DECISION SUPPORT SYSTEM FOR IMPROVED OPERATIONS, MAINTENANCE, AND SAFETY: A DATA-DRIVEN APPROACH

A Dissertation

by

PANKAJ GOEL

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Aniruddha Datta
Co-Chair of Committee,	Efstratios N. Pistikopoulos
Committee Members,	Shankar Bhattacharyya
	Yang Shen
Head of Department,	Miroslav Begovic

May 2020

Major Subject: Electrical Engineering

ABSTRACT

With industry 4.0, a new era of the industrial revolution with a focus on automation, interconnectivity, machine learning, and real-time data collection and analysis are emerging. The smart digital technology which includes smart sensors, data acquisition, processing, and control based on big data, machine learning, and Artificial Intelligence (AI) provides boundless opportunities for the end-users to operate their plants under more optimized, reliable, and safer conditions. During an abnormal event in an industrial facility, operators are inundated with information to infer and act. Hence, there is a critical need to develop solutions that assist operators during such critical events. Also, because of the obsolescence challenges of typical industrial control systems, a new paradigm of Open Process Automation (OPA) is emerging. OPA requires a Real-time Operational Technology (OT) services to analyze the data generated by the sensors and control loops to assist the process plant operations by developing applications for advanced computing platforms in open source software platforms.

The aim of this research is to highlight the potential applications of big data analytics, machine learning, and AI methods and develop solutions for plant operation, maintenance, process safety and risk management for real industry problems. This research work includes:

1. an alarm management framework integrated with data-driven (Key Performance Indicators) KPIs bench-marking, and a visualization tool is developed to address alarm management challenges;

2. a deep learning-based data-driven process fault detection and diagnosis method on cloud computing to identify abnormal process conditions; and

3. applications such as predictive maintenance, dynamic risk mapping, incident database analysis, application of Natural Language Processing (NLP) for text classification, and barrier assessment for dynamic risk mapping,

A unified workflow approach is used to define the data-sources, applicable domains, and develop

proposed applications. This work integrates data generated by field instrumentation, expert knowledge with data analytics and AI techniques to provide guidance to the operator or engineer to effectively take proactive decisions through “action-boards”.

The robustness of the developed methods and algorithms is validated using real and simulated data sets. The proposed methods and results provide a future road map for any organization to deal with data integration with such applications leading to productive, safer and more reliable operations.

DEDICATION

"It's not whether you get knocked down, it's whether you get back up"

- Vince Lombardi

To my Love *"Prerna"*, my mother, and my Late father.

This year marks a global pandemic (COVID-19) which has affected many lives. My thoughts and prayers are with all the first responders, doctors, and people affected.

ACKNOWLEDGMENTS

I would like to offer my sincerest gratitude and appreciation to my advisors Dr. Aniruddha Datta and Dr. Efstratios N. Pistikopoulos for their guidance, and immense support. I am indebted for the time and energy they have invested in me towards my growth as a scholar and practitioner. I appreciate their care, concern, and thoughtful teaching. They are terrific advisors and persons; it has been an honor to work with them. I would also like to thank Dr. Shankar Bhattacharyya for believing in me, guiding, and supporting me through thick and thin. Also, I would like to thank Dr. Yang Shen for his guidance and support throughout the research. I gratefully acknowledge Late Dr. Sam Mannan, for his vision, support, and encouragement during this research work.

I thank group members from Dr. Datta's group, Dr. Pistikopoulos's group and the Mary Kay O'Connor Process Safety Center. It is a pleasure to be part of such great groups of individuals. Thanks for your friendship, collaboration, and guidance. Also, I would like to thank Dr. Jason Moats, and Mr. Howard Meek for allowing me to teach, contribute, and share my experiences with the students at the Brayton Fire Field school.

I would also like to express my profound gratitude to my mentors Mr. Ramesh Deshabhotla, and Dr. Michael Shehane for their guidance. I would also like to thank Sheera Helms, and Katie Bryan for their extensive support during these years.

I cannot conclude without expressing my love and appreciation for my family and friends. To my wife Prerna: I am fortunate to have you in my life. You're my rock, thank you for always standing by my side. To my parents, my in-laws, and my brother: thank you for your love, support, and sacrifices. A special thanks to my friends Haswanth Vundavilli, Abhishek Mahajan, Aniket Bonde, for making my graduate school life memorable at A & M.

As a graduate student, it would have been easy to focus on my courses and research, without letting the unique spirit of the Aggieland impact me. I want to extend my gratitude to the Texas A & M University for providing me with exceptional opportunities to serve in numerous student leadership roles, serve the Aggie community which kept me motivated in my research journey.

It has been an extraordinary experience to be part of Texas A&M graduate program and Aggie Family.

I have received an incredible love and support from y'all. Thank you!!

It's a dream becoming reality.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a dissertation committee consisting of Professor Aniruddha Datta of the Department of Electrical and Computer Engineering , Professor Efstratios N. Pistikopoulos of the Department of Chemical Engineering as co-chairs and Professor Shankar Bhattacharyya and Professor Yang Shen of the Department of Electrical and Computer Engineering.

All work conducted for the dissertation was completed by the student independently.

Funding Sources

This research work was supported by funding from the Mary Kay O'Connor Process Safety Center (MKOPSC) including partial supports from Department of Electrical and Computer Engineering, Texas A&M Energy Institute.

NOMENCLATURE

A & E	Alarm and Event
ACP	Advanced Computing Platforms
AFDS	Alarm Filtering and Diagnostic Systems
AI	Artificial Intelligence
AM	Alarm Management
ANSI	American National Standards Institute
API	American Petroleum Institute
AR	Augmented Reality
ASM	Abnomral Situation Management
AWS	Amazon Web Services
BADPV	Bad Process Variable
BI	Business Intelligence
BiLSTM	Bi-directional Long Short Term Memory
BL	Bayeasian Learning
BP	British Petroleum
CHAID	Chi-squared Automatic Interaction Detection
CGMP	Currently Good Manu-facturing Practice
CM	Corrective maintenance
CMMS	Computerized maintenance management system
CNTK	Congnitive Toolkit
COMAH	Control of Major Accident Hazards
C & RT	Classification and Regression Tree

DCS	Distributed Control System
DL	Deep Learning
DOE	Department of Energy
DOT	Department ofTransportation
DRA	Dynamic Risk Analysis
EEMUA	The Engineering Equipment and Materials Users Association
ESD	Emergency Shut down System
FEED	Front End Engineering Design
FN	False Negative
FP	False Positive
GCS	Google Cloud Services
GUI	Graphical User Interface
HAZOP	Hazard and Operability Study
HMI	Human Machine Interface
HSE	Health ans Safety Executive
IDC	International Data Corporation
ISA	International Society of Automation
IoT	Internet of Things
IT	Information Technology
KPI	Key Performance Indicators
LFI	Learning From Incident
LIMS	Laboratory Information Management System
LOPA	Layersof Protection Analysis
LSTM	Long Short Term Memory
MIIT	Ministry of Industry and Information Technology

ML	Machine Learning
NASA	The National Aeronautics and Space Administration
NIST	National Institute of Standardsand Technology
NLP	Natural Language Processing
OGP	Oil andGas Producers Association
OPA	Open Process Automation
OSHA	Occupational Safety and Health Administration
OT	Operational Technology
PdM	Predictive maintenance
PFD	Process Flow Diagrams
PHA	Process HAzard Analysis
P & ID	Piping and Instrumentation Diagrams
PHMSA	Pipeline and Hazardous Material Safety Administration
PLC	Programmable Logic Controller
PM	Preventive maintenance
PSBDMS	Process Safety Big Data Management System
PSM	Process Safety Management
PV	process variable
R & D	Research and Development
RAGAGEP	Recognized and Generally Accepted Good Engineering Practices
RNN	Recurrent Neural Network
RPA	Robotics Process Automation
RTD	Resistance Temperature Detector
RUL	Remaining USeful Life
SCADA	Supervisory Control and Data Acquisition

SOP	Standard Operating Procedures
SVC	Support Vector Classifier
TEP	Tennessee Eastman Process
TN	True Negative
TP	True Positive
UN	United Nations
USEPA	United States Environmental Protection Agency
VR	Virtual Reality

TABLE OF CONTENTS

LIST OF FIGURES

FIGURE Page

LIST OF TABLES

TABLE Page

1. INTRODUCTION

Manufacturing technologies and methods have substantially improved since the first industrial revolution. We have made giant strides in technological development and are in the midst of smart manufacturing or 'Industry 4.0' which encompasses the word smart by integration of Artificial Intelligence (AI), Internet of Things (IoT), cyber-physical systems, and cloud computing. By implementing such technology options in part or full, we can build a smart network of machines, smart and intelligent devices, networks, data and systems. Besides an increase in productivity, users also achieve increased safety, quality, and reliability of the manufacturing units. While industry 4.0 is about digitalization, in the future we shall be entering the era of Industry 5.0 or fifth industrial revolution. Industry 5.0 will include defining and establishing a co-operation between human and machines, which results in a synchronization between the cognitive computing and human intelligence. Technologies such as cloud computing, Internet of Things (IoT), Artificial Intelligence (AI) and Augmented Reality (AR) / Virtual Reality (VR) are becoming indispensable in improving operational efficiency to drive profitability, asset reliability and availability, decision support, process safety and abnormal situation management. The intricacies of these technologies and their application of various key systems engenders challenges for research and development (R& D). With the real-time data coming from the field and advanced computing techniques it is easier to design and adopt new personalized tools and applications in manufacturing and operations.

1.1 Motivation

"Big Data" has transformed from a buzzword to a real value creator in recent years and is serving as a key enabler in boosting the performance of operations, economy, and businesses. Several countries and organizations have started various projects to harness the big data. In the United

*Reprinted in part with the permission from "Application of big data analytics in process safety and risk management" by Goel et al., 2017. *IEEE International Conference on Big Data*, (pp. 1143-1152), Copyright 2017 by IEEE.

†Reprinted in part with the permission from "How Big Data & Analytics can improve process and plant safety and become an indispensable tool for risk management" by Goel et al., 2019. *Chemical Engineering Transactions*, 77, 757-762, Copyright 2019 by AIDIC.

States, The Obama Administration launched the ‘Big Data Research and Development Initiative’ in 2012, and in 2016 the administration released “The Federal Big Data Research and Development Strategic Plan". This highlights the emerging big data capabilities and provides guidance for developing or expanding federal big data research and development (R&D) plans [2, 3]. In China, Ministry of Industry and Information Technology (MIIT) prepared a five year plan for developing big data infrastructure through standardized systems [4]. In Japan, big data is a key component of the national technological strategy since 2012. The United Nations (UN) established the “Global Pulse initiative" in 2009 to harness big data for development and humanitarian actions and published a report [5] highlighting the challenges and opportunities. According to [6, 7], a social, economic, and technical revolution has emerged around us, resulting in an exponential growth in the generation of data resulting in an “industrial revolution of data". This data is generated at different levels in the form of social media information, smart devices, Internet of Things (IoT), bank services, and reports *etc.* With the advancements in computing technologies, it is easier to store data (clouds, data warehouses), and draw insights with the help of tools such as artificial intelligence (AI), machine/deep learning, granular computing [8], cognitive computing, and computer vision. Big data has been defined differently by different users. The attributes of big data are defined as 7 V’s and listed as follows [9, 10, 11]:

- Volume: large amounts of data generated from devices.
- Variety: heterogeneity of data types, representation, and semantic interpretation.
- Velocity: data is generated at a rapid rate compared to the traditional systems and requires processing.
- Value: added value from the information extracted.
- Veracity: uncertainty, accuracy, and reliability of data.
- Variability: number of inconsistencies, variable data sources and data changes (dynamic).
- Valence: inter-connectedness, inter-relation.

A recent study conducted by IDC in 2019 [12] highlights the market share of evolving market of digital transformation worldwide. The data in Figure 1.1 shows that the United States and western Europe almost constitutes 54% of the market share for digital transformation. With this evolution, the focus on automation, inter-connectivity, machine learning, and real-time data collection and analysis is emerging. The smart digital technology that includes smart sensors, data acquisition, processing, and control based on big data, machine learning, and Artificial Intelligence (AI) provides boundless opportunities for the end users to operate their plants in a more optimized, reliable, and safer manner. In recent years, there has been an increasing interest in the field of big data analytics. It has been established that there exist large amounts of data in the energy industry. However, there is a need to develop methods combining domain knowledge to transform this data into meaningful information to return business intelligence.
According to a survey conducted in 2019 by KPMG [13], refer to Figure 1.2, 39 % of the participants mentioned they have adopted Intelligent automation (robotics process automation (RPA), artificial intelligence (AI), cloud technologies and smart machines). The other 32 % of the participants mentioned that they would adopt similar technologies within the next one year.

Also, with the advent of Open Process Automation (OPA), Real-time Operational Technology (OT) services are required to analyze the data generated by the sensors and control loops to assist the process plant operations. Hence, there is a critical need to develop solutions and applications based on open source software platforms that can work on advanced computing platforms either on-premise or at external data-centers. The existing work on the implementation of such technologies including big data analytics and AI applications predominantly focuses on applications in various fields such as healthcare, aviation industry, finance, energy industry, and the supply chain. However, within the energy industry, the application of big data analytics and AI in plant operation, maintenance, process safety and risk management is in it's nascent stages.

1.2 Current status of operation data analytics

In the last two decades, availability of data called for harnessing the data into meaningful information for Business Intelligence (BI). Big Data is a real value creator and a 'valuable asset'.

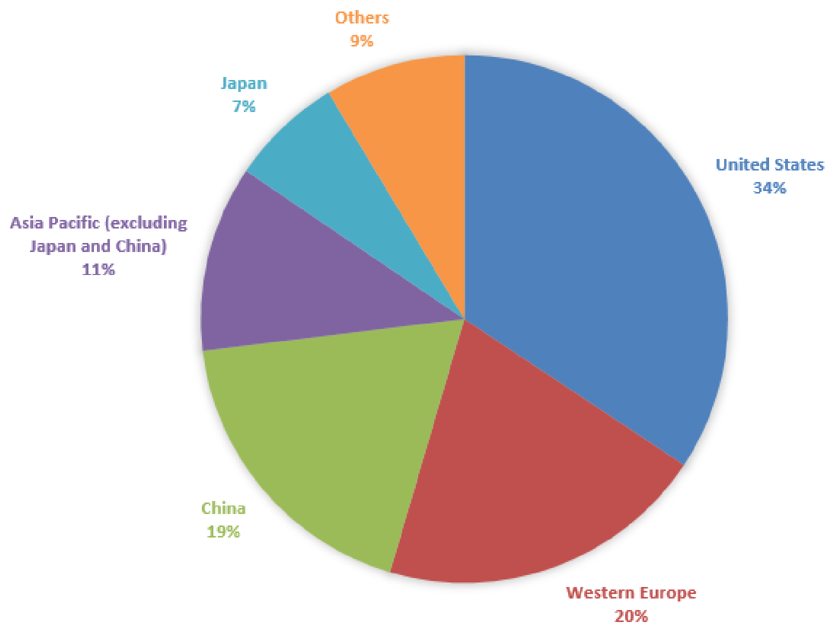


Figure 1.1: Share of digital transformation market worldwide 2019

Various industry sectors such as retail, social media, finance, banking, healthcare, professional sports and research and development use big data tools and techniques. Production and processing facilities in oil & gas are complex to operate. Some of the challenges in operating these facilities include inherently dangerous work environments, complex design and layouts, several operating envelopes, and budgetary constraints. Controlling the process on various levels is hampered by uncertainty. These days due to competition, and environmental constraints (including energy use), the pressure to operate as efficiently as possible has increased, and this leads in part to higher plant complexity, entailing again more uncertainty. Reducing uncertainty will lead to better decisions, and it will increase safety but it will need meaningful information that only can be acquired by collecting appropriate data and interpreting those. The latter requires reliable analytics. This forms the vision that will be further detailed below.

With recent technological advancements and adoption, industry operation generates a massive amount of data daily in various forms, sizes, and dimensions, which includes process plant operation data, regulatory agencies' data, and industry consortium data [7, 14] from disparate sources.

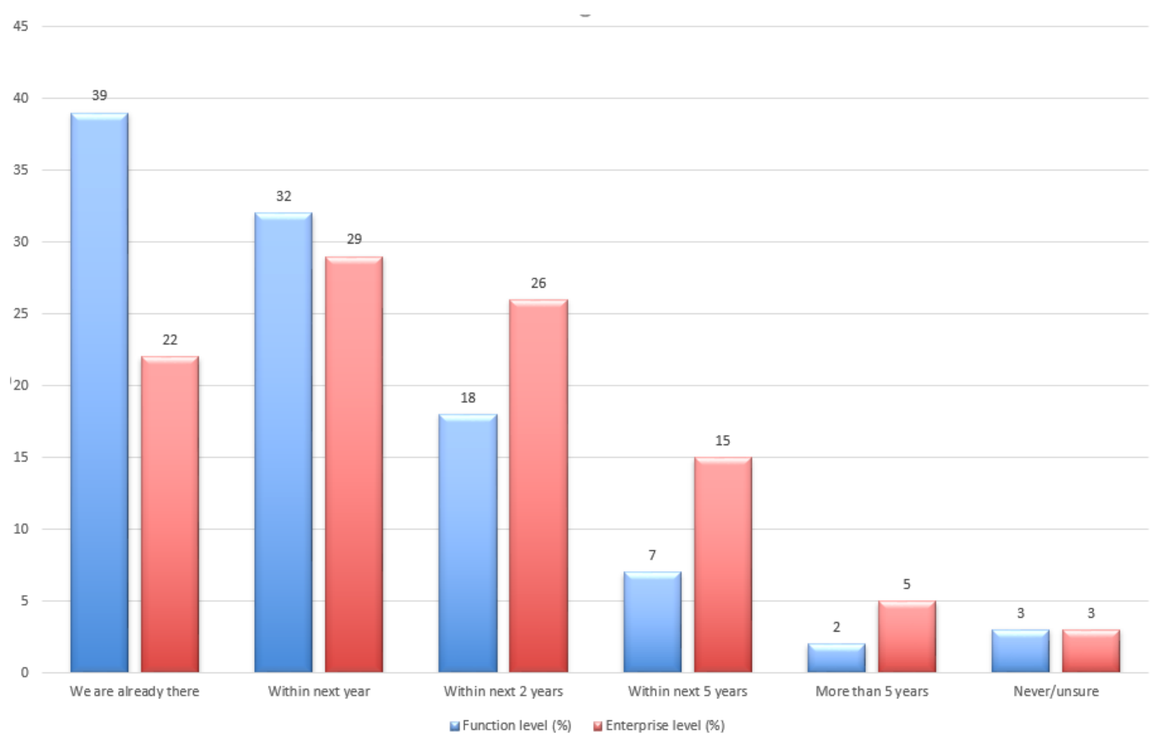


Figure 1.2: Intelligent automation adoption status in enterprise worldwide 2019

Process operation in a manufacturing facility comprises sensors, actuators, and a control system (Distributed Control System (DCS) or Programmable Logic Controller (PLC)) coupled with a historian to store the continuously generated data consisting of process and production parameters, alarm and event logs [15], and fault records. In addition to the process operation data, a manufacturing facility has data in the form of design data, operational data, Computerized Maintenance Management System, Laboratory Information Management System, Process Safety Management data including audit reports, hazard analysis reports, incident investigation reports, *etc.* The Regulatory agency data includes safety data and requirements pertaining to hazardous process materials and operations from the Department of Transportation (DoT), US Occupational Safety and Health Administration (OSHA), United States Environmental Protection Agency (USEPA) and similar agencies in other countries. Industry consortium data includes and not limited to data from American Petroleum Institute (API), Oil and Gas Producers Association (OGP), *etc.*

Figure 1.3 presents four different types of data-sets, static (remains fixed for a considerable

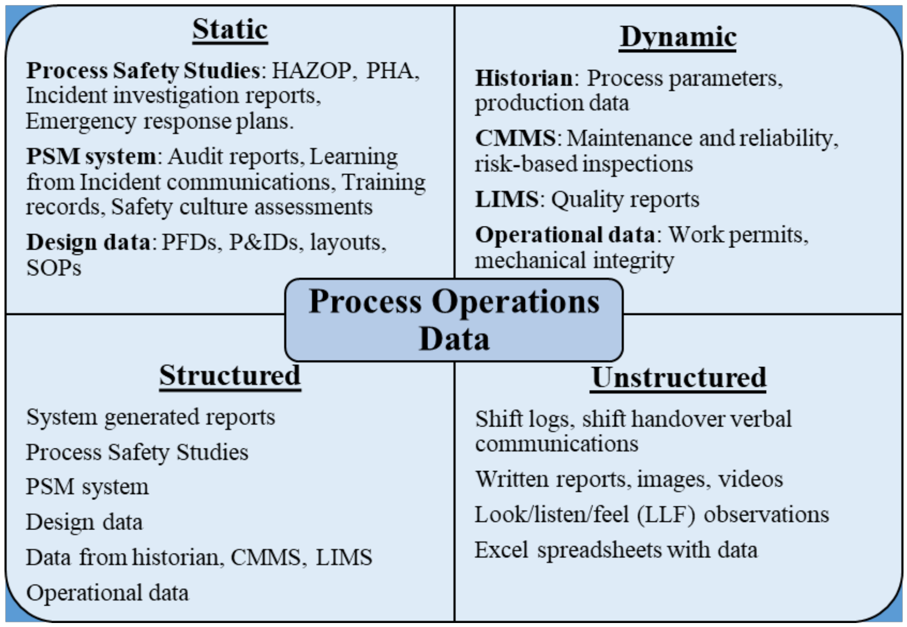


Figure 1.3: Process operations data and classification

amount of time), dynamic (changes with time within every few seconds, minutes, or in some cases in hours), structured (follows a pre-defined structure), and unstructured (no pre-defined structure). In some cases, there is an overlap or multiple attributes associated with the data-type. As industry operations are adopting digital solutions, the amount of data we collect has grown significantly. Approximately 80% of the data we generate from these sources is unstructured and requires additional processing and analyzing efforts to derive the results. Hence, in the current scenario, the challenge is to develop application/solutions to process and analyze the data. Data analytics is vital for inferring the information from the data and is defined as *a systematic application of an analytical process.* While implementing a data analytics solution, the real challenge is to identify the business requirements which includes identifying the needs for storage, processing, analyzing, and presenting the data. The overall process involves the ingestion of data through the presentation of the information. In some organizations, the challenges lie in ingesting a large amount of data, processing of large amount of data to produce insights, and in some cases analyzing the enormous data.

1.3 Data analytics Framework for industry

Figure 1.4 highlights the vision for this work in the process plant operations. As part of data integration, the data from various sources is ingested and combined together into a master database in the form of data warehouse (*a centralized repository of structured data for business reporting and analysis*) or data lakes (*a centralized repository to store data at any scale*). The sources for this data include on-premises databases, files, and some streaming data from various other sites/resources. An application domain selection includes selecting the application domain to perform data analytics and derive a solution. The last part is the application, which includes processing, calculating actionable insights, and disseminating the information to the end-users to assist in decision-making.

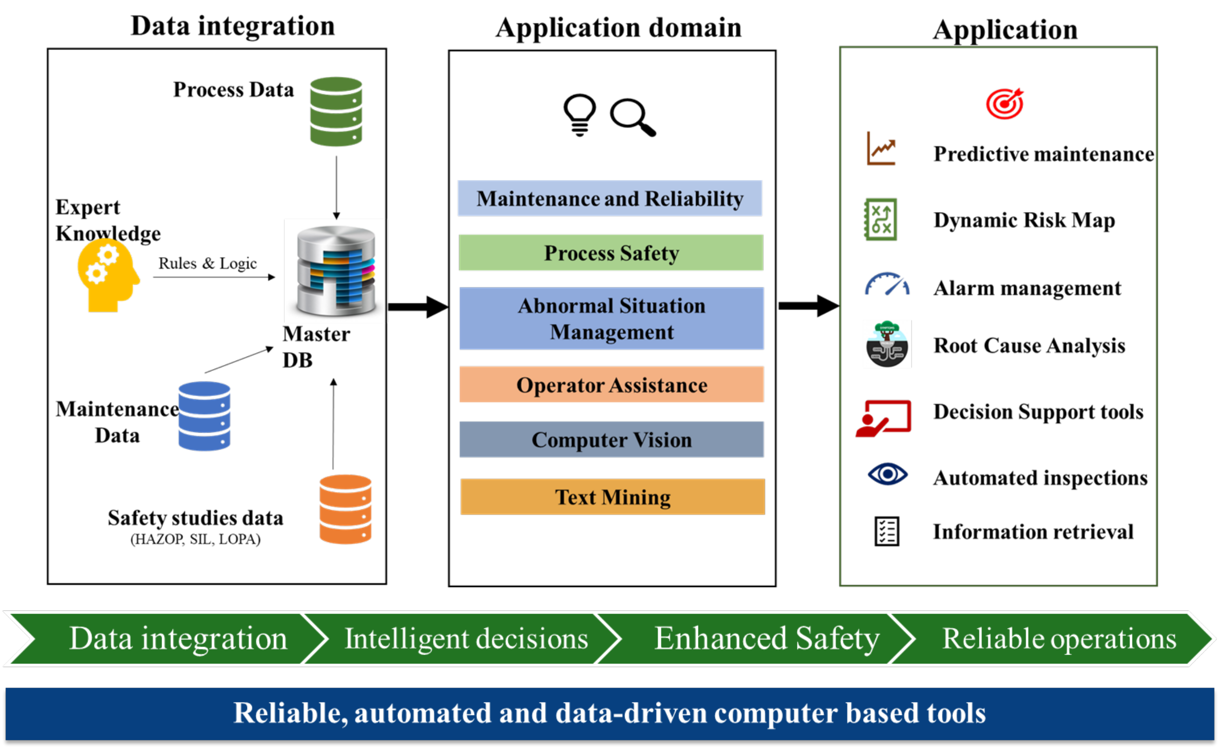


Figure 1.4: Data analytics framework

Such application methods assist users in making intelligent decisions to solve the real-world problems. The results help in enhanced safety and reliable operations of the unit. Considering the importance of data analytics in the process industry for decision making, the entire analytics process can be defined by a systems approach with six key stages as shown in Figure 1.5. It is important to note that the analytics process can start and stop at any stage. Moreover, the tasks can be addressed in multiple stages at the same time. The main stages of this life-cycle include:

1. Discovery: define goals and plans to achieve the goals, in other words, define the business requirement.

2. Data Preparation: define data requirements, implement methods involving collection, processing, and cleaning of data.

3. Model planning: perform exploratory analysis on data collected in step 2, which may include transforming data (eliminating noise, removal of dirty data, reducing skewness *etc.*), aggregation, integration, and data scrubbing.

4. Model building: identify the best model for the data and execute the model to ensure the model fits the data.

5. Results dissemination: communicate (within the organization) or publish (to outside entities) the results.

6. Operationalization: implement the solution in a live operational environment, monitor results and update any stage actions to get desired results.

The aim of implementing the data analytics life-cycle is to derive information to assist decision makers in various application domains. The information derived can be classified into four phases. (1) Descriptive analytics to determine what is happening by converting the data into visually interpreted information (histograms / charts / graphs) and classify the problem; (2) Diagnostic analytics to understand the cause of an event; (3) Predictive analytics to analyze the existing data set to predict the future based on data models; (4) Prescriptive analytics to analyze data and provide near real-time information to the user and assist in decision making. The complexity level of

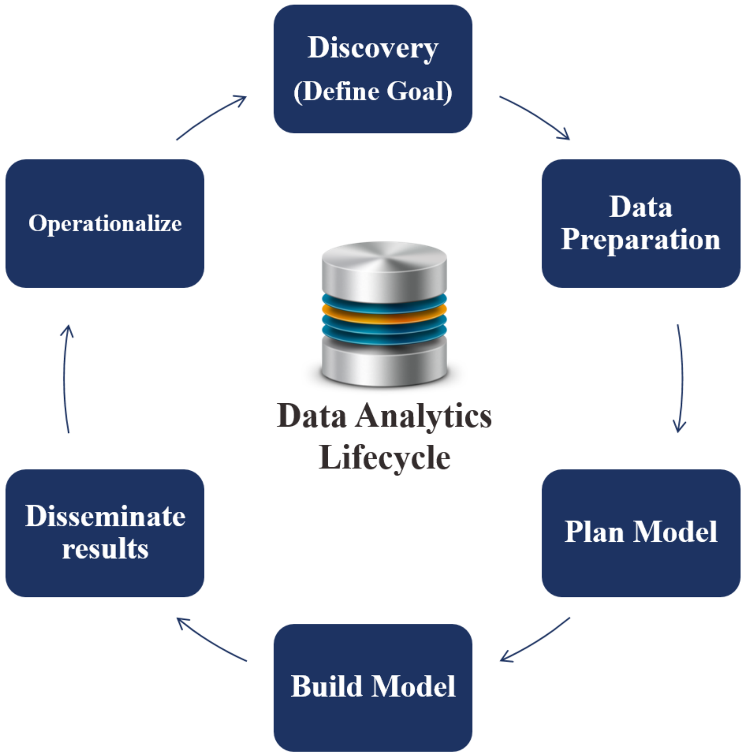


Figure 1.5: Data analytics life cycle

design, analysis and implementation and impact of the application rises at each phase of analytics application. The integration of expert knowledge with data is an integral requirement to ensure the results are addressing a real situation and helps the business needs. On the other hand, shiny new possibilities should not be adopted without reserve. In existing processes, management of change is required to investigate whether an item or provision will function well under all circumstances. This should include quality of system ergonomics, or in other words good interaction between human and machine.

1.4 Research objectives

The underlying theme of this work is in accordance with the statement: "From uncertainty how process risks can materialize to more organization resilience through better information from data". Our objective is to highlight the potential of big data analytics, machine learning, and AI methods in the area of plant operation, maintenance, process safety and risk management in the energy industry.

Traditionally the data in the process industry is 'big' and the industry is data rich and information poor. Recent evidence suggests that there is a potential opportunity to access the available data and enable users in accessing data and using it. The big data for the energy industry* requires: (1) Hardware infrastructure (smart sensors, actuators, storage, network, and computing systems), (2) Data processing and management (extraction, cleaning, normalizing, integrating and storage), (3) Analytics, and (4) Decision support. The disruptive computing hardware and methods including advanced data storage and processing, Machine Learning (ML), AI, data analytics, Natural Language Processing (NLP) are serving as a key enabler and boosting the performance of operations, economy, and businesses.

The objectives of this work are divided into three different application areas:

1. **Alarm management for industrial facilities** *(Covered in chapter 2)*
   (a) To address the challenges of alarm management and develop a framework for alarm management for industrial applications
   (b) To develop a data-driven alarm and event management method to benchmark the alarm system Key Performance Indicators (KPIs)
   (c) To validate the proposed method by evaluating alarm and event logs from an industrial facility and present insights to the user about improving the alarm management system as prescribed in standards and guidelines
2. **Process Fault detection and diagnosis for industrial processes** *(Covered in chapter 3)*
   (a) To develop a data-driven fault detection and diagnosis workflow to identify faulty process conditions
   (b) To validate the proposed method on a continuous process industrial data set

*Energy industry includes oil & gas industry, petroleum refining, chemical manufacturing, and power & utility generation.

3. **Advanced applications in process safety and risk management** *(Covered in chapter 4)*

    (a) To identify mechanical equipment failure proactively using data collected from sensors to reduce unwanted failures and maintenance costs (predictive maintenance monitoring)

    (b) To develop a layered approach based integrated dynamic risk mapping tool to highlight live risk of an operating facility (real-time risk profiles)

    (c) To develop a methodology to automate the process of incident database analysis

    (d) To develop methodology to automate the process of incident database classification based on Natural Language Processing (NLP)

1.5 Key Contributions

The key contributions of this work are:

1. A novel framework to categorize the process of the alarm management system in an industrial facility (design, rationalize, advance and intelligent). This framework can help end-users categorize their alarm management program. The framework follows a life-cycle approach, which includes bench-marking the alarm system and follows the re-design and re-rationalize steps if required.

2. An integrated method to calculate Key Performance Indicators (KPIs) and generate visualization plots. This provides an overall better approach to analyze the Alarm and Event logs and disseminate information to the user to take corrective actions to improve the overall alarm management program.

3. A novel data-driven workflow to integrate big data analysis, deep learning-based BiLSTM on a cloud platform, and reporting for process fault detection and classification. An automated hyper-parameter optimization method is used to identify the optimal hyper-parameters for a given data and designed network.

4. A data analytics and deep learning-based equipment failure prediction model to predict and classify the equipment failure proactively before an actual failure and help users save money and time in equipment maintenance.

5. A novel layered approach based dynamic risk mapping tool to integrate data from various resources in an operating facility and highlights the real-time risk profiles to assist users in making informed decisions.

6. An NLP based event classification based method to learn the patterns from the unstructured text generated in the form of reports and classify specific incidents based on the information provided by the user.

7. The proposed frameworks, workflows, and methods are developed on open-source software platforms (Python and R) which are cloud-ready. The cloud application enables users with the required computing power, scalability and flexibility of model design and application to improve overall decision making.

2. ALARM MANAGEMENT CHALLENGES, PROPOSED FRAMEWORK, AND APPLICATION EXAMPLE

Alarm systems play a crucial role in operating a process in the safer region and serve as a layer of protection in preventing the escalation of a process upset to an abnormal situation. *"An alarm is an audible and/or visible means of indicating to the operator an equipment malfunction, process deviation, or abnormal condition requiring a response"*[16]. In a recently published study [17], 76% of the respondents mentioned alarm rate to be an important factor in determining or predicting the process upset events. Alarm systems act as an early detection indicator that alerts the operator about the abnormal process condition [18, 19, 20] or malfunction of equipment in service. Designing an alarm system includes understanding the process, developing a master alarm database, defining operator actions and implementing in process control systems. The process of designing, implementing, understanding and operating systems of alarms is known as alarm management. Industrial process systems are monitored and controlled by sensors and actuators. Due to the ease in configuration techniques available at the software level, most of these sensors are configured as alarms in the control system. This has resulted in a higher number of alarms, poor system performance, additional workload on operators, and in some cases has led to abnormal situations. These situations can further escalate to catastrophic incidents, if not managed properly [21].

Alarm flooding is one of the causes due to which critical process alarms are being overlooked or judgmental errors being made by the operator. This results in losses for the operating company which may include both direct losses such as production loss, equipment damage or indirect losses such as reputation, fines,*etc.* which are sometimes humongous. Hence, there is a critical need to design and develop techniques to manage the alarm flooding challenges using the process information and alarm and event data. Both academia and industry have made efforts in addressing

---

*Reprinted with the permission from "Industrial alarm systems: Challenges and opportunities" by Goel et al., 2017. *Journal of Loss Prevention in the Process Industries*, 50, 23-36, Copyright 2017 by Elsevier.

†Reprinted with the permission from "A data-driven alarm and event management framework." by Goel et al., 2019. *Journal of Loss Prevention in the Process Industries*, 103959, Copyright 2019 by Elsevier.

the issues of reducing alarm flooding and operator work-load, enhance alarm design and effective alarm management strategies. The literature survey shows there are several methods derived in the past related to developing tools for operator assistance [22], methods for alarm shelving [23], co-relation analysis [24], finding redundant alarms [25], alarm flood classification [26, 27, 28], similarity analysis [29, 30, 31, 32], visualization [33], pre-processing of alarm data [34], pattern mining and detection of alarm flood sequence [35, 36], integrating process data into alarm analysis with the help of a tool developed in matlab [37]. A detailed list can be found in [19, 38].

From the discussion above, we can conclude that there are very few integrated tools/solutions available to address the issues related to alarm management based on analyzing the alarm and event logs generated from the control system. In this chapter we highlight the details of alarm system management, existing regulations, standards and guidelines, and challenges related to alarm management. In addition, some of the open research problems in the area of effective alarm management are highlighted. To address these, an alarm management framework is proposed, that integrates the alarm management life-cycle concept provided in ANSI/ISA-18.2 with data mining and analysis methods applied on alarm and event logs generated from a control system.

2.1 Alarm Management

Alarm management collectively refers to the process of understanding, designing, implementing and operating a system of alarms. According to the International Society of Automation (ISA) "*Alarm management is the set of processes that ensures an effective alarm system.*" The alarm system notifies operators about abnormal processes, conditions or malfunctions of the plant equipment [39]. Alarm systems serve as the backbone for ensuring the safe operation of a facility and meeting its production targets. Alarms also play an important role in ensuring the safety of the plant, and act as a layer of protection [40, 41], (a means of risk reduction) to prevent the escalation of an abnormal event to possibly catastrophic levels [1]. Figure 2.1 (adopted from [1] shows the different 'Layers of Protection' associated with a typical industrial process. A properly functioning alarm in addition to timely intervention by an operator can go a long way towards averting an

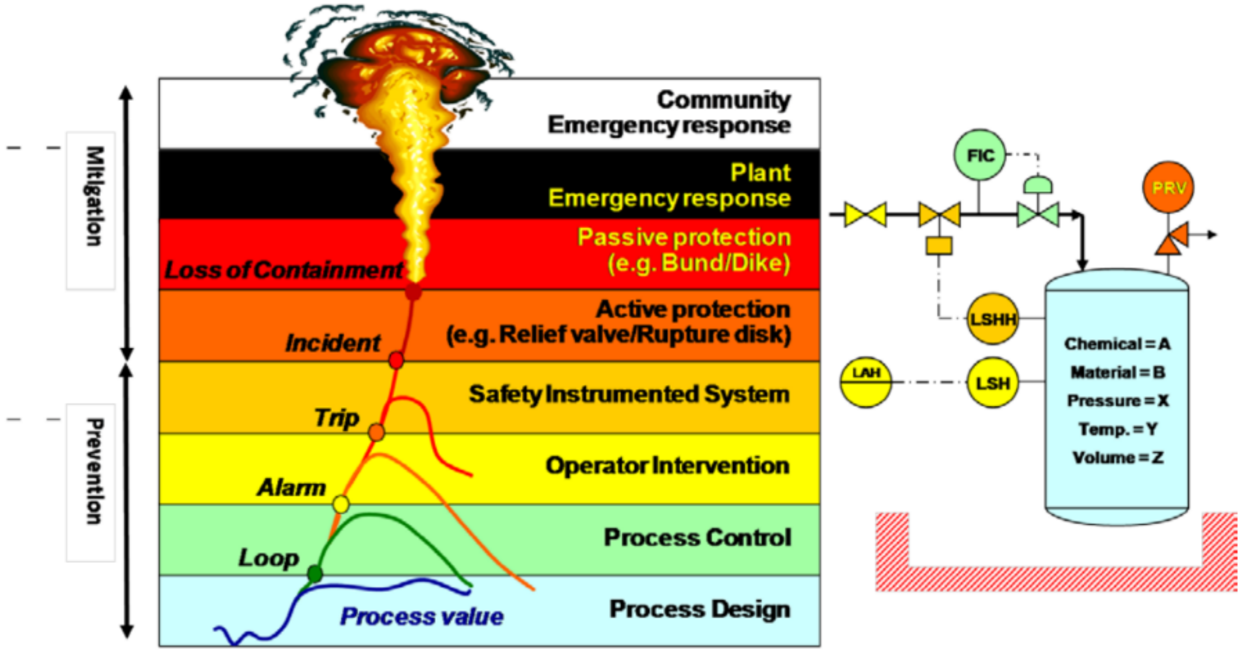


Figure 2.1: Layers of protection [1]

abnormal situation. When such intervention is delayed, the situation can escalate leading to plant shutdown, production loss or, in some cases, minimal or catastrophic incidents.

In a typical industrial setting, the information related to the alarms is communicated to the operator via a Human Machine Interface (HMI) or an Annunciator Panel. Systems such as alarm loggers or historians are used to create and save the data related to the alarms for future evaluations. A good alarm management program can help in operating the process closer to its optimal operating point resulting in lower production costs, higher quality, higher throughput and eventually safer operations. On the other hand , poor alarm management leads to downtime, unsafe situations and can also lead to industrial incidents as evident from past historical records [42]. For instance, during the investigation of the Milford Haven refinery explosion [43] , the Health and Safety Executive (HSE) found that the major causes of the incident were generation of too many alarms, poor prioritization, poor control room display design and alarm flood (275 alarms in 11 minutes) prior to the explosion [44, 45]. In another incident, BP Texas City [46] the major causes were the failure of key alarms to warn operators about the unsafe conditions in the tower and the nearby blowdown drum which led to an explosion and fire, killing 15 people and injuring 180. Some of the major incidents in the past that can be traced back to alarm management issues are listed in Table 2.1. Clearly, the entries in this table highlight the link between poor alarm management and process safety incidents. One can reasonably infer that an effective and robust alarm system would lead to better Process Safety Management (PSM) at manufacturing plant facilities. On the other hand, a poor alarm system reduces the overall ability of an operator to act on critical alarms during abnormal situations [47, 48].

2.2 Evolution of the area of alarm management

During the early developmental stages of the control systems associated with chemical and petroleum industries, wall-mounted process indicators, lamps, switches, and recorders were used to monitor, control and record process parameters. A rectangular array with slotted, labeled windows also known as a "lightbox" was used to indicate alarm occurrence to the operator with a flashing light (visual signal) and a horn (audio signal) [49]. Due to the limited space capacity of the panel and the hardware availability, the designers were able to configure only a limited number of alarms. With the advances in modern control, Distributed Control Systems (DCS) and Supervisory Control and Data Acquisition (SCADA) were introduced. These systems facilitated simplified reconfiguration, ease of operation and maintenance for current alarms as compared to their predecessors. Computerized scrolling lists and graphics screens associated with these systems essentially eliminated the earlier space constraints. Alarm system configuration became easier as it could be now achieved with just a few clicks as opposed to having to deal with hardware walls. Limited guidelines, simplified processes for configuring alarms, engineering and organizational work processes followed during the alarm system design and maintenance activities resulted in a larger number of configured alarms in a system contributing to the possibility of alarm floods [50, 51]. Additionally, alarms started being used as a tool to indicate system status instead of being used solely to detect abnormal situations.

A direct consequence of this was that even during the normal steady state operation, the operator would be exposed to various alarms, and sometimes too many to comprehend and act upon. During an abnormal situation, some of these status monitoring systems can become useless distractions and pose hindrance for an operator trying to promptly deal with the situation. Indeed, many of the incident investigation reports [43, 46] have highlighted scenarios of overloaded, bypassed or ignored alarms as one of the root causes for the incidents. It is also well documented that an ineffective alarm system can worsen an ordinary process upset which could lead to high financial and property losses for the organization involved.

