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Review

An analysis of process fault diagnosis methods from safety perspectives

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A B S T R A C T

Industry 4.0 provides substantial opportunities to ensure a safer environment through online monitoring, early detection of faults, and preventing the faults to failures transitions. Decision making is an important step in abnormal situation management. Assigning risk based on the consequences may provide additional information for abnormal situation management decisions to prevent the accident before it occurs. This paper analyzes the interconnections between the three essential aspects of process safety: fault detection and diagnosis (FDD), risk assessment (RA), and abnormal situation management (ASM) in the context of the current and next generation of process systems. The authors present their thoughts on research directions in process safety in Industry 4.0. This article aims to serve as a road map for the next generation of process safety research to enable safer and sustainable process operations and development.

Contents

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1. Introduction

Modern process plants are becoming more complicated due to process units' interconnectivity resulting from plantwide control and optimization. In such a plant, control systems connect with many sensors and actuators to control plant operations. The sensors aid in monitoring process conditions while the actuators control the process by physically adjusting the system's variables. Despite these monitoring and control measures, processes can drift beyond their safe operating range due to actuator, sensor, or system faults. These faults may lead to a system failure and ultimately cause a plant accident.

In process systems, potential accidents are prevented using layers of protection. Failures in such layers increase accident probability and lead to its consequences. Hazard identification, probability assessment, and the consequences of hazardous incidents, considering the layers of protection in a system, provide an understanding of the system safety status.

Hazard identification, FDD, RA, and mitigation action play vital roles in maintaining plant safety. Many researchers have reviewed hazard identification approaches [Dunjo et al. (2010); Cameron et al. (2017); Willey (2014)]. Also, there are several review articles on FDD methods, by [Gao et al. (2015); Zhong et al. (2018); Puncochar and Skach (2018); Md Nor et al. (2019); Hoang and Kang (2019)], and on RA in process systems, reviewed by [Khan and Abbasi (1998); Khan et al. (2010); Swuste et al. (2016); Amin et al. (2019)]. However, these articles focus on different process safety elements without defining the interrelation and the overall ASM process. For process safety management, the methods and models used must be analyzed in combination to obtain a holistic view of the safety management framework. Therefore, this article attempts to review and analyze process safety elements' methods and models, focusing on their interrelations. Specifically, the article focuses on addressing the following questions:

1. How can risk be used for fault diagnosis and abnormal situation management (process safety perspective)?
   a. How can fault detection and diagnosis be used from the process safety perspective?
   b. How is abnormal situation management practised from the process safety perspective?
   c. How are FDD and ASM integrated with the safety system?
   d. What are the key knowledge and technological gaps in the preceding areas?
2. How could operational risk be a tool for process safety management for Industry 4.0?
   a. What are the available approaches for operational risk assessment?
   b. What are the potential uses of machine learning techniques in assessing operational risk?
   c. What are the key knowledge and technological gaps in implementing novel machine learning tools in process safety management?
3. What is the way forward with Industry 4.0 to make a smart process plant a safe environment?

1.1. Interconnection between FDD, ASM, and RA

According to Iserman and Balle (1997), based on the SAFEPROCESS committee's definition, ASM is a centralized, continuous, and comprehensive process to prevent and control the potential hazards in process systems. Moreover, ASM should identify the deviation from normal operation to faulty and failure conditions and bring the system back to normal operation.

In the process industry, determining the risk margin, using appropriate modeling such as failure models, accident models, and risk models, helps to provide information to prevent the fault from becoming a failure condition.

A failure model evaluates the accident probability by determining system failure based on a data-driven or physical model approach. Similarly, the accident model relates to the causes and effects to address the consequences. However, to develop the failure model and the accident model, hazard identification will be an initial step. When fault leads to failure, the failure model and accident model can evaluate the possible hazards and consequences.

In the process industry, FDD, RA, and ASM may apply in a closed loop. FDDs approaches to determine the fault condition and are initiated to identify the possible hazard. The failure model and accident model evaluate the probability and consequences of the system hazard when the process systems fail to identify and control the system's fault condition by ASM. Assessing a risk margin using risk models gives feedback to ASM regarding the hazardous event. With the feedback information, ASM changes the decision to control the operation.

From the Industry 4.0 perspective, interconnecting FDD, ASM, and RA help to develop an intelligent safety system by learning the risk and taking necessary action autonomously to prevent the hazard.

1.2. Review framework

Several review articles on the recent methods and models for FDD and RA have been published and are available in the open literature. However, these methods have been limited in scope, mainly focusing on FDD methods. This review comprehensively studies ASM from a holistic perspective, discusses the past and present methods and techniques, and directs the future trend of process safety for Industry 4.0. The review's scope includes the topics directly related to system faults, failure analysis, RA, mitigation action, and process safety, published in journal papers. However, to discuss the FDD and ASM standards, some industrial standards and conference papers are used.

The rest of the paper is organized as follows: Sections 2 and 3 focus on past and present methods and models for FDD, and ASM's role to prevent hazards in process systems. Section 4 summarizes the past and present risk assessment models, failure models, and hazard identification to protect the plant from accident consequences. Finally, the last section highlights the next generation research needed for Industry 4.0 and its challenges.

2. FDD models and ASM methods from a safety perspective

Investigation of past accidents reveals that more than 70% of process accidents have been caused by technical and design failures, including piping system failure, deterioration of construction materials, corrosion and erosion, mass and heat transfer, and failure of the control system[Khan and Abbasi (1999); Duguid (2001) ; Kidam and Hurme (2013)]. Moreover, the AIChE center for chemical process safety investigation reports that almost all accidents are the ultimate result of deviation from expected operations. According to Bullemer and Laberge (2010); Bullemer et al. (2011); Eljack and Kazi (2016), abnormal situation management is involved and activated when primary process control fails to protect an operation from hazardous incidents.

ASM does not only mean exposing the process deviation by fault detection and early warning of abnormal situations, but also appropriately diagnosing the causes and making decisions to bring the process back to the normal operation. Therefore, by looking at the overall plant safety process, ASM lies between FDD and RA in the management of deviating operations. According to Dai et al. (2016), quantitative risk assessment ought to be the first essential step of ASM, to get an initial clear outline of the risk scenario to manage. FDD identifies the process deviation and diagnoses the root causes.

According to Venkatasubramanian (2001), basic process control became highly automated with the third industrial revolution. However, in the past decade, automation in ASM has not been realized significantly, and most of the process industries still rely on human operators. With the forthcoming industrial revolution and smart process plants, providing appropriate, reliable, and automatic decision support to the operators about abnormal situations will be an important factor. This section comprehensively reviews the past and present models for fault detection and diagnosis.

2.1. FDD model and methods review framework and article selection

Most of the fault detection and diagnosis models and their applications are available in public journals, conferences' symposiums, and magazine articles. In this section, the authors have made an effort to review, categorize, and summarize the technical articles published in scientific journals. Since this review's scope is limited to process fault detection and diagnosis, six key journals with similar aims and scope are selected.

The literature survey is performed based on the keywords: fault detection and diagnosis, abnormal situation management, fault causality analysis, fault tolerance, fault prevention, routine monitoring, and preventive monitoring.

The technical articles' direct relations to the review's scopes are filtered. A simple statistical analysis is done based on Scopus, the web of science, and IEEE Xplore. Fig. 2 summarizes the number of articles published from 1985 to the present.

Most of the recent articles related to the focused area in process systems are published in the International Federation of Automated Control (IFAC) papers online and IEEE access. Industrial Engineering Chemistry Research (I&EC research), Computers Chemical Engineering (CCE), Reliability Engineering and System Safety (RESS), and the Journal of Loss Prevention in the Process Industries (JLP) widely focus on FDD and related areas of processing system safety. I&EC research mainly focuses on physical or chemical-based experimental, theoretical mathematical, or informative work. CCE covers the topics related mostly to process dynamics, control and monitoring, abnormal event management, and process safety. Also, CCE has published a large number of articles related to fault detection and diagnosis and abnormal situations. JLP mainly emphasizes chemical and process plant safety. RESS is devoted to developing and applying complex technological systems' safety and reliability, mainly focusing on process industries.

2.2. FDD models and methods

Methods and models developed in the past years to detect and diagnose fault conditions use mathematical, analytical, data-driven, statistical, computational, and hybrid approaches. Based on the FDD methodology classification in the work of Chiang et al. (2001I); Venkatasubramanian et al. (2003I); Zhang and Jiang (2008); Mouzakitis (2013); Alzghoul et al. (2014), a refined classification of existing FDD methods is shown in Fig. 3.

According to Chiang et al. (2001I), since the early 1970s, fault detection and diagnosis in the process industry is classified into four primary methodologies: hardware redundancy, plausibility tests, analytical models, and signal processing methods. The hardware redundancy scheme initially developed the FDD method using identical hardware components redundant to the working system. The major drawback of this approach is that if an identical component system fails to generate the appropriate output, it may fail to detect the fault condition. The plausibility test highly relies on the investigation of physics laws in the system process component. When process systems become more complex, plausibility tests fail to detect fault conditions, due to the physics laws' assumptions and real-time system accuracy. After Industry 3.0, to tackle the drawbacks mentioned above, hardware redundancy and plausibility tests have been replaced by computer-based analytical or data-based models. Apart from these models, signal processing methods use steady-state condition evaluation of the process signals to evaluate the fault condition. However, for complex process systems with many process parameters, this method is insufficient.

In this review, we mainly focus on reviewing the current state of the FDD methodologies. Computerized analytical redundancies and software-based redundancy models are primarily focused and further categorized as 1. analytical model based 2. knowledge-based, and 3. data-driven methods.

2.2.1. Analytical model-based approaches

Analytical model-based approaches use first principles to develop mathematical models of the system. As shown in Fig. 4, these model outputs are compared with an actual plant's measured data to obtain the fault knowledge. The process systems measured data are incorporated with system noise, disturbance, and other uncertainties. Also, model output includes errors due to the model accuracy and design assumptions. Therefore, when processing residual using measured and model data, the appropriate threshold is applied to evaluate the analytical models' fault condition.

