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A Systematic Literature Review of Unsupervised Fault Detection Approach for Complex Engineering System

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ABSTRACT

Monitoring complex engineering systems is an important countermeasure in managing the risk of faulty events. Observing the response of each process flow will avoid further damages in the production cycle. Both fault-tolerant approach that bears with faulty events and scheduled maintenance that helps to reduce tool wearing are deeply involved in condition-based monitoring methods implemented in factories. Thus, identification of faulty equipment is need to avoid major breakdown in the production system. A classification framework shows good performance in classifying faulty events, but a labelled dataset is usually financially consuming. Machine learning (ML) techniques have become a prospective tool in the unsupervised fault detection (UFD) approach to prevent total failures in complex engineering system. However, the efficiency of UFD applications, on the other hand, is determined by the selected ML method. This paper presents a systematic literature review of ML methods applied for UFD, highlighting the methods explored in this field and the success of today's state-of-the-art machine learning techniques. This review focuses on the Scopus scientific database and provides a useful information on ML techniques, challenges and opportunities, and new research works in the UFD field.

1. Introduction

Nowadays, digitalization has been greatly influenced business operations and decision making. The main motivation is to further enhance production flow as well as better service quality within manufacturing sector [1]. The relation between factory operation, materials, transportation, communication and financial consumption were monitored in ensuring optimum production quality. In engineering system perspective, monitoring process operational conditions within the nominal values is important. This to ensure the signal consistency within ‘in control’ condition and reciprocally the ‘out of control’ condition jeopardies entire factory operations.

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At early study of fault detection (FD), focus will be on mathematical aspect of faulty system, but lately the paradigm changes to a data-driven approach. The reason is data availability is no longer an issue due to the digitalization of the monitoring system. However, the challenge remains against the existence of unlabelled data. Other than that, complex engineering characteristics influence the choice of FD approach. The interconnected components indicate multivariate and high-volume data. Different subsystems mean different signal types and conditions. Signal will contain dynamicity, nonlinearity, and noises. The combination of unlabelled data and complex engineering characteristics motivate the study of unsupervised approach in FD. Thus, the main goal of this review is to provide a general machine learning (ML) framework for the unsupervised fault detection (UFD) approach and summarize the latest research in this area. The two main data-driven frameworks of unsupervised approach i.e: clustering-based and novelty detection approach, are discussed and their relationships with complex engineering characteristics are explained.

Several review papers focusing on FD has been explored by researchers. Before, Venkatasubramanian *et al.,* provide a lengthy discussion on fault detection and diagnosis through three parts of discussion; model-based FD, historical based FD and search strategies of FD [2–4]. Further study done by Dai et al which divide the concept based on type of data from industrial system; model-based online data driven method, signal-based method and knowledge-based historical method [5]. Moving towards IR 4.0, Angelopoulos et al discussed the overall framework in tackling faulty issue in IR 4.0 perspective [6]. Other than that, Zhao et al elaborate the artificial intelligent as FD approach in building energy system whereas Bayer et al review artificial immune system as FD approach [7, 8]. Even though some of the review did provide a sub section on unsupervised FD study, but none to this date, based on author knowledge, a review that only focus on unsupervised fault detection approach has been done. Thus, this paper will fill this gap. The main goal of this study as follow

i. Provide an overview of general artificial intelligence and machine learning (ML) framework for the unsupervised fault detection (UFD) approach.
ii. Analyze and summarized the latest data driven UFD approach and the involved engineering field.

The remainder of this paper is organized as follows. Section 2 presents the methodology in conducting the systematic literature review process, Section 3 discusses the findings from literature review. Section 4 explains two basic frameworks for UFD approach, and Section 5 analyses the existing method based on collected literature review. Finally, Section 6 concludes the literature study.

2. Methodology

2.1 How Is the Literature Review Being Conducted?

The review was conducted to answer the following research questions

Q1. What are the conceptual frameworks of UFD?
Q2. What method relates to the framework?
Q3. How the UFD methods are employed in engineering system applications?

Scopus literature database, including relevant journals using specific keywords, was examined. The following works were excluded

E1. Unrelated to UFD.
E2. Works that do not include the technicality of the method or experiments.
E3. Any application unrelated to engineering systems.
E4. Works before the year 2010.

2.2 Execution

Several common keywords were used for searching related publications in this review. The specific keywords used while reviewing the Scopus database are described below

Scopus: (TITLE-ABS-KEY(unsupervised AND fault AND detection)) AND (monitoring) AND (LIMIT-TO(SUBJAREA , "ENGI")) AND (LIMIT-TO (DOCTYPE , "ar"))

The survey was performed on 25th February 2021. The total searched papers were 205, with 86 papers were selected for this review and 122 articles were rejected using the exclusion criteria E1 and E2.