Table 2.1: Incident list related to alarm management issues

List of incidents related to Alarm management issues						
Incident Detail				**Consequence**		
S. no.	**Incident**	**Year**	**Root cause related to alarms**	**Effect**	**Injuries | Fatalities**	**Financial Loss reported**
1	Three Mile Island	1979	Operator were loaded with numerous alarms, Several key alarms were misleading	Radioactive material released	0 | 0	$ 1-2 billion
2	Piper Alpha Oil rig	1988	Inadequate shift handovers, Issues with false alarms	Fire	0 | 167	$ 3.4 billion
3	Texaco Milford Haven refinery, UK	1994	Poorly prioritized alarms & design of displays, alarm flood	Explosion	26 | 0	£48 million
4	Channel tunnel fire, UK	1996	Rail control centers were flooded with alarms	Fire	0 | 0	£200 million
5	Tosco Avon Accident, Martinez. California	1997	No alarm on temperature indication and control system with high priority alarms	Auto-ignition of flammable hydrocarbon and hydrogen	46 | 1	Unknown
6	Longford gas explosion, Australia	1998	Inappropriate response for critical alarms	Fire and explosion	8 | 2	Unknown
7	Grangemouth refinery Scotland	2000	Significant alarm floods	Steam leakage	0 | 0	Unknown
8	First chemical corporation, Pascagoula Mississippi	2002	No action taken for alarm, System was not protected with enough layers of protection including alarms, safety interlocks and over pressure protection	Steam leakage	3 | 0	Unknown
9	BP Texas refinery incident	2005	Failed management of instruments and alarms	Fire and explosion	180 | 15	$1.5 billion
10	Bunce field oil storage, Hemel, Hemstead	2005	Shortcomings in design, provision and operation of the protection alarms and shutdown systems	Fire and explosion	40 | 0	£700 million
11	Kalamazoo River oil spill	2010	Numerous alarms from the affected Line 6B, but controllers thought the alarms were from phase separation, and the leak was not reported	Crude oil leakage into environment and nearby creek	326 | 0	$782.9 million
12	Columbia gas transmission corporation pipeline rupture Sissonville, West Virginia	2012	Controller didn't recognize the alert of leak	Explosion	0 | 0	$8.69 million

With the advances in automation, software and technology, the industrial facilities of today are becoming increasingly integrated. The number of devices in a plant monitoring and control system has increased dramatically over the past few decades. An increase in the number of devices has in turn led to an increase in the amount of data that the operator must assess and act upon as can be seen in Figure 2.2. This has not only increased the overall complexity of the plant but it also puts additional demands on the human operator. This becomes all the more challenging because the critical actions have to be taken within minutes to avoid an abnormal situation ("a plant operation deviates from its normal operating state"). During upsets, these systems affect the operators adversely and require a higher degree of response to monitor alarm systems and operate the process. These upsets sometimes result in alarm floods, which in turn can lead to incidents if not handled properly [52].

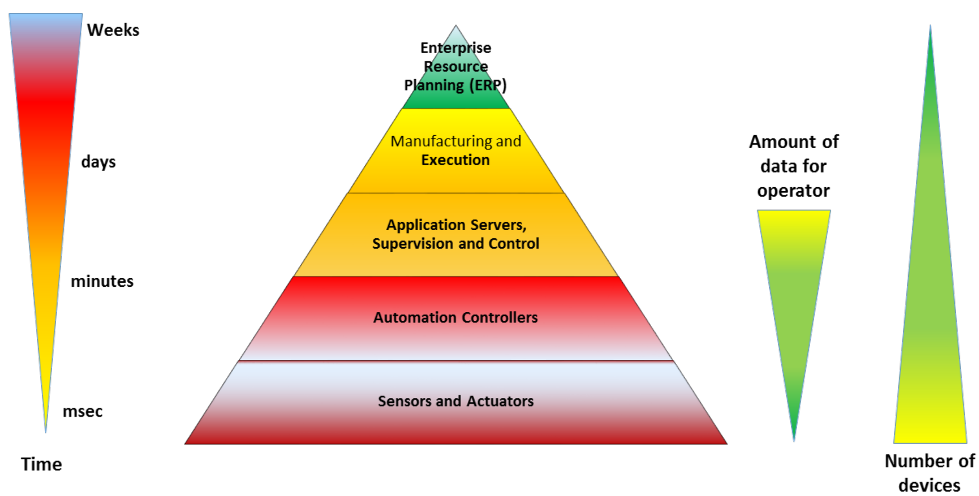


Figure 2.2: Automation pyramid

Before talking about alarm flooding and its consequences, it would be appropriate to nail down this concept using some quantifiable measures. Towards this end various authors have described an alarm flood situation as one where several hundreds of alarms appear on the screen within minutes of the upset condition and the appearance of these alarms has an adverse cascading effect on the complete plant operation [53, 54, 55]. Other researchers have also defined alarm flooding as a problem resulting from the inability of operators to take prompt actions mandated by the alarms appearing on the screen [56]. Ineffective operator alarm response during alarm flooding can have a significant impact on safety operations [57, 58] . Wilson [59] explained how the effect of high alarm load and high nuisance alarm can adversely affect the operator action and 50% of the operators surveyed indicated that the alarms during process upset were appearing too fast to handle. A human performance modeling study conducted by researchers [60] has also highlighted that operators can effectively handle an alarm rate of at most 11 alarms per ten minutes. A similar benchmark of 10 alarms per 10 minutes has been established in Engineering Equipment and Materials Users Association [44] guidelines.

According to a study conducted by [61] for a total of 15 facilities (4 oil refineries, 6 chemical plants, 1 pharmaceutical plant, 1 gas terminal and 3 power stations), with sizes ranging from medium (£50 million) to large (£500 million) facilities, the number of alarms installed were significantly high with a minimum of 500 alarms and a maximum of 10,470 alerts plus 4700 alarms. During normal operation, the alarms reported were in the range of 60 to 120 alarms per hour and in some cases, the operator estimate was as high as 200 alarms per hour. During upset conditions, the alarm load on the operators was in the range of approximately 390 to 3750 alarms per hour. In another study by Matrikon and published by Rothenberg [62] as shown in Table 2.2, the number of alarms appearing in various industries was significantly high as compared to the benchmarks given in the EEMUA guidelines. These studies have also highlighted and emphasized the need for proper alarm management.

Table 2.2: Cross-industry activation study

	EEMUA	**Oil&Gas**	**Petrochem**	**Power**	**Other**
Average alarms per day	144	1200	1500	2000	900
Average standing alarms	9	50 100	65	35	
Peak alarms per 10 min	10	220	180	350	180
Average alarms per 10 min	1	6	9	8	5
Distribution % (Low/Med/High)	80/15/5	25/40/35	25/40/35	25/40/35	25/40/35

To improve the overall alarm system, various methodologies have been introduced and implemented industry wide. These include alarm rationalization, alarm configuration procedure and practices, and design & maintenance methodologies [63, 64]. Although these methods have had a significant effect on reducing alarm floods, they have not succeeded in eliminating them completely [53, 65].

The various incidents listed in Table 2.1 make it clear that alarm processing techniques and presentation are in need of improvement. The industry has already made some improvements in this area by developing and publishing certain guidelines and standards to be followed while designing and managing alarm systems during the plant life cycle. The evolution of these documents is shown in the timeline in Figure 2.3. The guidelines and standards mentioned in Figure 2.3 have been compiled and developed with the help of various stakeholders and experts from industry from all over the world which makes them comprehensive, consistent and widely accepted. It is pertinent to note that these documents provide a set of guidelines or instructions to the user on the design of alarm systems with certain key performance indicators (KPI's) (discussed in detail in Section 2.7.2) against which all alarm systems are required to be benchmarked. However, these documents do not provide any detailed technical methodologies or steps to be followed to achieve these requirements. Therefore, there is a critical need for developing such techniques for effective and efficient alarm management.

2.3 Alarm systems and Current status

By definition, "*an alarm system is the collection of hardware and software that detects an alarm state, communicates the indication of that state to the operators, and records changes in the alarm state*" and an alarm is "*an audible and/or visible means of indicating to the operator an equipment malfunction, process deviation, or abnormal condition requiring a response*." [16].

According to the Engineering Equipment and Materials Users Association (EEMUA, 2013), the basic characteristics of an alarm are (refer to Figure 2.4):

1. **Uniqueness:** each alarm should indicate a unique process parameter; no duplicate alarm

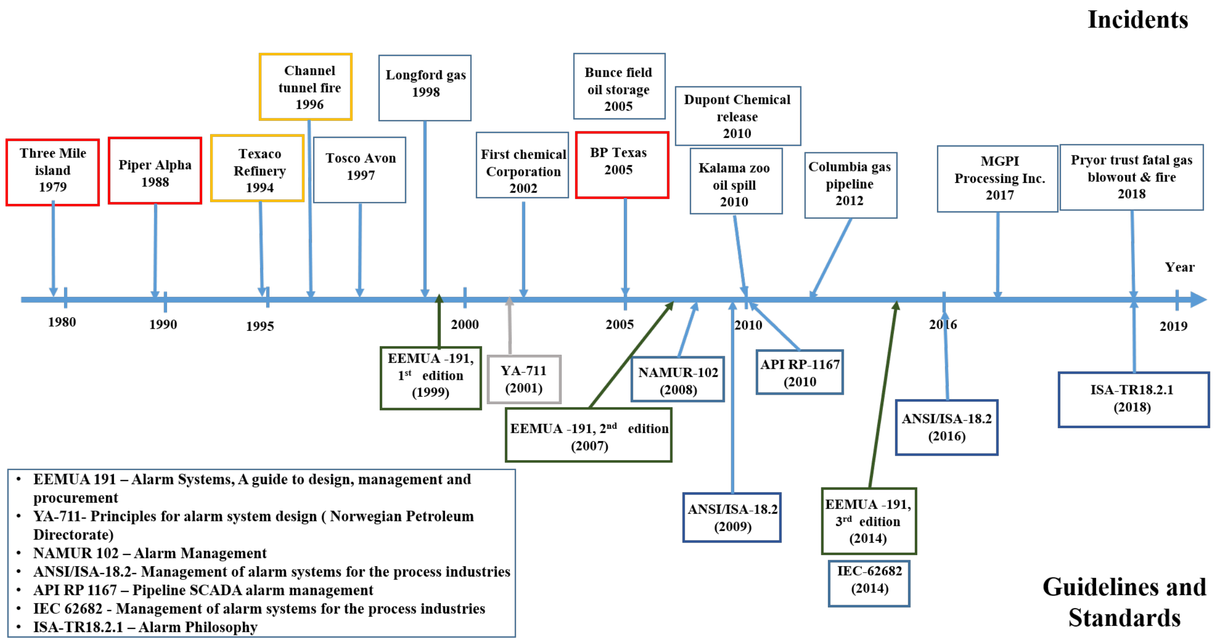


Figure 2.3: Evolution of alarm management

should be designed or defined in the control system

2. **Prioritization:** each alarm should be prioritized in such a way that the operator can clearly ascertain the criticality level of the alarm and respond accordingly

3. **Timeliness:** each alarm needs to appear on time; designing an alarm that appears too early or too late may have adverse consequences on the process operation and the operator response

4. **Understandability:** the alarm should have a suitable description which is easy to understand and use for diagnosing the triggering problem

5. **Relevance:** the alarm should be relevant to the process being monitored and should also have operational value

6. **Requiring response:** each alarm should require a definitive response from the operator

Alarms have been identified as effective tool for early detection of a process upset [18, 21] and are helpful in identifying the near misses followed by the appropriate actions to bring the process

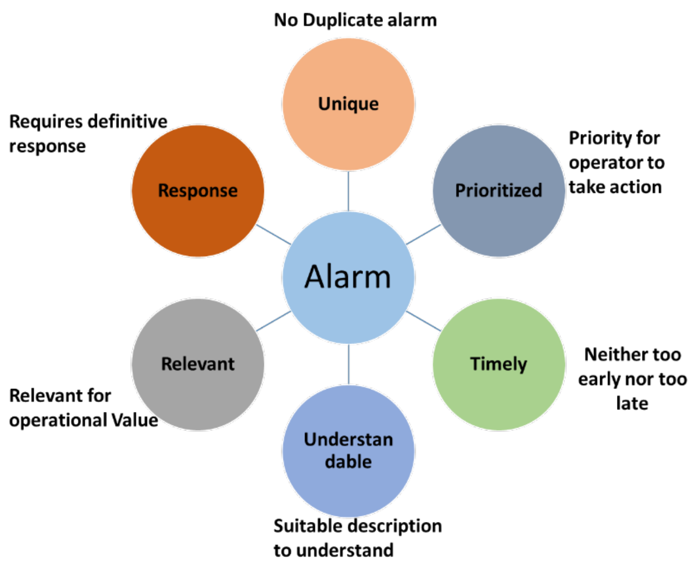


Figure 2.4: Characteristics of an alarm

back to normal operation [66]. Alarm systems are required for the correct, safe and efficient operation of plants and facilities [67]. When a variable moves above or below defined operating limits known as the Emergency Shut down System (ESD) limits; usually far apart from high/low and high-high /low-low alarm thresholds, the ESD system takes over from the DCS and brings process to a safe shutdown state. This is to ensure that the ESD acts as an independent protection system, uninfluenced by a malfunctioning DCS [66].

In a process control system, the alarm is generated by comparing the process variable (PV) value at a specific time with already configured set points (low or high) also known as alarm settings. An electronic circuit is used to actuate an alarm [68]. With a pre-configured priority level, the alarms are displayed in the alarm display window and dynamically stored in the DCS database [53, 69].

Alarms serve as the primary channel of communication between the automated control systems and the operator [70].The automation in an industrial process is used to transport, store and process the data generated into human-usable information. This information is used by the operator to monitor the process and take the required actions as needed. In a plant system, sensors (Resistance temperature detector, (RTD), a pressure detector, gas detector *etc*.), are used to measure the process parameters such as temperature, pressure or concentration of the gas respectively. The output from the sensor (analog or digital) is transmitted through the dedicated cable to the control system (PLC or DCS). These control systems are made up of various electronic circuits, logic and control structures and serve as the brain for the automated control system. The information is processed in the control system and is displayed on an HMI (Human Machine Interface) display. These displays have real-time process monitoring information and process parameters distributed over several screens depending on the size of the plant and the number of process inputs/output parameters. One such screen is the alarm display screen where all the alarms are displayed for the operator to notice and take subsequent corrective action. As shown in Figure 2.5, in the case of an activated alarm state, the operator needs to review the plant information, understand the current plant state, diagnose the problem and decide the sequence of actions before actually carrying them out. In certain cases, additional process display access and information is required before an action can be taken [71]. After the operator's action, the controller transmits the information to the actuator (Control valves, dampers *etc*.) in the field with the goal of setting the actuator variable to a desired value and bringing the process back to the normal state.

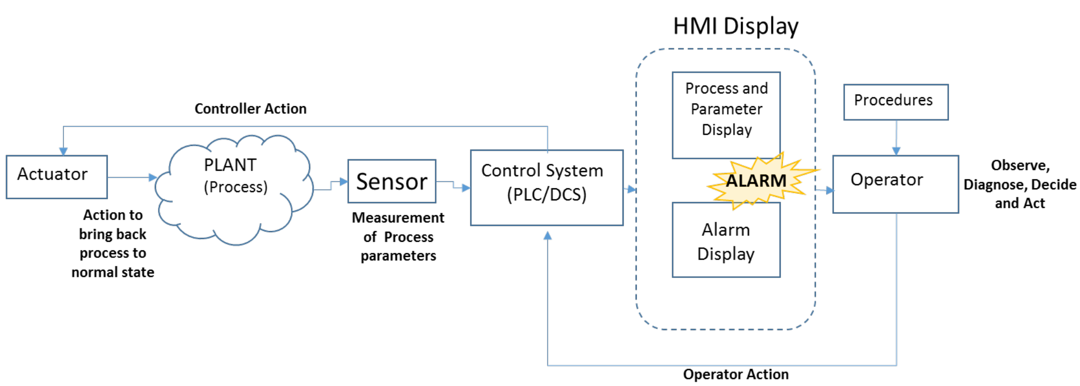


Figure 2.5: Alarm generation loop

Improperly designed alarm systems can escalate an abnormal situation.

1. **Some of the major symptoms associated with an unhealthy/ineffective alarm system are:**

    (a) Inappropriate or No master alarm database;

    (b) No operator action required in an alarm condition;

    (c) No clear guideline /specification for adding or deleting alarms;

    (d) Poor alarm testing procedures and records;

    (e) Operating procedures are not written considering alarms;

    (f) Change in alarm settings during shift changeovers;

    (g) Important alarms are missed during incidents;

    (h) Minor upsets result in a significant number of alarms that the operator cannot keep up with;

    (i) Alarms appear for a considerable amount of time (even 24 hours) or alarms are activated even when there is no upset condition;

    (j) Too many alarms with high priority.

2. **The root cause of these symptoms are:**

    (a) No approved design basis or plant wide/site-wise philosophy and alarm management procedures in place;

    (b) Alarms are constantly added (during Hazard and Operability Study (HAZOP) , Layers of Protection Analysis (LOPA), Process Hazard Analysis (PHA) studies) and rarely deleted;

    (c) Inadequate information in plant procedures and practices;

    (d) Inadequate operator training;

    (e) The alarm system and displays/ HMI's in use lack simplicity;

(f) Incorrect prioritization of alarms;

(g) Alarm limits and priorities are rarely reviewed during the operation of the plant;

(h) Ineffective corrective actions, plant equipment not in service and variations in plant operating conditions

(i) Lack of Management of Change procedures.

2.4 Alarm lifecycle

An alarm lifecycle process includes gathering detailed information about alarms from various sources. These sources include Front End Engineering Design (FEED), Process Hazard Analysis (PHA), historical data from process documents, manufacturer recommendations *etc.* On the basis of these sources, alarm limits and values are decided and instrument selection is done. All these alarm specifications are configured in automated systems such as Distributed control system (DCS), Programmable Logic Controllers (PLC) *etc.* for the monitoring and operation of the manufacturing process. The process information and deviation messages are then routed through computer systems to the operators in the form of process display and alarms. The alarm data is also sometimes recorded in the historian system with time mapping for future reference. To summarize, an alarm is an audio/visual announcement and messages (a buzzer/beep sound or flashing text, background color change or colored text) to the plant operator which is a result of process parameters crossing the safe or desired limit. The appearance of an alarm calls for the operator's attention or action. Once an alarm appears, the operator needs to perform either the action "silence the alarm" or "acknowledge the alarm" and take appropriate action using the Process Control System (PCS), keyboard or screen. ANSI/ ISA18.2 [39] defines the processes and procedures required to create an effective alarm management system. The general principles and processes in ANSI/ISA-18.2 are intended to be used in the life cycle management of an alarm system which is based on a programmable controller and a computer based Human Machine Interface (HMI). These requirements are presented as a standard, using the alarm management lifecycle as summarized in Table 2.3.

2.5 Regulatory approaches towards alarm management

Although using alarm systems is not a direct mandated requirement, nevertheless in Environmental Protection Agency (EPA), Occupational Safety and Health Administration (OSHA), Pipeline and Hazardous Material Safety Administration (PHMSA) and Currently Good Manufacturing Practice (CGMP) documents, one can find specific references to alarms. When alarm systems are used to monitor regulatory compliance values, they need to be managed and configured appropriately. Historically, alarm systems have not been considered during the early phases of the projects. They were usually introduced during the final stages of the project as an addendum to a typical vendor–offered package. In addition, alarms were designed without taking into account the uncertainties that are invariably present in the measurements. These issues have led to a lack of formal testing of the systems and excessive potential for nuisance alarms built into the system, which may cause issues related to safety and environment incidents, product quality and loss [47, 55, 72].

In the United States, OSHA CFR 29 1910 regulations [73] mention certain regulatory requirements specific to process safety and alarm management. Some of these include:

- "Recognized and Generally Accepted Good Engineering Practices" (a regulatory acronym for which is RAGAGEP) (1910.119(d)(3)(ii)),
- Engineering and administrative controls applicable to the hazards and their interrelationships such as appropriate application of detection methodologies to provide early warning of releases (acceptable detection methods might include process monitoring and control instrumentation with alarms and detection hardware such as hydrocarbon sensors) (1910.119(e)(3)(iii)),
- Written procedures (1910.119(d)(3)(ii)), maintenance training to plant personnel (1910.119(j)(3)), inspection and testing (1910.119(j)(4)), and
- Mechanical Integrity program for controls (including monitoring devices and sensors, alarms, and interlocks) (1910.119(j)(1)(v)).

Table 2.3: Summary of alarm management lifecycle

Stage/Phase	**Tasks**	**Inputs required**	**Desired Outputs**
Philosophy	Define Philosophy and requirements for the alarm management	Industry standards and practices, corporate standards and engineering practices	Alarm philosophy and requirement document
Identification	Find and list down potential alarms	Alarm database, Operating ranges/limits, PHA/LOPA reports, P& ID's, Operating procedures and safety specifications	List of all potential alarms for the facility
Rationalization	Alarm classification, prioritization, rationalization and documentation	Alarm philosophy document and list of all potential alarms	Master alarm database with design requirements
Detail design	Alarm design, HMI design	Master alarm database and design requirements	Completed alarm design
Implementation	Alarm testing and training	Completed alarm design and alarm database	Operational alarms and procedures for response to alarms
Operation	General plant operation where operator responds to alarms and plant is running in normal condition	Operational alarms and procedures for response to alarms	Alarm History/data
Maintenance	Inspection and testing	Alarm reports, alarm philosophy and inspection and testing procedures	Alarm reliability data
Monitoring and Assessment	Monitor alarms	Alarm history and alarm philosophy	Alarm monitoring reports and proposed changes
Management Of Change	Process to change, modify and delete alarms	Alarm philosophy and changes proposed	Approval for alarm changes
Audit	Periodic audits for alarm management processes and update philosophy document if required	Standards, audit protocols and alarm philosophy documents	Recommendations

This is further echoed by the EPA in EPA 112 (r) 40CFR 68 Risk Management Plan – Prevention program, Emergency response program and 40 CFR 68.67 (c) (3) and 48 CFR 68.73 (a) (5) respectively.

Also, OSHA has recognized the relevance of alarm management standards and best practices such as ANSI/ISA 18.2 and ANSI/ISA S84.01-1996. Lately, the OSHA Regional PSM Coordinators and Chemical Safety Board (CSB) now have approval to internally distribute ANSI/ISA-18.2 to their inspectors [74]. As an example of this, we refer to, the report of the U.S. Chemical Safety and Hazard Investigation Board about the Methyl Chloride Release (January 22, 2010) in the DuPont Belle plant in West Virginia [75] which found that problems with alarms were a major factor contributing to this incident. As a response to the incident, the US Chemical Safety Board recommends to "Establish and implement a corporate alarm management program as part of the DuPont PSM Program, including measures to prevent nuisance alarms and other malfunctions in those systems" .

Further, the American Petroleum Institute (API) has recently released API RP-1167 [76], Alarm Management Recommended Practices for Pipeline Systems. This API document is in full alignment with ANSI/ISA-18.2, and the Pipeline and Hazardous Materials Safety Administration (PHMSA) generally adopts API recommended practices in their regulatory language.

2.6 Cost benefits of alarm management

In the United Kingdom , the recent Control of Major Accident Hazards (COMAH) regulations [77] published in 2015 by UK Health and Safety Executive (HSE), mentions alarm management in various clauses related to design, prevention and mitigation measures for the plant. The (European Commission) EC Seveso III directive [78, 18] also mentions alarm management but doesn't contain any specific requirements. Hence, for safety critical alarms in Europe, alarm management is required by law [79]. With increased awareness in the area and stringent regulatory requirements, one may not be surprised to see negligence in plant management resulting in citations in the future.

As reported by the Honeywell abnormal situation management group estimates, a petrochemical company with six facilities can have \$ 50 to \$ 100 million annual losses resulting from upsets and abnormal situations. It was also concluded that the net losses due to plant upsets are in the range of 3-5% of the total output of the plant. According to the US National Institute of Standards and Technology (NIST), $ 20 billion of losses result annually due to plant upsets. Another paper [41] implicates poor alarm management as a leading cause of unplanned downtime and approx. $ 20 billion in production losses each year.

A study based on heuristic approaches, financial models and engineering judgment published in Hydrocarbon Processing [80] also discusses the financial payoff from improved alarm management in a 100000-bpd refinery. The annual benefits were calculated under various scenarios such as reduction is abnormal situations ($ 2.88 million), an increase in plant throughput ($ 1.68 million), reduction in avoidance maintenance ($ 1.11 million), and reduction in capital equipment repair ($ 0.22 million). These values are significant as compared to the expenses involved in implementing proper alarm management techniques.

2.7 Challenges in alarm management

During the early stages of evolution of alarm management techniques and procedures, many of the alarm systems were configured and implemented with limited guidance, and hence poor practices were implemented which continued to prevail. This approach has not only made alarm systems unmanageable but has also led to various incidents. A detailed analysis of these events/incidents makes one realize the cost of poor alarm management as highlighted in Table 2.1. With the recent establishment of standards and good engineering practices , and some of the major research work in this area, issues of alarm management have been resolved to make systems safer and more reliable. As a part of this work, the following challenges have been identified as ones that still need to be addressed for developing more advanced and effective AM systems:

2.7.1 Alarm variables and settings

During the era when hardware devices were used to show abnormal situations, only a few critical instruments could be deployed to show alarms and process deviations. This was due to the prohibitively high cost of the instruments and the size of the plant. As the control systems became modernized and computerized, configuring an alarm became increasingly easy. Nimmo [81] highlighted a situation where the number of alarms was increased from 150 (hardware alarms) to 14000 (software) alarms. Hollifield and Habibi [49] also noted a similar increase in one of the plants by mentioning that the increase over a period of 40 years was exponential from 100 to 4000. In another study [82], it was pointed out that with the help of the alarm rationalization methodology, a 50% reduction in the number of configured alarms could be achieved, while simultaneously reducing the nuisance alarms.

During the design of a plant, certain process setting values are provided by the licensor or by the engineering company. These settings are a part of the design documentation of the plant, which is used to configure the process parameters for control loop operation, alarms, trips *etc.* in a control system. Over a period of time, such settings may change due to changes in the process, equipment or other related factors. In some cases, the plant operation and maintenance teams make some changes to the settings without proper documentation, which could result in confusion at a future point in time. Hence, from time to time verification of all such settings should be carried out to ensure proper functioning of the alarm system. Another general practice usually followed during engineering is the configuration of multiple sensor alarms for a single process variable. In this case, all the sensors (required by process design safety considerations) are configured for the same setting. When an alarm appears, multiple alarms for the same process value will appear on the screen. This results in an increase in the number of alarms, and imposes an additional burden on the operator as he or she tries to diagnose and respond to the problem. A better way would be to have a common alarm configured for multiple sensors used for same fault (voting logic 1oo2 or 2oo3) by negating any fault of the sensor (such as BAD PV: Bad Process Variable) while applying the voting logic.

2.7.2 Key performance indicators (KPIs) bench-marking and alarm flooding

Key performance indicators are used in defining the performance level of an alarm system. The KPIs relate to basic usability metrics and benchmarking as defined in EEMUA 191 guidelines and ANSI/ISA 18.2 standard. These KPIs are defined over a period of time. These KPIs are used to measure features of the system against some pre-determined goals. Table 2.10 presents various KPIs as defined in the guidelines and standards. The values indicated should be the target KPIs for a plant. Initially, these target values may appear somewhat demanding, but they are achievable over a period of time. It is important to have a system of continuous improvement (Plan-Do-Check-Act, PDCA cycle) similar in nature to the Quality Management system to achieve these targets.

One of the main causes behind not meeting these KPI specifications is 'alarm flooding'. During complete alarm system management, alarm flooding is one of the major challenges that has to be overcome. The phenomenon of alarm flooding can occur due to several different causes such as improper engineering and work processes [51], incorrect configurations of alarm variables, problems in wiring connections of instruments, chattering and standing alarms, too many alarms configured for a single equipment or too many process parameters. We next provide some formal definitions of alarm flooding.

"*Alarm flooding is a condition during which the alarm rate is greater than what the operator can effectively manage (e.g. more than 10 alarms per 10 minutes)*" [44, 62, 49]. According to the ASM consortium, "*Alarm flooding is the phenomenon of presenting more alarms in a given period of time than a human operator can effectively respond to*" .

Alarm flooding results in additional workload on the operator and increases the likelihood of a critical alarm being missed [83, 84, 54]. The main reasons for alarm flooding are:

1. **Standing alarms:** alarms which remain in the alarm state for a long period of time. About 6% of them correspond to an actual plant problem [61, 85]

2. **Chattering alarms:** alarms which come on, then go off and come on again during a small period of time (*e.g.* 1 min). Chattering alarms are also defined as alarms which repeatedly toggle between the normal and activated states within a short period of time [39]. Chattering alarms, which are also known as cyclic alarms, are one of the major causes of nuisance alarms [84, 86] which account for almost 60% of the alarms in some cases [62]. Due to the presence of such a chattering alarm, the operator may not have enough time to detect, diagnose and take appropriate action. Some of the main causes of chattering alarms are:

(a) Noise/disturbances acting on the process variables [44]; and

(b) Repeated on-off actions of the control loop.

3. **Fleeting and/or momentary alarms:** alarms which turn on and off very quickly, but do not necessarily repeat [39].

4. **Repeating alarms:** alarms rising and clearing repeatedly over a period of time [44].

5. **Stale alarms:** "alarms which go into an activated state and do not return to the normal state for at least 24 hours" [16].

As mentioned in Section 1, alarm flooding has led to incidents which were caused because of important alarms being overlooked or judgmental errors being made. The direct and indirect losses due to such incidents are sometimes very huge. Hence, there is a critical need to come up with detailed procedures and techniques to deal with alarm flooding issues. Table 2.4 summarizes the efforts by several researchers to reduce alarm flooding and operator workload, and enhance alarm design, effective alarm management and its overall beneficial effect on process operations.

Table 2.4: Summary of research efforts to reduce alarm flooding and operator workload, and effective alarm management

Reference	Objective	Method/Result
(Carrera & Easter, 1991) [87]	Eliminate alarm flooding in power plants	Designed a system named 'AWARE' to assist the operator and provide action guidance
(Burnell & Dicken, 1997) [84]	Reduce operator workload in alarm conditions	Introduced techniques of auto-shelving and display shelving of repeating alarms
(Brooks, Thorpe, & Wilson, 2004) [88]	Clear an alarm during operations	Proposed an algorithm to identify the changes required for a process variable using historical data
(Hugo, 2009) [89]	Reduce alarm chattering	Proposed a method based on time series analysis to determine measurement and time alarm dead bands

Table 2.4 Continued

Reference	Objective	Method/Result
(Higuchi, Yamamoto, Takai, Noda, & Nishitani, 2009) [90]	Reduce the number of alarms	Used event correlation analysis technique to reduce the number of alarms
(Kondaveeti, Izadi, Shah, & Chen, 2011) [91]	Reduce chattering and nuisance alarms	Explained effective use of delay timers and latches to reduce such problems
(Arjomandi & Salahshoor, 2011) [92]	Alarm management	Introduced a state based approach based on different operational states for alarm management in a software framework
(Ahmed, Gabbar, Chang, & Khan, 2011; Dalapatu, Ahmed, & Khan, 2013) [93, 94]	Reduce number of alarms	Provided a methodology to group alarms on the basis of variable types, plant unit, correlations *etc.* by following a risk-based approach
(Folmer & Vogel-Heuser, 2012) [95]	Find redundant alarms	Developed an automatic analysis hybrid method based on finite automata
(Adnan, Cheng, Izadi, & Chen, 2013) [96]	Delay timer for alarms	Introduced generalized delay timer for triggering of alarm
(Adnan & Izadi, 2013) [97]	Delay timer for alarms	Studied the effect of filtering on delay of an alarm
(Butters, Guttel, Shapiro, & Sharpe, 2014) [98]	Find redundant alarms	Proposed a method based on statistical cluster analysis to identify redundant alarms in a system.
(Ahmed, Dalpatadu, & Khan, 2014) [94]	Assist operator during critical events	Used Bayesian network and inference event based methodology to calculate the probability of an event and used risk priority basis to assist operators to focus on critical events.

Table 2.4 Continued

Reference	Objective	Method/Result
(Cai, Zhang, Hu, Yi, & Wang, 2015) [99]	Find root causes of an alarm and reduce false/redundant alarms	Introduced a multi-round alarm management system (MRAMS) which is used to improve the diagnosis of root causes of an alarm and reduce false and redundant alarms.
(Lai & Chen, 2015) [100]	Predict root causes and locate bad designs	Developed an algorithm to find correlation between alarms during alarm flood and predict root causes, locate bad designs and predict future alarm floods
(Jia Wang, Li, Huang, & Su, 2015) [29]	Identification of consequential alarms	Identified the consequential alarms on the basis of data similarity analysis and process data causality analysis.
(Ahmed et al., 2011; Dalpatadu, Ahmed, & Khan, 2015) [93, 101]	Alarm annunciation	Introduced a Bayesian network event-based alarm system method for alarm annunciation.
(Zeng, Tan, & Zhou, 2016) [102]	Compute expected dead band and delay timers for an alarm	Proposed a method based on Markov-chain to compute the expected dead band and delay timers
(Zhu, Wang, Li, Gao, & Zhao, 2016) [103]	Predict alarm occurrence	Proposed a probabilistic model base n-gram model to predict the probability of an alarm using data stored in the DCS
(Rodrigo, Chioua, Hagglund, & Hollender, 2016) [104]	Alarm flood reduction	Determined the causal alarms of an alarm flood by analyzing alarm log, historical process data and performing process connectivity analysis

Table 2.4 Continued

Reference	Objective	Method/Result
(Chen & Wang, 2017) [105]	Multivariate alarm system to detect abnormal condition in process variable	Used adaptive time gradient (ATG) approach to find variations in the process variables
(Tan, Sun, Azad, & Chen, 2017) [106]	Univariate alarm system design	Rank order filter method proposed for calculating false alarm rate (FAR), missed alarm rate (MAR) and expected detection delay (EDD) for an alarm system design
(Jiandong Wang, Yang, Chen, & Zhou, 2017) [107]	Detect and remove nuisance alarms	Developed a method to detect, reduce nuisance alarms and designed delay timers for nuisance alarm caused by noises and disturbance
(Hu, Wang, Chen, & Shah, 2017)[108]	Cause and effect relationship among alarm variables	Developed a method based on transfer entropies with considering random occurrence delays and mutual independence of alarms
(Yu, Zhu, Wang, & Zhao, 2017) [109]	Abnormal data detection for multivariate alarm systems	Proposed a method to detect abnormal data from historical data by determining key turning points with spearman's rank correlation coefficients
(Hu, Chen, & Shah, 2017) [110]	Association rules for mode-dependent alarms	Proposed an automated data-driven method to find association rules between alarms by using alarm and event logs

2.7.3 Human Machine Interface (HMI) design

A display monitor also known as a Human Machine Interface (HMI) is used to monitor and change control process parameters and to take appropriate actions in order to manage the process. It is a critical part of an alarm management system and is one of the primary interfaces [58]. Alarms are displayed as a part of the HMI which acts as a signal to the operator to take appropriate action to run the process safely [88]. A poorly designed operator display may interfere with the operator's ability to take action during upsets. One of the key requirements for an HMI is to provide an alarm display to assist operators during the abnormal situations or unplanned plant upsets [57, 111]. Traditionally, alarms are shown on an HMI in the form of a list-display. [112, 55]) have explained the problem with these traditional list-based displays, in which during abnormal situations, the operator needs to scroll down to view alarms and could sometimes miss important alarms in the process. Indeed, [113] performed an analysis of near-misses and non-conformance and concluded that operator error was one of the main causes of such scenarios in 50-65% of the cases, resulting in 15-20% annual operational losses.

It has been repeatedly observed that poorly designed process display/graphics interfere in the handling of any significant disturbances. HMI's need to be designed to assist the operators rather than distracting them. A crowded HMI can lead to confusion during an abnormal situation and can form the perfect recipe for generating erroneous responses. Sometimes, the information of a single section of a unit could be scattered over two or three HMI screens which could also contribute to operator errors. Hence, it is essential to ensure that the HMIs provide the operators with quick and easy access to pertinent information so that abnormal situations can be averted. Kim [114] provided details about the computerized operator support system for online management of failures and emphasized man-machine systems for operator support and the incorporation of human factors principles while designing control rooms . Choi et al. [115] developed an on-line fuzzy expert system, called alarm filtering and diagnostic systems (AFDS), to provide operators assistance in understanding abnormal situations when they occur. Laberge et al. [58] performed a study which compared the operator response of a traditional list-based alarm summary display to that of an alarm tracker summary display (showing alarms as time series icons and short alarm descriptions). It was found that operators were able to perform much better (overall increase of 6%) with the newer displays in comparison to standard list based displays. In summary, by incorporating the human factors study approach, appropriate alarm management can be used to achieve maximum operator efficiency [116].

2.7.4 Lack of comprehensive philosophy document

The alarm philosophy document is the main guiding document for an effective alarm management system. This document contains the details of design, operations, and maintenance of the alarm management system [68]. For a new project, alarm philosophy document is prepared and approved during the design stage. In practice, it has been observed that although the philosophy document is available with the individual plant users (operators, maintenance personnel) it has rarely been used by them. Indeed, many of these users are not aware of the existence of such a document, let alone know its content. The document also lacks periodic revision which is essential after rationalization and implementation to record any learning, area of improvement, *etc.* The major use of the philosophy document is to provide guidance to people unfamiliar with the original alarm management scheme.

2.7.5 Inadequate operating procedures

As described in earlier sections, the appearance of an alarm usually calls for an operator action. The role of the plant operator is to make real-time decisions which are crucial for safe operation of the plant [59]. Many alarm problems arise due to not taking into consideration the operator's role and the overall alarm philosophy. Operators not only monitor the plant but also make decisions based on interpreting large volumes of information in real-time using their knowledge and experience [117]. It can be said that the operator's roles and actions have a significant impact on plant production and safety. Operating procedures have a significant impact on the operator's decision making during plant operation. These procedures can be treated as master documents for a plant facility. Such documents may be referred to by the operators during the day to day routine operation of the plant for the purpose of taking appropriate actions in response to both normal and abnormal situations. In general, standard operating procedures of a plant include details about the actions/next steps to be taken during startup, shutdown or normal operation. However, they do not provide specific guidance about actions to be taken during the occurrence of various alarms or alarm flooding.

2.7.6 Lack of resource management and allocation

The successful accomplishment of any task requires the committed buy in from all the stakeholders. The same is true in the case of alarm management. Indeed, alarm management is a continual process and needs commitment and participation from people at all levels. This process not only requires technical resources but needs proper planning, time and financial support. The management of an organization can play an important role in securing all these resources for the establishment of effective Alarm Management systems. Justifying the cost of alarm management to some of the stakeholders can sometimes be a challenge. Plant users (operators & engineers) usually understand the seriousness of the issues that come up in the context of alarms, but it is difficult to convince senior level management to plan and invest in strategies of alarm management. Sometimes even during the implementation stages, the participation from operators and engineers on the floor may be minimal due to other competing job responsibilities. This can hamper the overall schedule of activities and create a lackadaisical environment.

2.8 Identified research problems

An effective alarm system is one which provides relevant and required alarms for operator action. The process of alarm management can be initiated by following the alarm life cycle management. Studies have been carried out to improve the performance of alarm systems with the help of alarm rationalization, system maintenance and development of best practices [63, 64]. Some authors have described the following seven steps for an effective alarm management system: (1) developing and adopting alarm philosophy, (2) Bench-marking the alarm system, (3) Finding bad actors, (4) Performing alarm documentation and rationalization, (5) Implementing alarm audit and enforcement technology, (6) Implementing real-time alarm management, (7) Controlling and maintaining the improved alarm system. These steps have been utilized in the industry and are an effective way of managing alarms. A great amount of work has been carried out by researchers as summarized in Table 2.4. However, there is a need to develop these techniques further which can assist the user in implementing effective alarm management strategies. Some of the focus areas are listed in the following subsections. For each focus area, we will first list specific problems requiring attention and then proceed to elaborate on those problems.

2.8.1 Configuration of an alarm and identifying incorrect alarm variables

Two specific problems requiring attention under this focus area are: **Problem 1:** Selection of alarm variables for a process to achieve efficient, safer and reliable operation; and

Problem 2: Identifying incorrectly configured alarm variables and settings for an alarm system.

Selection of alarm variables for a process to achieve efficient, safer and reliable operation: An alarm is used to inform the operator about an abnormal situation. However, as a general practice alarms are configured for almost all the process variables without identifying the criticality or consequence of a missed alarm. It is therefore necessary to identify the relationship between the process variables and abnormal events. Once this relationship is identified, then the configuration of alarms will be more effective. Dalapatu et al., Takeda et al., Yang et al. [118, 119, 120, 121] have all explained this relationship based on historical data or process knowledge. With data-mining techniques, an integrated relationship between process knowledge and historical data can be explored to get the desired effective alarm system.

Identifying incorrectly configured alarm variables and settings for an alarm system: Incorrect alarm variables are also one of the major causes of alarm system problems. These issues need to be addressed as they create hindrance in the normal day to day operation. To ensure that each alarm is configured correctly, it has to be ensured that every alarm activation calls for an operator action. If there is no action required, then the alarm in question should be categorized as an alert. One of the challenges to identify such scenarios is to record and understand each operator action which requires a significant amount of infrastructure to store and analyze the operator actions.

2.8.2 Priority setting of an alarm

Two specific problems requiring attention under this focus area are:

Problem 3: Selection of alarm priority for a configured alarm variable; and

Problem 4: Design and selection of dead bands and delay timers for alarm variables.

Selection of alarm priority for a configured alarm variable: During a process upset there are hundreds of alarms which appear on an operator's screen. On the basis of the configured priority, the operator can take necessary corrective action. The general guideline for alarm priorities are [39] as shown in Table 2.5.

Table 2.5: Priority settings

Priority Type	**Level**	**Range**
3-priority levels	low, medium, high	$\sim$ 80% | $\sim$ 15% | $\sim$ 5%
4- priority levels	Low, medium, high, highest	$\sim$ 80% | $\sim$ 15% | $\sim$ 5% | $\sim$ <1%

Currently, the assignment of alarm priorities is static and there is a need for experimenting with dynamic alarm priorities and their implementation. Some of the work done in this area has been reported in the literature [122, 123, 124, 125].

Design and selection of dead bands and delay timers for alarm variables: In addition to the priority, configuration and design of the alarm system are also very important. By diligently following the recommendations in the standards, some of the alarm issues can be eliminated. Table 2.6 highlights the recommendations for alarm dead bands and delays which are useful in preventing "nuisance" alarms from popping up during plant operation.

Table 2.6: Delay times and dead bands

Signal Type	**Delay Time (On/Off timer)**	**Dead band (% of range)**
Temperature	60 seconds	1%
Flow Rate	15 seconds	5%
Level	60 seconds	5%
Pressure	15 seconds	2%

With the use of correct priorities, dead band and delay timer configurations, the alarm overload on the operator can be considerably reduced [49].