According to Chiang et al. (2001I); Venkatasubramanian et al. (2003I); Zhang and Jiang (2008), parameter estimation, state observer, and parity relations are the classified approaches in the analytical based FDD. Gertler (1998); Ding (2008); Isermann (2011) recommended for the analytical model-based approach primary contexts.

However, from recent research, applying merely analytical model-based FDD will be ineffective due to the process system's complexity. Table 1 summarizes some of the recently developed analytical based models.

2.2.2. Knowledge-based approaches

According to Fan and Lu (2008), the knowledge-based methods are appropriate when a detailed mathematical model is not available, and the number of inputs, outputs, and states is relatively small. However, with the development of computational applications and software packages, the knowledge-based method

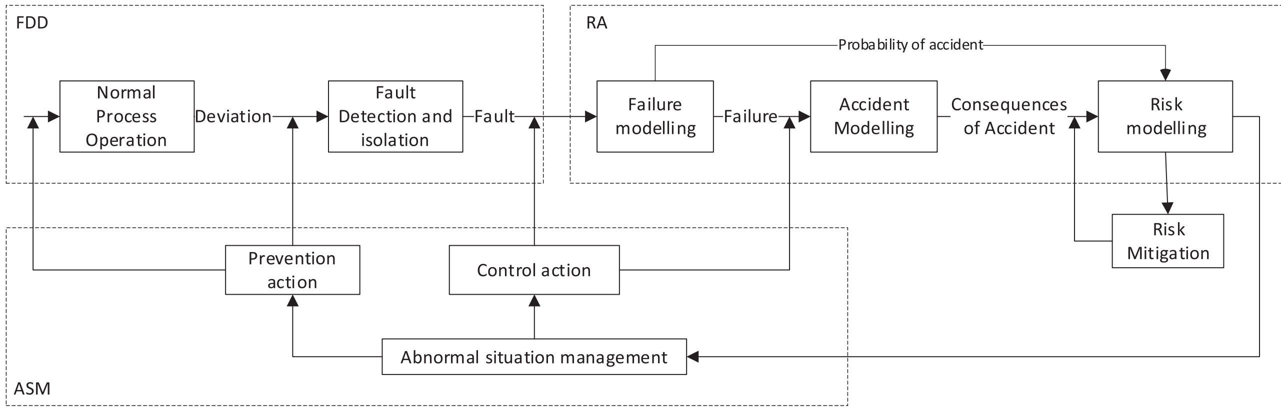


Fig. 1. The review framework based on the relationships among FDD, ASM, RA, and process safety.

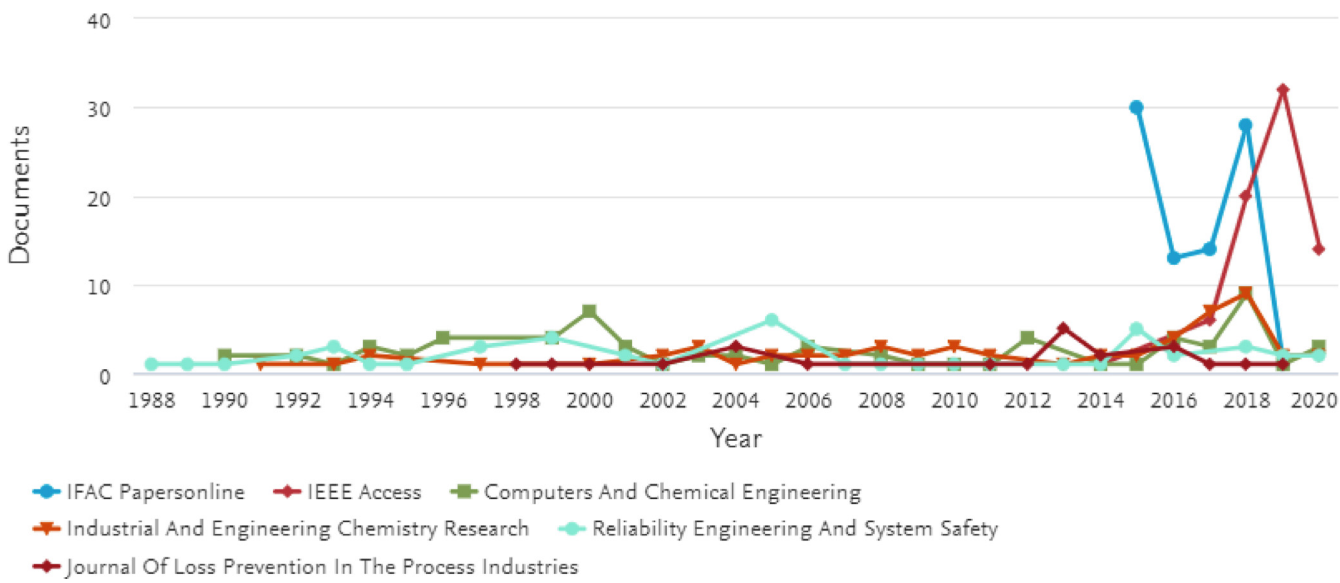


Fig. 2. Distribution of the number of articles related to fault detection and diagnosis in the process industry over the past twenty years. [As of 15th May 2020].

Table 1
Analytical model-based approach in FDD.

Model Classified	Method	References	Approach
As based on Parameter Estimation	Least squares (LS)	Isermann (1993)	Least-squares
		Cimpoesu et al. (2013)	Parameter estimation with recursive least squares
		Cimpoeşu et al. (2014)	Recursive Least Squares method with exponential weighting
	Regression Analysis	Wu and Liu (2017)	Recursive ridge regression parameter estimation
	Bounding Parameters	Verdiere and Jauberthie (2019)	Bounded error parameter estimation
		Zhou et al. (2020II)	Parameter uncertainty
State Estimation and Observer	Observer-Method	Patton and Chen (1997)	Observer-based approach
		Yan et al. (2015)	Observer approach with unknown input
		Jeong et al. (2019)	Observer gain matrix
	Kalman Filter	Kobayashi and Simon. (2005)	Bank of Kalman filter
		Huang et al. (2012)	Linear Kalman filter
		Heredia and Ollero (2009)	Kalman Filter
		Li and Olson (1991)	Extended Kalman filter
		Oehler et al. (1997)	Extended Kalman filter
		Rago et al. (1998)	Interacting Multiple Model Kalman filter
		Amoozgar et al. (2013)	Two-stage Kalman filter
		Mosallaei et al. (2007)	Decentralized Kalman filter
		Jayaram (2010)	Fast converting Kalman filter
		Yu. (2012)	Particle Filter
		Yin and Zhu (2015)	Intelligent particle filter
		He et al. (2013)	Kalman filter with least square residual
Parity space	State space-based method	Ding et al. (1999)	Parity relation based residual generation
		Odendaal and Jones (2014)	Parity space and CUSUM
		Hao et al. (2004)	Introduce stationary wavelet transform in the traditional parity relation based residual generator
	Input output-based methods	Gertler (1995)	Parity equations based on input output model

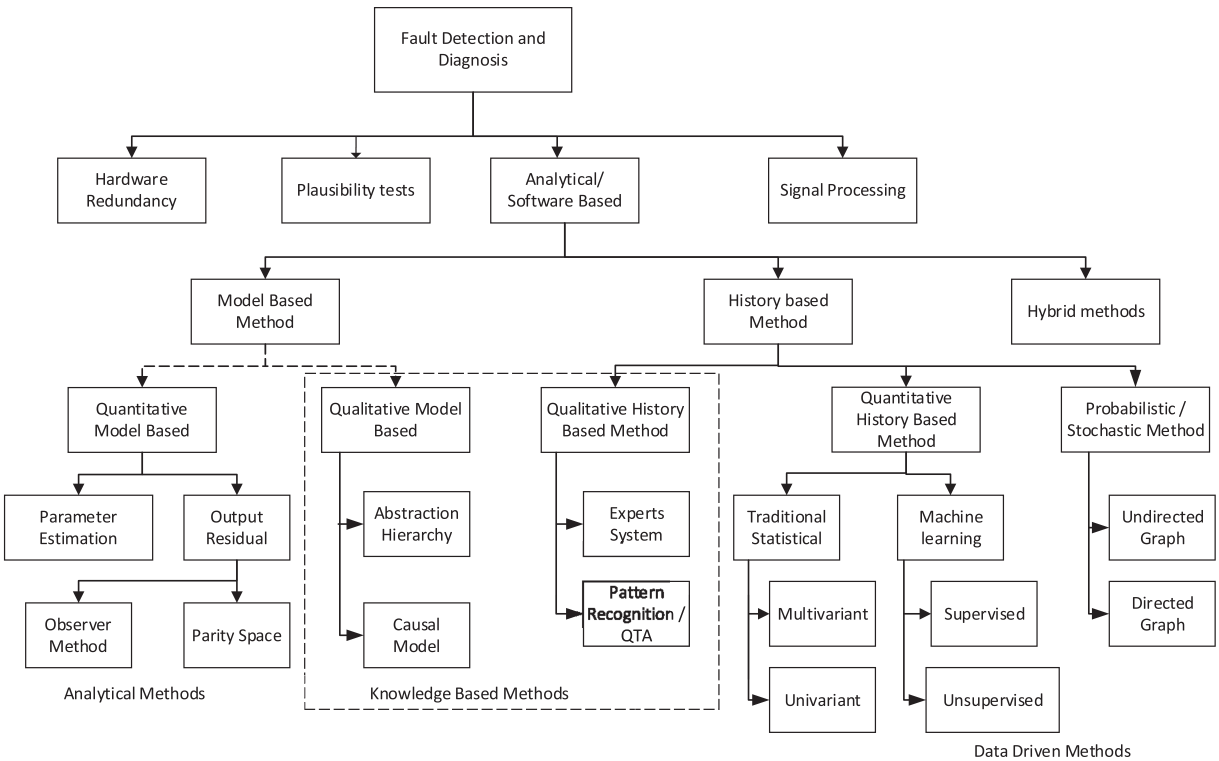


Fig. 3. Fault detection and diagnosis methodology classification (Adapted from Alzghoul et al. (2014)).

