

Accident Forecast Modeling of Oil and Gas Industries: A Research Proposal

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Abstract— The oil and gas industry is a major sector among other sectors and causes dangerous accidents. Therefore, the improvement of safety and the prevention of accidents plays important role in oil and gas industry. For analysis of accident or the identification of potential hazardous sources, accident forecasting is more and more important because of occurrence of frequent accidents. The Number of researchers developed different models depending on the available historical data based on past accidents for accident prediction & prevention. The Purpose of this paper is to present a research proposal on accident forecast modeling of oil and gas industries.

Index Terms— Bow Tie model, Neural Network, Bayesian Network, SHIPP, FRAM.

I. INTRODUCTION

Oil and gas industry is openly acknowledged as one of the most dangerous work sector. Fire, explosion and toxic gas release from the oil and gas industry kills huge number of employees, publics and damage assets and impact the environment (Selvan, Siddqui and Bahukhandi, 2015; Selvan and Siddqui, 2017). Major accidents such as Bhopal Disaster, Flixborough Disaster, Piper Alpha Disaster, Phillips 66 Disaster, DSM Chemical Plant Explosion, Texas City Refinery, Indian Oil Terminal fire etc. were results in death of many people, damage and impact on environment (Eckerman, 2005; Petrie, 1989). Due to the nature of hazardous material like flammability, toxicity, and reactivity strengthen the presence of hazard in every portion of oil refinery. Therefore identification and elimination of hazards is essential from the work system and organization (Patel and Sohani, 2016).

The accident model is a theoretical framework which characterizes how and why an accident occurs and describes the relation between causes and consequences. (Rathnayakaa, Khana and Paule, 2011; Qureshi, 2007; shanini, Ahmad and Khan 2014). The effective use of accident model is to analyze the accidents, predict and prevent the occurrences of accidents in the future. Number of researchers has developed different accident models and various approaches, for accident modeling and analysis. Existing accident models has their own capabilities and limitations and they vary mainly in the areas of their application, purpose, and focus. The traditional accident models mainly focusing on human, organizational and management factors. They are mainly descriptive models,

but not predictive. Also, available models are not able to model multiple risk factors considered in process systems in which interaction and relationship of system elements are complex and non-linear. They are not able to make use of information on abnormal events or accident precursors such as incident, mishaps, near misses etc. (Rathnayakaa, Khana and Paule, 2011). Therefore, there is a need of new methodology to model process accidents. Quantitative risk and reliability analysis technologies are widely applied in chemical process and offshore oil and gas industries in order to develop a preventative and mitigative strategy (Abimbola et al.,2015). Some of these technologies not only include conventional methods, but also include relatively new technologies, such as Markov chain, Petri network and Bayesian network (Bhandari et al.,2015). The conventional risk analysis methods are known as static, it is unable to capture the variation of risk as the change occurs in the operation and environment (Abimbola, Khan and Khakzad, 2014). In addition, they are using generic failure data, which makes them to be non-case-specific and introduces uncertainty into the results (Khakzad et al., 2013).

II. LITERATURE REVIEW

Hazard identification is a fundamental step in safety management system (Selvan, Siddqui and Bahukhandi, 2015). At this stage, several hazard identification techniques can be used, such as checklists, Preliminary Hazard Analysis (PHA), Hazard identification (HAZID), Hazard and operability (HAZOP) study, Job Safety Analysis (JSA), What-if analysis, Failure modes and effect analysis (FMEA), Fault tree analysis, Event tree analysis etc.

