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Mobile Application for Root Cause Analysis and Prevention of Unsafe Work Conditions in Oil and Gas Plants

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Abstract: Oil and Gas Plants are adopting various new policies continuously to ensure safety at work. Stop Work Authority (SWA) is one such newly adopted policy which grants any employee of a particular Oil and Gas plant the authority to stop any unsafe work in the location. Though many Oil &Gas corporations are adopting this policy, they are not able to fully enjoy the benefits the policy purports, due to the lack of a tracking and analytics mechanism for the SWA process. So this is what the current work proposes to do – implement a mobile application for tracking and recording SWA process, then analyse the data recorded to identify the factors that are responsible for such unsafe situations, these analysis results can then be used to prevent future occurrences of similar situations. Mobile application further makes it easy to communicate a situation to relevant stake holders, in real-time via device notifications, without any communication delays thus reducing the latency to respond to an unsafe situation.
Keywords: Unsafe work, Stop Work Authority (SWA), Frequent Patterns, Responsible factors, Root causes, Oil and Gas plants, Real-time communication, relevant stakeholders

I. INTRODUCTION

Risk management is an integral part of operations in many Oil and Gas corporations and several attempts are made to identify and reduce unsafe work conditions/risks in Oil and Gas plant operations [1], [2]. Several oil and gas companies are looking into Information Communication Technology (ICT) solutions to deal with risks. These companies have already started accumulating their data into databases. For these ICT solutions to succeed it is important that the following risk management requirements are met: (i) Timely access to all relevant information is critical to act up on a situation following catastrophic events. (ii) Quick response time, which is achieved by ensuring immediate distribution of all relevant materials to all interested stakeholders in real-time. Oil and gas companies are considering to adopt several new policies which purport the risk management requirements aforementioned. Stop Work Authority (SWA) [3] is one such policy, that Oil and Gas plants are newly adopting, which mainly focuses and encourages employees on avoiding unsafe work practices in Oil and Gas plants. Stop Work Authority policy has in it both the risk management requirements aforementioned. SWA encourages and empowers all employees to stop work if a hazardous condition exists. All the employees must be provided safe and healthful workplace, by their employers, which is free of any recognized hazards. Any employee has the right to refuse to work in a dangerous working condition and, any such refusal should not attract employer retaliation. Employees may be comfortable in refusing the work assigned to them if it is not safe, but they may fear retaliation, from work-order originator or work-permit issuer, in stopping other's work which they notice is unsafe, this fear of retaliation would vitiate the purpose of SWA policy. That is why the Stop-work Authority policy highlights these points:

1) All employees should be trained on stopping any unsafe work.
2) An investigation of the alleged unsafe situation should follow the act of exercising Stop-work Authority to find out if danger exists and if it does, the actions to be taken.
3) Employees should be assured, by their employers, that they will not face any retaliation from anybody.

SWA requires that employees be taught on how to intervene and stop an unsafe work without creating defensiveness. In a stop-work situation, i.e. when an employee-SWA Initiator exercises his Stop-work Authority, the alleged unsafe work is temporarily stopped and a fact-finding team is formed to investigate the situation. The SWA Initiator should be continuously notified of the fact-finding team's actions, decisions, recommendations and conclusions. Even if the fact-finding team's recommendation is not to recommend exercising SWA, because the alleged unsafe situation is not really that serious, the SWA Initiator should still be commended for his move otherwise he may feel humiliated and this will affect other employees' mindset, they may fear humiliation if their move is not approved. Fig. 1 illustrates a flow chart for the SWA process with typical stakeholders involved in it- Field Operations Head (FOH) the person who issued work permit on the work that is stopped using Stop-work Authority; work-order originator, the person who requested work-permit on the stopped work; Plant Officer (PO), Plant Manager (PM) and Maintenance Manager (MM) are the members of the fact-finding team chosen by the Field Operations Head.

