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Applications of Artificial Intelligence to Instrumentation Systems for Monitoring Complex Industrial Processes

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ABSTRACT

Instrumentation and Measurement (I&M) is a field which is constantly developing due to the emergence of new technologies. In recent years, with the rapid development in computer hardware and computational power, Artificial Intelligence (AI) has demonstrated remarkable successes in data analytics, thus offering new paradigm for the design and applications of new instruments and measurement systems. The applications of AI to I&M have made measurements of some quantities in industry possible or more cost-effective. This paper presents a review of recent AI based methods applied in different aspects of instrumentation systems for monitoring complex industrial processes with a particular focus on multiphase flow metering, combustion monitoring as well as carbon dioxide flow measurement under carbon capture and storage conditions. This review also explores how AI is playing an important role in expanding knowledge across the whole spectrum of I&M. Trends and future developments of AI methods in the field of I&M are also discussed.

KEYWORDS

Artificial intelligence; Machine learning; Multiphase flow metering; Combustion monitoring; Carbon capture and storage

1 Introduction

The recent advances in Artificial Intelligence (AI) have had a profound impact on nearly every element of our society, economy, way of life and technology. AI has been regarded as one of the core enabling components of the fourth industrial revolution[1]. The field of Instrumentation and Measurement (I&M) is no different and the potential incorporation of AI in I&M has been attempted for over two decades. I&M is crucial for carrying out industrial monitoring and scientific investigations, where measurement is the process of gathering information from physical world, and sensors and instruments are used to convert physical variables into meaningful output forms[2]. The field of I&M is rapidly developing by integrating new technologies such as AI, with a major objective to enhance the capabilities of conventional measurement systems and develop new instruments to meet industrial requirements. In recent studies, AI has effectively shown its potential in I&M either by increasing measurement accuracy of a device or calibrating it as well as fault diagnosis and industrial process monitoring. In I&M a single output may depend on a number of parameters, some of which are difficult to model analytically or simply unknown. As a result, developing an analytical model and generalizing it can be very complex. In such cases, AI is found to be an effective solution as it takes input from previously gathered data and generates a model that best matches the input to expected output. AI is especially practical when precise and accurate analytical modelling of a measurement system or instrument is highly complex, nonlinear, dynamic or sometimes impossible due to lack of knowledge about the system[1]. The extensive application of AI to I&M in recent years is an evidence that AI has revolutionised the I&M field[1, 3].

Although, the long-term goal of AI research is to give machines the same level of intelligence as humans, current AI is not really equivalent to biological intelligence. On a practical level, AI refers to a set of technologies that are mostly based on Machine Learning (ML) and used for data analytics, forecasting, object categorization, recommendations, intelligent data retrieval, predictions, and many more. ML is an application of AI that enables computers to draw information from data and learn from it on their own. In I&M, AI refers to the use of ML techniques as a tool to develop or enhance a measurement system in a particular domain, for example, reducing complexity of a measurement method or enhancing the performance of an instrument. Thus, in I&M as well as in this study, AI is referred to as “Applied AI”, which includes the applications of classical ML models as well as deep learning, artificial neural networks, fuzzy logic, evolutionary algorithms etc.[1].

Applied AI has gained substantial attention over the past few years because of its impressive performance in many areas of science, technology and commerce. The use of AI has extended to a multitude of applications due to the growth of computing power. It is a discipline that focuses on automatic optimisation of a model in order to make predictions or decisions by feeding them with new data[3]. It offers the potential to identify links between data/results that are not readily identifiable, and it also provides alternative lower computing cost pathways[4]. In the field of I&M, AI has been in use for a number of important applications, including measurement error estimation and compensation in case of multiphase flows, chemical reduction in combustion modelling or to evaluate CO_2 flow measurement under Carbon Capture and Storage (CCS) conditions. Yan et al.[5] presented a comprehensive review of applied AI models for multiphase flow metering with a particular focus on the measurement of individual phase flowrates and phase fractions. Brunton et al.[6] evaluated the background, current status, and

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future prospects of applied AI for fluid mechanics. Duraisamy et al.[7] discussed empirical models developed with applied AI for turbulence flow modelling. A review was carried out on applications of AI in aiding chemical reactions, combustion modelling, combustion measurement, engine performance prediction and optimization, and fuel design by Zhou et al.[3]. Ihme et al.[8] also reviewed AI techniques for applications in combustion engineering. In addition to conventional applications for regression and dimensionality reduction in combustion monitoring, they explored the versatility of combustion ML to areas of control, optimization, discovery, and modelling. Yan et al.[4], discussed about application of state-of-the-art AI models in both absorbent- and adsorbent-based CO_2 capture processes. For applied AI in CO_2 absorption, the authors focused on process simulation and optimisation, thermodynamic analysis, and solvent selections and design. As for CO_2 adsorption, the review discussed about applications of AI in adsorbent synthesis and characterisation, process modelling and optimisation, and process inversion.

Past studies on applied AI in I&M are dispersed throughout the literature, thus it is desirable to systematise this knowledge into a critical evaluation as well as lay out a likely pathway forward. I&M is very broad, which include soft sensing[9], fault diagnosis[10–12], health monitoring[13] etc, these topics are excluded to restrict the overall length of this paper. This study demonstrates the changes in applied AI models and their adaption in instrumentation systems for monitoring complex industrial processes. The literature survey carried out in this study focuses on physical implementation of hardware sensors or devices incorporating applied AI techniques for multiphase flow metering, combustion monitoring and CO_2 flow measurement under CCS conditions. However, the methodologies deployed in these application areas are transferable to other similar industrial scenarios.

2 Applied AI algorithms

This section discusses about different applied AI algorithms and their incorporation in different aspects of I&M field. The purpose of this section is not to provide mathematical foundation of the algorithms, but to familiarise the readers with applications of AI to I&M. Thus, it is important to differentiate between AI and ML algorithms. AI is usually conceptualised as intelligence demonstrated by machines opposed to biological intelligence displayed by humans or even animals[3]. AI is the overarching system whilst ML is a subset of AI. Arthur Samuel defined ML as the field of study that allows computers to learn from experience, without being explicitly programmed[14]. Later, Tom Mitchell provided a more formal definition which states that "a machine learns with respect to a particular task T, performance metric P, and type of experience E, if the system reliably improves its performance P at task T, following experience E"[15]. On the other hand, Deep Learning (DL) is a subfield of ML, and neural networks make up the backbone of DL algorithms. It is the number of node layers or depth of neural networks that distinguishes a single neural network from a DL model. A DL model must have more than three node layers[1, 8]. With the rise of DL, more advanced algorithms have come into existence and are increasingly being used in AI applications. Unlike traditional algorithms, these advanced deep neural networks can effectively mimic the cognitive functions of humans, leading to excellent performance in a wide range of AI applications in the I&M field[1].

Applied AI algorithms aim to identify patterns and relationships in a vast volume of data to make predictions and consequently help solving problems. Generally, AI is a useful tool for handling problems in complex and nonlinear physical as well as chemical processes[3]. Owing to rapid development of AI, its convenient deployment, and the improvement of hardware performance, AI has spread into the field of I&M. Many I&M problems daunting for a long time could be resolved by adopting applied AI algorithms. These algorithms provide various models for handling data, which can be mainly classified into three types: supervised learning, unsupervised learning and semi-supervised learning[3, 4, 8]. There are many specific models that exist for each of the types, as shown in Fig. 1.

Supervised learning models, are the most commonly used applied AI methods with relevance to I&M[8]. In supervised learning, a model is used to infer a hypothesis from a labelled dataset that establishes a relationship between inputs and outputs. Labelled data comprise a set of training examples, each of which comprises an input and a corresponding output or label. Once the model is well trained, predictions of the output for new input data can be achieved based on the relationship learned from training data. There are two types of supervised learning models, classification and regression, as shown in Fig. 1[3, 8]. Unsupervised learning refers to a technique where the model does not need to be supervised. It allows the model to discover patterns and information automatically with objective functions which are not defined with target data. Unsupervised learning models are trained using unlabelled data. An unsupervised learning model can be used for clustering (grouping data points based on their similarity), anomaly detection, learning latent variables, dimension reduction (identifying a subset of dependent variables that describe the data) etc.[3, 8]. Supervised and unsupervised learning models may be differentiated by their reliance on labelled data. The intersection of these models result in a category of methods that learn from both labelled and unlabelled data. Such semi-supervised learning models are attractive for the analysis of incomplete measurements and dealing with missing data, which is commonly encountered in combustion monitoring or multiphase flow metering[3, 8]. In addition, reinforcement learning is a category of semi-supervise learning algorithms that enables an agent to learn in an interactive environment by trial and error using feedback from its actions and experiences[8, 16].

The execution of any of the types of applied AI model can be achieved through the application of appropriate model. A brief description of common AI models applied in I&M is summarised in Table 1, which is updated from reference[4].