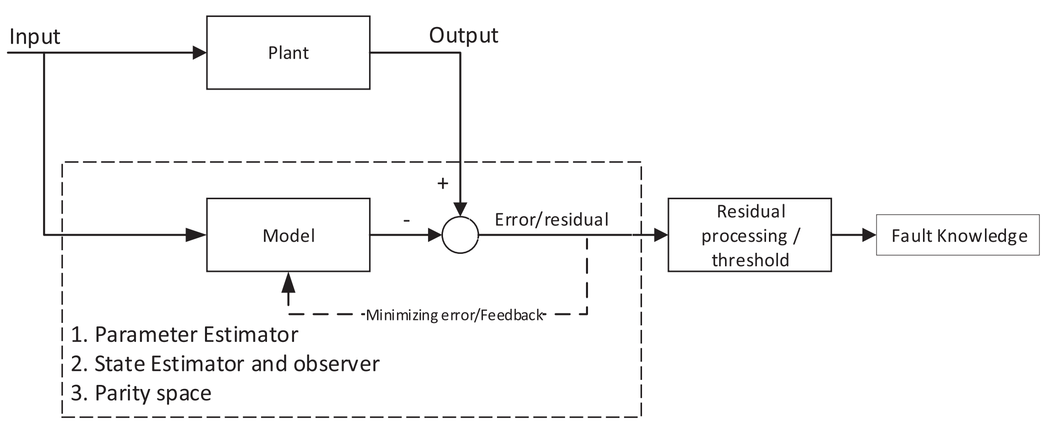


Fig. 4. General Schematic description of the analytical model-based method (Adapted from Ding et al. (1999)).

becomes more applicable to complex systems. There are not many recent survey articles published related to knowledge-based approaches based on FDD. However, Frank (1996); Venkatasubramanian et al. (2003II); Gandhi et al. (2011); Dai and Gao (2013) have performed comprehensive surveys of the qualitative approach for FDD.

Frank (1990); Venkatasubramanian et al. (2003II); Alzghoul et al. (2014) report that the knowledge-based methods are a qualitative approach of model-based and history-based methods. Causal analysis, expert systems, pattern recognition, and qualitative trend analysis (QTA) are commonly applied knowledge-based methods of FDD in process safety. As illustrated in Fig. 5, the knowledge-based FDD method is developed based on a large amount of data. Model-based qualitative methods are generated based on understanding the physical system and learn from the model's data, while historical based qualitative methods learn from the measured data.

Readers are recommended to read works by Chiang et al. (2001II) and the Vesely et al. (1981) for the model-based qualitative approaches' primary principles. Table 2 summarizes most of the commonly used knowledge-based approaches.

2.2.3. *Data-driven approaches*

Data-driven approaches are the quantitative approach of history-based models. According to Alzghoul et al. (2014); Yin et al. (2012); Fan and Lu (2008); Venkatasubramanian et al. (2003III), data-driven methods can capture information and be translated to knowledge without much information about the physical system. Therefore, these models do not rely on the system's first principles or in-depth system information, which means that data-driven approaches are most suitable for modern complex and large-scale process systems.

As shown in Fig. 6, data-driven models have been primarily developed offline using process history data with scopes for updating in real-time. However, data preprocessing and sampling/variable selection are essential steps to develop or update the model in both situations. According to Ge (2017), the preprocessing step improves the model input data's quality by

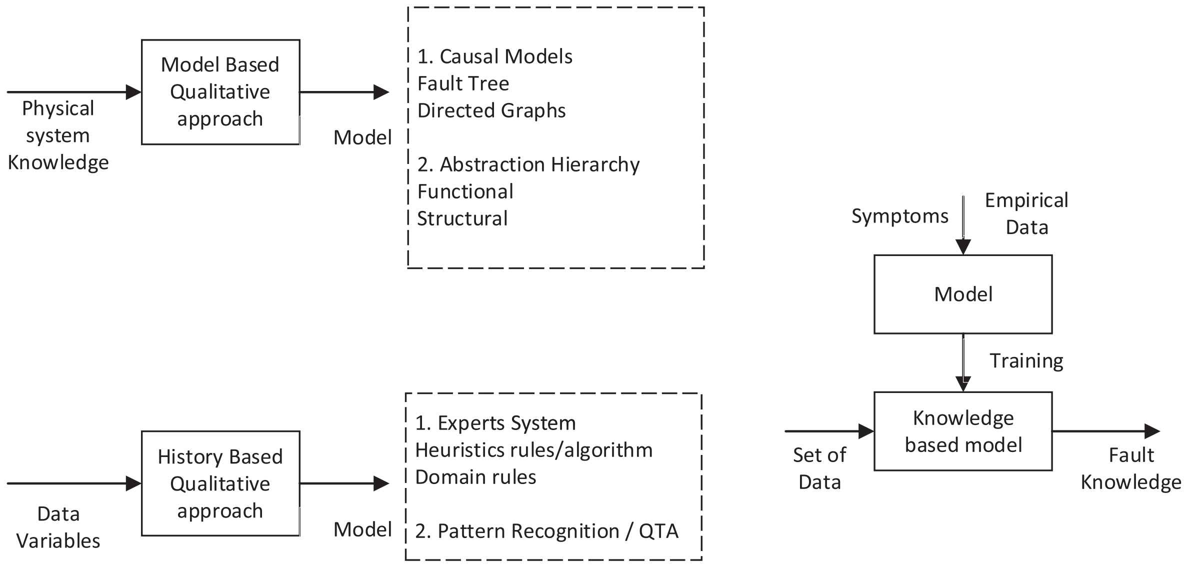


Fig. 5. Knowledge-based model.

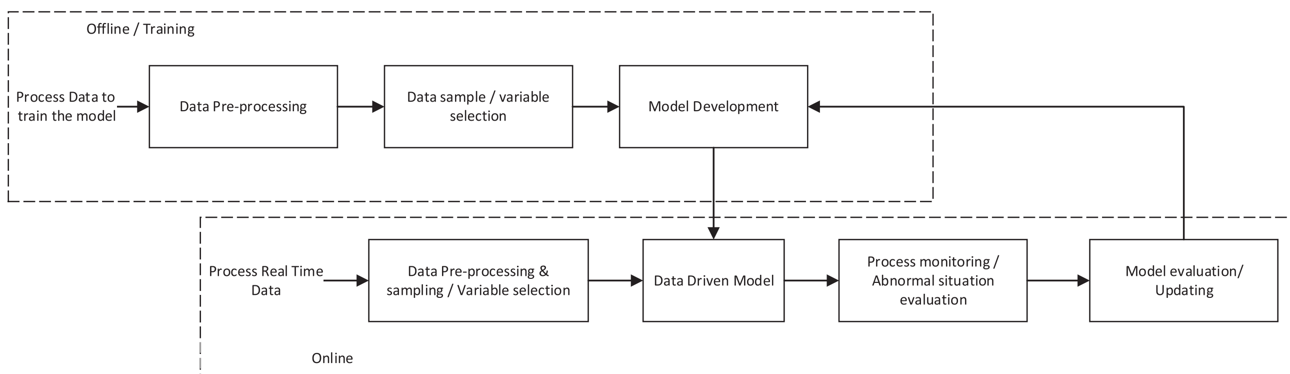


Fig. 6. The generic framework of Data-Driven Approach.

Table 2
Knowledge-based approach in FDD.

Knowledge-based model classification		Methods/model approach	References	Approach
Model-based Qualitative Method	Causal method	Fault tree Directed graph	Powers and Ulerich (1988), Antonio et al. (1995), Lapp and Powers (1977). Shiozaki et al. (1989), Chang and Yu (1990), Gao et al. (2010), Maurya et al. (2007), Mylaraswam and Venkatasubramanian (1997) .	Fault tree Stochastic approach
	Abstraction Hierarchy	Functional Structural	Ham and Yoon (2001), Bisantz and Vicente (1994). Lind (1999).	Functionally abstract information in FDD. Structural Approach.
History-based Qualitative method	Expert system	Heuristic Algorithm/rules	Lemos et al. (2013). Nan et al. (2008). Lo et al. (2007). Yap et al. (2013).	Fuzzy classifier Fuzzy logic system Fuzzy-genetic algorithm Fuzzy rules integrate with genetic algorithms
	QTA		Ram Maurya et al. (2003). Maurya et al. (2010).	(QTA) - Principle Component Analysis (PCA) QTA-based diagnostic system

supplying missing data, removing outliers, and normalizing. The sample/variable selection procedure determines the operating conditions of the system. A model can be developed based on the preprocessed input data by applying a statistical or machine learning approach.

The constructed models are verified and updated based on testing and real-time data. In the monitoring stage, the control limit or data pattern indicate abnormal events. Especially in machine learning approaches, a developed model can improve repeatedly based on real-time performance.