3. Results of the Systematic Literature Review

This section discusses the findings of the systematic literature review after considering the research questions and exclusion criteria in Section 1. Meanwhile, the boundary of the study follows the definition in Section 2. The collected literature review was analyzed using two main components: distribution throughout one decade of the ML FD approach and state-of-the-art ML technique for the UFD approach.

3.1 Publication Distribution Along the Years

Figure 1 shows the number of publications for UFD studies from 2010 until 2021. The bar chart shows an increment of UFD studies with the highest value in 2020. As for 2021, the chart indicates a continuity of UFD studies, but a more concrete conclusion could not be made because the date of this review is only until February 2021.

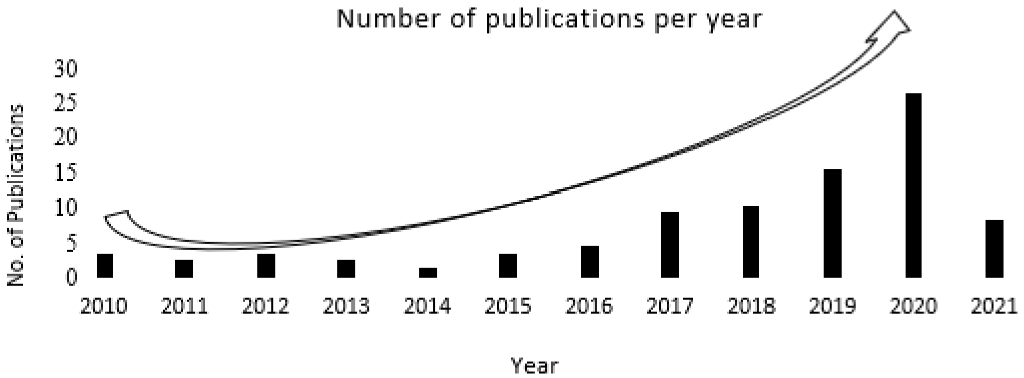

Fig. 1. Number of publications for unsupervised fault detection from 2010 until 2021

Figure 2 shows the number of publications for each method. This review identified seven methods that usually appear under UFD studies. The first one is the Prob, Stat, and Dist method that includes probability approaches (e.g., Gaussian mixture model (GMM), Dirichlet process (DP)) or statistical-based techniques, as well as the distance-based approach (e.g., K-means). The fuzzy logic approach is mainly related to the fuzzy c-means clustering. Principal component analysis (PCA) and independent component analysis (ICA) variants include KPCA and MICA. The support vector machine (SVM) method includes SVDD and shallow NN, which are basically only SOM and adaptive resonance theory (ART). The deep learning (DL) approach covers many variants (e.g., variants of deep autoencoder, long-short term memory (LSTM), restricted Boltzmann machine (RBM), and extreme learning machine (ELM)). Lastly, the final category (others) includes artificial immune system (AIS) and artificial ant colony. In 2010, only shallow NN and Prob, Stat, and Dist were used as the UFD methods and throughout the year, there were only two published studies for shallow NN. The same observation was reported for the categories of fuzzy logic, PCA and ICA variants, SVM, and others. The Prob, Stat, and Dist method showed a significant increment until 2020, whereas the DL approach showed a sudden increment from 2017 until 2020, with no study before this date. In early 2021 (until February 2021), the DL approach has already overtaken the Prob, Stat, and Dist approach in the UFD approach with four and two publications, respectively.

