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Modelling Case-Based Reasoning in Situation-Aware Disaster Management

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1. INTRODUCTION

Disaster management (DM) is the process of preventing, preparing for, responding to and recovering from the effect of disasters (Figure) (Haddow and Bullock, 2013). Situation-aware disaster management (SADIM) is a continuous decision-making and action taking process in disaster management using prior knowledge of situations in the environment. Disaster here is defined as a sudden occurrence or natural disruption resulting to enormous damages (Mendonca, 2007).

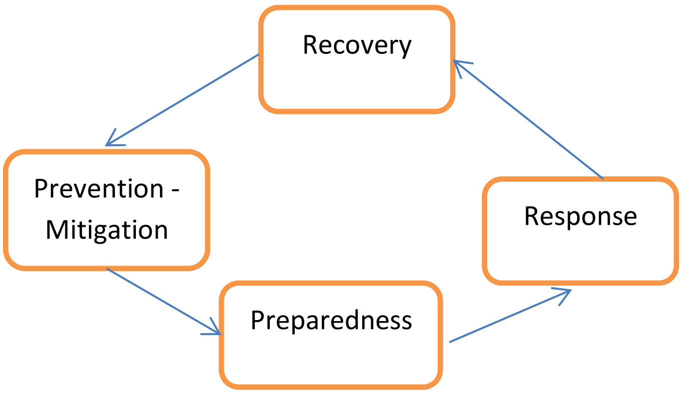

Figure 1: Disaster Management Framework

A prerequisite to informed decisions and appropriate actions in DM is the acquisition of situation awareness (SA). Endsley (1995) defines SA as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future".

One of the challenges in effective DM operations is accurate assessment of existing situations, collection of accurate and relevant pre- and post-disaster data, and analyse it. Assessment of current situations have an impact on the accuracy of decision-making and action taking processes of the phases of disaster management (Moreira et al., 2015).

Several decision strategies have been adopted in modelling situation-aware disaster management (SADIM) applications. Case-based reasoning (CBR) is one of such decision-making strategies. CBR is the process of using solutions of previous problems to solve a similar new problems. Current approaches in modelling CBR in situation-aware disaster management include using domain rules, statistical reasoning, and other methods for situation assessment and then using experiences of previous disaster cases (CBR) for disaster management decision support. The use of domain rules, statistics, and logic involve having a set of training examples from where generalization are drawn from to identify a situation which may possibly be eager generalisation (Otim, 2006). Case-based reasoning generalizes based on targeted situations and it is delayed until testing time (Otim, 2006). Hence, CBR is lazy in its generalisation which is helpful for emergency and complex situations in which there are a myriad of ways to have a situation generalised (Aamodt, 2004). Secondly, the use of rules, statistics, logic and other methods in emergency and uncertain scenarios are plagued with a knowledge elicitation bottleneck due to the lack of an explicit domain model (Kofod-Petersen, 2007). Requirements elicitation in CBR is a task of gathering previous cases and their histories rather than using explicit domain models. The task of implementation in CBR is simply to identify significant features that describe a situation. The task is easy compared to creating an explicit model (Otim, 2006).

In our earlier work, we developed the use of CBR to provide situation awareness (Nwiabu et al., 2012). The approach successfully provided understanding of current situations and anticipating future situations using experiences of past situations.

Based on our success in using CBR to provide SA and the success of prior work using CBR for decision supports in DM, this paper is proposing the use of CBR for providing SA combined with decision-making and action taking across all the phases of DM. These phases, referred to as "the disaster life cycle" (Figure 1) are not linear but are rather circular, to show its ongoing character (Fagel, 2000).

The paper evaluates the method developed through an implementation aimed at disaster prevention in the petroleum drilling domain for early kick detection to prevent blowout disaster. A blowout is a major disaster in drilling operation caused by a kick (influx). Kicks are inflow of formation fluids into the wellbores. Late detection of formation fluids can lead to inflow of fluids in an uncontrollable manner, which is called a blowout (Havard and Masoud, 2015). Blowouts are very hazardous in well drilling operation with negative environmental and a high financial impacts, such as in the 2010 Transocean Deepwater Horizon example (Havard and Masoud, 2015).

This work adopted action research (AR), a collaborative approach between researchers and domain experts to progressively solve organizational problems. There was collaboration with oil and gas practitioners to understand the tasks in the drilling domain. Drilling experts' requirements were captured and refined for redesign. User centred design (UCD), cognitive task analysis (CTA), hierarchical task analysis (HTA) and action research (AR) are combined to address the stated objectives. An experiential knowledge base is developed using historical data provided by experts. The method produced a Case-based situation-aware disaster management framework using CBR for both situation assessment and DM decision support. A comparative analysis of the results of this work (full CBR system) and prior work (partial CBR system) is carried out.

The remaining parts of the paper is as follows. The next section provides an overview of the existing situation-aware disaster management applications. We then present our methodology and the proposed framework of case-based Situation-aware disaster management (CABSADIM). Furthermore, we show how the framework can be applied in the oil and gas drilling domain and provide a system design for blowout prevention in drilling. The system's results are then evaluated and discussed.