(shanini, Ahmad and Khan, 2014). Special | Picture (with "Float over text" unchecked). Checklist analysis is the simplest technique, which involves questionnaires related to operation, organization, maintenance and other aspects, which need to be verified and checked against the process facilities. However, it has a limited analysis power, as it can only analyze one item per time and cannot be used effectively for complex systems and conditions. (Khan and Abbasi, 1998; Oyeleye and Kramer, 1988; Hyatt, 2003 and Ericson, 2005). "What if analysis" is the oldest hazard identification technique (CCPS, 1985) and is based on a set of "what if" questions to be answered. It is simple to use, but significant time and experience is required to develop questions, which are typically case-specific (Khan and Abbasi, 1998). HAZOP involves a team effort that gathers various forms of expertise to incorporate experiences and process information. As it is time-consuming, many studies have been carried out to include some level of automation in the procedure (Khan and Abbasi, 1998; McKelvey, 1988; Montague, 1990). HAZOP study is fully dependant on the knowledge, experience of the team participants. (Selvan, Siddiqui and Bahukhandi, 2015). There are number of accident models are available for accident prediction Sequential accident models explain accident causation as the result of a chain of discrete events that occur in a particular time order. One of the earliest sequential accident models is the Domino theory proposed by Heinrich in 1941 (Ferry, 1988). This model indicated that an accident can be prevented by either removing or reducing any single factor from the accident sequence. In this models cause-effect relationship between management, organization and human is not well-defined nor are they able to depict how these causal factors triggered the final outcomes or loss. Further, these models explain the accident causation as a one-dimensional sequence of events and do not take into account multiple causality of the accident process (Kjellen, 2000). In the 1980s, a new class of epidemiological accident models has been put forwarded to explain accident causation in complex systems. It said an accident is analogous to the spreading of a disease (Qureshi, 2007). Later on new models have been developed i.e. systemic accident models which describe an accident process as a complex and interconnected network of events. In systemic models, an accident occurs when several causal factors (such as human, technical and environmental) exist coincidentally in a specific time and space (Hollnagel, 2004). During the last decade formal methods are come into picture for building mathematically based models to conduct accident analysis. Formal methods can improve accident analysis by

emphasizing the importance of precision in definitions and descriptions and providing notations for describing and reasoning about certain aspects of accidents (Qureshi, 2007). In contrast, DSAMs have the advantage of simplicity due to their sequential structure and can represent non-linearity and interactions through the use of different model sequences within one framework. It uses real-time precursor data to estimate the likelihood of all possible end-states (McKelvey, 1988). Zheng and Liu, 2009 said that combined forecasting gives better result than individual. Some selected accidents models are described as follows.

A. Bow-tie model

Bow-tie analysis was proposed by University of Queensland in Australia in 1979. It has two parts left part shows fault tree analysis to identify causes of accidents and right part shows event tree analysis which identifies consequences of accidents (Shan, Liu and Sun, 2017; Khakzad, Khan and Amyotte, 2012). The Bow-tie method can be used in both qualitative analysis and quantitative calculation (Shan, Liu and Sun, 2017).

B. Bayesian Network (BN)

Bayesian network is a probabilistic technique based on graph theory and probability theory (Shan, Liu and Sun, 2017). In recent years, BN have been extensively used in studies involving dependability, safety, risk assessment and maintenance due to their ability to model probabilistic data by taking into consideration dependency analysis between events (Weber et al., 2012). This technique can also predict the probability of accidents and estimate posteriors of events depending on the BN configuration (Przytula and Thompson, 2000). Consequently, many studies have been carried out to convert FTA, ETA and reliability block diagrams (RBDs) into their equivalent BNs through the use of conditional probability tables (CPTs) (Toledano and Sucar, 1998; Bobbio, 2001; Bearfield and Marsh, 2005) to overcome the dependency associated with these conventional techniques. By establishing a probabilistic relational network, BN can describe and quantify the intricate cause-effect relationship among various complicated factors, like safety climate factors and human behavior factors. BN based model is developed to make predictions or identify the causes that have the greatest bearing on accidents (Kim and Seong, 2006; Martin, 2009; Zhang, Wang and Zhao, 2007). It has been proven to be an effective tool for accident probability estimation (Hanninen, Osiris and Kujala, 2014; Khakzad, Khan and Amyotte, 2013; Khakzad, Khan and Paltrinieri, 2014). It has also been

applied to analyze hazardous material transportation accidents (Zhao, Wang and Qian, 2012), occupational accidents (Garcia-Herrero et al., 2012) and safety culture in a nuclear power plant (Garcia-Herrero et al., 2013). Due to benefits such as suitability for complex system modeling, coping with uncertainty, versatility of BN, It is then possible to analyze the dynamic behavior of the modeled system.(Hanninen et al., 2014)