2.8.3 Handling nuisance alarms

A specific problem requiring attention under this focus area is:

Problem 5: Identifying nuisance alarms and generating solutions to reduce or eliminate such conditions: Designing a system to minimize the occurrence of nuisance alarms is one of the most important aspects of ensuring the proper operation of a plant. Nuisance alarms not only create trouble during normal operation, but they are also one of the main reasons for operator workload. Both fleeting and repeating alarms are also considered to be closely related to nuisance alarms. One way to eliminate nuisance alarms is to check and compare the normal process operation data with abnormal data. Some of the methods currently designed and developed to handle chattering and nuisance alarms are summarized in Table 2.4. However, it is to be noted that each alarm has a different cause and characteristics. Therefore, it is necessary to develop a methodology such that the nuisance alarms are either eliminated during the design, filtered or masked in order to make the alarm system more effective.

2.8.4 Developing advanced alarming techniques

A specific problem requiring attention under this focus area is:

Problem 6: Designing methodologies to reduce the alarm flooding in case of an abnormal condition: To reduce alarm flooding, some of the advanced alarming techniques can be used which are available with the different control systems in the market. Vernon et al. [65] concluded that meeting the EEMUA recommendations for the peak alarm rates during a plant upset is a challenging target and requires advanced practices, techniques and technology to assist plant operations. The alarm system in this case is able to track the process and decide when to present an alarm and when to suppress. Suppression is a technique used to assist in handling a high volume of alarms, occurring due to the inadvertent shutdown of equipment or an unplanned shutdown. The principle is to hide or mask alarms which no longer have any value to the operator and may result in the operator missing critical alarms, operator error, production loss and sometimes incidents. A good alarm system requires that a lot of process knowledge be integrated into the system to optimize the alarm generation, suppression and presentation, based on process expertise and operational experience [126]. Modern control systems can be selected with features and tools to configure the dynamic suppression of alarms on the basis of the state of the process or equipment (automatic alarm hiding). An example of successful suppression of alarms could be a situation where a compressor tripping would flood the operator screen in the absence of alarm suppression. However, by suppressing all alarms except for a few critical ones for the machine, the overloading of alarms can be decreased significantly. Advanced alarming is a technique to manage alarm rates and ensure the appearance of relevant alarms by dynamic modification of alarm behavior. In one instance, with the help of dynamic alarm management the total number of alarms during an upset in a 7 hour time frame period was reduced from 1450 to a much more manageable number [127]. Additional logic modeling is generally required to modify alarms. In general, alarm suppression is a valuable tool and there are three different types of suppression defined in the alarm management standards.

1. **Alarm shelving (manual suppression):** This process is typically initiated by the operator action, to temporarily suppress an alarm.

2. **Designed suppression (automatic suppression):** This process suppresses alarms with respect to operating conditions or plant states. A control logic is defined in the system which is used to determine the relevant alarms.

3. **Out of Service:** An alarm is considered to be out of service when it is manually suppressed for maintenance or testing.

Some of the current suppression techniques are summarized in Table 2.7. These techniques are followed in industry to avoid alarm flooding and overload on an operator.

Table 2.7: Alarm suppression types

Type of Suppression	**Description & Characteristics**	**Example**	**Problem**
State-based Suppression (Static Suppression)	Suppress alarms with pre-defined states of operation, equipment and process during a planned event: • Manually initiated transition • Time Frame: Short term (hours),long terms (months)	Reactor startup, Distillation column in start-up mode.	State alarms
Alarm Flood Suppression (Dynamic Suppression)	Suppress alarms which are not relevant and meaningful in case of an event and when the same process can lead to a hazardous situation	Compressor trip	Alarm flooding

Another technique is First-out alarming, which is prominently used in the industry for many years. In this technique a group of alarms are designed with a latching logic that latches in case of any single alarm trigger from the group. In this case only the first alarm is displayed and annunciated to the operator. The scan time for the grouped variables may affect the first-out logic and hence should be considered while designing such systems. In summary, there is a need to understand and design approaches applicable to the advanced alarming methods. An organization can achieve the required KPI's for an alarm system with the help of advanced alarming techniques (such as shelving, suppression *etc.)*.

2.8.5 Assisting operator in decision making

Two specific problems requiring attention under this focus area are:

Problem 7: Identifying root causes for an alarm and using a decision support system to provide guidance to the operator to take the appropriate action.

Problem 8: Designing HMI screens to ensure ease in detection, diagnosing and responding to the normal or abnormal conditions. Identifying root causes for an alarm and using a decision support system to provide guidance to the operator to take the appropriate action: The operator is a key player in the running of a plant. All the decisions are taken by the operator after observing and assessing the situation. Alarms constitute a means to assist the operator in operating the process within safe limits and maintaining the production rate. With advances in automation, the number of alarms appearing on the operator screen have gone up. Hence, it is a big challenge to ensure that the operator is assisted, instead of being hindered, by the alarm system during an abnormal situation. To do so, it is necessary to identify the abnormal conditions in the process, find the root cause of an alarm generated and provide directed guidance to the operator to take appropriate action. While developing such systems, plant operating states, complexity of both process and automation, and the dynamic nature of the process operations should be considered. It should be noted that individual process events can cause several alarms. The guidance related to an individual variable may not remain valid and should be accounted for. Methods should be developed on the basis of process variable measurements, settings, alarm series and/or historical data recorded. This can be achieved by developing decision support systems for the operators.

Designing HMI screens to ensure ease in detection, diagnosing and responding to the normal or abnormal conditions: HMI displays act as an interface between the operator and automated systems. It is very important that the design of the alarms and operator display screens are carried out simultaneously. HMI displays inform the operator about the abnormal situation with visual annunciation. HMI displays should be designed to fulfill various requirements such as clear information for understanding, situational awareness resulting in optimum efficiency of operations. These can be achieved with the help of proper layout design, color selection, ensuring the span of control (“assists operator by showing the overall picture of the plant and provides details about potential problems while working on other tasks using different display screens), proper selection of the required content, and linking the information from other systems such as enterprise resource planning systems (ERP), asset management systems, *etc*. While developing new methods, it is required to ensure that the HMI does not lose its primary function of being the process display.

In summary, the status of alarm systems has improved over the past two decades with the development of new guidelines, standards and academic research. However, there is still a critical need to address some of the major challenges related to alarm management. Industrial plants are suffering from poor performance and alarm flooding situations leading to minor or catastrophic incidents. With advancement in technology and new theoretical concepts, more advanced design and analysis methods which make use of process and alarm data, and process and operator's knowledge are called for. Hence, a holistic socio-technical approach is required for these systems. An effective alarm management framework can be designed with the help of existing standards, guidelines and technology available. A step-wise approach is required to achieve the desired outcomes and reduce alarm floods during normal and transient conditions. This process can start by developing the alarm philosophy document and rationalizing the alarm system. Once the bad actors and nuisance alarms are eliminated, advanced alarming techniques such as first-out logic, static and dynamic suppression can be used to eliminate alarm floods. Methods focused on reducing alarm flooding are still in the early stages of development and need more reliable and effective research solutions, before implementation in an industrial operation becomes feasible. Currently, industry is leaning towards cyber-physical systems for achieving industrial automation and therefore it is necessary to also design methods by focusing on such systems. Implementation of new mathematical tools, statistical tools and data analytics are required to provide support during plant operations to address the alarm design, alarm flooding, and poor performance issues. The role of the operator should always be taken into consideration while designing and implementing solutions to these problems. Section 2.9 highlights the proposed framework to address the challenges identified. A strategy to integrate the alarm system implementation and operational practices into the existing management systems is vital to make the plant operations safer and more profitable.

2.9 Alarm management framework

International Society of Automation (ISA) defines an alarm system as: *"the collection of hardware and software that detects an alarm state, communicates the indication of that state to the* *operators, and records changes in the alarm state"*[16]. Alarm management is defined as *"set of processes that ensures an effective alarm system"*. A typical industrial facility is operated by a control system (DCS or PLC or both), a Human- Machine Interface (HMI) is used to display the information related to process variables, operation and alarms. In some special cases such as in safety systems or a critical equipment the alarms and some critical controls are duplicated on an annunciator panel. Alarm historians are used to record and store the information comprising of alarms messages, process changes, and operator actions for future records and references. An effective alarm management program can help the users in operating the plant at both optimum and safer levels resulting in lower losses, increased throughput and higher quality.

One of the biggest challenges in alarm management for industrial facilities is the alarm floods.*"Alarm flooding is a condition during which the alarm rate is greater than what the operator can effectively manage (e.g. more than 10 alarms per 10 minutes)"*[16, 44]. Alarm floods result in abnormal situations and in some cases the situation may escalate to catastrophic incidents. In past few years, there have been several standards and guidelines developed comprising of instructions for the users to design and manage the alarm systems. Additionally, these documents provide detailed requirements related to certain KPIs for bench-marking the alarm systems. Some guidelines related to technical methodologies and steps are provided as a part of separate technical reports. Usually, the alarm management process in an industrial facility includes designing and rationalizing the systems. Advanced alarming techniques are used in only few cases. The use of data mining and analysis systems to harness the information from historians to improve alarm management system is very scarce.

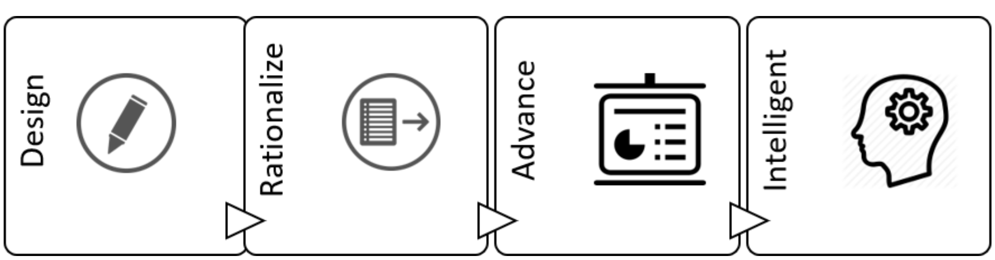


Figure 2.6: Alarm management framework

To address the various issues of alarm management, we propose an integrated alarm management framework based on ANSI/ISA 18.2 alarm management life-cycle and data mining and analysis methods as shown in Figure 2.6, which consists of four stages: design, rationalize, advance and intelligent. It is important to note that different actions and stages are required to be performed and implemented sequentially. The life-cycle is not a one time process and requires continual improvement and implementation. The four stages of the proposed alarm management framework are described below:

- **Design:** The design stage is the most critical part of an effective alarm management program. During the design stage, users design their alarm systems based on available standards, guidelines and best practices used in the industry, their own organization. It includes developing the philosophy document and the design requirements. A preliminary master alarm database is generated which includes the potential list of alarms for a facility. While designing alarm systems the important characteristics to be built into the design are [19]:

  1. **Action** - every designed alarm should require an operator action.
  2. **Priority** - priority selection for the alarms according to the rule of 85/15/5 for(Low/Medium/High) priorities.
  3. **Uniqueness** - alarm indicates the details about a single unique process parameter with a suitable description to understand the alarm.
  4. **Timeliness** - alarm appears on time and provides appropriate time for the operator to detect, diagnose and act.
  5. **Relevance** - alarm relevance for the operational value.

- **Rationalize:** The rationalize stage includes tasks of alarm classification, prioritization, rationalization and documentation. The rationalization process requires inputs such as alarm philosophy document and list of all potential alarms (initial master alarm database) which is generated during the design phase. The rationalization step provides the result in the form of master alarm database with design requirements. There may be a significant reduction in the configured alarms and the nuisance alarms after rationalization. The rationalization process can be implemented both during the design of a new system or to an existing running system to improve the installed alarm system.

- **Advance:** This stage includes advanced alarming techniques to manage the alarm floods in case of process changeover conditions such as start-up and shut-down. In such situations, suppression techniques are used [128], which work on the principle of hiding or masking the alarms which are not relevant to the operator after a particular process event. These techniques include: alarm shelving (manual suppression) initiated by the operator, designed suppression (automatic suppression) based on operating states or plant conditions (also known as static suppression) such as a reactor start-up and out of service alarms (also known as dynamic suppression) such as a compressor trip or an out of service equipment.

Table 2.8: Advanced alarming techniques

Suppression type	**Description**	**Example case**
Suppression based on state (Static)	Suppress alarm sequence when a pre-defined operation or equipment state is observed	Reactor start-up
Alarm flood suppression (Dynamic)	Suppress irrelevant alarms in case of an event while it can lead to a hazardous situation	Compressor trip

- **Intelligent (based on data analytics):** With advancement in digitization more data is being collected and stored daily by the operating companies. The energy industry is becoming 'data rich'. Data analytics is the key enabler to find out insights from the raw data for more informed business and operational decisions. Enormous amounts of data are generated by sensors and actuators for process operations, automatic or manual actions and safety that are stored in 'data-warehouses' or 'data lakes'. Data mining and analysis methods can be used to reveal the relationships between the data sets. The information generated from such methods can be shown to the user with the help of visualization tools. This provides an opportunity to derive business intelligence from the data and improve overall system performance [14]. Figure 2.7 highlights key phases of analysis to support improved operations, process safety and risk management. The process starts with collecting data and performing descriptive analysis to understand what is going on; a diagnostic analysis to understand why it is happening. In certain cases we can use a predictive approach to predict the future and the last step is prescriptive analysis involving real-time analysis and reporting. The value contribution and complexity of the solution increases at each step. The use of advanced analytics and expert knowledge is required in these cases to derive informed decisions and business intelligence. To perform analytics on a problem we need to follow a life-cycle approach as shown in Figure 2.8. The process starts with identifying the purpose of the study and questions which require answer or analysis. After this step the data is collected from various sources and aggregated to ensure the availability of required data and information for the study. The next step includes developing the methodology and performing analysis to find meaningful information and results. The obtained results are interpreted by experts and then disseminated to the end users for final evaluation. After evaluation if there are any changes required in the approach, the appropriate information is shared to update the purpose or evaluation. For the purpose of this study the data analysis life-cycle stages are defined as: (1) Purpose definition: address the issue related to alarm management, develop a methodology that can be used for analyzing alarm and event log; (2) Data Collection : For this study the data is collected from a DCS historian of a real industrial plant in appropriate template or format; (3) Data analysis : various methods developed for this stage are shown in Section 2.10; (4) Interpretation, dissemination and evaluation of results which are described in Section 2.11. In case of alarm management, the use of analytic tools can provide an opportunity to find out the bad-actors, improve the overall alarm management system and operate the plant systems at an optimized level. In this work, a method is developed for offline analysis for alarm and event logs and explained in next sections. The information generated from this stage can be used in other stages to enhance the alarm management program.

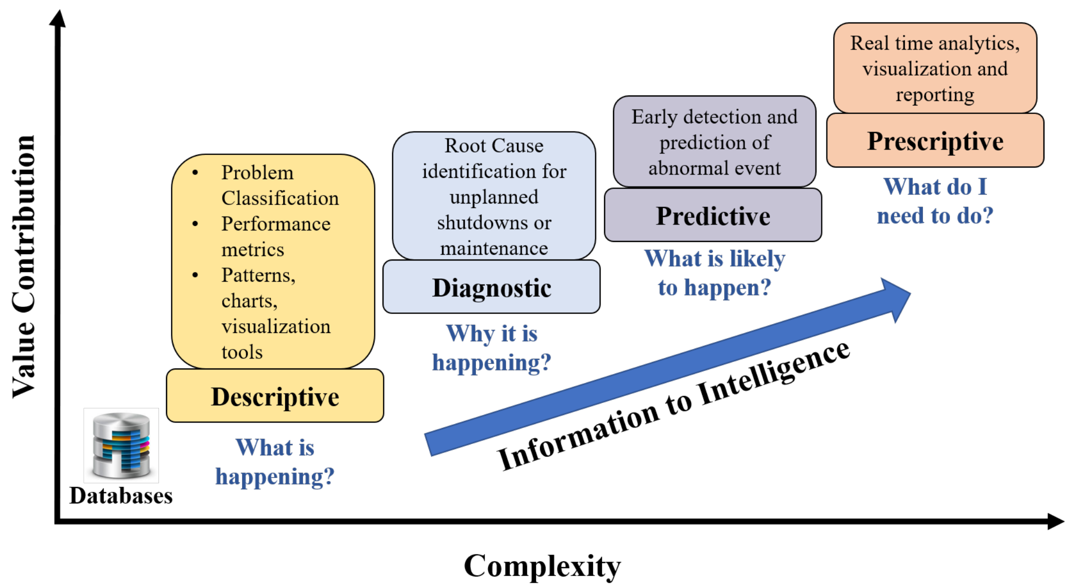


Figure 2.7: Data to Business Intelligence

2.10 Problem Formulation

An alarm serves as a medium to communicate the abnormal process event to the operator. A sensor is used to measure the process value and the output is wired as an analog or digital signal to the control system (DCS, PLC or ESD system). The transmitted signal is processed by the programs written and stored in electronic circuits, logic boards (also known as controllers) serving as the automated brain of the system. Post-processing the generated information is displayed to the operator on HMI displays in the form of process operations screens and alarm display screen. The operator uses the information to assess the process operation and takes necessary actions when needed. During the alarm activation state (equation 2.1), the operator reviews the state of

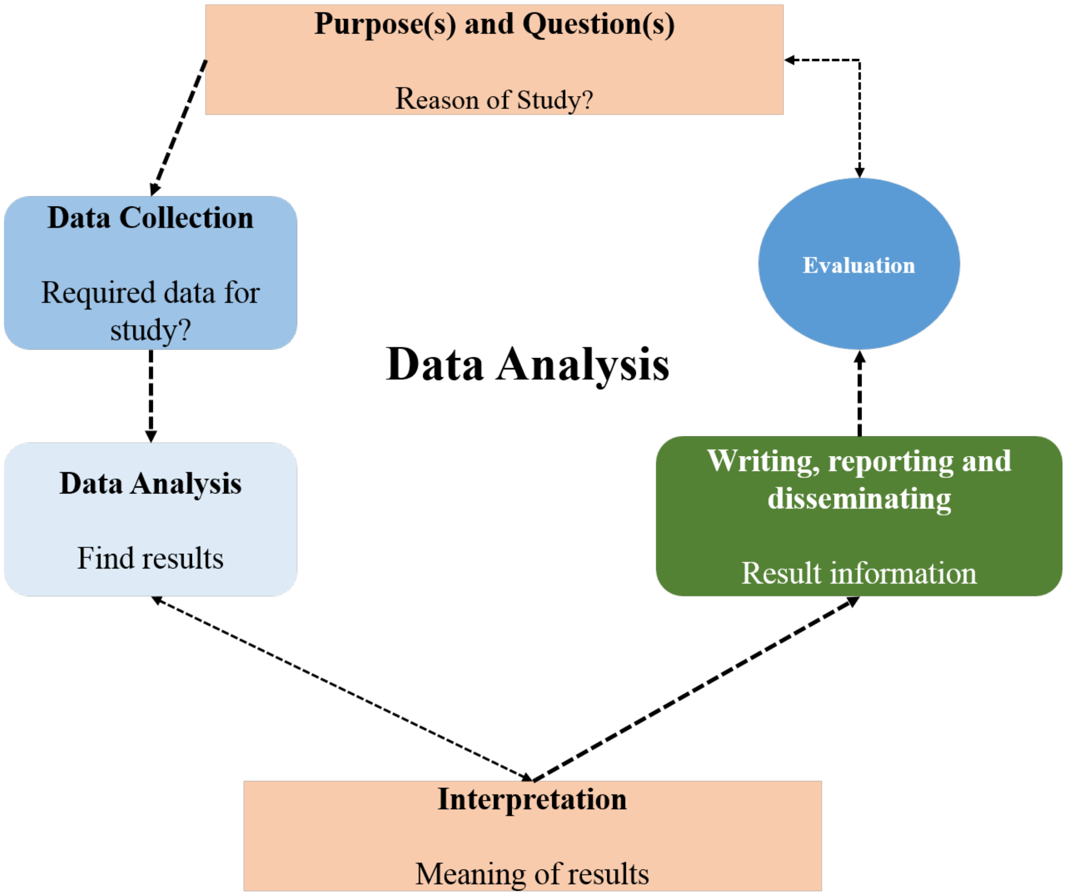


Figure 2.8: Data analysis as a life-cycle

process variables and other related plant information, comprehends the current plant state, detects and diagnoses the abnormal process situation and carries out the required actions to bring the process back to normal state. The operator's action activates a sequence of automated operations including a desired control action from the controller to the final control element (also known as the actuator) which brings back the process to a desired operating range [129]. These events are captured in Alarm & Event logs of a control system (DCS/PLC) historian as:

- ALM : alarm appeared,
- ACK : alarm acknowledged by an operator,
- RTN : process variable returned to a normal state.

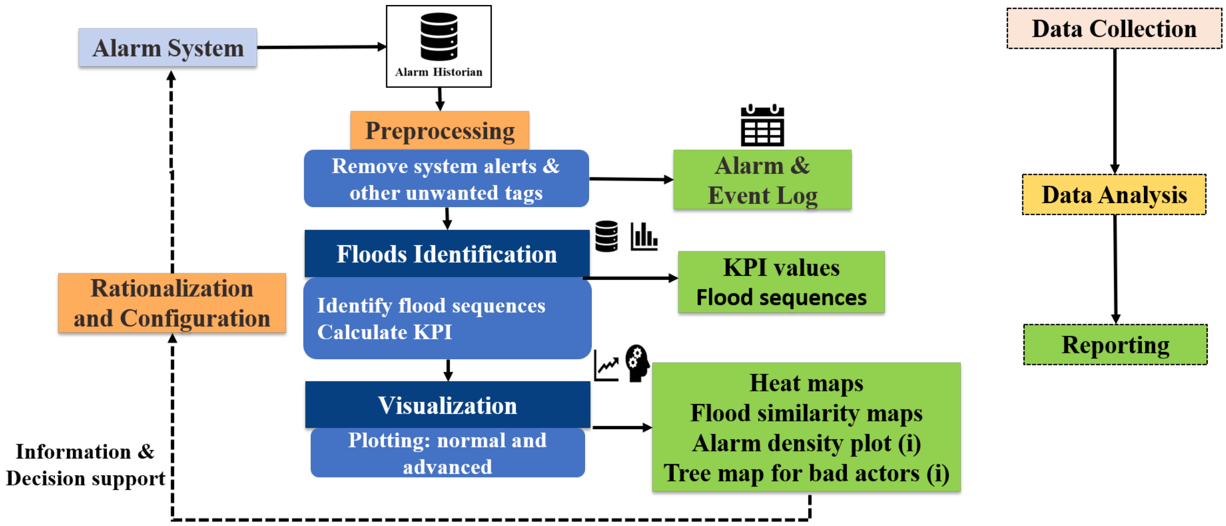


Figure 2.9: Methodology framework

Alarm and Event log data captured can provide very relevant and useful information regarding bad actors (*"an alarm that is suspect and cannot be relied upon to deliver accurate information to the operator, such as stale, chattering, duplicate or suppressed alarms"* [130]), flood sequences which will result in better alarm management performance. To demonstrate this, we have developed a methodology that uses an Alarm and Event log information and the previous knowledge of the process operation. This methodology includes following steps:

- **Step 1: Acquire and validate the data-set from alarm historian :** Alarm and Event log is stored in a historian of a process control system. This step includes acquiring the data from the historian in a relevant file format. The generated file is used in the next step.

- **Step 2: Pre-process the data-set to ensure correctness :** The alarm data-set not only includes the information of the process alarms, in some cases they include other information such as system failure alarms, hardware failure alarms too. It is important to filter these alarms from the process alarms. Also, time stamping needs to be checked to ensure the date and time stamp for each alarm is captured in the system. This process is shown in Algorithm 1. The output of this level is an Alarm and Event log which is used in subsequent steps.

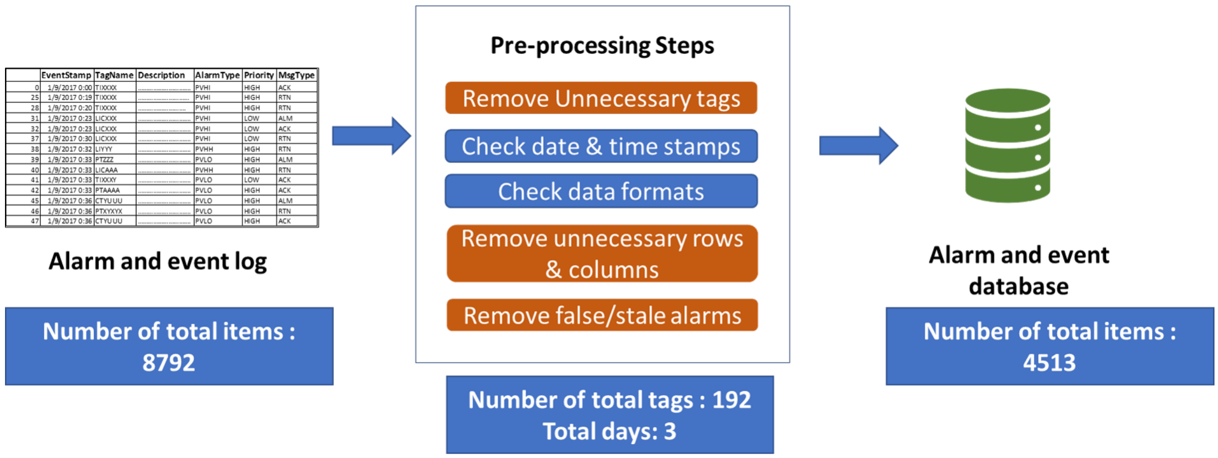


Figure 2.10: Alarm and Event log pre-processing

- **Step 3: Analyze and evaluate alarm flood clusters, patterns and KPI information :** The next step is to find the alarm floods from the Alarm and Event log generated in the pre-processing step. To ensure the correct values are collected and used again the data-set is checked for quality and flood sequences are identified and KPIs for the alarm system are calculated as mentioned in ISA 18.2 standard and EEMUA 191 guideline.

- **Step 4: Provide information to the users with visualization tools:** This information is necessary to understand the system performance. This step includes selection of appropriate methods and designing the visualization screens post analysis of the complete alarm and event logs.

Figure 2.9 highlights the complete process presented in this paper. For the purpose of the study, an alarm event (a_i) is defined as a binary-valued variable such that

$$a_i(t) = \begin{cases} 0, & \text{if } O(t) \in O_p, \\ 1, & \text{otherwise} \end{cases} \tag{2.1}$$

which means that the alarm is inactive (0) whenever the value of the operating condition $O(t)$ is in the normal operating condition O_p and active (1) in the case of a deviation. An alarm can be configured as Low or Low-Low alarm (where the value of the measured variable is below the operating condition limit) or High or High-High alarm (where the value of the measured variable is higher than the operating condition limit). A flood event, in this case, is defined as:

$$A = [a_1, a_2, \ldots, a_n], \tag{2.2}$$

where symbol [.] indicates a sequence, |A| is the cardinality of the sequence, the number of alarms is denoted by (n), and a_i is the alarm event occurring in a chronological order with a time stamp (t). a_i can be represented by a tuple with multiple attributes

$$a_i = (e_i, t_i, at_i, p_i, m_i) \tag{2.3}$$

where

- (e_i) is the alarm tag (such as FT, PT, TT, *etc.*),
- (t_i) is the time stamp of the alarm that occurred (HH:MM:SS or 11:00:25 format),
- (at_i) is the alarm type (Low, Low-low, High, HIgh-High *etc.*),
- (p_i) is the priority setting for each alarm (Low, Medium, High),
- (m_i) is the message type generated (ALM, ACK, RTN).

An alarm rate is calculated to identify the alarm floods in the alarm and event log database. Alarm rate is defined as number of alarms during a time period. The alarm rate $R(t)$ at a time t is defined as:

$$R(t) = \sum_{n=1}^{|A|} \sum_{k=\Delta T+1}^{t} a_i(k) \tag{2.4}$$

Here, ΔT is the difference between time stamp of a alarm tag in seconds and 600 seconds (10 minutes interval)

By using this alarm rate, the identification of alarm floods can be done by comparing the rate with a pre-defined threshold.

An indexing variable (ζ) can be used to show the presence of an alarm flood as:

$$\zeta(t) = \begin{cases} 1, & \text{if } R(t) \geq \tau_s \text{ and } \zeta(t-1) = 0 \\ 0, & \text{if } R(t) < \tau_e \text{ and } \zeta(t-1) = 1 \end{cases} \tag{2.5}$$

here, 0: No alarm flood condition

1: Alarm flood condition

$R(t)$: is the rate calculated from equation 2.4

τ_s: alarm count threshold (10 alarms over ten minutes)

τ_e: alarm count threshold (five alarms over ten minutes) with threshold conditions as defined in [16]

Algorithm 1: Pre-processing algorithm

Input: Alarm & Event dataset from an industrial process
Output: Processed Alarm & Event log (AE)
Read $\longleftarrow$ file with A = $[a_1, a_2, \ldots, a_n]$
Check - a_n for (e_n, t_n, at_i, p_i, m_i)
Remove - a_n with missing values
Remove - a_n if $a_n \in$ SYS OR Non-process tag
Return $\longrightarrow$ Processed Alarm & Event log (AE)

When an Alarm and Event log is captured from a control system, it includes alarms other than process variables (Non-process tags), such as system alarms, hardware alarms, *etc.* It is required to remove such alarms to obtain the correct picture of the process system. Hence, these alarms are removed as a part of the pre-processing of the database. The date and time stamps for each alarm and event are checked. While performing the analysis, it is important to check and validate the correct data format too. The available data is checked for data format accuracy after converting it into the data-frames. Any unnecessary rows and columns which don't contain complete information or with bad values are removed after consultation with an expert. The overall pre-processing method is shown in Figure 2.10. Once the pre-processing is complete an alarm log with only process variables is available for analysis. This log includes both normal sequence and the flood sequence of alarms. With the help of data mining and analysis methods, the KPIs are calculated .

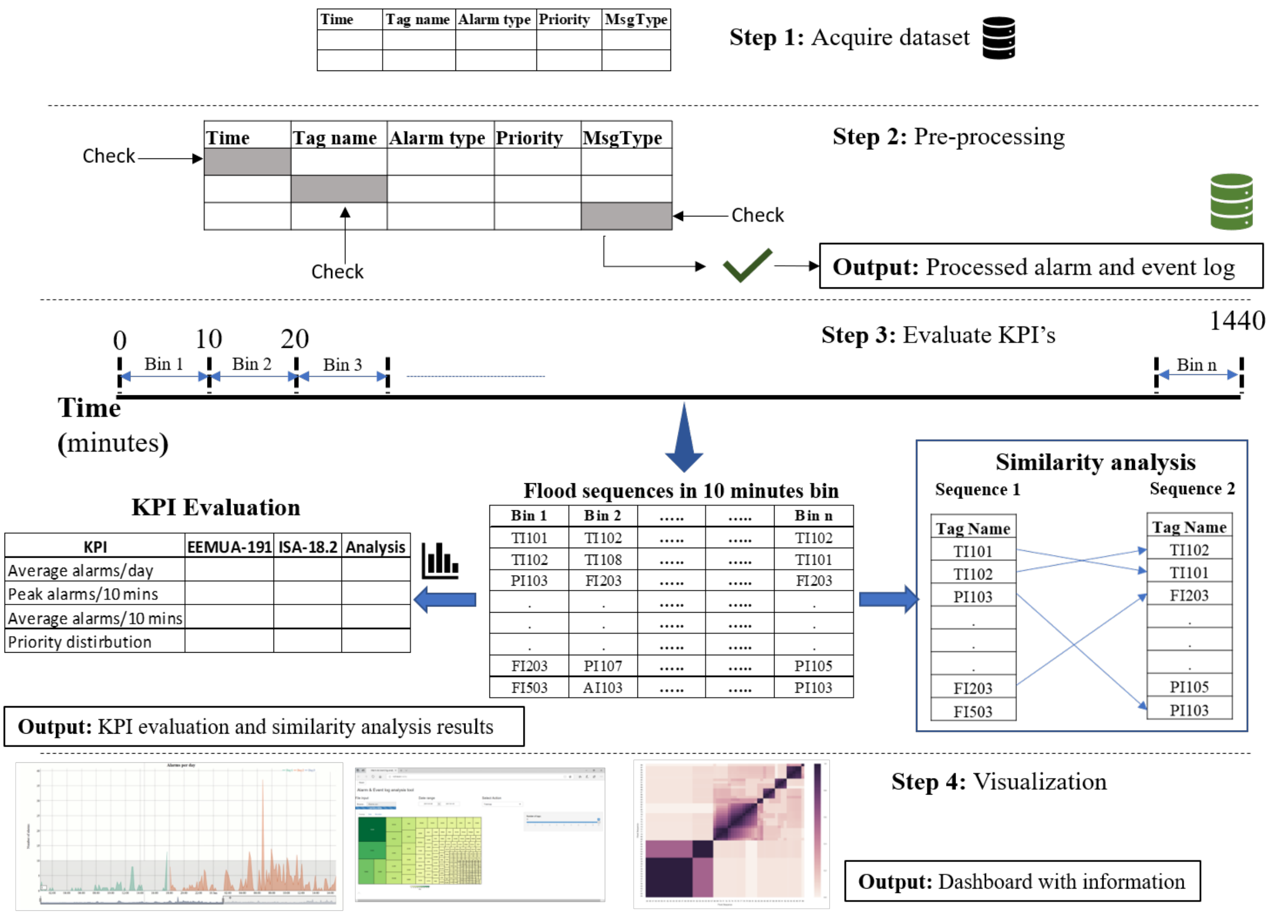


Figure 2.11: Illustrative motivating example

The average alarm rate per day is calculated by finding the total number of alarms appearing per day

$$R(t)_{avg.} = \sum_{n=1}^{|A|} \sum_{t=0}^{1440} a_i(k) \text{ (when } a_i(k) = \text{ALM)} \tag{2.6}$$

The peak alarm rate is calculated as the largest value of alarm rate $R(t)$ over a period of 10-minute interval

$$R(t)_{peak} = Max.\left(\sum_{n=1}^{|A|}\sum_{t=0}^{10} a_i(k)\right) \text{ (when } a_i(k) \text{ = ALM)} \tag{2.7}$$

The priority distribution for the data-set is calculated by counting the number of alarms appearing for a particular priority

$$A_{dis.} = \sum_{n=1}^{|A|} p_i(k) \text{ (when } p_i(k) \text{ = Low, Medium, High)} \tag{2.8}$$

Algorithm 2: Flood sequences and plotting algorithm

Input: Processed alarm & Event log (AE)

Output: Clustered alarm flood sequences

Read $\longleftarrow$ file (AE),

Check - a_n for (e_n and t_n)

Cluster $C_k : k = 1, 2, 3, ..., K$ such that C_k = ($A_i : i \in 1, 2, \ldots, N$)

for each (C_k) find similarity

Return $\longrightarrow$ Clustered alarm sequences

The flood sequences generated from Algorithm 2 are used to find out the similarity between the alarm floods for a pair of alarm flood sequences. The normalized similarity index (normalized between 0 and 1) for the alarm sequences is calculated based on the Jaccard index as given in [131], where given two alarm sequences X and Y, the alarm similarity index is calculated by:

$$SI(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \tag{2.9}$$

The normalized similarity index is plotted in the form of heat maps, where darkest color depicts the highest similarity between two alarm sequences.

A motivating illustrative example depicting the proposed method including data acquisition, pre-processing, KPI evaluation, and visualization is shown in Figure 2.11.

2.11 Industrial case study and results

This section demonstrates the implementation of the developed method. An industrial Alarm and Event log is used to demonstrate the functionality. The sample data-set details are given in Figure 2.12. The Alarm and Event log has various attributes such as event stamp (date and time of activation), tag Name (provide the instrument tag details), description, alarm type, priority and msgtype. The data for three days of a plant is used for analysis with 8793 alarms and events in three days for 192 unique instrument tags. The processed data-set is reduced to 4513 after removal of the system alarms and other undesired events as shown in Table 2.9 .

Table 2.9: Data-set details

Details	**Values**
Total items (alarms+events) before pre-processing	8793
Total items after pre-processing	4513
Total number of process tags	192
Total number of days	3

The pre-processed items were analyzed to find the KPIs such as average alarms per day, peak alarms/10 minutes, average alarms/10 minutes and priority distribution. These values were compared against the values prescribed in EEMUA 191 guideline [44] and ISA 18.2 standard [16]. The results are summarized in Table 2.10.

The following major observations can be made from the results:

- There are a significant number of average alarms on day 2 and day 3 operations (almost more than 3 times as specified in the standard).
- The number of peak alarms/10 minutes being considerably high on these days suggests alarm floods during these days.

- The average alarms/10 minutes are also high, signifying a poor alarm management strategy being followed.

- The prioritization captured in this case is observed as 63/30/5 for low/medium/high priority settings.

Table 2.10: KPI analysis for the alarm and event log

KPI	**EEMUA-191**	**ISA 18.2**	**Analysis result**
Average alarms/day	$<$144	$\sim$155	Day1:142 Day2:504 Day3:526
Peak alarms/10 mins	$<$10	$\leq$10	Day1:11 Day2:39 Day3:41
Average alarms/10 mins	1	$\sim$1	Day1:1 Day2:2.1 Day3:2.2
Priority distribution (L/M/H)	80/15/5	80/15/5	60/30/5/5(E)

After the pre-processing and KPI calculation, the visualization plots are generated for the dataset. The visualization provides the user with an opportunity to understand the system performance at a glance and address the issues related to alarm management. The key visualization methods used for this study are:

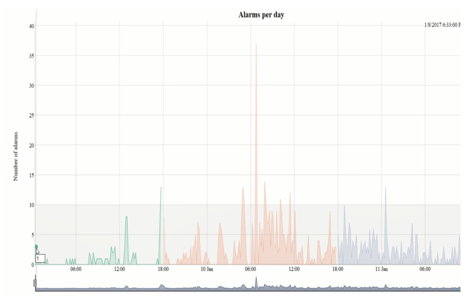
- **Alarm rate plot:** In order to understand the metrics, alarm rate plots are generated as depicted in Figure 2.13. These plots are line graphs which display the trends of alarm rate $R(t)$ by aggregating the number of alarms during a period of 10 minutes. The shaded dark area under the line represents the KPI alarm flood limit of 10 alarms per 10 minutes. Each day in

	EventStamp	TagName	Description	AlarmType	Priority	MsgType
0	1/9/2017 0:00	TIXXXX	....	PVHI	HIGH	ACK
25	1/9/2017 0:19	TIXXXX	....	PVHI	HIGH	RTN
28	1/9/2017 0:20	TIXXXX	....	PVHI	HIGH	RTN
31	1/9/2017 0:23	LICXXX	....	PVHI	LOW	ALM
32	1/9/2017 0:23	LICXXX	....	PVHI	LOW	ACK
37	1/9/2017 0:30	LICXXX	....	PVHI	LOW	RTN
38	1/9/2017 0:32	LIYYY	....	PVHH	HIGH	RTN
39	1/9/2017 0:33	PTZZZ	....	PVLO	HIGH	ALM
40	1/9/2017 0:33	LICAAA	....	PVHH	HIGH	RTN
41	1/9/2017 0:33	TIXXXY	....	PVLO	LOW	ACK
42	1/9/2017 0:33	PTAAAA	....	PVLO	HIGH	ACK
45	1/9/2017 0:36	CTYUUU	....	PVLO	HIGH	ALM
46	1/9/2017 0:36	PTXYXYX	....	PVLO	HIGH	RTN
47	1/9/2017 0:36	CTYUUU	....	PVLO	HIGH	ACK

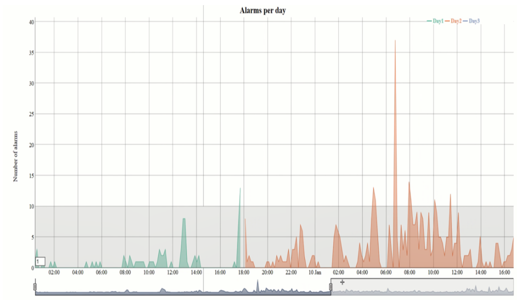
Figure 2.12: Sample data-set attributes

the plot is colored with a different color for easy interpretation. Day1 is depicted with green color, day2 is depicted with orange, and day3 with blue color. When a user hovers over a particular period, the details such as date, time and the number of average alarms at that time can be seen in the top-right corner section of the tool screen. The selection bar at the bottom of the screen provides the user with the option to zoom-in and zoom-out of the alarm rate plot and have a better understanding about the system during a given time frame.

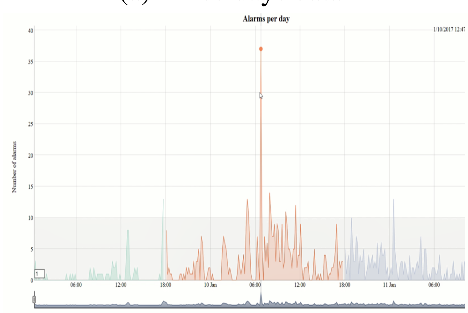
- **Tree map:** The tree maps (depicted in Figures 2.14, 2.15) are used to show the bad actors (alarm tags appearing multiple times) during an operation. The darker color and bigger size of the block indicates the presence of the alarm tag multiple times. By hovering over a block, the user can see the number of times the alarm tags have appeared. This is very useful for the user to get a summary of all the tags on one screen with relevant tag activation count information while performing the analysis.