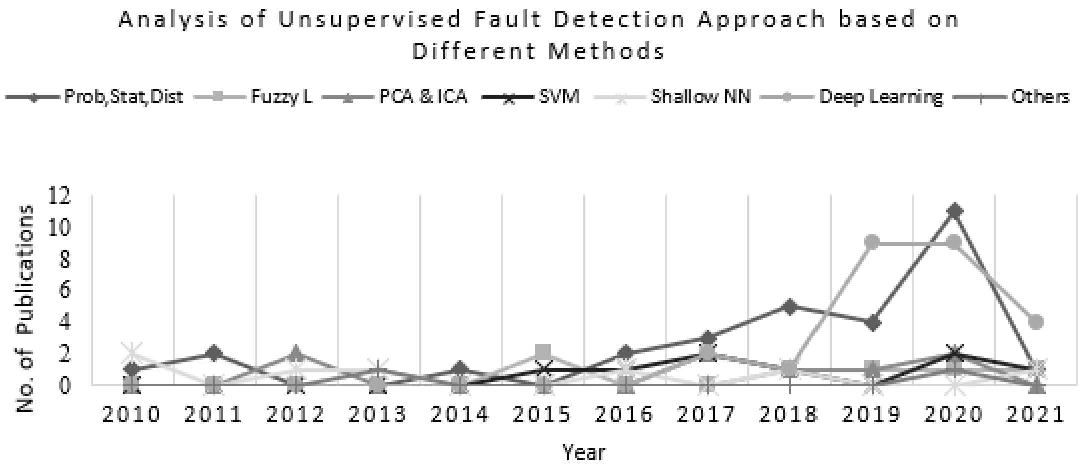

Fig. 2. Number of publications for unsupervised fault detection from 2010 until 2021 based on different methods

3.2 Complex Engineering System

This section focusses on the engineering areas that have adopted ML-based UFD. The sector covers eleven categories, such as process control system, transportation, space shuttle and satellite, power plant, manufacturing process, bearing and electrical motor, mechanical and building structure, medical engineering, and simulated numerical analysis that imitates the behaviour of a faulty dataset. The majority of the datasets are signal-based dataset and only three studies considered video-based dataset, which are [9–11]. The perspective of complex engineering characteristics has influenced the selection of ML approach for UFD. The nonlinearity of complex engineering systems is one of the most well-known engineering characteristics that has been given attention recently in choosing ML approaches [12]. The reason is linear-based UFD approach, such as PCA, is unsuitable to cater for the existing nonlinearity characteristic in engineering systems. Other than that, univariate data analysis is impractical in complex engineering systems, and many studies developed algorithms to cope with multivariable or multiparameter [13]. Besides, when considering massive variables in complex engineering systems, the number of variables or features selected will also affect the performance of FD [14,15]. Furthermore, the correlation between the variables also determines the UFD approach as simultaneous signal changes occur within an interconnected sensory system when a faulty condition occurs [16].

Another perspective related to complex engineering systems is continuous normal and faulty signal conditions. Extracting information from a time-series signal involves trend recognition capability. The challenge appears in recognizing signals with hidden noise and environmental effect that will affect the FD accuracy [17]. The same perspective for frequency-based signals also provides some challenges in extracting information [18]. For example, Soualhi *et al.,* [19] argued the difficulty in extracting information from a frequency-based current spectrum signal of an induction motor and solved it using artificial ant technique. Autocorrelation analysis is another point to be considered in UFD. Linear autocorrelation analysis captures the linear relationship between the time sequence of variables but not the nonlinear autocorrelation condition. Therefore, some studies considered the nonlinear autocorrelation method as the UFD approach, such as dynamic PCA (DPCA) [20]. The final perspective is the computational efficacy of the engineering system. Although ML ensures the accuracy of UFD, the computational processing time will affect the real-time decision-making process. For example, ideally, FD should provide ample time for corrective maintenance or repair. However, in the actual operational, if not consider the computational aspect, fault already occurred even before the ML determination of faults is completed [12,21].

4. Unsupervised Fault Detection Framework

4.1 Cluster-Based Fault Detection

In the clustering-based fault detection, the main aim is to group the normal data and faulty data accordingly. With this, given N patterns of data with distinguished features, the clustering method will group the data in M classes so that similar data are grouped together while accurately separating dissimilar data to other classes. Considering the unlabelled dataset, the value of M is unknown and requires iterative learning to ensure the accuracy of the clustering method. Figure 3 shows the general overview of the clustering framework [19,21,22] During offline learning, the massive collected data are pre-processed using normalization or standardization before entering the feature extraction and selection phase. After that, clustering method were used to determine the existing group iteratively until reach clustering performance index and accurate M value. To recognize which group, consider as faulty, expert knowledge were needed [23]. In addition, some of the study add another step of group-based modelling as reference model for online phase later [52].