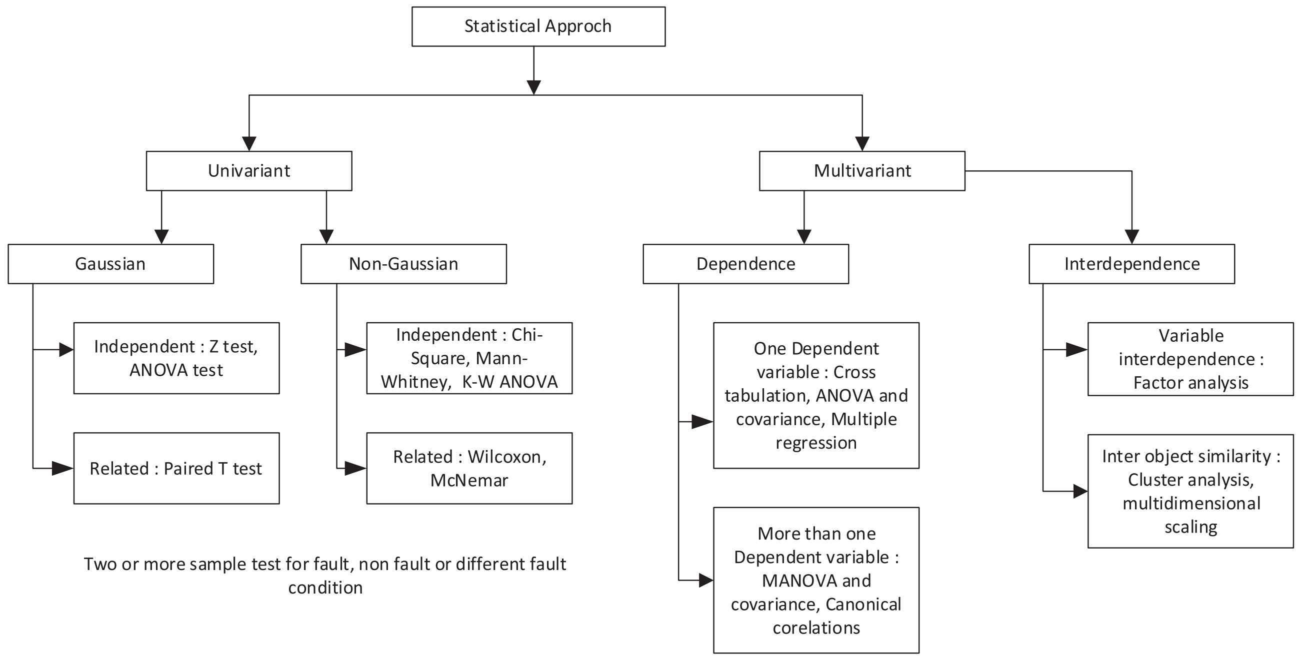


Fig. 7. Statistical methods used to evaluate the fault condition.

Yin et al. (2014) ; Arunthavanathan et al. (2020) classify data-driven approaches as traditional statistical and novel machine learning approaches. Traditional statistical models are designed to infer the relationships among the variables to estimate the model, using a sample population and hypothesis. In contrast, machine learning models are designed for more accurate predictions based on supervised or unsupervised learning.

2.2.3.1. Traditional statistical approach. According to Harris et al. (1999), data-based traditional statistical approaches are classified as univariate and multivariate. Almost all the real-time process systems contain multiple variables. Consequently, multivariate approaches are extensively used in recent data-driven approaches. However, in the univariate methods, each variable is monitored individually to obtain fault detection using each variable threshold limit. Fig. 7 classifies the traditional statistical approach applied to fault detection and diagnosis.

2.2.3.1.1. Univariate approach. According to Kano et al. (2003) ; MacGregor and Kourti (1995), statistical process controls (SPC) such as the Shewhart control chart, cumulative control charts (CUSUM), and exponentially weighted moving average control charts (EWMA) are broadly applied to investigate the univariate features in process systems. These methods attempt to distinguish between normal and abnormal operations by setting upper and lower control limits using estimations. According to Alauddin et al. (2018), univariate methods are commonly used for uncorrelated process data. Alternatively, when the process data variables are highly correlated, multivariate statistical analysis is used to develop the model.

2.2.3.1.2. Multivariate approaches. Due to the process complexity and highly correlated nature of process data, multivariate techniques have been extensively used in current decades. According to Qin (2012), principal component analysis (PCA) and partial least squares (PLS) methods have widely used Gaussian approaches, and the significant advantage of these methods is their ability to handle highly correlated data without preprocessing. According to Kourti and MacGregor (1995), these two methods are used for feature dimension reduction and are combined with other statistical hypothesis testing algorithms such as T^2, ANOVA, and the MANOVA test to make them ideal methods for complex system FDD. Readers are recommended to read works by Zhiqiang and Song (2013) ; Ding (2016) for multivariate approaches' primary principles. Table 3 includes the most recent cited journal articles related to univariate and multivariate approaches.

2.2.3.2. Machine learning approach. In this review, the authors distinguish statistical, knowledge-based, and machine learning approaches. Machine learning models learn from data based on pattern or inference without depending on rules. In contrast, knowledge-based models learn from data following rules, and statistical models formulate the relationships to develop knowledge from input data. Liu et al. (2018) ; Lei et al. (2020) have recently reviewed the machine learning approaches for fault detection and diagnosis. From their review based on the learning process, machine learning techniques are classified as supervised and unsupervised learning. In the supervised learning process, a user provides information to train the computation model how to learn, and in the unsupervised learning, the process model learns by itself.

2.2.3.2.1. Supervised machine learning. According to Dai and Gao (2013) ; Lo et al. (2019), supervised learning depends on a historical data set that contains a large amount of faulty and normal data. Therefore, it is required to collect all the fault condition data in the system-level approach to develop the model. However, it is challenging for a newly developed system to follow this approach, due to the lack of faulty data. The study has also identified the Neural Network (NN) and Support Vector Machines (SVM) are commonly used supervised machine learning techniques to categorize the fault conditions.

The use of NN in process systems for fault detection began in the late '80s. Hoskins and Himmelblau (1988); Venkatasubramanian and Chan (1989); Lit et al. (1990) investigated and applied NN based approaches to detect and diagnose the fault condition in process systems. The NN-based FDD algorithms are capable of handling nonlinear dynamic system data. Therefore, sufficient research interest was shown in the early 90s; however, due to the requirements for computation capability and data collection for normal and abnormal conditions, developing models based on NN has become complex.

Table 3
Data-Driven approach in FDD.

Data-Driven Model	Method	References	Approach
Traditional Approach	Univariate / Multivariate	Bin Shams et al. (2011).	CUSUM and PCA based approach
		Ahmed et al. (2012).	PCA based T^2 and Q statistics method
		Kourti and MacGregor (1995).	Statistical Process Control (SPC) based on PLS and PCA
		Kano et al. (2003).	Independent component analysis and SPC
		Bendjama et al. (2011).	PCA based Hoteling's T2 -statistic, Q-statistic and Q-residual contribution
Machine Learning	Supervised	Heo and Lee (2018).	Neural Network
		Sorsa and Koivo (1993).	Neural Network
		Widodo and Yang (2007).	Support vector machine
		Mahadevan and Shah (2009).	One-class support vector machines
		Senanayaka et al. (2017).	Support vector machine
		Yin et al. (2014).	Support vector machine
	Unsupervised	Harrou et al. (2019).	One - class support vector machine
		Amruthnath and Gupta (2018).	PCA T^2 statistic; hierarchical clustering, K-Means, Fuzzy C-Means clustering, and model-based clustering
		Jie (2012).	Support vector clustering (SVC)-based probabilistic approach
		Yan et al. (2020).	Generative adversarial network (GAN)
		Arunthavanathan et al. (2020).	Incremental one class NN
Probabilistic – stochastic	Bayesian Network	Zhang, You, and Jia (2017).	Bayesian network inference
		Lerner et al. (2000).	Hybrid dynamic Bayesian networks (DBN)
		Zhang and Dong (2014).	Multi-time slice dynamic Bayesian network with a mixture of the Gaussian output
		Atoui et al. (2015).	Bayesian network, and Conditional Gaussian Network (CGN)
		Zhao et al. (2020).	Dynamic Bayesian network with fuzzy sets theory
	HMM	Zhangt et al. (1998).	Hidden Markov chain model
		Rashid and Yu (2012).	Hidden Markov model-based independent component analysis
		Galagedarage and Khan (2019).	Hidden Markov Model (HMM) for abnormalities detection, and Bayesian Network (BN) diagnoses the root causes of faults
		Kouadri et al. (2020).	Machine learning (ML)-based Hidden Markov model (HMM) and the principal component analysis (PCA) model

The SVM based approach for FDD for nonlinear systems has been developed from statistical learning and pattern recognition, proposed by Vapnik (1995) ; Vapnik (1998). He introduces the kernel trick to create nonlinear binary classifiers and succeeds with the application. According to Corties and Vapnik (1995); Vapnik et al. (1997); Chapelle et al. (1999), SVM aims for classification by avoiding the general machine learning problems such as model selection, overfitting, nonlinearity, dimensionality, and a local minimum. After the invention of the kernel trick, SVM became one of the major research topics in FDD. According to Li and Wang (2005), SVM was initially developed for binary classification and has been effectively extended for multiclass classification with recent research.

SVM and NN approaches are capable of classifying normal conditions and fault deviation. However, to isolate and analyze the fault condition, these two approaches have required modification in the algorithm or are interfaced with other approaches, such as probabilistic or physical system models. Some of the recent approaches based on NN and SVM are delineated in Table 3. Moreover, supervised learning approaches are better suited for classification but cannot be generalized.

2.2.3.2.2. Unsupervised machine learning. One of the major drawbacks of supervised learning is that labeled data are required to train the model. However, in the process industry, generating data with such information will be a challenge. Consequently, the unsupervised learning approach has become popular in machine learning FDD in recent years.

Unsupervised machine learning models train with historical data without any fault condition classification labels. However, by finding a hidden pattern from the data, these models select classification tags using the algorithm. According to Dike et al. (2019) ; Purarjomandlangrudi et al. (2013), clustering and anomaly detection are widely used unsupervised model behaviours in FDD. Clustering is a process of aligning the set of data as a smaller group and is used for multiclass classification. Anomaly detection is a binary classification to determine the outlier. Recent unsupervised approaches for FDD are included in Table 3.

2.2.3.3. Probabilistic methods. The Hidden Markov Model (HMM) and the Bayesian Network (BN) based approaches commonly used FDD methods built on the stochastic probabilistic theories. HMM is a graphical model with random variables that uses the Markov property described by an undirected graph. The Bayesian network is a directed acyclic probabilistic graphical model applied in various applications, including FDD. Table 3 illustrates recent FDD approaches based on BN and HMM.