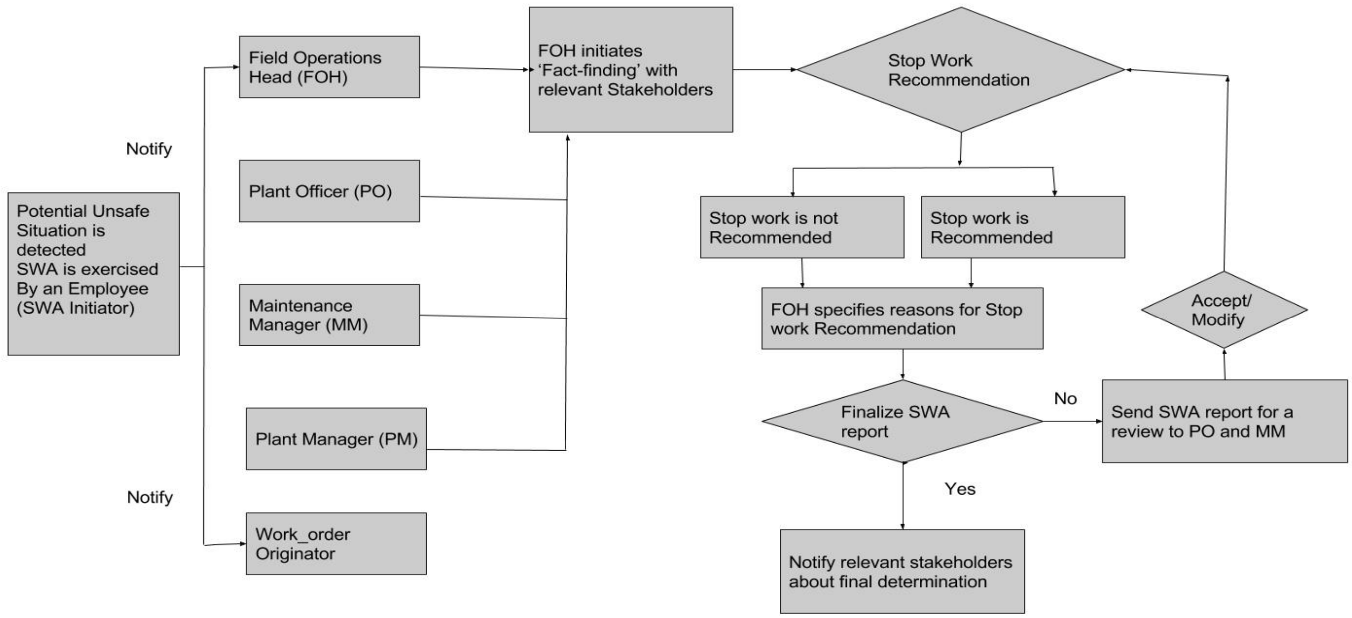

Fig. 1 An Illustration of Stop Work Authority process

A. Related Work

Several techniques are frequently being explored to leverage IT technologies to analyse data, accumulated from various sources, in many fields, however application of data mining techniques to accident databases is rare. Data can be generated from almost anything- either data is generated directly by the thing or data is generated on the thing. The focus of this work is limited to the data generated from situations and processes that are being labelled as hazardous/unsafe etc. The work described in [4] uses the database records of transportation accidents to find the explosion and ignition probabilities of inflammable spills using Event Tree Analysis (ETA). ETA was performed on the spill databases- HMIRS, by the Department of Transportation, and MINMOD, by the US Coast Guard, to find out the pattern in explosion and ignition probabilities.

The use of association rules to explore cause-effect relationships in occupational accidents is presented in [5] whose literature survey identifies 5 factors (worker, environment, project, management, time) responsible for accidents in construction industry. A database of 1300 accident and fatality reports, from construction and civil-engineering projects, are analysed using Apriori algorithm, for association rule mining, through 'Statistica Data Miner' Online Analytical Processing (OLAP) tool and the results indicated that a combination of factors (management and workers) are responsible for accidents and the conclusion was that occupational accidents can be avoided if the following steps are taken: promotion of safety management, providing work-safety training to workers, enhancing emphasis on safety procedures. An extension to work done in [5] proposes the use of Classification and Regression Tree (CART) data mining technique to analyse 1500 records of accident databases. The work in [6] analyses occupational accident databases in Finland using data mining techniques like decision-trees to identify if an accident falls into the Slip, Stumble and Fall (SSF) category and association rule mining is used to find correlation among factors, and it concludes that nothing unexpected was found but, application of data mining techniques supplemented the results of analysis.

The work in [7] describes how mobile applications can be used for detecting dangerous situations that can emanate while driving vehicles and suggests possible recommendations to avoid accidents. The work in [8] proposes an iOS application for reporting accidents eliminating the manual communication delays involved in reporting accidents and an easy on demand accident-report retrieval mechanism but, it does not provide any analytical results on the accident reports. The above works have motivated the work in this paper to integrate the data analytics and real-time communication of accidents into a single mobile application.

B. Proposed System

Basing on the points highlighted and the risk management requirements of SWA policy, it can be seen that any system that proposes to implement SWA policy digitally should implement the following functionalities:

1) A functionality to retrieve the details of a work on which SWA is about to be exercised.
2) A functionality to upload images as evidences for stopping a work using SWA.
3) A functionality to record/store all the data generated, during SWA process, in a database.
4) A functionality to notify all relevant stakeholders about the SWA events in real-time.
5) A functionality to facilitate the fact-finding team to specify their investigation outcome and review their action plans and recommendations.
6) A functionality to visualize the statistics on the data records created during SWA process.
7) A functionality to analyze the data records generated to find out the frequent patterns that are the root causes for unsafe work conditions.

