Deep Belief Network Based State Classification for Structural Health Diagnosis

Prasanna Tamilselvan
Wichita State University
1845 Fairmount St
Wichita, KS 67260
316-200-7549
pxtamilselvan@wichita.edu

Yibin Wang
Wichita State University
1845 Fairmount St
Wichita, KS 67260
661-754-2543
yxwang5@wichita.edu

Pingfeng Wang
Wichita State University
1845 Fairmount St
Wichita, KS 67260
316-978-5910
pingfeng.wang@wichita.edu

Abstract— **Effective health diagnosis provides multifarious benefits such as improved safety, improved reliability and reduced costs for the operation and maintenance of complex engineered systems. This paper presents a novel multi-sensor health diagnosis method using Deep Belief Networks (DBN). The DBN has recently become a popular approach in machine learning for its promised advantages such as fast inference and the ability to encode richer and higher order network structures. The DBN employs a hierarchical structure with multiple stacked Restricted Boltzmann Machines and works through a layer by layer successive learning process. The proposed multi-sensor health diagnosis methodology using the DBN based state classification can be structured in three consecutive stages: first, defining health states and preprocessing the sensory data for DBN training and testing; second, developing DBN based classification models for the diagnosis of predefined health states; third, validating DBN classification models with testing sensory dataset. The performance of health diagnosis using DBN based health state classification is compared with support vector machine technique and demonstrated with aircraft wing structure health diagnostics and aircraft engine health diagnosis using 2008 PHM challenge data.**

Index Terms— **Fault diagnosis, artificial intelligence in diagnostic classification, deep belief networks.**

ACRONYMS

BNN	=	back-propagation neural network
DBN	=	deep belief networks
GA	=	genetic algorithm
HS	=	health state
MD	=	Mahalanobis distance
PHM	=	prognostics and health management
RBM	=	restricted Boltzmann machine
SVM	=	support vector machine
SOM	=	Self-Organizing Map

NOTATION

x_i	=	p-dimensional vector
c_i	=	i^{th} class label
μ_j	=	mean vector of the training data
S_j	=	variance matrix of the training data
w_{ij}	=	synaptic weight between the i^{th} and the j^{th} neurons
s_i	=	state of the i^{th} neuron
$P(\cdot)$	=	probability distribution function
b_i	=	bias of the i^{th} neuron
w_{ij}	=	synaptic weight between the i^{th} and the j^{th} neurons
h_i	=	state of the i^{th} neuron in hidden layer
v_i	=	state of the i^{th} neuron in visible layer

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I. INTRODUCTION

EFFECTIVE health diagnosis provides multifarious benefits such as improved safety, improved reliability and reduced costs for the operation and maintenance of complex engineered systems. Research on real-time diagnosis and prognostics which interprets data acquired by smart sensors and distributed sensor networks, and utilizes these data streams in making critical decisions advances significantly across a wide range of applications [1]. Maintenance and life-cycle management is one area that is positioned to significantly benefit in this regard due to the pervasive nature of design and maintenance activities throughout both the manufacturing and service sectors. Maintenance and life-cycle management activities constitute a large portion of overhead costs in many industries [2]. These costs are likely to increase due to the rising competition in today's global economy. In the manufacturing and service sectors, unexpected breakdowns can be prohibitively expensive since they immediately result in lost production, failed shipping schedules, and poor customer satisfaction. In order to reduce and possibly eliminate such problems, it is necessary to accurately assess the current state of system degradation through effective health diagnosis. Two major research areas have tried to address these challenges: reliability and condition monitoring. Although reliability and condition monitoring are seemingly related, reliability focuses on population-wide characteristics while condition monitoring deals with component-specific properties. Furthermore, both fields of research have evolved separately. Research in the reliability area can be broadly classified into two subcategories. One category focuses on quantification of reliability and statistical analysis of time-to-failure data, such as [3] while the other deals with the development of physics-based models (e.g., fatigue, wear, and corrosion). In contrast, condition monitoring research uses sensory information from functioning system to assess their degradation states. Continuous monitoring of current health states through multi sensors notifies the performance degradation of component at both early and advanced stages of damage. Real time diagnosis of sensory data acquired from the overall sensor network and data analysis helps to make crucial decisions on significant improvement over wide range of applications. Some of the successful applications of condition monitoring include condition monitoring of bearings [6], machine tools [8], transformers [9], engines [10], and turbines among many others. Despite the success, effective diagnosis of current health state from the sensory data from multiple sensors is still an intricate problem and remains as a major challenge for the application of condition monitoring technique to complex engineered systems, mainly due to the complexity of the system and the heterogeneity of acquired sensory data. Thus, one of the most important tasks in multi sensor health diagnosis is to develop diagnostic procedure which can handle heterogeneous multi sensor signals and classify different health states based on the acquired sensory signals.