2.2.4. Current research trends in data-driven approaches and challenges for industry 4.0

Process data are becoming more sophisticated and highly correlated due to process systems' growth, based on technological progress and Industry 4.0. Therefore, shallow machine learning approaches are becoming insufficient to learn large deep process data. In recent years, deep learning approaches have been developed to learn mapping from collected featured data to detect faults. According to Hoang and Kang (2019), after the year 2006, Deep Learning (DL) became most popular in FDD, due to the continuous increase of computational ability in the past decades and the development of NN optimization algorithms.

Wu and Zhao (2020); Jia et al. (2018) ; Khan and Yairi (2018) have contributed surveys of recent deep learning approaches in FDD. They reported that the Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Autoencoder (AE), and Restricted Boltzmann Machine (RBM) enable widely

Table 4
The comparison of DL methods.

Deep Learning Model		Training Type	Training Algorithm	Use of ASM
CNN		Supervised	Gradient descent-based Backpropagation	Automated feature extraction, FDD, and Estimation of RUL
RNN		Supervised	Gradient descent and Backpropagation through time	RUL estimation, Failure prognosis, and FDD
AE	SAE	Unsupervised	Backpropagation	Anomaly detection, Failure Prognosis RUL estimation, and FDD
	VAE			Anomaly detection, RUL Estimation
RBM	DBM	Unsupervised	Backpropagation	Fault diagnosis.
	DBN			Feature extraction, Failure Prognosis, and FDD

Table 5
The recent DL approaches used in ASM.

DL Model		References	Approach and suggested ASM applications
CNN		Weimer et al. (2016) and Shaheen et al. (2016).	Automated feature extraction
		Yu and Zhao (2020), Wen et al. (2018), and Ince et al. (2016).	Fault identification, detection, diagnosis and, classification
			Estimate RUL
		Ren et al. (2018), Li et al. (2018), Yang et al. (2019), Zhang et al. (2019), and Xu et al. (2020).	Prognostic and health management
		Qu et al. (2019).	
RNN		Guo et al. (2017), Wu et al. (2018), Ma and Mao (2019), and Chen et al. (2020) .	Estimate RUL
			Failure prognosis
		Cui et al. (2017), Cheng et al. (2019), Liu et al. (2019), Tang et al. (2019), and Su et al (2020II).	FDD in chemical process
		Wu and Zhao (2020), and Zhang et al. (2020).	
Autoencoder	SAE	Zhou and Paffenroth (2017).	Anomaly detection
		Deng et al. (2019).	RUL Estimation
		Lin and Tao (2019).	Prognosis and health monitoring
	VAE	Lv et al. (2020), and Kim et al. (2019).	Anomaly detection
		Su et al. (2020I), and Verstraete et al. (2020).	RUL estimation
Restricted Boltzmann Machine	DBN	Wulsin et al. (2010).	Anomaly detection
		Zhang et al. (2017I).	RUL and health monitoring
		Zhang and Zhao (2017), and Wang et al. (2020).	FDD in process systems
	DBM	Hu et al. (2018I).	FDD in process systems
Hybrid	CNN-LSTM	Xia et al. (2020) and An et al. (2020).	Estimate RUL
		Yue et al. (2018).	Fault prognosis
	AE - LSTM	Park et al. (2019)	FDD

applied recent DL methods for FDD. Autoencoder approaches are further classified as stacked autoencoders (SAE) and variational autoencoders (VAE). As for RBM, methods are further classified as the Deep Belief Network (DBN) and Deep Boltzmann Machine (DBM). Shrestha and Mahmood (2019) ; Saufi et al. (2019) review and describe each deep learning approach's detailed architecture and algorithm in their review. Table 4 demonstrates the comparison and use of the deep learning model in FDD.

Beyond fault detection and diagnosis, DL models are used to evaluate the remaining useful life (RUL), failure prognosis, and system health monitoring. Therefore, current researchers mainly focus on DL approaches to develop future process safety tools for the smart plant. Table 5 illustrates the recent research contribution based on DL approaches. However, due to forthcoming approaches, a few contributions from other areas, and some of the conference articles with useful technical contributions, are also included in Table 5.

2.3. The comparison of FDD approaches

Based on the article reviews in sections 2.2.1, 2.2.2, and 2.2.3, FDD Analytical/Software-based methods are compared as follows in Table 6. This comparison relates to the fundamental classification of FDD.

3. ASM approaches to protect the hazard using FDD

Process systems can be protected from hazards by providing appropriate prevention and control by ASM. This section discusses the approaches and safety standards used in the process industry in ASM.

3.1. The recent trend in ASM approaches

ASM approaches aim to provide early detection and timely corrective action in the process industry. According to Rothenberg (2009) ; Hu et al. (2017), traditional ASM approaches such as Alarm Management (AM) and the Safety Instrumented System (SIS) alert the operators and take necessary actions for the system to proceed in a safe state. Whenever a system deviates from its normal operations, guidance on safety integrity levels, based on IEC 61508 and 61511 standards, determine SIS's required performance to reduce the system risk by implementing a Safety Instrumented Function (SIF). In many instances, this approach is ineffective due to the detection time and unplanned equipment shutdown. Further, most of the FDD approaches used in ASM fail to diagnose the source of faults. Therefore, in the past decade, ASM prevention and control highly rely on emergency shutdown and human interactions to repair the system. According to Rothenberg (2009); Mehta and Reddy (2015), most plants attempt to avoid an emergency shutdown if they can do so without any risk. However, if a shutdown occurs, plant operation will be significantly restricted, and this may lead to mass loss production, loss of profit in the economy, equipment damage, and a considerable degree of internal investigation.

3.1.1. Alarm management

Process alarm design, installation, and management are mainly based on industrial standards, e.g., EEMUA 191 British standards, and ANSI/ISA 18.2 American standards.

There are not many reviews of alarm management in the process systems published in past years. Alford et al. (2005); Wang et al. (2016); Goel et al. (2017) review the alarm manage-

Table 6
Qualitative comparison for FDD methods discussed in section 2.2.

	Model-Based Approaches	Knowledge-Based Approaches	Data-Driven Approaches	
			Statistical	Machine Learning
Diagnosis Ability	Good	Excellent	Satisfactory	Good
Detection Speed	Quick	Quick	Depends on data size	Depends on data size and computational speed
Isolability	Satisfactory	Good	Excellent	Good
Identifiability	Good	Satisfactory	Excellent	Good
Model Development Complexity	Hard	Medium	Easy	Easy
Handling nonlinearity	Poor	Satisfactory	Good	Excellent
Generalization Capability	Good	Satisfactory	Poor	Poor (Unworkable)
Robustness	Poor	Satisfactory	Good	Excellent

Table 7
Alarm management issues and recent contributions.

Alarm Management Issue	Reference	Contribution
Alarm Flooding	Cheng et al. (2013)	Smith-Waterman algorithm for pattern matching of alarm flood sequences used to eliminate the alarm flooding
	Rodrigo et al. (2016)	
	Hu et al. (2018II)	Determine the causes of alarms of an alarm flood
	Niyazmand (2019)	Detection of frequent alarm patterns using the Itemset mining method
	Shang and Chen (2019)	PrefixSpan sequential pattern recognition algorithm is used for alarm pattern detection
	Lucke et al. (2019)	The exponentially attenuated component analysis is used for an early alarm flood classification
	Fullen et al. (2020)	Online alarm flood classification
		Semi-supervised machine learning and cased based reasoning used for alarm flood issues
Operator workload	Adhitya el al. (2014)	Quantify the effectiveness of alarm management based on the human factor
	Ahamed et al. (2015)	Assist operator during critical events using the probability of the event and risk priority
	Hu et al. (2019)	Data-driven method is used to construct an operator workflow model in response to the alarm
Effective alarm management	Hu and Yi (2016)	Intelligent alarm management framework
	Goel et al. (2019)	Alarm and event management based on alarm historical log data set
	Peco and Garcia (2019)	False alarm management
	Hidri el al. (2020)	Sequential pattern mining is used for alarm management

ment guidelines, regulations, standards, and challenges in process systems. From their review, alarm flooding, nuisance alarms, and operator workload are major alarm management issues. Based on the investigations of major process industry accidents such as Mile Island (1979), Bhopal (1984), and disasters in three Milford Haven accidents, a common alarm management issue was identified as alarm flooding.

Many researchers have aimed to provide appropriate methods to eliminate alarm flooding in recent years. Some of the contributions are summarized in Table 7.

3.1.1.1. Recent trend in alarm design and installation. In general, when a fault is detected, a loud or flashing alarm is activated to alert the operator. However, this alarm does not provide more information regarding fault or failures. Rather than using a loud or flashing alarm, a graphical visualized interface will be a better solution for conveying the fault or failure information to operators. According to Hu and Yi (2016), in current decades, industrial alarms have been implemented using a Distributed Control System (DCS) or Programmable Logic Controller (PLC) interconnected with the Human-Machine Interface (HMI), helping to build the alarm system with visualized and graphical methods. According to Hollifield and Habibi (2007), all DCS's are installed with an inbuilt alarm display. Also, the DCS is the most scalable device, with a large number of input-output ports with appropriate data transmission facilities. Therefore, in recent decades, the DCS has been commonly used in alarm management.

3.1.2. Safety instrumented system (SIS)

The main drawback of alarm systems is the necessity of manual intervention of the operator. SIS was initially invented by the International Electromechanical Commission (IEC) in electrical, electronic, and programmable electronic safety-related systems, for IEC 61508 publication standards (1998). American standards ANSI/ISA 84.00.01 (2004), adopted with IEC 61511 standards (2003), support reliable SIS design in the process industry. Recently, the IEC 61511 standards (2016) have been updated with a focus on security levels and functional safety.

Based on the standards and according to Wang and Rausand (2014), the general SIS system comprises sensors, logic controllers, and actuator devices. Sensors sense the data from the operation (such as temperature, pressure, or flow data). Logic controllers are the heart of the system and process the operating data (PLC, DCS, or any microprocessor-based system), and an actuator controls the valves.