C. Artificial Neural Network (ANN)

ANN is an Information-processing paradigm. It is the highly interconnected neurons that enable this paradigm to deal with abstract or poorly defined problems (Naha, 2012). It has the following advantages: (a) there is no need to assume an underlying data distribution; (b) Applicable to multivariate non-linear problems; and (c) the transformations of the variables are automated in the computational process. However, ANN technique has several disadvantages including: (a) minimizing over-fitting requires a great deal of computational effort, and (b) the individual relations between the input variables and the output variables are not developed by engineering judgment so that the model tends to be a black box without analytical basis.(Sando et al., 2005)

D. System hazard identification, prediction and prevention (SHIPP) methodology

Within the SHIPP framework, all accident causations related to operational and technical, human, management and organizational aspects are included and formulated into seven prevention barriers. Among these, three barriers, i.e., release prevention (RPB), ignition prevention (IPB) and escalation prevention (EPB) are the same as in the off-shore model. Three barriers are new i.e., dispersion prevention (DPB), human factor prevention (HPB), and management and organizational prevention (M&OPB). The last barrier, i.e., damage control and emergency management prevention (DC&EMB), is a combination of the harm and loss barriers in the off-shore model with some modifications (Rathnayakaa, Khana and Paule, 2011).

The advantages of the SHIPP methodology are that it can be applied to assess the risk of the entire process system as well as subsystems and also identifies the system's hidden interactions and their consequences. Application of this methodology helps to determine the critical safety areas that should be prioritized to implement in order to prevent future accidents based on predictive accident occurrence and accident precursor data.(Rathnayakaa, Khana and Paule, 2011)

The SHIPP methodology comprises four phases: (1) system definition, (2) hazard identification and analysis, (3)

accident modeling and prediction, and (4) updating, decision making and implementation of accident prevention strategies. (Rathnayakaa, Khana and Paule, 2011)

E. Functional Resonance Accident Model (FRAM)

FRAM is a systemic accident analysis method that is developed from the fundamentals of resilience engineering, which is the study of why systems or objects work in the face of adversity, and also how to achieve robust and flexible designs that will work even when faced with unfavorable conditions.(Hollnagel, Woods and Leveson, 2006). It is based on four underlying principles:

- Failures and successes are equivalent to each other in such a way that they happen for the same reason. Alternatively, it can be said that things go wrong for the same reasons that they go right.

- Daily performance of socio-technical systems, including humans individually and collectively, is always adjusted to match the system conditions.

- Many of the outcomes of the system that we notice, and also the ones we don't notice, are emergent rather than resultant.

- Relations and dependencies must be described as they develop in a particular situation and not as cause-effect links. This is done through functional resonance (Hollnagel, 2012).

There are 4 steps to conducting a FRAM analysis. The first step is to identify and describe the functions necessary for work to succeed. The second step is to characterize the variability of the functions from step 1. The third step is to assess how the variability of each function affects the variability of the system as a whole. The fourth step is to identify ways to manage the possible uncontrolled performance variability (Hollnagel, 2012).

The function should be described in terms of the 6 parameters like inputs, preconditions, time, resources, controls and outputs. Inputs are items that are processed, transformed or needed to start the function. The output is the result of the function, which can be an entity or change of state. Preconditions are conditions that must exist before the function can be executed. Resources are consumed during the function to produce the output. Time is the temporal constraints on the function, with respect to the starting time, finishing time or duration. The control identifies ways that the function is monitored or controlled (Smith, 2017).

III. RESEARCH GAPS IDENTIFIED

Accidents in oil and gas industry gives catastrophic result to the industry and affect the country's economy. The

traditional accident models were developed are not suitable for prediction of the accident due to some limitations as stated above. Hence it is necessary to develop a model that predict and prevent accidents by considering all factors which are responsible to cause accident.

IV. PROBLEM STATEMENT

Problem Statement of the underlying research is to develop a model that predict and prevent the accidents in oil and gas industries, by identifying hazards & analyzing previous accident data. Such proposed model should be capable and effective enough in reducing risk & accidents and providing a safe and secure environment to organization's personnel.

V. OBJECTIVES

1. To study the various techniques used by oil and gas industry to identify the hazards
2. Identify different types of hazards, their causes and consequences
3. To analyze the previous accidents data
4. To study various accident prediction models
5. To develop an accident prediction model for oil and gas industry
6. Validate model by considering real data

VI. RESEARCH METHODOLOGY FLOWCHART

The full length research methodology flowchart has been developed and is available for reference.

