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Research paper

Fault Detection in Thermoelectric Energy Harvesting of Human Body

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Abstract

Background and Objective: Human health is an issue that always been a priority for scientists, doctors, medical engineers, and others. A Wireless Body Area Network (WBAN) connects independent nodes (e.g. sensors and actuators) that are situated in the clothes, on the body, or under the skin of a person. In the 21st century, advent the technology in different aspects of human life caused WBAN has a special value in future medical technology. Energy harvesting from the ambient or human body for self-independent from the battery or power supply is an important issue in WBAN. Photovoltaic energy harvesting (PVEH), piezoelectric energy harvesting (PEH), RF energy harvesting (RFEH), and thermal electric energy harvesting (TEH) are some techniques used for energy harvesting in WBAN. Fault detection and diagnosis is an important problem in engineering. Engineers and researchers are always trying to find better ways to identify, detection, and control the fault in different systems.

Methods: We consider a thermal electric generator (TEG) for measurement energy harvested from the human body and power generation on people at different ambient conditions. Also, we used data reduction methods including principle component analysis (PCA), linear discriminant analysis (LDA), and neural network methods including PCA and MLP, LDA and MLP, Dynamic PCA and MLP, Dynamic LDA and MLP to fault detection for thermal electric generator (TEG).

Results: This study shows different data reduction algorithm, in the case studied in this paper, can detect well and nonlinear methods have a more accurate answer than linear methods but implementing the linear methods are easier.

Conclusion: According to simulation results, all the methods discussed in this paper are acceptable for fault detection. In this paper, we introduce data reduction linear and nonlinear algorithm as new methods for fault detection in WBAN.

Introduction

Fault detection and diagnosis means is a deviation from the acceptable range of the variable or parameter to be measured. In other words, a fault is one of the physical characteristics of the system compared to normal conditions. When safety and reliability are the main parameters of system quality, fault detection and diagnosis are a way to improve these indicators [2], [15], [22], [23]. Manage and predicting the fault in different systems is a crucial target in fault detection and diagnosis. Identifying the fault location cause to improve system safety and reliability [4]. Also, it can reduce system maintenance costs.

An accurate and fast fault identification method can prevent the fault from spreading in the system and its consequences. Using fault detection methods causes the performance of the monitored system and any faults in the system are notified to the control unit before it leads to irreparable accidents [6]-[9].

Wireless sensor networks (WSN) have important applications in the scientific, medical, commercial, and military fields. Its application in medicine is also significant. Transferring medical care from a hospital setting to a home environment is an opportunity for patients to make optimal use of hospital resources, detect medical symptoms earlier, and reduce care costs ultimately. Wireless body area network (WBAN) devices have a wide range of applications and most of them use batteries to supply power [16], [17]. Researchers and engineers are trying to use ambient energy and human body energy to eliminate the batteries [1], [3], [5].

A. Related Works

The recent years, there has been a literature review that has attempted to highlight the key finding regarding fault detection issues of WBAN. Among these, some well-cited papers [2], [6], [8], [15] fault detection on wireless sensor networks(WSN) and wireless body area networks (WBAN). Data reduction methods are based on classification [3], [4], [9]. The fault detection in WSN and WBAN is a challenging problem due to sensor resources limitation and the variety of deployment fields. Energy harvesting is a process of extracting various types of energy from the environment or the human body through various methods. Lack of need to replace worn-out batteries, reducing maintenance costs due to checking and replacing batteries for wireless networks and the use of medical devices that can be installed inside the body are important reasons for using energy harvesters. So, the development of low-consumption wearable medical devices provides the necessary energy for them from the body itself and the replacement of this method instead of using batteries [11]- [13].

In this paper, we consider a thermal electric generator and use energy harvesting data in four cases, including 1) Normal data, 2) Thermal harvester module fault data, 3) thermal electric generator (TEG) fault data and 4) DC-DC conversion fault data. Then, we use data reduction methods to separate the fault from the normal data, [11], [17], [22].

Most machine learning and data mining techniques may not be effective for high-dimensional data in fault detection. So, we use a feature reduction algorithm to improve performance. In this paper, we have some supervised data and expect the linear discriminant analysis (LDA) [10] to be a better result than other methods for supervised data. So, LDA is more suitable for detection. A multilayer perceptron (MLP) [14] is a class of feed-forward artificial neural network (ANN). We use PCA-MLP, LDA-MLP, Dynamic PCA-MLP, and Dynamic LDA-MLP as other methods [18]-[21].