2. SITUATION-AWARE DISASTER MANAGEMENT APPLICATION

Situation awareness (SA) involves gathering, integrating, and interpreting cues in order to know what is happening in a domain.

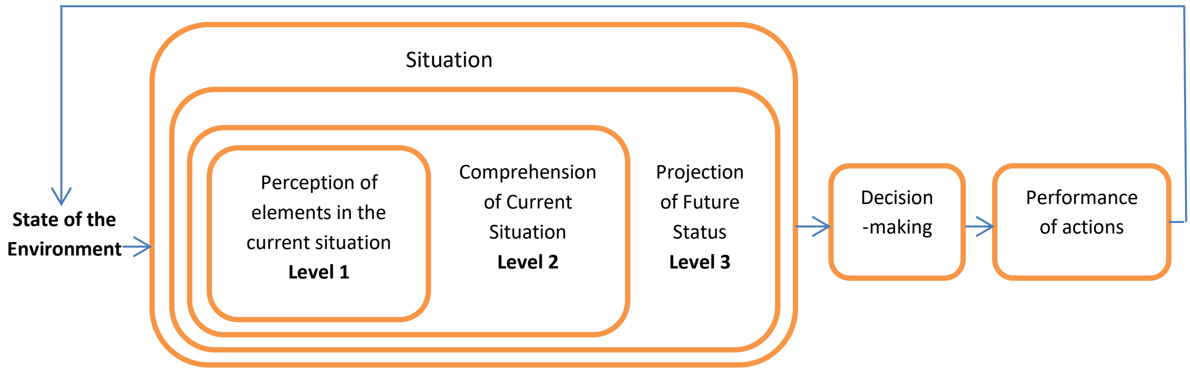

Figure 2: Endsley's SA Model (1995)

It provides prior knowledge of a current situation that supports useful decision making and action taking in all the phases of disaster management. The generally acceptable situation awareness model (Figure 2) (Endsley, 1995) presents situation awareness as mental representations consisting of three levels; perception (Level), comprehension (Level 2), and projection (Level 3) that assists operators in good decision-making and action performance.

Military aircraft crews during World War I were the first to recognised SA in solving problems (Press, 2000). In the mid-1970s, factors affecting aircrew were investigated by the US military ergonomists and situation awareness became an established concept from then onwards (Smith & Hancock, 1995). Human factors researchers later adopted the concept for studies of complex dynamic environments (Endsley, 1995). Situation-aware (SA) applications try to detect situations and react to them, being particularly useful to a domain task. Weichselgartner (2005) proposed holistic floodplain programs for flood prevention by integrating both vulnerability reduction and resilience intensification. The method obtained optimum results by integrating building codes, zoning ordinances, flood plain regulations etc, with corrective methods such as flood forecasting, channel improvement, coupled with monitoring and evaluation of risk reduction measures. Kung et al. (2008) designed an intelligent and situation-aware pervasive system (ISPS) to provide early warning signals to citizens on an impending debris-flow disasters. An architecture consisting of intelligent situation-aware agents (ISA), mobile appliances, and a case-based disaster management server that relied on wireless and mobile communications was proposed. Location-aware routing prediction method (LRPM) was used to decrease the latency of pictures and transmission traffic.

The literature suggests that response activities should be guided by relevant emergency response tools. Sapateiro and Antunes (2009) proposed a tool that adopted a conceptual model based on research work done with high reliability organizations and founded on SA models. The model presented a DM process as a set of dimensions that is correlated by responders working collaboratively in carrying out mitigating tasks. The model was evaluated by conducting experiments with two IT service desk (ITSD) teams operating in two different organizations in which systems failures may compromise business continuity. Similarly, Son and Pena-Mora (2007) proposed a method of using higher level of SA to improve first responders' decision-making and action-taking as a result of dynamic, chaotic, and distributed situations. The work produced a theoretical framework which supports high SA and collaboration among first responders, exploiting information technology facilities to gather, analyse, and share data disaster situation. The paper highlighted the relevance of SA in making disaster response systems efficient both physically and cognitively. It also discuss the usefulness of disaster response systems to responders in operational and strategic decision making. They recommended that systems developed to assist individuals or groups in disaster response should take into consideration complex social, behavioural, and technical interaction at individual and team levels for good SA acquisition and effective disaster management support.

Recently, Gibson et al. (2017) presented a framework on how SA can be used for earthquake disaster management at the preparedness, response and recovery phases. It proposed the use of technologies such as social media, dedicated mobile applications, and smart sensors (both wearable and environment). Integrating this data together with official data sources provided an effective earthquake disaster management at the preparedness, response and recovery phases.

