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Real-time Faults Prediction by Deep Learning with Multi-sensor Measurements over IoT Networks

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Abstract: The advancements in sensing, data processing, and communication technology have enabled machine learning systems to make confident decisions and made it possible to optimise the operations and maintenance of the physical assets, manufacturing systems and processes of prediction and prevention. In many industrial applications, it is critical to use deep neural networks that make predictions both fast and accurate, and can be applied to coupled multiple-input multiple-output (MIMO) system of complex industrial processes. However, due to the difficulty in correctly interpreting the multi-sensor data and extracting the desired information, and the strong nonlinearity and its nearly instantaneous response to disturbances, it is still very challenging to achieve accurate faults prediction and optimised performance in such a complex MIMO system. In this paper, we propose to transform the raw multi-sensor data into the time-frequency domain by developing fast lifting wavelet transform with computational efficiency to obtain a big feature vector containing all the relevant features from all of the sensors, and giving more informative signatures for faults prediction. To raise the power and capabilities of machine learning, we propose a novel machine learning system designed by building IoT networks to remotely collect data, and developing deep wavelet neural networks (DWNN) with Gaussian (Mexican hat) wavelet derived as activation functions to improve nonlinear fitting and convergence speed, and to process the real-time data for faults prediction. Experimental results demonstrate that features extracted in time-frequency domain can reveal the presence of a fault, and its type and cause can be explained by the trained DWNN over the IoT communication networks, where the sensing capabilities and the computational power are provided by the designed controller, transmitter and cloud server to track everything that is relevant to operations, such that by deep learning with real-time data analytics we can have a knowledge base from which to predict faults, correct errors, optimize system performance and maximise efficiency.

Keywords: Real-time faults prediction, Machine learning, Deep wavelet neural network, Activation function, Data analytics in time-frequency domain, Wavelet analysis for feature extraction.

1. Introduction

The advancements in sensing, data processing, and communication technology have enabled the systems to interact with the environment and optimize processes via learning through interactions [1]. In particular, the increasing number of sensors and, in general, the available data sources provide the real-time monitoring and diagnostics of machines, systems, structures and processes, to be ever more detailed and intelligent [2]. This increases the potential for generating added value along the entire value chain by massive collection, evaluation and analytics on sensor data, and results in that the systems and architectures for data processing are becoming more and more complex, as the number of sensors is constantly increasing. Therefore, correct handling and interpretation of the data have become very important for real added value to be generated from the sensor signals. Depending on the application, it may be difficult to interpret the discrete sensor data correctly and extract the desired information. In addition, the dependencies between multiple sensors need to be explored and correlations to be established. For complex tasks, simple threshold values and manually determined logic are no longer sufficient or do not allow for automated adaptation to changing environmental conditions. In Industry 4.0 applications, with the advances in artificial intelligence (AI) and machine learning (ML), real-time data from various sensors and intelligent systems over the internet of things (IoT) networks can now be remotely collected and processed to monitor machine conditions, detect faults, predict and optimise system performance, which offer ways to optimise the operations and maintenance of the physical assets, manufacturing systems and processes of prediction and prevention, by enabling the technological innovation that the industry needs [2]. For example, engine and equipment failures are often associated with the internal or environmental variables exhibiting unexpected behaviors. Continuous monitoring of such variables, predicting failures or degradation and taking actions can prevent such events and provide predictive maintenance planning and scheduling. Equipped with multiple sensors over the IoT networks, and enabled by deep learning to detect relevant status information of the actuators and to monitor the health status of specific components [3], this new data-driven model is improving and dramatically changing the way how system/machine/engine/component failures can be predicted before they happen and that the downtime of industrial machines, engines can be prevented or reduced, extending from detection of anomalies to complex fault diagnostics and immediate initiation of fault elimination, thus leading to increased productivity. The resulting cost savings and competitive advantages are essential as the evolution and convergence of many new technologies - mechatronic systems, controllers, edge and cloud computing, big data, machine learning and the IoT, are being adopted and providing the basis for increasing the self-awareness of the machine, allowing it to optimise its own performance for the given duty cycles, diagnose and compensate for non-catastrophic faults, and coordinate operations with other machines with minimal input from the operator. From the perspective of production and service management, establishing the intelligent and communicative systems can enable the processes to deal with the data flow from intelligent and distributed system interaction and to promote autonomous interoperability, agility, flexibility, decision-making, and efficiency [4].

For real-time decision-making to give an early warning for catastrophic system damage, the voluminous sensor data generated in the IoT network needs data analysis. While diagnosis involves identifying the cause of an existing problem, prognosis can predict the occurrence of a problem and its cause. In recent times, data-driven prognosis methods have been proven to be very effective due to the availability of better data acquisition methods with multiple sensors, IoT and ML techniques. However, the characteristics of sensor data are complex, involving high velocities, huge volumes, dynamic values and types, real-time updating, critical data aging, and interdependency between different data sources [5]. Furthermore, the sensor data pollute while perpetuating numerous obstacles until producing the required data analysis and real-time decision-making. These make it difficult to extract relevant features directly from raw data in order to interpret and produce a representable form that is deliverable [6], and a reaction towards the external trigger. We propose to transform the raw data into the time-frequency domain by developing fast lifting wavelet transform with computational efficiency to obtain a big feature vector containing all the relevant features from all of the sensors, and giving more informative signatures for faults prediction and detection.

