in Figure 3, is structured as follows:

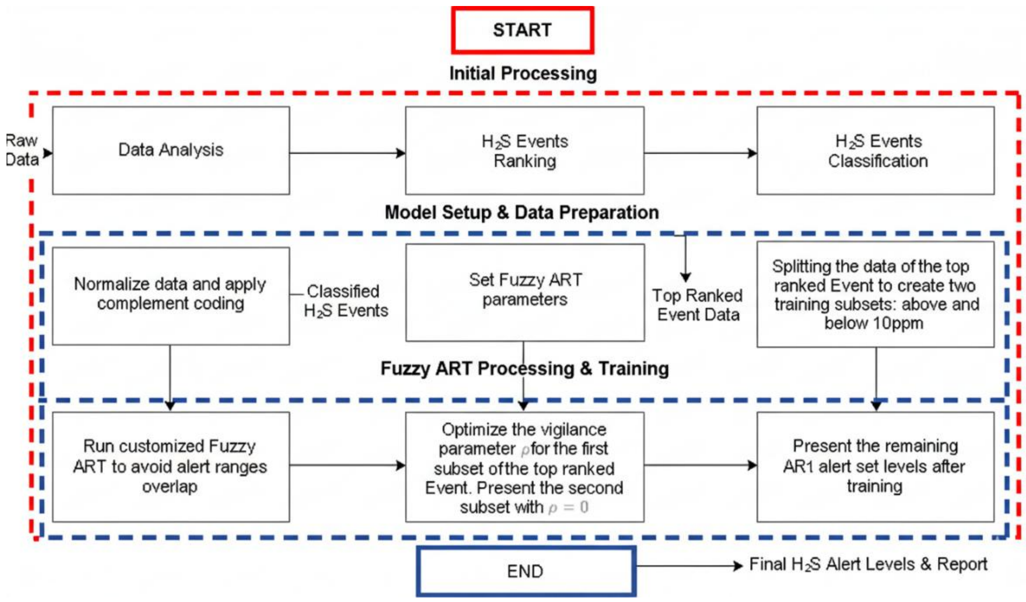

Figure 3—Adopted preprocessing and training algorithm using fuzzy ART.

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Policy recall: To evaluate the H_2S datasets and define the basic alert limits, the AI agent referenced the baseline HSE policy parameters and the baseline rules. Ranking the H_2S influx events on their highest realized concentrations enabled the model to rank the events based on hazard severity.

Event classification: The agent sorted the ranked events into hazard categories by concentration cut thresholds. For example, levels of $H_2S < 10$ ppm indicate low caution but levels of $H_2S \geq 10$ ppm signify high caution, enabling the classifier to order future clustering.

Data partition: The dataset for the top-ranking event was divided into two categories: concentrations less than and more than 10 ppm. The lower concentration trained the model initially, while the second tested the adaptable model under higher exposures. This work trained the fuzzy ART network on the baseline subset with the appropriate vigilance parameter (ρ) so that the networks would evolve into three initial clusters that corresponded to the three exposure patterns. Visualizing high concentrations: To maximize the expansion of the existing clusters instead of creating new classes, the second subset ($H_2S \geq 10$ ppm) was shown to the network with the vigilance parameter $\rho = 0$.

Progressive learning: The leftover events were added in a sequence, where $\rho = 0$, to continue to evolve by adjusting the existing classes. A secondary vigilance test was included in the AI agent's learning architecture to check the separation between the clusters and to avoid any overlap in the category boundaries. This improvement eliminated resonance, thereby increasing the stability and interpretability of the model because new data could add two extra categories, and by extension, create incompatible groups between two clusters. Based on the works of Seiffertt and Wunsch II [22] and [23], the concept of layered vigilance control in this study enabled the introduction of more complex and hierarchically structured ART architectures. In this way, the AI-driven H_2S agent refined its alert thresholds in real time, allowing for the evolution of static, rule-based monitoring to a self-learning, experience-based response with the capacity to recognize and analyze field conditions. Further theoretical details of the fuzzy ART algorithm, network architecture, and training methodology can be found in Appendix A.