For team operation in emergency management, Stiso (2013) presented a decision support system for emergency management that made data meaningful via a flexible common operational picture (COP) to multiple users rather than focusing on a particular user. With the solution individual users to direct the COP to their individual situation awareness needs together with maintaining access to the overall picture, by adopting interactive information overlays. A common operational picture requires shared SA. Harrald and Jefferson (2007) had earlier developed a shared situation awareness model for disaster response and recovery operation after observing that "data interoperability" which is assumed leads to COP and SA does not consider data semantic meanings. Data interoperability does not also take into account the dynamic nature of information during an extreme event. It observed that the method that overlooked the heterogeneous nature of DM will rather produce information overload than SA. It was also observed that information requirements for different operators in response and prevention of disaster are not the same. Furthermore, it was recognized that information that is required by one or more teams can be oversighted in course of consolidating information to have shared situation awareness.

Their proposal considered a computational structure for disaster management decision-making that is adaptive and creative in a distributed network. Their method supports collaboration and coordination of shared SA (SSA) by enhancing the ability to verify, analyse, transfer, and display information. Parva et al. (2012) used elementary loop of functioning (ELF) (multi-resolutional levels and an intelligent systems model) to discussed an architecture for network centric disaster management (NCDM). The architecture enables decision makers to achieve situation awareness related to their individual goals and shared situation awareness regarding their team goal based on specific goals and objectives.

Silva (2010) presented a approach for the building of SA systems using wireless sensor networks (WSN). The proposed method was used in building a system to assist in rescue operations in collapsed structures after disasters. The work provided six foundations, or design goals; Sensing Technology for SA system, radio frequency spectrum for SAs, advanced ad-hoc communication, wireless sensor networks with dual mode of operation, ultra-low power wake-up radio (WOR), and through-the-debris communication. The devices were used as a pre-disaster management tools to provide insight on how to effectively handle disaster preparedness plans. Finally, the design challenges of each of the foundations were evaluated.

Although there are SA systems for disaster management as presented above, there is still need for an established structural framework, that conforms to conventional design approaches. Lately, Moreira et al. (2015) proposed an ontology for disaster management which discusses how notions used for situation modelling can be harmonised in a known ontology, and how situation theory (Barwise, 1988) and situation awareness theory (Endsley, 1995) can leverage this process. Furthermore, they discussed how the resulting ontology can facilitate the development of SA applications by offering some modelling languages and their guidelines within the framework. This framework is centred on the situation concept aimed at supporting SA applications at both design time and run-time. The framework used an ontological language (OntoUML), based on the

Unified Foundational Ontology (UFO) for context modelling. Situation types, as specific patterns in the context, are modelled using the Situation Modelling Language (SML). The Business Process Management Notation (BPMN) is used to specify the reactions to changes to the situation state (activated and deactivated). However, the work ignored requirements analysis improvement and considered only conventional approaches such as interview with stakeholders. Moreira et al. (2015) also developed a distributed rule-based situation-aware disaster management application using the ontology. The design of the system addresses the absence of semantics in disaster situation modelling. It also addresses the effect of uncertainties on collaboration and information processing in disaster scenarios. The model-driven distributed rule-based platform enhanced productivity and interoperability in the development of SA systems for DM.

3. METHODOLOGY

An action research (AR) method is adopted in this work. AR was chosen because it influences the outcomes of the study it is use for. Through an action research process we were able to gain domain knowledge from participating domain practitionals on blowout prevention by early kick detection. From the drilling field, previous cases on kick detection were extracted and analysed. A case-based model was developed using these past experiences.

3.1 Action Research (AR)

AR is a method that supports collaborations involving researchers and practitioners to progressively solve organizational problems (Baskerville and Myers, 2004). The aim of using action research is to change the world through intervention (Baskerville and Myers, 2004). This research supports the improvement of practice as well development of knowledge (Baskerville and Wood-Harper, 2004). Knowledge is developed through the engagement in an open complex situation. Changing the approaches currently used enhances practice. AR researchers bring existing knowledge to the situation by successions of defined changes by reflecting on theory and action in a cyclic pattern (Avison et al., 2000). The outcome of a research is a theoretical premise that is refined and a success story of applying the theory in practice.

Baskerville and Myers (2004) define a set of practical principles that serves as foundations on which the action research approach is built. First, in an AR project, the action has to be established before the project commences. The aim of this research work is to model a system that will use data from wireless sensors to collect downhole and surface data to understand kick occurrence and provide early warning. The alertness in determining early possible kick indicators, such as change in the flow rate, change in the active pit volume, change in the pump pressure, and a cut in the drilling fluid are of the utmost importance to prevent a blowout incident. To keep the well under control for effective prevention of blowout, these signs must be carefully observed and react the to possitvely.

Secondly, there must be practical action in the organization. The action in the project work is to develop a decision support product that will assist operators in the oil and gas industry in preventing blowout during drilling operations. To achieve this goal, first, we must understand drilling tasks. It was therefore imperivtive for us to collaborate with domain experts for us to understand the tasks in the domain, elicit the experts’ requirements, and specify the requirements for the design process.

Thirdly, the action should underpin theory development. Through our project we developed and evolved the case-based situation-aware disaster management framework through the action research approach. In developing a system, the team of experts provided us with data on detected kick occurrences in their organizations through indicators. Each kick occurrence situation has task descriptions (solutions) that were carried out to prevent it from degenerating into a blowout. All the approaches are action-based learning methods that works iteratively (Nwiabu et al., 2011). Combining these methods in this work enables us carry out user-related activities, build on theoretical prior knowledge and solutions based on agreed priorities and constant evaluation.