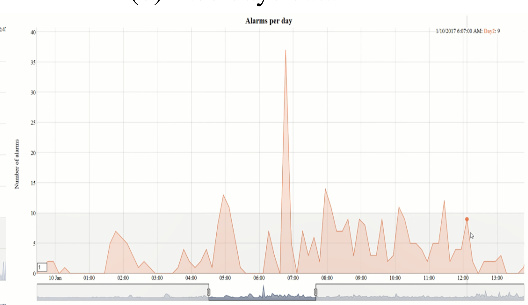
(a) Three days data



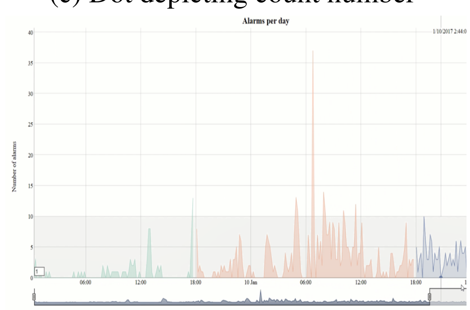
(b) Two days data



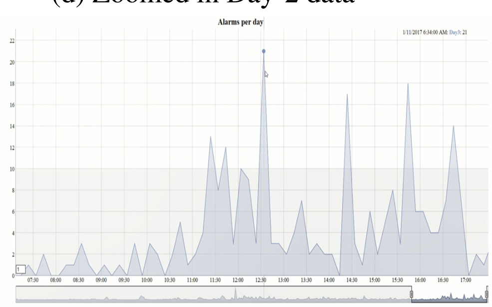
(c) Dot depicting count number



(d) Zoomed in Day-2 data



(e) Selection feature bar at bottom



(f) Zoomed in Day-3 data

Figure 2.13: Interactive alarm/day plots showing alarm information for three days

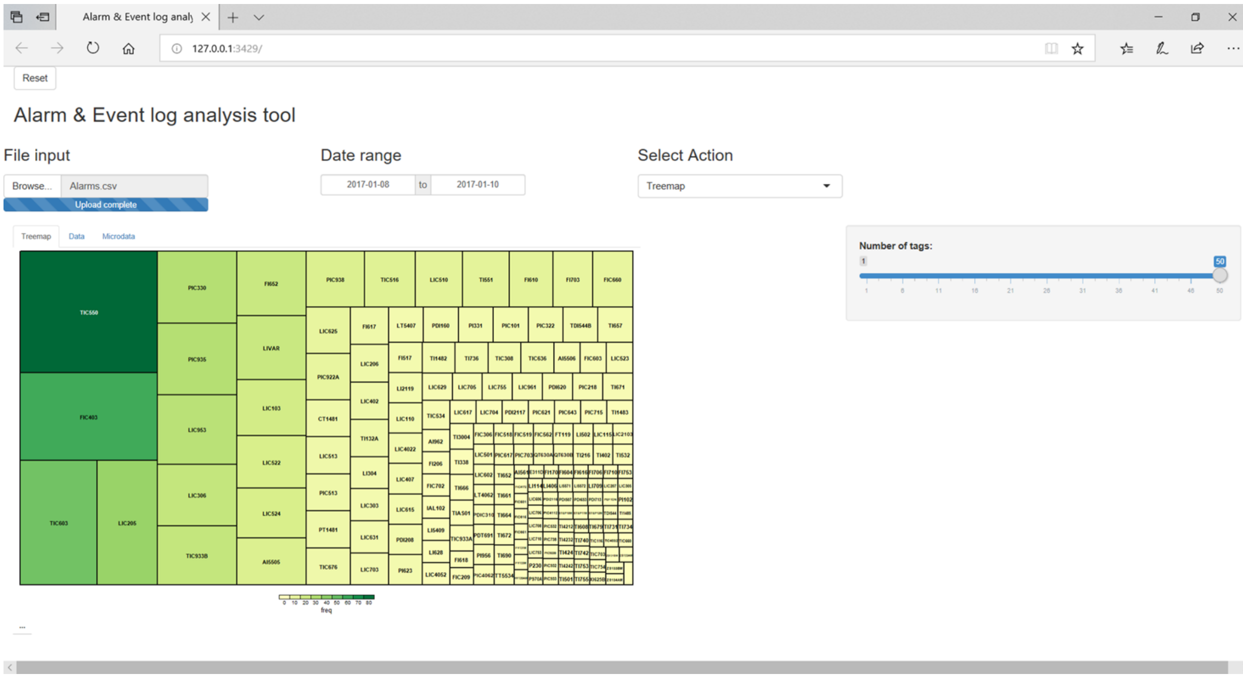


Figure 2.14: Tool screen shot

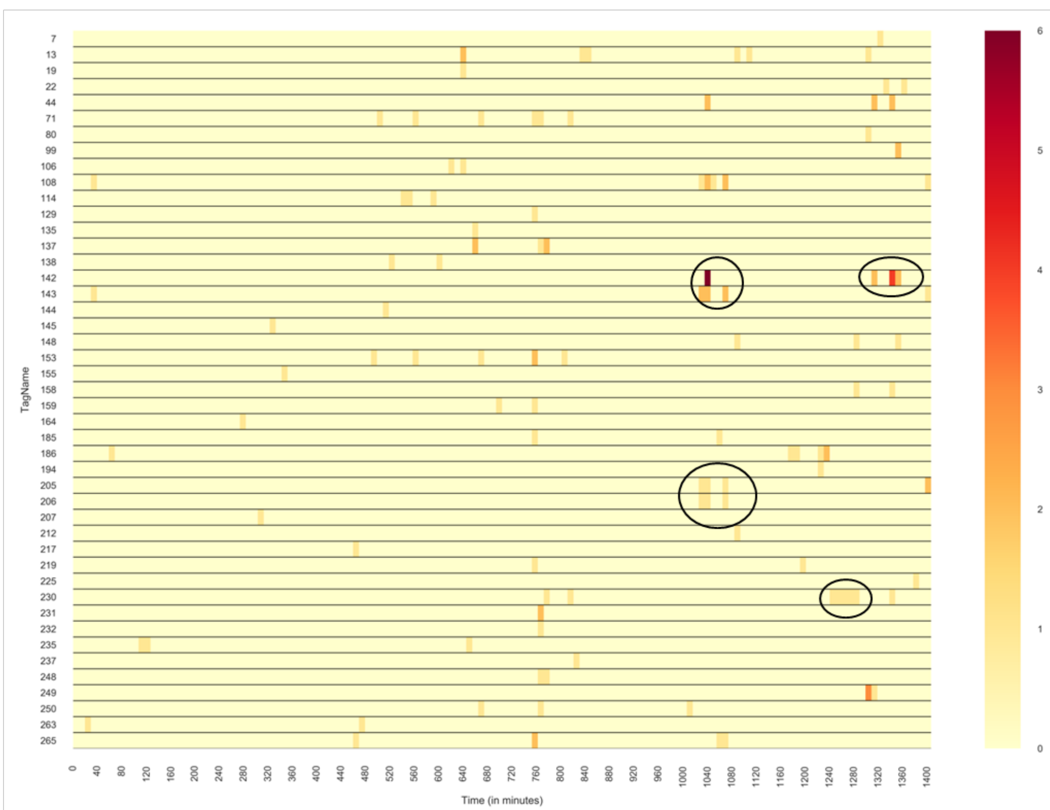


Figure 2.16: Day 1 tag information

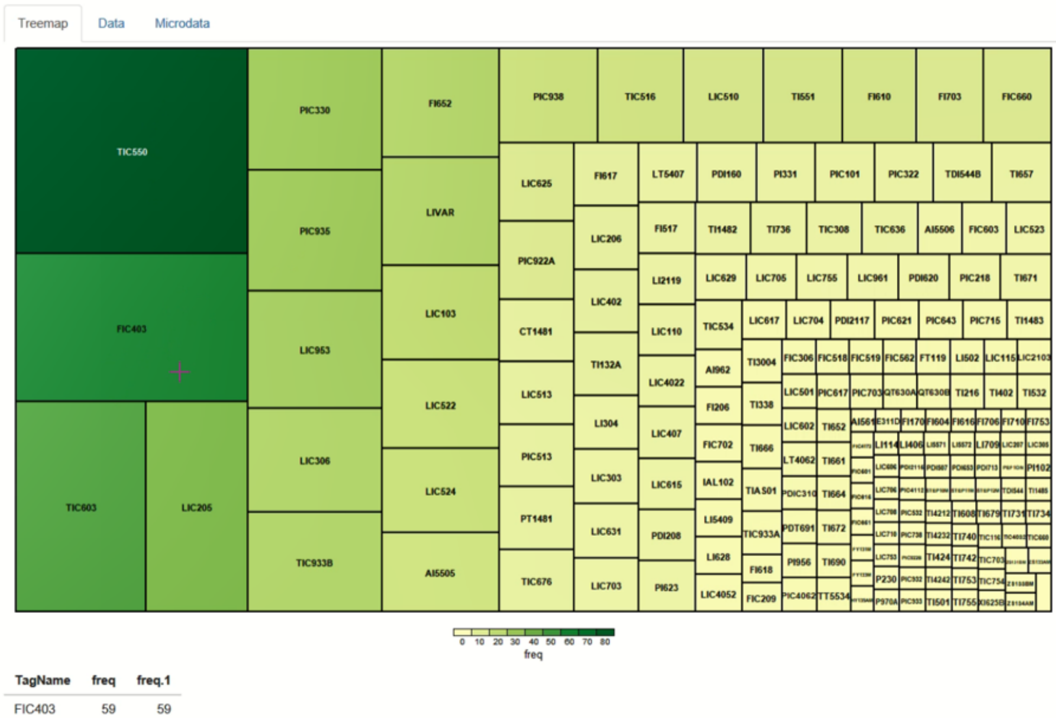


Figure 2.15: Tree map showing tag information

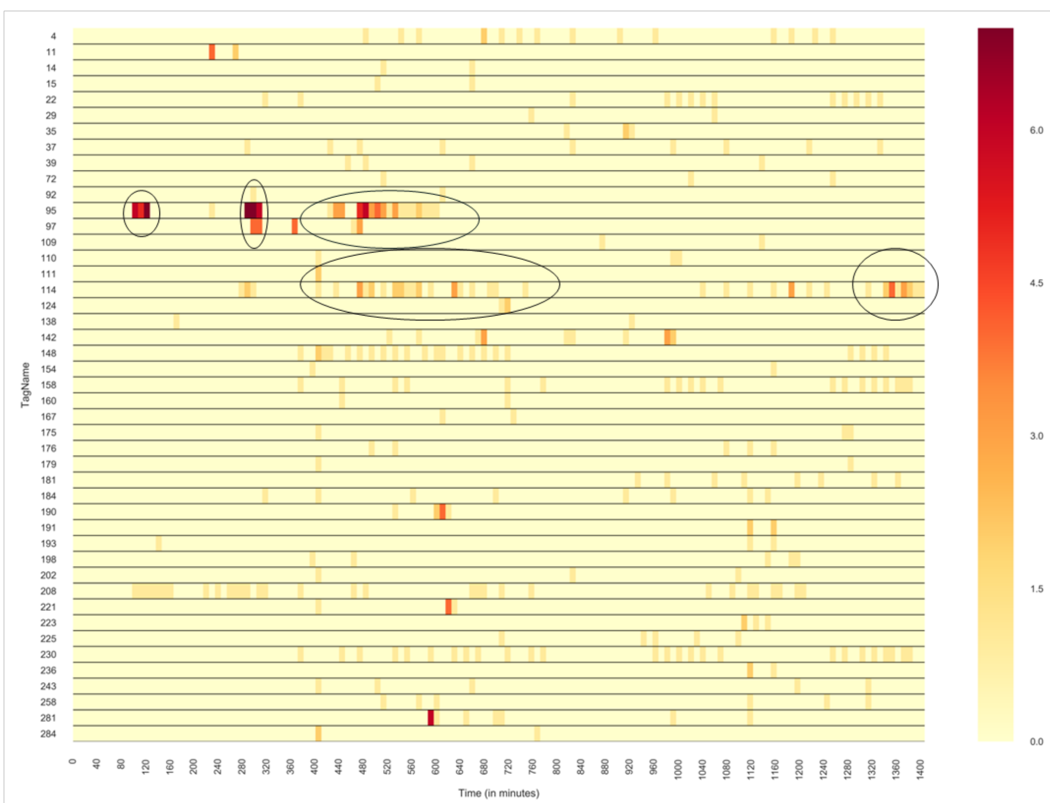


Figure 2.17: Day 2 tag information

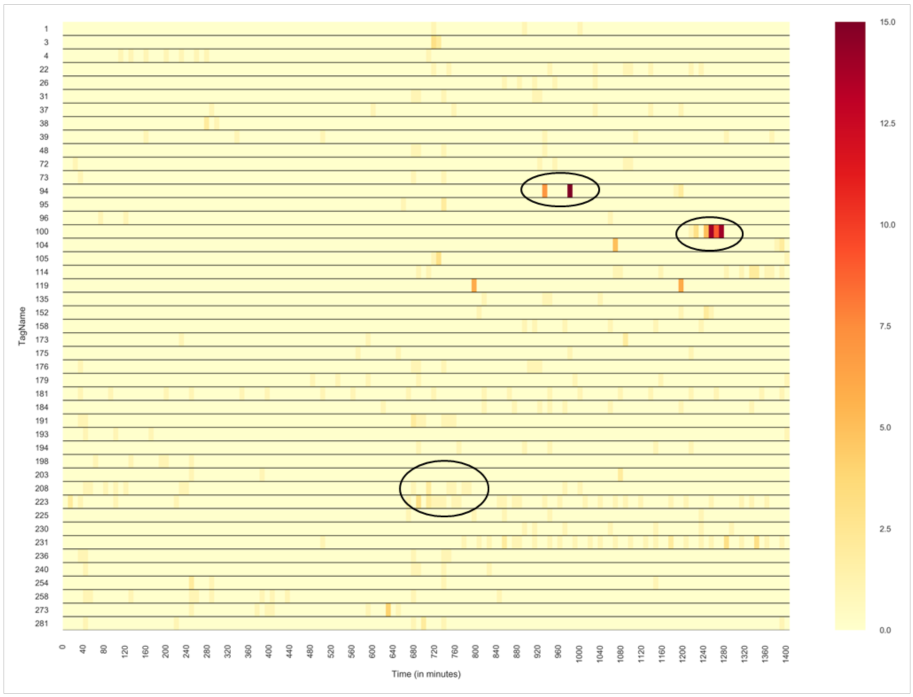


Figure 2.18: Day 3 tag information

Figure 2.19: Similarity analysis for alarm flood clusters (part I)

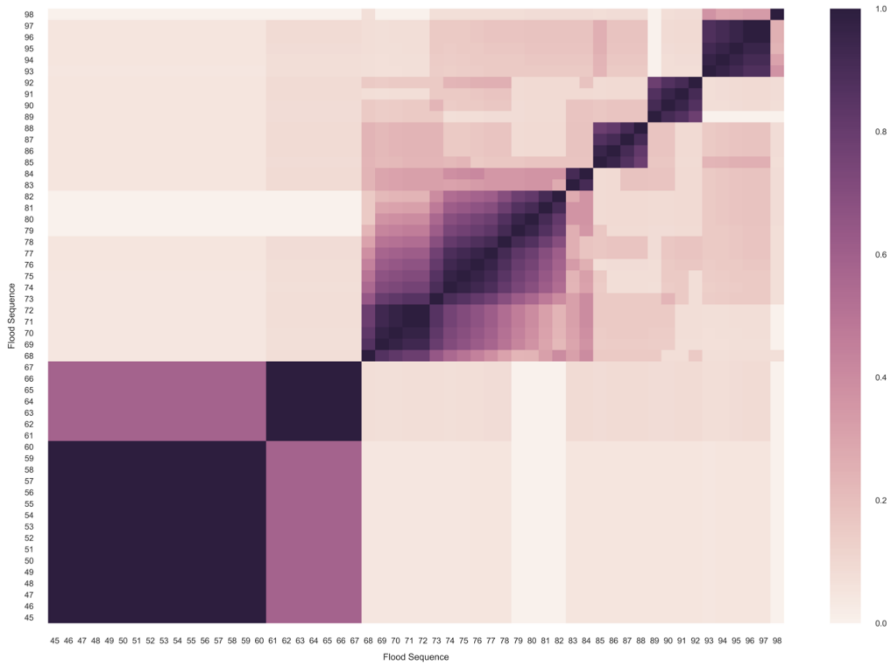


Figure 2.20: Similarity analysis for alarm flood clusters (part II)

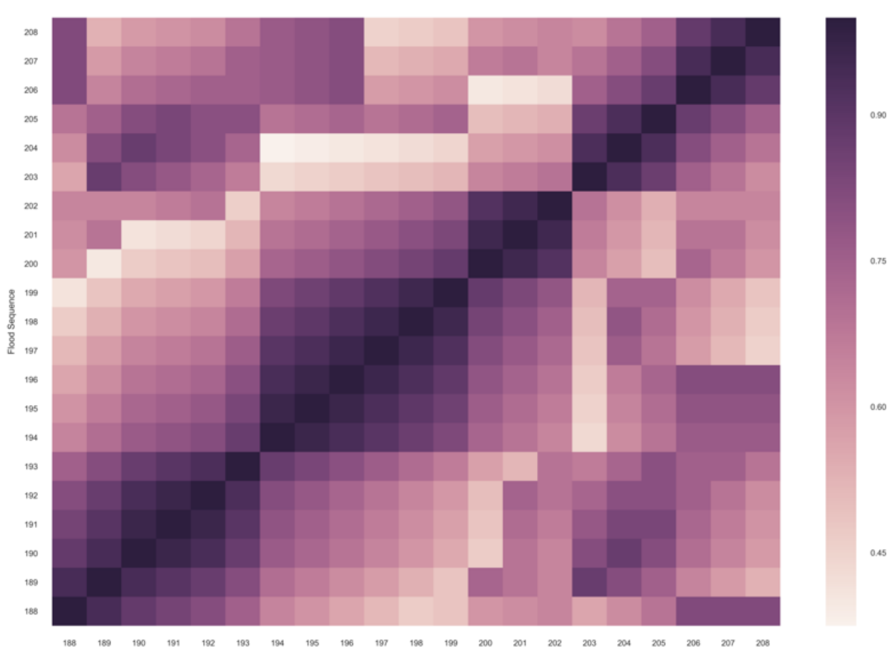


Figure 2.21: Similarity analysis for alarm flood clusters (part III)

- **Heat map:** The heat maps for the top 45 alarms tags with the highest count appearing during the 24-hour time period are plotted in Figures 2.16, 2.17, 2.18. The data values in the heat map are shown as colors; color bar on the right side of the heat map provides the number of times the alarm occurred on each day. The rectangular block shows the count of alarms per 10 minutes for each tag.
  Some conclusions that can be drawn from Figures 2.16, 2.17, 2.18 are as follows:
  - For Day 1 that there are some bad actors which appear as alarms several times during a 10-minute interval. *e.g.,* tag 142 appeared during 1040-1050 minutes 6 times alone.
  - During the same time frame, there are a few other tags which appeared multiple times resulting in a total number of alarms per 10-minutes as $>$10 alarms. Hence, such maps can be used to perform tag-wise detail analysis and observe the patterns and bad actors during an alarm flood or normal sequences. These tag values can be cross-checked with the tree map plots generated earlier.

- **Similarity plots:** A similar analysis is illustrated which shows a significant number of flood patterns due to several tags activating alarms in a 10 minutes time frame. The similar pattern was observed during the KPI calculation for Day 2 and Day 3. To understand the relationship between the alarm flood sequence, the correlation plots are developed as shown in Figures 2.19, 2.20, 2.21. A correlation test is used to evaluate the association between two or more variables. In this case, we are using the correlation test to find an association between the sequences of alarm floods as described in equation 2.9. As observed from the figure, sequence 203 & 189 and 204 & 190 are highly correlated. On further investigation, it is observed that these sequences have similar tags which appeared in these sequences. Similar, analysis is performed on different alarm flood sequences to find the similarity between the sequences.

2.12 Summary

Industrial alarm system management has improved over the past few years. However, there are still some critical challenges related to alarm management that need to be addressed. The advancement in automation technology and the increase in connected devices has resulted in a higher number of alarms, poor system performance, additional workload on operators, and in some cases has led to abnormal situations. To provide a solution to these challenges, we showed an alarm management framework with four distinct levels - design, rationalize, advance, and intelligent. In addition, this paper proposed a method to reduce alarm flooding by the use of data mining methods on Alarm and Event logs from an industrial control system which can be integrated to ANSI/ISA 18.2 alarm management life-cycle process. A real industrial data set is used to demonstrate the proposed method. As the data-set size increases it is more challenging to calculate the metrics for alarm management manually. The metrics for alarm management also known as KPIs were calculated with the proposed method and bench-marked against the available guidelines and standards. The KPIs were used to understand the alarm system performance and identify gaps at a glance. The visualization tools in the form of alarm rate plots, tree maps, heat map and similarity maps plotted for the data set to infer the data with ease and provide meaningful information related to the bad actors and assist in the overall decision making. The information generated from the proposed method can be used during the different stages of the alarm management life-cycle process for an operating plant with a well established alarm philosophy document and a plan in place. These can be used in either step of the proposed framework *e.g.,* to re-design or re-rationalize the alarm system by revisiting the master alarm database and address the requirement of each tag identified as a bad actor; design advanced alarm suppression rules based on the results obtained as similar tag sequences and thereby address issues related to the bad actors and alarm flooding.

3. PROCESS FAULT DETECTION: A DEEP LEARNING CLOUD BASED SOLUTION

3.1 Introduction

With advancements in modern industrial measurement and control technologies, operating industrial processes is becoming complex and challenging. The swift evolution of sensor and data acquisition technologies aids in better and higher resolution of data measurement, collection, and overall process monitoring. In addition to these benefits, such technologies provides a challenging environment for the individuals operating the facilities. With a high amount of signals to interpret and respond to in case of an abnormal event, the probability of missing a critical action increases which may ultimately lead to a process safety incident.

To enhance the overall process operation, there has been a substantial progress made in the areas of process monitoring, fault detection and diagnosis, and root cause identification. On the other hand, industry has started an initiative Open Process Automation Forum (OPAF) that will make process control and automation systems more modular and open to address challenges related to the obsolescence. Open Process Automation (OPA) requires a Real-time Operational Technology (OT) services on Advanced Computing Platforms (ACP) to analyze the data generated by the sensors and control loops to assist the process plant operations. Hence, there is a critical need to develop solutions and applications based on open source software platforms that can work on ACPs either on-premise or external cloud servers.

This work provides a basic introduction and theory of LSTM networks. A deep learning based BiLSTM model with auto-tuning of hyperparameters and adaptive optimizer to detect process fault conditions. The developed method is applied to a well known industrial case study (TEP) for fault detection and diagnosis. The proposed method is developed in Jupyter Notebooks (locally run web applications containing live code, figures, results, and mark-up text) in Python language.

3.2 Long-Short Term Memory (LSTM)

Traditional neural networks have been used by various researchers in the area of supervised fault detection and diagnosis. For a chemical process operation the value of a process variable at current time (t) is dependent on the value observed at a previous time step $(t-1)$, because of the time dependent characters tics of the variables under under monitoring and control. Traditional neural networks lack the ability to capture such dependencies and reasoning about the previous time step events. Generic RNNs also encounter the problem of vanishing/exploding gradient. This problem arises due to multiplicative gradient that exponentially increases or decreases with the number of layers selected *i.e.,* small wrights can lead to the situation of vanishing gradient and large weights can lead to the situation of exploding gradients. Due to this the network has a limited ability to learn high temporal relationships between the data. To address this, a Recurrent Neural Network (RNN) known as Long-Short Term Memory (LSTM) inspired by logic gates of computer for this study. LSTM is a special type of RNN designed by [132].

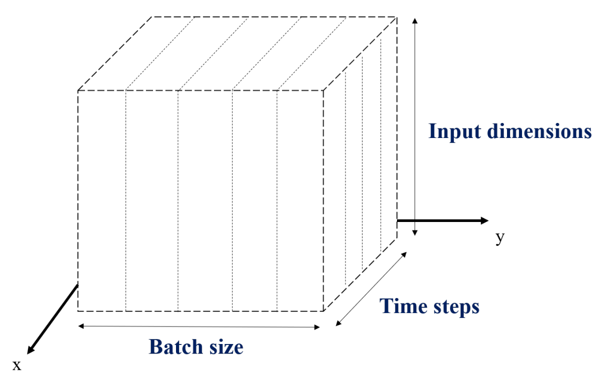


Figure 3.1: LSTM data requirements

The input data to a LSTM network is a three-dimensional tensor *(batch size, time-steps, features or input dimensions)* as shown in Figure 3.1. Where,

- *batch size* comprises of one or more samples/sequences;

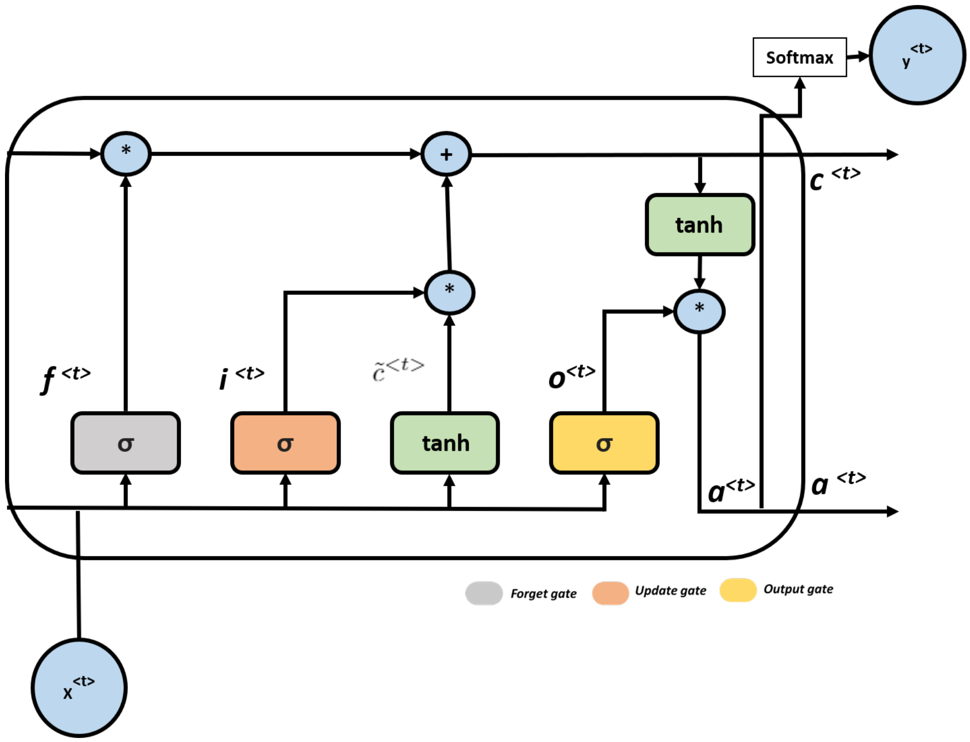


Figure 3.2: LSTM cell

- *time-steps* is an observation in the sample;
- *feature or input dimensions* is one observation at a time step.

LSTM cell as shown in Figure 3.2 is the basic building block of a LSTM network as shown in Figure 3.3. LSTM network has a chain like structure integrated with different repeating modules. The LSTM cell has gated memory cells known as input gate, forget gate and output gates. These gates are non-binary gates, but are mapped by a sigmoid (σ) activation function in [0, 1] range, where 0 indicates inhibition and 1 indicates activation of the cell. These gates help cells learn and remember information for a substantial time. The equations governing the LSTM network are shown in Equations 3.3, 3.4, and 3.5 derived from the equation 3.1 (used to calculate an activation for RNN). LSTM networks can be used to predict future based on the values from current and past by using an inherent property of LSTM cell that is *'learning non-linear dependencies among multiple inputs'*.

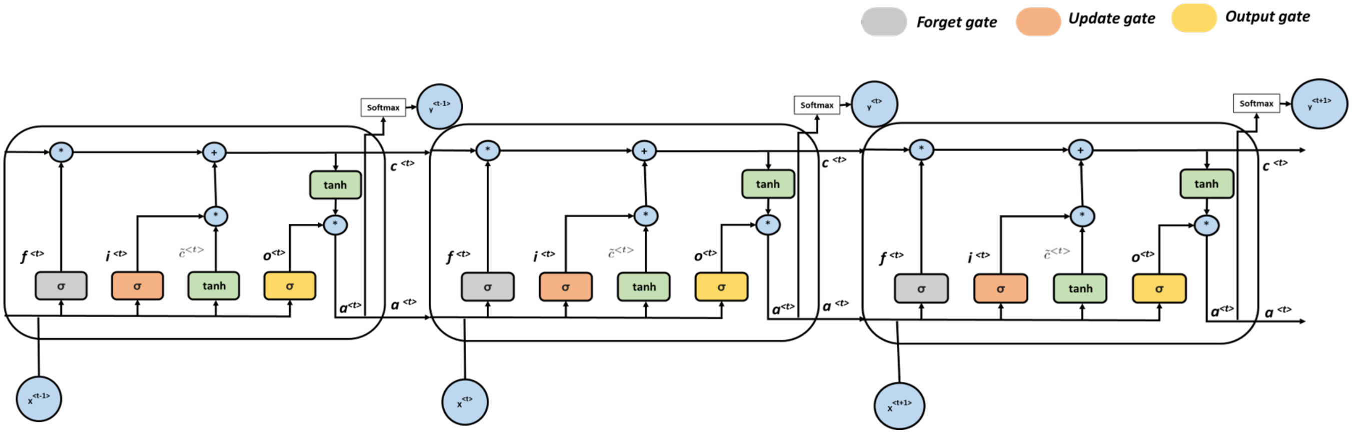


Figure 3.3: LSTM network with multiple cells

Activation for RNN

$$a^{<t>} = g(W_a[a^{<t-1>}, x^{<t>}] + b_a) \tag{3.1}$$

where,

- $a^{<t>}$ is an activation at time (t);
- g is the activation function used for the network;
- W_a is the weight vectors for the gates;
- $a^{<t-1>}$ is the activation at previous time step (t-1);
- $x^{<t>}$ is the input vector;
- b_a is the bias.

Candidate value for updating memory cell

$$\tilde{c}^{<t>} = tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c) \tag{3.2}$$

Where,

$$\tanh = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

Update Gate

$$\Gamma_u = \sigma(W_u[a^{<t-1>}, x^{<t>}] + b_u) \tag{3.3}$$

Where,

$$\sigma(sigmoind) = \frac{1}{1 + e^{-z}}$$

Forget Gate

$$\Gamma_f = \sigma(W_f[a^{<t-1>}, x^{<t>}] + b_f) \tag{3.4}$$

Output Gate

$$\Gamma_o = \sigma(W_o[a^{<t-1>}, x^{<t>}] + b_o) \tag{3.5}$$

Update value to the memory cell

$$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + \Gamma_f * c^{<t-1>} \tag{3.6}$$

Where, $c^{<t-1>}$ is the previous cell memory; and * is element-wise multiplication between two vectors

Output activation at time (t)

$$a^{<t>} = \Gamma_o * c^{<t>} \tag{3.7}$$

The hyperparameters used in LSTMs are:

(a) *Epochs and batch size* which decides the quality of prediction,

(b) *Learning rate* which controls the model weights, model learning speed, and ultimately the model performance.

In addition to the tuning requirements, selecting the best optimizer for the problem is also an important criteria. The data shuffling should not be performed during either of the steps of testing, validation, or fitting of the model to ensure the temporality is preserved in the data. For this study we have used a deep BiLSTM which includes multiple layers of the LSTM cell networks. The hyperparameters are tuned automatically to identify the optimum values and the desired model performance. The details of the method are shown in Section 3.3.

3.3 Proposed workflow

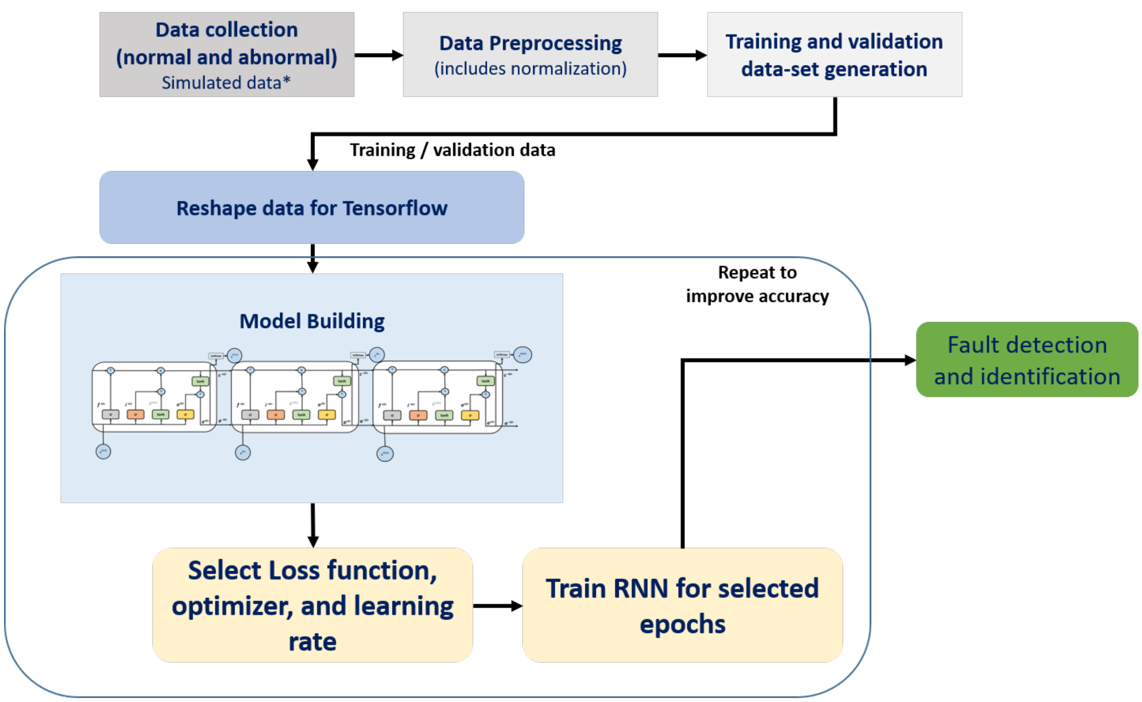


Figure 3.4: Proposed deep learning based method

For any AI model development and application, we need three things:

1. **Input data** that include the raw information related to the problem in hand

2. **Expected output** that includes the information about the correct output at a given instance of the data

3. **Algorithm effectiveness** that include a method to measure if the algorithm is performing at the desired level and accuracy.

The derived models help in transforming the input data to meaningful outputs by learning relations. A deep learning model uses successive layers for representation of data.

In case of process monitoring in an industrial setting, such data is collected and stored in plant historian or IP-21 system for future analysis. This data has various key information and parameters that can depict both the normal and abnormal behavior of the process. For this study we use similar data set to highlight the application of the proposed workflow. For any such industrial system the overall methodology can be classified into four steps:

- **Step 1: Data collection:** One of the most important aspect for a data-driven methodology and application is the availability and quality of the data. This means that the model developed in such instances is as good as the available data at user disposal. Hence, it is very important to collect data that depicts the true conditions of the problem being addressed. This involves the details of each process variable (measured or manipulated) with respective time-steps.

- **Step 2: Pre-processing and data generation:** Once the data is collected and stored the next step involve performing data quality assessment. This step involves methods such as

  1. Data cleaning that constitutes outlier identification, removal of outliers and noisy data, and incase there are missing sensor values then perform missing value imputation.

  2. Data transformation that constitutes scaling and normalization to ensure equal weights for each variable and to reduce biasing during the model building step.

- **Step 3: Model building:** The basic principle and structure for the LSTM network used in this study is described in Section 3.2. A multi-input problem can be modeled easily with the

LSTMs. In this case we have developed a model with multi-input and single output (binary classifier) depicting the presence (1) or absence (0) of a process fault condition.

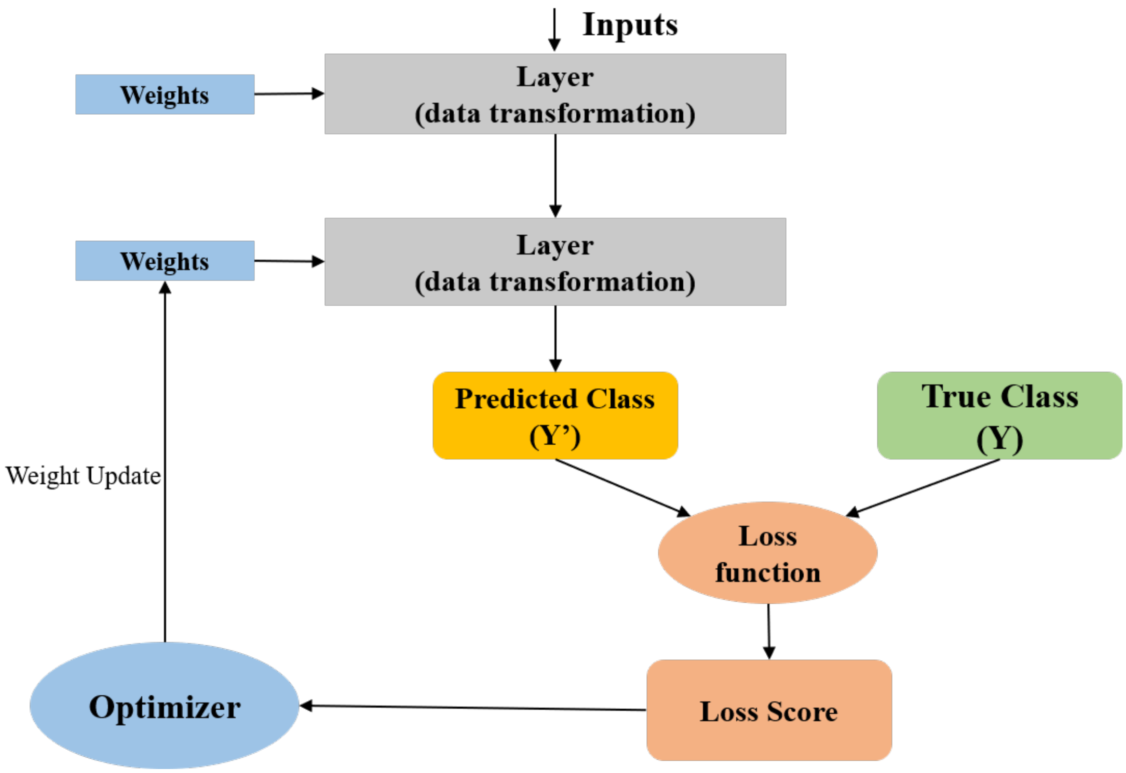


Figure 3.5: Loss function to adjust weights

We start with defining the layers of LSTM network and the input shape parameter. To reduce the overfitting we have used dropout regularization method. A trick used in deep learning is to use the loss score as feedback for the optimizer to adjust the weights of the network to ensure the loss is minimized as shown in Figure 3.5. The optimizer uses a back propagation algorithm to find the best weights for the designed network. The optimizer used for this study is Adam optimizer (an adaptive learning rate method) instead of the classical stochastic gradient descent (SGD) method. It is a combination of two algorithms RMSprop and SGD with momentum. Adam is designed for training deep neural networks, which uses adaptive learning rate methods to identify learning rate for each parameter by using first and second moments of gradients to adapt the learning rate for each weight used for the network following the rules below:

For Momentum

$$V_{dW} = \beta_1 V_{dW} + (1-\beta_1)dW; \tag{3.8}$$

$$V_{db} = \beta_1 V_{db} + (1-\beta_1)db; \tag{3.9}$$

$$V_{dW}^{corrected} = \frac{V_{dW}}{(1-\beta_1^i)}; \tag{3.10}$$

$$V_{db}^{corrected} = \frac{V_{db}}{(1-\beta_1^i)}; \tag{3.11}$$

For RMSprop

$$S_{dW} = \beta_2 S_{dW} + (1-\beta_2)dW^2; \tag{3.12}$$

$$S_{db} = \beta_2 S_{db} + (1-\beta_2)db^2; \tag{3.13}$$

$$S_{dW}^{corrected} = \frac{S_{dW}}{(1-\beta_2^i)}; \tag{3.14}$$

$$S_{db}^{corrected} = \frac{S_{db}}{(1-\beta_2^i)}; \tag{3.15}$$

The weight update is given as:

$$W = W - \alpha . \frac{V_{dW}^{corrected}}{\sqrt{S_{dW}^{corrected}} + \epsilon} \tag{3.16}$$

$$b = b - \alpha . \frac{V_{db}^{corrected}}{\sqrt{S_{db}^{corrected} + \epsilon}} \tag{3.17}$$

where,

- α is the learning rate
- V is the exponential average of gradient along the parameter
- S is the exponential average of squares of gradients along the parameter
- β_1, β_2 are the hyperparameters with values 0.9 and 0.99 respectively.

By using these equations the overall objective is to minimize the cost function given by:

$$J(W,B) = \frac{1}{m} \sum_{i=1}^{m} L(y'^i, y^i) \tag{3.18}$$

- **Step 4: Model implementation:**

Typical deep learning networks require higher order of computational power. A normal computer CPU is not able to address such requirements. For this study due to the magnitude of data and problem in hand we have used multiple GPU's with CUDA interface. The complete model code is written in Python 3 with tensorflow backend installed on Keras. The overall code is a Jupyter notebook which can be used on other cloud services such as Amazon Web-services (AWS).

3.4 Industrial case study and results

Based on the theory and methodology provided in Sections 3.2, 3.3 is applied on a public benchmark, Tennessee Eastman Process (TEP) case study (widely used for plant-wide control, fault detection and diagnosis research, and statistical process monitoring) to demonstrate the effectiveness. The details are available in Section 3.4.1.

3.4.1 Process description and data-set details

TEP is an industrial process with five main units: a reactor (where exothermic reaction occurs), Vapor-liquid Separator, Stripper, Compressor, and a mixer. The overall process flow diagram is shown in Figure 3.6. There are total of 52 variables with 41 measured shown in Table 3.1 and 11 manipulated variables shown in Table 3.2.