Through continuously acquiring sensor data to perform specific tasks, machine learning systems can carry out complex processes by learning from data with features extraction, rather than following the pre-programmed rules, allowing a more compelling and robust control architecture with optimised performance to be built on [7]. Automatic learning also vastly improves product quality by faults detection and condition monitoring that can introduce predictive maintenance systems into production processes, replacing visual inspections that can execute quality controls more accurately and efficiently. Indeed, deep learning is regarded as a foundational technology for complex applications such as faults prediction and predictive maintenance, and can be applied to coupled multiple-input multiple-output (MIMO) system of complex industrial processes. However, due to the strong nonlinearity and its nearly instantaneous response to disturbances, faults prediction with optimised performance in such a complex MIMO system is difficult to achieve [8]. It is required to build up appropriate research environments, and obtain datasets that can be used to explore and raise the power and capabilities of machine learning, where commonly used deep neural networks require improvements in nonlinear fitting and convergence speed. In this paper, we propose a novel machine learning system designed by building IoT network to remotely collect data, and developing deep wavelet neural networks using nonlinear Gaussian (Mexican hat) wavelet with sparsity as activation functions, to process the real-time data with features extraction in the time-frequency domain for faults prediction and detection to reduce downtime and increase productivity.

2. Machine Learning System

Real-time machine learning system is designed as shown in Fig. 1, where by designing printed circuit boards (PCBs) as machine controllers, signal collectors and transmitters, the IoT communication networks could be built for real-time remote monitoring, predicting failures or degradation, taking actions, and optimising system performance by machine learning, so that the predictive control and maintenance for highly efficient operation of industrial systems can be achieved [2]. The IoT allows objects to be sensed or controlled remotely across the built network, where fibre optic communication has been developed to increase data rates without electromagnetic or radio frequency interference (EMI/RFI), and to provide a cost effective way to transmit more sensor data with guaranteed safety. The wireless communication network based on self-developed protocol by an ultra-high frequency (UHF) radio frequency (RF) can achieve up to 2 km wireless link. With the IoT communication network built, real-time faults prediction and detection based on multi-sensor measurements can be performed by deep learning, so that we can have an eagle-eye view of every event while or before it's happening. It also enables real-time big data analytics to optimise decision making and performance, and to enhance productivity and e□ciency, creating an opportunity to apply real-time machine learning for advanced control, management and maintenance, by collecting data from all sources on the IoT networks, where qualitative and quantitative data analysis can build the next generation decision support system. This means current systems can be upgraded to suit the next generation needs of actioning changes in a process to optimise the efficient use of industrial systems, thus creating opportunities for industry 4.0 to be implemented with modernised products, systems and services, and also to improve precision, flexibility, and profitability. By real-time machine learning, the designed controller is able to predict and optimise control parameters to minimise energy consumption, while by real-time processing of measurement data provided by dedicated sensors installed in the machine, the system can enable autonomous decision making based on the online diagnosis of the correct machine with right condition, leading to increased machine reliability towards zero defects. Predictive maintenance based on condition monitoring by measuring such as vibration, acoustic, motor current etc., can then be planned and scheduled, such that we can have a knowledge base from which to correct errors and improve efficiency.

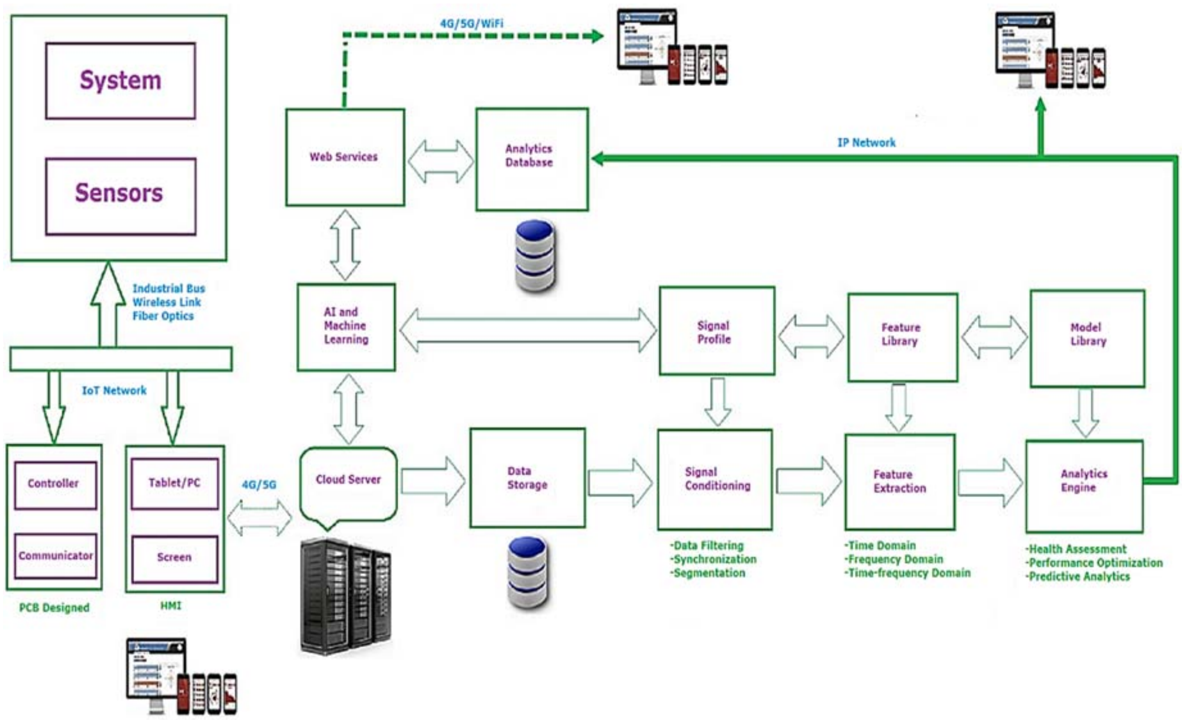

Fig. 1. Real-time machine learning system.