Finally, the real context of the problem (i.e. blowout situation) provides the crucible for the reasoning and action in the design processes. One author acted as participant observer for over a year. The work was carried out in collaboration with a team of twelve experts from three multinational oil companies in Nigeria consisting of three drilling engineers, three mud loggers, three members of the Blowout Task Force (BTF), and three members of the Blowout Management Team (BMT). The domain experts provided knowledge and insights on the trend in the industry. They also participated in the design, development and evaluation of the system, and reflected on the outcomes that shaped the lessons from the study.

3.2 General Domain Knowledge

A domain knowledge that will provide effective reasoning to the system must have logical relations between the parameters involved in kick detection, and information about how far the parameters are deviating from normal. We used structural and casual relations to interconnect relationships between parameters in the knowledge module. We went further, using cognitive task analysis (CTA) method in identifying goal structures and cognitive processes that underpin the way experts perform kick detection tasks. The approach also involved carrying out a Task Analysis (TA) which requires gathering of task data and documenting it to understand each individual operator's responsibilities to complete a specific task. Finally, a task description based on different indications was produced.

To understand the details of task actions, associated decisions and goals, we used hierarchical task analysis (HTA), a popular form of task analysis. The method provided an approach of breaking down kick detection actions into smaller sub-tasks.

3.3 Case Base Modelling

Case based reasoning (CBR), an approach that will store data describing kick occurrence and implement processes of reusing this information to solve similar new problems, was adopted. CBR, an analogical reasoning method (Aamodt, 1994), have the following steps:

(a) Collect data;

(b) Identify current problems;

(c) Take decision on acquired data if they are enough to define a current occurrence. If they are not enough,

(d) Carry out further studies;

(e) Search the library for similar previous problems;

(f) Present some likely kick formation hypothesis and their solutions in descending order with regards to the new problem;

(g) Interact with the operator to select the most similar problem. Present tasks to be performed;

(h) When the case has been solved, data from the current situation is used to updated the library. The new case to be retain will contain information on success or failure on kick detection. The information will determine the strategy to be used in the future, i.e. to help solve a new problem or avoid repetition of past mistakes (Aamodt, 2004).

Using the notion of CBR, one hundred cases were collected from three oil and gas firms. We developed a case base using the 100 cases. A particular kick occurrence with the indicators suggesting its occurrence constitutes the “problem attributes”. On the other hand, tasks carried out to prevent kick from degenerating into a blowout constitute the “solution attributes”.

To evaluate the system, the drilling operation control room of one of the firms was used. Experts collected real time data on situations in the wellbore from downhole wireless sensors. Features of the situations collected from sensors are fed into our system to retrieve similar past situations on kick occurrence. Solutions to similar past situations are examined by experts to see how they can be applied in new situations. An adapted and workable solution to the new situation is retained. The fully CBR system (CBR for SA and DM) was used together with a partial CBR system (CBR for DM only) for two drilling operations. A comparative analysis was carried out between solutions from the two systems.

4. CASE-BASED SITUATION-AWARE DISASTER MANAGEMENT FRAMEWORK

The case-based situation-aware disaster management (CABSADIM) framework (figure 3) was developed through the adaptation of our prior work. The formation of the framework was derived from the iterative action-based engagement on the industry problems. It was built on three principles to solve disaster management: situation awareness (SA); case base reasoning (CBR); and decision-making. The work is aimed at presenting the usefulness of case base reasoning in assessing an ongoing situation as well as carrying out decision-making in disaster management. We shall discuss two separate components; SA cognitive process, and DM decision-making process, using experiences (CBR) in both of them.

4.1 <u>Situation awareness cognitive process:</u>

The situation awareness component of the framework receives inputs from context and state of the environment. Contexts are the things that uniquely identify the situations. The evolving situation and the condition of the environment at a particular moment in time constitutes the state of the environment. There are three main steps to be taken to achieve SA.

Perception of Elements in the Current Situation: Perception is the first step towards acquiring situation awareness. It involves gathering of data, assessing the attributes of relevant data in the environment to derive their status. The choice of what to perceive and understand is dependent on each unique domain and context (Endsley, 1995).