TEG is a new technology and the fabricated samples did not have the desire performance. So, fault detection results not very acceptable. Fault detection methods may have different results for different devices. We use the linear and nonlinear algorithms and compare them to choose the best solution for this type of device. The purpose of this paper is to use some new solutions and algorithms based on feature extraction and neural networks for fault detection in TEG.

B. Contribution

This review paper highlights the overall fault detection of WBAN. In more concrete points, the contributions of this study are classification, data reduction, and wireless sensor networks.

C. Structure of the Paper

In this paper, we proposed new methods for fault detection in WBAN using data reduction algorithms. Moreover, we considered a TEG as a case study and show simulation results with a different algorithm. Finally, we will discuss the results and compare them. Also, the ability of these methods for fault detection was examined. This paper is organized as follows: The background of WBAN, fault detection, TEH, and control strategy, introduces the case study and their properties, explain the theory of PCA and LDA, simulation, results, conclusion and comparison between methods.

Background

The number of patients affected with chronic diseases is increasing day by day. Intermittent and transient faults are the largest source of failure for body sensor networks. A detailed overview of WBAN is presented in the next sub-section.

A. Wireless Body Area Network (WBAN)

WBAN is a collection of multiple sensors attached to or in the body, which are used to receive different physical parameters, such as body temperature, blood sugar level, heart rate, pulse rate, respiratory measurement, and even the amount of calories, burnt after exercise, etc. WBAN is not only used in medical applications but is also in multi-media and gaming applications. Several sources of non-electric renewable energy exist all around us. Power from these sources can be harnessed using appropriate hardware and converted to electrical form to fulfill energy requirements, referred to as energy harvesting. In general, energy harvesting in WBAN is classified into two-source, the human body, and the ambient. Energy source from the human body consists of a biochemical type such as Glucose, Lactate, and endocochlear potential, and biomechanical type such as blood pressure, heartbeat, breathing, and locomotion. Energy source from ambient include sun, RF, heat, motion, and other sources can be further minimized energy constraints.

B. Fault Detection

The fault is an unpermitted deviation of at least one characteristic property or variable of the system from standard behavior. Fault detection is a determination of faults present in the system and the time of detection. Fault can be also classified taking into account the time-variant behavior of a fault. Three classes include abrupt, incipient, and intermittent can be distinguished.

C. Thermoelectric Energy Harvesting (TEH)

Body energy harvesting is the primary alternative for batteries to enhance the functionality of wearable and wireless devices and has been the subject of many recent investigations. A large amount of human energy is released in the form of heat. Therefore, technologies for body heat harvesting using thermoelectric devices have been central for many investigations. The amount of generated power from thermoelectric energy harvesters depends on the size, position, type, and efficiency of the harvesters. The thermoelectric phenomenon has been known since the discoveries made by Seebeck in 1851, followed by Peltier in 1834 and Thomson in 1851. Thermoelectric materials provide reliable conversion of heat to electricity and vice versa.

D. Control Strategy

Generally, we have two main types of control for fault-tolerant, robust control, and adaptive control. Robust control is a fixed controller designed that tolerates changes of the plant dynamics. The controlled system satisfies its goals under all faulty conditions. Fault tolerance is obtained without changing the controller parameters.

It is, therefore, called passive fault tolerance. However, the theory of robust control has shown that robust controllers exist only for a restricted class of changes of the plant behavior that may be caused by faults. Further, a robust controller works suboptimally for the nominal plant because its parameters are fixed to get a trade-off between performance and robustness. Adaptive control is controller parameters adapted to changes of the plant parameters. If these changes are caused by some fault, the adaptive control may provide active fault tolerance.

However, the theory of adaptive control shows that this principle is particularly efficient only for plants that are described by linear models with slowly varying parameters. These restrictions are usually not met by systems under the influence of faults, which typically have a nonlinear behavior with sudden parameter changes.