REAL-TIME H_2S MONITORING AGENT BASED ON AI

Hydrogen sulfide (H_2S) is a colorless, heavier-than-air gas that migrates easily on the ground and accumulates in low-lying or poorly ventilated spaces. It has a strong odor reminiscent of rotten eggs, which can be detected by most humans at concentrations as low as 1 ppm, with a sweet taste that manifests at slightly higher levels. However, with long-term, low-level exposure or at high concentrations, the human olfactory system also develops olfactory fatigue, meaning that even in the presence of this gas, olfactory perception is inhibited or lost. Desensitization can occur within minutes or even instantaneously at high exposure concentrations, without direct sensory detection, highlighting the need for automated, intelligent monitoring devices.

Due to these risks, oil and gas companies and regulatory bodies limit the exposure of employees working in H_2S-prone environments. Most HSE establish guidelines for standardized alarms in accordance with this scale of tolerances:

Level 1 (Caution): 5 ppm (visual alert); ongoing monitoring continues.

Level 2 (Critical): 10 ppm (audible alarm); urgent evacuation and respiratory protection are required. established.

In the current work, the existing hardware-based H_2S simulator employed in field testing was replaced by a fully digital, AI-based H_2S monitoring agent, thus introducing a self-learning software system that fits within an embedded grid of real-time mud-logging and sensor networks.

The AI H_2S agent passively analyzed the streaming data from the H_2S detectors deployed in critical areas, such as the rig floor and the shale shaker, as the system learned from the historic field data of 21 wells and 41 H_2S events. By applying the fuzzy ART neural architecture, the agent can conduct unsupervised pattern recognition to identify, classify, and recategorize alerts within dynamic operational settings. It learns, sets adaptive alert classifications (i.e., green for safe, yellow for warning, or red for critical) that are directly related to those HSE policy thresholds, but is constantly improving, adapting, or upgrading to new standards based on discoveries made by the neural learning model. Moreover, the adopted unsupervised machine learning using fuzzy ART allows the monitoring system to train

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and cluster data based on the H2S events and their exposure levels, which lead to maintain stabile and versatile drilling environment.

In comparison between static alarm systems and the presented AI-driven agent, Figure 4 demonstrates that AI agent is more efficient than an alarm signal: it analyzes exposure patterns in a an early stages, can predict gas build-up, and also can generate data-based advisory outputs in a timely manner for intervention. By integrating real-time data analytics, adaptive unsupervised learning, and field-specific knowledge, this system presents a paradigm shift to smart, autonomous H2S safety management that ensures the welfare of personnel, equipment, and the environment for sour-gas drilling operations [21].