The reaction occurring in the reactor are given by:

$$\begin{aligned} A_{(g)} + C_{(g)} + D_{(g)} &\rightarrow G_{(l)}, \\ A_{(g)} + C_{(g)} + E_{(g)} &\rightarrow H_{(l)}, \\ A_{(g)} + E_{(g)} &\rightarrow F_{(l)}, \\ 3D_{(g)} &\rightarrow 2F_{(l)}. \end{aligned} \tag{3.19}$$

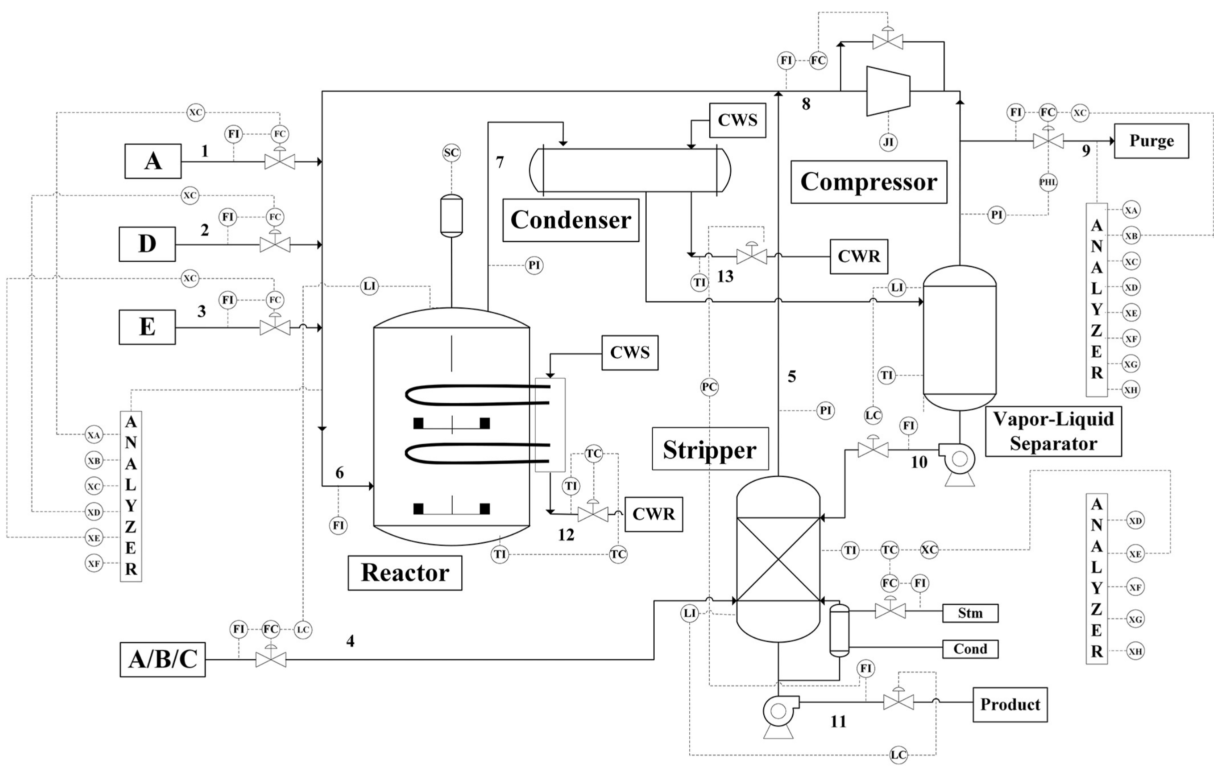


Figure 3.6: The Tennessee Eastman process

Table 3.1: TEP measured variables

Variable Number	Description	Measurement type
1	Feed A (Stream 1)	Process
2	Feed D (Stream 2)	Process
3	Feed E (Stream 3)	Process
4	Total Feed (Stream 4)	Process
5	Recycle Flow (Stream 8)	Process
6	Reactor Feed Rate (Stream 6)	Process
7	Reactor Pressure	Process
8	Reactor Level	Process
9	Reactor Temperature	Process
10	Purge Rate (Stream 9)	Process
11	Product Separator Temperature	Process
12	Product Separator Level	Process
13	Product Separator Pressure	Process
14	Product Separator Underflow	Process
15	Stripper Level	Process
16	Stripper Pressure	Process
17	Stripper Underflow (Stream 11)	Process
18	Stripper Temperature	Process
19	Stripper Steam Flow	Process
20	Compressor Work	Process
21	Reactor Cooling Water Outlet Temperature	Process
22	Separator Cooling Water Outlet Temperature	Process
23	Component A (Stream 6)	Composition
24	Component B (Stream 6)	Composition
25	Component C (Stream 6)	Composition
26	Component D (Stream 6)	Composition
27	Component E (Stream 6)	Composition
28	Component F (Stream 6)	Composition
29	Component A (Stream 9)	Composition
30	Component B (Stream 9)	Composition
31	Component C (Stream 9)	Composition
32	Component D (Stream 9)	Composition
33	Component E (Stream 9)	Composition
34	Component F (Stream 9)	Composition
35	Component G (Stream 9)	Composition
36	Component H (Stream 9)	Composition
37	Component D (Stream 11)	Composition
38	Component E (Stream 11)	Composition
39	Component F (Stream 11)	Composition
40	Component G (Stream 11)	Composition
41	Component H (Stream 11)	Composition

Table 3.2: TEP manipulated variables

Variable Number	Description
42	D Feed Flow (Stream 2)
43	E Feed Flow (Stream 3)
44	A Feed Flow (Stream 1)
45	Total Feed Flow (Stream 4)
46	Total Feed Flow (Stream 4)
47	Purge Valve (Stream 9)
48	Separator Pot Liquid Flow (Stream 10)
49	Stripper Liquid Product Flow
50	Stripper Steam Valve
51	Reactor Cooling Water Flow
52	Condenser Cooling Water Flow

The data-set for this study is taken from Harvard dataverse [133] that contains simulated data from both normal and abnormal events (IDV(1) to IDV(20)) as shown in Table 3.3. Each simulated set involves 500 simulations with total of 10,500 simulations for the complete data-set. The training data-set sample range us 1 to 500 with each measurement sampled at 3 minutes for a total duration of 25 hours, and testing data-set sample range is 1 to 960 with same sampling at training data for a total duration of 48 hours. The distribution details of the selected data-set are shown in Annexure A.

Table 3.3: Process faults and types in the Tennessee Eastman Process data set

Fault number	Process Variable	Type
IDV(1)	A/C feed ratio, B composition constant	Step
IDV(2)	B composition, A/C ration constant	Step
IDV(3)	D feed temperature	Step
IDV(4)	Reactor cooling water inlet temperature	Step
IDV(5)	Condenser cooling water inlet temperature	Step
IDV(6)	A feed loss	Step
IDV(7)	C header pressure loss-reduced availability	Step
IDV(8)	A, B, and C feed composition	Random variation
IDV(9)	D feed temperature	Random variation
IDV(10)	C feed temperature	Random variation
IDV(11)	Reactor cooling water inlet temperature	Random variation
IDV(12)	Condenser cooling water inlet temperature	Random variation
IDV(13)	Reaction kinetics	Slow drift
IDV(14)	Reactor cooling water valve	Sticking
IDV(15)	Condenser cooling water valve	Sticking
IDV(16)	Unknown	Unknown
IDV(17)	Unknown	Unknown
IDV(18)	Unknown	Unknown
IDV(19)	Unknown	Unknown
IDV(20)	Unknown	Unknown
IDV(21)	The valve fixed at steady state position	Constant position

3.4.2 Analysis and results

The data-set described in Section 3.4.1 is used for implementation and testing of the the deep BiLSTM network for the fault classification. This section highlights the key results obtained for this study. The following steps were performed:

- **Step 1: Data collection:** The data for this study was collected and transformed in the form of dataframes.

- **Step 2: Pre-processing and data generation:** Once the data is stored in the dataframes, a data quality check is performed to fins out any missing values. There were no missing values, hence no data inputation was performed. As shown in Table 3.3 there are total of 21 faults in the data-set. We have selected Fault numbers (1, 2, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 16, 17, 18, 19, 20) for this study. The complete data-set was divided using 70-30 rule for generating training and testing data. Also, the data was transformed and normalized to reduce the bias due to variable weights in the model building step.

- **Step 3: Model building:** This step includes designing and testing of the deep learning model and test the designed model. It involves transforming the data into tensors, model building including selecting the loss function, optimizer to be used during training of the model and selecting the learning rates. These selections help in ensuring the method will work at the desired level of accuracy and classification.The layers of LSTM network were defined. The network was trained and tested multiple time by tuning the hyper-parameters to find the best results. To reduce the over-fitting we have used dropout regularization method. The optimizer used for this study is adam optimizer.

- **Step 4: Model implementation:**

  Once the model was trained the overall model was tested on the testing data. The overall accuracy of two best models obtained is shown in Figures 3.7 and 3.8. The overall accuracy of the model is approximately 91% for model 1 and 93% for model 2. Model 2 is used in next steps to check the individual fault classification. The fault classification accuracy heat map is shown in Figure 3.9. As evident from the figure, some of the faults (Fault numbers: 1, 2, 5, 6, 7, and 14) were classified with highest precision (99%). Other faults (Fault numbers: 4, 8, 11, 12, 13, 17 and 18) were classified with an accuracy in the range of 81% - 94%.

The model generated here can be used to classify the faults online as well with similar input data-sets providing an overall accuracy of 93%. Also, the model accuracy can be improved by adding more data to the model. This will help model in generalizing the data and provide more accurate results.

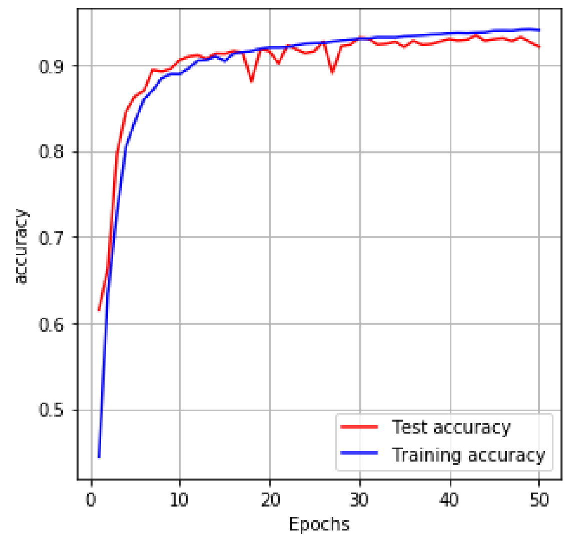


Figure 3.7: Model 1 accuracy

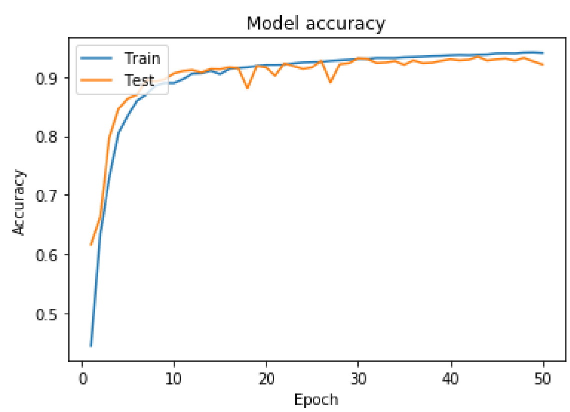


Figure 3.8: Model 2 accuracy

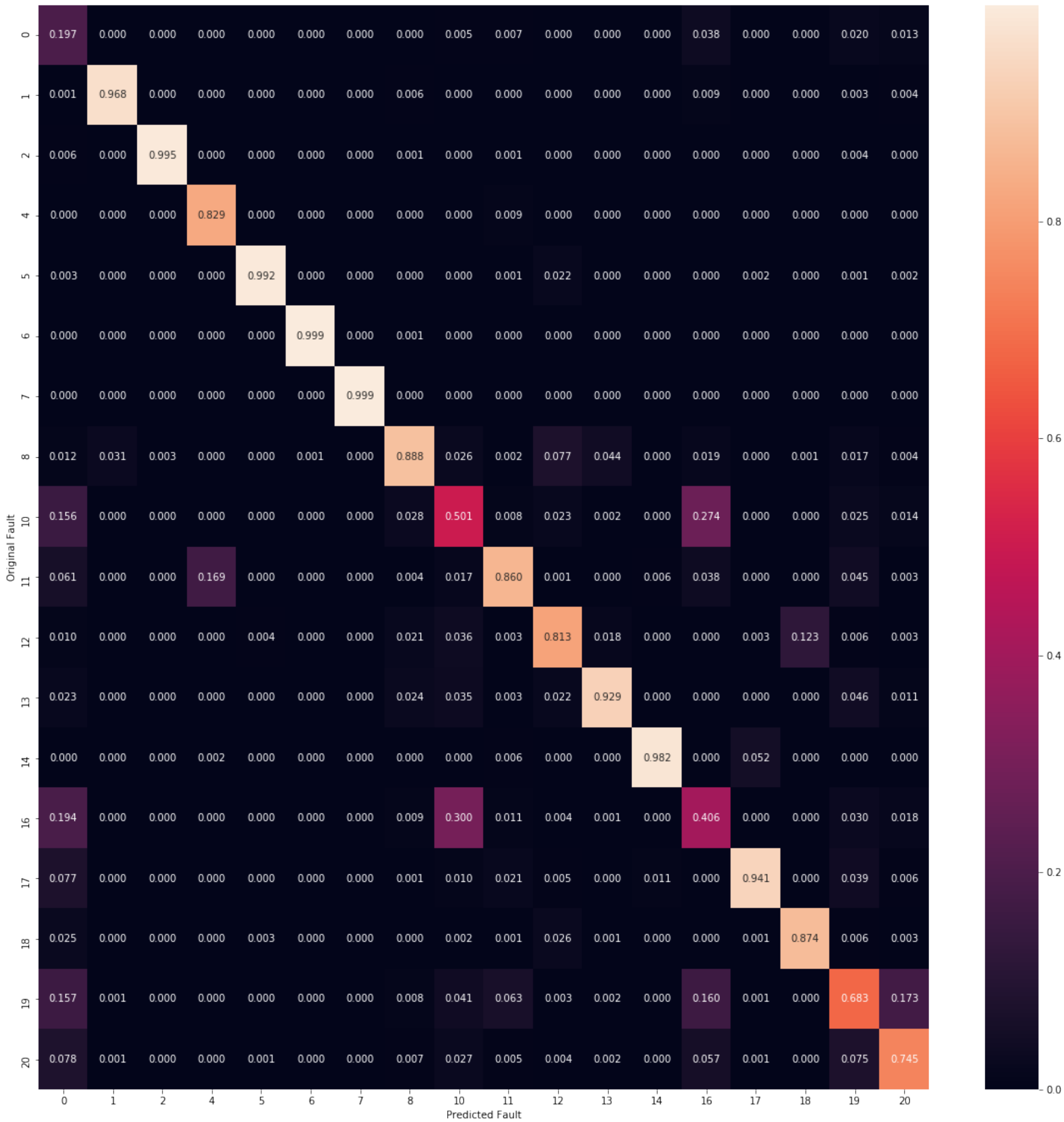


Figure 3.9: Map depicting fault classification accuracy values (model2)

3.5 Summary

In this work we provide the basic introduction and theory of LSTM networks. A deep learning based BiLSTM model with auto-tuning of hyperparameters and adaptive optimizer is developed to detect process fault conditions from process variable data values. The developed method is applied to a well known industrial case study (TEP) for fault detection and diagnosis. The proposed method is developed in Jupyter Notebooks (locally run web applications containing live code, figures, results, and mark-up text) in Python language. Google Cloud Platform is used for demonstration of the method. The proposed method can classify the faults for the given data-set with 93% accuracy. This information can be used to classify the process fault condition in an industrial facility and develop a guidance tool to provide prescriptive corrective information to the operator.

The main contributions of this work include:

1. A novel data-driven workflow to integrate the big data analysis, deep learning based BiLSTM on cloud platform, and reporting for process fault detection and classification.

2. An automated hyper-parameter optimization method is derived and used to identify the optimal hyper-parameters for the given data and designed network.

3. The proposed workflow and method is developed entirely on an open source software platform (Python). We use well know industrial plant problem to demonstrate the features and capabilities of proposed method.

4. The proposed workflow is cloud-ready and highlights the use of cloud computing to process data and run the proposed models in an effective manner. The cloud application enables users with the required computing power, scalability and flexibility of model design and application to improve overall decision making.

4. APPLICATIONS IN PROCESS SAFETY AND RISK MANAGEMENT

Emerging sensors, computers, network technologies, and connected platforms result potentially in an immeasurable collection of data within plant operations. The data can be captured in various types, sizes, and dimensions. Most of the data in these cases is unstructured or semi-structured. (Big) data and analytics have appealed to both practitioners and researchers in industry and academia with a promising potential to provide insights by uncovering invisible patterns and trends from this data. The application of data analytics is in its early stages and there is a need for organizations to design and adopt data strategy and architectures with data analytics including machine learning tools and artificial intelligence techniques to design and prototype solutions by processing voluminous data generated from disparate sources. This information is the key for an organization to improve the operational efficiency by reducing downtime and making operations more reliable and safer. In this work, we discuss the prospects of using (big) data analytics integrated with cloud services to improve plant operations. The chapter outlines the vision and a systematic framework highlighting the data analytics life-cycle in the area of process safety, risk management, and environmental protection.This work provides the basis of application of big data analytics in process safety that would provide valuable insights. This would result in more informed policy, strategic, and operational risk decision-making leading to a safer and more reliable industry. Different case studies in process safety and risk management area are used to demonstrate the application areas. It is concluded that a well-balanced integrated approach including machine supporting decisions integrated with expert knowledge and available information from various key resources is required to enable more informed policy, strategic, and operational risk decision-making leading to safer, reliable and more efficient operations.

---

[*] Reprinted in part with the permission from "Application of big data analytics in process safety and risk management" by Goel et al., 2017. *IEEE International Conference on Big Data*, (pp. 1143-1152), Copyright 2017 by IEEE.

[†] Reprinted in part with the permission from "How Big Data & Analytics can improve process and plant safety and become an indispensable tool for risk management" by Goel et al., 2019. *Chemical Engineering Transactions*, 77, 757-762, Copyright 2019 by AIDIC.

4.1 Big Data Analytics and Application

In addition to the attributes of big data mentioned in Section 1.1, it is essential that mechanisms exist for visualization and understanding of the information and relations between the data and the inference of meaningful information out of it returning, what is called, business intelligence (BI). This requires data storage and management, hardware and software resources, appropriate domain knowledge, and new methods and technologies. Combining big data with analytics can provide a significant advantage to make timely and efficient decisions related to 1) cost, 2) time, 3) product development, and 4) optimization. A humongous amount of data is captured and stored in different formats (structured, semi-structured and unstructured), from different sources (sensors, machines, applications, web, IoT) and stored by the organizations. The data is captured, stored, processed in batches or real-time with the help of algorithms or mechanical processes. Application of these methods vary for different sectors, ranging from aviation, automotive industry, banking and capital investments, communications , energy, utilities and mining, government, health industry, insurance, retail, technology *etc.* It is important for these industries to make most out of the weak signals from several key data sources both structured and unstructured and deliver a real time impact for an easy, quick and efficient decision making. Organizations and industries are exploring data analysis methods to discover insights and prepare personalized solutions to the challenges faced [134]. Some of the potential key areas and big data methods applications related to them are highlighted in Table 4.1.

Table 4.1: Big Data application by industry

Energy industry	**Health-care**	**Supply chain**	**Finance**	**Customer focused**
Regulation and policy	Clinical decision support	Supply chain optimization	Advanced forecasting	Customer segmentation
Frauds, cybersecurity, risk management	Individual analytics	Customer satisfaction	Governance, risk and compliance	Brand & Sentiment analysis
Operational performance, optimization	Personalized medicine	Product reviews, profitability	Financial performance, frauds	Pricing, Profitability, satisfaction

4.2 Process Safety Big-Data Management System

4.2.1 System introduction

Considering the significance of big data in process safety, this study establishes the Process Safety Big Data Management System (PSBDMS). As shown in Figure 4.1, this system is a two-pronged approach comprising of Challenges and Elements. The challenges are policy related, strategic, and operational that act as Drivers for big data analytics in process safety and risk management. The elements include data, stakeholders, methods, and technology that act as Enablers. Each of these elements has sub-elements to contribute to the overall process of PSBDMS.

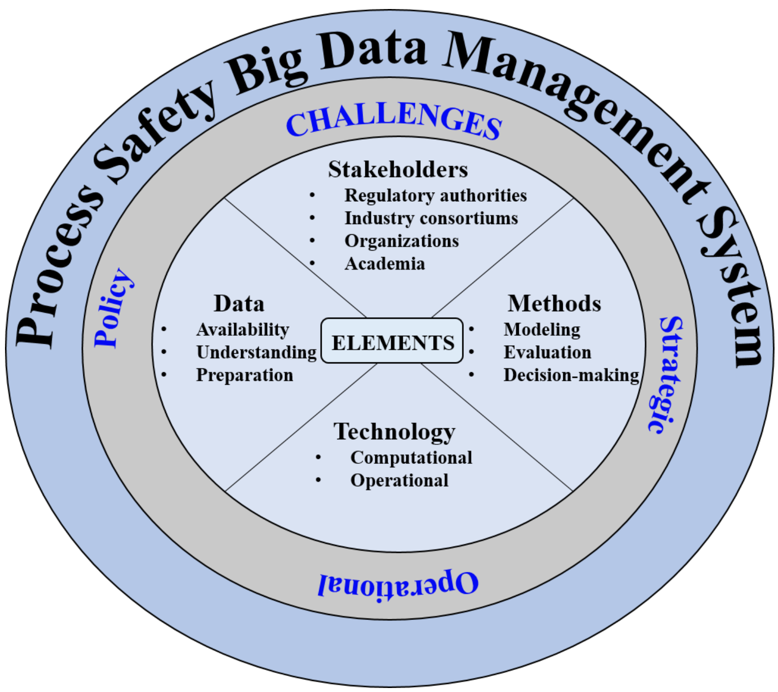


Figure 4.1: Process Safety Big Data Management System

4.2.2 Process Safety Data

Within the energy industry, data is generated continuously from various sources and available in different formats. Process safety related data can be broadly categorized into three different

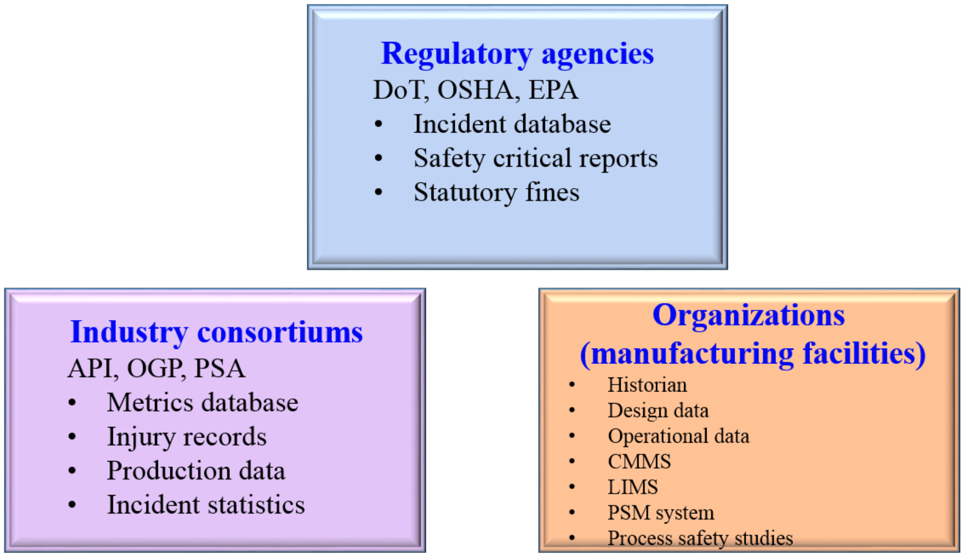


Figure 4.2: Process safety data sources

levels as depicted in Figure 4.2.

- Data collected by regulatory agencies such as Department of Transportation (DoT), Occupational Safety and Health Administration (OSHA), United States Environmental Protection Agency (USEPA) and similar agencies in other countries. Some examples of databases are incident statistics, statutory fines;

- Data collected by industry consortiums such as American Petroleum Institute (API), Oil and Gas Producers Association (OGP), and many more. Some examples of databases are metrics system, injury records, production data;

- Data collected by organizations (manufacturing facilities) such as chemical plants, oil and gas exploration units *etc.* These databases are further classified into seven areas based on the source and type of data. These are as follows:

  – Historian: process parameters, production data, machine monitoring, system fault records.

  – Design data: process flow diagrams (PFDs), piping and instrumentation diagrams (P&IDs), plant layouts, standard operating procedures (SOPs), insturment and equipment datasheets.

- Operational data: work permits, mechanical integrity and quality insurance data.
- Computerized Maintenance Management System (CMMS): maintenance and reliability records, risk-based inspections and filed visit records.
- Laboratory Information Management System (LIMS): quality reports, lab test reports.
- Process Safety Management (PSM) system: audit reports, Learning From Incident (LFI) communications, training records, safety culture assessments.
- Process safety studies: process hazard analysis (PHA)/ hazard and operability studies (HAZOP), emergency response plan evaluation studies, incident investigation reports.

4.2.3 Process Safety Challenges

Many authors have established that one major challenge in process safety is that incidents continue to occur [18, 116, 135, 136]. Also there is an increase in the development of different process safety and risk assessment methodologies and tools over the past few decades (1970-2020) [18]. From the data application viewpoint, we believe that in each of those development stages, data was collected and utilized in some form in the past. However, a systematic approach has not been established to implement process safety big data management. This gap can be filled with the incorporation of PSBDMS in addition to current risk assessment and mitigation methods. Some of the critical questions, which most risk assessors deal with are as follows - what is the right or uniform format for data collection?, what data are relevant and important to collect?, are our plants/facilities becoming any safer?, which metrics are significant and have an impact on safety?, can we analyze the health or effectiveness of safety barriers in plants?, and what will be an effective maintenance schedule? The incorporation of PSBDMS will address the above-mentioned questions at different levels. Challenges related to these questions can be categorized into policy, strategic, and operational as presented in Figure 4.3. It provides the three different levels of process safety challenges based on the stakeholders (regulatory agencies, industry consortiums, and manufacturing facilities) of the PSBDMS:

- Policy: This refers to the policy or rule making related challenges. These can be addressed by the regulatory agencies. Analysis of current databases can help infer knowledge on which other data may be relevant to collect, or effective usage of collected data, or prioritizing the inspection schedule for some facilities based on the analysis of collected data.

- Strategic: This refers to the industry consortiums such as API, and OGP, which collect data for industrial sectors. Analysis of these databases can help in the identification of robust metrics that influence the process safety significantly, or improvement of data collection and management structure, or improvement in monitoring with insights on new metrics

- Operational: This refers to the manufacturing plants/facilities, which collect a wealth of data within the organization. Analysis of these databases can help in the identification of weak signals, or evaluation of the effectiveness of safety barriers, or recognition of optimal maintenance schedule, or barriers prioritization and resource allocation for emergency response based on dynamic risk profiles.

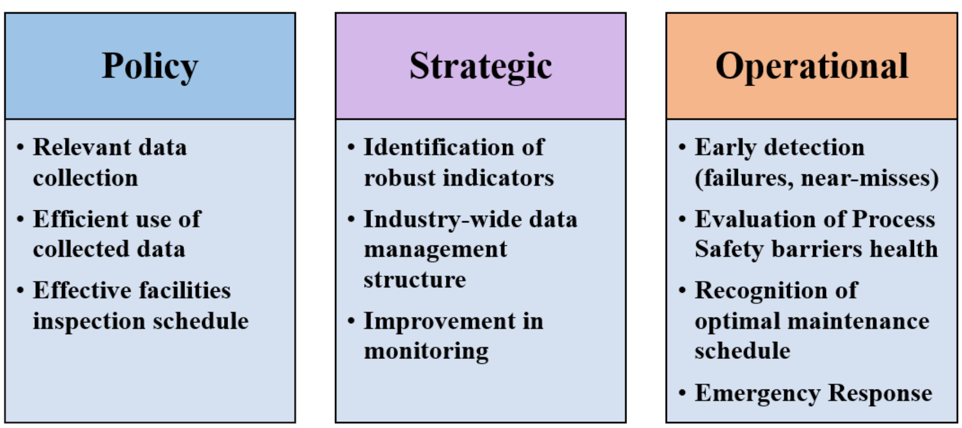


Figure 4.3: Challenges in process safety

4.2.4 Data analytics application and benefits

As explained in previous sections, there exist huge amounts of data that is being generated related to process safety at different levels-regulatory agencies, industry consortiums, and plant/facility. Based on data science, this raw data needs to be subjected to the process of pre-processing or cleaning in order to organize it into information. The data in the form of information or developed databases is then available for use by analysts to extract value from it and convert it into intelligence. These then lead to appropriate actions and support decision-making. Figure 4.4 highlights PSBDMS items for various phases to support improved process safety and risk management. These phases are established following the [137] model with steps: data understanding, data preparation, modeling, evaluation, and deployment. After the first phase of collection of process safety databases, the following phases help in answering process safety questions:

- **Descriptive analytics:** deals with determining what happened and converting the data into information such as pattern charts or histograms.
- **Diagnostic analytics:** refers to data presentation to understand why something happened or underlying causes for undesirable situations or events.
- **Predictive analytics:** refers to developing models on existing datasets to extract information on what will happen or predict future trends.
- **Prescriptive analytics:** refers to support decision-making or what should be done by use of advanced analytics.

Some of the significant benefits of implementing PSBDMS are as follows:

- Dynamic evaluation of risk profile of a facility with the support of real time visualization.
- Safer and reliable operations by incorporation of insights from data analytics enabling optimal maintenance schedules to avoid unplanned shutdowns.

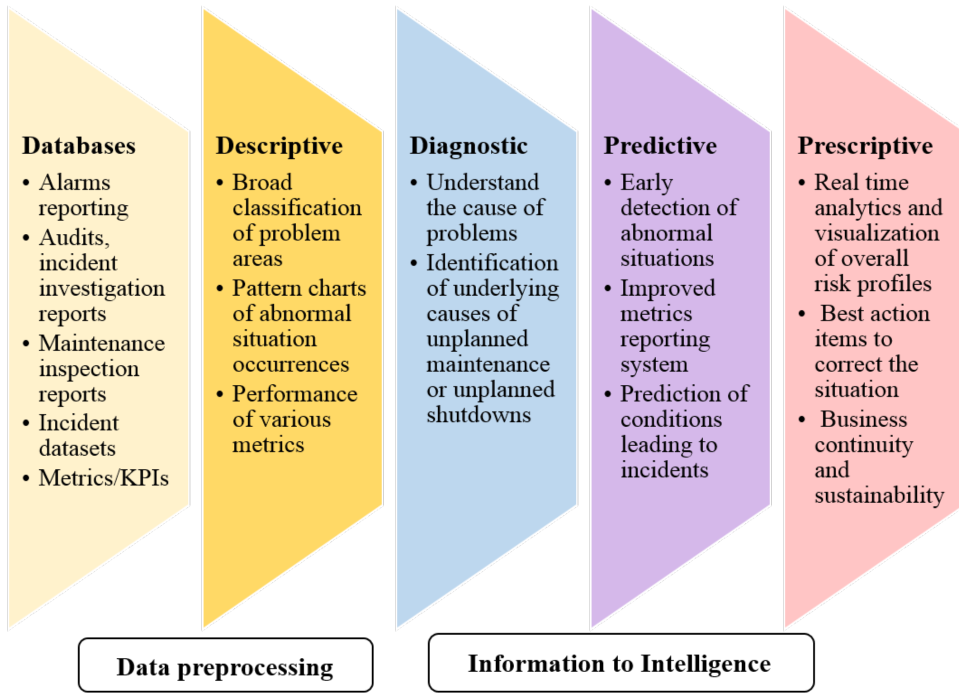


Figure 4.4: PSBDM model phases

- Resource allocation towards risk reduction and mitigation utilizing information on risk ranking for various areas in the facility.

- Effective action items from trending and analysis of process safety indicators.

- Improve monitoring by the introduction of new metrics and/or revision of existing metrics.

- Correlation development and use of detailed analysis (structured and unstructured data) to improve audits, incident investigations, hazard evaluation studies.

- Development of visualization dashboards for personnel from different levels within the organization.

For the above mentioned challenges and benefits, some of the application examples are described in Section 4.3 as case studies.

4.3 Case studies

In plant operations, data is captured from various heterogeneous sources which requires pre-processing and data-integration for further analysis and insight generation. In this section, we represent data-driven tools for maintenance and reliability, process safety, and text mining applications in process safety and risk management domains. To demonstrate the application of data analytics, deep learning, machine learning, and NLP, we have used different application areas to show the effectiveness of proposed methods to achieve goals of automated intelligent decision making leading to enhanced safety and more reliable operations.

4.3.1 Case study I: Pipeline and Hazardous Materials Safety Administration (PHMSA) incident database analysis

Table 4.2: Details of PHMSA datasets used for analysis

Details	**Dataset-A (2002-2009)**	**Dataset-B (2010-2017)**
Number of data points	3029	2969
Number of missing values	81	0
Number of states for reported incidents	48	33
Property damage range for reported incidents(millions)	\$0 to \$150	\$0 to \$ 840
Number of unique commodities	4	5
Number of unique causes of incidents reported	8	8

Most of the organizations in the oil & gas industry have implemented process safety management which involves capturing the details related to near-misses or an incident along with other

PSM elements. Similarly, several federal agencies such as DoT capture similar information related to their jurisdictions. From these databases important trends, areas of concerns and improvement methods can be derived to reduce the losses due to downtime, injuries, property damage and environmental impact. A detailed analytics plan can be used to address the challenges and derive the information for the stakeholders. One of the main challenges during analysis is how to select specific variables from hundreds of variables and draw meaningful conclusions [138]. To demonstrate the application of such analysis on an incident reporting database, we used a publically available dataset of HAZMAT incident from PHMSA website [139], processed it to build a predictive model and validated it with the help of Python [140] and IBM SPSS Modeler [141]. The summary of the database is described in Table 4.2. Two datasets A and B have been used in this analysis. In general the missing data is imputed during the analysis; however, in this case it is not possible since the database is an incident database, based on actual scenarios and investigations. Hence, the missing values observed were discarded. For ease in visualization following changes were made to the datasets:

1. The description for commodity classification was made short.
2. The description of commodities and causes for both datasets were made universal.

The data analytics methods were used to analyze the data and machine learning techniques to categorize and predict the significance of the incident. This was based on the available data, model generation and application of the model. For this purpose, one of the significance criteria was used based on property loss>=$50,000USD [139]. First a descriptive analysis was performed in Python to understand the datasets available and understand the nature of the incidents, types of commodities involved as illustrated through a graphic in Figure 4.5 and to categorize the states based on number of incidents, a choropleth map shown in Figure 4.6 is prepared using 'Python'[140] and 'Plotly'[142]. To prepare a predictive model for the incident significant classification, first the dataset from 2002-2009 was used to train the model and generate various decision rules with IBM SPSS Modeler. The details observed from different methods used for the purpose of model gen-

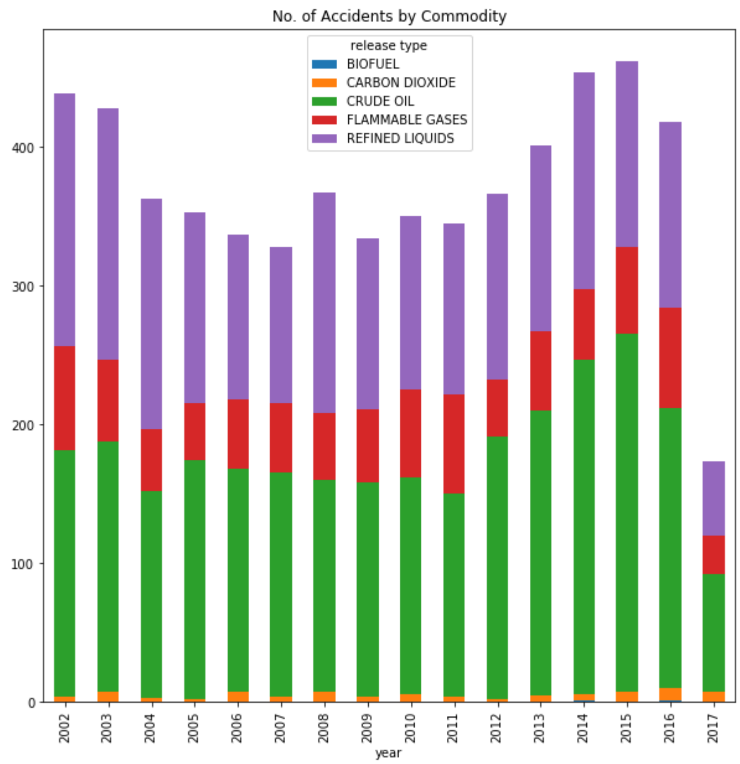


Figure 4.5: No. of accidents by commodity

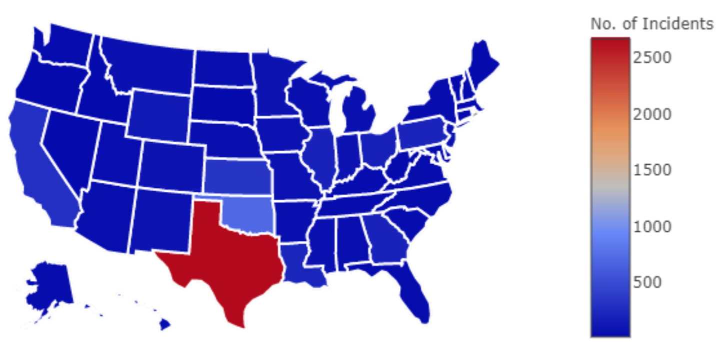


Figure 4.6: Choropleth incident map (developed from PHMSA database: 2002-2017)

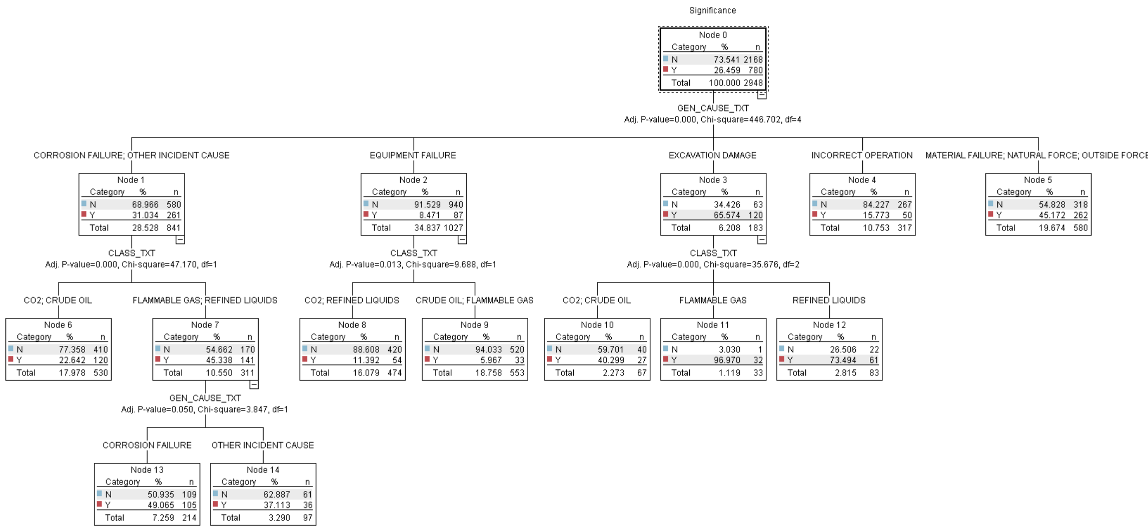


Figure 4.7: CHAID tree for dataset A

eration and deployment are show in Table 4.3and a chi-squared automatic interaction detection (CHAID) tree is shown in Figure 4.7. Out of the mentioned models, classification and regression tree (C&RT) was selected as it was providing the predictions at a higher accuracy according to the significance rule defined prior to the study.

Table 4.3: Models tested on datasets

Model	Lift	Overall Accuracy
No property loss selected		
CHAID	1.916	75.91
Random tree	1.882	72.8
C&R tree	1.831	75.916
Property loss selected		
CHAID	3.333	96.4
Random tree	3.333	96.4
C&R tree	3.333	100

The C&RT results are shown in Figures 4.8 and 4.9 for dataset A and dataset B respectively.

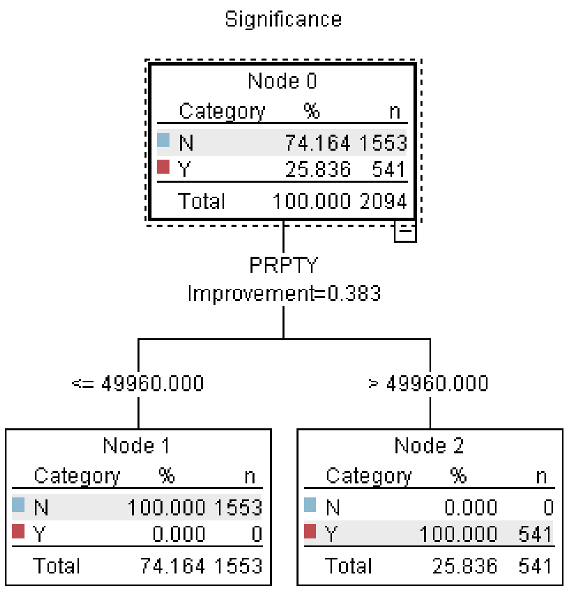


Figure 4.8: Tree for datset A

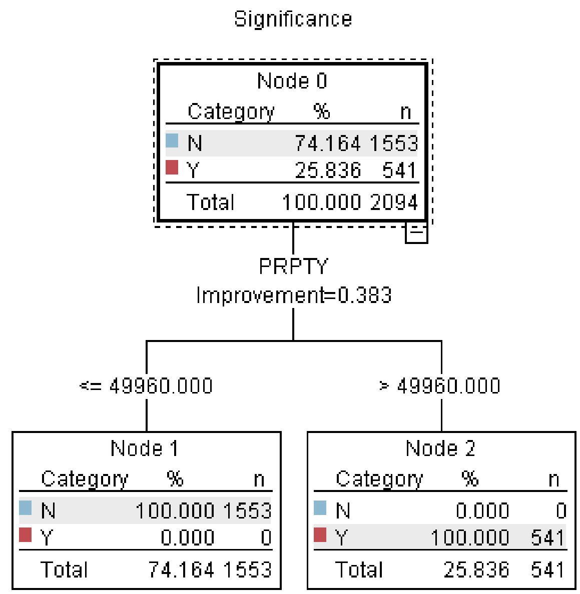


Figure 4.9: Tree for datset B

	IYEAR	ACSTATE	PRPTY	CLASS_TXT	GEN_CAUSE_TXT	$R-Significance	$RC-Significance
1	2010....	TX	250350....	CRUDE OIL	EQUIPMENT FAILURE	Y	0.998
2	2010....	TX	44150.0...	CRUDE OIL	EQUIPMENT FAILURE	N	0.999
3	2010....	OK	387.000	FLAMMABLE GAS	INCORRECT OPERATION	N	0.999
4	2010....	OK	64515.0...	FLAMMABLE GAS	CORROSION FAILURE	Y	0.998
5	2010....	IL	860700....	CRUDE OIL	CORROSION FAILURE	Y	0.998
6	2010....	TX	17550.0...	CRUDE OIL	CORROSION FAILURE	N	0.999
7	2010....	OK	125355....	FLAMMABLE GAS	MATERIAL FAILURE	Y	0.998
8	2010....	KS	28762.0...	REFINED LIQUIDS	CORROSION FAILURE	N	0.999
9	2010....	TX	205645....	CO2	MATERIAL FAILURE	Y	0.998
10	2010....	TX	4055.000	CRUDE OIL	EQUIPMENT FAILURE	N	0.999

Figure 4.10: Predicted significance of dataset B

The predicted significance result for dataset B is shown in Figure 4.10. It is observed that for dataset B, the generated model based on C&RT is able to predict the significance of the event with 96% accuracy. As there was no missing information the model was able to predict with great accuracy. Such studies and models are useful in identifying the areas of concern both from the organization's and regulatory authorities' perspective. At the same time, such systems can be used to interpret the historical data available as reports, notes and copies to understand the importance of reporting and learning from incidents. Similar results could be further utilized by agencies to allocate resources optimally towards prioritization of inspections and understanding the key focus areas.