Despite the challenges faced in system health diagnosis, there is another isolated group of research specific to pattern classification in image processing field which specializes mainly on the classification process. The problems faced in health diagnosis of system with heterogeneous multi-sensor data are more similar to the pattern classification problems with high dimensionality of data. In both cases, the learning complexity grows exponentially with the increase of heterogeneity and dimensionality of acquired sensory data[10][11]. The analysis of these identical problems in different applications motivated to the emergence of perfect collaboration in their learning techniques. In the past decade, pattern classification technique moved into the new platform of learning procedure called deep machine learning [11]. Therefore, there is a critical requirement of utilizing the advantages of deep machine learning techniques into the system health diagnostics. Current research work in the diagnostic classification with system health management does not utilize the advantages of evolving deep machine learning process. Thus, this study proposes an efficient way to utilize the benefit of deep machine learning process to handle the complexity of sensory signals for the application of structural health diagnosis.

This paper presents a novel deep machine learning method, Deep Belief Networks (DBN) to handle multi-sensor health diagnosis state classification. DBN has recently become a popular approach in machine learning for its promised advantages such as fast inference and the ability to encode richer and higher order network structures. The DBN works based on the Restricted Boltzmann Machine and learns layer by layer of the deep network. The proposed diagnostic methodology can be structured in three consecutive stages: first, defining health states and preprocessing the sensory data for DBN training and testing; second, developing DBN based classification models for the diagnosis of predefined health states; third, validating DBN classification models with testing sensory dataset. The performance of health diagnosis using DBN based health state classification is compared with five existing classification methods and demonstrated with two case studies. The rest of the paper is organized as follows: Section 2 presents the related work of health diagnosis with existing state of the art classification techniques; Section 3 details the proposed health diagnosis approach with DBN based classification; Section 4 demonstrates the developed diagnosis approach with case studies; Section 5 summarizes the presented research and the future work.

II. RELATED WORK

Due to the complexity of system degradation characteristics and potential heterogeneity of sensory signals, multi-sensor health diagnosis of complex engineered systems remains as an intricate problem. Consequently, machine learning techniques and statistical inference techniques are often employed to solve this problem. Significant advances have been achieved of applying classification techniques based on machine learning or statistical inferences, which result in a number of state-of-the-art health state classification methods, such as the back-propagation neural network (BNN) [12], self-organizing maps (SOM) [15], genetic algorithm (GA) [16], the support vector machine (SVM) [13], and the Mahalanobis distance (MD) [18]. This section surveys the current literature and briefly discusses the working principle and capabilities of the different existing classification techniques.

The machine learning diagnosis methodology can be broadly classified into supervised and unsupervised learning techniques. This paper focuses on the supervised learning process in diagnostic classification. The supervised learning is the process of learning a relationship between the input value and the desired target value in the form of set of patterns having both input object and the desired target output. The error values are evaluated and given as feedback to the learning model to get potential solution. The learnt relationship/function from the training data is used as a classifier model to predict the unlearnt and unknown patterns. The diagnosis methodology employing the artificial neural network is the imitation of working technique of human brain's neural network. The artificial neural network technique can be broadly divided into two types of important classification techniques: the BNN and the SOM. BNN is a supervised learning technique which possesses a basic neural network structure with three different types of layers: the input layer, the output layer and the hidden layers [12]. BNN model is trained by optimizing the synaptic weights and biases of all neurons till a desired classification rate is obtained. Using BNN, the health diagnosis problem is solved as the health state prediction problems by neural networks. Compared with the BNN, SOM also works based on neurons. However, it is an unsupervised learning technique. The SOM training process determines a closest best-matching unit distance to the input vector [15], which will be used to construct class boundaries graphically on a 2 dimensional map. The complexity of distance determination increases with close classification criterion. The BNN and the SOM have been used as state classification methods for the health diagnosis applications [12]. The main drawback of the BNN and SOM is the over-fitting of the data to the classification model and leads to the significant error values in complex scenarios. The AI research was further developed to the evolutionary optimization technique, GA which work based on the process of gene evolution [16]. This evolution involves four important processes: inheritance, mutation, selection, and crossover [16]. The GA training process used for diagnosis and predicting the health state of the system becomes more complex with increasing heterogeneous nature of sensory signals.

The SVM is a state-of-the-art technique for multi-dimensional classification based on supervised learning. The SVM method will be used later in Section 4 of this paper for the comparison study with the proposed multi-sensor health diagnosis approach using DBN based state classification. The SVM organizes input data D into two sets of vectors in an n-dimensional space as

$$D = \{(\mathbf{x}_i, c_i) \mid \mathbf{x}_i \in R^p,\ c_i \in \{0,\ 1,\ 2\},\ i = 1, 2,\ \ldots,\ n\ \} \quad (1)$$

where the c_i is i^{th} class label (e.g., 0, 1, or 2), indicating the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a p-dimensional real vector, shows the preprocessed p-dimensional sensory data. With the organized input data, the SVM constructs hyper-planes with maximum margins to divide data points with different c_i values. A hyper-plane can be written as a set of points $\mathbf{x}$ satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0 \quad (2)$$

where vector $\mathbf{w}$ is a normal vector that is perpendicular to the hyper-plane. The parameter $b/\|\mathbf{w}\|$ determines the offset of the hyper-plane from the origin along the normal vector $\mathbf{w}$. We want to choose the $\mathbf{w}$ and b to maximize the margin, or distance between the parallel hyper-planes of the margin. The optimization problem is defined as

$$\begin{aligned} &\text{minimize} \quad \tfrac{1}{2}\|\mathrm{w}\|^2 \\ &s.t. \quad c_i\left(\mathrm{w} \cdot \mathrm{x}_i - b\right) \geq 1 \end{aligned} \quad (3)$$