2.1 Neural networks

ANN is a type of computing algorithm that simulates how the human brain analyses and processes information. The network of neurons in the human brain serves as an inspiration for ANNs[24]. In an ANN, the biological neurons are modelled by a set of processing units known as artificial neurons. ANNs are a desirable option in I&M due to their capacity to capture nonlinear relationships existing in the data. The initial research in I&M using ANNs concentrated on shallow feedforward architectures such as Multilayer Perceptron (MLP)[8] and Radial Basis Function (RBF)[5] neural networks. However, shallow ANNs can get stuck in local minima during training or may suffer from overfitting while increasing structural complexity[9]. Later, Huang et al. introduced the Extreme Learning Machine (ELM) using the Moore inverse learning algorithm[25], which outperformed conventional backpropagation based MLPs in terms of performance and learning speed. ELM is a feedforward neural network with only one hidden layer and has been used for the concentration

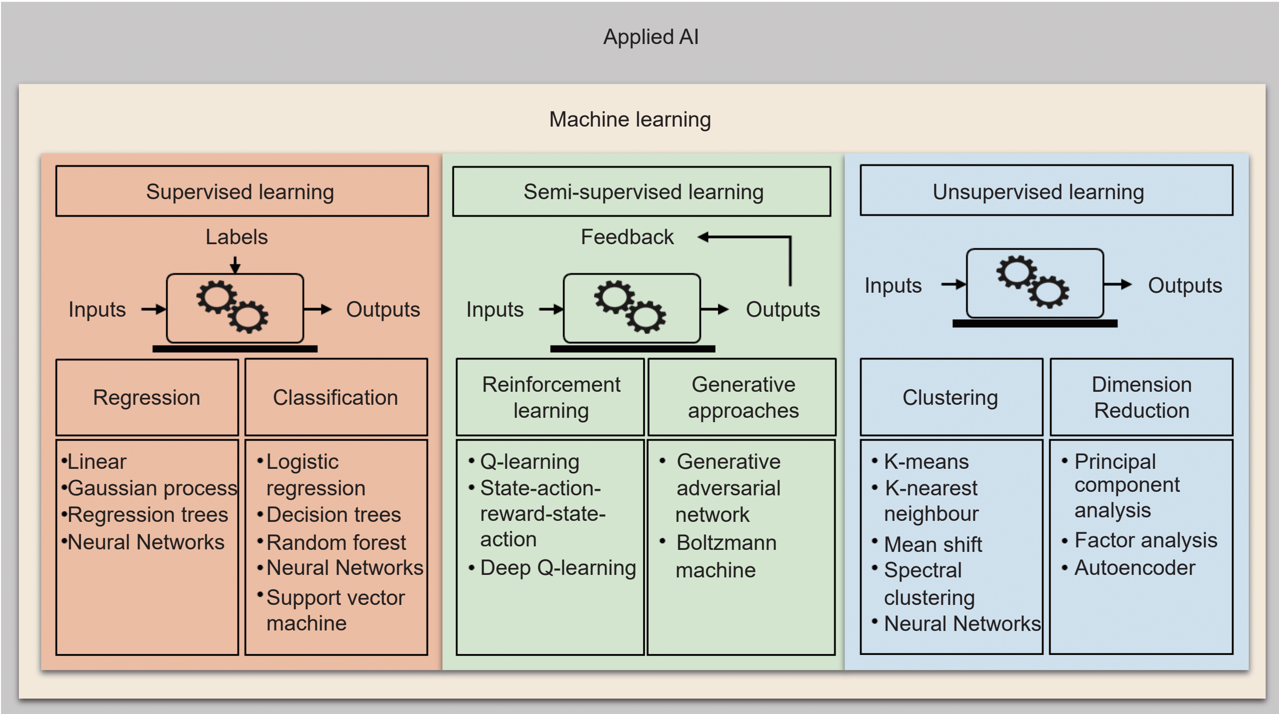

Fig. 1 Types of applied AI models with examples.

Table 1 Common applied AI models used in I&M.

Model name	Model type	Description
Linear regression[17]	Regression	By fitting a linear model with coefficients, this algorithm correlates each data feature to the output, thus assisting in predicting future values.
Gaussian Process Regression (GPR)[18, 19]	Regression	It is a non-parametric Bayesian approach to regression, this algorithm interpolates Gaussian process governed by prior covariance. It calculates the probability distribution over all admissible functions that fit the input data and calculates posterior using the training data. Finally, computes the predictive posterior distribution on test data.
Partial Least Square (PLS)[20]	Regression	It transforms the correlated variables into a new set of variables (i.e., latent space) that are uncorrelated or orthogonal to each other. This transformation reduces the dimensions of the input space, without losing much of the information in the original data. It then constructs mapping between the latent spaces of both dependent and independent variables.
Decision tree[21]	Regression and classification	This interpretable algorithm performs by splitting values of data features into branches at decision nodes until a final decision output is established.
Naïve Bayes[22]	Regression and classification	This algorithm is based on the Bayes' theorem which updates the prior knowledge of an event with the independent probability of each feature that can affect the event.
Support Vector Machine (SVM)[5]	Regression and classification	This algorithm operates by transforming the required data and determining the optimal boundary (hyperplane) between the various outputs.
Random forest[8]	Regression and classification	The algorithm is an ensemble of decision trees characterised by improved accuracy. It operates by generating a multitude of decision trees and uses either the modal vote or average prediction for classification or regression tasks respectively.
AdaBoost[23]	Regression and classification	This is an ensemble algorithm that combines multiple weak algorithms to obtain an improved output.

measurement of pulverised fuel flow[26].

With the rise of DL, there has been a trend toward using different Deeper Neural Network (DNN) architectures to overcome the limitations of shallow neural networks. Some recent works on applied AI in I&M are focused on DNN architectures such as the Recurrent Neural Network (RNN)[27] or Convolutional Neural Network (CNN)[28, 29]. RNNs are feed-forward neural networks with feedback connections and consists of numerous successive recurrent layers. RNN focuses on modelling in temporal domain. In an RNN the outputs from neurons are used as feedback to the neurons of the previous layer. These feedback connections enable them to retain useful information from previous time steps which are then processed with the data from the current time step[27]. As a result, they are able to identify and learn temporal patterns from data, which might not be highly effective with conventional feedforward network architectures[9]. This makes RNNs suitable candidates in the I&M field as some parameters (e.g. flame shape) are quite dynamic and time-dependent in nature. RNN has been applied for multiphase flow measurement in producing well by Alakeely et al.[27].

In some cases RNNs are not capable of handling long-term dependencies because of the gradients vanishing problem during training[30]. To overcome this issue, variants of the RNN such as the Long Short-Term Memory (LSTM)[31] and the Gated Recurrent Unit (GRU)[32] neural networks have been introduced. The LSTM presents a memory cell that can handle time-delayed data processing. There are three gates that make up these memory cells of an LSTM—the input, output, and forget gates. These gates can regulate how information is remembered and forgotten. Due to this process the LSTM can learn long-term dependencies, which is not present in an RNN. Instrumentations for highly time-dependent industrial processes can benefit greatly from this trait[9]. For instance, in a complex industrial process, when a variable changes, the quality parameter may not update immediately. Instead, it could display a delayed reaction. Since, RNNs cannot manage long-term dependencies, they might be unable to capture such dynamics. In such cases, the LSTM networks therefore offer a plausible substitute. The GRU is a simplified form of the LSTM, which is computationally more efficient compared to LSTM. Unlike LSTM, the GRU uses only two gates: the reset and update gates. The update gate is achieved by combining the input and forget gates of the LSTM[32].

On the other hand, some applications may require spatial information in the process data, due to the potential existence of spatial correlations among process variables[28, 29]. Conventional feedforward neural networks and other traditional ML algorithms often fall short in capturing such information. The CNN has proven to be effective in achieving such tasks. The CNN is a type of DL model for processing data that has a grid pattern, such as images. The CNN is inspired by the network of neurons in the visual cortex of the human brain and it is designed to automatically as well as adaptively learn spatial hierarchies of features from low- to high-level patterns[33]. The CNN is a mathematical construct that is typically composed of three types of layers: convolution, pooling, and fully connected layers. The first two, convolution and pooling layers, perform feature extraction, whereas the third, fully connected layer, maps the extracted features into final output, such as regression. In CNN one layer feeds its output into the next layer[28, 29]. CNNs provide excellent solutions for modelling complex industrial process instrumentation especially in the field of combustion. CNNs have been used for instantaneous flow rate measurement of gas-liquid flow in [28] and combustion regime identification in [29].

Recently, combining multiple applied AI models owing to the advantages or limitations of each other to solve measurement problems in complex industrial processes is becoming widespread. A combination of CNN and LSTM models is reported in a number of studies for multiphase flow metering[34, 35] and for combustion instability monitoring[36], as CNN-LSTM models can provide both spatial and temporal information.

2.2 Generative models

Small data samples for training/testing/validating applied AI models are a common problem in I&M. Many applied AI models often require thousands or sometimes millions of training examples to generate expected results. However, for some instrumentation systems, it is difficult or sometimes impractical to acquire a comprehensive dataset. In such scenarios, Generative Adversarial Network (GAN) can be used as a sample generation technique to increase the number of data samples, for industrial processes with small datasets due to slow sampling rates of quality variables. The GAN was first introduced by Goodfellow et al.[37], the aim of GAN is to generate synthetic data that resembles the original data distribution. GAN is an unsupervised DNN architecture that consists of two neural networks competing against each other in a zero-sum game framework. These two networks are termed generator and discriminator, they are able to analyse, capture and copy variations within a dataset. The generator captures the distribution of training data and produces new data samples, while the discriminator differentiates between the synthetic data and original data. The generator and the discriminator are trained simultaneously until the generator becomes capable of generating new data that are very close to the original data. GAN and its extensions are quite useful in many I&M applications where a significant amount of data are missing[38, 39]. For instance, Bode et al.[40], introduced a physics informed GAN based sub-filter modelling approach for turbulent reactive flows, that employs unsupervised DL with a combination of super-resolution adversarial and physics-informed losses to accurately predict sub-filter statistics in a wide range of Reynolds numbers.

2.3 Autoencoder

An autoencoder is an unsupervised or semi-supervised (depending on its utilization) learning algorithm with a fully connected neural network architecture[9]. It consists of two components: an encoder and a decoder. The encoder is responsible for extracting important features from the unlabelled input data, by mapping the input variables to a lower dimensional latent space. The task of the decoder is to reconstruct the original data from the latent features extracted by the encoder, such that the reconstruction loss is minimized. Once the autoencoder is successfully trained, the decoder part is discarded and the encoder is used to map the input data to a lower dimensional latent space[41]. Hence, autoencoders can be used as an effective means of dimensionality reduction for industrial process data. A suitable regression algorithm can then be used to map the latent space to the output space to make accurate predictions. Variational autoencoders are based on a probabilistic framework compared to the deterministic autoencoder algorithm. They encode the inputs as distributions instead of points, resulting in better feature extraction. The ability of variational autoencoder to reduce the original input space to a multivariate Gaussian distribution has been effective in reducing the misdetection of process faults, and hence they have widely been used for combustion process monitoring[42,43].

2.4 Self-Organizing Map (SOM)

A Kohonen map or a SOM is another type of ANN that deals with unsupervised or semi-supervised learning problems[9]. An SOM maps the input space to a lower dimensional space, called the 'map' while maintaining the underlying structure of the input space. Hence SOMs can be used as an effective dimensional reduction technique for high-dimensional industrial process data[44].