4.3.2 Case study II: Predictive model for equipment failure

A key element in Process Safety Management is Mechanical Integrity (MI) that is associated with equipment reliability and maintenance. Equipment reliability has been studied by many researchers in the field due to its significance in avoiding mechanical problems [143, 144, 145]. Predictive maintenance is an important component in the MI system and plays a key role in improving reliability to reduce the probability of unexpected shutdowns, production losses due to equipment downtime, and safety incidents. Prediction of these problems would improve operations and support effective maintenance. Various kinds of operational data for equipment such as vibration and other condition monitoring data, planned or unplanned maintenance event data, fault occurrence, failures are collected from different systems such as CMMS, historian *etc.* in the manufacturing facility. With the use of this historical data and application of data analytics, model based failure predictions of equipment or equipment parts can be made.

A case study of a pump is used to demonstrate the application of data analytics for failure prediction. The data types used for this study are – time-series data which consists of vibration and voltage (hourly), fault logs (vibration, voltage) for two parts (rotor, motor), planned and unplanned maintenance records, and failure of the parts. Synthetic datasets were generated following certain statistical distributions in programming language R for the year 2016 [146]. For these datasets, complexities were added and certain reasoning was followed to make them similar to real situations. For example, outliers were placed in the time series vibration and voltage data; actual failures were assigned for the higher number of days since last replacement of a part. Features to predict the health of the pump are extracted from these data sources by using the time-stamps from time-series data. Table 4.4 shows the different extracted features to develop the prediction model [147, 148, 149]. Figure 4.11 provides the snapshot of all features that are incorporated in the training formula.

For the modeling process, features dataset is divided into training and testing datasets. The

	DateandTime	Voltmean	Vibmean	Voltsd	Vibsd	Voltmean24	Vibmean24	Voltsd24	Vibsd24	Sum_fault1
1	1/2/16 0:00	216.667	2.485	5.13160	0.07618	217.958	2.465	6.53738	0.07041	0
2	1/2/16 3:00	220.333	2.522	4.04145	0.03402	218.000	2.475	6.20659	0.07205	0
3	1/2/16 6:00	225.000	2.459	4.00000	0.05336	218.708	2.471	6.73394	0.07087	0
4	1/2/16 9:00	222.000	2.439	10.44031	0.05218	219.250	2.461	6.82865	0.07045	0
5	1/2/16 12:00	221.333	2.496	5.68624	0.06490	220.167	2.470	6.58501	0.06687	0
6	1/2/16 15:00	213.667	2.483	2.08167	0.09416	219.500	2.469	6.44711	0.06981	0

	Sum_fault2	Days.since.last.Part_1.rep	Days.since.last.Part2.rep	Failure
1	0	0.750	0.750	none
2	0	0.875	0.875	none
3	0	1.000	1.000	none
4	0	1.125	1.125	none
5	0	1.250	1.250	none
6	0	1.375	1.375	none

Figure 4.11: Extracted features snapshot

Table 4.4: Details of features extracted for the dataset

Variable	**Extracted features**
Vibration	3-h and 24-h rolling meand and standard deviation
Voltage	3-h and 24-h rolling meand and standard deviation
Faults	Number and type of faults
Maintenance	Days since last replacement of pump parts
Failures	Actual failures

training dataset comprises of the first eight months of data and the testing data comprises of the last four months. Figures 4.12 and 4.13 illustrates the results of pump predictive maintenance model for three classes– ‘None’ represents no failure, ‘Part_1’ represents failure of the rotor, and ‘Part_2’ represents failure of motor. Table 4.5 represents the confusion matrix, which gives the true positives (TP), true negatives (TN), false positives (FP), false negatives (FN) for classes. It is observed from this matrix that 964 of the 967 ‘None’, 2 of the 3 ‘Part_1’, and 3 of the ‘Part_2’ classes were predicted correctly. Table 4.6 provides the metrics such as precision, recall, F factor,overall accuracy,and kappa score to interpret the robustness of the model.It is observed that for prediction of ‘Part_2’ failures, the model does not yield good results. This could be due to the use of synthetic data in the model, real datasets would provide a more accurate analysis and prediction of the failures. Application of similar studies would aid in the early recognition of failures, time for operations to adapt, cost reduction in maintenance by following a good strategy and improve safety by reducing unexpected failures.

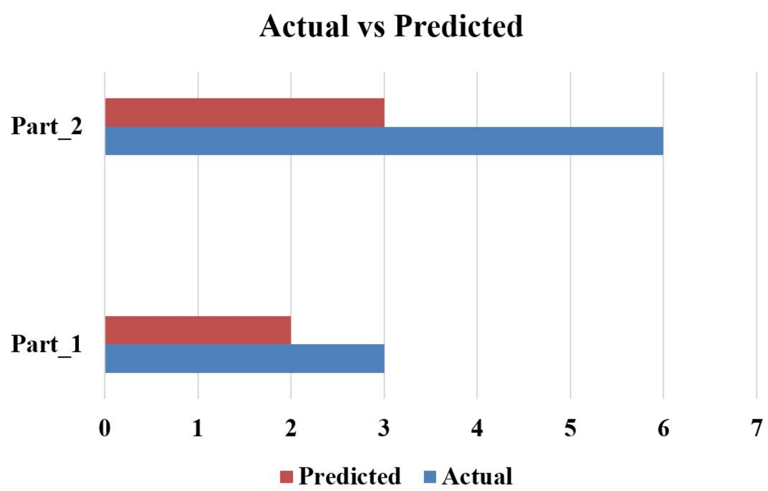


Figure 4.12: Actual vs Predicted (Part_1, Part_2 class)

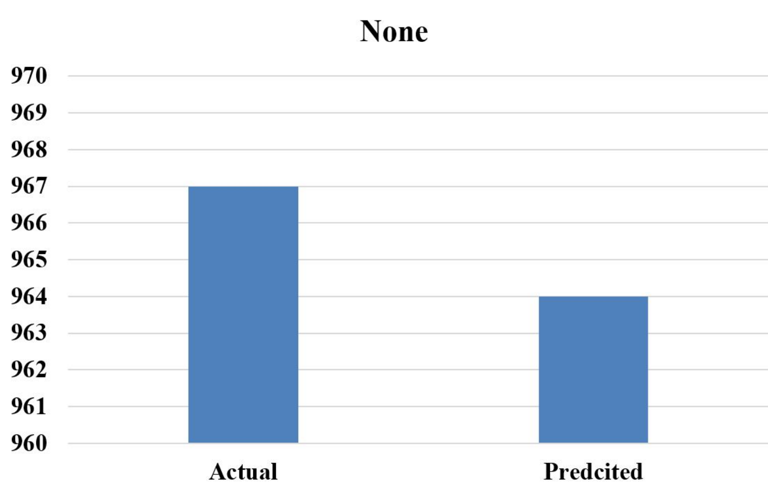


Figure 4.13: Actual vs Predicted (None class)

Table 4.5: Evaluation Metrics for confusion matrix

Actual	**Predicted**		
	None	**Part_1**	**Part_2**
None	964	0	3
Part_1	1	2	0
Part_2	3	0	3

Table 4.6: Evaluation Metrics for confusion matrix

	Precision	**Recall**	**F**
None	0.99587	0.99689	0.96388
Part_1	1	0.67	0.8
Part_2	0.5	0.5	0.5

Overall accuracy: 0.99283
Kappa score: 0.58539

4.3.3 Case study III: Dynamic risk mapping

Manufacturing facilities such as chemical plants, offshore platforms have been recognized as complex socio-technical system by researchers [18]. Facilities have various subsystems and/or components that have complex interactions, which result in changing operations environment. This affects the risk profile of the facilities and hence it is important to study the emergent behavior of these interactions within the complex systems. So far, the body of literature that is concerned with dynamic risk profiles due to emergent behavior of complex process systems using big data analytics is small. In this section, a systematic methodology is described and developed. For this purpose, the process unit system is reproduced as a system of layers as illustrated in Figure 4.14. Based on this system of layers, a dynamic risk profile is obtained by the incorporation of the wealth of data generated in the facility from various sources such as historic information, Centralized Maintenance Management System (CMMS), operational data, and Process Safety Management (PSM) system in the form of indicators [17]. With the real plant data, the risk could be assessed also applying contributions from safety culture survey data, audit reports and more.

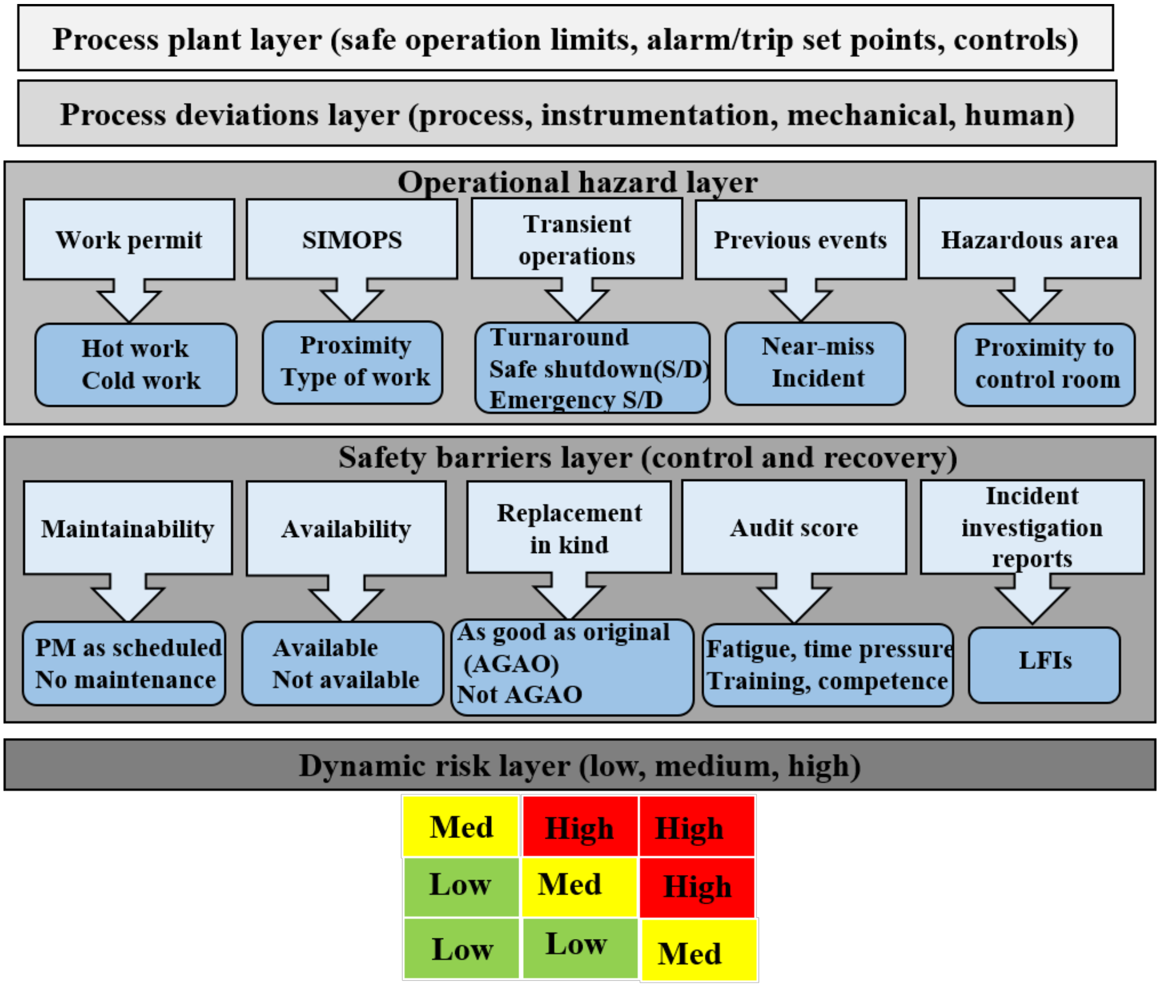


Figure 4.14: Big data dynamic risk analysis framework

The dynamic risk evaluation involves different steps similar to a Layer of Protection Analysis (LOPA) study. As illustrated in Figure 4.17, the following is a step-wise methodology that involves layer-wise analysis from plant layer to safeguards layer to calculate the final risk as low, medium or high as indicated in the matrix of Figure 4.14:

Step 1 Scenario identification: To define a scenario in details applying basic fault and event tree. Fault tree analysis helps to identify the initiating and basic events leading to the top event. Event tree analysis supports the identification of safety barriers in place to prevent and mitigate the consequence. F_1 (see Figure 4.17, layer 2) is evaluated from the scenario analysis in the form of initiating scenario probability leading to a risk of major consequence. Depending on the scenario, this follows different combinations of AND/OR gate calculations.

Step 2 Plant operations assessment: This step deals with identification of the dynamic factors based on the operational hazard layer. These could be from issued work permits, ongoing SIMOPS (simultaneous operations), transient operations, previous events, and hazardous area classification. Outcome of this step is Operations Hazards Factor F_2 acting as an additional factor leading to increased event probability: in the conventional case it is not considered, in the dynamic case $F_2 \leq 1$. Contributions to F_2 by various operational activities are time-averaged, composed as AND gates, while the smaller the value the larger the effect.

Step 3 Barrier health assessment: This step is a combination of identifying the existing control and recovery barriers available for the scenario and assessment of their health, based on the conditions of items from the safety barriers layer. Here, F_3 is evaluated after dividing the probability of failure on demand (PFD) of each protection layer, assumed independent of the others (IPLs), by a corresponding penalty factor. The penalty factors are determined based on indicators of maintainability, availability, replacement and audit (see Figure 4.15). F_3 is derived from the product of penalty factors adapted PFDs (LOPA approach).

Factor	Penalty
Maintainability	
PM as per schedule	1
No Maintenance	0.5
Availability	
Available	1
Unavailable	0.5
Replacement in Kind	
As good as original	0.8
Not as good as original	0.1
Audit Score	
Training and competence	
No records	0.1
Partial records	0.4
Complete records	1
Fatigue	
No fatigue reported	1
Slight fatigue reported	0.5
Extreme fatigue reported	0.2

Figure 4.15: Penalty factors

Step 4 Calculation: The final step is to calculate the risk of a major consequence occurring from the collected operations data. The proposed method follows LOPA approach, incorporating additional factors based on the data from dynamic operations. Equation 4.1 is used to calculate risk of a major consequence as shown below:

$$R = F_1 * \frac{F_3}{F_2} \tag{4.1}$$

4.3.3.1 Example case study

An accident scenario is considered to analyze and map the dynamic risk profile. This type of dynamic risk profile analysis would support more informed operational decisions, improved maintenance plans, work execution strategies, and overall safer and more reliable operations. The way data mining is performed is as follows: At any moment in time discrete parameter values (true [1] or false [0]) will be read by the risk calculation module at a suitable time frame sequence. Beside the parameter values inputs to the risk calculation module are user defined weights for the fourth layer parameters expressing the degree of effectiveness of the relevant parameter.

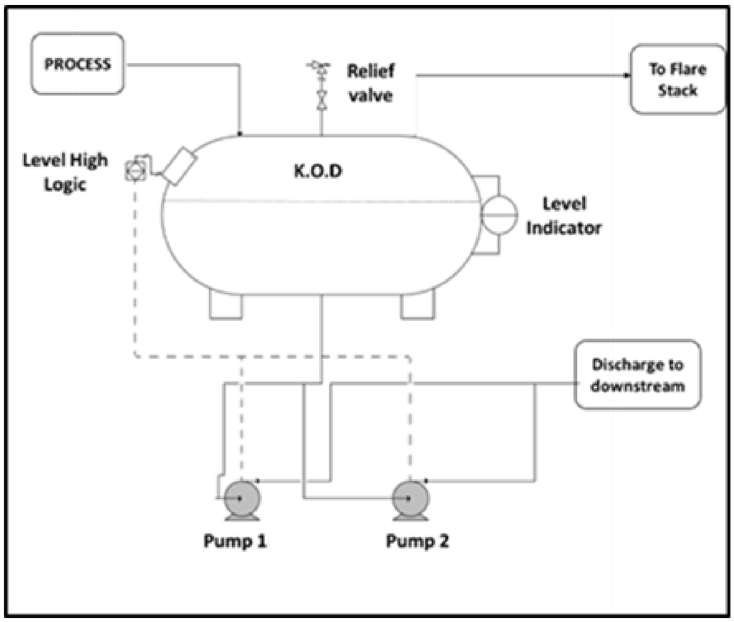


Figure 4.16: Knock Out drum with piping

The example scenario as shown in Figure 4.16 concerns a knock out drum (K.O.D.) which includes a level switch and a level transmitter indicator. During the normal operation the process stream is captured in the K.O.D. The liquid from the process stream is discharged with the help of pumps as soon as the level reaches a set point measured by the level switch. High level occurs 2 to 3 times per day. If at high level increase continues a hazard situation of a major risk event is due to liquid discharge to the flare stack causing liquid-carryover and spreading of fire or even explosion. For the purpose of the study, we assume that level indication may malfunction, that of the two pumps in the process stream one is under maintenance and the other may fail to start, and that the upstream process may be under upset condition (isolation valve fails). In this case, the following three barriers are available:

1. **Barrier 1:** High level switch (LSH) and Basic Process Control System cutting off flow to K.O.D. with an operator response;

2. **Barrier 2:** Operator checking that BPCS is working; and

3. **Barrier 3:** Pressure Relief Valve connected to the vent line.

In conventional risk assessment analysts do not explicitly consider various variables related to human and organizational factors, nor do they consider changes in the conditions and in input data. The latter, such as component failure data may have been determined over the years in the plant but are often estimates based on information from elsewhere. The effect of correlation and dependencies are usually ignored. Even for this simple scenario variants are imaginable which may worsen the situation, such as the sticking of the pressure relief valve. Anyhow, for this simplified example in the static QRA maintenance influences, which can appear as issuing work permits, simultaneous nearby maintenance operations, which can be a threat to the plant or others, are not considered ([1] in layer 3 of the left table of Figure 4.17). Hence, due to ignoring operational hazards and health or robustness of barriers the calculated risk seems Low (rounded value $2.10^{-5}/yr$).

However, the dynamic risk mapping approach developed in this study is using data from the plant informing us on various parameters for the operations (layer 3), such as whether hot work occurs. Also, results of health of barriers by maintenance inspection and testing results (layer 4) can be monitored. If needed this can be followed by repair, or e.g. replacement with a similar instrument, hence confirming availability or not. In case activities are on, hazard values for different operations are assigned based on experience, for example, a value of 0.4 for hot work. For these values expert estimates can be used applying methods described earlier. In the course of time updates may be established. This way we get a different value of risk depending upon the actual daily operations in the plant. In this example scenario the value of risk at a certain time and given conditions is calculated to be Medium (rounded value $6.10^{-4}/yr$).

Hence, we can see that with the help of dynamic risk mapping by considering more realistic sce-

Layer 1: PLANT		
Liquid level	80%	
Layer 2: DEVIATIONS		
High level	85%	
Deviations	**Probability of failure**	
Level indicator malfunction	0.020	
Pump 1 fails to start	0.167	
Pump 2 under maintenance	0.025	
Upstream system malfunction	0.025	
F1	0.049	
Layer 3: OPERATION HAZARDS		
Work permit system		
SIMOPS Proximity		
SIMOPS Type of work		
Transient operations		
Previous events		
Hazardous area proximity to Control Room/Process unit		
F2		
Layer 4: SAFEGUARDS		
IPL1: Level switch and Operator response	0.037	
IPL2: Basic Process Control System	0.035	
IPL3: Pressure Relief Valve	0.001	
F3	1.28E-06	
Output: RISK		
Intiating Event Frequency (F1)	0.049	
Operations Hazard Factor (F2)		
Probability of failure on Demand (F3)	1.28E-06	
Risk (High level frequency 2-3/day, hence risk of major consequence)	6.32E-08	(per day)
	1.89E-07	(per 3 days)
	2.31E-05	(per year)
Risk	Low	

Not Considered

Layer 1: PLANT		
Liquid level	80%	
Layer 2: DEVIATIONS		
High level	85%	
Deviations	**Probability of Failure**	
Level indicator malfunction	0.020	
Pump 1 fails to start	0.167	
Pump 2 under maintenance	0.025	
Upstream system malfunction	0.025	
F1 (Initiating malfunction probability)	0.049	
Layer 3: OPERATION HAZARDS		
Category	**Factor Value**	**Factor**
Work permit system	0.4	Hot work
SIMOPS Proximity	0.6	Near
SIMOPS Type of work	0.8	Cold work
Transient operations	1	NA
Previous events	1	NA
Hazardous area proximity to Control Room/Process unit	1	NA
F2	0.2	
Layer 4: SAFEGUARDS		
IPL1: Level switch and Operator response	0.037	PFD
		Preventive maintenance as per schedule
		Available
Penalty factor	0.4	Partial records
Score	0.092	
IPL2: Basic Process Control System	0.035	PFD
		Preventive maintenance as per schedule
		Available
		Complete records
IPL3: Pressure Relief Valve	0.001	PFD
Penalty factor	0.5	No maintenance
		Available
		Complete records
Score	0.002	
F3	6.42E-06	
Output: DYNAMIC RISK		
Initiating malfunction probability (F1)	0.049	
Operations Hazard Factor (F2)	0.2	
Probability of failure on Demand (F3)	6.42E-06	
Risk (High level frequency 2-3/day, hence risk of major consequence)	1.64E-06	(per day)
	4.74E-06	(per 3 days)
	5.76E-04	(per year)
Dynamic Risk	Medium	

Figure 4.17: Conventional vs dynamic risk mapping

narios and failure values we have a very different and more realistic value of risk. This risk value is not constant and may change depending on various key scenarios during the plant operations. In reality even more factors can be taken into account.

4.3.4 Case Study IV: Failure prediction for mechanical equipment (Predictive Maintenance Monitoring)

Heavy rotating equipment such as pumps, compressors, *etc.* play an important role in the process plant operation. These are the prime movers in the plant required to transport and maintain the required pressure and flow to the process equipment. Failure to maintain the integrity of the equipment may lead to downtime, production loss, or sometimes safety incidents. Usually for plant maintenance, team follows following strategies for any mechanical, electrical or instrumentation equipment, (1) Preventive maintenance (PM), which includes performing routine inspection, maintenance, and replacement of parts to ensure the equipment is available for the operation; (2) Corrective maintenance (CM), which includes performing maintenance once the equipment breaks down. (3) Predictive maintenance (PdM), [150] which includes performing maintenance by predicting and reducing failure conditions of the equipment via monitoring performance and condition of the operating equipment through sensor measurements. Industry uses PM and CM as a part of routine maintenance processes. With the advancement in sensor technology, digital and computing technologies, industry is exploring opportunities to improve the plant operation with the help of PdM. PdM provides an opportunity for the end-user in establishing an effective maintenance strategy by providing information about the predicted failure occurrence. This helps in reducing the offline time of the equipment, and production loss time, and hence increasing the overall Return on Investment (ROI). With PdM analysis users can pre-order the spare required for the upcoming maintenance by advance planning. PdM requires periodic condition monitoring, which involves monitoring optimal use of machines via sensors during process operations. Condition monitoring involves online (continuous monitoring), periodic (at a certain period), and remote (from a remote location). Condition monitoring help collect data from the process and machines to perform the analysis. In this work, we propose a method for PdM based on data mining and deep learning. We use the sensor data from equipment to predict the failure of the equipment and program it in python (an open source software platform) [151]. Figure 4.18 shows the overall proposed method that involves the following two steps,

$*$ Keras (open-source neural-network library written in Python) with Microsoft Cognitive Toolkit CNTK as backend [152]; RNN is Recurrent Neural Network, LSTM is Long Short-Term Memory.

1. Data collection and processing: This step includes acquiring the dataset, loading and basic pre-processing. The data is often noisy, incomplete (having missing values), inconsistent and erroneous. The pre-processing step helps in resolving these issues. Pre-processing involves checking the quality of data and ensure that enough data values are available for further processing including feature engineering and model building.

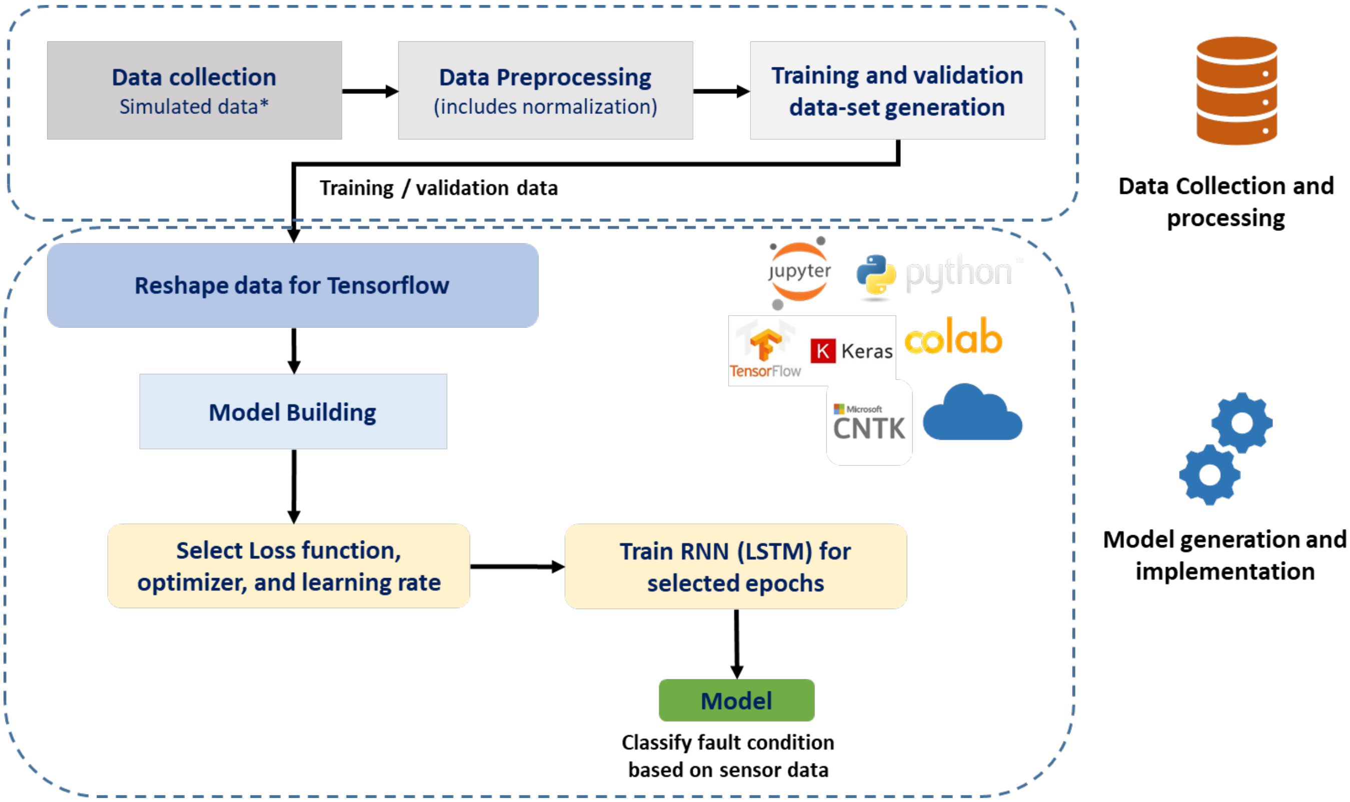


Figure 4.18: Data mining and deep learning based predictive maintenance model

2. Model generation and implementation: This step includes designing and testing of the deep learning model and test the designed model. It involves transforming the data into tensors, model building including selecting the loss function, optimizer to be used during training of the model and selecting the learning rates. These selections help in ensuring the method will work at the desired level of accuracy and classification. Once the model is built, the same can be used for additional analysis on similar datasets.

It is challenging to get industry data to show the functionality of the proposed method. Unfortunately, industry is reluctant to share, but we could use a dataset from NASA from a turbo engine available for public use and analysis [153]. This dataset is similar to the sensor measurements recorded during the condition monitoring of equipment in a process plant. The dataset used for this study comprises multiple multivariate time series reading with total 33,631 readings. The measurement readings are from total of 100 engines. In this scenario, the engine operates normally and develops a fault over a period. With the help of the proposed method, we are predicting if a specific engine will fail within (a) cycles? The number of fault conditions during the operation based on measured sensor values. Figure 4.19 shows a snapshot of the dataset.

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s13	s14	s15	s16	s17	s18	s19	s20	s21	RUL
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	2388.02	8138.62	8.4195	0.03	392	2388	100.0	39.06	23.4190	191
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	2388.07	8131.49	8.4318	0.03	392	2388	100.0	39.00	23.4236	190
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	2388.03	8133.23	8.4178	0.03	390	2388	100.0	38.95	23.3442	189
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	2388.08	8133.83	8.3682	0.03	392	2388	100.0	38.88	23.3739	188
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	2388.04	8133.80	8.4294	0.03	393	2388	100.0	38.90	23.4044	187

5 rows × 27 columns

Figure 4.19: Dataset snapshot

The data-set includes three different files training, testing and ground truth data. The training and testing data included engine_id, settings, and sensor reading information. Failure information was included in training data and not in testing data. The ground truth data provided RUL (remaining useful life)/ working cycles for the test data details. We checked the data types of each variable and found no missing values. For the exploratory analysis of the data, we performed checks on the relevance of features by conventional statistical operation such as standard deviation, log standard deviation and an ordered list of top variance features. We can observe that some features stand out. Furthermore, we generated a heat map to understand the correlation between each variable. Figure 4.20 shows a heat map, a higher value (>0.75) shows a higher correlation between the variables.

Next, we performed data pre-processing, which involved creating labels based on RUL for failure. As we have a task to classify only two equipment states, fault and no-fault, we defined a binary classification process. We normalized the data (with min-max normalization) to address the issue arising from different ranges of features during model training. This in return improved the overall accuracy of the model and we moved to the analytics step.

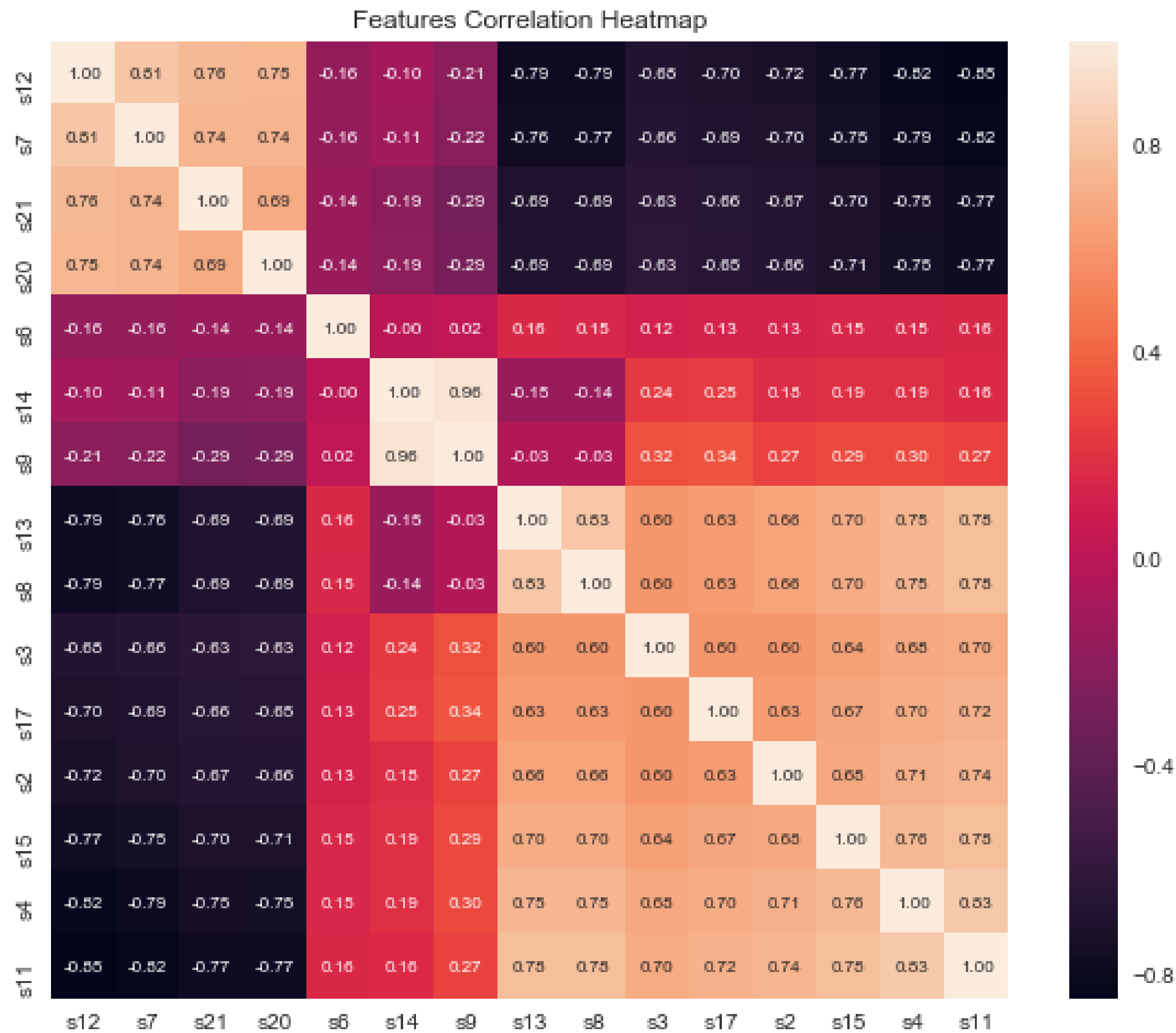


Figure 4.20: Correlation heatmap of features

For a traditional machine learning model, feature engineering is performed manually (Identify features*. This method limits the use of a same model in other applications. A deep learning model performs feature engineering and extract features automatically. In this problem, we use LSTM (Long Short Term Memory). LSTM is an RNN (Recurrent Neural Network), which can learn through long term dependencies between the variables due to the network ability of keeping results

*Feature, measurable property of the object to be analyzed, in this case it is the measured variables or sensor readings of many time steps. For any LSTM network, we use window size (number of measurements) to look back the number of values to identify dependencies with current measured value and perform feature engineering. We perform the model building in Keras with Microsoft's Cognitive toolkit (CNTK) as backend [154]. The structure of the network is a stacked LSTM network and includes, the first LSTM layer (100 units) with a dropout layer, second LSTM layer (50 units) with a dropout layer (A dropout technique involves ignoring randomly selected neurons during training. We have used a dropout rate of 20$\%$.), the last layer with a sigmoid activation based dense layer (1 unit). We compile the model with Adam optimizer with binary_crossentropy loss. This algorithm optimizes stochastic objective functions in a first-order gradient-based fashion. Next, we fit the model and the design the model with 97$\%$ accuracy. Figure 4.21, shows the classification details of the trained model.

Model Training		
Accuracy	0.9738	
No fault	12459	72
Fault	337	2763
	No Fault	**Fault**

Figure 4.21: Confusion matrix for trained model

To test the developed model for classification we use the test data to predict the failure condition by selecting data from last cycle data of each engine. We calculate various parameters to understand the correctness of the model by the following measures,

$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)}$

$Precision = \frac{(TP)}{(TP+FP)}$, measure of model to yield only relevant instances

$Recall = \frac{(TP)}{(TP+FN)}$, measure of model to yield all relevant instances

$F1Score = 2 * \frac{(PrecisionxRecall)}{(Precision+Recall)}$, single metric combining recall and precision using harmonic mean

Where,

TP (True Positive), labeled data positive and actual data positive

FP (False Positive), labeled data positive and actual data negative

TN (True Negative), labeled data negative and actual data negative

FN (False Negative), labeled data negative and actual data positive

The model can predict the fault condition with 95.69% of accuracy. The Figure 4.22 provides the detail results including precision, recall and F1 score.

Model Testing	
Accuracy	0.9569
Precision	0.9565
Recall	0.88
F1-Score	0.9166

Figure 4.22: Model measures and Confusion matrix for testing of model

Similar to this example, we can perform analysis on other datasets using deep learning to predict the failure of equipment and plant equipment maintenance. For any such application, we need to understand the data and select function parameters of the network. The developed LSTM network model as shown in Figure 4.18 can be used to predict the fault conditions in future based on the sensor measurements captured and inserted as input to the network.

4.3.5 Case Study V: Classification of text based on Natural Language Processing (NLP)

Text data is unstructured data and unique to a user. Text mining or text data mining is generating information from the text by the use Natural Language Processing (NLP) [155] and machine learning methods. One of the most adopted NLP applications in various fields is text classification. We use text classification to classify the text/text documents into a user-defined category. An application of these methods in other domains include classifying an e-mail as spam or non-spam, sentiment analysis on social media, categorizing of user reviews or categorizing articles into pre-defined groups, *etc.* In process industry, we can use similar methods to perform analysis on unstructured safety related text data of different type and generated in various formats. 'We have used an example of incident data published by US Occupational Safety and Health Agency (OSHA).'

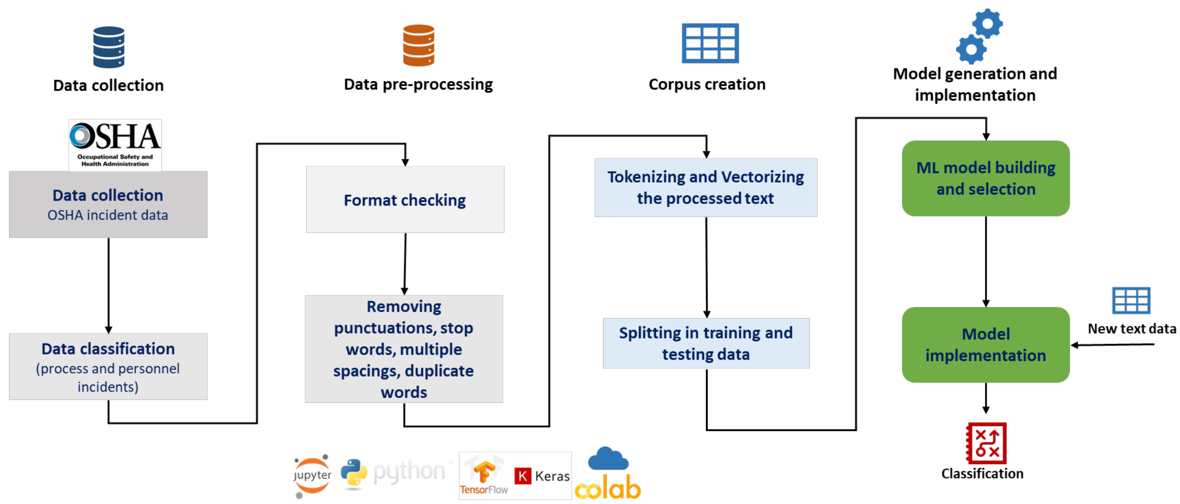


Figure 4.23: Model building and implementation for text classification on US OSHA incident data

A text classification method involves following three steps,

1. **Data exploration and preparation:** This step includes acquiring the data-set, loading and basic pre-processing. The data is noisy, incomplete, and erroneous. The pre-processing step helps in resolving these issues. Pre-processing involves transforming text data into vectors understandable by computers, checking the quality of data and ensure that enough data values are available for further processing including feature engineering and model building.

2. **Feature engineering:** This step includes identifying various key-features from the data-set and generate a comprehensive machine learning model. In case of NLP the feature engineering steps includes tokenizing and vectorizing the text into computer readable format. After

this step the data is divided into training and testing dataset. The training data is used to train several machine learning models to find the best model for the problem and testing data is used to check the accuracy of the designed models.

3. **Model generation and implementation:** This step includes designing and testing of various machine learning models and identifying the best suited-model for similar given datasets. Once the best model is picked, it can be used to classify the similar text which is never used earlier.

In this case study, we demonstrate a supervised text classification method to categorize the data downloaded from the online database (OSHA, 2019) as shown in Figure 4.24. We pre-process the data, perform feature engineering, generate the classification model and implement the model for the future classification of entered text data into a relevant category as shown in Figure 4.23.

Unnamed: 0	Summary_NR	Reporting_ID	Event_Date	Event_Time	Classification	event year	Event_Description	Event_Keywor
1	14409932	626600	07-OCT-87 12.00.00.000000 AM	NaN	Process	87	One killed, one injured when overpressurized j...	WORK RULES,BOILER,EQUIPMEN FAILURE,EXPLOSION,.
2	14412035	626600	20-NOV-87 12.00.00.000000 AM	NaN	Process	87	Employee dies of asphyxia from hydrogen sulfide	ASPHYXIATED,CPR,PPE,HYDROGEN SULFIDE,WORI RULE.
3	14412035	626600	20-NOV-87 12.00.00.000000 AM	NaN	Process	87	Employee dies of asphyxia from hydrogen sulfide	ASPHYXIATED,CPR,PPE,HYDROGEN SULFIDE,WORI RULE.
4	14317796	317020	28-FEB-90 12.00.00.000000 AM	NaN	Personnel	90	EMPLOYEE KILLED WHEN RUN OVER BY BACKING TRUCK	BACKING UP,WHEEL,DUMP TRUCK,FALL,STRUCI BY,RUN.
5	14316491	317000	21-MAR-94 01.14.00.000000 PM	NaN	Process	94	Employees injured by sludge when tank explodes	EXPLOSION,TANK,CONSTRUCTION,WELDING,SLUDGI

ws × 70 columns

Figure 4.24: Snapshot of the OSHA dataset of in total 556 incidents for model training

The dataset used for this study covers a total of 556 incidents, each having 70 columns of data. However, for the event classification as a process or personnel incident, we are using information from event description. First, we remove the missing value rows and add a column (category_id) depicting the Event classification as an integer (in this case we have only two classes hence the classification is in 0 or 1/ binary). After cleaning the data as shown in Figure 4.25, we use it for the next steps. Figure 4.26 shows the complete classification of the downloaded dataset as personnel or process incidents. We can see classes in this case are imbalanced and we have more details for the process classification than personnel classification. In such cases, we cannot use the standards algorithms as it will bias them towards the process classification in this case. Hence, we will use careful consideration to ensure the classifier model predicts the values with higher accuracy.