VII. CENTRAL RESEARCH THEME

A. Central Research Questions:

1. What are the factors that have contributed to the occurrence of accidents in oil & gas industry?
2. What is the need of accident forecasting?
3. What are the different hazards Identification Techniques?
4. What are the advantages and disadvantages of different accident forecasting models?
5. How to carry out analysis of previous accident data?
6. What are the different tools available for accident forecast modeling?
7. Are the conventional tools are sufficient for hazards Identification and prevention?
8. How to select appropriate model for specific accident?
9. Which accident forecasting model is suitable for oil and

gas industry?

10. How accidents occur in oil & gas industry affects environment?
11. What is the contribution of different safety barriers in accident prevention?
12. What is the role of human error in accidents within oil and Gas industry?
13. How maintenance has influenced some of the major accidents in the oil and gas industry?
14. What are the responsibilities of management or industry to prevent harmful accidents?.
15. Can we use near-miss data for accident prevention?

B. Hypothesis Statements:

1. Proportion of accidents in oil and gas companies is quite higher than those of other sectors.

| Sr. No. | Tool Used | References | Purpose of using tool | Application | Future Scope |
|---------|--|---|---|---------------------------------|--|
| 1 | Bow Tie Model, Fuzzy Bayesian Network | Xian Shan, Kang Liu, and Pei-Liang Sun, 2017 | To identify the potential risk factors for leakage of natural gas pipelines and its consequences. Then it is converted into Bayesian network. To carry out forward prediction and backward diagnosis | Natural Gas Pipelines | Include historical & statistical data. Carry out sensitivity analysis |
| 2 | Bow Tie method, Bayesian Network | Aubong Li, Guoming Chen, Hongwei Zhu, 2016 | Bow Tie model is used to find causal relationship between pipeline leakage and potential accident scenarios. BN is used to overcome the difficulties of bow-tie in modeling uncertainties and conditional dependency | submarine oil and gas pipelines | -- |
| 3 | Bayesian Network | Ming Yang, Faizal Khan, Paul Ameyum, 2015 | It is used for probability estimation and loss functions are applied for consequence assessment | Bhopal disaster | Consideration of human factors & multi-variate loss functions to estimate losses |
| 4 | Bayesian Network, ETA | Valeria Villa, Valerio Cozzani, 2016 | Safety barriers performance has been assessed by means of specific gates, depending on barriers states and classification | Chemical & Process Industry | -- |
| 5 | Monte Carlo simulation, fuzzy logic, Bayesian analysis | Om Prakash Yadav, Niguse Chondray and Cassa Biles, 2008 | MCS used to capture the impact of manufacturing variability on system performance. Fuzzy logic maps the effect of environmental factors on system performance degradation. With Bayesian network initial system reliability is updated to take into account the effect of environmental factors. | Aerospace shuttle launch system | The results depend on the quality of the information derived from different sources, expert's judgment in fuzzy formulation, and assumptions |
| 6 | SHIPP, Bayesian Network | Sajid et al, 2015 | It is applied to estimate posterior probabilities, or update the safety barrier success/failure probabilities of end events | LNG process safety | Uncertainty analysis needs to be included and non-cyclic network must be considered. |
| 7 | SHIPP, HAZOP, FTA, ETA, Bayesian Network | Sandh Rameshwar, Faizal Khan, Paul Ameyum, 2012 | The prior probability distribution of the rate of abnormal event occurrence, is considered to follow a gamma distribution with distribution parameters α and β . This is updated using the Bayesian updating mechanism which is employed to combine sample information (likelihood information) with prior information to arrive at precise posterior (updated) information. To test and validate the SHIPP methodology by applying the technique to an LNG facility | LNG | -- |
| 8 | Fuzzy Inference System And Neural Network | Wenbo Wu, 2015 | Used for risk assessment | Oil and Gas Pipeline | consider more failure risk factors, Inverse ANN methodology can be implemented to have a better understanding of the inputs' weight |
| 9 | Neural Network | Dhruv et al, 2012 | To predict water saturation in an oilfield | petroleum industry' | -- |
| 10 | Artificial Neural Network | Duseem Abdelhadi, 2012 | Failure prediction for oil pipelines depending on the available historical data on pipelines accidents. | Oil and gas pipelines | The ANN models could be integrated with Fuzzy Theory (NeuroFuzzy). |