For MIMO systems of industrial processes, such as the multi-sensor signals as input to predict and detect time of faults as output, they can be modelled by the form of regression problem aimed at predicting:

$$Y = f(X) + \epsilon, \quad (1)$$

where $f(X)$ is an unknown function with inputs X and outputs Y, and ϵ is typically a white additive noise process represented by a random matrix. Prediction can be achieved by the nonlinearly mapping or fitting that models the observed past data, and we aim to minimise the mean squared error (MSE) between the actual inputs and predicted outputs at the training process.

For one input X_i and one output Y_m, we have

$$Y_m = f(X_i) + \epsilon_m$$

If $X_i = (x_t, x_{t-1}, x_{t-2}, \cdots, x_{t-j})$ represents the past data, and $Y_m = (y_{t+1}, y_{t+2}, \cdots, y_{t+k})$ denotes the prediction with k steps, the time-series forecasting would be:

$$(y_{t+1}, y_{t+2}, \cdots, y_{t+k}) = f(x_t, x_{t-1}, x_{t-2}, \cdots, x_{t-j}) + \epsilon_m, \quad (2)$$

where $i, j, k, m \in \mathrm{Z}$ (Z is the set of all integers). The prediction is a complex nonlinear mapping where deep wavelet neural networks (DWNN) with nonlinear fitting can be used for faults prediction by monitoring multi-sensor signals with feature extracted in time-frequency domain.

3. Feature Extraction in Time-frequency Domain

For faults prediction, wavelet analysis that reveals time and frequency variant characteristics of faulty signal, can be used to zoom into a local region of interest in time-frequency domain, for fast and accurate monitoring and detection of any abnormal/fault operating condition. To extract features, a correlation coefficient between each signal and the healthy signal is assigned to the signal using wavelet analysis. With the property of time-frequency localisation, wavelets can detect the transient components related to large changes in signals [9]. For any given signal, wavelet transform can decompose this signal into many functions through translations (time index k) and dilations (frequency index j) of a single function called a mother wavelet, defined as $\Psi(t)$. The discrete wavelet transform (DWT) version is ($\Psi_{j,k}(t) = 2^{-j/2}\Psi(2^{-j}t - k)$) $j, k \in Z$, (Z represents the set of integers). A discrete wavelet transform maps the time domain signal of *y(t)* into a real-valued time-frequency domain and the signals are described by the wavelet coefficients as

$$y(t) = \sum_{j=1}^{J} \sum_{k=1}^{K} w_{j,k} \Psi_{j,k}(t) + \sum_{k=1}^{K} a_{J,k} \varphi_{J,k}(t), \quad (3)$$

where $w_{j,k}$ are wavelet (detail) coefficients and $a_{J,k}$ are the approximation coefficients which represent the smoothed part of the signal, $\varphi_{J,k}(t) = \varphi(2^{-J}t - k)$ is scaling function. The DWT is

$$w_{j,k} = \left|2^j\right|^{-\frac{1}{2}} \int_{-\infty}^{\infty} y(t) \overline{\Psi}\left(\frac{t - k2^j}{2^j}\right) dt, \qquad a_{J,k} = \int_{-\infty}^{\infty} y(t) \overline{\varphi}_{J,k}(t) dt \quad (4)$$

where $\overline{\Psi}, \overline{\varphi}$ denote the complex conjugate of mother wavelet Ψ, scaling function φ respectively.

The wavelet transform (WT) is a tool for carving up functions, operators, or data, into components of different frequency, allowing one to study each component separately. Wavelet analysis provides a mapping that has the ability to trade off time resolution for frequency resolution and vice versa. It is effectively a mathematical microscope, which allows the user to zoom on features of interest at different scales and locations. However, the need for improvement of wavelets comes from a shortcoming that is inherent because of its construction. Second generation wavelets were named when the concept of lifting was introduced [10], and opened a new direction to construct wavelets which are not necessarily translates and dilates of one fixed function. A construction using lifting is entirely spatial, and therefore ideally suited for building second generation wavelets when Fourier techniques are no longer available. Second generation wavelets are more general in the sense that all the classical wavelets can be generated by the lifting scheme. The lifting scheme makes optimal use of similarities between the high and low pass filters so as to achieve a faster implementation of WT. To give more flexibility to design wavelet filter with linear phase for fast implementation, we propose to use biorthogonal wavelet transform by lifting scheme [10].