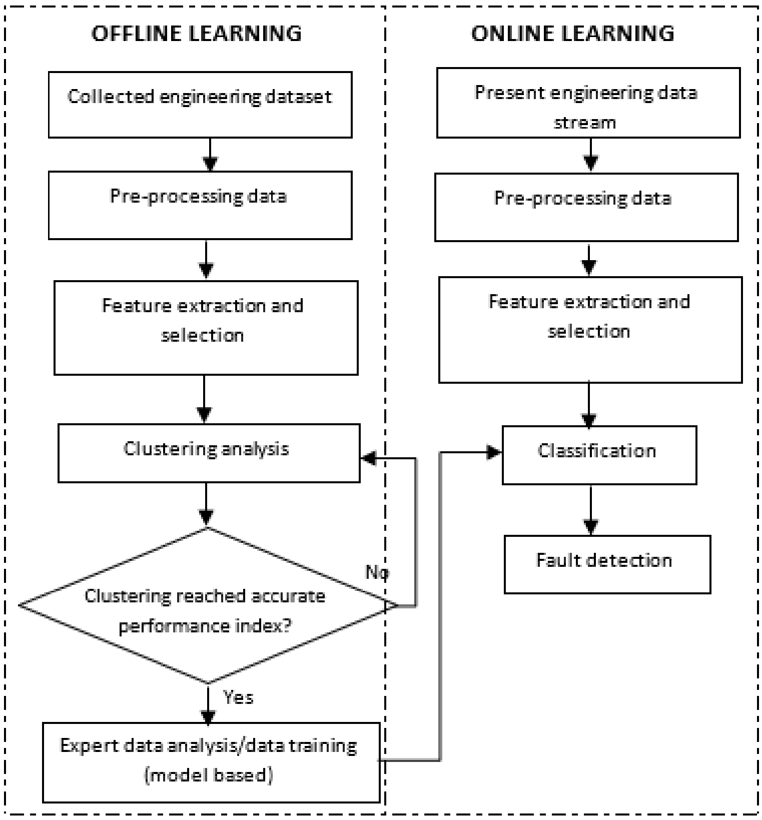

Fig. 3. Cluster-based fault detection

4.2 Reconstruction-Based Fault Detection/ Novelty Detection/ One-Class

The reconstruction-based fault detection framework usually relies on the accuracy of the benchmark model (see Figure 4). The benchmark model usually only depends on normal condition dataset. From this, a threshold value is calculated and any deviation from the threshold value, are considered faulty events. Thus, this approach will only produce either 'faulty' or 'non-faulty' condition or can be called one-class problem. Other than that, since this framework learn the nominal signal condition, any rare occurrence can be also considered as novelty detection problem. The general framework can be seen at Figure 4 [24–27]. With this, there are two main components in seeing a reconstruction based unsupervised fault detection; choices of benchmark model and determination of threshold value.