Solving the optimization problem above will eventually provide a set of optimized $\mathbf{w}$ and b that define the classification margins [14].The above described methods, the BNN, the SOM, the GA and the SVM, are different machine learning techniques for health state classification. Unlike these methods, the MD is a classification technique based on statistical inference using the statistical distance measure. The MD measure shows the degree of the deviation of the measured data point $\mathbf{x}_j$ from a reference training set ($\boldsymbol{\mu}$), which can be calculated as

$$D(\mathbf{x}_j) = \sqrt{(\mathbf{x}_j - \boldsymbol{\mu}_j)^T \mathbf{S}_j^{-1} (\mathbf{x}_j - \boldsymbol{\mu}_j)} \quad (4)$$

Where $\mathbf{x}_j = (x_1, x_2,\ \ldots,\ x_n)$ is a multi-dimensional data vector, $\mu$and $\mathbf{S}$ are the mean vector and variance matrix of the reference training data set. Wang *et al* classified different health states using this statistical measure and the testing dataset was classified into one health state with a minimum MD measure [18]. The advantages and potentiality of different algorithms can be combined to overcome some of the drawbacks of the existing algorithms. Some of the researches combined two or more existing machine learning techniques to form hybrid AI models of different AI algorithms. Zhang *et al* proposed a bearing fault diagnosis methodology using multi-scale entropy (MSE) and adaptive neuro-fuzzy inference system [19]. Saimurugan *et al.* presented a multi component fault diagnosis of rotational mechanical system based on decision tree and support vector machine [20].

Despite the demonstrated applicability of the above mentioned classification methods, continuous health monitoring through multi-sensor health diagnosis remains as one of the challenge problems to be addressed in the field of state classification and health degradation detection[21].In general, the complexity of the classification models increase with increase in number of sensors and heterogeneity of sensory signals. There is another set of research in the field of classification techniques apart from condition monitoring and diagnostics health management, which is pattern recognition and classification in image processing field and from which we could use its potentiality and capability to the diagnostics health management area. The problems faced in the diagnostic classification problem with multi sensors are much more comparable to the pattern classification problems with high dimensionality of the data. To address these problems, pattern classification in last decade entered into a novel paradigm in artificial intelligence learning procedure called deep machine learning technique. The requirement of handling multiple heterogenetic sensory signals in the diagnostic classification and the advantage of deep machine learning techniques to handle high dimensionality of data motivated to the emergence of perfect collaboration in their learning techniques. Current literature in the diagnostic classification with system health management does not utilize the advantages of evolving deep machine learning process; therefore, this paper proposes an efficient way to utilize the benefit of deep machine learning process to handle the complexity of sensory signals in diagnosis process.

Multi layered deep networks enhance the classification capability for complex problems. DBN follows non-local generalization unlike other machine learning methods such as support vector machine, Gaussian process and Kernel PCA [22]. Local generalization does not handle complex varying functions of variables. DBN support complex situations and classification of closer classes. DBN is the recent offspring of supervised machine learning with deep learning capability, fast inference, fast unsupervised learning and the ability to encode richer and higher order network structures [22]. The following section details the health diagnosis approach using the DBN based state classification.

III. System Health Diagnosis Using DBN

This section details the proposed multi-sensor health diagnosis approach using DBN based state classification. Subsection A overviews the DBN architecture and the methodology involved in DBN machine learning. Subsection B presents the learning function and the validation process of DBN for health state classification. Subsection C presents the overall procedure of proposed multi sensor health diagnosis approach using DBN based state classification.

A. Deep Belief Network Architecture

This subsection introduces the DBN architecture and the general methodology involved in the DBN machine learning. DBN employs a multilayered architecture which consists of one visible layer and multiple hidden layers as shown in Figure 1. Visible layer of DBN accepts the input data and transfers the data to the hidden layers in order to complete the machine learning process [22]. The DBN structure is similar to the stacked network of the Restricted Boltzmann Machine (RBM) [23]. Each RBM consists of two layers, namely visible layer and hidden layer. As noted by the name, the connections between the nodes within each RBM layer (visible layer or hidden layer) are restricted. The process of transformation of data from visible layer to the hidden layer is finished through a sigmoid activation function based on RBM learning rule [23]. An example DBN structure is shown in Figure 1. It consists of three stacked RBMs, as layer 1 (visible layer) and layer 2 (hidden layer 1) forms the first RBM 1, layer 2 (hidden layer 1) and layer 3 (hidden layer 2) forms the second RBM, and layer 3 (hidden layer 2) and layer 4 (hidden layer 3) forms the third RBM.