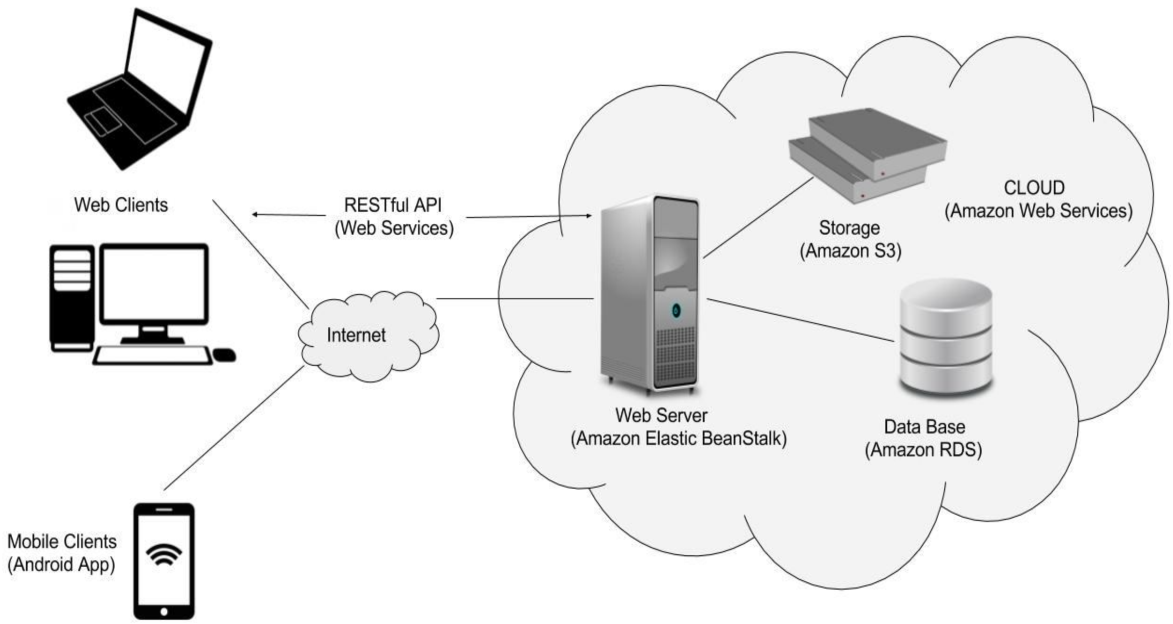

Fig. 2 Proposed System Architecture

This work envisages mobile application and a responsive web application as a feasible solution to implement all the functionalities aforementioned. Fig. 2 shows the proposed System Architecture with mobile and web clients accessing services and resources hosted on a cloud via Internet using RESTful API [19]. The mobile application is developed for Android platform and for mobile devices without an Android platform a responsive web application is developed which can be accessed both from desktops and mobile devices. These mobile and responsive web applications allow employees to retrieve relevant information on works being carried out in a location, exercise SWA through the application itself by specifying their reasons and uploading evidences/pictures that substantiate their reasons. All the relevant stakeholders, identified from work-permit details, are then notified of the SWA event in real-time via mobile device notifications. This real-time communication of SWA events helps avoid the inherent delays associated with manual communications, thus facilitating quick response to unsafe situations. These real-time notifications will keep the SWA Initiator and other relevant stakeholders informed about the timely decisions and actions being taken against an SWA situation. Leveraging the mobile application employees can exercise SWA virtually from any location in an Oil and Gas plant where unsafe work is being carried out and can also take pictures of unsafe work conditions and upload them immediately which is not possible if the system is implemented as a desktop application. The convenience of sitting in office and analyzing records is offered by web application. That is why this work implements both mobile and responsive web applications but, emphasizes on mobile application as it allows real-time communication via device notifications which is not possible with web application.

II. IMPLEMENTATION METHODOLOGY

First thing to be considered for implementing the proposed system/application is the data that the application uses and generates. Several database relations are created for complete implementation of the proposed application, below described are those that are of significant importance in the SWA process, these relations are as follows:

1) 'Work_orders' relation which holds the details of a particular work, identified by unique identifier, that has to be carried out at some location.
2) 'Work_permits' relation which holds the permit details of associated work_order, from work_orders relation.
3) 'SWA_reports' relation which holds the details of SWA event, like evidences, actions taken, recommendations etc., referencing a work_permit, from work_permits relation, on which SWA is exercised.

Coming to the data needed for finding frequent patterns the above three database relations collectively have 25 attributes but, all that data is not needed because some attributes are completely unique and other attributes are populated following an SWA event, so they can't be responsible for Stopping work. This work has identified 8 attributes that can be responsible factors for SWA event or unsafe work condition. Table 1 lists these 8 attributes and describes them briefly. 'SWA Initiator' attribute is taken from SWA_reports relation, the other attributes of this relation are used for analyzing frequent patterns as will be described in section 4. 'Work-order Originator, Plant Id, Unit Id, Equipment Id, Assigned department' attributes are taken from work orders relation. 'Work-permit Issuer and Job type' attributes are taken form 'work permits' relation. Frequent patterns are formed from these 8 attributes/factors – combinations of factors that contribute the existence of unsafe working conditions. The frequent patterns are generated from a frequent pattern mining algorithm implementation. The details of frequent pattern mining is described in detail in section 3. After deciding on the data that would be used for analytics now is the time to consider what technologies can be leveraged to implement the proposed mobile and web applications-the details of technologies that will be used to store and retrieve data; run analysis on reports; display results, enable real-time data communication.