Case Study

Thermoelectric energy harvesting of human body heat represents a promising alternative candidate for energy harvesting. This method is independent of external factors. One of the most common methods used in thermoelectric energy harvesting is a wearable thermoelectric generator (TEG) heating system. A thermoelectric generator is a device that includes two aluminum oxide ceramic headers and is surrounded by Polydimethylsiloxane (PDMS) to help insulate and reduce the amount of heat lost when transferred from the heat spreader to the TEG. TEG can be generally classified in m-TEG that have macroscopic thermolegs and are manufactured using classic fabrication technology, and μ-TEG that have a high number and density of TC and are produced with microfabrication techniques. In this paper, we consider a wristband that includes seven thermal harvester modules that their collection makes TEG. Another device we use in the wristband is DC-DC conversion. Each part thermal harvester module, thermal electric generator (TEG), and DC-DC conversion may have a problem and cause make fault for the system. Fault detection for energy harvesting from the body has some advantages such as:

- Since, energy harvesting from the body provides power supply, fault in the system cause power off the device.
- The cost of thermal harvester module, TEG, and DC-Dc conversion is high and it is not economical to replace them.
- Proper fault detection improves system performance.
- Fault detection can improve the WBAN device in the next versions.

Seven harvester modules can be attached to the wrist while maintaining high wearability and are connected electrically in series and thermally in parallel to maximize the produced open-circuit voltage. The thermal harvester is connected to a DC-DC conversion and energy storage circuit, an application circuit completes the device. All element integrates into an elastic band that wraps comfortably around the wrist. Figure 1 Shows TEG arrangement on the wrist.

Theory

We considered two types of the method include linear such as PCA, LDA, and nonlinear with help of the MLP algorithm. The base of nonlinear methods is usually neural networks. The expansion of fault detection in theory in various fields cause better efficiency of methods in practice. In this section, we will discuss the theory of linear methods.

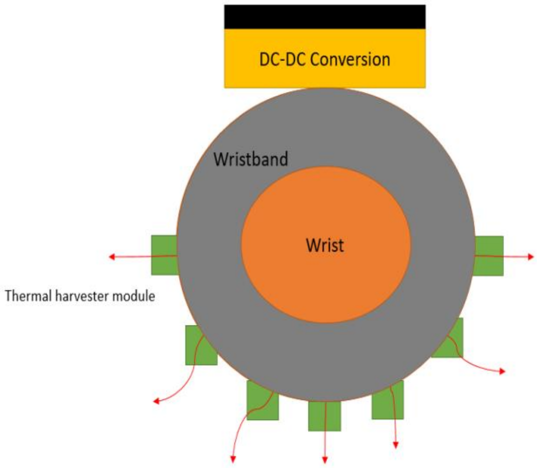

Fig. 1: TEG arrangement on the wrist.

A. Principle Component analysis theory

Principle component analysis consists of n sampled data that each of them containing m of the selected variable.

The data set can be displayed as: $X \in R^{n\times m}$. First, the mean of the data is calculated by using (1) and the variance values of the data are calculated using Equations (2), (3), and (4). The Table 1 Shows the frequency-time indicators.

We will use a table 1 Properties in PCA and LDA algorithms.

$$\overline{X}(m)=\sum_{j=1}^{m}\frac{\sum_{i=1}^{n}X(i,j)}{n} \tag{1}$$

$$\text{X(n,m)}=\sum_{j=1}^{m}\sum_{i=1}^{n}\{X(i,j)-\overline{X}(j)\} \tag{2}$$

$$\text{X(m)}=\sum_{j=1}^{m}\sqrt{\frac{1}{n}\sum_{i=1}^{n}\{X(i,j)-\overline{X}(j)\}^2} \tag{3}$$

$$\text{X(n,m)}=\sum_{j=1}^{m}\sum_{i=1}^{n}\{X(i,j)/\sigma_x(j)\} \tag{4}$$

then, the covariance matrix of the data is calculated using (5).

$$\text{C}=\frac{1}{n-1}X^TX \tag{5}$$

The singular values of the above covariance matrix are:

$$\text{C}=\text{V}\Lambda\text{V}^T \tag{6}$$

In (6), Λ is a diagonal matrix that contains the eigenvalues of the covariance matrix. V is a matrix of eigenvectors for Covariance matrix C. In this solution, by arranging the matrix of eigenvalues from larger to smaller, the main components are identified.

In fact, the eigenvalue in each row is related to the number of that component.