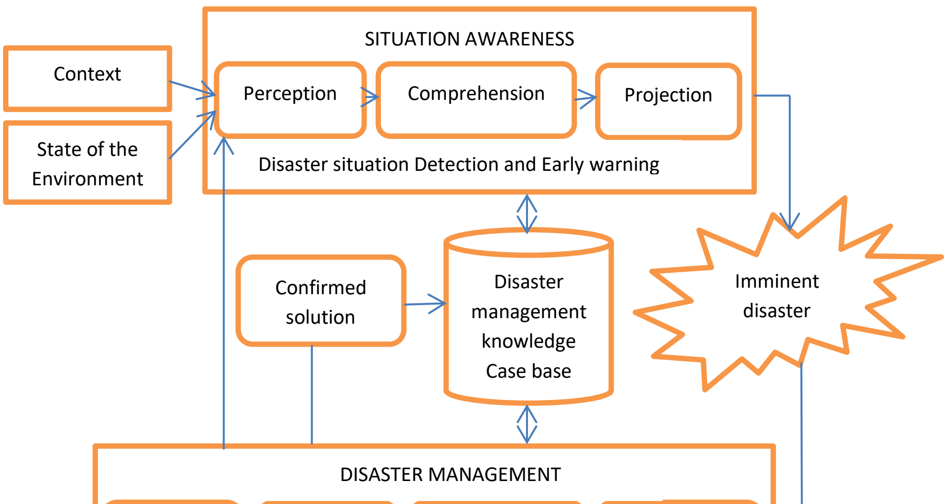

Figure 3: Case-based Situation-Aware Disaster Management Framework

Experience, in individual's working and long-term memories, shapes what to focus on and how. Knowledge contained in the long term memory assists in mental representation of the crews. The elements are structured into relevant events which are classified into groups using individual's long-term memories (Kofod-Peterson, 2007). Therefore, perception also involves having the ability to classify information into understood representations.

In the drilling operation, kick occurrences are monitored using kick detectors. The primary kick detectors are flow-out sensors, installed to detect an increasing flow rate, and pit volume totalizer-sensors (PVTs) installed to continuously measure the present fluid level in the mud tanks (Fraser et al., 2014). Furthermore, trip tanks serve as accurate volume detectors through stopping circulation following tripping.

Comprehension of Current Situation: Comprehension is the second stage of situation awareness. At Level 2, the perceived attributes of Level 1 are integrated. Also, at Level 2, the disjointed elements of Level 1 are synthesised. At comprehension,the picture of the elements are organized and the significance of objects and events are understood. Level 2 SA has as its foundation, experimental-based mental models stored in long-term memory where new information and existing knowledge are combined to form a wholistic picture of the situation.

In oil and gas drilling, a collaboration of the operator's previous knowledge of the situation, mental picture of sub tasks, experience and expectations provides the understanding that kick could be occurring. For example, an engineer will use their experience to understand that an increase in drilling rate is an indication that a porous or fractured formation may have been entered, and thus there is a risk of underbalanced pressure (Tost et al., 2016).

Projection of Future Status (Level 3): Projection is the last level (level 3) of SA. The projection level enables the anticipation of the future state of the domain. To achieve projection, the status and dynamics of the elements of level 1 must be known together with understanding of the situation (Level 2). The mental model of operators built from experience makes it possible for them to use the understanding of level 2 to anticipate possible future state of the environment. Knowledge from level 3 (projection) forms the bases for decision on the most favorable actions to achieve goals. The anticipatory reasoning of level 3 SA provides an early warning to the decision maker to be alert of imminent disaster.

Projecting that a kick is on the way during drilling may result in an increase in attention for any change in penetration rate. Through experience, engineers are able to project how the situation may develop with reference to past case experiences.

4.2 <u>Disaster Management Decision-making process</u>

Making good decisions and performing the right task such as shut-in, together with reasoning on what could be the cause of kick occurrence requires knowledge of the future state of the environment. Every disaster management phase; prevention, preparedness, response, and recovery requires specific decision-making and actions. Making use of experience in previous cases helps in decision-making and action-taking in a similar new disaster situation.

Prevention/Mitigation: Prevention/mitigation efforts are measures that attempt to prevent or reduce the impact of disaster when they occur. The efforts requires that the risk associated with the anticipated hazard are analyzed and then develop strategies to minimise the likelihood that hazards will translate to disasters. With good SA and sound experience on how previous disasters were handled, man-made disasters can be prevented and natural disasters mitigated. The case base model in the proposed framework contains previous disaster cases and how they were prevented. With early warning alert from situation awareness, operators search for similar disasters to see how they were prevented.

For example, an operator can search for blowout preventive measures using an observed kick occurrence indicator. Prevention approaches could be to increase the hydrostatic pressure by circulating in a heavier kill fluid or to activate the blowout preventers and closing in the well by isolating the wellbore from the surface (Ayesha et al., 2015).

Preparedness: When disaster cannot be prevented or mitigated, operators have no option but to move on to the preparedness phase. Preparedness involves carrying out planning, training, and educational activities in readiness for disaster based on SA warning. Situation awareness assists decision makers with the level of preparedness in advance in accordance with projected time, scope of disaster, exposure, and vulnerability. Case based reasoning provides an operator with a means to adapt past successful preparedness plans to equip operators for a new response and recovery operation.

In drilling operations, preparedness is carried out by developing plans aimed at regaining control of blowouts. The plans are called blowout contingency plans (BCP) (Abimbola et al., 2015). Poor initial decisions under stressful conditions are traceable to many blowout problems. Planning using previous experiences reduces the pressure of competitions and personal attachments. Planning provides the operators time to review competing proposals.