TABLE I
FACTORS RESPONSIBLE FOR UNSAFE WORK CONDITIONS

Responsible Factors	
Factor	Description
SWA Initiator	The person who has exercised SWA on a work_permit
Work-Order Originator	The person who requested permit for a particular work
Work-Permit Issuer	Field Operations Head who issued permit for a work_order
Plant Id	The oil & gas plant at which work is being carried out
Unit Id	The unit of the plant at which work is being carried out
Equipment Id	The equipment on which the work is being done
Assigned department	The department of the Oil and gas plant to which work is assigned
Job Type	The type of work like hot work, cold work, working at height etc.

This work has chosen to utilize cloud services to realize the resource requirements of the application, because of the various benefits cloud computing offers [21], over traditional approaches. Amazon Web Services (AWS) is the chosen cloud services platform. AWS provides several cloud services out of which this work's implementation uses the following three services:

1) 'Amazon Elastic Bean Stalk' computing service is used for running Web server and analytics engine/program.
2) 'Amazon Relational Database Service (RDS)' is used to retrieve and record the data that is used by and generated from the application.
3) Amazon Simple Storage Service (S3)' is used to store and retrieve the images that are uploaded as evidence during SWA process.

PostgreSQl is the database management system utilized for creating relations and storing records in them. PostgreSQl database engine is run on an Amazon RDS instance which provides user credentials and a connection string to connect to the remote database being hosted by RDS. Amazon S3 provides simple web service interface to store and retrieve files. In Amazon S3 the files are stored as objects in containers called buckets and each of these objects and buckets can be secured by specifying various levels of permissions to create, delete and list the objects, to various user roles. Amazon S3's objects can be accessed via uniform resource locator (URL) from an authenticated application which has the S3 access credentials. Amazon Elastic Beanstalk provides the deployment platform for deploying the web application on a Tomcat web server instance running on a Linux host. The web application running on Elastic Beanstalk's instance connects to the S3 and RDS instance to store and retrieve necessary content. The mobile client is implemented for Android using Android SDK, the responsive web application is designed using web technologies – HTML, CSS, Java Script, and JQuery and at the server side is the JSP programming.

Representational State Transfer (REST) technology [19] is chosen to communicate data between client devices and the server because REST is stateless and it is proven that RESTful architecture offers better performance than Simple Object Access Protocol SOAP protocol [20]. REST architecture treats all services, files etc. as resources that can be accessed and altered via URLs using standard HTTP methods-GET, PUT, POST, and DELETE. REST allows data to be encoded in light-weight Java Script Object Notation (JSON) data interchange format reducing the communication overhead. The RESTful web services used by mobile and web applications are programmed in Java and are deployed on the web server instance running on Amazon Elastic Bean stalk.

III.FREQUENT PATTERN MINING

For analysing the data records generated from SWA process and finding out root causes for unsafe situations we will have to find out the factors and combinations of such factors that contribute to the existence of unsafe situations. This can be done by mining 'frequent patterns' in the data records. In the context of data records a 'pattern' is a recurring set of data items, 'frequent patterns' are those patterns that are more frequent among all records. Such frequent patterns have frequent data items (factors) that are responsible for majority of unsafe situations. This work chooses 'FP-Growth' algorithm for mining frequent patterns. The FP-Growth Algorithm, as described by Han in [9], is an efficient and scalable frequent pattern mining algorithm which compresses and stores the crucial information about frequent patterns in an extended prefix-tree structure called frequent-pattern tree (FP-tree). This work has chosen FP-Growth algorithm as it is proved in the work [9] that it outperforms other popular methods for mining frequent patterns, e.g. the Apriori Algorithm [10] and the TreeProjection [11]. In some later works [12], [13], [14] it was proved that FP-Growth has better performance than other methods, including Eclat [15] and Relim [16].

The FP-Growth algorithm improves performance by finding frequent patterns without using candidate generation. FP-growth algorithm works based on divide-and-conquer [17] strategy, the association information of attributes is stored in a data structure called FP-Tree (frequent pattern-tree). The algorithm works as follows:

1) In first step the input database is compressed to create a FP-tree instance representing represent frequent items.
2) In second step the compressed database is divided into a set of conditional databases, where each conditional database is associated with one frequent pattern.
3) In the last step each conditional database is mined separately.

The search costs incurred in looking for short frequent patterns and then concatenating them to form long patterns are reduced using the strategy, aforementioned, adopted by the FP-growth algorithm. The work done by Han in [9] proposes two algorithms which can be collectively used to mine frequent patterns. The first algorithm is to construct the 'FP-Tree', the second algorithm is the 'FP-Growth' algorithm that uses the FP-Tree constructed to generate frequent patterns. Both of these algorithms are presented below.

A. Algorithm 1: FP-tree construction

Input: Two dimensional array of data records and a minimum support threshold.

Output: FP-tree of data records

Method: Constructing the FP-Tree.

1) Scan the two dimensional array once. Collect the set of frequent items, and their support count, call this set F. Sort the set F in descending order based on support value forming an F-list, the list of frequent items.