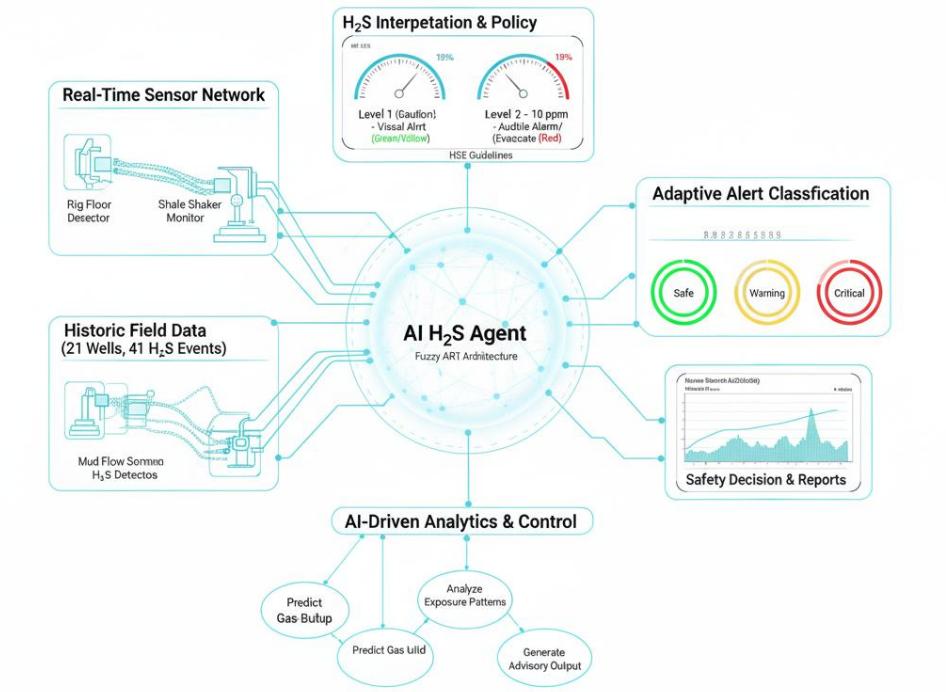

Figure 4—AI-driven H2S safety monitoring in the drilling rig.

RESULTS AND DISCUSSION

The previous H2S data from 12 wells that had been drilled in the formations at Tayarat and Umm Er Radhuma [6] were extended in this study to 21 wells with 41 H2S intrusions. This enhanced AI-driven H2S monitoring agent used alert levels that originate from both drilling operator Health, Safety, and Environment (HSE) policy and the fuzzy ART network ranges.

The H2S log interpretation utilized three colors (i.e., green, yellow, and red), based on the H2S concentration. Applying the HSE policy adopted by drilling operators, the integration of the H2S log interpretation with the data streaming mimicked the mud logger, as shown in Figures 5-A1 and 5-A2 for H2S Events 8 and 16, respectively. This log interpretation assists in determining the time of exposure for each alert level. The total time exposure was 38.1 min and 27.1 min for Events 8 and 16, respectively. The time exposure for the three alert levels for various H2S concentrations are presented in green (0-5 ppm), yellow (5-10 ppm), and red (+10 ppm), as shown in the pie charts (Figures 5-B1 and 5-B2) and Figure 6.

Figures 5 A1 and A2 present the real-time H2S sensor readings for Events 8 and 16, demonstrating the effect of the alert thresholds (5 and 10 ppm, respectively). Figures 5 B1 and B2 correspond to charts visualizing the time-exposure distribution across green (safe), yellow (warning), and red (critical) zones. This figure clearly illustrates that even small baseline shifts can influence alert classification in an AI-driven H2S agent.