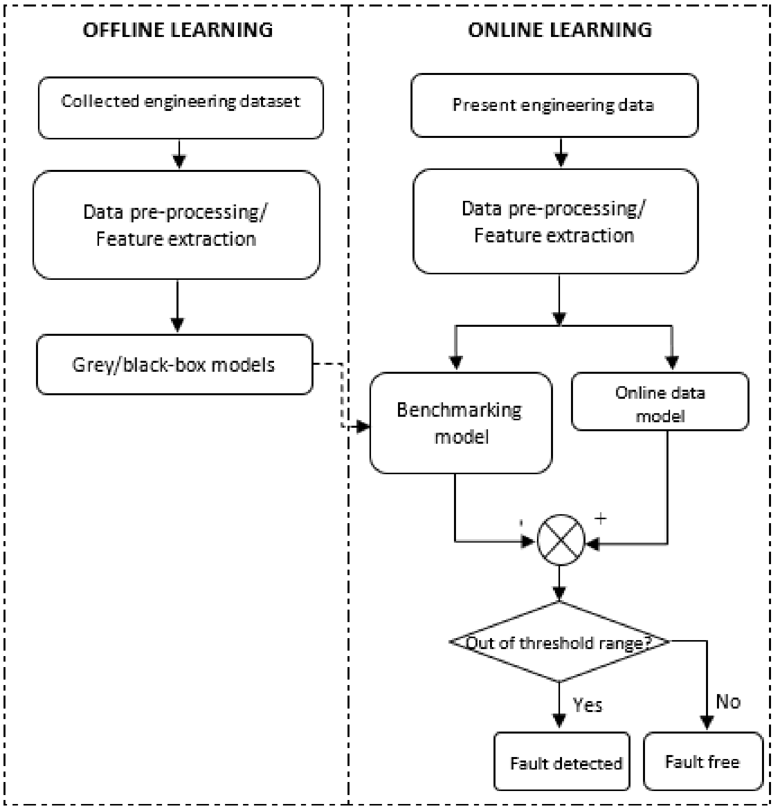

Fig. 4. Novelty detection/ One-class/ Reconstruction-based fault detection

5. Unsupervised Fault Detection Techniques

5.1 Probabilistic, Statistical, and Distance-Based Approach

The UFD framework under this approach will usually emphasize on two main parts which the description of nominal data condition, statistically or based on distances and utilizing probability inference to distinguish between the faulty cases. Tong *et al.,* [14] used the Mahalanobis distance to calculate the distance for each subspace and combined it with the unique probability index for fusion-based Bayesian decision-making. Jialin *et al.,* [20] also used Bayesian decision-making with reconstruction-based contribution (RBC) information from previous faulty events in determining the fault variables in a process plan system. Zheng *et al.,* [28] (proposed normalized relative RBC (rRBC) with minimum risk Bayesian (MRB) decision-making to reduce the misdetection rate. Moghaddass and Sheng [29] applied a Bayesian hierarchical structure to develop the mapping between the input and output with minimum dependence on data distribution or parametric assumption. The result showed a strong modeling capability for FD, but the usage was limited with fewer data points and low dimension. Yamada *et al.,* [30] considered a huge amount of data in their study. The study proposed a combination of information from exact tests and statistical chi-test to determine the faulty condition. The most familiar statistical approach for UFD is the statistical process control (SPC) chart, which is still relevant to this date. However, Liu *et al.,* [31] argued that the SPC data analysis is unsuitable for nonparametric conditions. The study improved SPC with DP to overcome SPC weakness. Meneghetti *et al.,* [32] evaluated the feature selection approach for UFD of an insulin pump, and the histogram-based outlier scored the highest accuracy for FD.

Leveraging the dynamicity in complex engineering systems, recursive density estimation (RDE) is one of the choices for anomaly detection [23,33]. RDE utilizes real-time data and calculates the deviation between the present and previous data continuously. In other words, the method measures the closeness of the data sample at a given instantaneous time. Any far deviation from the density distance can be consider as faulty condition. In distance-based approach, An *et al.,* [34] utilized Mahalanobis and Euclidean distances in determining the weight for minimum spinning tree. Similarly, McLeay *et al.,* [35] used the Mahalanobis distance to measure the difference between a new sample and a threshold value. Lu *et al.,* [36] adopted dynamic time warping (DTW) to measure the dissimilarity between points to find the optimal minimal distance in feature space. A special case using video as an input for FD, Anthony and Chua [9] utilized dynamic time and space warping (DTSW) to measure the similarity of video alignment path for FD decision-making. Other than that, rather than focusing on point-based data, Mack *et al.,* [37] produced two-dimensional pairwise distance matrix between objects as the feature extraction approach prior to clustering for FD. Meanwhile, Christensen *et al.,* [38] applied a moment matrix for FD in a refrigeration system. The most common problem when including the dynamicity of engineering systems is the information loss throughout the time period. Song *et al.,* [39] considered both time and frequency domains in the acoustic emission signal in retaining the characteristics of the signal. Linear discriminant analysis (LDA) was proposed, where dimension reduction could increase the sensitivity of feature detection and also clustering by fast search and find of density peaks (CFSFDP). Moreover, by considering the timely batch process condition, finding both local and global discriminant structures of data provide a challenge in FD study. Thus, Zhang *et al.,* [40] used discriminant global preserving kernel slow feature analysis (DGKSFA) to overcome this problem by combining discriminant analysis and the GKSFA model. Some of the ML approaches did not consider the temporal effect on UFD; hence, modifications were made to solve this concern. Meneghetti *et al.,* [41] placed a section for time series data modification of the local outlier factor (LOF) and connectivity-based outlier factor (COF). Wang *et al.,* [42] discussed the importance of temporal analysis as a part of FD when the goal of the study is to detect an early fault. The statistical approach of periodogram was utilized to analyze time-frequency vibration signals and graph analysis was used to determine faulty and nonfaulty events.

In the clustering approach for UFD, K-means, GMM, density-based clustering (DBSCAN), and isolation forest are among the frequently chosen ML approaches for UFD [32,43–46]. Among them, the accuracy of K-means and DBSCAN depends on the initial center or number of clusters, k. Therefore, [21] proposed a frequency domain-based correlation distance measure to improve the selection of K-means clustering approach, whereas [44] plotted a graph of k versus distance in neighbourhood to find k. Instead of using distance, [31] developed a graph of cluster k versus neighbor radius to determine the optimum k. Another aspect in the UFD clustering approach is when considering nonlinear engineering systems. Gao *et al.,* [47] mentioned the difficulty in finding an implicit discrimination structure under a nonlinear system and proposed locality-preserving robust latent low-rank recovery (L2PLRR) that covered a high-dimensional nonlinear system by preserving the local characteristics. In addition, with a similar operating magnitude, the control limit for a nonlinear system will remain the same in the presence of a new operating mode. Hence, this brings another challenge in UFD systems with multivariate multimode systems. Tan *et al.,* [24] described the condition of a multimode system in detail and incorporated Dirichlet process, nonstationary discrete convolution, and kernel principal component analysis (DP-NSDC-KPCA), whereas Chen *et al.,* [48] used the probabilistic Dirichlet process Gaussian mixed model (DPGMM) to identify the operating region.