2) Create the root node for FP-tree, T, and label it as "null". For each row of 2D array do the following:

a) Select the frequent items in row and sort them according to the order of F-list. Let the sorted frequent-item list in row be [l | L], where l is the first element and L is the remaining list. Call insert_tree([l | L], T).

b) The function insert_tree([l | L], T) is performed as follows. If T has a child N such that N.item-name = l.item-name, then increment N 's count by 1; else create a new node N , with its count initialized to 1, its parent link linked to T , and its node-link linked to the nodes with the same item-name via the node-link structure. If L is nonempty, call insert_tree(L, N) recursively.

3) *End process:* The output of Algorithm 1 is a frequent-pattern tree named 'fp-tree' and it is supplied as input to the Algorithm 2 to mine frequent patterns.

B. Algorithm 2: Frequent Pattern mining

Input: The FP-tree (fp-tree) constructed from Algorithm 1 and minimum support (minsup) threshold.

Output: An array of frequent patterns where each row represents a frequent pattern.

Method: call fp-growth (fp-tree , null);

Procedure fp-growth(Tree, a)

{

1) if Tree contains a single path P then
2) let the multipath part be Q replacing the top branching node with null root
a) for each Combination (C) of nodes in path P do
b) generate pattern C ∪ a with support = minsup of nodes in C let fpset(P) be the set of patterns generated
3) else let Q be the Tree, for each item b in Q do
a) generate pattern C = b ∪ a with support = b.support
b) construct C's conditional-pattern base and C's conditional FP-Tree TreeC
c) if TreeC ≠ ø
d) call fp-growth(TreeC , C);
e) let fpset(Q) be the set of patterns generated
4) return (fpset(P) ∪ fpset(Q) ∪ (fpset(P) x fpset(Q)))}

If the fp-tree has a single-prefix path then the comprehensive list of frequent patterns are generated in three parts: first the frequent patterns, satisfying minsup, for single-prefix path (P) are generated, next the frequent patterns for multipath (Q) are generated and finally the comprehensive set of frequent patterns is obtained as shown in step (3) of Algorithm 2.

IV. RESULTS AND ANALYSIS

The results generated by this work's mobile and web applications are two types:

1) Graphical Results- which are statistics on responsible factors described in Table 1 presented as graphs.
2) Frequent Patterns list- frequent patterns generated from the FP-growth algorithm implementation.

Before looking into the results for insights it is necessary to validate the results to ensure credibility of the application. For this purpose WEKA tool [18] is used. WEKA is a data mining tool which has implementations of several data mining algorithms, including FP-Growth, for mining frequent patterns. Since the FP-growth implementation of WEKA does not support nominal/string attributes, (which are the type of data generated from this work's application) the data records are supplied as input to 'Apriori' algorithm which is also a frequent pattern mining algorithm. Both 'Apriori' and 'FP-growth' generate same outputs but the computational performance of FP-growth is better than Apriori that is why this work has chosen to implement 'FP-growth' algorithm, but the results of Apriori implementation can be used to validate the results from our application.

Fig. 3 Graphical results generated by mobile application

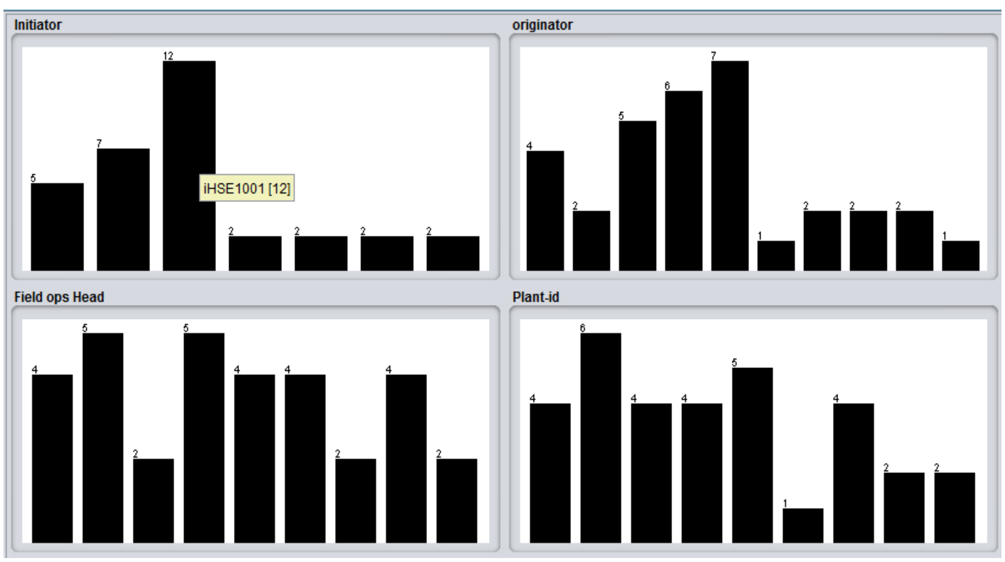

Fig. 4 WEKA tool's graphical results

The graphical results show the number of SWAs (#SWAs)/unsafe work conditions that a particular factor is responsible for. In Fig. 3 shown do the graphical results, from this works implementation, generated on 32 data records extracted from the three data base relations mentioned in section2 comprise the 8 attributes presented in Table 1. The same 32 data records are supplied to WEKA tool and as can be seen from Fig. 4 the tool generates graphs that are same as those shown in Fig. 3. To make the comparison more clear - the 'tool tips' in the 'Initiator/SWA Initiator' category of graphs from both the figures can be seen to representing same results. Fig. 3 shows that in SWA Initiator category the attribute/factor 'HSE1001' is responsible for '12' SWAs (#of SWAs). Similarly Fig. 4 shows that data item 'iHSE1001' has '12' records in its support, and this validates the graphical results. Graphical results present only an overview of statistics they alone can't be used for gaining deep insights.