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| 7 | SHIPP, HAZOP, FTA, ETA, Bayesian Network | Saman Babooshah, Faisal Khan, Paul Ampofo, 2012 | The prior probability distribution of the rate of abnormal event occurrence, λ , is considered to follow a gamma distribution with distribution parameters α and β . This is updated using the Bayesian updating mechanism which is employed to combine sample information (likelihood information) with prior information to arrive at precise posterior (updated) information. To test and validate the SHIPP methodology by applying the technique to an LNG facility | LNG | -- |
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|----|--|--|---|---|---|
| 11 | ARIMA, neural network | Jepp, et al, 2014 | Prediction for the entire series of natural gas consumption using REF neural network. | Natural gas demand forecast | -- |
| 12 | Fault trees, Bayesian networks, FRAM | Doug Smith, Faisal Khan, Rocky Taylor, 2016 | In this paper, three approaches to safety are examined: fault trees (FT), Bayesian networks (BN), and the Functional Resonance Analysis Method (FRAM). | A case study of a propane feed control system is used | -- |
| 13 | High Reliability organization model | Abdullah Alotuman, 2016 | Introduces safety management | oil and gas industry | -- |
| 14 | Bayesian networks | Maria Hassan, 2014 | examined the benefits and challenges when Bayesian networks are applied for maritime accident prevention and safety modeling | Marine application | mutual information analysis and sensitivity analysis should be conducted |
| 15 | Time series analysis, ARIMA | H. R. Djalal, H. A. Chamsah, and A. D. Mohammed, 2013 | Time plot analysis was used in this research work to analyze the pattern of gas produce and utilized from 1970 to 2009. | Petroleum Corporation | -- |
| 16 | FMEA, Fuzzy Logic | Rezaeei et al, 2015 | The paper considers the practical application of the FMEA method to assess the operational reliability of the oil refineries' equipment, which is a pressing problem for the oil-producing regions and countries. | Oil and gas industry | In future we may use combined forecasting, i.e. FMEA, fuzzy logic, ANN |
| 17 | Swiss cheese model, QRA, and Ziggas bow-tie model | Liqiong Chen, Xia Li, Tao Cui, Basim Ma, Hong Lin and Ziggas Zhong, 2017 | To supplement quantitative risk assessment, this article proposes a safety barrier-based accident model for oil and gas stations based on the Swiss cheese model. | Syncretic oil pumping-gas compression station. | Combined quantitative analysis and qualitative analysis for safety management of a complex system |
| 18 | HAZOP, QRA, Event tree analysis | R. Iqbal, Syhan, Dr. Nejat Adnan Siddiqui, 2017 | The fire, explosion assessment and toxic gas dispersion are conducted in order to evaluate, how it effects on people, asset and environment | Natural Gas Gathering Station & Pipeline Network' | To find the overall QRA study including existing facilities and shall be compares with risk criteria. |
| 19 | ANN | Abbasy et al., 2014 | To evaluate and predict the condition of offshore oil and gas pipelines based on several factors besides corrosion | offshore oil and gas pipelines | -- |
| 20 | Bayesian network, Dempsters-Shafer evidence theory | Jiancong Wu, Rui Zhou, Shengqi Xu, Zhongwei Wu, 2017 | In this paper, the Bayesian network (BN) was employed to probabilistically analyse natural gas pipeline network accidents. | Natural gas pipeline network accidents | -- |

- Learning from near misses, future unsafe situations that could have more serious consequences can be prevented.
- Repair is the most common solution for gas leakage.
- One of the barriers in reporting accidents is the employee's unwillingness to report on their own or their colleagues' behavior.
- Deficiencies in maintenance have been significant contributors to the occurrence of major accidents.
- The numbers of accidents are more in developed countries than in developing countries.
- Implementation of model requires effective support and collaboration between trade unions, industry associations, employers and government agencies.
- Every proposed initiative needs support and commitment from top management of the firm.
- The consistent reporting system will aim at diagnosing and maintaining an accurate record and instances of accidents.
- Accident forecasting can assist experts in making decisions and necessary plans before occurrence of unpleasant outcomes.

VIII. RESOURCES NEEDED

Expertise Required

- Reliability Engineering expertise.
- Expertise from different Oil and Gas Industries
- Analytical tool expertise.