Table 1: frequency-time indicators

Feature	Equation
peak to peak	$\lvert\max(X_i)-\min(X_i)\rvert$
RMS	$\sqrt{\frac{1}{N}\sum_{N=1}^{N}(X_i)^2}$
Kurtosis	$\frac{\frac{1}{N}\sum_{N=1}^{N}(X_i-\bar{X})^4}{(\frac{1}{N}\sum_{N=1}^{N}(X_i-\bar{X})^2)^2}$
Crest factor	$\frac{\mathrm{X_{peak}}}{\mathrm{X_{RMS}}}$
Skewness	$\frac{\frac{1}{N}\sum_{N=1}^{N}(X_i-\bar{X})^3}{(\frac{1}{N}\sum_{N=1}^{N}(X_i-\bar{X})^2)^{3/2}}$
Impulse factor	$\frac{X_{peak}}{\frac{1}{N}\sum_{N=1}^{N}\lvert X_i\rvert}$
Average power	$\int_0^{f_{\max}}S_x(f)df$
Mean Frequency	$\frac{\int_0^{f_{\max}}f*S_x(f)df}{P_x}$
Median frequency	$\int_0^{f_{maz}}S_x(f)df=\int_{f_{med}}^{f_{maz}}S_x(f)df$

B. Linear discriminant analysis theory

The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible. LDA tries to make the classes very crowded in the destination space and classed be scattered.

In other words, maximize the following cost function:

$$J(w)=Max\frac{W^TS_BW}{W^TS_WW} \tag{7}$$

S_B is a scattering matrix between classes and defined as follows:

$$\text{S}_B=\sum_{i=1}^{C}N_i(\mu_i-\mu)(\mu_i-\mu)^T \tag{8}$$

$$\mu=\frac{1}{N}\sum_{\forall x}x \tag{9}$$

$$\mu=\frac{1}{N_i}\sum_{\forall x\in\omega_i}x \tag{10}$$

S_W is the scattering matrix in the classes and defined as follows:

$$S_W = \sum_{i=1}^{C} S_i \quad (11)$$

$$S_i = \sum_{\forall x \in \omega_i} (x-\mu_i)(x-\mu_i)^T \quad (12)$$

Prove the optimal W for the optimization problem posed in (7) is equal to the vector of the properties corresponding to the largest value properties of the matrix is $S_W^{-1} S_B$. In the next part, we use linear and nonlinear methods in simulation, show results, and discuss them. Fig. 2 shows the simulation methods diagram include PCA, LDA, MLP-PCA, MLP-LDA, MLP-DPCA, and MLP-DLDA.

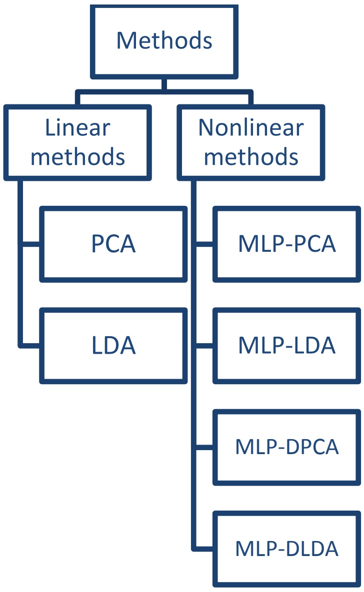

Fig. 2: Simulation methods diagram.

Simulation and Results

The purpose of using fault detection methods is advanced monitoring, fault management, improve reliability, accessibility, and optimal maintenance. Researchers use a variety of methods and algorithms for fault detection in different systems but in general, fault detection methods are divided into two main groups based on signal analysis and based on the process model. In methods based on signal analysis, one or more measurable signals in the system are analyzed using various algorithms such as PCA or LDA and any unauthorized change in signal properties indicates a fault in the system. Signal-based methods are the most common methods of fault detection. In this paper, we used signal-based methods with the linear algorithm include PCA and LDA and nonlinear algorithms include PCA-MLP, LDA-MLP, Dynamic PCA-MLP, and Dynamic LDA-MLP.

In the following, we analyze each of this algorithm:

A. Principle Component Analysis (PCA)

Principle component analysis is a simple way to extract important variables from a large set of variables in a data set. PCA method extracts a low-dimensional set of features from a high-dimensional set to analyze more information with fewer variables. In the PCA algorithm, we must first obtain the covariance matrix and then calculate the eigenvalues and eigenvectors. If the scale of the properties is very different, we use the time characteristics of the signal to synchronize. In our case study, scale properties not very different. So, we consider linear PCA without the time characteristics of the signal. The results are shown in Fig. 3 and Fig. 4.