1 Frequent Patterns comprising less than 30%

Responsible Factor	#SWAs	(✓ + ✗)
SWA Initiator: Simon Jones (Field_Operations_Head)	7	(5 + 2)
Unit ID: PT1001-UT1001	5	(3 + 2)
SWA Initiator: James Crowe (Plant_Supervisor)	5	(3 + 2)
Plant ID: PT1001	6	(3 + 3)
Field Ops Head: Christian Eastwood (Field_Operations_Head)	5	(4 + 1)
Field Ops Head: Tim Smith (Field_Operations_Head)	5	(4 + 1)
Work Order Originator: David Jones (Plant_Supervisor)	7	(4 + 3)
Plant ID: PT1009	5	(4 + 1)
Work Order Originator: Tom Smith (Maintenance_Supervisor)	6	(5 + 1)
Work Order Originator: James Crowe (Plant_Supervisor)	5	(5 + 0)
Job Type: Trivial	8	(3 + 5)
---Combined Factors---		
--2 Combinations--		
unit-id: PT1001-UT1001 , *department:* Plumbing	5	(3 + 2)
plant-id: PT1001 , *department:* Plumbing	5	(3 + 2)
department: Plumbing , *initiator:* HSE1001	5	(5 + 0)
unit-id: PT1001-UT1001 , *plant-id:* PT1001	5	(2 + 3)
job type: Trivial , *department:* Plumbing	8	(3 + 5)
plant-id: PT1009 , *originator:* MS1004	5	(4 + 1)
--3 Combinations--		
unit-id: PT1001-UT1001 , *plant-id:* PT1001 , *department:* Plumbing	5	(3 + 2)

2 Frequent Patterns comprising 30%-60%

Responsible Factor	#SWAs	(✓ + ✗)
SWA Initiator: Richard Sandler (HSE_Manager)	12	(10 + 2)
Department: Plumbing	12	(7 + 5)

Fig. 5 List of frequent patterns generated by the mobile application this work implemented

The 'Frequent patterns' generated from this work's implementation of FP-growth algorithm represent the factors and set of factors (combinations) that are frequently held responsible for unsafe situations. These results can be used to reduce the contribution of such factors in future. For user convenience the frequent patterns generated by this work's implementation are divided into three categories: one that comprise less than 30% of total SWAs/unsafe situations, second set comprising 30%-60% and third set comprising more than 60% of total SWAs. The frequent patterns in each of the above categories are further categorized based on the number of factors present in each pattern, ranging from only one factor to a combination of up to eight factors.

The frequent patterns shown in Fig. 5 are those that are generated from 32 records comprising the 8 attributes specified in Table 1 with a minimum support threshold of 15% (0.15) which is 5 records. A lower threshold is chosen for this data set because choosing higher threshold did not produce any results (frequent patterns), the results in Fig. 5 show that there are 18 frequent patterns that are responsible for less than 30% of total SWAs (unsafe situations) and there are 2 frequent patterns in the 30%-60% category, out of 18

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frequent patterns 11 patterns are contributions from only one factor, 6 patterns from combination of 2 factors and 1 from combination of 3 factors. Fig. 6 shows the output of the WEKA tool's Apriori algorithm on the same data set from which results of Fig. 5 are produced, both these figures can be compared to see that they are same results proving the validity of the results shown in Fig. 5.