For example, the highest blowout control operation called Kuwait 1991 was pre-planned using previous experiences. Kuwait Oil Company (KOC) in October 1990, knew that Iraq has planned to blowup oil wells. In the Houston offices of O'Brien-Goins-Simpson, Blowout contingency plans were made. Plans on equipment and materials, required services using several scenarios were made. Budgets for blowout control were prepared. Contracts were awarded and signed with relevant intervention agencies before Iraq carried out the act in late February 1991. A good preparedness plan was formed with the use of experienced operators capping all 698 blowouts in 250 days from the 4th of March to the 8th of November 1991 (Sneddon et al., 2006).

Response: Response occurs in the immediate aftermath of a disaster. Response works are decisions and tasks performed during and immediately after a disaster. Ideally, response is the implementation of already established disaster preparedness plans. CBR provide operators with effective response decisions and actions.

In a blowout disaster, as soon as analysis on the mode of intervention has been carried out and choice of actions to the taken made, the Blowout Task Force uses their years of experience to reorganize and implement the experience-based preparedness plan using available resources. Past experiences assist the BTF in planning, operations, equipment procurement, kill procedures, safety, documentation and administration, modification and manufacturing.

Recovery: Disaster recovery, the last phase of DM involves restoring, rebuilding lives and infrastructure impacted by a disaster. Using experience of successful past recovery approaches saves time and money in recovery operations. Secondly, in a continuous and recursive DM process, the result of the recovery phase is fed into the mitigation phase for another round of assessment. The process is continuous until normality is restored. But in a continuous situation-aware disaster management process, the result of the recovery phase is fed into the perception phase of situation awareness where the result is integrated to the current situation of the environment for another round of assessment.

Blowout recovery is handled by the Blowout Management Team (BMT) which is comprised of experienced representatives from across the organization with the expertise and authority to deal with the after-effects of a blowout. The BMT decides upon the immediate course of action using their experience. They carry out or recommend how organization can cleanup oil spillages after a blowout.

5. BLOWOUT DISASTER PREVENTION USING THE FRAMWORK

Using the framework for blowout prevention, design involved the incorporation of the case-based model to the SA cognitive process and to the Prevention phase of disaster management (figure 4). This is our proposed general framework for disaster prevention. Here it is applied to early kick detection in order to prevent blowout.

5.1 <u>Wellbore (Kick) Perception</u>

At this stage, drillers continuously monitor and gather data from the wellbore and using their experience to recognize patterns. Drillers must be able to pay close attention to every single detail from kick detectors.

This work uses data from the following detectors from two Niger Delta oil and gas wells:

a. Flow-out sensors, installed to detect an increasing flow rate;
b. Pit volume totalizer-sensors (PVTs), installed to continuously measure the present fluid level in the mud tanks;
c. Trip tanks as accurate volume detectors during tripping;
d. Topside gauges measuring increase in drilling rate, changes in the weight-on-bit, and deviations in standpipe pressure;
e. MWD tools registering wellbore and formation pore pressures.

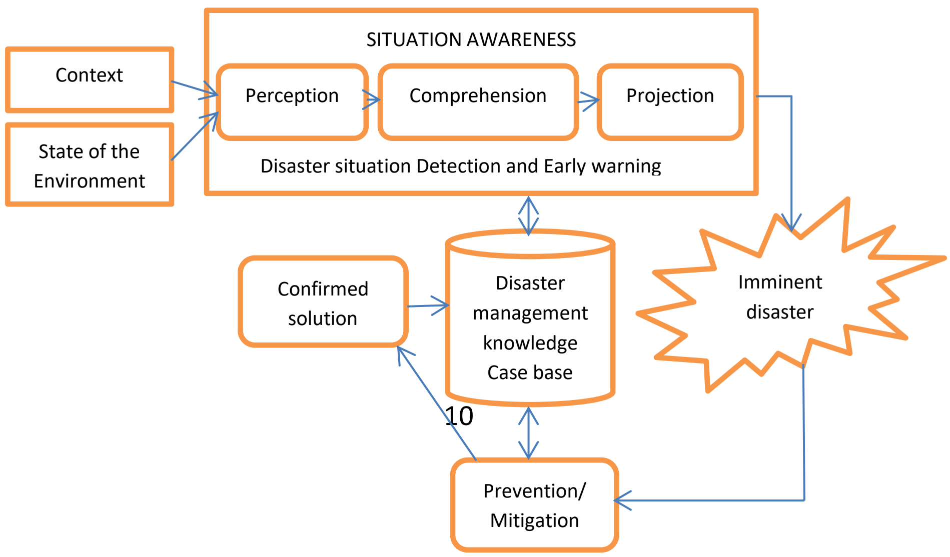

Figure 4: Case-based Situation-aware Disaster Prevention

5.2 <u>Wellbore Comprehension (Kick Detection)</u>

The perceived detectors data are analyzed using experiential knowledge to see if there will be any kick indictor such as; change in flowrate, change in active pit volume, drilling break, change in pump pressure, drilling fluid cut.