Tools Used

- Bayesian Network (BN)
- System Hazard Identification, Prediction and Prevention (SHIPP) Software's needed
 - For quantitative risk assessment: SAFETI Micro V
- 6.5.1, LEAK, NEPTUNE
- For Bayesian Network: NETICA, Graphical Network Interface (GeNIe) software
- SPSS (Statistical Package for the Social Sciences)

IX. TECHNICAL FEASIBILITY CHECK

Data required for the research will be made available through surveys/interviews, experts inputs, questionnaires, literature, past accident data from ERP and other sources, real time data from systems, data will be collected from industry and there systems.

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(IJERMCE)****Vol 3, Issue 4, April 2018****X. ECONOMICAL VIABILITY CHECK**

The research may receive the grants from TEQIP, Ph.D. Funding, University Funding, AICTE Funding, Funding from Indian Oil, Industrial Funding etc.

XI. FINANCIAL EXPENSES REQUIRED

The research requires Recurring expenses (Field work and travel, Conferences, Contingency including special needs, Internet etc.) of Rs. 1,50,000/- ,Nonrecurring expenses (Equipment, Software, Book and journal) Rs. 1,95,000/- and total expenses sum up as Rs. 3,45,000/-.

XII. SAMPLING TECHNIQUE

The sampling technique shall be used for this research is stratified sampling because, in this the population is divided into several sub-populations (stratum) that are individually more homogeneous than the total population and then we select items from each stratum to constitute a sample. Since each stratum is more homogeneous than the total population, we are able to get more precise estimates for each stratum and by estimating more accurately each of the component parts, we get a better estimate of the whole (Kothari, 1990).

XIII. SAMPLE DESIGN

Following are the steps in sample design

1. Type of universe: Accidents in Oil & gas Industry
2. Sampling unit: Near miss, mishaps, incidents, accidents, process hazards, Operational hazards, organizational hazard, onshore, offshore, pipelines etc.
3. Size of sample: This refers to the number of items to be selected from the universe to constitute a sample. In this research effect of sample size on result will be identified by varying it from 20, 50, 100 etc. (Kothari, 1990).

XIV. DATA COLLECTION PROCEDURE

Primary data: Collection of data through open-ended questionnaires to the workers and managers, Personal interviews with people who are likely to have experience or knowledge of the accident or incident were commenced, survey & observation of locations where incident/accident took place. Secondary data: Accidents Report, Accident/Incident Record, Accident notification and investigation reports, technical publications, literature, manuals, handbooks, books and journals, official

publications of the Central government, state governments, local bodies, etc.

XV. DATA ANALYSIS

The data are divided into two main subsets: operating data and the testing subset. The operating data are used to train the model and the testing subset to determine how well the model works. The operating data are further divided into training and validation, depending on the nature of the problem and the amount of the data available. There is no rigid rule in terms of selecting the amount of operating and testing data. However, generally the number of operating data is selected to be greater than the testing data. This is in order for the training to capture the overall heterogeneity and variability of the selected sample. However, if fewer data samples represent the overall variability in the data, then selecting more training data than the testing might not be visible (Bulushi et al., 2012).

XVI. EXPECTED RESULT

Identifying different hazards their causes and consequences plays important role in development of oil and gas industry. Current research will develop new framework to predict & prevent the accident, reduces the impact of accident on environment, loss of injuries to the workers, damage assets etc.

XVII. VALIDATION

Results may be validated by, Comparing two models with each other, Comparing model with real life data, by carrying Sensitivity Analysis, out of 100% data available use 80% data for training the model and remaining 20% data for testing (validation) purpose.

XVIII. PROJECT DELIVERABLES

1. Industry: The current research will provide the useful solution and guideline for the industries to develop the model which will predict and prevent the accidents which are going to happen in industry.
2. Academics: This research will provide the new dimension to the academic which will help in modeling their teaching aligned with the requirement of industry.
3. Market: This research will help industries to improve their processes, services and operations which will gain customer confidence and the faith in the company; this in turn will help to secure key

position in the market.

XIX. EXPECTED CONCLUSION

This research provides a model which will use to predict and prevent the accidents occurs in oil and gas industries. This research will used to reduce the number of undesirable accidents in industry that cause huge damages to the environment, facilities and even in some cases disabilities or abnormalities in people. This research introduces safety behavior among the workers.

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