SIS's have been implemented to prevent the process systems or plants from becoming a hazardous environment. Therefore, the failure rate and reliability of the SIS play major roles in industrial implementation. Reliability calculation goals are frequently allocated to each safety instrumented function (SIF) performed by an SIS, and detailed reliability analysis is carried out to prove compliance to these calculated goals. Lundteigen and Rausand (2010) define the function that is performed by an SIS as SIF. SIF targets for reliability in the process industry are set by IEC 61508 and IEC 61511 standards. These standards are used to measure reliability and distinguish among four safety integrity levels (SIL). The reliability calculation goal determines the average probability of failure on demand (PFD). Current approaches for SIS reliability analysis are summarized in Table 8.

3.2. ASM challenges in industry 4.0

A smart process system for Industry 4.0 requires automated SIS and repair to bring the abnormal condition to normal operation without human intervention. Therefore, fault detection time and repairing process time will play major roles in next-generation ASM research.

Moreover, a fault to failure transmission is a critical issue in ASM. Past decades of research trends demonstrate that process systems' early warning and timely diagnosis help prevent loss by appropriately modeling the failure condition. Adhitya et al. (2014) performed an experimental study to quantify

Table 8
SIS reliability analysis methods.

Reliability quantification methods	References
Reliability block diagram (RBD)	Guo and Yang (2007) proposed PFD calculation using a reliability block diagram
Fault tree analysis (FTA)	Misumi and Sato (1999) FTA using priority AND gates
	Beckman (2001) introduced the safety loop for PFD calculations
	Belland and Wiseman. (2016), FTA uses to evaluate the PFD of SIS
Markov Models (MM)	Bukowski (2006) Markov model with constant failure rates
	Langeron et al. (2008) Multiphase Markovian approach
	Liu and Rausand (2011) Based on different demand modes
Petri-Net (PN) approach	Innal et al. (2010) PFD calculation is based on FTA, MM, and PN
	Liu and Rausand (2013) Used PN modeling
Monte Carlo (MC) Simulation	Catelani et al. (2015) MC simulation
	Kaczor et al. (2016). MC and RBD

an early warning system's benefit. They found that early warning was effective to reduce diagnosis delay, and this was subjectively perceived to be beneficial by the experiment's contributors. However, it did not improve the diagnosis accuracy.

4. Review of risk assessment approaches

A process accident generally follows the sequence of initiation (starting event for the accident), propagation (maintaining or expanding an event to prolong an accident scenario), and termination (an event that stops the accident). Hazardous events continuously change in each stage of accident scenarios. Therefore, appropriately investigating the accident scenario at each stage is important in process safety management to identify the hazardous environment. System failures cause process systems accidents. Therefore, investigating system failure will be the initial starting point to determine the hazardous event and examine the accident's initiation.

By properly evaluating the risk assessment and applying appropriate ASM to the process, the system will help control a system hazard before it leads to an accident. As shown in Fig. 1, when the fault to failure transition leads to an accident, the failure model determines the system failure probability, consequences of failure are quantified by the accident model, and risk models assess the risk based on the obtained failure probability and consequences.

Many researchers have reviewed methods and tools for process safety, including hazard identification, risk assessment, and safety management based on accident models and failure models. Khan and Abbasi (1998) ; Khan et al. (2015), have investigated the available risk assessment techniques and methods. Khan et al. (2010) have developed a risk-based approach to measure process safety using a set of safety performance indicators. Swuste et al. (2016) have investigated leading and lagging safety indicators for process safety. Amin et al. (2019) recently performed a bibliometric analysis of process safety under the key areas, performance tools, and leading research contributions. This section reviews the past and present failure models, accident models, and risk models that aid decision making during abnormal situation management.

4.1. Review framework and the selection of the articles

Most of the risk assessment approaches are available in public journals, conferences' symposiums, and magazine articles. However, this review article summarizes the technical articles published in scientific journals. Since this review's scope is limited to process systems, seven key journals with similar aims and scope are selected; the number of publications in the journals is summarized in Fig. 8.

The literature survey is performed based on the keywords: Quantitative risk assessment, Risk assessment, Failure models, Accident models, Consequence Model, Risk model, Risk Analysis, and Failure analysis. The technical articles' direct relations to the scopes are filtered for the study. A simple statistical analysis is done based on Scopus, the web of science, and IEEE Xplore.

The largest number of articles related to the subject areas are published in RESS, JLP, and CCE. The foci of RESS JLP and CCE are discussed in Section 2.1. The Risk Analysis journal provides a crucial point for new developments in the field of risk analysis. Safety Science has mainly focused on articles based on accidents and disasters of special significance. Process Safety Progress mainly addresses hazardous chemical management and leak prevention, risk assessment, process hazard evaluation, and preventive maintenance related to process safety. Papers related to process system safety, including modeling, accident investigation, risk assessment, and safety-related topics, are the main concern areas for Process Safety and Environmental Protection.

4.2. System failure, risk assessment, and risk mitigation

According to Dai et al. (2016), process system design or plant implementation are the main factors in hazard identification and RA. If a system or a plant applies proper abnormal situation management, alarm management, and SIS, the probability of a hazardous event might be reduced. However, when a fault occurs and leads to failure and an accident, investigating the accident scenario and finding the accident's cause will be the RA's starting process.

Using the RA in the safety perspective of system failure analysis, it is important to investigate the systems' fault, failure condition, and the accident that occurred due to the failure. Therefore, investigating and modeling the fault to failure probability by failure modeling, and studying the accident scenario with initiating events and consequences with the accident model, will be the first tasks for the RA perspective of system failure.

The relationships among RA, FDD, and ASM are discussed in Fig. 9. Using the appropriate fault analysis, process systems can implement appropriate safety barriers to reduce accident probability. Therefore, developing accurate accident models based on process system failure may suggest the required fault detection and diagnosis models and alarm or SIS management applicable to the system.

4.3. Review of accident and failure models

Accident modeling is a methodology used to relate the cause and consequences of the incident that leads to the accident from system failure. It is necessary to analyze hazard identification and risk assessment based on the available process information to evaluate the system's risk from a process failure perspective with an accident model. According to the Center for Chemical Process Safety (2008), relative ranking, hazard checklists, hazard surveys, safety reviews, what-if analysis, failure mode and effect analysis (FMEA), and hazard and operability (HAZOP) studies are commonly used hazard identification methods in the process industries. According to Tyler (2012), HAZOP is the most widely used hazard

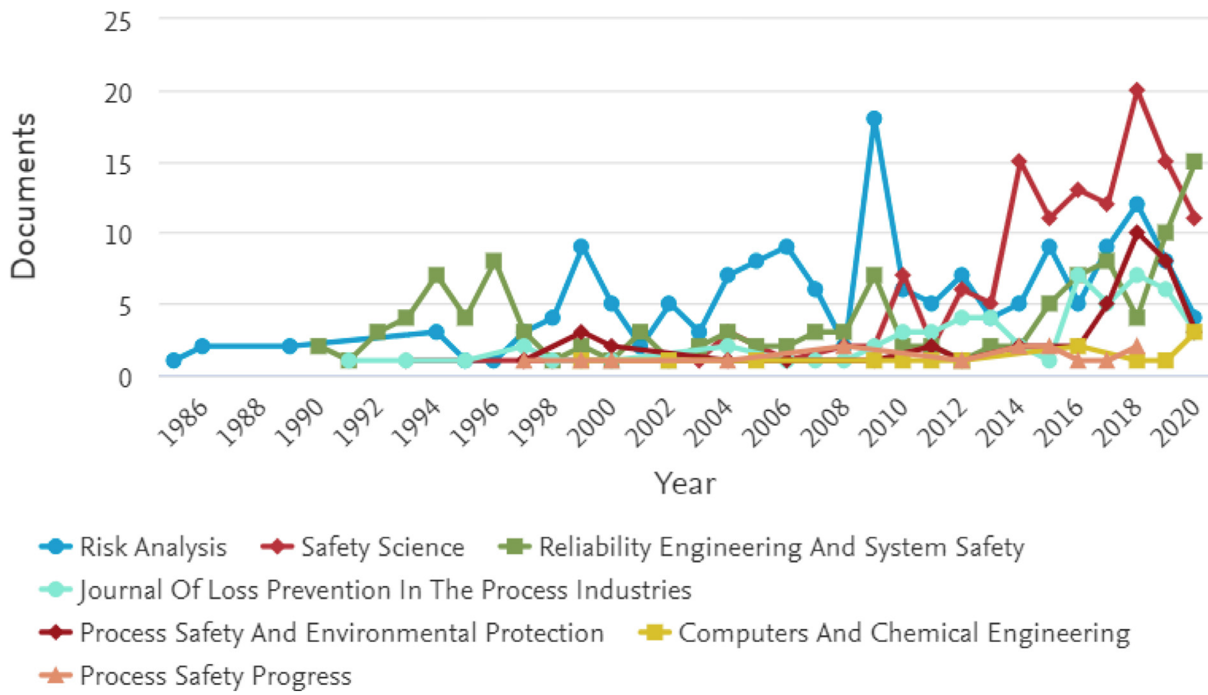


Fig. 8. Risk assessment review article published in the relevant journals [As of 27th July 2020].