Since the nature and location of wells determine kick tolerance level, there was a need to integrate detectors data with contextual data of the wells. Kick tolerance evaluates the intensity at which shut-in can be carried out at weak zones along the wellbore without exceeding the threshold value of fracture pressure (Mosti et al., 2017).

To analyse kick tolerance, the following factors are considered..

a. Wellbore mud weight during influx.
b. Pore pressure at a specific depth potential source of influx;
c. Vertical depth and inclination of casing shoe;
d. Fracture resistance at weak point;
e. Diameter of wellbore in the open hole;
f. Vertical depth and inclination of wellbore;

Table I Example of input dat for kick tolerance evaluation are shown below:

Table I: Contexual data for kick tolerance for two Niger Delta wells

Variable	Well 1	Well 2
Drill collar length, ft.	950	800
Casing depth in ft.	3000	7000
Casing size	16’ ’	9-5/8’ ’
Fracture grad. At csg shoe, ppg	15	17
Mud weight, ppg	12	13
Bit size	14-1/2’’	8-1/2’’
Drill pipe size	5.5’’	5’’
Drill collar size	8’’ x 3’’	6.5’’ x 3’’
Well depth in ft.	5000-12000	6000-11000

To compute kick tolerance, we assumed that there is no compressibility, and that temperature and pressure are constant. Steps for calculating kick tolerance are as follows.

Step 1, (H_{max}), We used mud weight, kick fluid density, fracture gradient, predicted pore pressure minus safety margin pressure (e.g. 70 bar in Niger Delta) to calculate the vertical height of a gas influx. P_f represents the pore pressure. $p_{shoe,max}$ represents the fracture gradient at shoe, p_{mud} stands for the mud weight. $G_{i,shoe}$ represents the intensity of the influx when it is at the shoe, h_{TD} represents the total depth, h_{csg_shoe} stands for the depth of the casing shoe.

$$P_{shoe,\max} = P_{LOT} - p_{safety} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Using Driller's method to evaluate pressure at the casing shoe is expressed as

$$P_{shoe,\max} = P_f - P_{FG} - g(h_{TD} - h_{csg\_shoe} - H_{\max})p_{mud} \ldots\ldots(2)$$

The maximum height of kick/ gas using calculated maximum pressure at casing shoe is expressed as

$$H_{max} = \frac{P_{shoe,max} - Pmud\left(h_{TD} - h_{csg\_shoe}\right)g}{g \; x \; P_{mud} - G_{i,shoe}} \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Second step, we multiply H_{max} , the maximum height of kick/gas with $Ca_{a,dp}$, the annular capacity factor around the drill pipe to have (V_{shoe}), the influx volume at the casing shoe

$$V_{shoe} = H_{max} x Ca_{a,dp} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Step 3: Furthermore, Boyle's law is used to convert influx volume at the casing shoe V_{shoe} to downhole volume V_1. Similarly, P_{shoe} and $.P_p$ represents casing shoe pressure and predicated pore pressure respectively.

$$rV_{shoe} = V_{shoe} x \frac{P_{shoe}}{P_p} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Another volume V_2 was evaluated using Bottom Hole Assembly (BHA) data. The steps for calculating V_2 is similar to that of V_1 . The only difference is the last step where pipe capacity $Ca_{a,dp}$, is used for V_1 and drill collar capacity $Ca_{a,dc}$ is used for V_2.

$$V_2 = H_{max} x Ca_{a,dc} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Comprehension involves recognising relative changes in the drilling parameters. A number of common indications were simulated from kick tolerance calculation that a kick has occurred, including changes in pump pressure, reduced drill-pipe weight or weight-on-bit, increased volume in the pit tank or increased flow rate, and immediate increase in drilling rate (Abimbola et al, 2015).

5.3 <u>Wellbore Projection</u>

Projection involves the use of mental simulations of how events may evolve so as to take preventive measures. From past experience, an increase in drilling rate indicator, together with some contextual data, was interpreted as an indication that a porous or fractured formation may have been entered, and thus there is a risk of underbalanced pressure (Tost et al., 2016). A rise in pit level in the mud or trip tank is likely to be a result of influx of formation fluid. This can also cause a decrease in pump pressure. As drilling mud is denser than formation fluid, an increased weight-on-bit was recalled in case of a kick, due to the reduction in the buoyancy force (Abimbola et al., 2015).

5.4 Blowout Prevention/Mitigation

From the CBR model, when an indicator is encountered, the application will use past cases to suggest kick occurring situation and tasks to be performed to stop it from degenerating into blowout (Figure 4). The blowout preventive tasks recommended by the system were examined by the drilling professionals. Where recommended tasks do not provide complete solution to kick occurring situation, the tasks are manually adapted by the experts (Aamodt, 1994). Successful blowout preventive and repaired tasks are stored for future use.