Classical implementation of WT uses two band filter bank (FB) with recursion on its low pass (LP). Equivalent polyphase representation is depicted by polyphase matrix $\widetilde{P}(z)$, which is assembled from even and odd filter components. Output of the FB analysis part is then:

$$\begin{bmatrix} LP \\ HP \end{bmatrix} = \widetilde{P}(z) \begin{bmatrix} y_{even} \\ z^{-1} y_{odd} \end{bmatrix}, \quad (5)$$

where HP denotes high pass and y_{even} is the even part of the signal, and y_{odd} is the odd part.

$$\widetilde{P}(z) = \begin{bmatrix} \widetilde{h}_e(z) & \widetilde{h}_o(z) \\ \widetilde{g}_e(z) & \widetilde{g}_o(z) \end{bmatrix} \quad (6)$$

For any filter pair (h, g) with $\det[P(z)] = 1$, always exist factorization of $P(z)$ [11]:

$$P(z) = \begin{bmatrix} K & 0 \\ 0 & \frac{1}{K} \end{bmatrix} \prod_{i=m}^{1} \left\{ \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \right\} \quad (7)$$

Eq. (7) allows ladder realization of $\widetilde{P}(z)$ by reversible lifting steps followed with normalization by factor K as shown in Fig. 2.

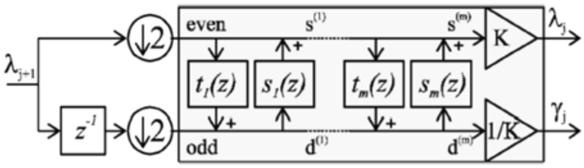

Fig. 2. Ladder structure of lifting steps.

Signal is partitioned into even and odd components that are then mutually predicted by t_i (to zero signal in HP part) and updated by s_i (to retain in LP part signal moments). After normalization, the algorithm is recursively applied to the LP part. Backward transforms simply undo all ladder steps from right to left using reversed operators. So by lifting wavelet transform, signals can be decomposed into a series of subband signals with the use of a multi-resolution analytical property, where features related to faults prediction and detection are extracted in time-frequency domain, and can be used to train and test the deep learning model.

4. Deep Wavelet Neural Networks

To better map the inputs to outputs with highly nonlinear relationships, we construct deep wavelet neural networks (DWNN) as shown in Fig. 3.

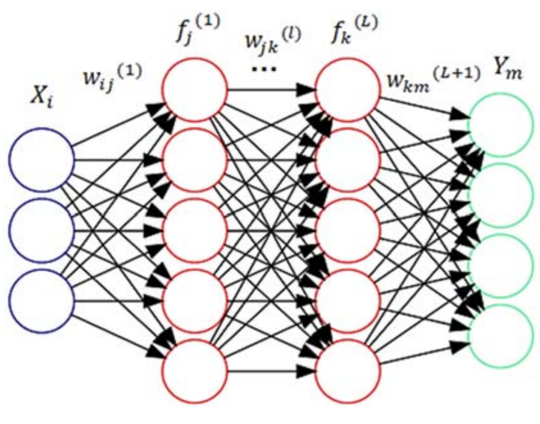

Fig. 3. A deep wavelet neural network (DWNN).

The prediction output Y_m can be expressed by deep prediction rule:

$$\begin{aligned} Y^{(1)} &= f^{(1)}\left(W^{(1)}X_i + B^{(1)}\right), \\ Y^{(2)} &= f^{(2)}\left(W^{(2)}Y^{(1)} + B^{(2)}\right), \\ &\vdots \\ Y^{(L)} &= f^{(L)}\left(W^{(L)}Y^{(L-1)} + B^{(L)}\right), \\ Y_m &= W^{(L+1)}Y^{(L)} + B^{(L+1)}, \end{aligned} \tag{8}$$

where f is a wavelet function that is used as activation function to construct the DWNN, W is the weight matrix and B denotes bias. Rewrite Eq. (2) by the analysis of variance (ANOVA) expansion [12]:

$$\begin{aligned} y(t) &= f\big(x_1(t), x_2(t), \cdots, x_n(t)\big) + e(t) \\ &= f_0 + \textstyle\sum_{i=1}^{n} f_i\big(x_i(t)\big) + \\ &\quad \textstyle\sum_{1\le i<j\le n} f_{ij}\big(x_i(t), x_j(t)\big) \\ &\quad + \sum_{1\le i<j<k\le n} f_{ijk}\big(x_i(t), x_j(t), x_k(t)\big) + \cdots \\ &\quad + \sum_{1\le i_1<\cdots<i_m\le n} f_{i_1 i_2\cdots i_m}\big(x_{i_1}(t), x_{i_2}(t), \cdots, x_{i_m}(t)\big) \\ &\quad + \cdots + f_{12\cdots n}\big(x_1(t), x_2(t), \cdots, x_n(t)\big) + e(t), \end{aligned} \tag{9}$$

where $i_1, i_2, \cdots, i_m, m, n \in \mathrm{Z}$.

For any function $f \in L^2(\boldsymbol{R})$, the form of wavelet decomposition is

$$f(x) = \sum_j \sum_k c_{j,k}\psi_{j,k}(x) = \sum_{m=1}^{M} c_m \psi_m(x) \tag{10}$$

For an n-dimensional wavelet

$$\psi^{[n]} = \psi^{[n]}(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} \psi(x_i)$$

If we choose Gaussian wavelet functions, we have

$$\psi^{[n]} = \psi^{[n]}(x_1, x_2, \cdots, x_n) = x_1 x_2 \cdots x_n e^{-\frac{\|x\|^2}{2}}, \tag{11}$$

where $\|x\|^2 = \sum_{i=1}^{n} x_i^2$. In this study, we use Mexican hat wavelet as activation functions. It is the negative normalised second derivative of a Gaussian function and has admissibility condition and a symmetric structure.

$$\psi_{mexh}(t) = \frac{2}{\sqrt{3}\pi^{\frac{1}{4}}}(1 - t^2)e^{-\frac{t^2}{2}} \tag{12}$$