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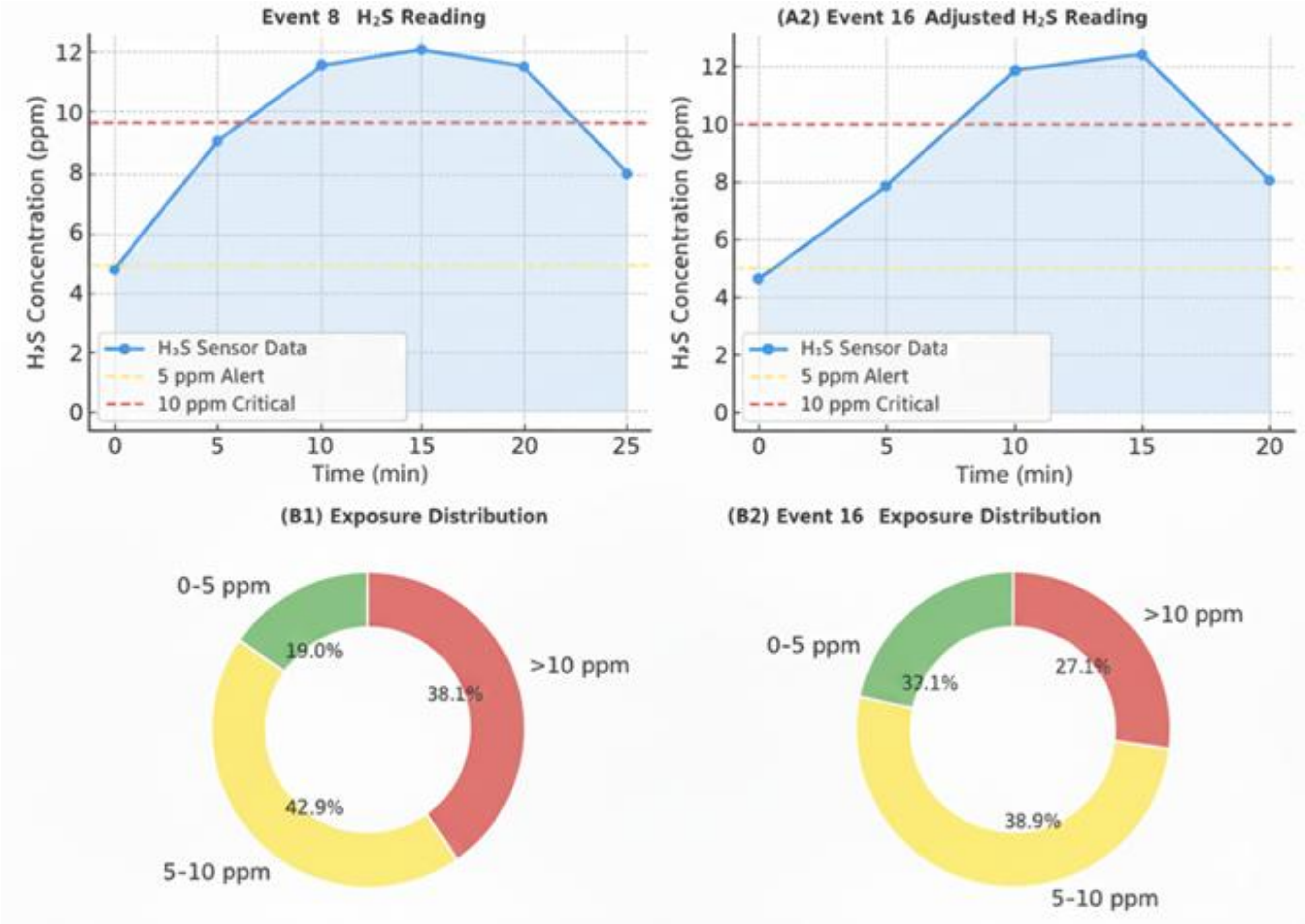

Figure 5— H2S real-time monitoring results: for A1 and A2, the H2S sensor reading interpretation used the HSE set of alerts for events 8 and 16, respectively; for B1 and B2, the pie charts show the H2S time exposure distribution for Events 8 and 16, respectively.

Using the adopted approach (presented in Figure 3), the H2S events' data were preprocessed, with the results illustrated in Figure 6. First, the algorithm determined the minimum and maximum H2S concentrations for each event. Second, the approach sorted all events in descending order from the maximum concentration (Event 10, with 24.9 ppm) to the minimum (Event 41, with 5.2 ppm). Third, based on these ranked events, the system classified the H2S influxes into two levels of caution (High Caution, with an H2S concentration greater than 10 ppm, where the drilling rig should be evacuated) and (Low Caution, with an H2S concentration lower than 10 ppm, where the drilling rig's visible alert is triggered). Fourth, the algorithm split the data of the top-ranked H2S event (which ranged to 10 ppm), as shown in Figure 7, and created a training subset from the data to use in fuzzy ART. This set up the H2S simulator alert levels and then accumulated the learning using the remaining H2S intrusion data (Figure 6).

Utilizing the fuzzy ART processing steps, the current approach optimized the vigilance parameter for the top-ranked H2S event to produce three clusters that correspond with the H2S AI-driven agent's three level of alerts; an example using Event 10 is shown in Figure 7.