6 RESULTS AND DISCUSSION

Two systems; the proposed full CBR system and a partial CBR system were used by experts for evaluation as shown in Table III. Comparing recommendations (tasks) from the full CBR model and recommendations from the partial model shows that there was significant improvement in predictions for problem solving using the full CBR system (Table II). Three drilling engineers, three mud loggers, three members of the Blowout Task Force (BTF), and three members of the Blowout Management Team (BMT) working as experts in well control in three oil and gas companies in the Niger Delta of Nigeria participated in the experiment. The experts evaluated the solutions and decided if the recommended tasks could be reused. The engineers analyzed the recommended tasks from the two systems to identify most relevant solutions. Independent variables were “types of system” and “accuracy of system”. The two types of system were full CBR model and partial CBR model. The accuracy of system as an independent variable that represents how accurately tasks can solve problems. In determining the percentage accuracy of these recommendations, a ten-fold cross validation method is adopted to validate the approach. The accuracy of the full CBR model was 0.8 (80%) as against 0.7 (70%) of the partial CBR model (Table II).

TABLE II: Mean Accuracy

EVALUATIONS	1	2	3	4	5	6	7	8	9	10
Partial CBR	0.71	0.75	0.70	0.78	0.73	0.77	0.70	0.74	0.78	0.72
Full CBR	0.84	0.83	0.86	0.87	0.80	0.84	0.89	0.80	0.82	0.88

Apart from the number of accurate predictions, experts were also interested in the degree of similarity between the retrieved case identified by the two techniques and the case involved in the query (i.e. the new problem). To assess the two models to identify the one that retrieves past problems nearest to the new problems, experts selected a set of test cases from the library and reviewed for this purpose. The two models were then assessed against each test case. Normally, among retrieved cases there is a “best match”. Expert assessed the solutions of the best matches of the two systems comparing with known solutions to determine their capabilities based on this similarity assessment, the results are shown below (Table III).

TABLE III: Similarity Assessment

TEST CASE	Case 10	Case 73	Case 38	Case 50	Case 65	Case 94
Partial CBR	43	51	84	26	36	48
Full CBR	68	17	84	57	91	48

For example, using case 10 which is a problem of change in pump pressure as a test case, the best match for the partial CBR method is case 43 which has the solution as “decrease in circulating pressure or increase in pump strokes”. The best match to case 10 using the full CBR model method is case 68 with the solution as “Flow check, if static then interpret that influx is not occurring, check out for washed out equipments and take action on downhole equipments”. The solutions were not the same because the recognized indicators from the SA processes of the two systems were not the same. Analyzing the full CBR model’s indicators against the partial CBR model’s indicators, it was discovered that the use of CBR for SA in the full CBR model provided good SA that helped in the retrieval of relevant solutions.

Similarly, using case 73, a problem of drilling break as a test case, the best match for the partial CBR method is case 51 and the solution is “Flow check; If not flowing, continue drilling”. The best match for the full CBR method is case 17 and the solution is “Pick up off bottom with pumps still on, Drill further 3 – 5ft and remain vigilant”. On evaluating the actions recommended by the methods which also favored the full CBR model, it was observed that the full CBR method understood that the new situation may carry higher pressure and porous formation and it was needless to recommend “Flow check”.

Having case 50, a change in Active pit volume as a test case, the partial CBR method retrieved case 26 with solution the “Flow check; shut in” as its best match. The full CBR method retrieved case 57 with the solution “Look for source of gain or loss, interpret gain or loss to know cause of influx before shut in” as its best match. On evaluating the solutions, according to experts, the full CBR system’s solutions will be cost effective due to its specific nature. Experts attributed the relevance of solutions from the full CBR system to proper recognition of situations (indicators).

With case 38 as an unsolved case, both methods have their best match as case 84. Case 38 is a problem of change in flowrate, a case of some percentage increase in gas trend. The solution of the best match (case 84) is “Flow check, check change in active pit volume, attend to active pit volume trend, gather change in volume data in the last few minutes”. All the experts agreed that the unanimous recommendations of the two methods are acceptable steps to solving the problem. Unlike case 38, experts disagreed with both methods on their unanimous recommendations on case 94. Case 94, a problem of active pit volume was used as a test case. Both methods retrieved case 48 as best match. The solution of case 48 is “Check for mud transfer” but experts said the right action is “Shut in” since it was a flowing situation. According to experts, checking for mud transfer is an action that should be taken in a static situation.

7 CONCLUSION

The paper presents the design of a situational-aware decision support system that applies case-based reasoning techniques. Following an action research project a framework was devised and used to design the system. The implementation of the framework at the prevention phase of disaster management has shown the potential that CBR improves SA in the process of DM in general and disaster prevention in particular. Perceptive skills of attending to evolving situations are vital for the initial stage of disaster prevention.

Experience is a key factor in how individual's working and long-term memories direct what to perceive and how to perceive them. Interpreting perceived cues to comprehend that a disaster is on the way requires the collaboration of operators expectation, task specific mental picture, operator's prior understanding of the situation and experience. Anticipating evolving situations leading to disaster based on comprehension is necessary for good decision-making and effective action-taking.

Future work will implement the framework in disaster preparedness. The work will center on how case-based SA can assist operators with a good preparedness plan based on projected scope and time of disaster, exposure, and vulnerability. The work will provide a template for case-based situation-aware disaster preparedness from past experiences that will equip operators to be ready for response and recovery.

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