2.5 Deep-Belief Network (DBN)

A DBN is another DL algorithm based on unsupervised or semi-supervised learning (depending on its utilization)[9]. It is a multi-layer neural network constructed by stacking multiple individual Restricted Boltzmann Machines (RBMs). Each RBM can extract nonlinear features from the data through an unsupervised learning approach[45]. After this initial unsupervised learning phase, a supervised learning stage is implemented to map the extracted features to the output data[9].

2.6 Fuzzy logic

Fuzzy logic[5] provides inference mechanism that enables approximation reasoning, it models human reasoning capabilities in the knowledge-based systems and deals with imprecision and uncertainty. It consists of fuzzy sets, membership functions and rules set for solving various computational problems. In the fuzzy system theory, an element belongs to a set with a certain degree (partial membership). The degree of membership is referred to as a membership value and is commonly represented by a real value in [0,1]. Fuzzy set, therefore, provides a powerful computational paradigm for extending the capability of binary logic in ways that enable a much better representation of knowledge in a specific application. Mamdani and Takagi–Sugeno (T–S) are the most common classes of Fuzzy Inference System (FIS)[5]. A Neuro Fuzzy System (NFS) is a hybrid intelligent model which combines the low-level learning ability of neural networks and the high-level, human-like reasoning ability of fuzzy logic systems[9]. A Takagi-Sugeno Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed and applied to a wellhead flow-test dataset to assist in the prediction and control of multi-phase flow rates of oil and gas through the wellhead chokes. The ANFIS model was used due to its ability to capture process nonlinearities and adapt to varying process conditions[46].

2.7 Evolutionary algorithm

Evolutionary algorithms are a class of algorithms inspired by the principles of genetics and natural selection. They provide alternative solutions to the problems where heuristic solutions are not available or unsatisfactory[5]. Although, there are a variety of evolutionary algorithms all of them are based on the concept that, when the individuals of a population compete for limited resources, only the fittest individuals in the population survive. This concept can be applied to an optimization problem, where an objective function needs to be maximized or minimized[9]. Genetic Algorithm (GA), Genetic Programming (GP) are two of the most representative approaches of evolutionary algorithms[5]. An evolutionary algorithm such as GA has been used to search and select a set of closure relationships for an experimental field dataset that minimizes the error in the measured pressure gradient in gas-liquid flow measurement [47]. An immune evolutionary algorithm helps optimizing the parameters of a Least Squares SVM (LS-SVM) system for predicting the burning zone temperature of a rotary kiln[48].

2.8 Classification of applied AI algorithms

Fig. 2 illustrates the classification of applied AI algorithms discussed in this section. Given the variety of the algorithms, which one to be used in a given application depend on a number of factors, including task category, type and structure of the expected output, type and size of the dataset, accuracy-interpretability considerations, number of features, linearity, computational complexity of the model. In many applications several algorithms may be combined (referred to as ensemble models) to improve model performance in terms of accuracy and robustness[4]. A well-trained applied AI model should have good generalization ability, i.e. the ability to predict unknown data. If a trained model only fits the training data, but performs poorly on untrained test data, it is likely to be over-fitted. There are several approaches to improve the generalization ability of applied AI models, such as splitting datasets, cross validation, early stopping etc. A detailed discussion on such techniques is available in [3].

3 Applied AI enhanced instrumentation for monitoring complex industrial processes

I&M is concerned with methods or instruments for measurement, detection, tracking, monitoring, characterization, identification, estimation, or diagnosis of a physical phenomenon, measurement theory including uncertainty, calibration, etc. It is therefore not surprising that applied AI is becoming increasingly widespread in I&M. Applied AI can present compelling and useful solutions to certain measurement challenges in circumstances when accuracy of end measurement is more crucial than knowing exactly how the system operates[1]. In this section, recent progresses in applying AI techniques to multiphase flow metering, combustion monitoring and CO_2 flow measurement under CCS condition are reviewed and discussed.

3.1 Multiphase flow metering

Multiphase flow is defined as a simultaneous flow of materials with two or more different phases (i.e. gas, liquid or solid) or unseparated components (e.g. water and oil)[49]. It is widely seen in many industrial processes. Oil/gas/water mixtures are perhaps the most common gas-liquid or liquid-liquid two/three-phase flows during the processes of production, transportation and custody transfer in oil and gas industry. Hydraulic transport of solids such as coal-water, paper pulp, drilling mud and clays, iron concentrates and phosphate matrix, in type of slurry flow is

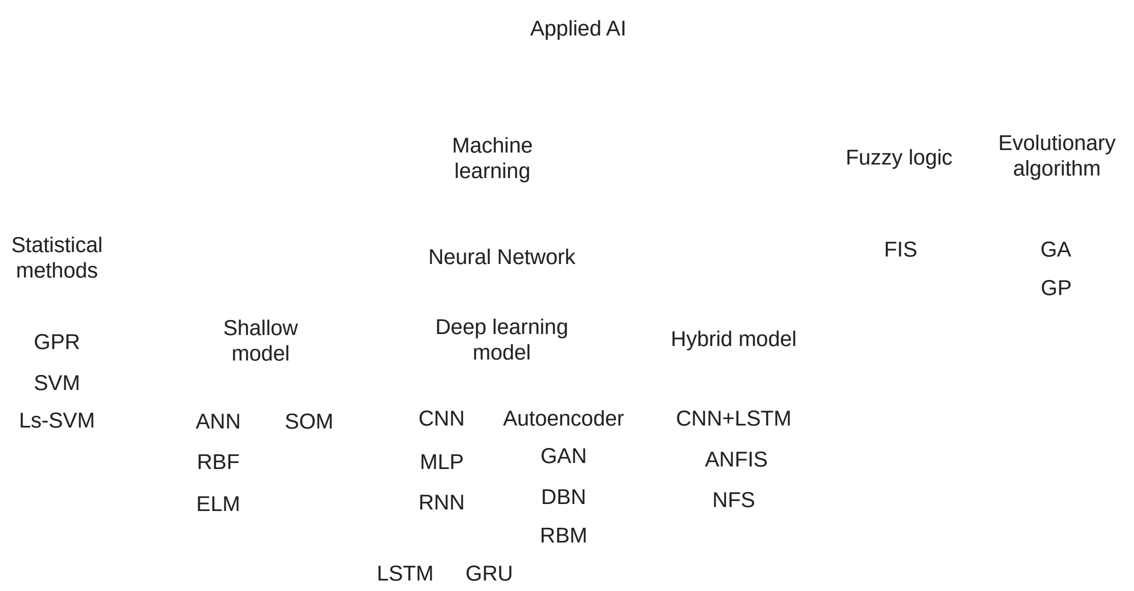

Fig. 2 Classification of applied AI algorithms.

employed in the mining, chemical, pharmaceutical and food industries. In such industrial processes accurate measurement of multiphase flow is highly desirable to realize flow quantification, operation monitoring, process optimization, and product quality control[5]. The applications of AI to multiphase flow metering discussed in this study are mainly concentrated on the estimation of phase flowrates and phase fractions and the identification of flow regime. The estimation of phase flowrates and phase fractions is equivalent to solve a problem of function approximation while the identification of flow regime is a classification problem. There are different flowmeters and sensors available to measure these parameters, however, the relationship between sensor outputs and flowrate or fraction of each phase cannot be deduced theoretically. Recent advances in applied AI have provided alternative approaches to resolving these problems and extend the capability of traditional methods. This section discusses the applications of AI models to some of the most commonly used flowmeters and sensors for multiphase flow metering.

3.1.1 Gas-liquid flow

Fan and Yan[50], presented an neural network based method to obtain gas and liquid flowrates of air-water two-phase slug flow in a 50 mm bore horizontal pipe through conductance probes. It can be seen from Fig. 3 that five characteristic parameters of the mechanistic slug flow model, including translational velocity, slug holdup, film holdup, slug length and film length were extracted from the conductance signals and used as inputs to the neural network. A Back Propagation feedforward Neural Network (BPNN) with ten hidden nodes was adopted to predict gas and liquid flowrates. Experimental assessment of the measurement system was conducted with air superficial velocity from 0.58 to 1.86 m/s and water superficial velocity between 0.35 to 1.62 m/s. Results suggested that the overall performance was within ±10% of full scale for the prediction of both liquid and gas flowrates.

Xu et al.[51] proposed a novel approach to the measurement of wet gas flow using a throat-extended Venturi meter and applied AI models. A BPNN model and an SVM model were developed to estimate the gas flowrate and liquid flowrate through the static and dynamic features of differential pressures. Experimental tests were carried out with natural gas and water two-phase flow on a 2-inch test rig. The gas flowrate was between 0.0139 and 0.0444 m^3/s and liquid flowrate ranging from 3.0556×10^{-4} to 0.0015 m^3/s. It was found that both ANN and SVM models were valid in the approximation of the complex relationship between the signal features and the two-phase flowrates. With the usage of the BPNN, the mean prediction error and standard deviation were 3.14% and 4.22% for gas flowrate, respectively, whereas the mean and standard deviation were 4.77% and 6.33% for water flowrate, respectively. Through the SVM model, the mean and standard deviation of the relative prediction errors were 2.86% and 4.39%, respectively, for gas flowrate, whereas the mean and standard deviation were 4.25% and 6.09%, respectively, for water flowrate.

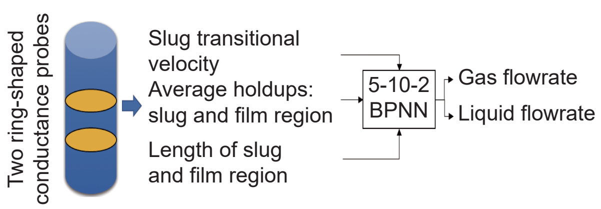

Fig. 3 Measurement system based on two ring-type conductance probes and ANN.