For the drilling service companies, the simulator's three LED colored lights, in descending order of concern (i.e., red, yellow, and green) correspond respectively to the H2S concentration (i.e., +10, 5-10, and 0-5 ppm), illustrated in Table 1. The AI H2S monitoring agent's fuzzy ART produced the appropriate LED after learning from the network training based on the input of H2S concentration from the 41 H2S events.

Table 1 displays the simulator alert levels that resulted from the H2S events' data that were sorted in series using the fuzzy ART steps in Figure 3 (i.e., well-by-well after the preprocessing steps illustrated in Figure 6). First, the data of

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the top-ranked H2S event (Event 10) was divided into two subsets: (1) Subset 1 encompassed data up to 10 ppm to be trained by fuzzy ART, and (2) Subset 2 consisted of data greater than 10 ppm. Second, the vigilance parameter was optimized for the H2S event Subset 1, to determine the optimal levels for the three categories. This was accomplished by noting the number of categories in relation to the vigilance values); these correspond to the simulator's three colors, which are presented in Figure 7. Third, Subset 2 was presented to fuzzy ART with a customized feature to avoid the overlap of the H2S set of alert ranges. Finally, fuzzy ART was trained on all the other H2S events to accumulate the data and complete the training process. The same procedure was employed for all the remaining processed wells, except during the splitting and vigilance optimization steps, which were only applied to the top-ranked H2S event (see Table 1). Also, when using fuzzy ART, the lower set of alerts monotonically decreased, whereas the upper set of alerts monotonically increased.

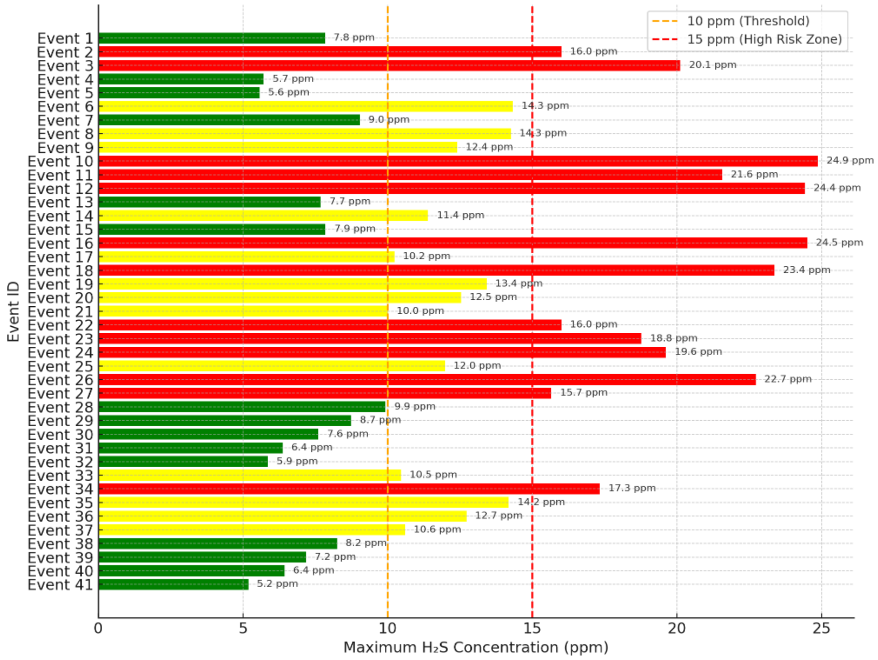

Figure 6—Fuzzy ART input classification map: H2S event distribution by caution level.