Each successive layer in the DBN follows the same transformation concept and passes the regularity throughout the DBN architecture [24]. The overall learning process of the DBN classifier model is described by the flowchart shown in Figure 2. As shown in the figure, the model inputs include preprocessed batch data, total number of layers in the DBN classifier model, total number of hidden neurons in each hidden layer and maximum number of epochs for the training process. These input parameters are initialized before the start of the training process. Each layer of the DBN is trained using the RBM learning rule and data is transferred from bottom visible layer (data layer) to higher invisible layers throughout the DBN architecture [22]. Weights between visible and hidden layers and biases of the neurons in each DBN layer are optimized until the minimum training error is achieved. The learning process continues through an iterative process from a lower layer to a higher layer till the maximum number of layers is trained. During the DBN layer by layer training process, each RBM is individually trained and the weights and biases are saved for further analysis. Notice that the DBN layer by layer training is an unsupervised learning process where the class labels of the training data are not provided. The label information of the training data will be used during the succeeding supervised learning process, namely the back-propagation classification training. Detail steps involved in the RBM training process are explained in the following subsection.

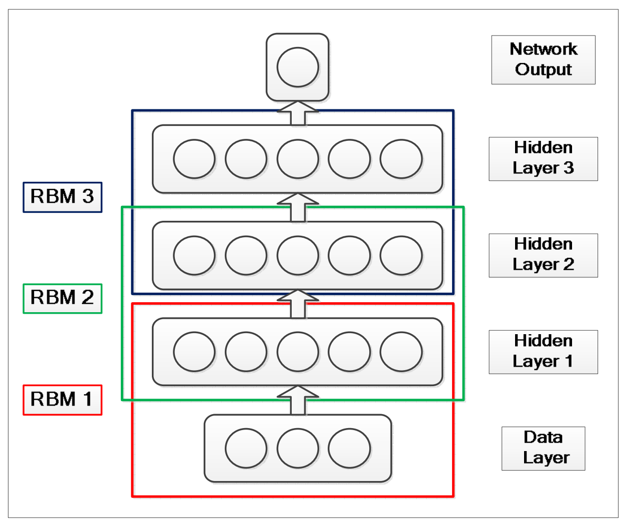

Figure 1: Deep Belief Network Structure

B. Training and Validation of DBN Classifier Model

This subsection discusses the training and validation methodology for DBN classifier models. As discussed in subsection A, the DBN is structured with stacked RBMs. Hence, the training process of DBN classifier model is completed through training each RBM structure individually and sequentially using the RBM learning rule. Each RBM unit consists of two layers and a number of neurons in each layer. There is no synaptic weight connection between neurons within the same layer. Thus, the major training parameters considered in the RBM training process are the synaptic weights between layers and the states and the bias of neurons. The state of each neuron in one RBM layer is determined successively through transforming the states and bias of the neurons from the prior layer with corresponding synaptic weights to the successive layer. The transformation function used in the training process is the sigmoid function [23] as:

$$P(s_i = 1) = \frac{1}{1 + \exp(-b_i - \sum_j s_j w_{ij})} \tag{5}$$

Figure 3 shows the iterative learning process for the RBM units. At the beginning of this training process, the synaptic weights and biases of all neurons in each RBN layer are initialized. After the initialization, the RBM units will be trained iteratively with input training data. Each training epoch consists of two phases, the positive phase and the negative phase. The positive phase transforms the input data from the visible layer to the hidden layer whereas the negative phase converts the data from the hidden layer to the successive visible layer. The positive and negative phases of RBM learning can be expressed mathematically as Eqs. (6) and (7) respectively [26]. Eq. (6) denotes the sigmoid transformation of the hidden layer state to the visible layer state and Eq. (7) shows the sigmoid transformation of the visible layer state to the hidden layer state.