In Comparison with the ANN model, the SVM model was clearly of merit as the means of the relative prediction errors of the gas and water flowrates were improved by 8.9% and 10.9%, respectively. An intelligent multi-sensing system incorporating near-infrared, Differential Pressure (DP), acoustic emission sensors and a venturi flowmeter was designed by Zhao et al.[52] for gas-liquid flow measurement. The interaction and disturbance information of the gas-liquid phase were detected using the sensing devices and used as inputs to the Least Absolute Shrinkage and Selection Operator (LASSO) regression model for predicting the mass flowrate of liquid. Experimental results of this study demonstrated that the relative errors were within ±20% for liquid mass flowrate measurement.

Shaban and Tavoularis[53] proposed a method for the measurement of gas-liquid flowrates in a vertical upward pipe using DP signals. The Probability Density Function (PDF) and the power spectral density of the normalized DP signals were obtained and processed by Principal Component Analysis (PCA) and independent component analysis. The two-phase flow regime was firstly identified through the application of the elastic maps method on the PDF of the DP signals. Then a multi-layer BPNN taking the extracted features as inputs was developed for each flow regime (slug, churn and annular) to produce phase flowrates. Experimental results suggested that the average relative errors of liquid flowrates for slug, churn, annular flow regimes were -0.3%, -0.1% and -0.4%, respectively, and the average relative errors of gas flowrate were 5.5%, 0.5% and 0.6%, respectively.

Liu et al.[54] used MLP and RBF to estimate the mass flow measurement errors of a 1-inch Coriolis mass flowmeter on a horizontal pipe for gas-liquid two-phase flow. As shown in Fig. 4, four parameters including temperature, damping, density drop and mass flowrate were used as inputs to the MLP and RBF. Then the mass flow readings from the Coriolis flowmeter were corrected with the estimated mass flow errors. Experimental tests were conducted with the liquid mass flowrate ranging from 1.5 to 3.6 kg/s and density drop up to 35%. Their proposed model was able to limit the mass flow measurement errors within ±2%. Safarinejadian et al.[55] proposed an FIS based method to correct the mass flow measurement errors of a Coriolis mass flowmeter for gas-liquid two-phase flow. The FIS accepted damping, density drop and apparent mass flowrate as inputs to generate the corrected mass flowrate. Hou et al.[56] developed a digital Coriolis flow transmitter to maintain the flow tube oscillation under two-phase flow conditions, later tested it on a commercial 1-inch Coriolis flowmeter. The authors used a feedforward ANN for online correction of mass flow measurement errors under gas-liquid two-phase flow conditions. The apparent liquid mass flowrate and observed density drop were used as inputs to the ANN. Experimental results showed that, when water flowrate varied from 3 to 15 kg/min with Gas Volume Fraction (GVF) up to 25%, the flowrate errors were within ±3.5% while density errors were within ±1.5%.

Zheng et al.[57] proposed a measurement system using a turbine flowmeter, conductance sensors and SVM to identify the flow

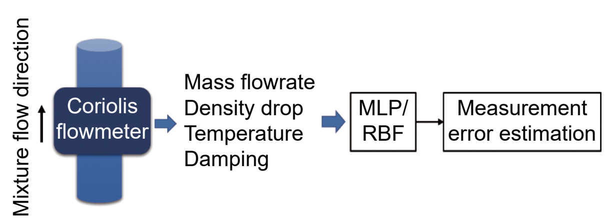

Fig. 4 Measurement system based on Coriolis flowmeter and ANN.

pattern and obtain the water cut of air-water two-phase flow in a vertical upward pipe with an inner diameter of 18 mm. As shown in Fig. 5, the flow pattern was identified through chaotic attractor morphologic analysis of the conductance signals. Polynomial regression was used to obtain the total flowrate of the mixture from the rotating speed of the turbine. A total of 10 features were extracted from fluctuant conductance signals in both time and frequency domains together with the average of rotating speed of the turbine to estimate the water cut of the mixed flow. These features were used as inputs to the SVM model. The total flowrate of gas-water flow ranged from 0.1 to 2.5 m^3/h during the tests. Experimental results suggested that the success rate of the flow pattern identification was higher than 96% and the average errors of the water flowrate and gas flowrate measurements were 7.36%.

3.1.2 Gas-solid flow

Wang et al.[19] presented a GPR based method to measure the cross-sectional particle velocity distribution in a square-shaped pipe using electrostatic sensors, as shown in Fig. 6. The electrostatic sensors include twelve pairs of strip-shaped electrodes. The GPR model is developed to infer the relationship between the input variables of velocities and the cross-sectional velocity distribution of particles in nine areas of pipe cross-section. In this study, the authors implemented PCA[8] to determine the key features prior to model training. The relative error of the proposed model was within ±3% under all test conditions. Results obtained of this study suggest that the electrostatic sensor in conjunction with the GPR is a feasible approach to obtain the cross-sectional velocity distribution of pneumatically conveyed particles in a square-shaped pipe.

Abbas et al.[58] introduced a technique for the mass flowrate measurement of pneumatically conveyed solids in a circular pipe based on multimodal sensing and applied AI models. The multimodal sensing system is comprised of an array of ring shaped electrostatic sensors, four arrays of arc-shaped electrostatic sensors, and a DP transducer, as illustrated in Fig. 7. Applied AI models, including ANN, SVM and CNN were established through statistical features extracted from the sensing system. In order to avoid redundancy and to determine the key features partial mutual information were also calculated prior to model training. Experimental work was conducted on a laboratory-scale rig to train and test the models on both horizontal and vertical pipelines with particle velocity ranging from 10.1 to 36.0 m/s and mass flowrate of solids from 3.2 to 35.8 g/s. Experimental results suggest that the ANN, SVM, and CNN models predict the mass flowrate of solids with a relative error within ±18%, ±14%, and ±8%, respectively, under all test conditions. The predicted mass flowrate measurements with the ANN, SVM, and CNN models are repeatable with a normalized standard deviation within 14%, 8%, and 5%, respectively, under all test conditions.

3.1.3 Liquid-solid flow

Chowdhury et al.[18] presented a GPR based method for the mass flowrate measurement of sand-water two phase slurry. The GPR was utilized in two 50 mm bore Coriolis flowmeters with their measuring tubes in upward and downward orientations, respectively, on a horizontal pipe section. A series of experimental tests were conducted on a purpose-built slurry test rig under a rage of mass flowrates (8 200-20 000 kg/h) and solid volume fractions 0-1.6%. It was found that the original error of Coriolis flowmeter in upward orientation was lower (-1.1%) than that in downward orientation (-1.4%). As shown in Fig. 8, apparent mixture mass flowrate and density were extracted from the Coriolis flowmeters and used as inputs to the GPR model. Experimental results demonstrated that the proposed GPR method was able to achieve slurry mass flowrate measurement with an error within ±0.2% for both of the flowmeters under all test conditions.

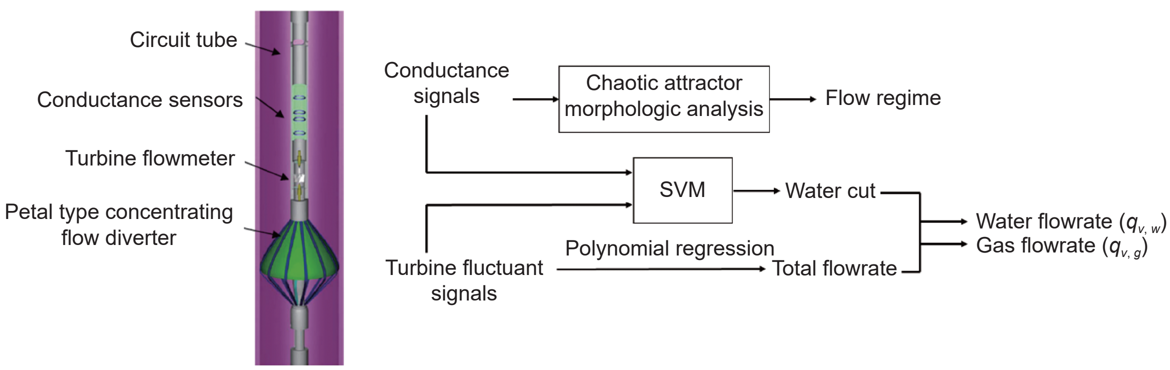

Fig. 5 Measurement system based on conductance sensors, a turbine flowmeter and SVM[5,57].

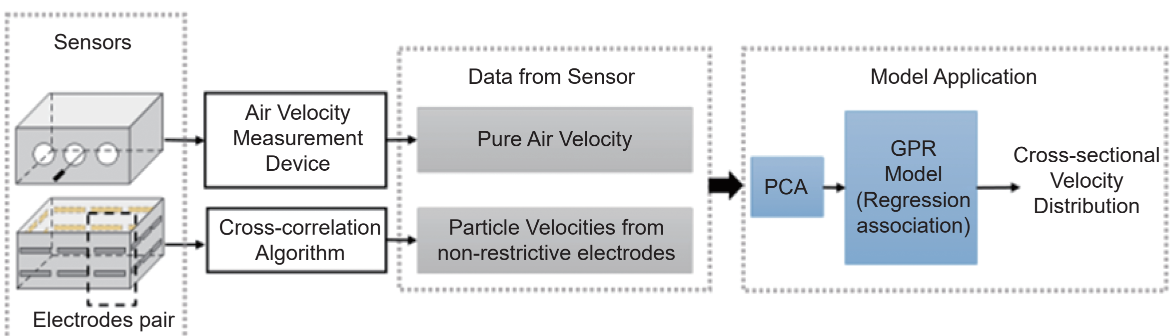

Fig. 6 Measurement strategy of the cross-sectional velocity distribution of pneumatically conveyed particles in a square shaped pipe through electrostatic sensing[19].