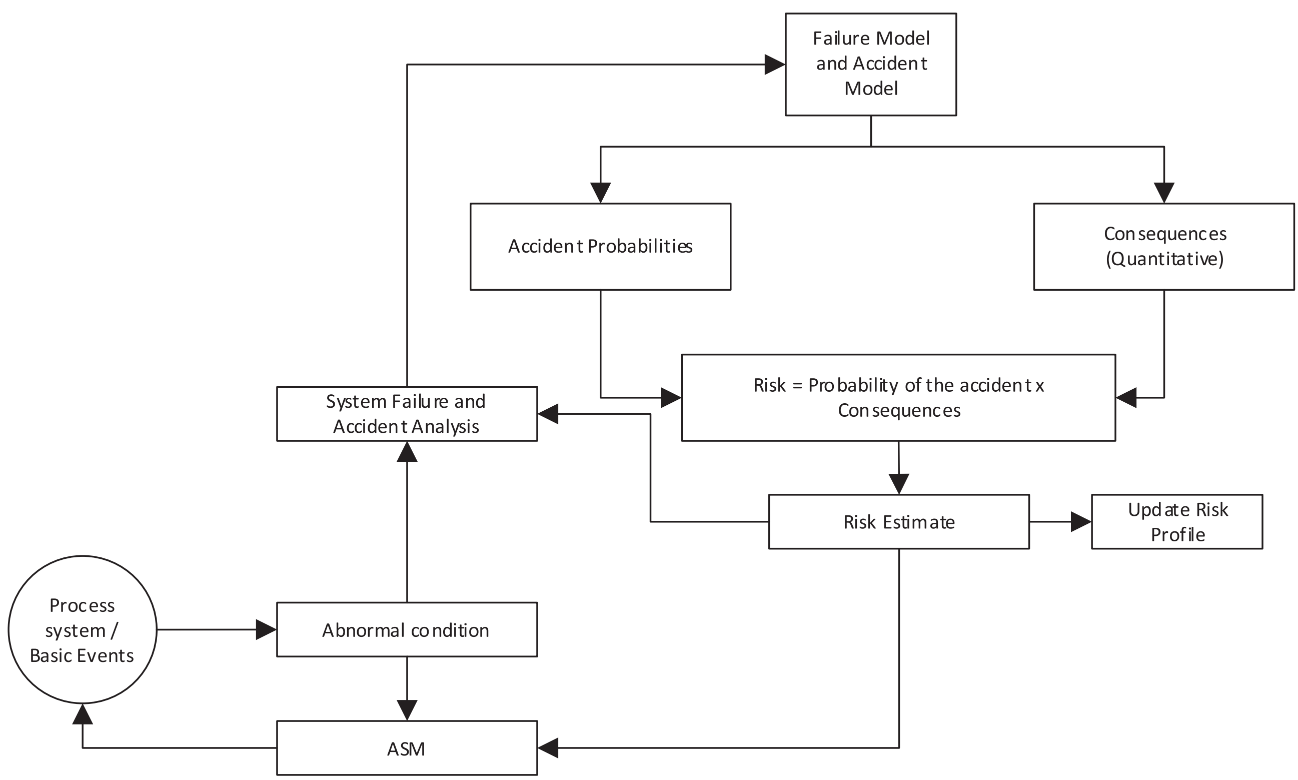
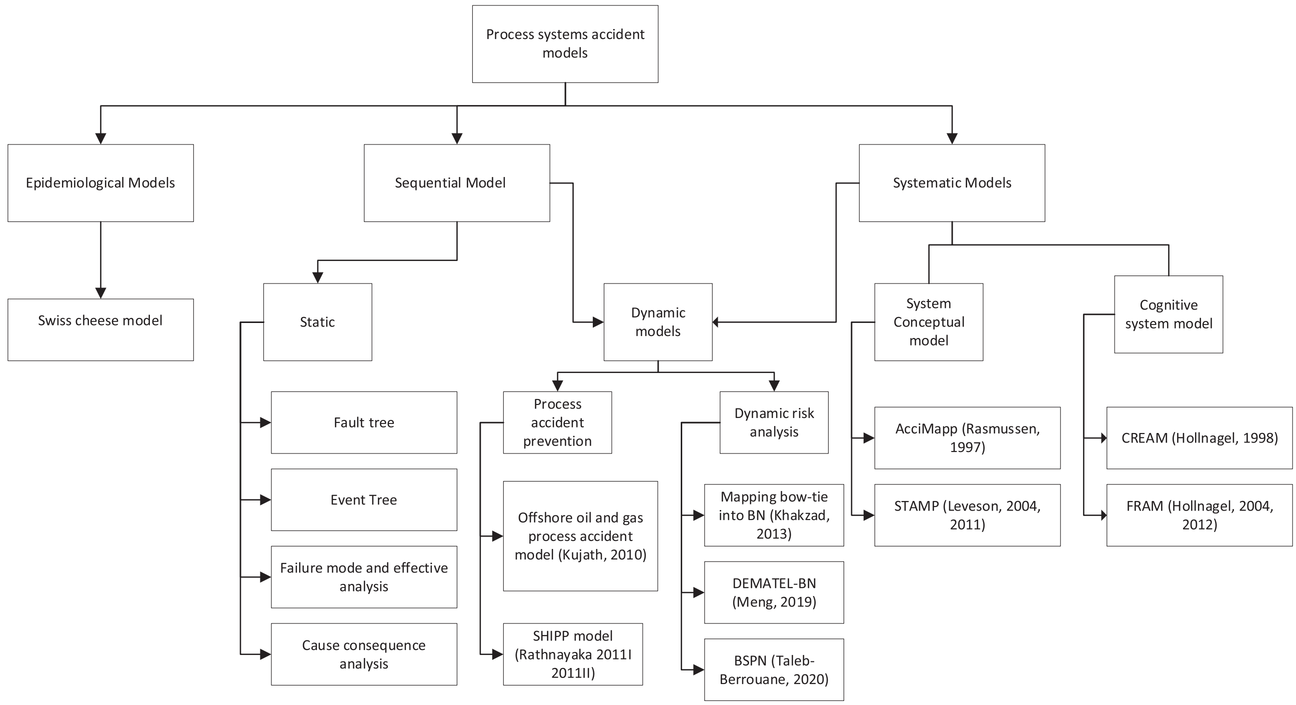


Fig. 9. Process system failure to accident relationship based on risk assessment.

identification approach in the process industry, and its study approach has been modified over the years, based on evolving technologies.

4.3.1. Accident models classifications

According to Qureshi (2007), accident models' development starts with the domino theory introduced by Heinrich in 1941. Different reviewers have classified accident models. Qureshi (2007) classified the models into traditional and modern accident models. Al-Shanini et al. (2014) have further classified traditional models into sequential and epidemiological models, and modern accident models are classified into systematic and formal models. In their recent review, Fu et al. (2020) classified accident models as linear and nonlinear, based on the accident's logical sequence. On the basis of accident models currently used in the process industry and from the work of Hollnagel (2002),



System hazard identification, prediction and prevention (SHIPP) ; Decision making trial and evaluation laboratory (DEMATEL) ; Bayesian Network (BN) ; Bayesian Stochastic Petri Nets (BSPN) ; Systems- theoretic accident model and processes (STAMP) ; Cognitive reliability and error analysis method (CREAM) ; Functional resonance accident models (FRAM)

Fig. 10. Process system accident and failure models and reference citation (adopted from Al-Shanini (2014)). References cited in figure are Kujath et al., 2010; Rathnayaka et al., 2011I; Rathnayaka et al., 2011II; Rasmussen, 1997; Leveson, 2004; Leveson, 2011; Hollnagel, 1998; Hollnagel, 2012; Hollnagel and Goteman, 2004.

accident models in process systems are also classified as sequential models, epidemiological models, and systemic models in this review.

Sequential models represent the accident as the outcome of a series of individual steps, based on the order of occurrence of the accident. Epidemiological accident models describe an accident as analogous with a disease, resulting from a combination of latent and active system failures.

Systemic accident models are based on system theory; rather than treating accidents as a sequence of cause-effect events, accident models describe losses as the system's unexpected behaviour based on the system component's uncontrolled operation. According to Yousefi et al. (2018), systemic accident models must be developed, due to process systems complexity. However, these models are mainly used by academic researchers to analyze accidents.

Dynamic sequential accident models classified by Al-Shanini et al. (2014), and dynamic risk analysis based on sequential models, represent the accident scenario and combine with other systemic approaches to accommodate nonlinear and complex interactions as dynamically updating features in a single model. Accident prevention models, dynamic risk assessment, and commonly used process accident models are classified in Fig. 10.

4.3.2. The recent trend in accident models and failure models

Dynamic risk assessment, dynamic safety analysis, and dynamic accident models are forthcoming keywords and research areas for process accident models. According to Khakzad et al. (2013); Meng et al. (2019); Taleb-Berrouane et al. (2020), the dynamic Bayesian network and Petri-nets are commonly used approaches to study the dynamic behaviour of the system. Combining these approaches with conventional accident models will result in the development of dynamic accident models in the future.

4.4. Review of risk modeling

After the Industry 3.0 era, risk assessment has emerged as an essential and systematic tool that plays a critical role in overall safety management. Many reviewers have reviewed and classified process systems' safety-related risk assessments in the past. Khan and Abbasi (1998) presented a comprehensive analysis of the quantitative and qualitative risk assessment models available up to 1998. Tixier et al. (2002) listed and reviewed 62 risk analysis approaches in both qualitative and quantitative terms for general plant industries. Marhavilas et al. (2011) reviewed and presented the qualitative, quantitative, and hybrid risk assessment approaches from 2000 to 2009. Researchers have focused on quantitative and hybrid approaches in recent decades, due to their safety risk mitigation and decision-making abilities. Necci et al. (2015) reviewed quantitative risk assessment for process industries, specifically regarding the domino accident theory. Villa et al. (2016) reviewed risk assessment methods to enable dynamic risk assessment for next-generation implementation. Recently, Kabir and Papadopoulos (2019) reviewed and comprehensively described Bayesian network approaches and Petri net approaches used in the risk assessment process.

From the view of Haimes (2004) ; Li et al. (2016), RA methods are classified as quantitative, qualitative, and comprehensive methods. According to Villa et al. (2016) ; Li et al. (2016), qualitative techniques are based on analytical estimation and human ability. The quantitative approaches quantify the risks and further estimate and express them using mathematical relations based on real-time accident data. The comprehensive methods effectively incorporate the benefits of qualitative and quantitative methods. Therefore, these approaches are currently widely used in risk assessment techniques. Fig. 11 summarizes the present risk assessment model classifications.