	Classification	Event_keyword	category_id
0	Process	WORK RULES,BOILER,EQUIPMENT FAILURE,EXPLOSION,...	0
1	Process	ASPHYXIATED,CPR,PPE,HYDROGEN SULFIDE,WORK RULE...	0
2	Process	ASPHYXIATED,CPR,PPE,HYDROGEN SULFIDE,WORK RULE...	0
3	Personnel	BACKING UP,WHEEL,DUMP TRUCK,FALL,STRUCK BY,RUN...	1
4	Process	EXPLOSION,TANK,CONSTRUCTION,WELDING,SLUDGE	0

Figure 4.25: Cleaned dataset

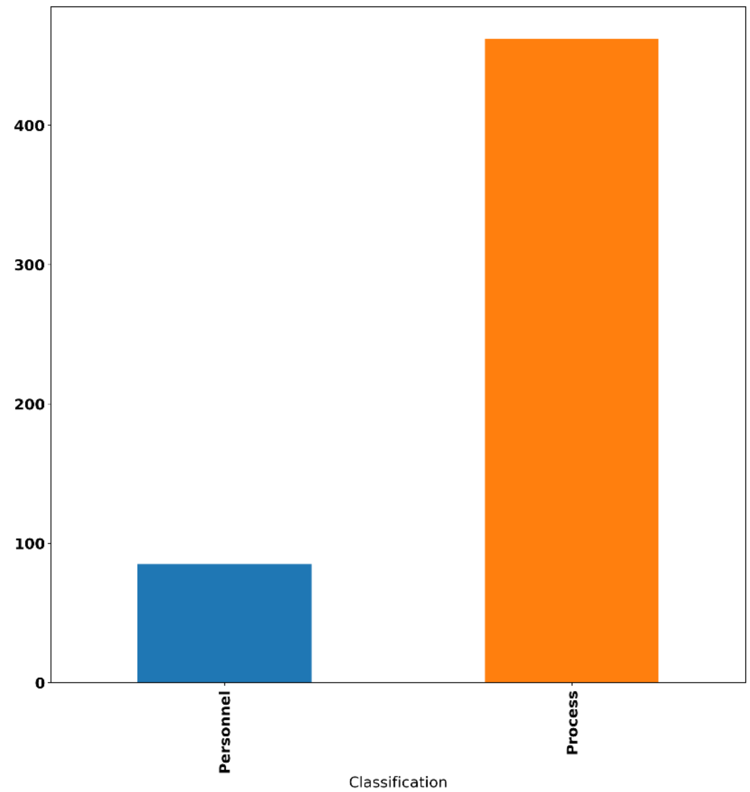


Figure 4.26: Classification of dataset

4.3.5.1 Representing text

Computer algorithms cannot process the text in its original form and requires a vector form of the document text. Hence, the text analytics task includes text conversion into a desired, manageable and machine interpretable depiction. During pre-processing, the first step involves converting the text into the lower case to have all the data in same format *e.g.,* Process and process becomes same as process and process. The second step involves removing the punctuations to have a reduced data size and higher computing efficiency. The last step involves tokenizing the text to have minimal meaningful word units.

After pre-processing we perform feature engineering, which is the foundation of NLP. The common approaches used to extract features from the text includes, bag of words, n-gram models, tf, tf-idf (term frequency inverse document frequency). For our study, we used the tf-idf method in python by writing code and using Pandas [156], Scikit-Learn [157], and matplotlib [158] libraries. A tf-idf method involves statistically calculating the word importance to a document or text collection [159]. We calculated the term frequency (tf), the number of times a word appears and inverse document frequency (idf) the measure of importance of the term. The word importance is proportional to the number of times a word appears and is offset by the word frequency in the document. After, calculating the tf-idf weight vectors and the data transformation, we trained the classifier to predict the classification into a process or personnel incident. We benchmarked Logistic regression, Linear Support Vector Machine, Naïve Bayes, and Random Forest based machine learning models for the classification as represented in Figure 4.27.

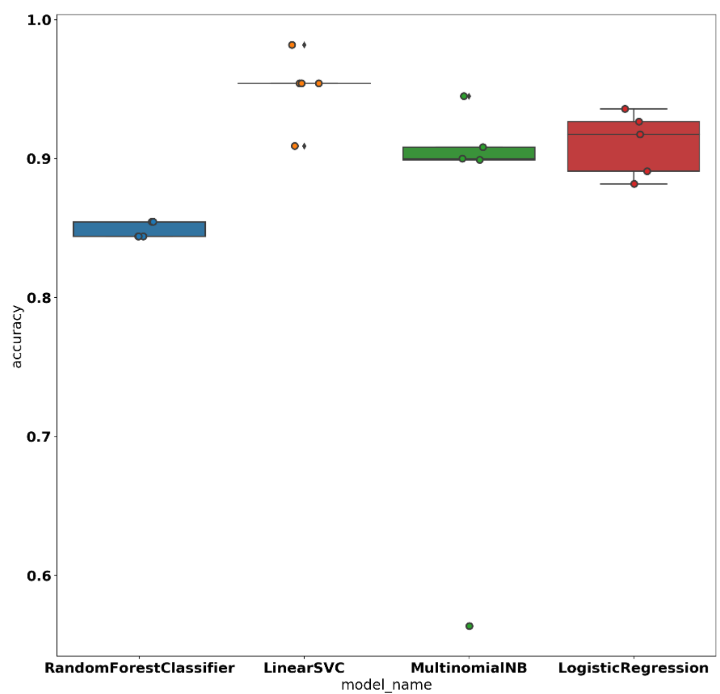


Figure 4.27: Benchmark results for machine learning models

```
model_name
LinearSVC                 0.950659
LogisticRegression        0.910509
MultinomialNB             0.843186
RandomForestClassifier    0.848240
```

Figure 4.28: Model accuracy

As we can see from Figures 4.27 and 4.28, both Linear Support Vector Machine classifier and Logistic regression has considerably better prediction accuracy than the other two machine learning models. Hence, we will use the most suited model with highest accuracy to predict the class of the testing dataset. As seen in Figure 4.29, most of the test data is accurately classified into the respective classes as a process (152), and personnel (25) (refer to the diagonal values). There are 4 values which were mis-classified as a process (4) instead of personnel by the model. We can see that overall accuracy of the model for the dataset is 98% . Figure 4.30 shows the detailed classification report for the test dataset.

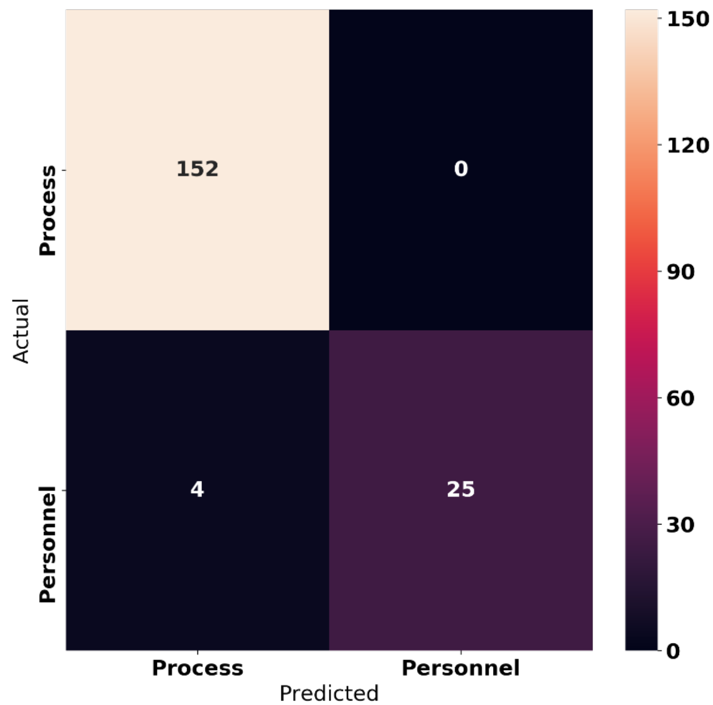


Figure 4.29: Classification results of Linear SVC

	precision	recall	f1-score	support
Process	0.97	1.00	0.99	152
Personnel	1.00	0.86	0.93	29
avg / total	0.98	0.98	0.98	181

Figure 4.30: Classification report for Linear SVC model

Similar to this example, we can use NLP methods to analyze the unstructured data type such as a text to infer the information necessary for decision making. The proposed solution for text analysis can work on pdf files, word files, or text files and not on handwritten documents or scanned documents as this requires more robust models and Optical Character Recognition (OCR) methods to infer and understand the text.

4.3.6 Case Study VI: Barriers assessment for dynamic risk mapping (DRA)

In this case study, a barrier assessment model that is quantitative and data-driven is described. Often, we take credit for these barriers without assessing the effectiveness of these measures. In this study, we use Bayesian methods to evaluate the health of barriers by incorporating both the technical and social aspects in an integrated way [21]. It may be less known but causation modeling Bayesian approach and Bayesian network have largely been developed for artificial intelligence purposes. So, in this case study emphasis is on analytics and not on big data, although when considering a longer time span cloud stored data is needed. The scenario utilized for this case study is the flash drum in an offshore oil and gas platform represented in Figure 4.31. The level control valve is bypassed manually and fully opened. The isolation block valves are closed. Due to this, there is gas accumulation resulting in over-pressure and loss of containment. After the loss of containment has happened, two mitigation barriers gas detector and operator response are being analyzed.

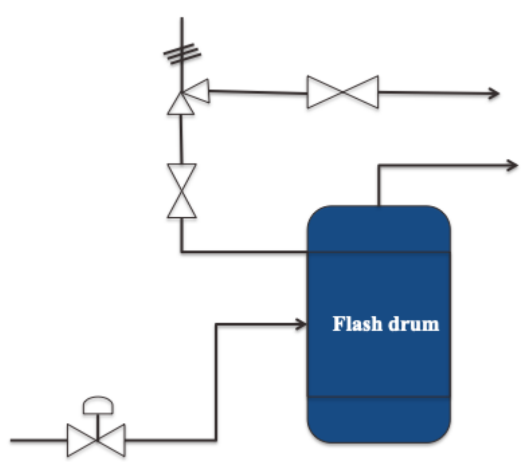


Figure 4.31: Flash drum scenario

In this barrier assessment model, following three items are considered,

- Uncertainty quantification

- Plant and operations data
- Consideration of social factors.

4.3.6.1 Gas detector model

For the gas detector model, the flow diagram consisting of the procedural steps, which are taken to calculate the posterior distribution of parameters using Bayes theorem are depicted in Figure 4.32. The Bayesian methodology provides a way to update our prior information about the model parameters using sample information. Generally, the prior information is summarized in the form of a probability rule called the prior distribution of the model parameters. The posterior distribution of the parameters is proportional to the product of the likelihood and the prior distribution.

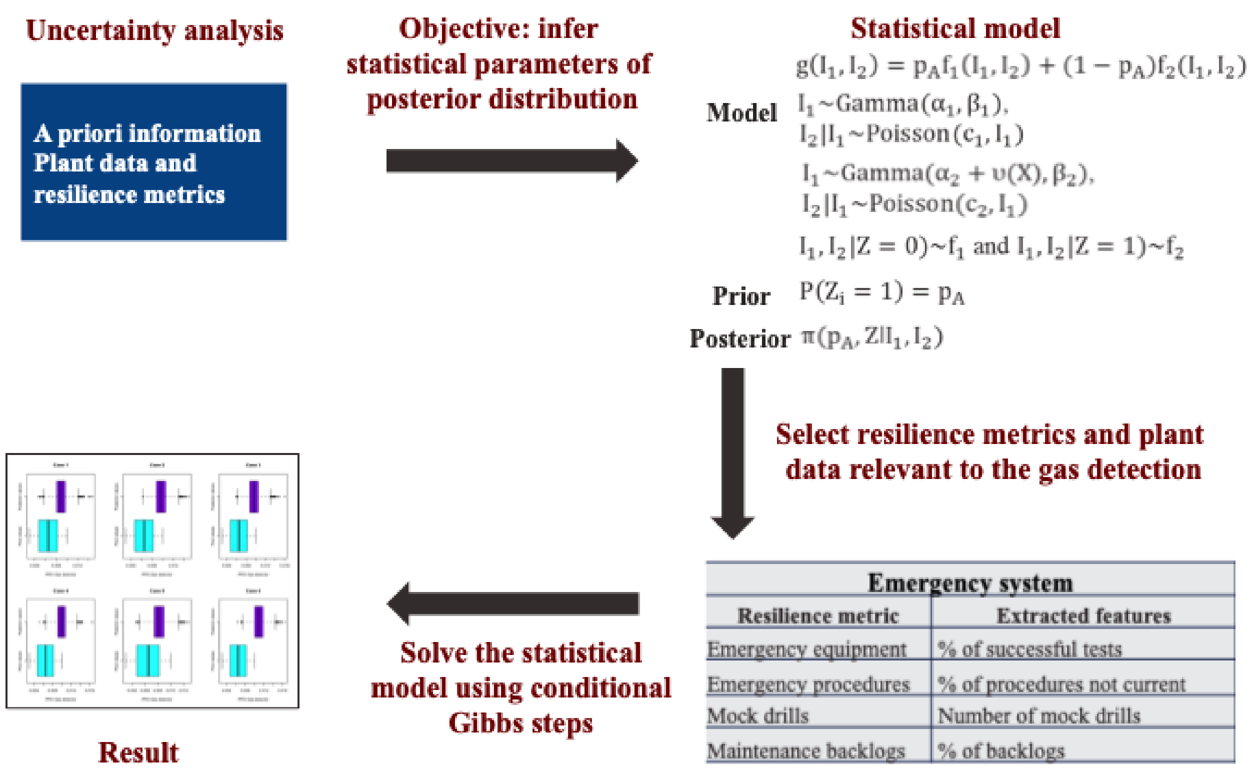


Figure 4.32: Flow diagram for the gas detector model

The objective is to estimate the probability of failure for gas detector given the detector's operating characteristics and information from plant data or in other words infers the statistical parameters of posterior distribution of failure. Here, we aim to adequately quantify the uncertainty. We use two variables current load (I_1) and number of unplanned maintenance jobs (I_2).

Following are the steps for this analysis,

1. Obtain data for current load (I_1) and unplanned maintenance (I_2) from process historian and CMMS (Computerized maintenance management system).

2. Model joint distribution for I_1 and I_2 when gas detector is working normal.

3. Model joint distribution for I_1 and I_2 for the condition when gas detector is likely to fail by incorporating the information from resilience metrics $\mu(X)$ such as successful tests on emergency equipment, emergency procedures being current, mock drills, and maintenance backlogs. Resilience metrics are not common yet and are to be collected over a longer time similar to KPIs, see [17].

4. Define prior distributions on parameters that explain the joint distribution of I_1 and I_2based on domain knowledge.

5. Apply Bayes theorem to calculate the posterior distributions for parameters.

6. Introduce latent variables for the two conditions, normal working and likely to fail.

7. Use Gibbs sampling algorithm to obtain posterior samples drawn from the posterior distribution of parameters.

Synthetic datasets were generated following certain statistical distributions in programming language R. For these datasets, complexities were added and certain reasoning was followed to make them similar to real situations. Figure 4.33 summarizes the results with boxplots of prior and posterior samples of gas detector failure probability. It is also observed here that the concentration of the posterior distribution centers around the truth with a very small spread.

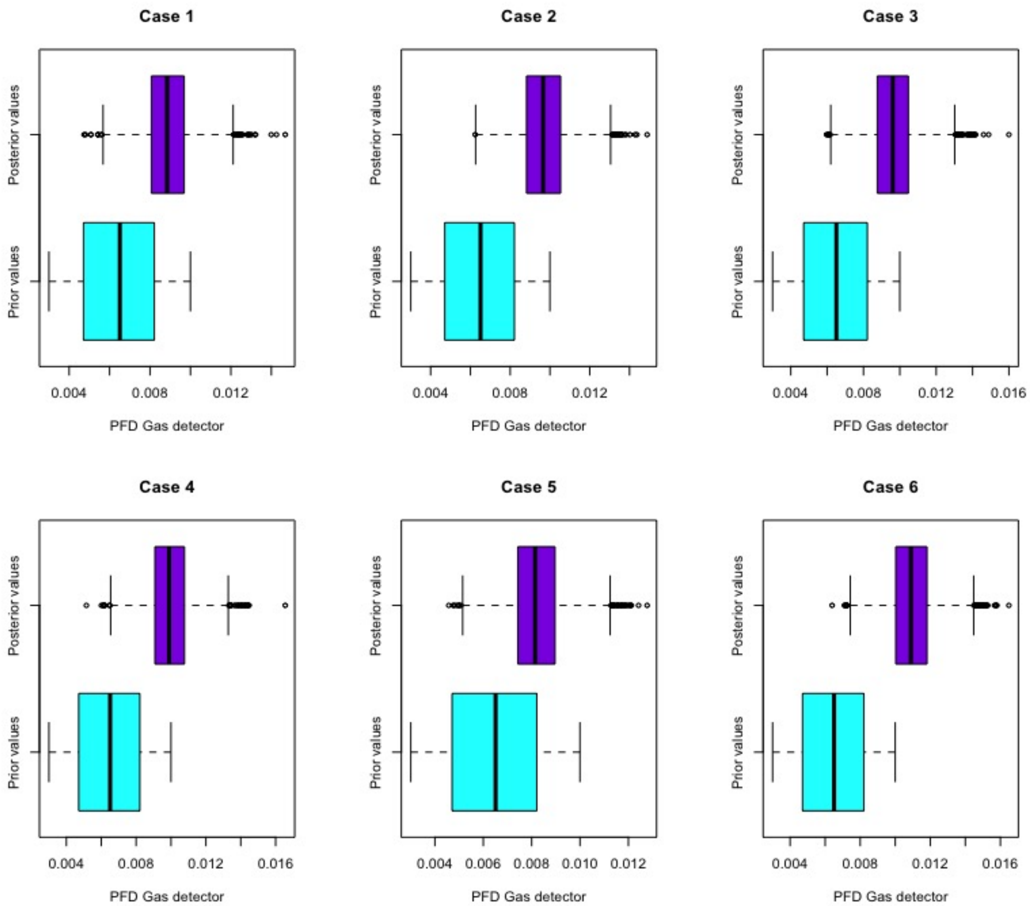


Figure 4.33: Gas detector results for prior and posterior probability of failure

4.3.6.2 Operator error probability model

The objective is to enhance the operator error probability base distribution using performance data. Following are the steps for this analysis, also shown in Figure 4.34,

1. Obtain data for operator error probability.
2. Identify relevant resilience metrics such as emergency plans reassessment, corrective actions taken, competency, and training sessions.
3. Estimate a model for operator error with weakly informative priors.

4. Applying Bayes regression, simulate from the posterior distribution of the model to obtain posterior distribution for operator error failure probability.

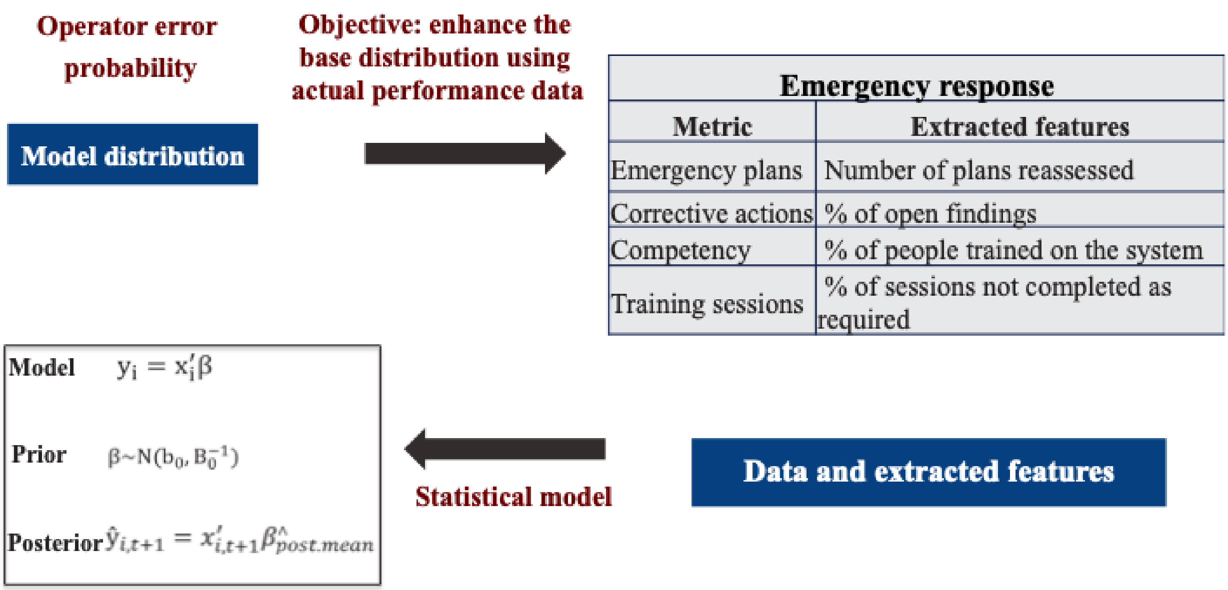


Figure 4.34: Flow diagram for the operator error model

Table 4.7 summarizes the results for two operator actions – alarm acknowledgement and alarm evaluation and action. Both prior and posterior probabilities are listed in the Table.

Table 4.7: Operator error probability

Results of operator error probabilities		
Operator Action	**Prior error probability**	**Posterior error probability**
Alarm acknowledgement	0.28	0.36
Alarm evaluation and action	0.42	0.49

Overall, this study strengthens the idea described in the previous sections to utilize data for enhanced intelligence and also emphasizes the incorporation of both technical and social aspects. Such applications would lead to safer, reliable, efficient, and profitable process systems.

4.4 Implementation challenges

As shown with the examples, there are exciting opportunities available to implement various key data analytics methods to the data generated in the operating facilities. However, these opportunities come with some challenges.The key characteristics related to implementation of these technologies include objectivity, accuracy, resiliency, privacy, interpretability, reliability, security, and privacy. In this section, we have compiled current research and implementation challenges of data analytics including ML and AI applications [7, 160]. Among these, some are due to data characteristics, some are caused by available models and methods, and some by data processing technology limitations. Another major cause is the lack of strategic initiative in business plans and clear strategy of an organization. This section provides an overview of the challenges and classifies the research and implementation challenges related to data analytics, machine learning, AI into three broad categories, technology, methodology and business challenges which can either occur in isolation or in groups.

4.4.1 Technology Challenges

- **Data Complexity :** Some of the challenges arise from the characteristics of the data itself. The data collected from various resources has seven attributes as described in Section 1. The data complexity challenge involves, (1) large heterogeneous, ubiquitous volume and dynamically updating datasets generated from the connected devices, (2) Complex data-structures including some inconsistencies (missing values or noise) in both structured and unstructured datasets, (3) non-homogenous data generated at high frequency, (4) data storage in distinct sources including plant historians, e-mails, handwritten memos, *etc.* (5) rapidly and constantly changing data, (6) extracting value out of the structured, semi-structured and unstructured datasets efficiently with minimum to no loss, and (7) disseminating the information to the user in comprehensible format. Consequently, these challenges pose questions to manage, integrate, process and derive information. Hence, due to data complexity it becomes a significant task for users to derive intelligence from the data.

- **Infrastructure and data management:** The data collected in an organization comes from different sources which usually is disorganized and located in dispersed silos. In some instances, the information is duplicated. The industrial applications of (big) data and analytics at large scale requires network, storage and software infrastructure to implement the technology and the application. Additionally, the data collected from various resources in industry is complex and large in size, which warrants for software/tools to clean, normalize, extract and integrate data for further processing. The technologies such as cloud services, remote servers, data warehouses and data lakes can be explored to find appropriate solutions to manage and process data. A balance between 'quality of data' vs 'quantity of data' is required to ensure the available data for analysis is relevant, has necessary features to support the human users. While a proof-of-concept is easy to design and develop, for a real-time access and assessment of the data a fast and reliable network system is needed. A careful evaluation of the available options between generic software and application specific custom-made tools is required.

- **Analytics and decision support:** The aim of developing new data-based tools in an organization is to perform analysis on big datasets and derive information based on various analysis techniques. This information is further used for identifying the weak signals, evaluating safety barriers, dynamic risk mapping [161], and assisting the users in taking appropriate decisions. The key requirements for this is data quality and loading. Additionally, relevant computing resources are required to perform required steps on the data. A real-time (near) analysis is required to assist operators in decision support [14]. Integrating the prior domain knowledge and information to the analysis is the key to ensure the value generation for decision support.

- **Data Security and Privacy:** Data security and privacy is one of the key challenges to be addressed while developing data-based solutions and encompasses both technological and business challenges. In industry sensors, actuators and controllers allow users to operate and collect real-time data related to operations, actions and business metrics. Data and analytical tools are becoming the new value creators in the industry. Implementing new technologies and methods requires addressing the risks related to security, privacy, including unauthorized access of infrastructure including control systems and network devices by third parties with a criminal intent. This in return will help the organizations to keep their business advantage and operate safely, securely, and reliably [162].

4.4.2 Methodology and Process Implementation Challenges

Applying advanced computer analysis to harness information is a daunting task which involves data collection, integration, analysis and provide information in a comprehendible form. These steps are a part of a data lifecycle process as explained in Section 1.3. The key challenges related to the process are the process of data recording and managing ownership of data. While for a smaller organization this task is easier, for larger organization with business operations in multiple cities, states, countries it requires a huge time, effort, and resources to manage data recording and ownership. Integrating such data in single location also poses challenges related to infrastructure, security, privacy, and sometimes regulatory matters. Another, key challenge is managing the knowledge available within the organization and affiliates for competitive advantage [163]. While using data analytics and AI can help such organizations in marketing, supply chain, customer acquisitions; an integration with models based on physics and data, working with interdisciplinary teams, and defining the methods to solve a problem can help in plant operations. While developing prototypes is a better way to infer the impact on the business needs, identifying and addressing the issues related to scaling the technology or methodology are the key steps for success of designing and implementing the solutions. Use of cloud computing infrastructure can also provide a new dimension to the businesses. While data analytics and AI methods have tremendous potential and benefits to the end users, there are potentially huge risks. Integration and inter-connectivity of different data sources increases vulnerability to sabotage and manipulation of the data and information. Hence, organizations and governments must create regulations and policies to address these concerns while adopting new policies.

4.4.3 Business Challenges

- **Business plan and mission:** Big data and analytics are becoming one of the large value contributors to an organization's business footprint. Organizations need to create a strategic plan and business case to identify the potential opportunities and design outcome-based solutions. An enterprise wide practical, relevant, evolutionary and integrated strategy is required to be implemented. This requires a holistic review of the initial plan and collaboration within the individuals from business, IT, operations, and other relevant teams. The strategic planning helps in setting the priorities, developing and rationalizing the data management architecture, outlining road map to phase out legacy systems and adopt new technology, improving effectiveness of data processing, and anticipating the benefits of big data analytics to help current business needs. Additionally, identifying the use cases and prioritizing them to support the business plan is required to achieve the desired goals.

- **Cost of technology infrastructure:** While data-driven methods empowers the end users to analyze large and diverse volume of data to make key operational and business decisions, they all come at an expense to the user. This includes the costs associated with managing the data recording, storage, analysis, and information dissemination [164]. It is important to understand the business needs, data infrastructure and management systems, the value such technology brings, and overall direct/indirect impact on the efficiency. These factors will assist in predicting the cost associated with implementing and maintaining such solution applications.Another important factor to keep in mind is competency and domain knowledge. It is very important that application developers' working on the potential solutions have the required domain knowledge and competency to understand the problem, solution requirements, and ensure the analysis/results are comprehendible.

- **Governance and privacy:** The privacy of data for any organization is critical. As discussed earlier, this is due to the fact that the data is one of the key business drivers, and can bring competitive edge to the business. Hence, there is a need to develop the data management and governance strategy, which may include data linking from different sources, operational sites in various geographical locations safely to ensure the value of the data is harnessed and retained as a part of the organization. Another important concept in future may appear as to aggregate and share or sell data, while retaining control and competitive advantage.

4.5 Summary

The application of big data analytics in process safety and risk management is evolving. Its application would provide valuable insights for more informed policy, strategic, and operational risk decision-making leading to a safer and more reliable industry. This work represents a beginning in gathering process safety related data and harnessing the value of the data collected to improve process safety at these facilities. A system framework called PSBDMS on process safety big data is presented and various sources and types of data and challenges that can be solved using big data analytics are described. Large amounts of data are and will continue to be generated and collected in this area in the three different levels of PSBDMS - regulatory, industry consortiums, and manufacturing facilities. The challenge is to develop ideas and methods for analyzing data for detecting abnormal situations, optimizing processes, bench marking performance and preventing catastrophic failures. Different case studies in process safety and risk management area are used to demonstrate the application areas. These applications can be further developed into mature models and methods.

5. CONCLUSIONS AND FUTURE WORK

Big data and analytics comprise a variety of software and hardware technologies that can be applied in numerous ways in a diversity of applications. The focus on digital infrastructure including IoT in the industry creates an unprecedented amount of data. The data is stored in various types, sizes, and dimensions. This has warranted a powerful and streamlined approach, demand for new technologies, and intelligent analytics to boost competitive insights and efficiency within an organization.

5.1 Conclusions

Big data and analytics have appealed to both practitioners and researchers in industry and academia with a promising potential to lower uncertainty and discover insights from this data, and hence increase quality of decision making. The application of these technologies is in its early stages and requires solution development and deployment. The information generated from such solutions is the key for an organization to unlock the power of data and improve the operational efficiency by reducing downtime, managing risks, and making operations more reliable and safer.

Data-driven methods are used to address the challenges related to alarm management in industrial facilities, process fault detection and diagnosis, and in various application areas in process safety and risk management. A unified workflow approach is used to define the data-sources, applicable domains, and develop proposed applications. This work integrates data generated by field instrumentation, expert knowledge, data analytics and artificial intelligence techniques to provide guidance to the operator or engineer to effectively take proactive decisions through “action-boards”

The key contributions of this research work are:

1. A novel framework to categorize the process of the alarm management system in an industrial facility (design, rationalize, advance and intelligent). This framework can help end-users categorize their alarm management program. The framework follows a life-cycle approach, which includes bench-marking the alarm system and follows the re-design and

re-rationalize steps if required.

2. An integrated method to calculate Key Performance Indicators (KPIs) and generate visualization plots. This provides an overall better approach to analyze the Alarm and Event logs and disseminate information to the user to take corrective actions to improve the overall alarm management program.

3. A novel data-driven workflow to integrate big data analysis, deep learning-based BiLSTM on a cloud platform, and reporting for process fault detection and classification. An automated hyper-parameter optimization method is derived and used to identify the optimal hyper-parameters for a given data and designed network.

4. A data analytics and deep learning-based equipment failure prediction model to predict and classify the equipment failure proactively before an actual failure and help users save money and time in equipment maintenance.

5. A novel layered approach based dynamic risk mapping tool to integrate data from various resources in an operating facility and highlights the real-time risk profiles to assist users in making informed decisions.

6. An NLP based event classification based method to learn the patterns from the unstructured text generated in the form of reports and classifies specific incidents based on the information provided by the user.

7. The proposed frameworks, workflows, and methods are developed on open-source software platforms (Python and R) which are cloud-ready. The cloud application enables users with the required computing power, scalability and flexibility of model design and application to improve overall decision making.

5.2 Future Directions

Within the specific research areas, following aspects could be looked into for further development:

1. **Alarm management for industrial facilities**

   (a) Additional visualization options can be identified and added to the proposed visualization directory to enhance the dissemination of information and the overall user experience.

   (b) The process operation data can be integrated to enhance the classification of the alarm and event messages and find the correlations. This will help in designing more advanced and informed solutions for operator assistance in decision making.

2. **Process Fault detection and diagnosis for industrial processes**

   (a) The proposed method can be extended to classify a process failure or a malicious cyber-security attack. Once the event is classified, the appropriate remedial actions can be recommended to avoid undesired events.

   (b) The root cause analysis can be integrated with process fault detection to identify the variable/s causing the process upset and disseminate the information of root-causes to the operator on HMI screen.

3. **Advanced applications in process safety and risk management**

   (a) Prescriptive maintenance methods can be designed by integrating predictive maintenance with optimization theory to identify the best maintenance schedule and prescribe actions once the equipment failure is predicted.

   (b) Interactive dashboards on HMI screens can be created to highlight the risk of each process unit. This will help the users in taking more informed decisions and preventing incidents in the facility.

   (c) NLP with deep learning can be used to create a text generator that can assist users in writing information and reports. This will help in standardizing the writing style of users, documentation, and record keeping.

REFERENCES

[1] T. Stauffer and P. Clarke, "Using alarms as a layer of protection," *Process Safety Progress*, vol. 35, no. 1, pp. 76–83, 2016.

[2] M. K, "Administration issues strategic plan for big data research and development," 2106.

[3] B. D. S. S. Group *et al.*, "The federal big data research and development strategic plan," 2016.

[4] Xinhua, "China to manage big data through standardized system.," 2017.

[5] E. Letouzé *et al.*, "Big data for development: Challenges & opportunities, new york: Un global pulse (white paper): Big data for development: Opportunities & challenges (2012)," *Retrieved on*, vol. 13, 2016.

[6] D. Maltby, "Big data analytics," in *74th Annual Meeting of the Association for Information Science and Technology (ASIST)*, pp. 1–6, 2011.

[7] L. Chiang, B. Lu, and I. Castillo, "Big data analytics in chemical engineering," *Annual review of chemical and biomolecular engineering*, vol. 8, pp. 63–85, 2017.

[8] A. Skowron, A. Jankowski, and S. Dutta, "Interactive granular computing," *Granular Computing*, vol. 1, no. 2, pp. 95–113, 2016.

[9] P. Bellini, M. Di Claudio, P. Nesi, and N. Rauch, "Tassonomy and review of big data solutions navigation," *Big Data Computing To Be Published 26th July*, 2013.

[10] Y. Demchenko, P. Grosso, C. De Laat, and P. Membrey, "Addressing big data issues in scientific data infrastructure," in *Collaboration Technologies and Systems (CTS), 2013 International Conference on*, pp. 48–55, IEEE, 2013.

[11] D. E. O'Leary, "Big data', the 'internet of things'and the 'internet of signs," *Intelligent Systems in Accounting, Finance and Management*, vol. 20, no. 1, pp. 53–65, 2013.

[12] S. Liu, "Digital transformation market share by region 2019," Oct 2019.

[13] "Adoption status of intelligent automation (ia) technologies in organizations worldwide as of 2019," Mar 2019.

[14] P. Goel, A. Datta, and M. S. Mannan, "Application of big data analytics in process safety and risk management," in *2017 IEEE International Conference on Big Data (Big Data)*, pp. 1143–1152, IEEE, 2017.

[15] P. Goel, E. Pistikopoulos, M. Mannan, and A. Datta, "A data-driven alarm and event management framework," *Journal of Loss Prevention in the Process Industries*, vol. 62, p. 103959, 2019.

[16] ANSI/ISA-18.2, "Management of alarm systems for the process industries," *International Society of Automation (ISA)*, 2016.

[17] P. Jain, R. Mentzer, and M. S. Mannan, "Resilience metrics for improved process-risk decision making: survey, analysis and application," *Safety science*, vol. 108, pp. 13–28, 2018.

[18] P. Jain, H. J. Pasman, S. P. Waldram, W. J. Rogers, and M. S. Mannan, "Did we learn about risk control since seveso? yes, we surely did, but is it enough? an historical brief and problem analysis," *Journal of Loss Prevention in the Process Industries*, 2016.

[19] P. Goel, A. Datta, and M. S. Mannan, "Industrial alarm systems: Challenges and opportunities," *Journal of Loss Prevention in the Process Industries*, vol. 50, pp. 23–36, 2017.

[20] A. Pariyani, W. D. Seider, U. G. Oktem, and M. Soroush, "Dynamic risk analysis using alarm databases to improve process safety and product quality: Part i—data compaction," *AIChE Journal*, vol. 58, no. 3, pp. 812–825, 2012.

[21] P. Jain, H. J. Pasman, S. Waldram, E. Pistikopoulos, and M. S. Mannan, "Process resilience analysis framework (praf): A systems approach for improved risk and safety management," *Journal of Loss Prevention in the Process Industries*, vol. 53, pp. 61–73, 2018.

[22] J. P. Carrera and J. R. Easter, "Advanced alarm management in the aware system," in *Nuclear Science Symposium and Medical Imaging Conference, 1991., Conference Record of the 1991 IEEE*, pp. 1389–1393, IEEE, 1991.

[23] E. Burnell and C. Dicken, "Handling of repeating alarms," in *Stemming the Alarm Flood (Digest No: 1997/136), IEE Colloquium on*, pp. 12–1, IET, 1997.

[24] F. Higuchi, I. Yamamoto, T. Takai, M. Noda, and H. Nishitani, "Use of event correlation analysis to reduce number of alarms," in *Computer Aided Chemical Engineering*, vol. 27, pp. 1521–1526, Elsevier, 2009.

[25] J. Folmer and B. Vogel-Heuser, "Computing dependent industrial alarms for alarm flood reduction," in *Systems, Signals and Devices (SSD), 2012 9th International Multi-Conference on*, pp. 1–6, IEEE, 2012.

[26] M. Lucke, M. Chioua, C. Grimholt, M. Hollender, and N. F. Thornhill, "Online alarm flood classification using alarm coactivations," *IFAC-PapersOnLine*, vol. 51, no. 18, pp. 345–350, 2018.

[27] S. Charbonnier, N. Bouchair, and P. Gayet, "Fault template extraction to assist operators during industrial alarm floods," *Engineering Applications of Artificial Intelligence*, vol. 50, pp. 32–44, 2016.

[28] G. Dorgo, P. Pigler, and J. Abonyi, "Understanding the importance of process alarms based on the analysis of deep recurrent neural networks trained for fault isolation," *Journal of Chemometrics*, vol. 32, no. 4, p. e3006, 2018.

[29] J. Wang, H. Li, J. Huang, and C. Su, "A data similarity based analysis to consequential alarms of industrial processes," *Journal of Loss Prevention in the Process Industries*, vol. 35, pp. 29–34, 2015.

[30] J. Wang, H. Li, J. Huang, and C. Su, "A data similarity based analysis to consequential alarms of industrial processes," *Journal of Loss Prevention in the Process Industries*, vol. 35, pp. 29–34, 2015.

[31] F. Yang, S. L. Shah, D. Xiao, and T. Chen, "Improved correlation analysis and visualization of industrial alarm data," *ISA transactions*, vol. 51, no. 4, pp. 499–506, 2012.

[32] K. Ahmed, I. Izadi, T. Chen, D. Joe, and T. Burton, "Similarity analysis of industrial alarm flood data," *IEEE Transactions on Automation Science and Engineering*, vol. 10, no. 2, pp. 452–457, 2013.

[33] S. R. Kondaveeti, I. Izadi, S. L. Shah, T. Black, and T. Chen, "Graphical tools for routine assessment of industrial alarm systems," *Computers & Chemical Engineering*, vol. 46, pp. 39–47, 2012.

[34] Z. Mannani, I. Izadi, and N. Ghadiri, "Preprocessing of alarm data for data mining," *Industrial & Engineering Chemistry Research*, 2019.

[35] T. Niyazmand and I. Izadi, "Pattern mining in alarm flood sequences using a modified prefixspan algorithm," *ISA transactions*, 2019.

[36] W. Hu, T. Chen, and S. L. Shah, "Detection of frequent alarm patterns in industrial alarm floods using itemset mining methods," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 9, pp. 7290–7300, 2018.

[37] W. Hu, S. L. Shah, and T. Chen, "Framework for a smart data analytics platform towards process monitoring and alarm management," *Computers & Chemical Engineering*, vol. 114, pp. 225–244, 2018.

[38] M. Lucke, M. Chioua, C. Grimholt, M. Hollender, and N. F. Thornhill, "Advances in alarm data analysis with a practical application to online alarm flood classification," *Journal of Process Control*, vol. 79, pp. 56–71, 2019.

[39] A. ISA, "Isa-18.2: Management of alarm systems for the process industries," *International Society of Automation. Durham, NC, USA*, 2016.

[40] S. Jenkins, "Guidelines for engineering design for process safety," *Chemical Engineering*, vol. 119, no. 9, pp. 9–10, 2012.

[41] T. Stauffer, N. Sands, and D. Dunn, "Alarm management and isa-18–a journey, not a destination," in *Texas A&M Instrumentation Symposium*, 2010.

[42] R. Srinivasan, J. Liu, K. Lim, K. Tan, and W. Ho, "Intelligent alarm management in a petroleum refinery," *Hydrocarbon processing*, vol. 83, no. 11, pp. 47–54, 2004.

[43] Health and S. Executive, "The explosion and fires at the texaco refinery, milford haven, 24 july 1994," 1997.

[44] EEMUA-191, "Alarm systems: A guide to design, management and procurement," *EEMUA*, vol. Edition 3, 2013.

[45] A. Nochur, H. Vedam, and J. Koene, "Alarm performance metrics," *IFAC Proceedings Volumes*, vol. 34, no. 27, pp. 203–208, 2001.

[46] U. CSB15, "Investigation report, refinery explosion and fire, bp-texas city, texas, march 23, 2005," 2007.

[47] J. S. Alford, J. Kindervater, and R. Stankovich, "Alarm management for regulated industries," *Chemical engineering progress*, vol. 101, no. 4, pp. 25–30, 2005.

[48] I. Nimmo, "It's time to consider human factors in alarm management," *Chemical engineering progress*, vol. 98, no. 11, pp. 30–38, 2002.

[49] B. R. Hollifield and E. Habibi, *Alarm management: A comprehensive guide: Practical and proven methods to optimize the performance of alarm management systems*. Isa, 2011.

[50] T. Bergquist, J. Ahnlund, and J. E. Larsson, "Alarm reduction in industrial process control," in *Emerging Technologies and Factory Automation, 2003. Proceedings. ETFA'03. IEEE Conference*, vol. 2, pp. 58–65, IEEE.

[51] N. A. Stanton and C. Baber, "Alarm-initiated activities: an analysis of alarm handlingby operators using text-based alarm systems in supervisory control systems," *Ergonomics*, vol. 38, no. 11, pp. 2414–2431, 1995.

[52] D. Beebe, S. Ferrer, and D. Logerot, "The connection of peak alarm rates to plant incidents and what you can do to minimize," *Process Safety Progress*, vol. 32, no. 1, pp. 72–77, 2013.

[53] M. Bransby, "Design of alarm systems," *IEE Control Engineering Series*, pp. 207–221, 2001.

[54] D. Campbell-Brown, "Alarm management experience in bp oil," in *Colloquium Digest - IEEE*, vol. 1, pp. 1–1, IEEE.

[55] H. Zwaga and H. Hoonhout, "Supervisory control behaviour and the implementation of alarms in process control," in *Human factors in alarm design*, pp. 119–134, 1995.

[56] P. T. Bullemer, M. Tolsma, D. Reising, and J. Laberge, "Towards improving operator alarm flood responses: Alternative alarm presentation techniques," *Abnormal Situation Management Consortium*, 2011.

[57] J. Folmer, D. Pantförder, and B. Vogel-Heuser, "An analytical alarm flood reduction to reduce operator's workload," in *International Conference on Human-Computer Interaction*, pp. 297–306, Springer, 2011.

[58] J. C. Laberge, P. Bullemer, M. Tolsma, and C. R. Dal Vernon, "Addressing alarm flood situations in the process industries through alarm summary display design and alarm response strategy," *International Journal of Industrial Ergonomics*, vol. 44, no. 3, pp. 395–406, 2014.

[59] A. Wilson, "Alarm management and its importance in ensuring safety," in *IEE Colloquium on Best Practices in Alarm Management (Digest No. 1998/279)*, pp. 6–1, IET, 1998.