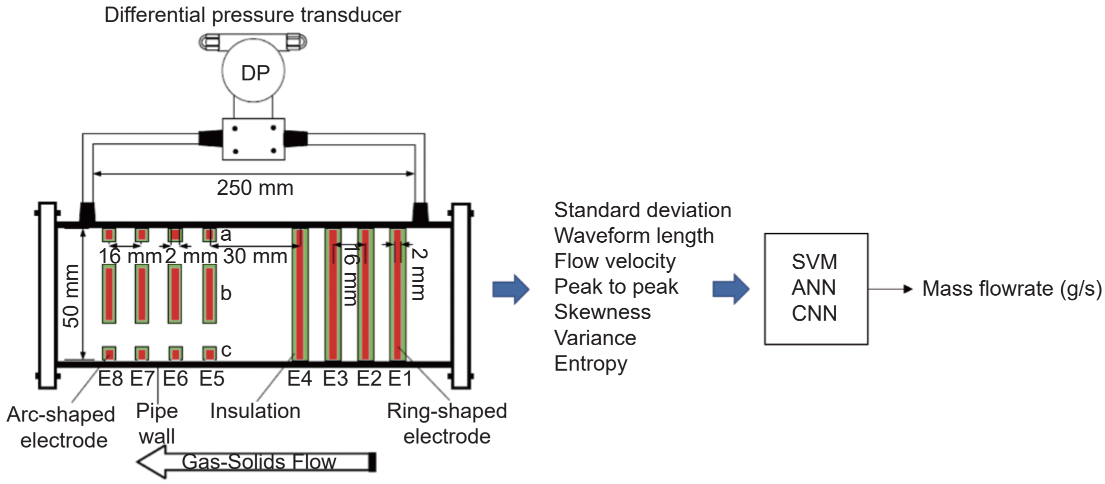

Fig. 7 **Mass flowrate measurement of pneumatically conveyed solids through multimodal sensing and ML modelling[58].**

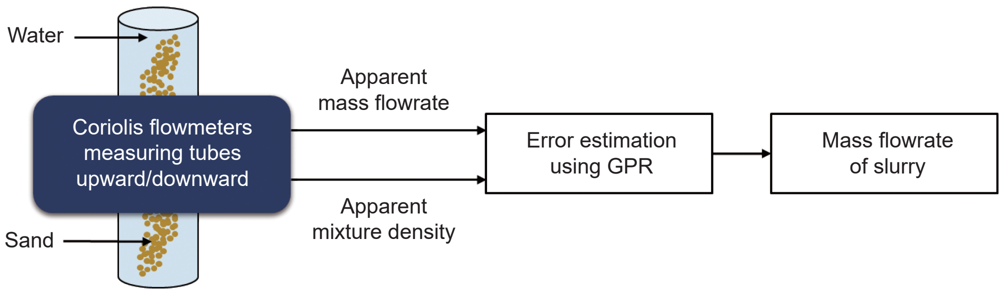

Fig. 8 **Principle and structure of the proposed slurry mass flow measurement system[18].**

Trabelsi et al.[59], conducted an experimental investigation combined with ANN in order to characterize the rheological behaviour of ice slurries. Two additives were used, namely ethylene glycol and propylene glycol, for three initial concentrations 5%, 14% and 24% while the ice fraction varied from 5% to 65%. Flow ramp tests were carried out under steady state conditions using a hybrid rheometer. An ANN model was developed and validated using a database in the literature. Fig. 9 illustrates the structure of ANN based rheological characterisation of ice slurry. The ANN model has proven to be a valuable and inexpensive tool for predicting the rheological behaviour of ice slurry for different operating conditions since it does not require additional time-consuming experiments.

Machin et al.[60], presented an electrical impedance sensor-based slurry density measurement system. The authors proposed a novel technique namely, Electrical Impedance Fingerprinting (EIF), which utilises phase information obtained from non-invasive micro-electrical tomography sensors to extract the aqueous phase conductivity in multi-component slurries. EIF characterises formulation properties, in-situ, based upon electrical impedance sensing and ANN. The literature outlined the development of EIF and its application to monitor aqueous phase conductivity in multi-component slurries, containing sands and clays. EIF predicted this conductivity with high accuracy and a Root Mean Square Error of 0.055 mS/cm.

Traditional sensors incorporating applied AI techniques provide an effective solution to the measurement of phase flowrates and phase fractions. Table 2 summarises the sensors used, experimental conditions, and measurement errors of some of the studies on multiphase flow measurement that used applied AI models. It should be noted that 'GVF variation' in Table 2 represents the absolute error of the measurement from the reference value, MAE is the mean absolute error and NRMSE is the normalised root mean square error, while the rest of the results is the averaged relative error in the measurements from the reference values.

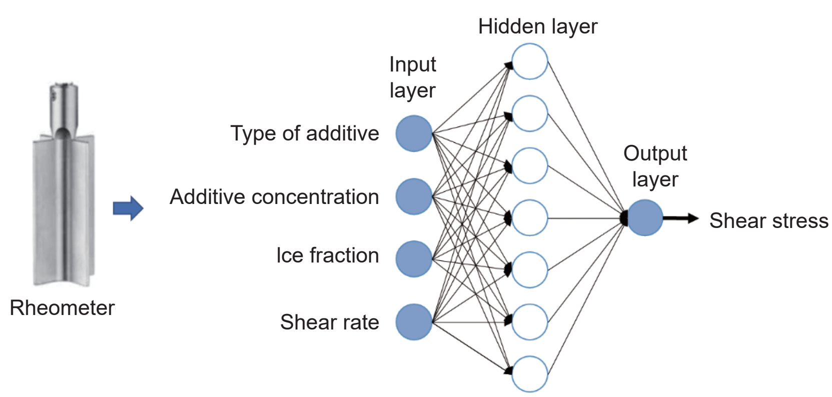

Fig. 9 **ANN based rheological characterisation of ice slurry[59].**

Table 2 Applications of AI with traditional sensors and flowmeters

Sensors	Applied AI model	Multiphase flow	Average error
Ultrasonic sensor[61]	ANN	Air-oil	GVF variation: ±4.2
Throat-extended Venturi[51]	ANN	Natural gas-water	$q_{v,}$: 3.14%, $q_{v,}$: 4.77%
Throat-extended Venturi[51]	SVM	Natural gas-water	$q_{v,}$: 2.86%, $q_{v,}$:4.25%
DP sensors[53]	ANN	Air-water	v_g: 2.4%, v_l: – 0.3%
Conductance sensors[50]	ANN	Air-water	v_g , v_l: < ±10%
Laser diode, photo diode array[62]	SVM	Nitrogen-water	GVF variation < 7%
Conductance + Turbine flowmeter[57]	ANN	Air-water	v_g , v_l: 7.36%
Capacitance + Conductance + Ultrasonic + DP + Venturi[63]	ANN	Oil-water	v: < 5%
Capacitance + Conductance + Ultrasonic + DP + Venturi[64]	ANN	Oil-air-water	v_o: 6.2%, v_g: 4.68%, v_l: 3.91%
Coriolis flowmeter[54]	ANN	Air-water	$q_{m,}$: < ±2%
Coriolis flowmeter[65]	ANN	Air-heavy oil	$q_{m,}$: < 1–5%
Coriolis flowmeter[66]	ANN	Gas-liquid CO_2	$q_{m,}$: 5%
Coriolis flowmeter + water cut meter[67]	ANN	Oil-air-water	$q_{m,}$: ±2.5%, $q_{m,}$: ±5%, $q_{m,}$: ±6%, ±15%
Coriolis flowmeter[55]	Fuzzy system	Air-water	–
Coriolis flowmeter[68]	Neuro-Fuzzy	Air-water	–
Coriolis flowmeter[56]	ANN	Air-water	$q_{m,}$: < ±3.5%
Coriolis flowmeter[69]	SVM	Oil-water	q_m: < ±1%, $q_{m,}$, $q_{m,}$: < ±8%
Coriolis flowmeter + DP[70]	ANN / SVM / GP	Air-water	$q_{m,}$: < ±2%, GVF: < ±10%
Coriolis flowmeter[71]	ANN	Gas-liquid CO_2	$q_{m,}$: < ±2%
Electrostatic sensor[72]	ANN	Salt-air	v_s , $q_{m,}$: < ±15%
Capacitance + Electrostatic sensor[73]	ANFIS	Coal-biomass-air	C_b: 1.2%, C_c: 0.7%
Capacitance + Electrostatic sensor[26]	ELM	Coal-biomass-air	C_b: 2.1%, C_c: 1.2%
Coriolis flowmeter[74]	LSTM	Air-water	q_m: 3.57%
Impedance sensor + high speed camera[34]	CNN+LSTM	Oil-water	v: 0.77% (MAE)
Ultrasonic sensor array[75]	LSTM	Water-crushed ceramic	q_v: < 2.57%
Ultrasonic sensor[76]	CNN + LSTM	Oil-gas-water	–
DP + Near-infrared + Venturi + Acoustic emission[52]	LASSO	Water-compressed air	q_{ml}, GVF: < ±20%
Venturi meter + Electrical capacitive tomography sensor[77]	Temporal CNN	Oil-gas	-
Electrical Impedance Sensor[60]	ANN	Water-sand	Density < 5%
Coriolis flowmeter + pressure + temperature + DP sensor[78]	MLP + Logistic Regression	Hydrate slurry	-
Ultrasonic transducer[79]	ANN	Drilling mud-water	Density 0.84-0.95% (MAE)
Acoustic sensor[80]	Time-delay NN	Sand-gas	q_{ms}: 0.18, C_c: 0.17 (NRMSE)
Venturi + Pressure sensor + temperature sensor[28]	CNN	Oil-water-air	$q_{v,}$: 9.25% (MAE), $q_{v,}$: 7.16% (MAE)
Microwave sensor[81]	CNN	Oil-water-gas	Water to liquid ratio: 5.2% (MAE)
Electrical capacitance sensor + Electromagnetic sensor[39]	GAN	Air-Water-Fe_3O_4 (Solid)	Phase fractions < 0.15%

Here, = concentration of biomass, = concentration of coal, = concentration of sand, = mass flowrate of the mixture, = mass flowrate of gas flow, = mass flowrate of liquid flow, = mass flowrate of oil flow, = mass flowrate of solid flow, = mass flowrate of water flow, = volumetric flowrate of the mixture ; = volumetric flowrate of gas flow, ; = volumetric flowrate of liquid flow, = velocity of the mixture, = velocity of gas flow, = velocity of liquid flow, = velocity of oil flow, = velocity of solids flow.