Fig. 3: Train data after linear PCA.

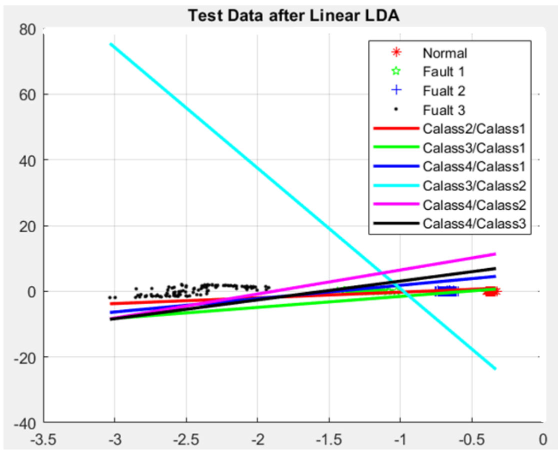

Fig. 4: Test data after linear PCA.

The results show that data have good separable and fault detection with linear PCA algorithm is a good solution for this problem.

In our case study, results show good detection and identification. Scattering between DC-DC conversion is more than the other class.

B. Linear Discriminant Analysis (LDA)

LDA is a statistical method to reduce the size of data and identify classes by maximizing the ratio of scatters between groups to scatters within groups. LDA method is similar to the method used by Ronald Fisher to determine the degree of differentiation between groups and became the basis for the analysis of variance. The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible. The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible. The solution proposed by Fisher is to maximize a function that represents the difference between the means, normalized by a measure of the within-class scatter. Table 2 shows the pseudocode of the LDA algorithm.

LDA has some limitations such as:

- LDA produces at most C-1 feature projections.
- LDA is a parametric method since it assumes unimodal Gaussian likelihoods.
- LDA will fail when the discriminatory information is not in the mean but rather in the variance of the data.

Variants of LDA include non-parametric LDA, orthonormal LDA, generalized LDA, and multilayer perceptrons. One of the disadvantages of the LDA method is that the maximum number of dimensions creates C-1, which C is the number of classes and if the number of classes is small, but the number of features is large, it will not be a good result.

Algorithm 1. LDA

Input: The Total data in N classes

Output: Classified data

1. Compute the average of each class and the average of total data from (9) and (10).
2. Normalize the data.
3. Compute between class scatter and in the class scatter by (8) and (11).
4. Compute eigenvalue and eigenvector of $S_W^{-1}S_B$.
5. Consider the eigenvectors corresponding to the eigenvalues that are bigger than others as optimal W.
6. Solve the optimazation problem by a linear classifier.

Table 2. **Pseudocode of LDA.**

The second limitation for the LDA is a response to be optimal, the data must be Gaussian, otherwise, a good response may not be obtained or even a very bad response may be obtained. Third, if the information is not averaged but is scattered, then the LDA would be wrong. In supervised data, the LDA method is a proper way to feature reduction and fault detection. Train data and test data after the LDA result shown in Fig. 5 and Fig. 6. The Linear LDA result shows better classification than the linear PCA. Although, both methods show good results and fault detection has been acceptable in both methods.

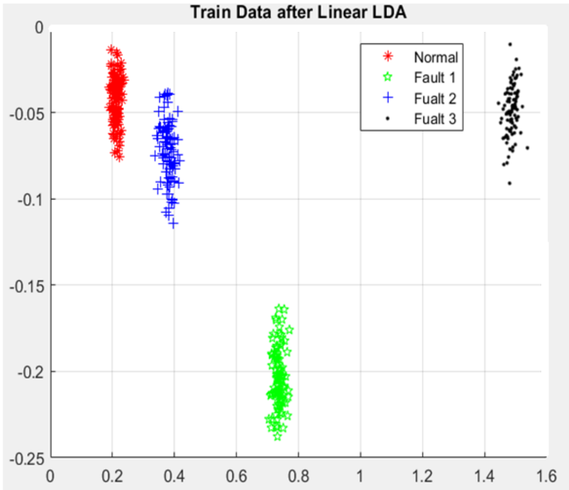

Fig. 5: Train data after linear LDA.