5.2 Fuzzy Logic

The main attraction of the fuzzy logic approach in UFD is the capability of providing values in imprecise linguistic terms, such as ‘very’ and ‘less’ in terms of membership function. Due to this reason, Baraldi *et al.,* [49] used fuzzy logic approach to extract transient features in a nuclear steam turbine system and cluster faulty events using fuzzy c-means (FCM). Similarly, Wang *et al.,* [15] using the FCM method to learn prior conditions in a gas turbine exhaust; however, rather than only clustering, the study used FCM as a reference for multiclass FD approach in online state recognition using SVM. Ftoutou and Chouchane [50] improved the FD rate in FCM clustering FD with modified S-transform and two-dimensional non-negative matrix factorization for the time-frequency analysis of vibration signals. Seri *et al.,* [51] defined the health index status of a monitoring system using the fuzzy approach of ‘important attention’, ‘medium attention’, and ‘no attention’ in defining the maintenance requirement inside a rotating machine. Lughofer *et al.,* [52] chose fuzzy logic to build the causal relation network between sensor channels to lower the misdetection rate. Regarding the high volume unlabeled data, Zhao *et al.,* [53] utilized the ability of deep belief network (DBN) for extracting features with an improved adaptive nonparametric weighted-feature Gath-Geva (ANWGG) fuzzy clustering algorithm in the UFD approach for a rolling bearing.

5.3 Principal Component Analysis and Independent Component Analysis

One of the main approaches in monitoring process control is PCA and partial least squares (PLS). The main advantage is the ability of the model in finding a strong correlation between variables in the collected data log. Liu *et al.,* [20] utilized the advantage of PCA by implementing PCA in developing a contribution plot for a complex engineering system. However, due to the high number of variables in the system, the smearing effect influenced the nonfaulty variable, where the issue was solved by improving the reduction of combined index (RCI). Although PCA and PLS are efficient solutions for monitoring multivariate process control, these approaches are prone to the assumption of multivariate Gaussian distribution or limited to the linear response of engineering systems. Thus, improvements have been made to overcome this constraint. Tong *et al.,* [54] mentioned that the ICA method is more suitable in handling a non-Gaussian process monitoring system. The study presented modified ICA (MICA) that solved the conventional ICA approach prone to the randomness initialization step and conducted a proper way to choose an appropriate independent component (IC) to ensure the relevance toward an FD system. Furthermore, the authors ensembled multiple MICA with different nonquadratic functions and used Bayesian inference to further improve the online UFD framework. The team further enhanced the framework with double layer MICA in [55]. Li *et al.,* [56] proposed ensemble kernel principal component analysis-Bayes (EKPCA-Bayes) to improve the detection accuracy for nonlinear engineering systems. Pacella [57] studied FD under the conditions of multichannel profile data with two multilinear extensions of PCA. Elshenawy *et al.,* [58] combined adaptive PCA and multivariate contribution analysis to cater for the time-varying characteristic in industrial-based fault monitoring.

5.4 Support Vector Machine

The main goal of SVM in FD is to determine the best hyperplane decision boundary for accurate classification of FD conditions. The method utilizes the kernel trick to the nonlinear dataset to further enhance data condition so that a clear hyperplane boundary appears in the distribution. In the framework of UFD, one of the strengths of SVM is to become the learning model for online monitoring. For example, Langone *et al.,* [59] used kernel spectral clustering (KSC) for the first learning of historical data to distinguish between faulty and nonfaulty conditions. Based on the information from KCL, least square SVM (LSSVM) was applied as a model learner for online detection. Moreover, one-class SVM approach was formulated based on novelty detection, which can be directly considered as UFD. Fang *et al.,* [10] chose one-class SVM as the unsupervised anomaly detection approach for sewer pipelines. Borges *et al.,* [60] evaluated the performance of the higher order statistic approach for feature extraction and one-class SVM for FD, whereas Dias *et al.,* [61] achieved 95.7% reduction in computational time when using one-class SVM with adaptive correlation-based feature selection. Further exploration in the field of SVM was carried out by Wang *et al.,* who studied another variant of SVM in FD (i.e., support vector data description (SVDD)) to cater the imbalanced dataset in UFD learning. Wang *et al.,* [62] analysed the sequence of batch process using two multiple SVDD for monitoring and segmenting linear discriminant to detect faulty conditions. Interestingly, Wu *et al.,* [11] utilized a video surveillance dataset to detect faults in an industrial system rather than normal data logs and proposed the appearance and motion SVM (AMSVM), which incorporated multimodal information with one-class SVM approach.