Its derivative is also a Gaussian function:

$$\psi'_{mexh}(t) = \frac{2t}{\sqrt{3}\pi^{\frac{1}{4}}}(t^2 - 3)e^{-\frac{t^2}{2}}$$

Thus, the expansion component $f_{i_1 i_2\cdots i_m}(x_{i_1}(t), x_{i_2}(t), \cdots, x_{i_m}(t))$ can be expressed by DWNN model:

$$\begin{aligned} & f_{i_1 i_2\cdots i_m}\left(x_{i_1}(t), x_{i_2}(t), \cdots, x_{i_m}(t)\right) = \\ & \textstyle\sum_{j=j_m}^{J_m} \sum_{k_1\in K_j} \cdots \\ & \sum_{k_m\in K_j} c_{j;k_1,\cdots,k_m}\psi^{[m]}_{j;k_1,\cdots,k_m}\left(x_{i_1}(t), x_{i_2}(t), \cdots, x_{i_m}(t)\right), \end{aligned} \tag{13}$$

where $k_1, k_2, \cdots, k_m, j_m, J_m, K_j \in \mathrm{Z}$.

Compared with commonly used deep neural networks, using nonlinear Gaussian (Mexican hat) wavelet with sparsity as activation functions in the DWNN model can improve nonlinear fitting and convergence speed with adaptive learning rate, so that the power and capabilities of machine learning can be raised.

To predict faults from multi-sensor measurements, DWNN network is constructed. Fig. 4 gives an example of DWNN network to train 4 sensor signals as input, and faults prediction as output including predicting the time when system is operating at normal, or first warning, second warning, and fault detected when or before it is happening. After faults prediction and detection, the machine learning system will also be trained to learn and diagnose what cause the faults and what actions can be taken to prevent or reduce them if an early warning of faults is given by deep learning.

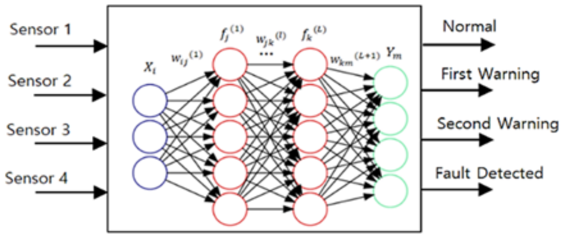

Fig. 4. Faults prediction by DWNN.

5. Experiments

To evaluate the proposed DWNN for faults prediction with multi-sensor measurements, unmanned medical air plant to provide oxygen was set up as shown in Fig. 5. It consists of four compressors and one oxygen generator (OG) to compress and purify oxygen for hospital users.

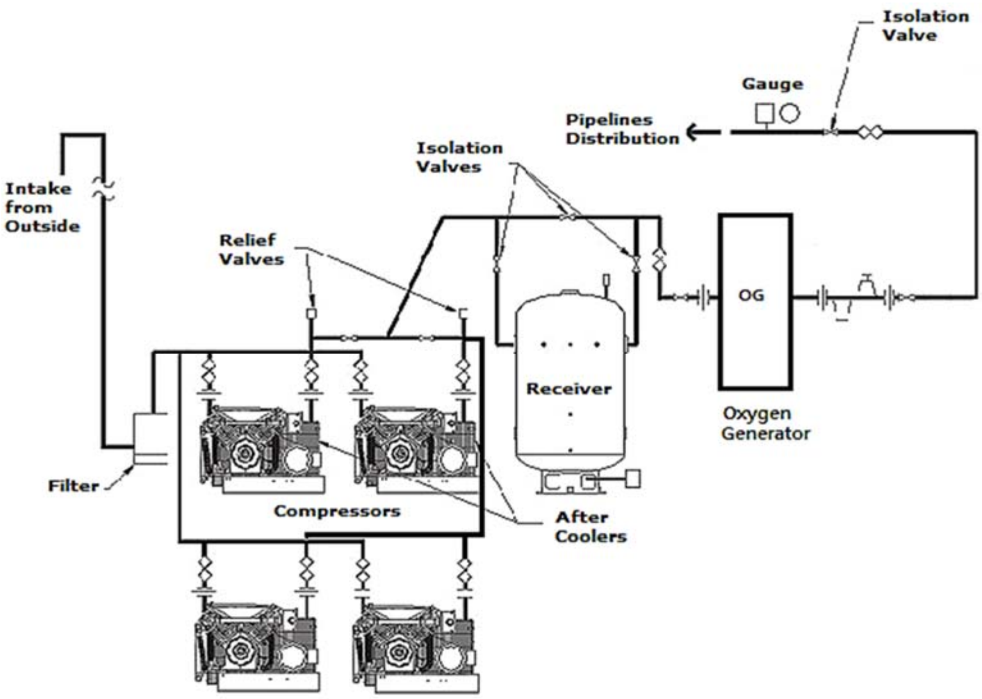

Fig. 5. Unmanned medical air plant for oxygen supply.