3.2 Combustion monitoring

In order to have a safe and economic combustion process, it is crucial to meet the need for a high-quality combustion monitoring, diagnosis and emission prediction system. In addition to the strict environmental legislations that requires very careful combustion management, the low-quality fuels and fuel blends from a variety of sources have worsened the problems of flame stability in recent years. Many specialists and scholars have made remarkable progress on flame-imaging/video analysis to achieve an in-depth understanding of combustion mechanism, however, the combustion monitoring of different fuels under a wide range of conditions remain a challenge because of the inherent complexity of combustion processes. With the development of AI, the exploitation of high-fidelity models and the reduction or calibration of traditional models using ML has been proven, and many related studies have been conducted[3,8].

3.2.1 Combustion process monitoring

In power generation industries boilers should be operated under optimised conditions to maintain high combustion efficiency and low pollutant emissions. Abnormal combustion states due to drifts or faults in a combustion system can result in not only reduced efficiency and increased emissions but also enormous negative impact on the health of the system. Flame imaging incorporating applied AI is considered to be a promising approach for monitoring combustion process as it provides the operators with 2-D (two-dimensional) measurements about the furnace[82]. Several studies have been carried out for combustion process monitoring based on flame imaging techniques.

Sun et al.[83] applied kernel PCA for the diagnosis of abnormal operation conditions on a heavy oil-fired combustion test facility. Chen et al.[84] proposed an online predictive technique for furnace performance monitoring based on dynamic imaging and the combination of Hidden Markov Model (HMM) and multiway PCA. Li et al.[82] and Chen et al.[85] constructed an ELM using flame image features to recognise the burning state (i.e., over burning, normal burning, or under burning) in a rotary kiln. Wang and Ren[86] also suggested a flame imaging and applied AI based method for recognising combustion conditions in a pulverised coal-fired rotary kiln. These methods were designed for detecting the process under individual operation conditions, i.e., the single-mode process where only a normal condition is considered.

Bai et al.[87], proposed a monitoring method for variable combustion conditions by combining digital imaging, PCA and RWN techniques, as illustrated in Fig. 10. Based on flame images acquired using a digital imaging system, the mean intensity values of RGB (Red, Green, and Blue) image components and texture descriptors (computed based on the grey level co-occurrence matrix) were used as the colour and texture features for model training. In the proposed model, PCA was used to extract the key features of input vectors. By establishing the RWN model for an appropriate principal component subspace, the computing load of recognising combustion operation conditions was significantly reduced. In addition, Hotelling's T^2 and Squared Prediction Error (SPE) statistics of the corresponding operation conditions were calculated to identify the abnormalities of combustion. The proposed approach was evaluated using flame image datasets obtained on the PACT 250 kW Air/Oxy-fuel Combustion Test Facility. Variable operation conditions were achieved by changing the primary air and secondary air to territory air splits. The results demonstrate that, for the operation conditions examined, the condition recognition success rate of the proposed PCA-RWN model was over 91%, which outperforms other applied AI classifiers (SVM, ANN, and k-nearest neighbour (k-NN)[17]) with a reduced training time. The results also show that the abnormal conditions exhibit different oscillation frequencies from the normal conditions, and the T^2 and SPE statistics were capable of detecting such abnormalities.

3.2.2 Combustion stability monitoring

Combustion instability is a well-known issue that is closely related to decreased combustion efficiency and increased pollutant emissions. Therefore, monitoring combustion stability is crucial for ensuring furnace safety and maximising efficiency. However, it is challenging to create a reliable monitoring model using conventional methods. Recently, applied AI based techniques have attracted significant attention in the field of combustion stability monitoring[88]. DL[1, 8] based techniques are used to automatically extract discriminative features from raw data through multiple layers of nonlinear transformation. Such techniques not only overcome the deficiency of inferior representational ability of the traditional shallow models (i.e. linear discriminant analysis) but also revoke the tedious feature extraction and selection process[89].

Choi et al.[90] built a supervised applied AI model that takes ResNet[91] (a variation of CNN) architectures as the backbone and integrated fusion layers to classify combustion instability. The labelled data for training were obtained by synchronized flame imaging and pressure measurements. Wang et al.[92] established a multi-layer CNN to identify the combustion state and measure heat release rate. Their study demonstrated that representative features are the key factors for obtaining satisfactory monitoring performance in terms of prediction accuracy. Han et al.[89] used a stacked sparse autoencoder to extract image features from flame images of ethylene under different combustion conditions. Subsequently, the extracted features were clustered into two groups (i.e. stable and unstable), and the stability index of each

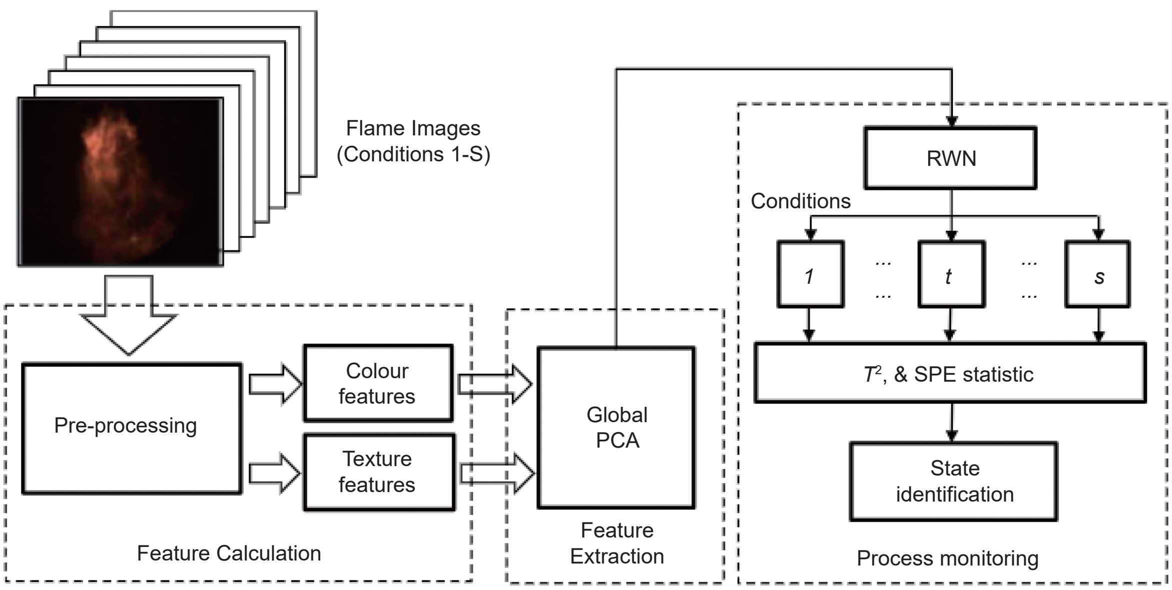

Fig. 10 Scheme of PCA- Random Weight Network (RWN) based multi-mode combustion process monitoring[87].

image was calculated. Based on previous operations for generating labelled data, direct nonlinear mappings based on a DNN were built between the image features and the labels (stability labels and index) for fast combustion state prediction. Qiu et al.[93] proposed an unsupervised framework, which combines convolutional autoencoder, PCA, and HMM to monitor the combustion condition by the uniformly spaced flame images.

Recently, Zhou et al.[94], investigated the applications of DL methods to track combustion instabilities using time-averaged flame images. Experiments were conducted on the BASIS (Beihang Axial Swirler Independently-Stratified) burner under a range of operating conditions in order to cover a variety of flame shapes. They established a CNN namely BIM (BASIS Image Monitor) to identify the thermoacoustic states of the flames in advance and extract information from their forms, as illustrated. in Fig. 11. For training and testing purposes, experiments were conducted under 112 different operating conditions, and the resulting flame images were used as an input into BIM. Features extracted by BIM and visualized by Class Activation Maps (CAM) method reflected the underlying statistical links between flame images and their stabilities. Several phenomena (lift-off flame, flame-wall interaction, outer shear layer flame and fuel mixing process) and their contributions to stabilities were captured and quantified by CAM. Their proposed model exhibited an accuracy of 99% under all test conditions.

3.2.3 Prediction of pollutant emissions

Combustion performance, and emission characteristics of fossil fuels in Internal Combustion Engines (ICEs) are always topics of interest to engineers and researchers. More than 99% of ICEs are today powered by fossil-based fuels[95]. However, these fuels are neither renewable nor a clean energy source. Thus, there is an accelerating popularity among researchers aiming to make fossil fuels more efficient and cleaner sources of energy[96]. Biofuels are accepted as the best alternative additives to fossil-based fuels due to their properties being close to those of conventional diesel fuels. However, they have more oxygen atoms but lower heating values, and their specific fuel consumption is higher. This can lead to higher fuel consumption, lower thermal efficiency, and higher Nitrogen Oxides (NOx) emissions. NOx emission is accepted as the most harmful exhaust gas emission from diesel engines[97]. Considerable studies were conducted in the last decade and achieved reasonable success in predicting NOx emissions in various combustion systems through applied AI[98]. A number of models, including ANN[24], SVM[5], ELM[99], DBN[100], LS-SVM[101] and DL[102] models were also proposed for NOx emission prediction based on the flame radical images.

Tosun et al.[103] predicted the CO, NOx, and CO_2 emissions of a Compression Ignition (CI) engine fuelled with diesel and nanoparticle blends. The authors used ANFIS, regression analysis, and ANN algorithm to predict the emission responses. It was reported that ANFIS performs better for emission prediction compared to ANN and regression analysis. Jafarmader et al.[104] predicted engine performance and emission characteristics using a Wavelet Neural Network (WNN) with a stochastic gradient algorithm. In the training stage of the algorithm, the authors used engine speed and nanoparticles percentages. It was declared that the WNN is a very accurate and useful method to predict nonlinear responses of CI engines. In another study, Saraee et al.[105] investigated the impacts of CO_2 nanoparticles' addition into the diesel engine on the performance and emission characteristics. The authors also predicted these characteristics with the aid of ANN algorithm. It was shown that ANN exhibits good results in emission prediction of CI engine responses. In [97], the performance of a CI engine fuelled with various metal-oxide based nanoparticles (Al_2O_3, CuO, and TiO_2) were investigated experimentally and their emissions were predicted using the different applied AI algorithms, including DL, ANN, k-NN, and SVM for different engine speeds (1 500 – 3 400 rpm). The authors also carried out a comparative analysis in between these models and DL has outperformed other models in terms of R^2 value. The study focused on brake specific fuel consumption, brake thermal efficiency, exhaust gas temperature, CO and NOx emissions. Although, previous studies have frequently reported that the usage of biofuels in diesel engines has resulted in higher fuel consumption, lower thermal efficiency, and higher NOx emission. However, this study proved that the doping of nanoparticles into the diesel fuel has a big advantage in terms of NOx emission, fuel consumption, and thermal efficiency indicators in comparison with those of both conventional diesel fuel and biofuel added diesel fuel.