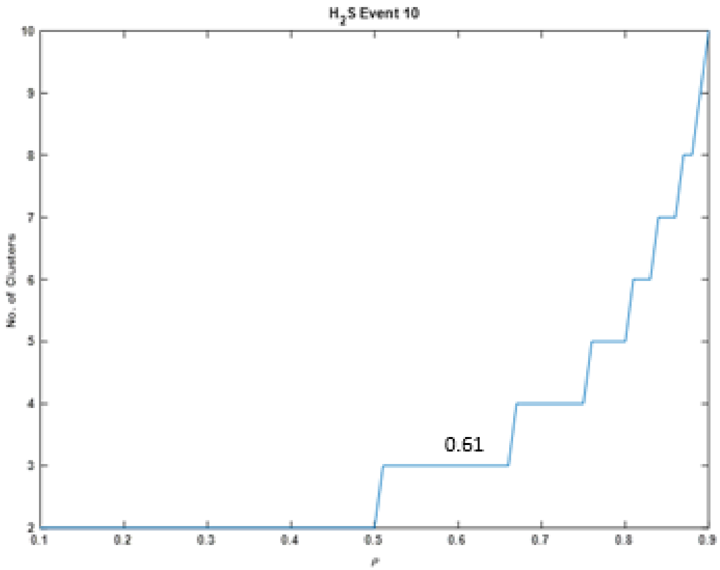

Figure 7—Event 10 fuzzy ART output

One significant aspect of the AI-based, H2S monitoring agent shown in Figure 8-A is that it relied on color-coded alarms that match conventional HSE regulations, as shown in Table 1. Before any H2S enters, the system shows a

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green LED. The yellow LED lights up when hydrogen sulfide first appears and levels rise to 5 ppm, meaning that the levels are not within safe limits. The red LED alarm is triggered when the concentration increases above 5 ppm, indicating a high-risk situation.

Additionally Figure 8-B shows the alert behavior that the fuzzy ART model learned from the 41 historical H_2S incidents employed in this work. Table 1 illustrates that the alarm levels constantly change on a well-by-well basis when new H_2S data is sent to the fuzzy ART network. The HSE-based simulator and the fuzzy ART agent set alarm thresholds differently (Figure 8 A–D), confirming the multiple benefits of the AI-driven method: Early intrusion detection: The small yellow section in Figure 8-B reveals that the system can identify H_2S incursions earlier than non-AI static systems, thus producing more time for drilling teams to prepare for any higher concentrations.

The fuzzy ART classifier perceives hazardous levels earlier and across a larger range than the HSE policy (Figure 8-A), which only calls concentrations "significant," rather than distinguishing between several levels of concern. Sustained vigilance: After the first red alert spike in Figure 8-A, personnel could think the danger had passed. However, Figure 8-B illustrates that fuzzy ART continues to send precautionary signals, signifiying that the crew should remain attentive.

Identification of prolonged exposure: Figure 8-D displays the fuzzy ART system sending a yellow signal when there are protracted periods of moderate H_2S exposure. This is especially critical because long-term exposure can have a cumulative effect on the lungs, even with levels below those considered high risk. The fuzzy ART model is adaptive and data-driven, making it a better warning system by maintianing awareness of the surroundings, thus improving safety during drilling operations in H_2S-bearing formations.