$$P(v_k = 1 \mid h) = sigm(-b_k - \sum_j h_j w_{jk}) \tag{6}$$

$$P(h_j = 1 \mid v) = sigm(-c_j - \sum_j v_j w_{jk}) \tag{7}$$

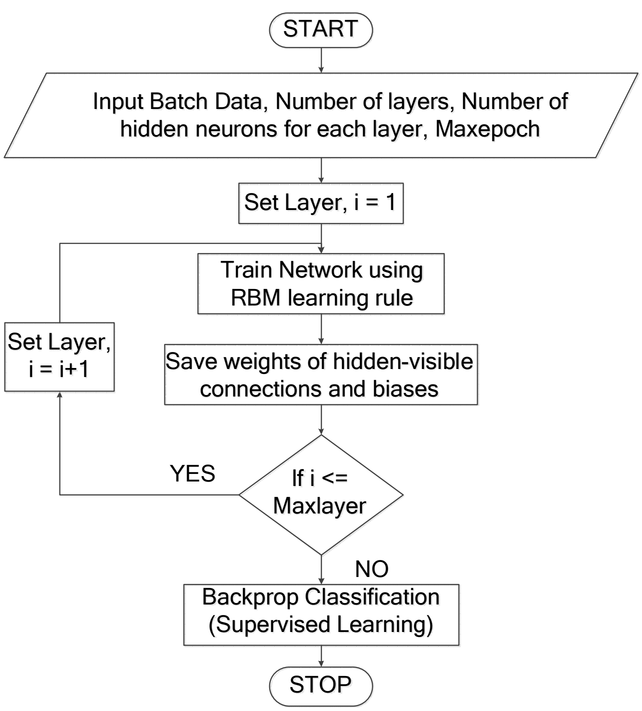

Figure 2: Flowchart of the DBN Classification Process

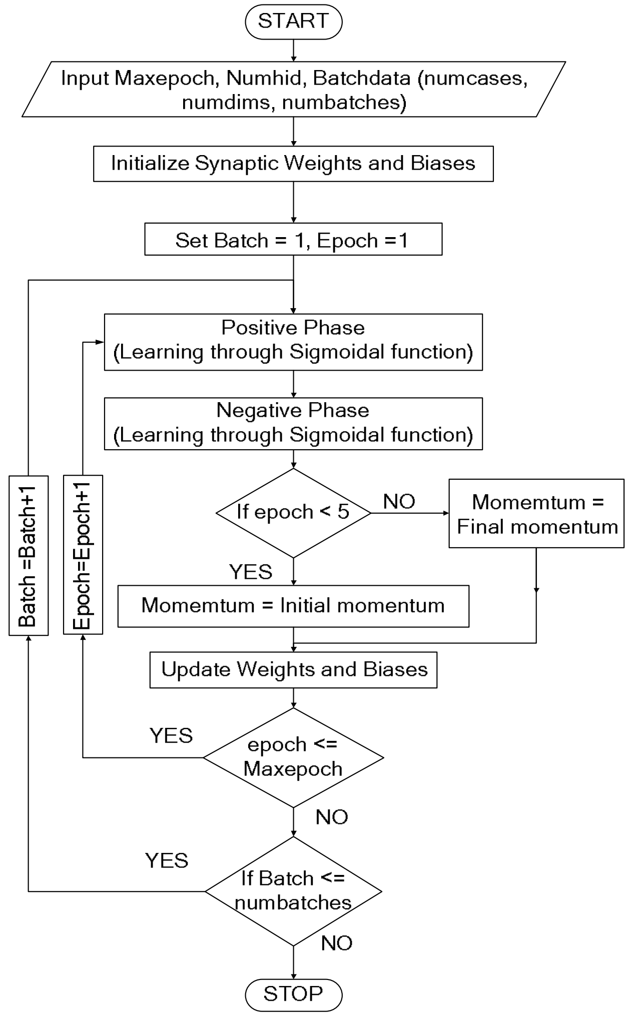

Figure 3: Iterative Learning Process of RBM Units

The training parameters of the RBM for the DBN classifier model are continuously optimized until the maximum number of training epochs has been reached. This completes the training of one RBM and this process will be continued until all RBMs in the DBN structure are trained. This iterative learning process that trains one individual RBM at a time successively is referred to as the layer by layer DBN training process.

Figure 4 demonstrates the unsupervised DBN learning process using a sample DBN structure with four hidden layers. Considering the training process for the first RBM unit in the DBN structure as shown in Figure 4(a), the input data is first given to the visible layer of this RBM unit. The next step is to transform the input data from the RBM visible layer to the hidden layer using visible layer parameters. While the training epoch reaches its maximum number and the training of the first RBM is accomplished, the hidden layer of this RBM unit becomes the visible layer of the second RBM unit. The training process is continued for the second and the third RBM units as shown in Figures 4(b) and 4(c) respectively. The training of the DBN is accomplished through the successive training of each individual RBM unit, as shown in Figure 4(d).After the successive layer by layer learning process, the next step of the DBN training is the supervised learning process, which will be accomplished by the back-propagation training algorithm. The supervised learning process further reduces the training error and improves the classification accuracy of the DBN classifier model. The supervised learning uses labeled data for the training of the DBN model. Unlike the unsupervised DBN training process that considers one RBM at a time, the back-propagation DBN training process considers all DBN layers simultaneously. The training error is calculated using model outputs and the target label data. The parameters of the DBN classifier model are updated in order to minimize the training error [26]. The back-propagation learning is continued until the network output reaches the minimum training error. After the supervised back-propagation training process, the trained DBN classifier model can be further fine-tuned to improve the classification accuracy through certain fine-tuning algorithms. In this study, the conjugate gradient approach is employed for the DBN classifier model fine tuning purpose. More information regarding the DBN fine tuning can be found in the reference [22].