Based on the choice of fixed speed compressor, and with remote monitoring of multi-sensor signals over the built IoT networks and real-time machine learning for faults prediction, the measurement signals of mains current (to measure status of compressor operating), flow rate (at pipeline output), oxygen line pressure (at pipeline output), oxygen purity (to measure the quality of oxygen) are remotely collected over IoT networks and processed at cloud server, where deep learning by DWNN is performed. The measurement data analysis shown in Fig. 6 is from data of 4 sensors recorded in about one week's time, during which faults were detected because oxygen purity was lower than a preset level that is not acceptable for medical use. Fig. 7 shows the same signals in frequency domain, indicating strong fundamental (compressor loading period) and harmonic frequencies, and details of multi-sensor measurement signals in time domain are shown in Fig. 8, where the system was operating at normal conditions with no fault being detected. It can be seen that under normal conditions, compressors are operating at a loading and off-loading cycle, and that makes the sensor values of flow rate and oxygen line pressure vary at the same cycle.

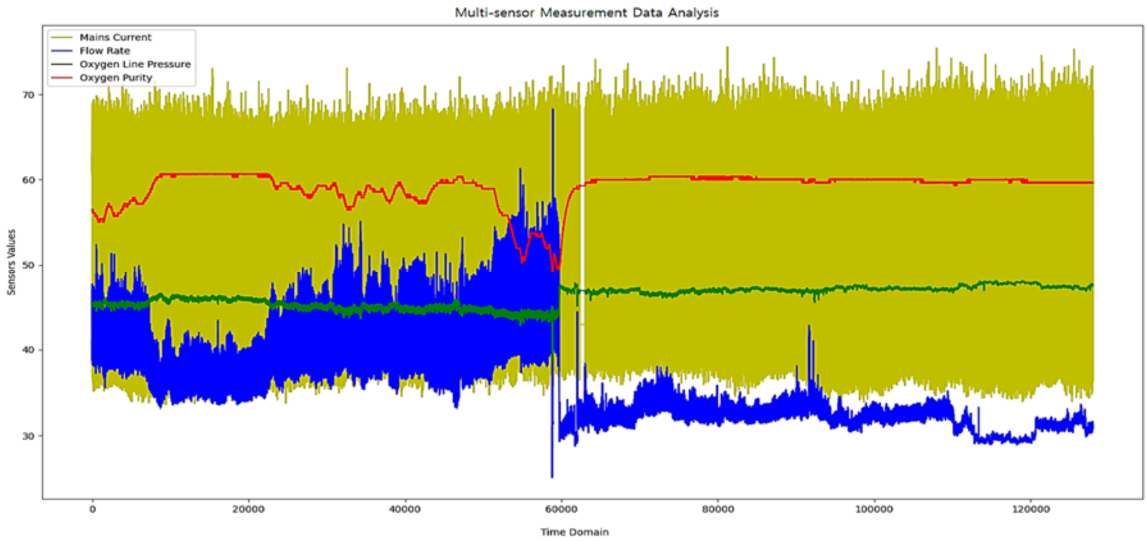

Fig. 6. Multi-sensor measurement signals in time domain.

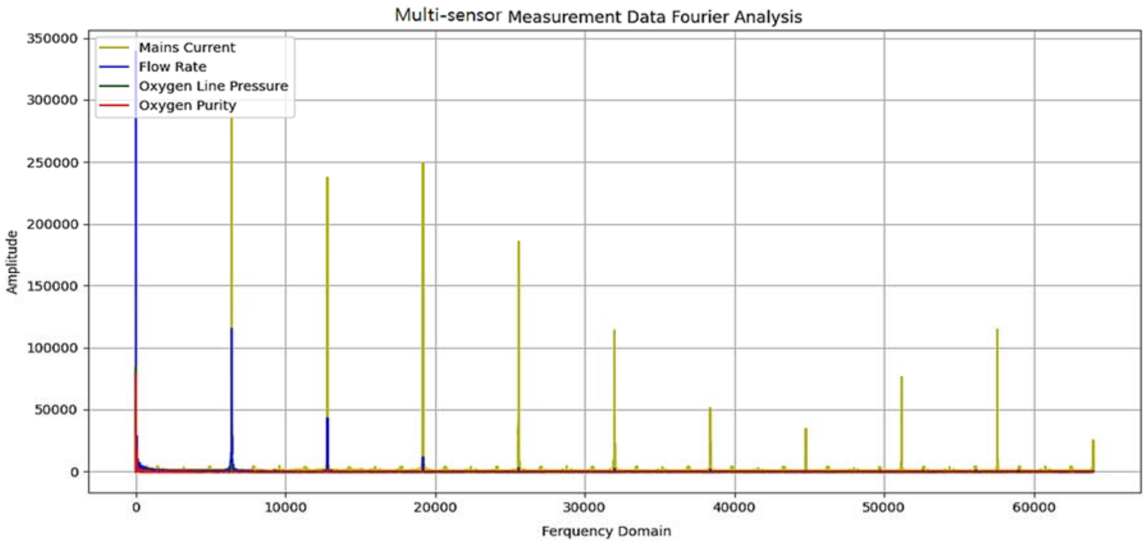

Fig. 7. Multi-sensor measurement signals in frequency domain.