Table 3—Simulator Alert Levels by Color

Database	Green Range (ppm)	Yellow Range (ppm)	Red Range (ppm)	ρ	Number of Data Points
HSE Policy	0.00–5.00	5.00–10.00	10.00–10+		
Event 10	0.00–3.49	3.68–7.17	7.25–24.87	0	321
Event 16	0.00–3.49	3.68–7.21	7.25–24.87	0	321
Event 12	0.00–3.49	3.65–7.21	7.25–24.87	0	438
Event 18	0.00–3.50	3.65–7.21	7.25–24.87	0	393
Event 11	0.00–3.57	3.65–7.22	7.25–24.87	0	747
Event 3	0.00–3.57	3.65–7.23	7.25–24.87	0	625
Event 2	0.00–3.59	3.65–7.23	7.25–24.87	0	890
Event 22	0.00–3.59	3.65–7.23	7.25–24.87	0	453
Event 6	0.00–3.59	3.65–7.23	7.25–24.87	0	372
Event 8	0.00–3.59	3.65–7.23	7.25–24.87	0	363
Event 19	0.00–3.61	3.64–7.23	7.25–24.87	0	237
Event 20	0.00–3.61	3.64–7.23	7.25–24.87	0	324
Event 9	0.00–3.61	3.64–7.23	7.25–24.87	0	666
Event 14	0.00–3.61	3.64–7.23	7.25–24.87	0	312
Event 17	0.00–3.61	3.64–7.23	7.25–24.87	0	783
Event 21	0.00–3.61	3.64–7.24	7.25–24.87	0	498
Event 7	0.00–3.61	3.64–7.24	7.25–24.87	0	390
Event 15	0.00–3.62	3.64–7.24	7.25–24.87	0	834
Event 1	0.00–3.62	3.64–7.24	7.25–24.87	0	310
Event 4	0.00–3.62	3.64–7.24	7.25–24.87	0	711
Event 13	0.00–3.62	3.64–7.24	7.25–24.87	0	779
Event 5	0.00–3.63	3.64–7.24	7.25–24.87	0	576

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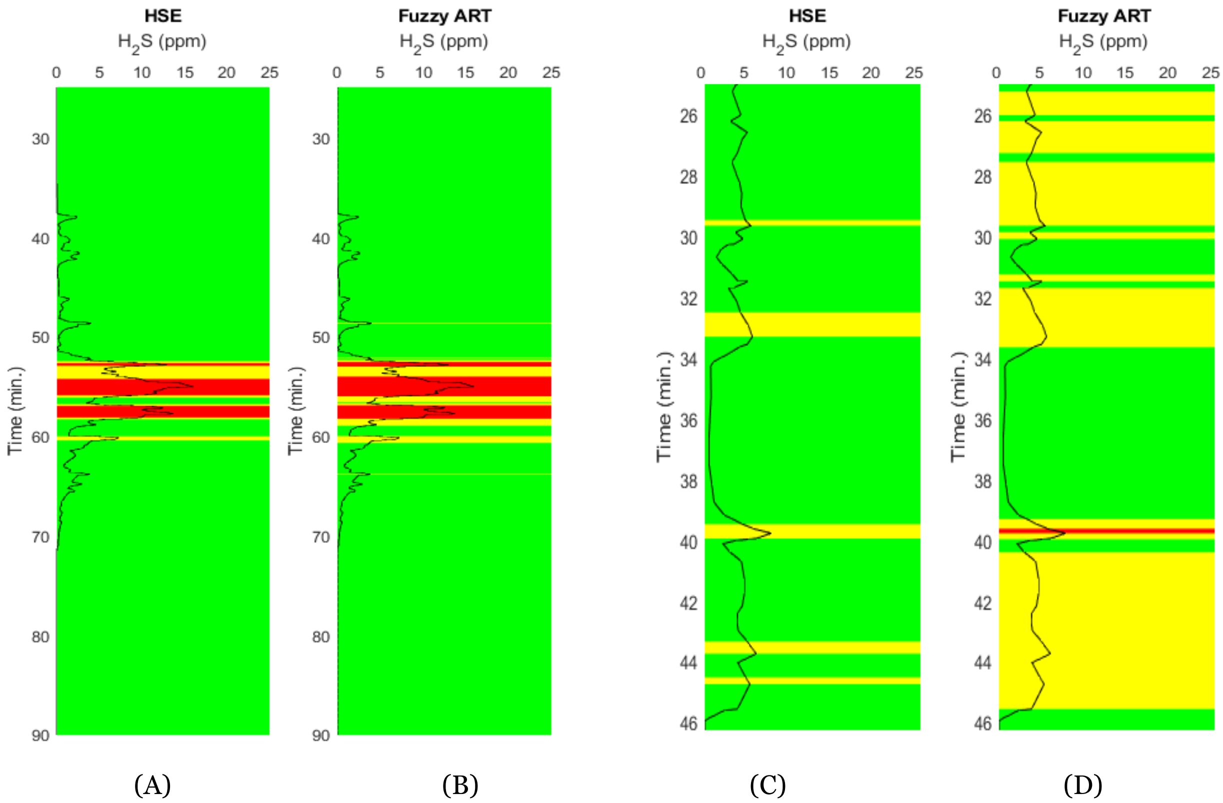