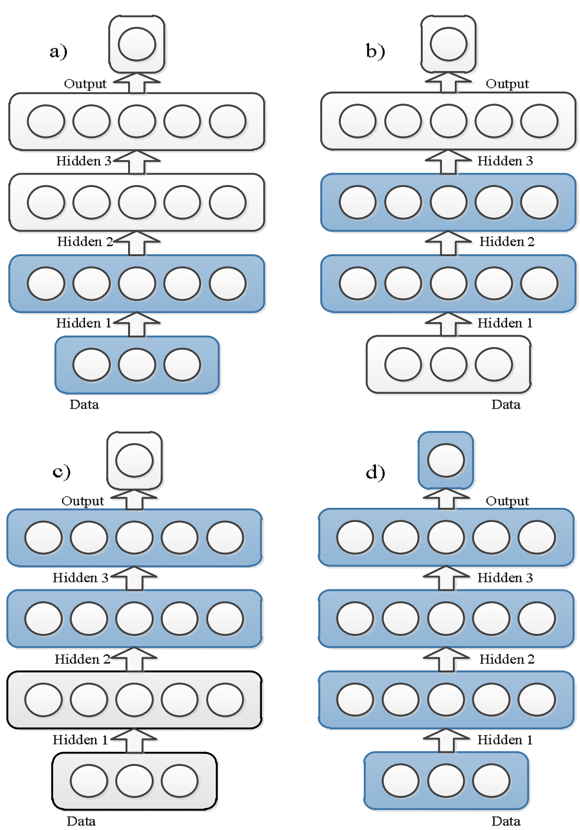

Figure 4: Layer by Layer Training of DBN

After the DBN training and fine tuning process, another crucial step required to check the validity of the trained DBN classifier is the model validation. Through the model validation process, the trained DBN model will be assessed for its classification validity. The synaptic weights and biases saved during the DBN training process are utilized for determining misclassification errors. The validation process of the DBN classifier model is involved in two steps: 1) misclassification error for training data and 2) misclassification error for testing data. Misclassification errors are used as the metric to validate the performance of trained DBN classifier model and determined as the ratio of number of correct classified states to the total number of states in the input data. The misclassification error is determined for both training and testing data sets. Based on the percentage of misclassification errors, DBN model can be validated and then applied for the health diagnosis based on real time sensor data.

C. General Procedure for DBN Classification

Table 1 lists the proposed generic procedure for DBN classification in multi sensor health state detection. The primary step in diagnosis is to define the diagnosis scope and possible system health states. The definition of diagnostic process of system is described through different possible health state conditions. The data collection from different sensors over the sensor network is the next part of the process. DBN cannot use the raw sensory data directly for the continuous monitoring. Therefore, preprocessing of the data becomes more essential step to convey the required information for the classification process. Preprocessed data with known classes is utilized for developing and training DBN classifier model. Architecture of DBN model is altered based on the training of input patterns with different known health states. DBN classifier model is validated using misclassification error determination process[22]. Steps 4 -6 in Table 1 is iteratively repeated until the model reaches the minimum misclassification error. Completely trained and validated DBN model is set to classify unknown sensor signal to its corresponding known health states.

Table 1: Procedure for DBN Classification

Step 1:	Define the diagnosis problem and health states
Step 2:	Collect and preprocess the sensory data for each predefined health state
Step 3:	Develop DBN classifier models
Step 4:	Train the DBN classifier models using training data
Step 5:	Determine misclassification of classifier models
Step 6:	Perform diagnosis using trained DBN classifier models

IV. HEALTH DIAGNOSIS APPLICATIONS

The multi-sensor health diagnosis approach using the DBN based state classification is demonstrated with two structural health diagnosis applications. The first case study used in this paper is aircraft wing structure health diagnosis. The second case study employs 2008 IEEE PHM Challenge data for aircraft engine health diagnosis. The performance of the developed health diagnosis method using the DBN classifier model for first case study is compared with BNN, SOM, SVM and MD classification technique. The second case study is compared to the SVM classification technique and the results are discussed.

A. Aircraft Wing Structure Health Diagnosis

Health diagnosis of the aircraft wind structure is considered to be much harder due to a highly uncertain operating environment of the aircraft, such as humidity, temperature, pressure, speed and variable loading conditions [27]. Aircraft frame undergoes huge stress due to these variable uncertain factors. The uncertain operating environment results in different wing structure failure mechanisms, such as corrosion, delamination, cracks. These failure mechanisms will be developed gradually and lead to aircraft wing failures. To avoid catastrophic failure of aircraft, continuous health monitoring and diagnosis of aircraft wing structure are needed. The structural health monitoring of aircraft wing structure can be carried out by placing sensors on aircraft wings and continuously collecting the sensory signals for wind structure health diagnosis. Therefore, an intelligent multi sensor health diagnosis for aircraft wing structure is crucial to classify the different working states. This section details case study of aircraft wing structure using the developed DBN based multi-sensor health diagnosis.

One rectangular panel with two symmetric plates of the aircraft wing structure, as shown in Figure 5, is modeled and simulated in ANSYS. The four end corners of the wing structure are fixed with bolt joint connections. The sensors are allocated in the center of the wing structure to analyze the vibrations due to variable loads experienced by the wing structure as shown in the Figure 5. The sensor network conveys the degradation signals of the structure to analyze the failure. The variable cyclic load is applied at the center of the left side plate. The vibration response from the simulated wing structure shows the accumulation of more stresses near to the variable load area as shown in Figure 6. Sensor network detects the aircraft wing structure degradation in three health state conditions. The first health state condition is no fault condition (Health State 1, HS_1). The second health state (Health State 2, HS_2) is defined as the failure of the bolt joint A as shown in Figure 5.The failure of the joint is simulated through changing the boundary condition of the simulation model. Similarly, the third health state is defined as the failure of the bolt joint B (Health State 3, HS_3).