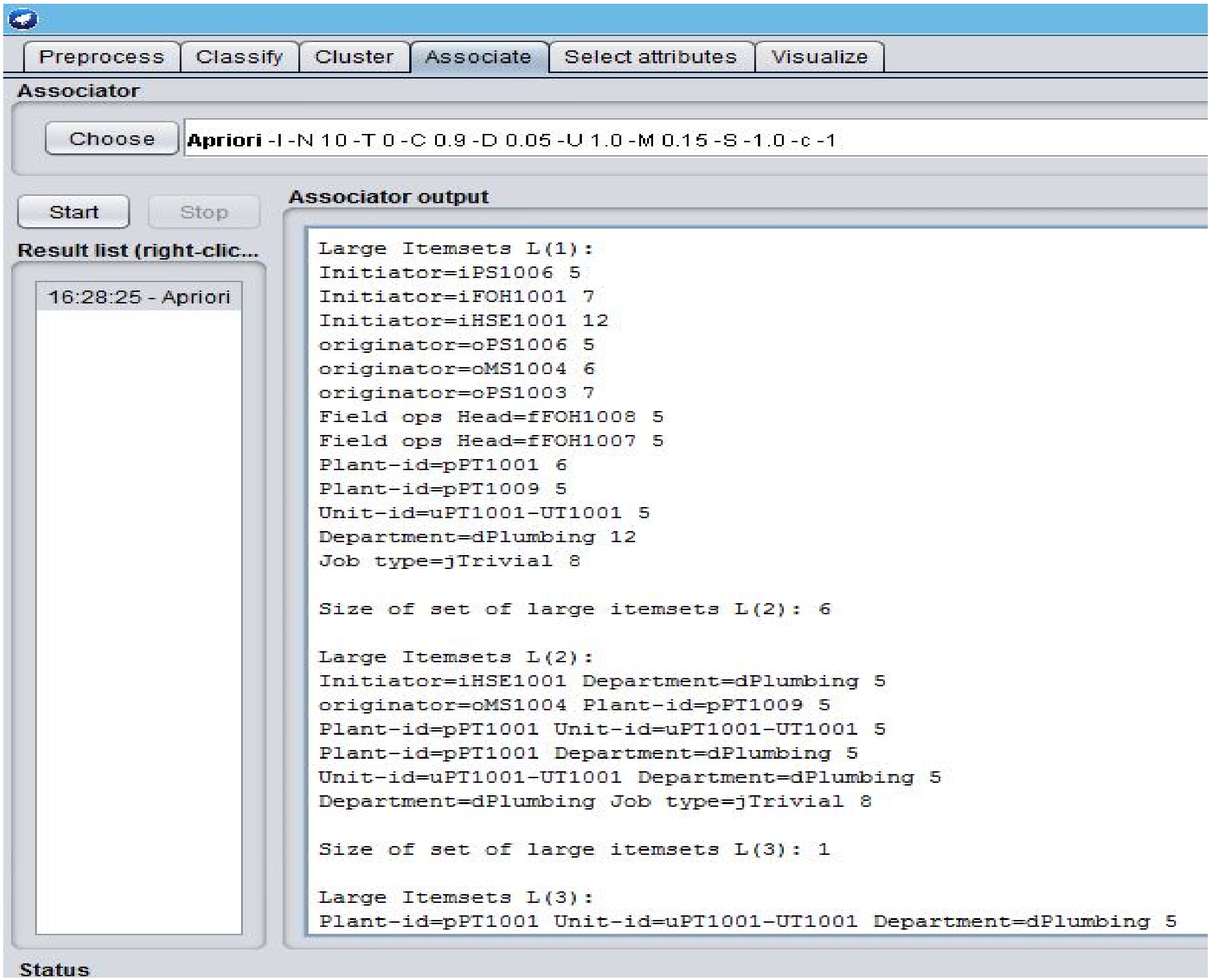

Fig. 6 WEKA tool's output of frequent patterns

The frequent patterns shown in Fig. 5 can be further analyzed using the values shown under the 'tick' and 'cross' marks, present against each frequent pattern separated by a plus symbol, in green and gray colors respectively. The values under the tick and cross marks are the results of fact-finding team's conclusion of an alleged unsafe situation as safe or unsafe. The values under tick mark in green color show that the fact-finding team's conclusion is in favor of exercising SWA for the number of SWAs the value represents, which means that the alleged unsafe situation is actually unsafe. The values in red color under cross mark show that fact-finding team's conclusion is not in favor of exercising SWA, which means that the alleged unsafe situation is not unsafe. These values under tick and cross marks reveal how many unsafe situations are actually detected against the total number of alleged unsafe situations (#SWAs). For example from Fig. 5 it can be seen that in 30%-60% category we have the SWA Initiator-Richard Sandler with total 12 SWAs out of which 10 SWAs are in favor of Richard Sandler proving the genuineness of his actions and that he is not raising any false alarms. On the other hand in less than 30% category and in combination of 2 factors we have 'job type: trivial, department: plumbing' being held responsible for 8 SWAs/unsafe situations out of which only 3 are concluded as being truly unsafe which means these 2 factors cannot be held responsible for unsafe situations and there is something else that needs to be checked to see what is making these 2 factors to be targeted for unsafe situations.

V. CONCLUSION

Information Technology enabled process tracking and data recording mechanisms, for handling unsafe work conditions, will help accumulate quality data that can later be used for analyzing the unsafe situations to gain insights into the root causes for such situations. This work has implemented a mobile application leveraging various technologies like cloud computing, RESTful web services, mobile & web technologies and data analytics algorithms for the purpose of recording and analyzing the data records that are generated from unsafe work conditions. The application analyzes recorded data to find out the frequent patterns (root causes) contributing to unsafe situations and these analysis results can then be used to prevent future unsafe situations by reducing the contribution of identified frequent patterns to the existence of unsafe conditions.

Future work will concentrate on enhancing the current work with 'automated processes' for unsafe situation detection using 'IOT' and 'Machine Learning' concepts like video based recognition and deep convolution networks. As the current work's implementation provides for storage of pictures taken on unsafe work conditions, a machine-learning model can be developed for object and scene detection, and 'Multimedia Sensors' can be deployed in the operation sites to monitor the environment in real-time. Video stream from such multimedia sensors can be continuously fed to the model, developed using machine-learning algorithms, to identify unsafe situations by comparing stored images of unsafe situations with real-time video frames being streamed from the multimedia sensors.