5.5 Shallow Neural Network

The term shallow NN is used to avoid misunderstanding with the DL approach, which is also build based on neural network architecture. The term 'shallow' significantly relates to the neural network structure that usually consists of only one hidden layer at most [63], whereas the DL approach has multiple hidden layers of neural networks. One of the most used shallow NN methods for UFD is self-organizing map (SOM). The main reason behind the choice of SOM is due to its non-linear modelling capability and suitability for online monitoring [64, 65]. Cao *et al.,* [13] analysed the impact of SOM map size and topological structure in learning the relationship between variables in a nonlinear system. The study also agreed with the computational efficiency of SOM, which is suitable for a real-time industrial monitoring system. The neural network structure of SOM mapping consists of input and output neurons that are related by weight. The same neuron structure is also seen between neighbouring neurons. Meng *et al.,* [66] utilized this structure to learn health signal conditions. Training the signal through SOM brings the weight vector near or far from the input and continuous learning makes the weight as representative for the input space, which eventually clusters the signals between faulty and nonfaulty conditions. Chalouli *et al.,* [67] introduced a two-stage clustering framework for vibration signal FD. The first stage is considered as feature extraction and selection, which focused on a statistical-based feature extractor for time-frequency domain signals and modified K-means as feature selection. In the second stage, SOM was used to determine normal and faulty conditions. Fadda and Moussaoui [68] combined PCA and SOM for frequency-based FD of bearing machines. Calvo-Bascones *et al.,* [69] proposed a framework for FD considering the dynamicity of the system. At first, the operating mode was clustered using K-means and later, each mode was inputted individually to SOM to learn the signal health behaviours. After that, similarity and distance indicators were determined to calculate the deviation of signals compared to normal conditions. Another type of shallow NN used as UFD is ART. Fernando and Surgenor [70] analysed the performance of ART compared to the rule-based method for an automated assembly machine. From the study, the researcher concluded that the rule-based approach is better than ART under the circumstance that the inaccurate parameter tuning would eventually create a new unknown fault and the operator needs to identify the fault type. Although the rule-based method requires more parameters, the method could generate the faulty symptom when an unknown fault occurs. However, the study mentioned that further investigation is needed before making generalization as

ART may give better performance in complex systems compared to the rule-based approach, where the rule would become difficult to model.

5.6 Deep Learning

The DL approach has gained popularity in the FD approach due to achievements in image recognition, text classification, and audio processing [71]. The deep architecture of a neural network is advantageous for extracting the signal of a complex engineering system. Hand-crafted feature extraction limits the FD approach to certain engineering conditions [72]. This is where most of the DL approach covers the gap in the ML approach for UFD. Tao *et al.,* [73] proposed the ST-CatGAN method to solve FD and diagnosis involving vibration signals from a rolling bearing. The short-time Fourier transform (STFT) technique was used to remove redundant information, which was then inputted directly to categorical generative adversarial networks (CatGAN) to reduce the dependency on human expert and manual intervention. Michau *et al.,* [74] evaluated the performance of hierarchical extreme learning machine (HELM) for high-dimensional UFD. Initially, the autoencoder-extreme learning machine (AE-ELM) was used to extract the features of the signal to minimize the reconstruction error. Then, one-class ELM would take the AE-ELM output to learn the health indicator to identify any faults in the system. Qu *et al.,* 2017 [72] utilized sparse coding with dictionary learning and further enhanced the dictionary learning using an AE. Amarbayasgalan *et al.,* [75] investigated a UFD framework for a high-dimensional nonlinear system with noise. The team proposed deep autoencoders with density-based clustering (DAE-DBC) in solving the issue. DAE was used to extract low-dimensional representation and apply the model as a benchmark model for reconstruction errors in determining the threshold value. Later, the low-dimensional data were classified using density-based spatial clustering of applications with noise (DBSCAN). Hallgrímsson *et al.,* [76] using an AE as a dimension reduction method and correlation analysis for a nonlinear triple tank system. Another characteristic of complex engineering system is that the data are collected through multichannel and multimodal signal data with multi-subsystems. Liu *et al.,* [22] proposed a framework of variational autoencoder with multi-branch residual module with dilated convolution modules (MRD-CluVAE) for 50 channel data collected, whereas Li *et al.,* [77] proposed fusing convolutional generative adversarial encoders (fCGAE) for 12 different joint bearings in three synchronous bands.