C. PCA and MLP

Multilayer perceptron (MLP) is a class of feedforward artificial neural networks (ANN). In an MLP, there will be at least three-node layers:

- Input Layer
- Hidden Layer
- Output layer

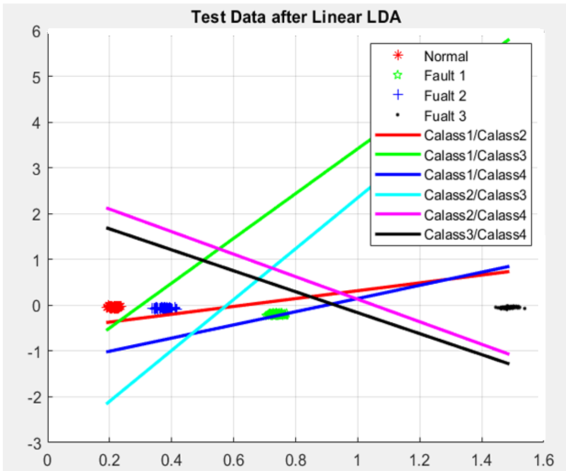

Fig. 6: Test data after linear LDA.

Neural network nodes, called neurons, are the computational units in a neural network. In the neural networks, the outputs of the first layer (input) are used as the inputs of the next layer (hidden). After a certain number of layers, the output of the last hidden layer is used as the input of the output layer. We obtain the optimal number of neurons in the middle layer. The method of network training is the Levenberg-Marquardt algorithm. Figure 7 is shown the neural network schematic used in this problem.

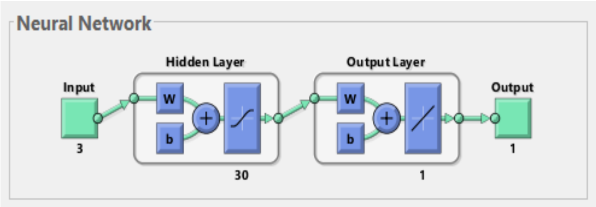

Fig. 7: Neural network schematic.

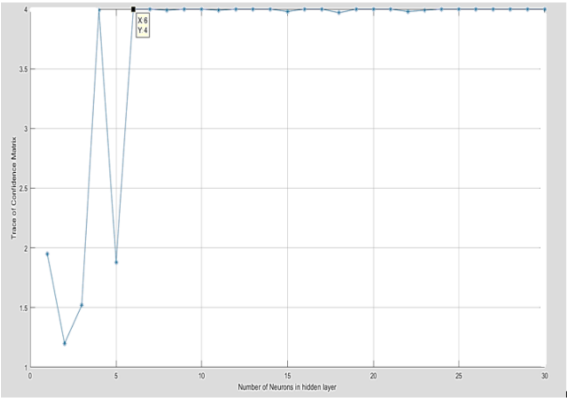

Fig. 8: Trace of confidence matrix for different number of middle layer neurons.

Table 3: Confidence matrix

	Normal	Fault1	Fault2	Fault3
Normal	1	0	0	0
Fault1	0	1	0	0
Fault2	0	0	1	0
Fault3	0	0	0	1

As shown in Fig. 8, the optimal value for middle layer neurons is 6. The classification results for 6 neurons in the middle layer are shown in Table 3. It can be seen due to the sum of the elements on the original diameter, the nonlinear MLP method gives a good answer like the linear data methods. The reason for this increase in diagnostic accuracy is the nonlinear activator function used in the neural networks.

D. LDA and MLP

In this section, we use the neural network as a classifier. Moreover, feature vectors are reduced with the LDA method that is considered as the input of the neural network. Train and find optimal neurons are like part C. The method of network training is the Levenberg-Marquardt algorithm.