400 sets of random samples are generated for each health state from the aircraft wing structure simulation model considering the uncertain load condition applied. The first 200 sets of random samples are saved as training data and the rest are saved as testing data. The different cases are listed in the Table 2 and the classifier models for BNN, SOM, MD, SVM and DBN are developed for each case separately. The DBN classifier model is trained using the training data and validated using the testing data. The developed DBN model is trained for 50 epochs with the RBM learning rule. The trained model is further fine-tuned using conjugate algorithm. For the first case, the trained DBN classifier model is tested with both training and testing data sets, with the classification rates of 100% for the training sets and 96.5% for the testing sets respectively. The classification results from different classification methods are compared with the results of DBN classifier model.

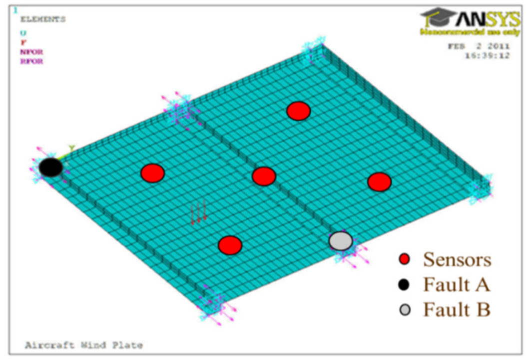

Figure 5: Sensor Network and Fault Locations

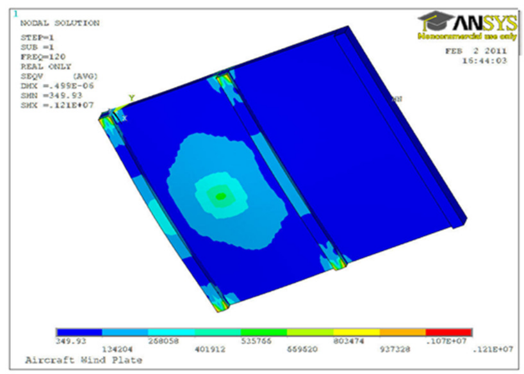

Figure 6: Simulated Aircraft Wing Design

Table 2: Case Study 1 – Different Cases

Case	Training set HS_1 / HS_2/ HS_3	Testing set HS_1 / HS_2/ HS_3
C1	200/200 /200	200 /200 /200
C2	75 /75/75	200 /200 /200
C3	75 /50/50	200 /200 /200

The BNN model is implemented and simulated with one hidden layer and ten hidden neurons. Best network model classified training and testing data with the classification rates of 86% and 85.67%. There are more overlapping of data points in SOM model from different health states and there are no distinct clusters formed for each of the three health state conditions. The MD based classifier model is developed and simulated for the both training and testing data sets. The classification rates of training and testing data are found to be 91.67% and 92% respectively. The classification rates of the trained SVM model for training and testing data found to 100% and 88.77% respectively. Although the training data set is classified completely correct, the testing data set is classified at 88.77%. Similar process is carried out for all the three cases and the classification results are listed in the Table 3.

Table 3: Case Study 1 – Classification Results Comparison

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
BNN	86.00	88.00	88.40	85.67	84.93	86.13
SOM	79.83	75.55	82.86	79.17	72.50	79.17
MD	91.67	90.67	92.00	92.00	92.93	93.07
SVM	100	100	100	88.77	82.80	83.60
DBN	100	100	100	96.50	93.67	94.17

The classification rates of the training and testing data are higher in DBN classifier model compared to four other existing classification approaches, as shown in Table 3. The higher classification rate obtained by the DBN classifier model, compared with other existing techniques, is mainly due to the three-fold learning stages namely unsupervised training, supervised training and fine-tuning.

B. 2008 PHM Challenge Data Problem

2008 PHM Challenge data problem is demonstrated in this case study. The data comprises of multivariate time series signals that are collected from an aircraft engine dynamic simulation process. Each time series signal is derived from a different degradation instance of the stochastic simulation of the same aircraft engine system [28]. The complete data for each cycle of each unit consists of unit ID, cycle index, 3 values for an operational setting and 21 values for 21 sensor measurements. The initial conditions of different engines start with different health conditions and simulated sensor data are contaminated with measurement noise. The operational setting values have significant effect on the engine performance and degradation behaviors, resulting in distribution of six different operation regimes. The 21 sensory signals were collected from six different operation regimes of 218 engine units. The objective of this case study is to classify the different health conditions based on the sensory signals.

The stepwise procedure for preprocessing the data is clearly explained in the Table 4. Out of 21, sensory signals from 7 sensors are selected for complete 218 engine units. Each cycle of each unit is assigned to corresponding operational regime class based on its operational setting values. The complete data is divided into four health conditions based on its proximity to the failure with its corresponding regime data. Each regime data with four health conditions is divided into training and testing dataset. The classifier models for each regime is trained separately and tested with the testing dataset. The training and testing set of each regime is randomized and divided into 100 mini-batches along with its corresponding target dataset. The mini-batches are given as an input to the DBN classifier model and trained using RBM and back-propagation learning. The trained DBN classifier model is tested with the testing dataset.