Studies have shown that the flame characteristics are closely related to the combustion stability and NOx emissions[106], therefore employing flame data, such as temperature maps

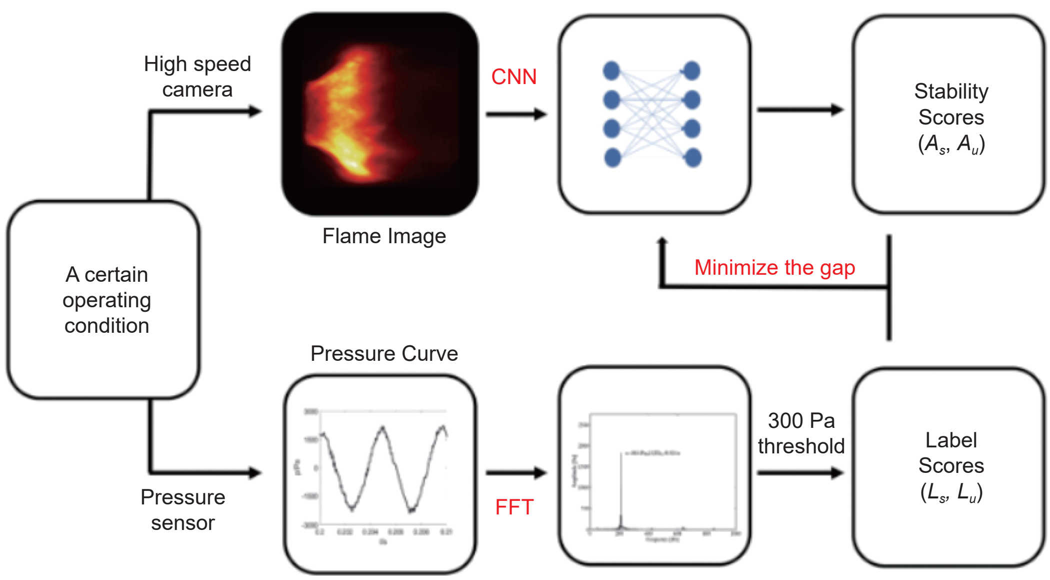

Fig. 11 Data processing procedure of the BIM model [94]

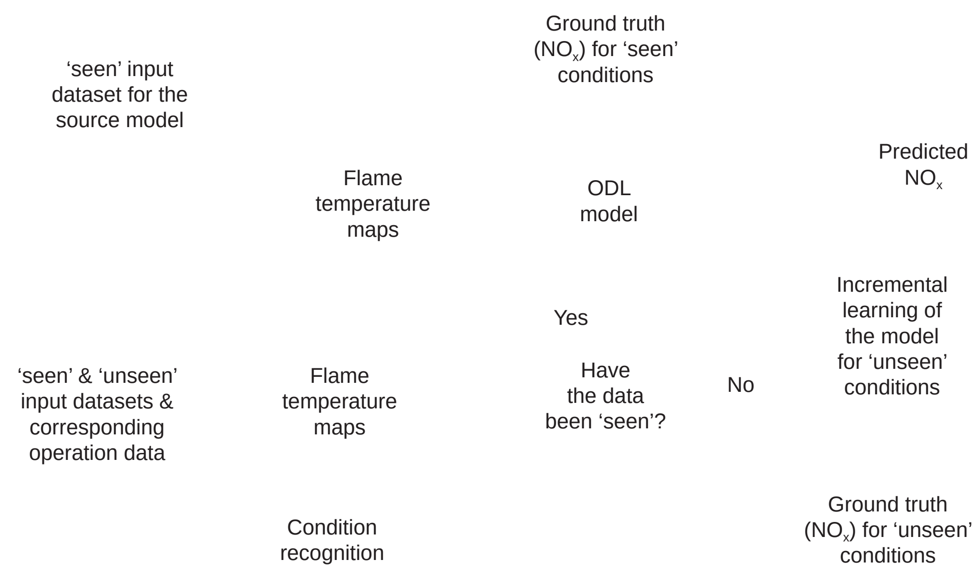

Fig. 12 Block diagram of online DL model for NOx prediction[98].

directly into the model, will increase the performance of NOx prediction and improve the efficiency of the model. Recently, a flame imaging-based Online Deep Learning (ODL) model has been developed for predicting NOx emissions from an oxy-biomass combustion process for "seen" and "unseen" combustion conditions by Qin et al.[98]. Fig. 12 illustrates the block diagram of the ODL model proposed for NOx prediction. Flame temperature maps, obtained under a range of operation conditions from an air/oxy fuel combustion test facility, were used as input dataset. The ODL model was constructed based on CNN by updating the model incrementally only using "unseen" datasets to reach improved accuracy and efficiency. A new objective function that consists of regression loss and distillation loss was introduced in the ODL model to improve the prediction accuracy. The test results revealed that the proposed ODL model was capable of predicting NOx emissions for both "seen" and "unseen" conditions with a mean absolute percentage error less than 3% even after three updates. The authors concluded that, in comparison with the conventional CNN, the ODL model has an incremental learning ability which gave a great potential to their proposed ODL model for online NOx prediction in practical combustion systems under variable operation conditions with improved accuracy and efficiency.

3.3 CO_2 flow measurement under CCS

CCS plays a critical role in future decarbonisation efforts to meet the Paris agreement targets and mitigate the worst effects of climate change[4]. The COVID-19 pandemic has led governments around the world to utilise it as an opportunity to "Build Back Better" with "Green Growth" and a "Green Industrial Revolution"[107]. Part of this recovery plan involves the deployment of CCS at significant scales to meet net zero pledges and limit warming to 1.5℃. CCS is essential for decarbonisation of many sectors that cannot be decarbonised by other process changes and is planned to achieve 10 Mt CO_2 captured per year by 2030 in the UK. In light of these, more affordable CCS is not just desirable, but also essential. There are many well developed CCS technologies available and have the potential for improvements that can encourage CCS deployment. A time and cost-efficient way of advancing CCS is through the application of AI[4]. In [4], the authors carried out a through discussion on the applications of applied AI in CCS. This study focuses on how the captured CO_2 is transported from the capture points to the storage sites.

Pipeline transportation of CO_2 in the dense phase is regarded as the most cost-efficient and safest solution over a long distance[108]. Accurate flow metering of CO_2 in CCS pipe networks is crucial for an optimised design and economical operation of CCS processes. For instance, it is reported that each percent of accuracy improvement will save ?200k per year for a CCS project in Norway[4]. However, CO_2 is expected to be transported near the critical point, which is very close to the expected operational condition of transportation pipelines. A small change in line temperature and pressure may lead to a significant change in the phase of CO_2, resulting in gas–liquid two-phase CO_2 flow. Impurities produced using different capture methods may also affect the phase behaviours of CO_2 flow. Mass flowrate measurement of CO_2 flow is essential for the fiscal purpose in CCS projects.

Henry et al.[65] reported a case study which achieved the errors of mass flowrate within 1–5% in the measurement of gas oil two-phase flow based on a Coriolis flowmeter and an ANN under the condition of 1 kg/s to 10 kg/s in flowrate and less than 60% in GVF. The same measurement system was also employed to measure slugging two-phase CO_2 flow at the pressure of 5.52–7.03 MPa and the temperature of 4–32℃[66]. Results show that the reading difference between the Coriolis flowmeter and other sales meters over several weeks is usually within ±5%.

Comparative investigations into the performance of applied AI algorithms for gas–water two-phase CO_2 flow metering were conducted by Wang et al.[109]. Three applied AI algorithms (ANN, SVM and GP) were developed to estimate the liquid mass flowrate and GVF. The inputs to the applied AI algorithms were obtained from a Coriolis flowmeter and a DP transducer, as shown in Fig. 13. For the mass flowrate measurement, the input variables were apparent mass flowrate, apparent density, damping and DP, while for GVF measurement, the apparent mass flowrate, density and DP were taken as inputs. Experimental tests were conducted with liquid mass flowrate from 700 kg/h to 14 500 kg/h and GVF between 0 and 30%. Results demonstrated that SVM outperformed ANN and GP. For liquid mass flowrate

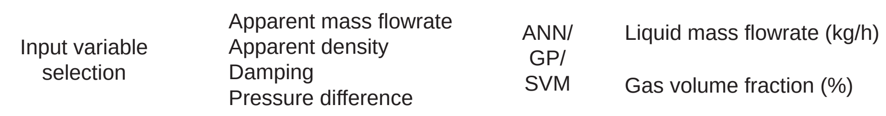

Fig. 13 **CO_2 flow measurement system based on Coriolis flowmeter and ANN/GP/SVM[109].**

measurement with the SVM model, 93.49% of the experimental data yield a relative error less than ±1% on the horizontal pipeline, while 96.17% of the results are within ±1% on the vertical installation. The SVM model predicted the gas volume fraction with a relative error less than 10% for 93.10% and 94.25% of the test conditions on the horizontal and vertical installations, respectively.

Wang et al.[71] developed a flow-pattern-based LS-SVM model to measure the GVF of gas–liquid two-phase CO_2 flow through Coriolis mass flowmeters in both horizontal and vertical pipelines. The developed classification model was incorporated in the system to recognise the flow pattern and LS-SVM model for the mass flowrate metering of gas–liquid two-phase CO_2 flow. Fig. 14 illustrates the principle of the flow measurement of gas–liquid two-phase CO_2 flow. Their proposed model yield errors less than ±2% for mass flowrate measurement of gas-liquid CO_2 flow on the horizontal pipeline and ±1.5% on the vertical pipeline over flowrates from 250 kg/h to 3 200 kg/h. The errors in the estimation of CO_2 GVF were within ±10% over the same range of flowrates.