[60] D. V. C. Reising, J. L. Downs, and D. Bayn, "Human performance models for response to alarm notifications in the process industries: An industrial case study," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 48, pp. 1189–1193, SAGE Publications Sage CA: Los Angeles, CA, 2004.

[61] M. Bransby and J. Jenkinson, "Alarm management in the chemical and power industries: Results of a survey for the hse," in *IEE Colloquium on Best Practices in Alarm Management (Digest No. 1998/279)*, pp. 5–1, IET, 1998.

[62] D. H. Rothenberg, *Alarm management for process control: a best-practice guide for design, implementation, and use of industrial alarm systems*. Momentum Press, 2009.

[63] J. Errington, J. Errington, D. V. Reising, and C. Burns, *Effective alarm management practices*. ASM Consortium, 2009.

[64] J. Kvalem, K. Haugset, and F. Øwre, "The simulator-based halden manmachine laboratory (hammlab) and its application in human factor studies," 2000.

[65] D. Reising and T. Montgomery, "Achieving effective alarm system performance: results of asm (registered trademark) consortium benchmarking against the eemua guide for alarm systems," *Atlanta, GA, United States, American Institute of Chemical Engineers, New York*, pp. 10016–5991, 2005.

[66] A. Pariyani, W. D. Seider, U. G. Oktem, and M. Soroush, "Incidents investigation and dynamic analysis of large alarm databases in chemical plants: A fluidized-catalytic-cracking unit case study," *Industrial & Engineering Chemistry Research*, vol. 49, no. 17, pp. 8062–8079, 2010.

[67] M. Bransby and J. Jenkinson, "Alarming performance," *Computing & Control Engineering Journal*, vol. 9, no. 2, pp. 61–67, 1998.

[68] M. MANNAN and H. WEST, "1.6 process alarm management," *Instrument Engineers' Handbook: Process control and optimization*, p. 59, 2006.

[69] A. B. Skjerve and A. Bye, *Simulator-based human factors studies across 25 years*. Springer, 2011.

[70] E. Bristol, "Improved process control alarm operation," *ISA transactions*, vol. 40, no. 2, pp. 191–205, 2001.

[71] B. R. Mehta and Y. J. Reddy, *Industrial process automation systems: design and implementation*. Butterworth-Heinemann, 2014.

[72] T. B. Sheridan, "Supervisory control," *Handbook of Human Factors and Ergonomics, Third Edition*, pp. 1025–1052, 2006.

[73] O. Safety, "Health standards, general industry,(29 cfr 1910)," *Occupational Safety and Health Administration, OSHA*, 1992.

[74] M. Carrigan, "Alarm management pas." 2012.

[75] CSB, "E.i. dupont de nemours & co., investigation report, report no. 2010-6-i-wv," Report REPORT NO. 2010-6-I-WV, U.S. Chemical Safety and Hazard Investigation Board, September 2011 2011.

[76] R. API, "1167," *Pipeline SCADA Alarm Management*, 2010.

[77] G. Kowalczyk, P. Davison, and J. S. Evans, "The control of major accident hazards (comah) regulations–forthcoming legislative changes and the role of public health england," *Chemical Hazards and Poisons Report*, p. 30, 2014.

[78] S. Directive, "Directive 2012/18/eu of the european parliament and of the council of 4 july 2012 on the control of major-accident hazards involving dangerous substances, amending and subsequently repealing council directive 96/82/ec," *Official Journal of the European Union L*, vol. 197, pp. 1–37, 2012.

[79] M. Hollender, T.-C. Skovholt, and J. Evans, "Holistic alarm management throughout the plant lifecycle," in *2016 Petroleum and Chemical Industry Conference Europe (PCIC Europe)*, pp. 1–6, IEEE, 2016.

[80] T. Ayral, J. Bilyk, and K. Brown, "Case history: Quantifying the benefits of alarm management," *Hydrocarbon Processing*, 2013.

[81] I. Nimmo, "Rescue your plant from alarm overload," *Chemical Processing, January 2005*, 2005.

[82] C. Timms, "Hazards equal trips or alarms or both," *Process Safety and Environmental Protection*, vol. 87, no. 1, pp. 3–13, 2009.

[83] S. B. Azhar and M. J. Rissanen, "Evaluation of parallel coordinates for interactive alarm filtering," in *Information Visualisation (IV), 2011 15th International Conference on*, pp. 102–109, IEEE.

[84] E. Burnell and C. Dicken, "Handling of repeating alarms," in *Stemming the Alarm Flood (Digest No: 1997/136), IEE Colloquium on*, pp. 12/1–12/4, IET.

[85] J. Liu, K. W. Lim, W. K. Ho, K. C. Tan, R. Srinivasan, and A. Tay, "The intelligent alarm management system," *IEEE software*, vol. 20, no. 2, pp. 66–71, 2003.

[86] J. Wang, F. Yang, T. Chen, and S. L. Shah, "An overview of industrial alarm systems: Main causes for alarm overloading, research status, and open problems," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 2, pp. 1045–1061, 2015.

[87] J. P. Carrera and J. R. Easter, "Advanced alarm management in the aware system," in *Nuclear Science Symposium and Medical Imaging Conference, 1991., Conference Record of the 1991 IEEE*, pp. 1389–1393, IEEE.

[88] R. Brooks, R. Thorpe, and J. Wilson, "A new method for defining and managing process alarms and for correcting process operation when an alarm occurs," *Journal of hazardous materials*, vol. 115, no. 1-3, pp. 169–174, 2004.

[89] A. J. Hugo, "Estimation of alarm deadbands," *IFAC Proceedings Volumes*, vol. 42, no. 8, pp. 663–667, 2009.

[90] F. Higuchi, I. Yamamoto, T. Takai, M. Noda, and H. Nishitani, "Use of event correlation analysis to reduce number of alarms," *Computer Aided Chemical Engineering*, vol. 27, pp. 1521–1526, 2009.

[91] S. R. Kondaveeti, I. Izadi, S. L. Shah, and T. Chen, "On the use of delay timers and latches for efficient alarm design," in *2011 19th Mediterranean Conference on Control & Automation (MED)*, pp. 970–975, IEEE, 2011.

[92] R. K. Arjomandi and K. Salahshoor, "Development of an efficient alarm management package for an industrial process plant," in *2011 Chinese Control and Decision Conference (CCDC)*, pp. 1875–1880, IEEE.

[93] S. Ahmed, H. A. Gabbar, Y. Chang, and F. I. Khan, "Risk based alarm design: A systems approach," in *Advanced Control of Industrial Processes (ADCONIP), 2011 International Symposium on*, pp. 42–47, IEEE.

[94] S. Ahmed, P. Dalpatadu, and F. Khan, "Conceptual framework for an event-based plant alarm system," in *Intelligent Control and Automation (WCICA), 2014 11th World Congress on*, pp. 491–496, IEEE.

[95] J. Folmer and B. Vogel-Heuser, "Computing dependent industrial alarms for alarm flood reduction," in *International Multi-Conference on Systems, Signals & Devices*, pp. 1–6, IEEE, 2012.

[96] N. A. Adnan, Y. Cheng, I. Izadi, and T. Chen, "Study of generalized delay-timers in alarm configuration," *Journal of Process Control*, vol. 23, no. 3, pp. 382–395, 2013.

[97] N. A. Adnan and I. Izadi, "On detection delays of filtering in industrial alarm systems," in *Control & Automation (MED), 2013 21st Mediterranean Conference on*, pp. 113–118, IEEE.

[98] T. Butters, S. Guttel, J. Shapiro, and T. Sharpe, "Statistical cluster analysis and visualisation for alarm management configuration," in *Asset Management Conference 2014*, pp. 1–6, IET.

[99] Z. Cai, L. Zhang, J. Hu, Y. Yi, and Y. Wang, "Comprehensive alarm information processing technology with application in petrochemical plant," *Journal of Loss Prevention in the Process Industries*, vol. 38, pp. 101–113, 2015.

[100] S. Lai and T. Chen, "Methodology and application of pattern mining in multiple alarm flood sequences," *IFAC-PapersOnLine*, vol. 48, no. 8, pp. 657–662, 2015.

[101] P. Dalpatadu, S. Ahmed, and F. Khan, "Bayesian method for event-based alarm annunciation," *IFAC-PapersOnLine*, vol. 48, no. 21, pp. 832–837, 2015.

[102] Z. Zeng, W. Tan, and R. Zhou, "An alternative method to compute the expected detection delay for deadbands and delay-timers," in *2016 12th IEEE International Conference on Control and Automation (ICCA)*, pp. 149–154, IEEE, 2016.

[103] J. Zhu, C. Wang, C. Li, X. Gao, and J. Zhao, "Dynamic alarm prediction for critical alarms using a probabilistic model," *Chinese Journal of Chemical Engineering*, vol. 24, no. 7, pp. 881–885, 2016.

[104] V. Rodrigo, M. Chioua, T. Hagglund, and M. Hollender, "Causal analysis for alarm flood reduction," *IFAC-PapersOnLine*, vol. 49, no. 7, pp. 723–728, 2016.

[105] K. Chen and J. Wang, "Design of multivariate alarm systems based on online calculation of variational directions," *Chemical Engineering Research and Design*, vol. 122, pp. 11–21, 2017.

[106] W. Tan, Y. Sun, I. I. Azad, and T. Chen, "Design of univariate alarm systems via rank order filters," *Control Engineering Practice*, vol. 59, pp. 55–63, 2017.

[107] J. Wang, Z. Yang, K. Chen, and D. Zhou, "Practices of detecting and removing nuisance alarms for alarm overloading in thermal power plants," *Control Engineering Practice*, vol. 67, pp. 21–30, 2017.

[108] W. Hu, J. Wang, T. Chen, and S. L. Shah, "Cause-effect analysis of industrial alarm variables using transfer entropies," *Control Engineering Practice*, vol. 64, pp. 205–214, 2017.

[109] Y. Yu, D. Zhu, J. Wang, and Y. Zhao, "Abnormal data detection for multivariate alarm systems based on correlation directions," *Journal of Loss Prevention in the Process Industries*, vol. 45, pp. 43–55, 2017.

[110] W. Hu, T. Chen, and S. L. Shah, "Discovering association rules of mode-dependent alarms from alarm and event logs," *IEEE Transactions on Control Systems Technology*, vol. 26, no. 3, pp. 971–983, 2017.

[111] J. Tuszynski, J. E. Larsson, C. Nihlwing, B. Öhman, and A. Calzada, "A pilot project on alarm reduction and presentation based on multilevel flow models," in *Proceedings of the Enlarged Halden Programme Group Meeting, HPR-358, Storefjell, Gol, Norway*, 2002.

[112] C. Mattiasson, "The alarm system from the operator's perspective," 1999.

[113] M. Bransby and J. Jenkinson, "Alarm management in the chemical and power industries: Results of a survey for the hse," in *Colloquium Digest -IEEE*, pp. 5–5, IEEE Institution Of Electrical Engineers.

[114] I. S. Kim, "Computerized systems for on-line management of failures: a state-of-the-art discussion of alarm systems and diagnostic systems applied in the nuclear industry," *Reliability Engineering & System Safety*, vol. 44, no. 3, pp. 279–295, 1994.

[115] S. S. Choi, K. S. Kang, H. G. Kim, and S. H. Chang, "Development of an on-line fuzzy expert system for integrated alarm processing in nuclear power plants," *IEEE Transactions on Nuclear Science*, vol. 42, no. 4, pp. 1406–1418, 1995.

[116] M. S. Mannan, O. Reyes-Valdes, P. Jain, N. Tamim, and M. Ahammad, "The evolution of process safety: current status and future direction," *Annual review of chemical and biomolecular engineering*, vol. 7, pp. 135–162, 2016.

[117] A. Adhitya, S. F. Cheng, Z. Lee, and R. Srinivasan, "Quantifying the effectiveness of an alarm management system through human factors studies," *Computers & Chemical Engineering*, vol. 67, pp. 1–12, 2014.

[118] P. Dalapatu, S. Ahmed, and F. Khan, "Alarm allocation for event-based process alarm systems," *IFAC Proceedings Volumes*, vol. 46, no. 32, pp. 815–820, 2013.

[119] K. Takeda, T. Hamaguchi, N. Kimura, and M. Noda, "A method of designing plant alarm system based on first alarm alternative signals for each assumed plant malfunction," in *Proc. 6th Int. Conf. Process Syst. Eng.(PSE ASIA)*, pp. 25–27, 2013.

[120] K. Takeda, T. Hamaguchi, M. Noda, N. Kimura, and T. Itoh, "Use of two-layer cause-effect model to select source of signal in plant alarm system," in *International Conference*

on Knowledge-Based and Intelligent Information and Engineering Systems, pp. 381–388, Springer, 2010.

[121] F. Yang, D. Xiao, and S. L. Shah, "Optimal sensor location design for reliable fault detection in presence of false alarms," *Sensors*, vol. 9, no. 11, pp. 8579–8592, 2009.

[122] C. Basu, K. Das, J. Hazra, and D. P. Seetharam, *Enhancing wide-area monitoring and control with intelligent alarm handling*. 2013.

[123] E. Blaauwgeers, L. Dubois, and L. Ryckaert, "Real-time risk estimation for better situational awareness," *IFAC Proceedings Volumes*, vol. 46, no. 15, pp. 232–239, 2013.

[124] A. Tchamova and J. Dezert, "Intelligent alarm classification based on dsmt," in *2012 6th IEEE International Conference Intelligent Systems*, pp. 120–125, IEEE, 2012.

[125] J. Zhu, J. Zhao, and F. Yang, "Dynamic risk analysis with alarm data to improve process safety using bayesian network," in *Proceeding of the 11th World Congress on Intelligent Control and Automation*, pp. 461–466, IEEE, 2014.

[126] P. Urban and L. Landryová, "Process knowledge building an optimized alarm system," in *Proceedings of the 2015 16th International Carpathian Control Conference (ICCC)*, pp. 563–566, IEEE, 2015.

[127] L. D. Jensen, "Dynamic alarm management on an ethylene plant," *Honeywell Users Group, Nice France*, 1995.

[128] D. H. Rothenberg, *Alarm management for process control: a best-practice guide for design, implementation, and use of industrial alarm systems*. Momentum Press, 2009.

[129] B. R. Mehta and Y. J. Reddy, *Industrial process automation systems: design and implementation*. Butterworth-Heinemann, 2014.

[130] P. Grosdidier, P. Connor, B. Hollifield, and S. Kulkarni, "A path forward for dcs alarm management," *Hydrocarbon processing*, vol. 82, no. 11, pp. 59–68, 2003.

[131] M. Fullen, P. Schüller, and O. Niggemann, "Defining and validating similarity measures for industrial alarm flood analysis," in *2017 IEEE 15th International Conference on Industrial Informatics (INDIN)*, pp. 781–786, IEEE, 2017.

[132] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[133] C. A. Rieth, B. D. Amsel, R. Tran, and M. B. Cook, "Additional Tennessee Eastman Process Simulation Data for Anomaly Detection Evaluation," 2017.

[134] A. Oussous, F.-Z. Benjelloun, A. A. Lahcen, and S. Belfkih, "Big data technologies: A survey," *Journal of King Saud University-Computer and Information Sciences*, 2017.

[135] MARSH, "The 100 largest losses 1974-2015."

[136] P. Jain, A. M. Reese, D. Chaudhari, R. A. Mentzer, and M. S. Mannan, "Regulatory approaches-safety case vs us approach: Is there a best solution today?," *Journal of Loss Prevention in the Process Industries*, vol. 46, pp. 154–162, 2017.

[137] P. Chapman, J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth, "Crisp-dm 1.0 step-by-step data mining guide," 2000.

[138] S. Anand, N. Keren, M. J. Tretter, Y. Wang, T. M. O'Connor, and M. S. Mannan, "Harnessing data mining to explore incident databases," *Journal of Hazardous Materials*, vol. 130, no. 1, pp. 33–41, 2006.

[139] PHMSA, 2017.

[140] G. Van Rossum *et al.*, "Python programming language.," in *USENIX Annual Technical Conference*, vol. 41, p. 36, 2007.

[141] I. S. Modeler, "14.2 algorithms guide," *IBM Corporation*, 2011.

[142] P. T. Inc., "Collaborative data science," 2015.

[143] F. I. Khan and M. M. Haddara, “Risk-based maintenance (rbm): a quantitative approach for maintenance/inspection scheduling and planning,” *Journal of loss prevention in the process industries*, vol. 16, no. 6, pp. 561–573, 2003.

[144] M. Čepin, “Optimization of safety equipment outages improves safety,” *Reliability Engineering & System Safety*, vol. 77, no. 1, pp. 71–80, 2002.

[145] W. Qingfeng, L. Wenbin, Z. Xin, Y. Jianfeng, and Y. Qingbin, “Development and application of equipment maintenance and safety integrity management system,” *Journal of Loss Prevention in the Process Industries*, vol. 24, no. 4, pp. 321–332, 2011.

[146] R. C. Team, “R: A language and environment for statistical computing. vienna, austria: R foundation for statistical computing; 2014,” 2014.

[147] H. Wickham, *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York, 2009.

[148] “scales: Scale functions for visualization.”

[149] Statisticat and LLC., *LaplacesDemon: Complete Environment for Bayesian Inference*, 2016. R package version 16.0.1.

[150] P. Jain, E. N. Pistikopoulos, and M. S. Mannan, “Process resilience analysis based data-driven maintenance optimization: Application to cooling tower operations,” *Computers & Chemical Engineering*, vol. 121, pp. 27–45, 2019.

[151] T. E. Oliphant, “Python for scientific computing,” *Computing in Science & Engineering*, vol. 9, no. 3, pp. 10–20, 2007.

[152] F. Chollet *et al.*, “keras,” 2015.

[153] A. Saxena, K. Goebel, D. Simon, and N. Eklund, “Damage propagation modeling for aircraft engine run-to-failure simulation,” in *2008 international conference on prognostics and health management*, pp. 1–9, IEEE, 2008.

[154] F. Seide and A. Agarwal, “Cntk: Microsoft’s open-source deep-learning toolkit,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 2135–2135, 2016.

[155] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa, “Natural language processing (almost) from scratch,” *Journal of machine learning research*, vol. 12, no. Aug, pp. 2493–2537, 2011.

[156] W. McKinney, *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython*. " O’Reilly Media, Inc.", 2012.

[157] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, *et al.*, “Scikit-learn: Machine learning in python,” *Journal of machine learning research*, vol. 12, no. Oct, pp. 2825–2830, 2011.

[158] J. D. Hunter, “Matplotlib: A 2d graphics environment,” *Computing in science & engineering*, vol. 9, no. 3, pp. 90–95, 2007.

[159] C. D. Manning, P. Raghavan, and H. Schütze, *Introduction to information retrieval*. Cambridge university press, 2008.

[160] K. Nagorny, P. Lima-Monteiro, J. Barata, and A. W. Colombo, “Big data analysis in smart manufacturing: A review,” *International Journal of Communications, Network and System Sciences*, vol. 10, no. 3, pp. 31–58, 2017.

[161] P. Goel, H. Pasman, and A. Datta, “How big data & analytics can improve process and plant safety and become an indispensable tool for risk management,” *Chemical Engineering Transactions*, vol. 77, pp. 757–762, 2019.

[162] J. Kurose and K. Marzullo, “The federal big data research and development strategic plan,” tech. rep., Technical Report, The Networking and Information Technology Research and . . . , 2016.

[163] C. Mazzel and N. Duffy, “Putting artificial intelligence (ai) to work,” *Innovation matters: insights on the latest disruptive technologies. EY Global*, 2018.

[164] J. Shaw, F. Rudzicz, T. Jamieson, and A. Goldfarb, “Artificial intelligence and the implementation challenge,” *Journal of medical Internet research*, vol. 21, no. 7, p. e13659, 2019.

APPENDIX A

PROCESS FAULT DETECTION NETWORK AND DATA

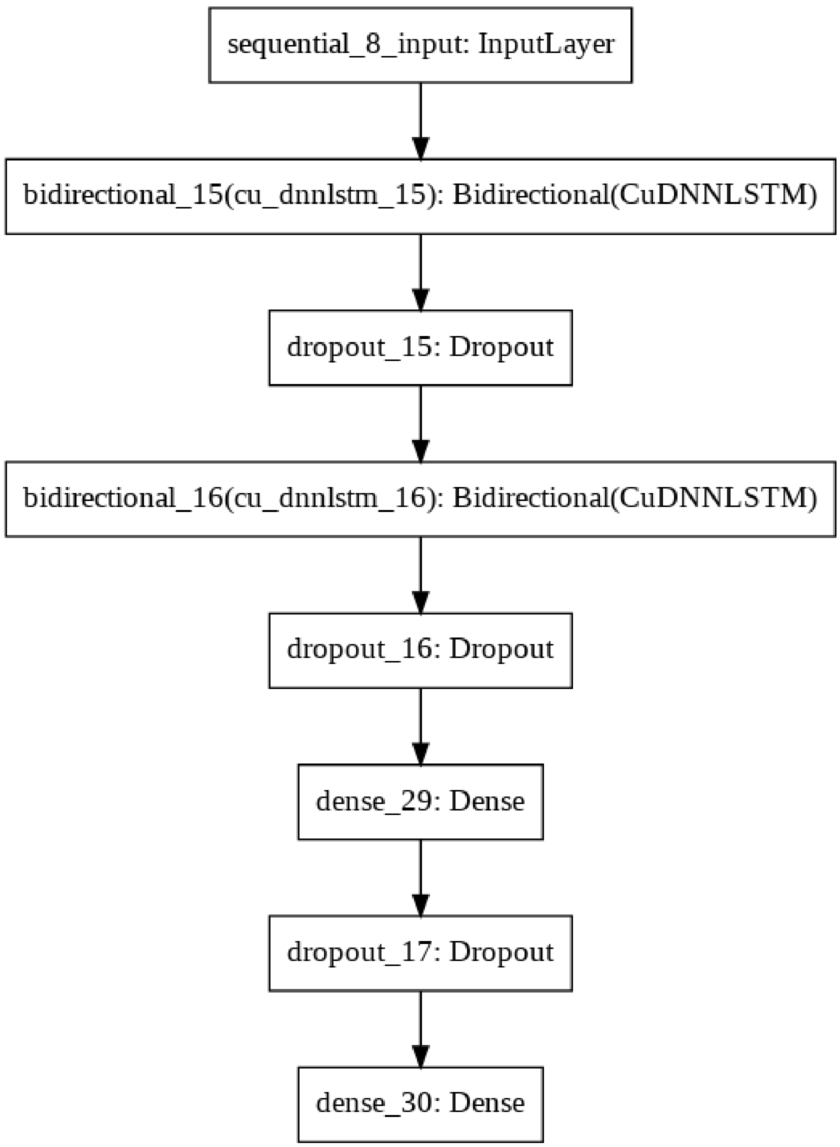


Figure A.1: LSTM model

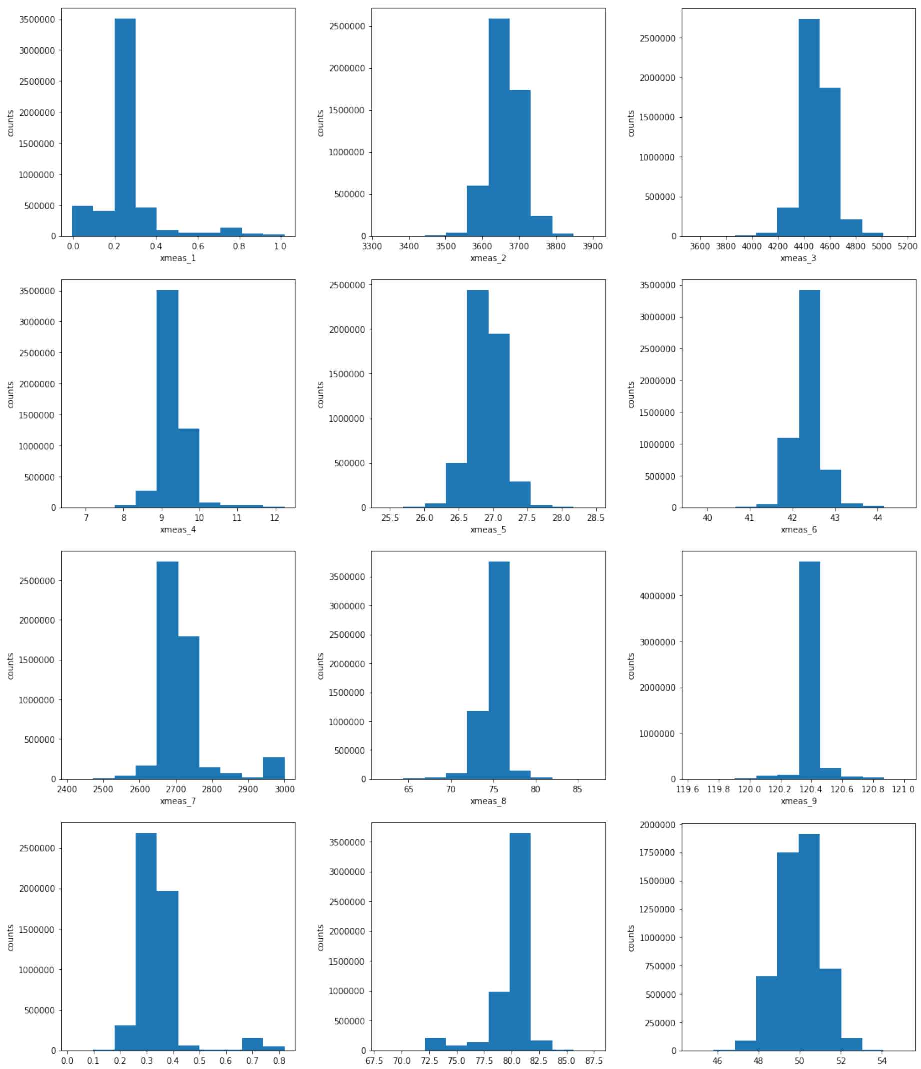


Figure A.2: Distribution of measured variables

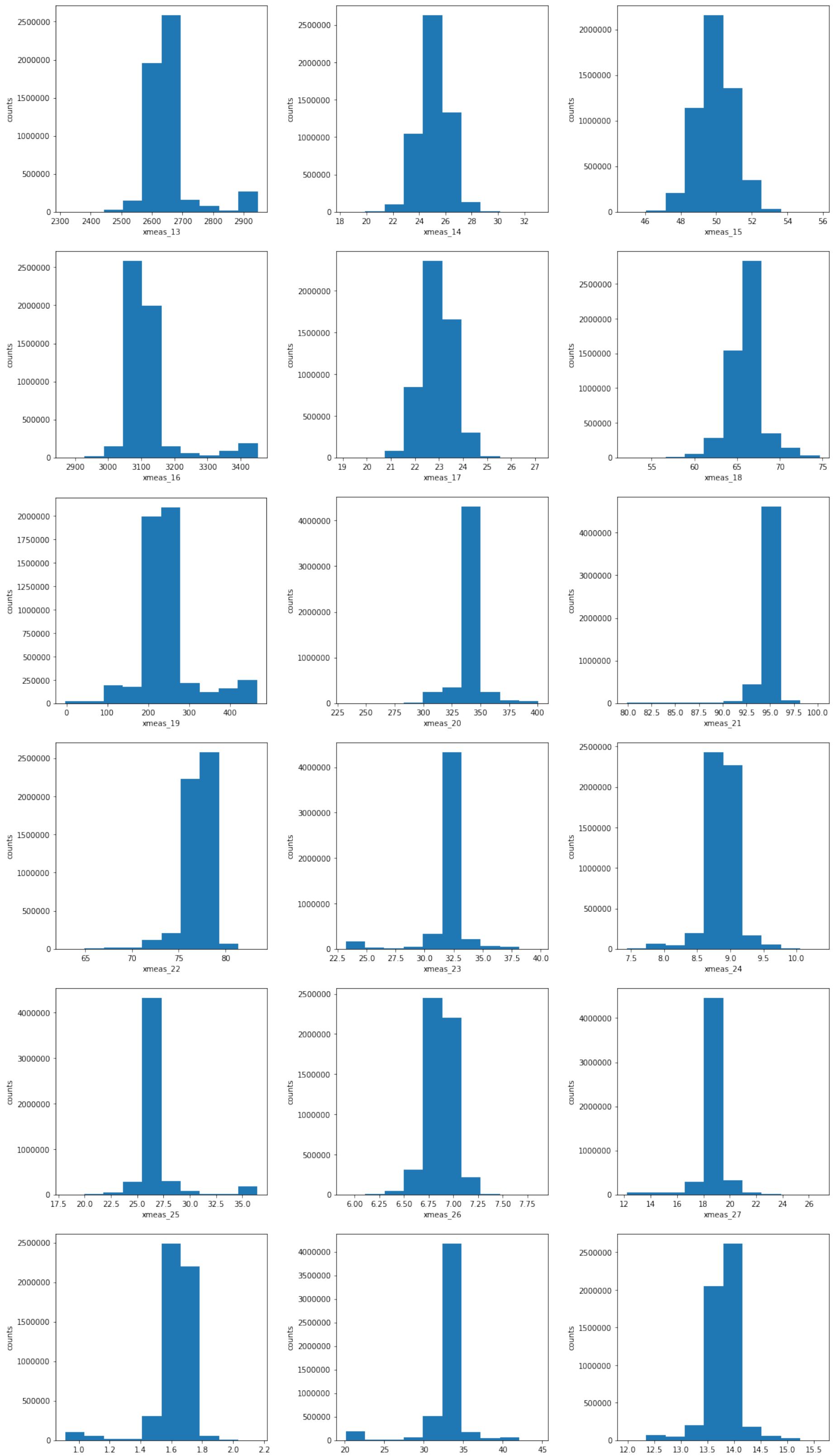


Figure A.3: Distribution of measured variables

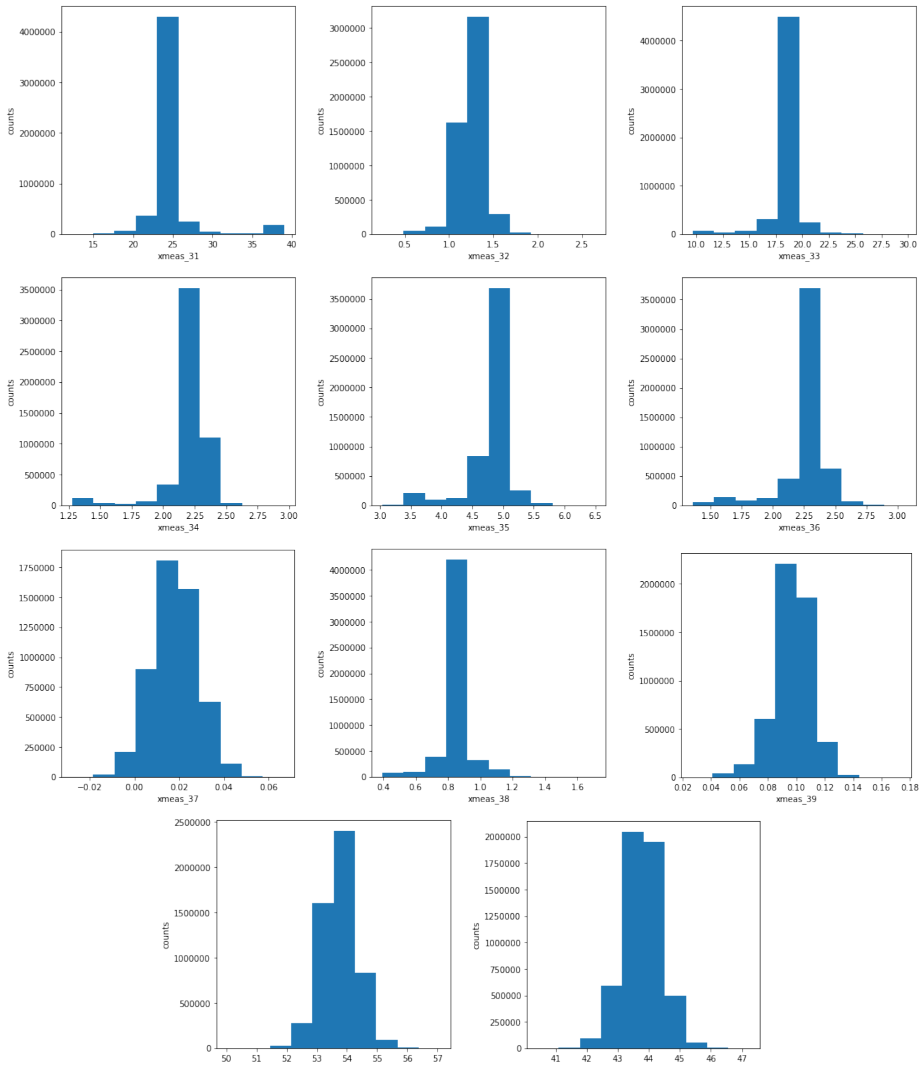


Figure A.4: Distribution of measured variables

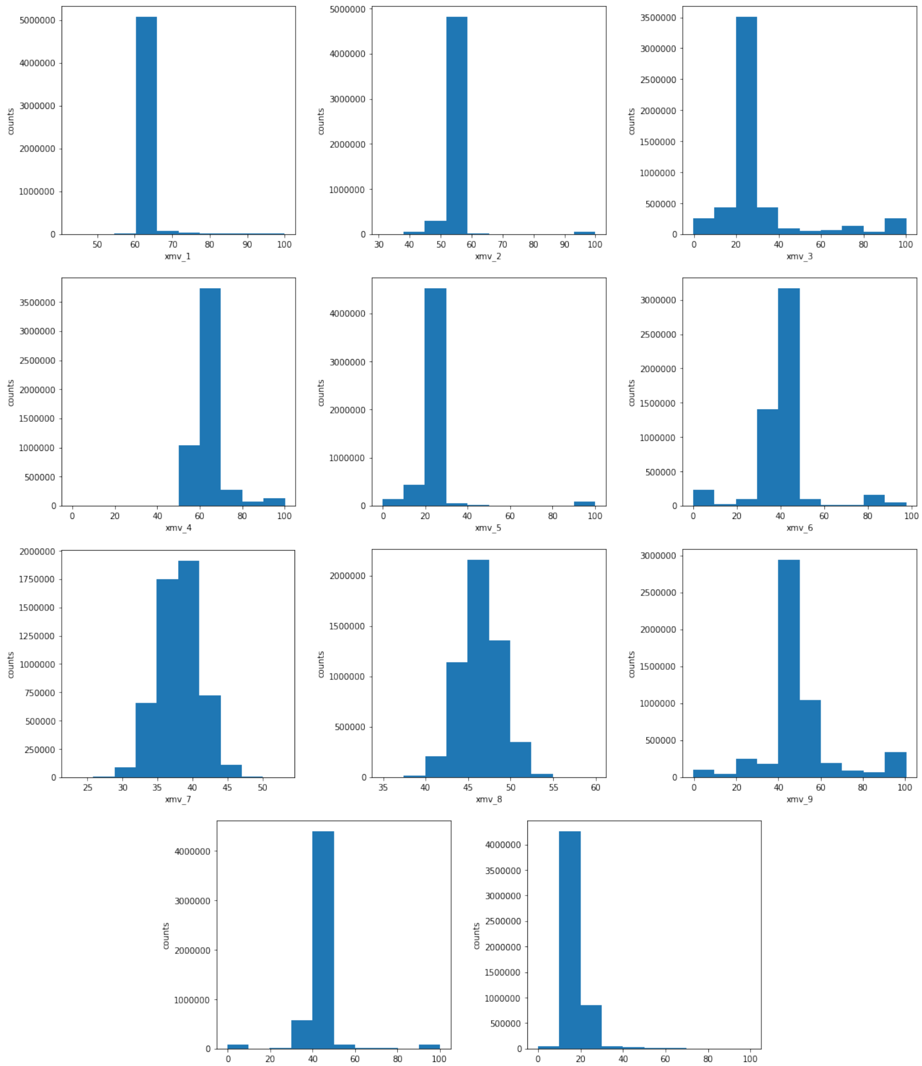


Figure A.5: Distribution of manipulated variables

APPENDIX B

RUN WINDOW FOR LSTM NETWORK

Train on 201280 samples, validate on 80480 samples

Epoch 1/50 201280/201280 [==============================] - 105s 521us/step - loss: 1.7669 - acc: 0.4440 - val_loss: 1.2474 - val_acc: 0.6153

Epoch 2/50 201280/201280 [==============================] - 103s 511us/step - loss: 1.1229 - acc: 0.6338 - val_loss: 1.0718 - val_acc: 0.6633

Epoch 3/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.8394 - acc: 0.7284 - val_loss: 0.6933 - val_acc: 0.7967

Epoch 4/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.6219 - acc: 0.8047 - val_loss: 0.5305 - val_acc: 0.8458

Epoch 5/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.5395 - acc: 0.8339 - val_loss: 0.4734 - val_acc: 0.8635

Epoch 6/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.4560 - acc: 0.8601 - val_loss: 0.4508 - val_acc: 0.8701

Epoch 7/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.4284 - acc: 0.8704 - val_loss: 0.3765 - val_acc: 0.8944

Epoch 8/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.3826 - acc: 0.8848 - val_loss: 0.3866 - val_acc: 0.8924

Epoch 9/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.3696 - acc: 0.8897 - val_loss: 0.3798 - val_acc: 0.8957

Epoch 10/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.3729 - acc: 0.8895 - val_loss: 0.3513 - val_acc: 0.9058

Epoch 11/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.3522 - acc: 0.8963 - val_loss: 0.3439 - val_acc: 0.9099

Epoch 12/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.3206 - acc: 0.9054 - val_loss: 0.3460 - val_acc: 0.9115

Epoch 13/50 201280/201280 [==============================] - 102s 507us/step - loss: 0.3200 - acc: 0.9060 - val_loss: 0.3395 - val_acc: 0.9074

Epoch 14/50 201280/201280 [==============================] - 102s 507us/step - loss: 0.3068 - acc: 0.9103 - val_loss: 0.3376 - val_acc: 0.9135

Epoch 15/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.3261 - acc: 0.9045 - val_loss: 0.3296 - val_acc: 0.9130

Epoch 16/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2973 - acc: 0.9133 - val_loss: 0.3294 - val_acc: 0.9163

Epoch 17/50 201280/201280 [==============================] - 103s 512us/step - loss: 0.2916 - acc: 0.9149 - val_loss: 0.3274 - val_acc: 0.9146

Epoch 18/50 201280/201280 [==============================] - 103s 512us/step - loss: 0.2878 - acc: 0.9163 - val_loss: 0.4358 - val_acc: 0.8807

Epoch 19/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2811 - acc: 0.9189 - val_loss: 0.3117 - val_acc: 0.9187

Epoch 20/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2732 - acc: 0.9205 - val_loss: 0.3171 - val_acc: 0.9159

Epoch 21/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2742 - acc: 0.9204 - val_loss: 0.3709 - val_acc: 0.9019

Epoch 22/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2717 - acc: 0.9208 - val_loss: 0.3108 - val_acc: 0.9230

Epoch 23/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2640 - acc: 0.9233 - val_loss: 0.3136 - val_acc: 0.9182

Epoch 24/50 201280/201280 [==============================] - 103s 511us/step - loss: 0.2595 - acc: 0.9249 - val_loss: 0.3211 - val_acc: 0.9135

Epoch 25/50 201280/201280 [==============================] - 103s 511us/step - loss:

0.2571 - acc: 0.9255 - val_loss: 0.3230 - val_acc: 0.9161

Epoch 26/50 201280/201280 [==============================] - 103s 510us/step - loss: 0.2579 - acc: 0.9258 - val_loss: 0.2829 - val_acc: 0.9276

Epoch 27/50 201280/201280 [==============================] - 102s 507us/step - loss: 0.2492 - acc: 0.9275 - val_loss: 0.3833 - val_acc: 0.8904

Epoch 28/50 201280/201280 [==============================] - 101s 502us/step - loss: 0.2463 - acc: 0.9286 - val_loss: 0.3044 - val_acc: 0.9218

Epoch 29/50 201280/201280 [==============================] - 101s 504us/step - loss: 0.2430 - acc: 0.9297 - val_loss: 0.3146 - val_acc: 0.9237

Epoch 30/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2402 - acc: 0.9309 - val_loss: 0.2709 - val_acc: 0.9319

Epoch 31/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2392 - acc: 0.9309 - val_loss: 0.2748 - val_acc: 0.9309

Epoch 32/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2352 - acc: 0.9325 - val_loss: 0.3005 - val_acc: 0.9240

Epoch 33/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2344 - acc: 0.9324 - val_loss: 0.2957 - val_acc: 0.9248

Epoch 34/50 201280/201280 [==============================] - 102s 504us/step - loss: 0.2345 - acc: 0.9324 - val_loss: 0.2921 - val_acc: 0.9273

Epoch 35/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2290 - acc: 0.9336 - val_loss: 0.3143 - val_acc: 0.9208

Epoch 36/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2283 - acc: 0.9341 - val_loss: 0.2892 - val_acc: 0.9284

Epoch 37/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2286 - acc: 0.9348 - val_loss: 0.3018 - val_acc: 0.9237

Epoch 38/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2236 - acc: 0.9357 - val_loss: 0.3053 - val_acc: 0.9245

Epoch 39/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2214 - acc: 0.9361 - val_loss: 0.3038 - val_acc: 0.9275

Epoch 40/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2184 - acc: 0.9370 - val_loss: 0.2905 - val_acc: 0.9304

Epoch 41/50 201280/201280 [==============================] - 102s 506us/step - loss: 0.2153 - acc: 0.9376 - val_loss: 0.2912 - val_acc: 0.9285

Epoch 42/50 201280/201280 [==============================] - 102s 507us/step - loss: 0.2160 - acc: 0.9372 - val_loss: 0.2997 - val_acc: 0.9297

Epoch 43/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2141 - acc: 0.9379 - val_loss: 0.2833 - val_acc: 0.9348

Epoch 44/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2132 - acc: 0.9382 - val_loss: 0.3010 - val_acc: 0.9282

Epoch 45/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2077 - acc: 0.9400 - val_loss: 0.2869 - val_acc: 0.9303

Epoch 46/50 201280/201280 [==============================] - 102s 505us/step - loss: 0.2058 - acc: 0.9402 - val_loss: 0.2797 - val_acc: 0.9314

Epoch 47/50 201280/201280 [==============================] - 101s 503us/step - loss: 0.2058 - acc: 0.9400 - val_loss: 0.2976 - val_acc: 0.9279

Epoch 48/50 201280/201280 [==============================] - 101s 503us/step - loss: 0.2011 - acc: 0.9414 - val_loss: 0.2872 - val_acc: 0.9327

Epoch 49/50 201280/201280 [==============================] - 101s 502us/step - loss: 0.2002 - acc: 0.9417 - val_loss: 0.3083 - val_acc: 0.9268

Epoch 50/50 201280/201280 [==============================] - 101s 503us/step - loss: 0.2037 - acc: 0.9408 - val_loss: 0.3294 - val_acc: 0.9214