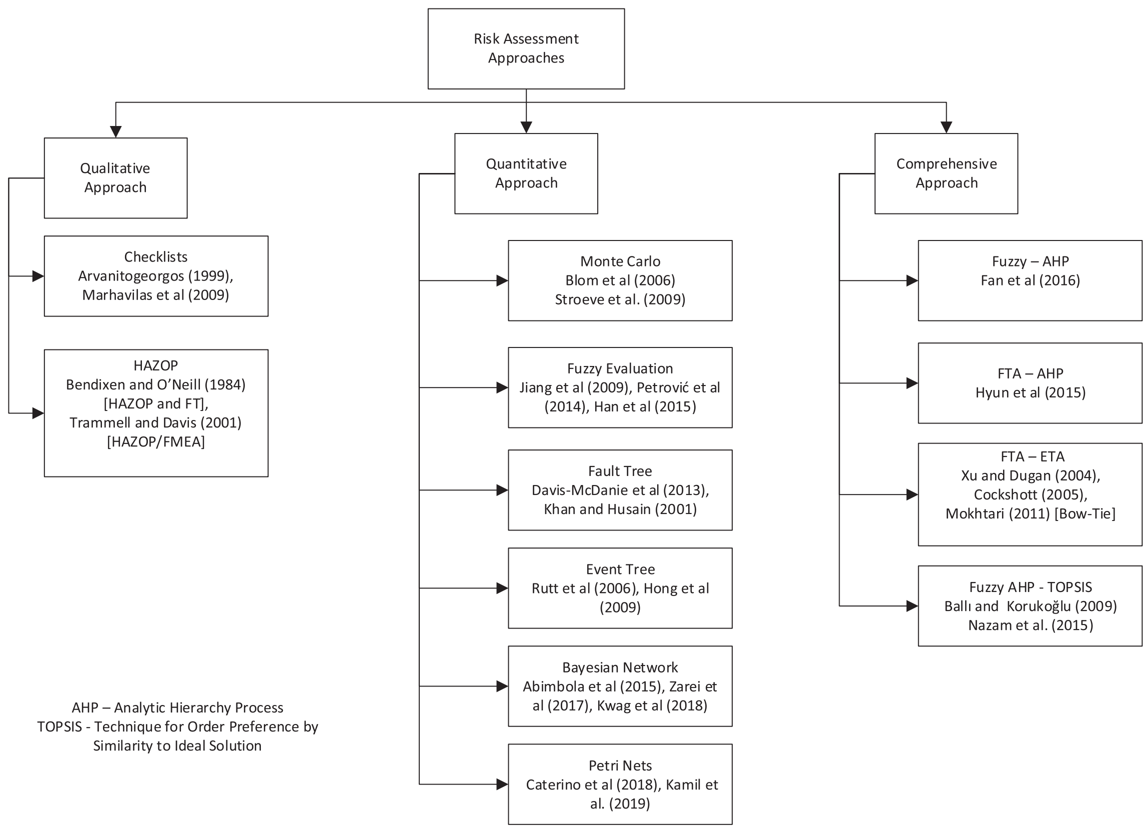


Fig. 11. Risk assessment approaches. References cited in figure are Hyun et al., 2015; Jiang et al., 2009; Kamil et al., 2019; Khan and Husain, 2001, Kwag et al., 2018; Abimbola et al., 2015; Marhavilas, 2009; Mokhtari et al., 2011; Nazam et al., 2015; Petrović et al., 2014; Rutt et al., 2006; Stroeve et al., 2009; Trammell and Davis, 2001; Xu and Dugan, 2004; Zarei et al., 2017; Arvanitogeorgos, 1999; Ballı and Korukoğlu, 2009; Bendixen and O'Neill, 1984; Blom et al., 2006; Caterino et al., 2018; Cockshott, 2005; Davis-McDanie et al., 2013; Fan et al., 2016; Han et al., 2015; Hong et al., 2009.

Table 9
RA ML model recent approach summary.

Method/Model	Reference	Approach
ANN	Tanguy et al. (2016).	Natural Language Processing
	Xiang et al. (2017).	Mamdani Fuzzy Neural Network
	Ayo-Imoru and Cilliers (2018).	ANN to train both simulator and plant parameters.
	Mamudu et al. (2020).	Multilayer perception ANN
SVM	Zhou et al. (2020I).	Hazard identification and prediction using SVM
Decision Tree	Alexander and Kelly (2013)	Decision Tree is used as a black box
K-means	Duan et al. (2019).	FMEA model using double hierarchy hesitant fuzzy linguistic term sets and k-means clustering is developed to evaluate and cluster the risk
	Wang and Li (2020).	K-means based risk assessment using pipeline data
Naïve Bayes	Zhang et al (2017II).	Naïve Bayes classifier
Random Forest	Dogru and Subasi (2018).	Random forest classifier

4.5. Machine learning approaches for RA and industry 4.0 challenges

Machine learning algorithms have aided risk assessment in recent years. However, there are very few articles found which relate them to process systems. Due to Industry 4.0 and an increase in intelligence ability in the dynamically changing risk, process system researchers intend to apply machine learning algorithms for dynamic risk assessment in the near future.

Paltrinieri et al. (2019); Hegde and Rokseth (2020) recently reviewed machine learning approaches for risk assessment. They report that the automotive and construction industries are leading the adoption of ML for risk assessment. Furthermore, they have found that ANN, SVM, Decision Tree, K-means, and Naïve Bayes are the most commonly used machine learning approaches in RA. Most recent ML approaches from other process-related applications for RA are summarized in Table 9.

5. Next-generation process safety and risk management based on process system failure

With extended technology, process system plants become more complex and advanced. Hence, process safety will be a challenging topic in the upcoming years. According to Kamble et al. (2018); Lee et al. (2019); Angelopoulos et al. (2020), Industry 4.0 and smart industrial development process system confer several effects on the design and development of the largest plant industry. This will profoundly affect FDD methods and models, risk assessment approaches, and ASM strategies.

Based on Industry 4.0, next-generation plant development might improve with smart technologies such as smart sensors, IoT, and advanced communication. As a result of smart plants and physical system complexity, data-based approaches with a large amount of data can be more operable to implement FDD and

RA models and methods. Therefore, handling large process system data, big data analysis, and cloud computing may involve model implementation.

With the changes in the next generation of process plant based on the Industry 4.0 era, some of the impacts on process safety elements models and methods are as follows:

1. Due to a large amount of sensor data, to detect the abnormal behaviour of the system, deep learning approaches may be more employable models in future FDD. When implementing learning from a large amount of data, the processing time must be considered from a safety perspective. Therefore, data processing, computation, and speed of data communication will significantly affect the models.
2. Process plant's prognosis and health management based on failure prognosis and RUL are a current trend in fault detection and diagnosis. Failure prognosis can predict the failure, and RUL can predict the gap in time between fault and failure. A hybrid approach based on data-driven models, such as supervised and unsupervised machine learning, and system model descriptions such as graphical, stochastic approaches, will be forthcoming models for developing failure prognosis and RUL.
3. To implement the SIS's with automated fault correction before system failure, success of future ASM will depend on skillful utilization of the following Industry 4.0 technologies: Industrial Internet of Things (IIoT), Cybersecurity with a wireless communication layer, Real-time constraints including data digitization and extensive data processing, big data and cloud computing, system modularization to replace or expand individual modules, intelligent advanced controllers, digital twins (a combination of IoT and ANN).
4. The ability to implement repair, replacement, or maintenance for basic controllers based on the fault prognosis and RUL will be another contributor in process plant economics.
5. With Industry 4.0 era and smart plants, system safety highly depends on the sensors and other physical components, such as controller devices, communication devices, protocols, and actuators. Therefore, the reliability of the components will be a primary concern in process safety.
6. With smart technologies and combining plant units with digital communication may increase failure probability, and risk. Therefore, implementing risk assessment models with different scenarios will challenge the next generation. Developing accident models based on the dynamic risk assessment will be another addition to process safety.

Overall, the next generation in process safety highly depends on electronics, communication, advanced controller devices, and computational algorithms such as machine learning and state-space stochastic models. However, dealing with the smart plant, the Industry 4.0 era, and with frequently modifying safety standards in process safety will be an incredible challenge for forthcoming safety generation.

6. Conclusions

This review's main objective is to illustrate the safety framework for the process industry by integrating fault detection and diagnosis, abnormal situation management, and risk assessment. The review's main scope was restricted to published journal articles on topics directly related to these three areas. Limited conference papers and industrial standards were also reviewed to discuss the safety levels and standard industrial approaches related to process safety. Overall, this review article mainly focused on researchers interested in process systems and process safety.

It is noted that FDD researchers tend to focus more on data-driven quantitative approaches than model-based system descriptions and knowledge-based methods. Moreover, rather than traditional fault detection and diagnosis, implementing failure prognosis and remaining useful life approaches are becoming a major topic in current and future research, to facilitate predict the failure scenario as early as possible. Less complex smaller applications may involve analytical modeling approaches. However, large scale complex applications will continue to use data-driven approaches to evaluate the fault condition.

This paper also summarizes the abnormal situation management industry standards and techniques, including alarm management and safety instrumented system approaches, to maintain safe operation in process systems.

Failure models, accident models, and risk models are further reviewed in this article. The transition from static risk assessment considering a single accident scenario to a dynamic quantitative accident scenario has been a recent dominant trend and a prospective upcoming research area.

Finally, with improving technology and the upcoming smart industry integrated safety framework, research interest is discussed. To keep up with Industry 4.0, fault detection and diagnosis must focus on early failure prognosis, and process needs to operate in more autonomous fashion including automation of the abnormal situation management tasks. The risk assessment should also focus on the evolving nature of risk to consider potential design and operational failure scenarios. However, appropriate data collection and failure probability prediction, dynamic risk forecasting, autonomous safety instrumented system development, and obtaining risk margins for abnormal situation management will be a technical challenge for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Rajeevan Arunthavanathan: Conceptualization, Methodology, Software, Investigation, Writing - original draft, Writing - review & editing. **Faisal Khan:** Conceptualization, Methodology, Formal analysis, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Salim Ahmed:** Methodology, Validation, Formal analysis, Writing - review & editing, Supervision, Funding acquisition. **Syed Imtiaz:** Methodology, Writing - review & editing, Supervision, Funding acquisition.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compchemeng.2020.107197.

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