Shao et al.[110] achieved the GVF measurement in a horizontal CO_2 pipeline based on a 12-electrode capacitive sensor and applied AI models, as shown in Fig. 15. Three applied AI models, BPNN, RBF Neural Network (RBFNN) and LS-SVM, were established. Unlike the flow pattern recognition approach, reconstructed images are usually not required for GVF measurement.

The GVF measurement of gas-liquid two-phase CO_2 flow was achieved without the time-consuming image reconstruction of the flow pattern. Experiments were conducted under both steady-state and dynamic flow conditions. For steady-state flow conditions, the mass flowrate was set from 200 to 3 100 kg/h while the GVF was from 0–84%. Under dynamic flow conditions the gas phase CO_2 was rapidly increased from 120 kg/h to 400 kg/h and then decreased while the liquid CO_2 was fixed at 1 500 kg/h. Measurement results show that the RBFNN outperforms the other two models. Errors were mostly within ±7% and ±16% under steady-state and dynamic flow conditions, respectively.

4 Future Trends

The detailed information presented in Section 3 confirms that applied AI has paved the way to promising solutions to existing and/or unresolved issues in I&M. The use of applied AI in I&M has significantly escalated in the recent years and it is expected to gain more attention in the years to come. This widespread trend is stimulated in part by the fact that an abundance of datasets is available for training applied AI models. In earlier years, many applications suffered from the scarcity of available training data. In previous reviews[3,4,8], the authors discussed about datasets available in various areas of I&M. Currently, the infrastructure for accessing datasets is still at an early stage. A key practice among the I&M community could be to create benchmark datasets for a variety of well-defined I&M problems as well as to establish common and relevant metrices to evaluate applied AI models performance.

It has been found that ANN is most widely used in almost all the aspects of I&M. However, the structural parameters of ANN are required to be adjusted during training process and normally determined through trial-and-error. Although ANN has provided effective solutions in many cases, it is based on empirical risk minimization and all the parameters are tuned iteratively, therefore, ANN may suffer from overfitting. In such cases, SVM based on structural risk minimization offers an alternative option in some applications. In comparison with ANN and SVM, there are less applications of fuzzy logic, probabilistic reasoning and evolutionary algorithm to multiphase flow metering, combustion

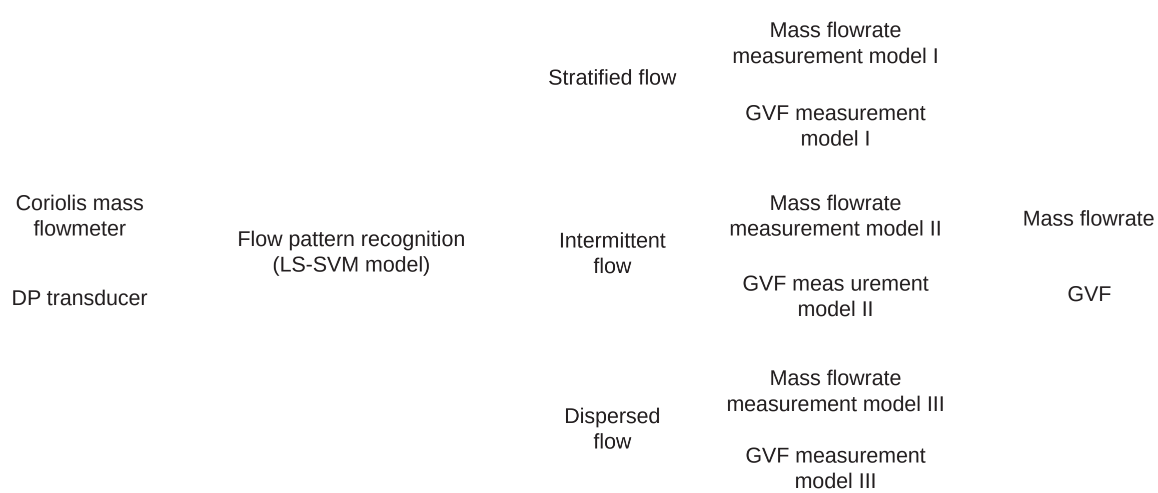

Fig. 14 **Principle of the flow pattern-based model for mass flow metering and GVF predication on horizontal or vertical pipes[71].**

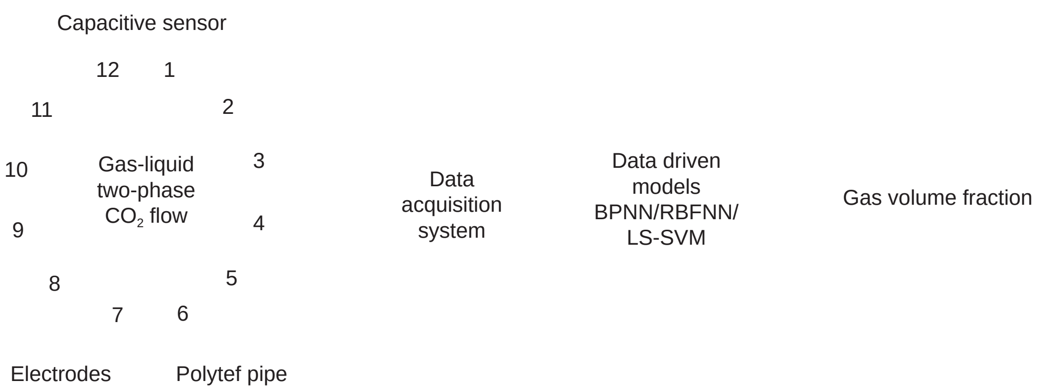

Fig. 15 Principle of GVF measurement of CO_2 using capacitive sensor[110].

monitoring and CO_2 flow metering under CCS conditions. Some knowledge-based systems combing ANN and fuzzy logic such as ANFIS have been developed[73]. Such hybrid models exploit the strength and advantages of both techniques and offer a new dimension in the field of I&M. Moreover, applied AI is a better option than conventional methods for solving problems which are difficult to describe by analytical or mathematical models. The successful applications, as reviewed, suggest that applied AI will have an increasingly greater impact on I&M in the coming years. In addition, since DL can model high-level abstractions in data using architectures consisting of multiple nonlinear transformations[5], it is expected that more applications of DL to I&M would emerge over the next few years.

Digital twins are general concepts that integrate Multiphysics, multiscale and probabilistic simulations of an instrumentation system using available physical models, sensor updates and other information to mirror the behaviour of its corresponding hardware counterpart[3]. In contrast to the component-level analysis that is typically targeted in reacting-flow calculations, digital twins often describe entire engineering systems in order to monitor the behaviour and health of a virtual counterpart under various parametric trajectories. For example, in the combustion sector, digital twins offer new perspectives for enabling fuel-flexible operation of propulsion systems and health monitoring of power-generation systems[3]. Meanwhile, the incorporation of applied AI in combustion with both high-fidelity simulations and system-level modelling can result in accurate and real-time simulations required for digital twins. Specific technologies relevant to anomaly detection and health monitoring, can be broadly applied to sensor data and time-history data, which are typically integrated with simulation capabilities within the digital-twin paradigm. Given the development of various regression and classification techniques discussed in this study, it is within reach to assess various applied AI approaches in order to compare strategies for these distinct aspects of digital-twin technologies through benchmark datasets.

It should be noted that soft sensors or inferential sensors incorporating applied AI models can provide real-time estimations of hard to measure quantities. Applied AI base soft-sensing technology can contribute greatly for online predictions, process monitoring and process fault detection, as well as sensor fault detection and reconstruction[9]. Moreover, physical sensors may not be suitable for certain applications because of many factors including harsh/hostile working environments which lead to frequent service requirements, disturbances to the process flow and product quality, measurement delays, access requirements, and high costs. This makes it difficult or impossible to measure certain process variables directly using physical sensors[9]. For instance, slurry flow metering using a Coriolis flowmeter, though applied AI models can be used to accurately predict mass flowrates. However, due to the abrasive property of slurry the flowmeter tubes can get eroded. In such cases, a soft sensor trained with a classification model can be used for real-time condition monitoring of a Coriolis flowmeter tube(s) for early detection of erosion. Moreover, soft sensing technology can make a good contribution in digital twin technology.

Although, many successful studies based on the combination of AI and I&M research have been undertaken, there is still a long way to go before we can see wide deployment of AI based measurement systems in practice. Unlike physics-based modelling, applied AI models such as those based on a neural network does not understand Newton's law, or that mass cannot be negative, there are no physical constraints with the model, thus it does not know when and how it is violating the law of physics. Therefore, developing physics-informed applied AI models for I&M research will be critical for extending hybrid AI and I&M research from laboratory scale conditions to full-scale industrial applications. However, transparency and interpretability are important for industrial applications, improving the interpretability of AI models and using physics-informed AI could improve the generalization ability of the models. In addition, reliable datasets that are truly representative of the actual industrial processes to be monitored or measured are most critical in the implementation of AI based I&M systems. Meanwhile, in-situ training or on-plant validation of applied AI models in such I&M systems is also important provision, if reliable plant reference data are available.

The availability of a wide range of intelligent algorithms has provided researchers with the flexibility to choose the most suitable algorithms for given applications. Although applied AI is a powerful tool and proven to be effective in I&M, it is worth mentioning that the model performance usually depends on the size and quality of datasets. These models are particularly useful for resolving complex and nonlinear problems in industry [4]. Nevertheless, applied AI in I&M is still in its infancy and there is much to be explored in the near further.

Conclusions

This review has attempted to define the present state-of-the-art in the applications of AI in the general area of instrumentation systems for monitoring complex industrial processes. This review has been focused on the three key areas of I&M, including multiphase flow metering, combustion monitoring and CO_2 flow measurement under CCS conditions. Discussion on how applied AI has its impact in all of these areas has been given.

Although, extensive research has been conducted to advance many aspects of I&M by incorporating applied AI models, it is still a long way to deploy such measurement systems in industry. A range of complex and difficult measurement problems remain to be resolved by engineers, practitioners and researchers. With the recent advances of AI in handling imprecise, uncertain, ambiguous, incomplete and subjective data and information, applied AI models and hybrid variants provide possible solutions to various measurement challenges.

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