Table 4: Procedure for Preprocessing PHM Challenge Data

Step 1:	Selected 7 sensory signals out of 21 sensory signals from complete engine simulation data
Step 2:	Collected 7 sensor data for each cycle of 218 engine units
Step 3:	Assigned different operational regime class based on its operational setting values
Step 4:	Divided the complete data into four health conditions based on its proximity to the failure
Step 5:	Divided each regime data into training and testing set according to each case

Table 5: Case Study 1 – Different Cases

Case	Training dataset %	Testing dataset %
C1	50	50
C2	30	70
C3	70	30

Table 6: Case Study 2 – Regime 1 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
DBN	92.03	91.02	85.26	90.51	89.24	84.13
SVM	90.32	89.01	84.94	91.72	88.73	84.32

Table 7: Case Study 2 – Regime 2 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
DBN	96.41	93.22	92.15	95.22	92.15	90.21
SVM	93.33	92.53	92.41	91.31	90.93	89.83

Table 8: Case Study 2 – Regime 3 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
DBN	95.61	93.22	92.55	94.66	91.36	91.12
SVM	94.94	92.37	91.42	93.31	90.57	90.56

Table 9: Case Study 2 – Regime 4 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
DBN	94.24	93.22	91.24	92.88	91.89	92.36
SVM	94.63	92.41	90.86	93.31	91.37	90.35

Table 10: Case Study 2 – Regime 5 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	C2	C3
DBN	92.73	91.52	90.91	91.84	90.33	90.55
SVM	91.84	93.73	89.56	90.48	92.2	89.11

Table 11: Case Study 2 – Regime 6 Classification Results

Methods	Classification Rate Training (%)			Classification Rate Testing (%)		
	C1	C2	C3	C1	Case 2	Case 3
DBN	96.31	95.41	93.23	95.18	93.46	92.41
SVM	95.92	94.31	92.93	94.19	93.08	91.46

The different cases for each regime are listed in the Table 5 and the classifier models for SVM and DBN are developed for each case of each regime separately. The classification rates of training and testing dataset of each model are determined and each regime results are listed in Tables 6 to11 respectively. As shown in the tables, the classification rates of the health states are higher in DBN classifier model in all the cases, when compared to SVM based diagnosis approach. The main reason of higher classification rate by DBN is due to its three fold training approach. The DBN structure is trained by both supervised and unsupervised learning in a single training process. The fine tuning algorithm increases the effectiveness of the DBN classifier model. These factors helped DBN model to perform better than the other compared models.

V. CONCLUSION

This paper presented a novel multi-sensor health diagnosis method using DBN based state classification. The DBN classifier model employs a hierarchical structure with multiple stacked Restricted Boltzmann Machines and works through a layer by layer successive learning process. The developed multi-sensor health diagnosis approach can be structured in three consecutive stages: 1) defining health states and collecting sensory data for DBN training and testing, 2) developing DBN based classification models for the diagnosis of predefined health states, and 3) validating DBN classification models with testing sensory dataset. The feasibility of health diagnosis using DBN based health state classification was demonstrated with two case studies and the diagnosis performance was compared with different diagnostic approaches. Case study results indicated that DBN classifier model generally results in a higher classification rate for multi-sensor health diagnosis of complex systems, compared to other existing classification methods. The DBN will be further investigated for the multi-sensor health prognosis applications.

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BIOGRAPHIES

Prasanna Tamilselvan *received his bachelor degree in Mechanical Engineering in 2007 from Anna University, India and his Master degree in 2010 in Industrial and Manufacturing Engineering from Wichita State University, USA. He is currently pursuing his doctorate in Industrial and Manufacturing Engineering at Wichita State University. Prasanna is working as a graduate research assistant in Reliability Engineering Automation Laboratory and working as Adjunct Faculty in Industrial and Manufacturing Engineering teaching bachelor’s courses at Wichita State University. Prasanna’s expertise is in the areas of machine learning applications in failure diagnostics, prognostics and health management (PHM)* **.**

Yibin Wang *received a B.A in international business from Qingdao University of Science & Technology, China in 2007 and a M.A in Economics from Wichita State University in 2011. He is currently a graduate student in the Department of Industrial and Manufacturing Engineering and working as a graduate research assistant in Reliability Engineering Automation Laboratory at Wichita State University. Yibin’s expertise is in the areas of maintenance policy analysis, prognostics and health management (PHM), and PHM cost benefit analysis.*

Dr. Pingfeng Wang *is currently an assistant professor in the industrial and manufacturing engineering department at Wichita State University. Dr. Wang got his bachelor degree in Mechanical Engineering in 2001 from The University of Science and Technology in Beijing, China. After the college, he worked 3 years for Dell Inc. as a computer quality engineer. After working in industry for 3 years, Pingfeng went back to graduate school and got his Master degree in 2006 in Applied Mathematics from Tsinghua University in China. From 2007 to 2010, Pingfeng studied in the University of Maryland at College Park and graduated with a Ph.D. degree in reliability engineering. Dr. Wang’s* *expertise is in the areas of reliability analysis and design for complex systems, structural health prognostics, and condition-based maintenance. Dr. Wang has written over 20 research articles in these areas, including one ASME Best Paper Award in 2008. Since joining WSU as a faculty member in 2010, Dr. Wang has focused his research on developing methodologies to integrate the reliability based complex system design with health prognostics to improve the overall system resilience and sustainability.*