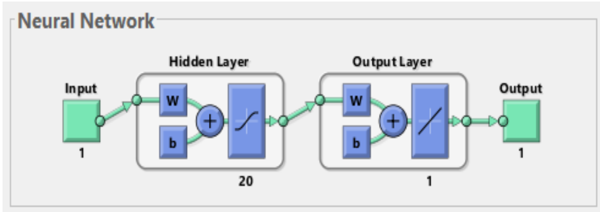

Fig. 9: Neural network schematic

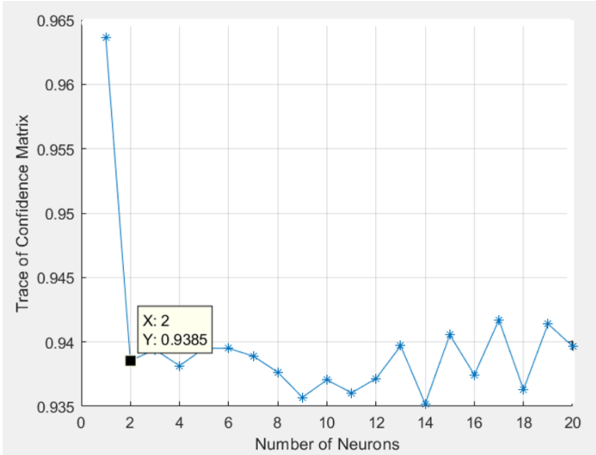

Fig. 10: Trace of confidence matrix for different number of middle layer neurons

Figure 9 is shown the neural network schematic used in this problem. According to Fig. 10, the number of optimal neurons in the middle layer is 2. The confidence matrix is shown in Table 4.

Table 4: Confidence matrix

	Normal	Fault1	Fault2	Fault3
Normal	1	0	0	0
Fault1	0	1	0	0
Fault2	0	0	1	0
Fault3	0	0	0	1

According to Fig. 10, the number of optimal neurons in the middle layer is 2. The confidence matrix is shown in Table 3.

E. Dynamic PCA (DPCA) and MLP

A novel dynamic PCA (DPCA) algorithm is proposed to extract explicitly a set of dynamic latent variables with which to capture the most dynamic variations in the data. Dynamic Principal Component Analysis (*DPCA*) and Artificial Neural Networks (*ANN*) are compared in the fault diagnosis task. Both approaches are processed history-based methods, which do not assume any form of model structure and rely only on process historical data. Furthermore, the neural networks classifier is trained by a Multilayer perceptron (MLP).

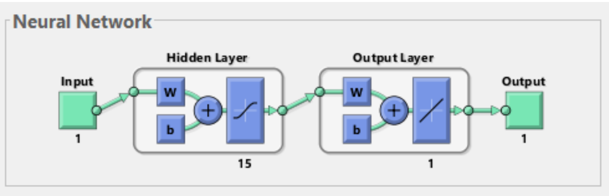

Fig. 11: Neural network schematic.

Table 5: Confidence matrix

	Normal	Fault1	Fault2	Fault3
Normal	1	0	0	0
Fault1	0	1	0	0
Fault2	0	0	1	0
Fault3	0	0	0	1

Figure 11 is shown the neural network schematic. As shown in Fig. 12, the optimal value for middle layer neurons is 2. The classification results for 2 neurons in the middle layer are shown in Table 5. The sum of the elements on the original diameter shows the nonlinear MLP method is a good answer like the linear method.

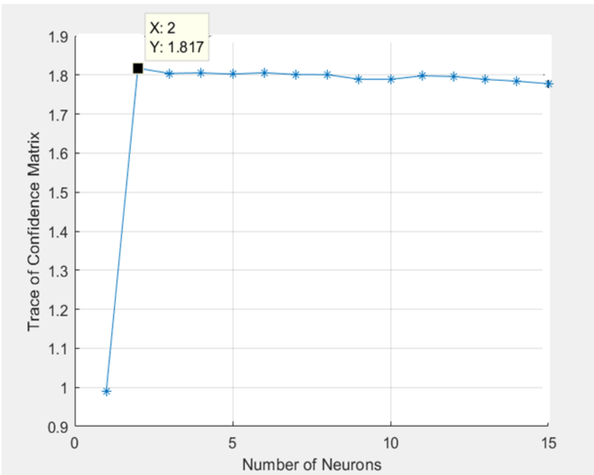

Fig. 12: Trace of confidence matrix for different number of middle layer neurons.

F. Dynamic LDA (DLDA) and MLP

Dynamic networks are networks that contain delays or integrators for continuous-time networks and that operate on a sequence of inputs. In this section before reducing the dimension, we add the delay of the feature to findings the feature space and then apply the LDA dimension reduction algorithm to large data.

The goal of the Dynamic LDA and MLP methods is to reduce dimension and classification. So, we have three optimal value parameters; include:

- Number of middle layer neurons for the MLP neural network
- Number of eigenvectors corresponding to large eigenvalues in Dynamic LDA
- The optimal amount of delay for the Dynamic LDA method

The method of network training is the Levenberg-Marquardt algorithm. Figure 13 is shown the neural network schematic used in this problem.