Figure 8—H2S log interpretation alert level settings. A and C: HSE policy. B and D: trained AI H2S monitoring agent using fuzzy ART.

CONCLUSIONS

This study sought to enhance the ability of the drilling operator to detect the real-time intrusion of H2S and to accurately evaluate the exposure duration when drilling in hydrogen sulfide-bearing strata. Traditionally, the exposure assessment framework employed HSE policy ranges in the field, determining identical limits for all wells irrespective of the actual H2S concentration or operative conditions. Thus, this paper proposed an unsupervised learning method to mitigate this constraint, based on fuzzy ART to dynamically adjust the three-tiered H2S alert system (i.e., green, yellow and red LEDs) based on the built-in behavior of the H2S data. The model learns from network training on past occurrences to create alarm levels that are closer to the real condition underneath the surface. One key benefit of such technology is that there is a large disparity between the alert levels that HSE-based systems commonly employ and the ones generated by the fuzzy ART classifier. This interval allows drilling crews time to prepare for potentially harmful levels of H2S, which may also be rising. This approach demonstrates a more intelligent, experience-based implementation for setting simulator alarm thresholds, to identify and assist the operator in rapidly and safely reacting to H2S inflow. This gives the system a robust and flexible approach to reduce the threat to drilling operators in areas where H2S is likely to be present. Therefore, the AI-driven approach represents a step up towards intelligent safe drilling operations. Since, AI enhanced the H2S monitoring which help in an early detection, autoamtic evaluation of the exposure time, and optimization the alarm system, through the integration of real-time risk interpretation, unsupervised machine learning, and adaptive clustering. This improved procedure transformed regular monitoring systems into proactive, self-learning safety devices, resulting in safer and more sustainable drilling processes under severe H2S.

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APPENDIX A: FUZZY ADAPTIVE RESONANCE THEORY NETWORK

Fuzzy adaptive resonance theory (ART) [13] is capable of processing input that is either analog or binary. Prior to training, the data must be preprocessed such that each input component is calibrated so as to fall within the range from zero to 1 and also complement coded. Initially, an uncommitted category (neuron) is initialized with its weight vector w equal to 1. Let x be an input pattern, then a choice function is computed as follows:

$$T_j = |x \wedge w_j| / (\alpha + |w_j|) \quad \text{(A-1)}$$

where $\wedge$ represents a component-wise fuzzy AND minimum operator:

$$(x \wedge w)_i = \min(x_i, w_i) \quad \text{(A-2)}$$

where $\alpha > 0$ represents the choice parameter. A winning category J is activated in layer F2 by maximizing the choice function:

$$J = \arg \max_j [T_j] . \quad \text{(A-3)}$$

Next, a vigilance test is performed with category J:

$$\rho \leq |x \wedge w_J| / |x| \quad \text{(A-4)}$$

where the vigilance parameter is represented by $\rho \in [0,1]$. If such inequality holds, then resonance is triggered and learning occurs as in the following equation, A-5:

$$w_J(new) = \beta(x \wedge w_J(old)) + (1-\beta) w_J(old) \quad \text{(A-5)}$$

where $\beta \in [0,1]$ is the learning parameter. If the selected neuron J is not a part of the match criterion, it is discontinued, and the model will search for a new category. If there is not a category that will satisfy this vigilance check, the program will create a new one to correspond to the input pattern x..