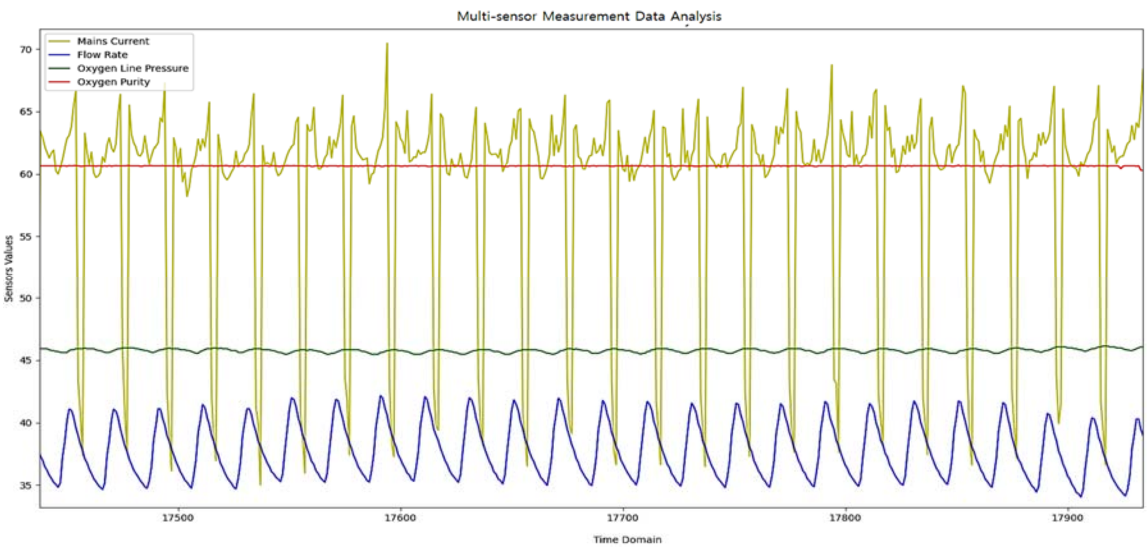

Fig. 8. Details of multi-sensor measurement signals in time domain.

The collected data analysis in time domain (as time series: a sequence of data indexed by successive time points) can only provide limited information for faults prediction, giving no warning before they happen. Therefore there is a need to represent the data information contained within such time series in a more detailed or meaningful form, where features can be extracted to reveal the change of operation conditions. As wavelets are able to give a time-frequency representation of a signal, we developed fast lifting wavelet transform that can create a representation of the signal in both the time and frequency domain, allowing efficient access of localised information about the signals. Fig. 9 shows the same signals as in Fig. 6 represented in time-frequency domain, where each signal is decomposed by wavelets into low and high frequency parts. Thus the features extracted in the time-frequency representations can be used to feed the DWNN network for predicting faults. The training was performed offline to obtain the optimal network parameters. Tests can be performed online to predict the timing of system conditions in four stages: normal, first warning, second warning, and fault detected if there is any. Fig. 10 gives a detailed example of how they are detected and thus can be used for deep learning to predict before they appear.

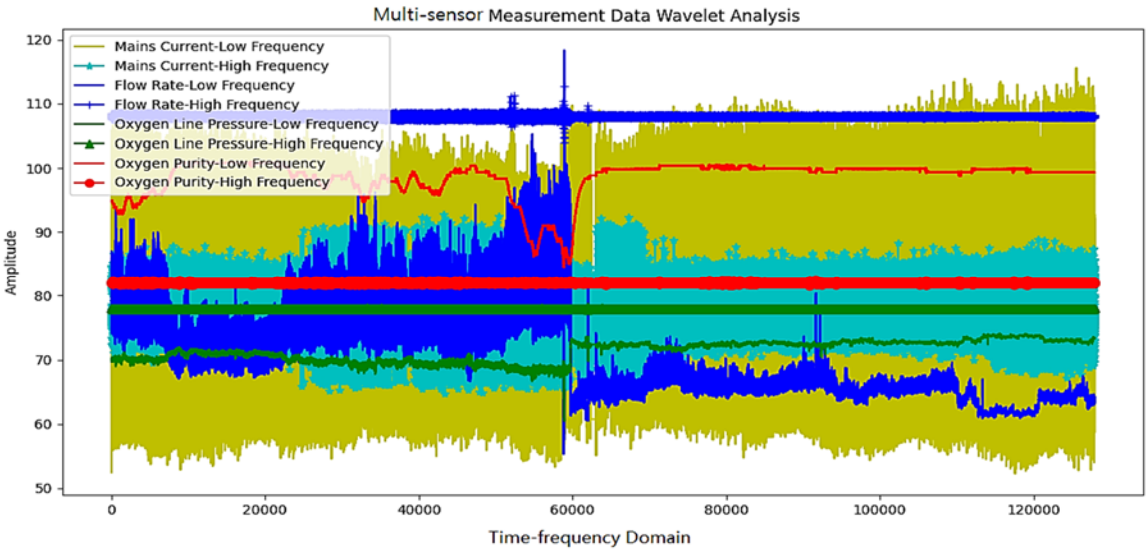

Fig. 9. Multi-sensor measurement signals in time-frequency domain.