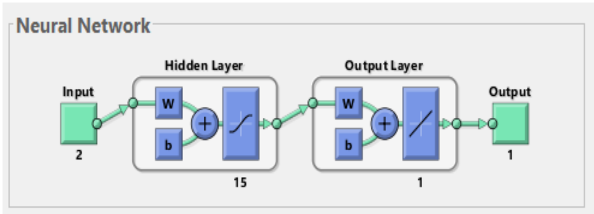

Fig. 13: Neural network schematic.

According to Fig. 14, the number of optimal neurons in the middle layer is 6. The confidence matrix is shown in Table 6.

The ideal state of separation in MLP methods is to maximize the diagonal of the confidence matrix. The diagonal matrix is the best result of the separation. So, fault detection is well detected in all methods.

If data are separable, use the linear and nonlinear methods to give us the desired answer. Therefore, the optimal design and fabrication can improve the efficiency of the devices, and fault detection is more easily.

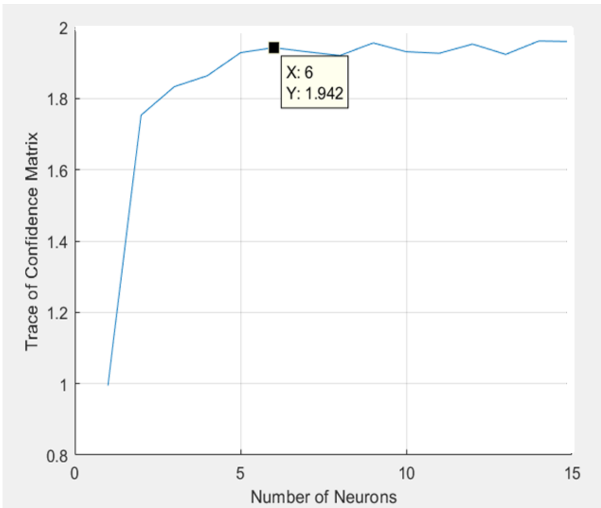

Fig. 14: Trace of confidence matrix for different number of middle layer neurons.

Table 6: Confidence matrix

	Normal	Fault1	Fault2	Fault3
Normal	1	0	0	0
Fault1	0	1	0	0
Fault2	0	0	1	0
Fault3	0	0	0	1

Conclusion

In modern industry, fault detection and isolation (FDI) is very important to enhance the system reliability, prevent serious system performance deterioration, and to ensure optimal process operation. In this paper, some classification approach has been proposed for fault detection in a case study of WBAN. Our proposed solution is based on PCA, LDA, and MLP techniques. Due to the high importance of medical technologies and their relationship with human health, rapid fault detection in these systems is vital.

We considered supervised data from a wristband in modes normal, thermal harvester module fault, TEG fault, and DC-DC conversion fault. Then analyzed this data with help of the linear methods include linear PCA and linear LDA and nonlinear methods with help of neural networks include PCA-MLP, LDA-MLP, Dynamic PCA-MLP, and Dynamic LDA-MLP algorithms. Results show fault in all methods were well detected. We expected the LDA method has the best solution because this method can detect supervised data well. Although, data were good separable and faults were well detected in all methods. In the nonlinear method is difficult to predict the best algorithm between different methods because the neural network follows a nonlinear function and forecasting nonlinear function is too difficult. Results are shown linear LDA is better detection than linear PCA but in general, the nonlinear methods show better results than linear methods. However, we choose the ideal state of confidence matrix with random parameters in the nonlinear methods. The data used were reasonably separable and this is a good reason for the accuracy of the results.

Table 7: Compare between methods

	Fault detection	Linear method	Nonlinear method	Optimal result	Fixed result	Random result	good efficiency
PCA	✓	✓			✓		✓
LDA	✓	✓			✓		✓
PCA-MLP	✓		✓	✓		✓	✓
LDA-MLP	✓		✓	✓		✓	✓
DPCA-MLP	✓		✓	✓		✓	✓
DLDA-MLP	✓		✓	✓		✓	✓

The comparison between methods is shown in the Table 7.

The mentioned results can be developed and used in WBAN.

Author Contributions

Every author has equally contributed to accomplish the targeted results.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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