REFERENCES

[1] Robert Bigliani, "Reducing Risk in Oil and Gas Operations", white paper, IDC Energy Insights, 2013. Retrieved from: http://documentum.opentext.com/wp-content/uploads/2017/06/minimizing-operational-risk-in-oil-gas-industry.pdf
[2] Sam Mannan. "Lee's Loss Prevention in the process Industries: Hazard identification, Assessment and Control", 4th edition, Elsevier, 2012.
[3] K. W. Morrison, "Stop-Work Authority: Empowering workers to halt a dangerous situation," May, 2015 Retrieved from: http://www.safetyandhealthmagazine.com/articles/12346-stop-work-authority.
[4] Ronza, J.A. Vilchez, J. Casal , "Using transportation accident databases to investigate ignition and explosion probabilities of flammable spills", Journal of Hazardous materials, Elsevier, Barcelona, 2007
[5] Ching-Wu Cheng, Chen-Chung Lin, Sou-Sen Leu, "Use of association rules to explore cause–effect relationships in occupational accidents in the Taiwan construction industry", In Safety Science, Volume 48, Issue 4, 2010, Pages 436-444, ISSN 0925-7535
[6] Noora Nenonen, "Analysing factors related to slipping, stumbling, and falling accidents at work: Application of data mining methods to Finnish occupational accidents and diseases statistics database", In Applied Ergonomics, Volume 44, Issue 2, 2013, Pages 215-224, ISSN 0003-6870
[7] Alexander Smirnov, Alexey Kashevnik and Igor Lashkov, "Human-Smartphone interaction for Dangerous situation Detection and Recommendation Generation while driving", In Proc.18th Int. Conf. Speech and Computer, Springer, Budapest 2016.
[8] Bin Hussin, M.F. Jusoh, M.H. Sulaiman et.al. "Accident Reporting System using an iOS Application", In Proc. 2014 IEEE Int. Conf. on Systems, Process and Control, Kuala Lumpur, December, 2014.
[9] J. Han, H. Pei, and Y. Yin. "Mining Frequent Patterns without Candidate Generation". In: Proc. Conf. on the Management of Data (SIGMOD'00, Dallas, TX). ACM Press, New York, NY, USA 2000.
[10] Agrawal, R. and Srikant, R. 1994. "Fast algorithms for mining association rules". In Proc. 1994 Int. Conf. Very Large Data Bases (VLDB'94), Santiago, Chile, pp. 487–499.
[11] Agarwal, R., Aggarwal, C., and Prasad, V.V.V. 2001." A tree projection algorithm for generation of frequent itemsets". Journal of Parallel and Distributed Computing, 61:350–371.
[12] B.Santhosh Kumar and K.V.Rukmani. "Implementation of Web Usage Mining Using APRIORI and FP Growth Algorithms". Int. J. of Advanced Networking and Applications, Volume: 01, Issue 06, Pages: 400-404 (2010).
[13] Cornelia Gyorödi and Robert Gyorödi. "A Comparative Study of Association Rules Mining Algorithms".
[14] F. Bonchi and B. Goethals. "FP-Bonsai: the Art of Growing and Pruning Small FP-trees. Proc. 8th Pacific-Asia Conference on Knowledge Discovery and Data Mining", (PAKDD'04, Sydney, Australia), 155–160. Springer-Verlag, Heidelberg, Germany 2004.
[15] M. Zaki, S. Parthasarathy, M. Ogihara, and W. Li. "New Algorithms for Fast Discovery of Association Rules". Proc. 3rd Int. Conf. on Knowledge Discovery and Data Mining (KDD'97), 283–296. AAAI Press, Menlo Park, CA, USA 1997.
[16] Christian Borgelt. "Keeping Things Simple: Finding Frequent Item Sets by Recursive Elimination". Workshop Open Source Data Mining Software , 66-70. ACM Press, New York, NY, USA 2005.
[17] Jiawei Han and Micheline Kamber, "Data Mining: Concepts and Techniques". 2nd edition, Morgan Kaufmann, 2006.
[18] Eibe Frank, Mark A. Hall, and Ian H. Witten (2016). "The WEKA Workbench. Online Appendix for 'Data Mining: Practical Machine Learning Tools and Techniques' ", Morgan Kaufmann, Fourth Edition, 2016.
[19] Leonard Richardson, Sam Ruby, and David Heinemeier Hansson, "*Restful Web Services*", Paperback, O'Reilly Media, May 2007, ISBN: 0596529260.
[20] Smitha Kumari, Santanu Kumar Rath. "Performance comparison of SOAP and REST based Web Services for Enterprise Application Integration" .Proc. Int. Conf on Advances in Computing, Communications and Informatics (ICACCI). IEEE, Kochi, India 2015.
[21] Hoang Dhin Thai, Ping Wang." A survey of mobile cloud computing: architecture, applications, and approaches". Article in Wireless Communications and Mobile Computing, Wiley press 2013.