Accurate learning of feature representation among the collected signals is essential when considering UFD. The accurate representation of normal signals against faulty signals and clear boundaries between several types of faults will reduce the misdetection rate in UFD. Yu and Zhang [27] stated the same on concern in their study of an industrial process. In order to extract the intrinsic geometrical information from the signals, the team proposed manifold regularized stacked autoencoders (MRSAE) that preserve the local and global structures of the signal representation. Zhang *et al.,* [78] used unsupervised extreme learning machine (UELM) could only hold the local structure of feature information and upgraded the method with global preserving unsupervised kernel extreme learning machine (GUKELM) to identify the global feature information and optimize the number of hidden layers in UELM. A similar concept was proposed by Zhao *et al.,* [53] using ELM as the learning base for FD and enhanced the method with Cauchy graph to extract the local and global structural information with the name of multiple-order graphical deep extreme learning machine (MGDELM) approach. Besides, signals are affected by changing the engineering environment. Furthermore, the operating modes change for a new production. These characteristics could affect the learned DL method. Xiao *et al.,* [79] discovered useful information in changing working condition signals by maximizing the mutual information (MI) between the input and output of DL and implementing a variational AE for feature learning. Guo *et al.,* [80] combined multiple stages of clustering, deep autoencoder (DAE), and one-class transfer learning (OC-TL) to improve the false alarm rate for multimode working condition.

In UFD approach, the application of DL does not only focus on feature extraction, but some study utilized DL as an alternative approach for one-class classification or novelty detection. Santana *et al.,* [81] explored an AE as one-class FD approach with only normal data and verified the approach robustness even without a pre-processing method. A different approach by Sun and Sun [82] only used a DL method, namely stacked denoising autoencoder (SDAE) for feature extraction and combined with density grid-based clustering for grouping the features to relevant groups. The threshold value is vital in one-class detection. Li *et al.,* [83] argued that a fixed threshold value is impractical in a complex engineering system; thus, the authors proposed deep small-world neural network (DSWNN) with the adaptive threshold method. The threshold value is usually determined based on the reconstruction value of a benchmark model. Ellefsen *et al.,* [84] tested five types of DL for the reconstruction-based FD approach, traditional feedforward neural network with one hidden layer (1FNN), AE, variational autoencoder (VAE), and LSTM, and summarized that the accuracy of DL was between 99.393% and 99.531%. Principi *et al.,* [85] obtained 99.11% accuracy for multilayer perceptron with the autoencoder approach for UFD with log-Mel coefficient as features, whereas [86] applied RBM as the FD benchmark model and achieved 99% accuracy.

The temporal dependence in the time series of a complex engineering system will influence the fault prediction in the system. This study relies heavily on sequence learning in a period of time while retaining the spatial structure of the signal. Sliding window is one of the chosen methods for sequence learning in FD. Chen *et al.,* [48] combined sliding window with a convolutional variational AE to detect real-time incipient faults in a robotic system. Jiang *et al.,* [16] combined sliding window with a denoising autoencoder (DAE) for nonlinear multivariate FD of a wind turbine system to capture the temporal relation. Recurrent neural network variants are also among the selected approaches for temporal learning, such as LSTM [87,88] and gated recurrent unit (GRU) cells [89].

5.7 Others

There are only two methods in this section, which are ant colony clustering and artificial immune system (AIS). Abid *et al.,* [90] proposed AIS as the basis of UFD framework for multidomain FD. The framework consists of three parts. The first part involves a multidomain feature extraction approach using real-valued NSA (RNSA). Later, the dimension reduction process uses k-NN clustering and autoencoders. The framework is completed by genetic algorithm (GA) as the optimization approach. Soualhi *et al.,* [19] studied a signal with harmonics from an induction motor. The team extracted features using Park's vector approach and cluster using artificial ant colony approach (AAC).

6. Conclusions

Monitoring activities in engineering systems produce a huge amount of data collected in a timely basis and stored in the company data logging. Massive data collection could be used to extract important information of the past, current, and future of the system's condition. Recognizing faulty components could help in preventing damages to the overall system. These benefits have motivated research of FD activity. However, among the collected datasets, very few are appropriately labelled for supervised fault classification activities. This study chose to embark on the UFD approach with the motivation of direct application on complex systems using existing data without intervening in the daily activities of the system. An extra experimental study will be conducted to determine if the approach is only suitable for labelled data, hence limiting the current approach. The scope of this study and the database used to answer all questions related to this topic are explained at the early stage. Two types of frameworks under UFD are discussed to give an overview of the study. The number of references used and the increasing trend throughout the years are described, where the methods are divided into seven groups. Each group is described with the state-of-the-art approach and how the method solves problems in complex engineering systems.

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