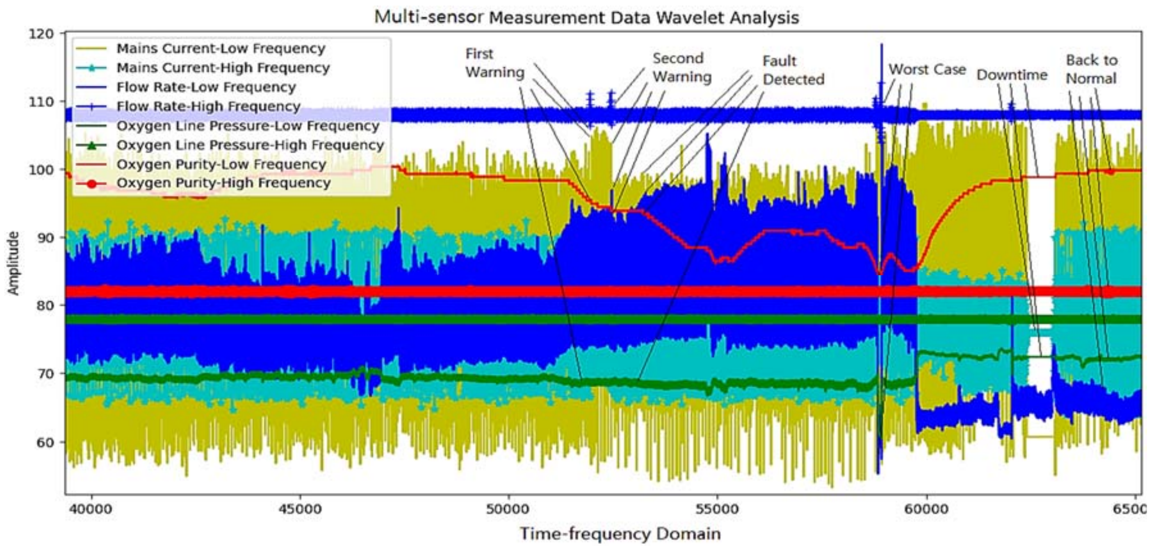

Fig. 10. Details of multi-sensor measurement signals in time-frequency domain.

As shown in Fig. 10, detailed information reflecting the change of operation conditions can be obtained in the low and high frequency components. It is noted that before faults are detected, there are two patterns that signify large changes of system conditions, at the same time, values of oxygen purity and oxygen line pressure keep decreasing. So by time, they are classified as first warning (start at data point 51948) and second warning (start at data point 52446). At data point 53284 fults are detected and triggered by low oxygen purity that is not acceptable. Then faulty condition continues and at data point 58908 it reaches the worst case when the values of oxygen purity and oxygen line pressure are both at their minimums. After that point, values of both oxygen purity and oxygen line pressure are increasing, but still conditions are not getting back to normal. At data point between 62400 and 63097, compressors stop and this is marked as downtime. Then compressors restart and eventually at data point 63856, flow rate has dropped, system is recovered and back to normal.

In faults prediction and detection, the presence of faults is verified in an unsupervised manner by abnormal/fault detection algorithms, but will be learnt and optimised later by the machine learning system. The system will also diagnose each fault and perform cause analysis based on importance ranking explained by the model library. As the extracted features can only indicate the presence of a fault, its type and cause still need to be found. While the most relevant feature that is considered as the fault present in the system, it is very often related to a potential or unique type of component fault, and also can be related to more than one fault, hence it is important to establish a human knowledge base to perform the explanability, from which the cause is analysed and error can be corrected.

For example, the above detected faults can be attributed to the high demand of oxygen at a special time, when the flow rate increased at a very high level, the system could not generate enough output due to the limited capacity of compressors and that would lead to a system failure, leading to a low oxygen purity and line pressure that were detected by the system as a fault. Before it happened, there were many features/signs that indicated the trending and thus warnings were given. This is learnt by the system so that knowledge is accumulated in the database for real-time decision-making.

Experimental results have demonstrated that by the trained DWNN with multi-sensor measurements, edge and cloud computing over the IoT communication networks, where the sensing capabilities and the computational power are provided by the designed controller, transmitter and cloud server to track everything that's relevant to operations, the real-time machine learning system can perform qualitative and quantitative data analysis to build the next generation decision support system that can monitor machine conditions, detect faults, predict and optimise system performance, action changes in a process to optimise the efficient use and operations of complex MIMO systems. Data analytics by deep learning can also help us to establish a knowledge base from which to correct errors, perform predictive maintenance procedures to prevent the failure without unnecessary interruptions, thus improve efficiency and maximize profitability.

6. Conclusions

Due to the difficulty in interpreting the multi-sensor data correctly and extracting the desired information, and the strong nonlinearity and its nearly instantaneous response to disturbances, it is still very challenging for system equipped with multiple sensors over IoT networks to achieve accurate faults prediction and optimised performance in complex multiple-input multiple-output (MIMO) systems. In this paper, the new data-driven model proposed is improving and dramatically changing the way that real-time faults prediction can be achieved through transforming the raw multi-sensor data into the time-frequency domain by developing fast lifting wavelet transform with computational efficiency to obtain a big feature vector containing all the relevant features from all of the sensors, and giving more informative signatures for faults prediction. To accurately predict and detect relevant status information of the actuators and to monitor the health status of specific components, the machine learning system developed, where the sensing capabilities and the computational power are provided by the designed controller, transmitter and cloud server to track everything that is relevant to operations, has enabled confident decision making, and faults prediction and predictive maintenance, which can be applied to coupled MIMO systems of complex industrial processes. By building IoT network to remotely collect data and developing deep wavelet neural networks (DWNN) with Gaussian (Mexican hat) wavelet derived as activation functions to improve nonlinear fitting and convergence speed, and to process the real-time data for faults prediction, data analytics can help establish a knowledge base from which to correct errors, perform predictive maintenance procedures to prevent the failure without unnecessary interruptions, thus to improve efficiency and maximize profitability.

Experimental results have demonstrated that by the trained DWNN with multi-sensor measurements, edge and cloud computing over the IoT communication networks, the real-time machine learning system can perform qualitative and quantitative data analysis to build the next generation decision support system that can monitor machine conditions, predict and detect faults, and optimise system performance, action changes in a process to optimise the efficient use and operations of complex MIMO systems.

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