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ENGINE FAULT DETECTION USING NEURAL NETWORKS

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Abstract— **A number of fault detection systems for vehicle maintenance, repair have been developed in recent years. These systems are used for diagnosing variety of faults in the vehicle and are available at service level. A wavelet neural networks model is constructed based on wavelet frame theory and neural networks technology. The model is validated through the testing that simulates the faults of engine. RBF neural networks are trained to detect and diagnose the faults, and also to indicate fault size, by recognising the different fault patterns occurring in the dynamic data.**

Index Terms— **Neural Networks, Fault Detection, Wavelet Neural networks, RBF Neural Networks.**

1. Introduction

The automobile's working will be directly influenced by the running states of the engine. To clear the fault's which occur in the engine will cost much, and will have to spend a lot of time on it in order to rectify those faults. A variety of diagnosis methods have been proposed under the umbrella of model-based techniques. The feature of all these techniques is that some form of mathematical knowledge of the process of interest along with inputs and outputs are used to generate more information about that process. This redundant information is then used in a diagnostic process to arrive at decisions regarding fault or no fault conditions. Occurrence of a fault influences various system parameters which deviate from their normal values. A typical fault table indicates relation between various vehicle parameters. The amount by which the parameter value is deviated depends upon the type of fault.

* Radial Basis Function (RBF) and Multilayer Perceptron (MLP) are examples of supervised neural networks whereas ART2 and Kohonen network of unsupervised networks. Supervised networks have been shown to exhibit better classification capabilities than unsupervised networks. In our project, four different

faults with four different levels of intensities are considered i.e. air leakage in the intake-manifold, Exhaust Gas Recycle (EGR) valve stuck in different positions, intake manifold pressure and temperature sensor faults.

* The wavelet neural networks is a new neural network model depended on the great breakthrough in wavelet analysis technology. It fully utilizes the capability of time frequency Analysis of the wavelet and self-leaming of the neural networks. To apply wavelet nerve network in handling and analyzing the engine vibration signal can improve the accuracy of diagnosis. It has very important meaning not only in the academic field but also in the practice in the field of engine fault diagnosis.

2. Related Work

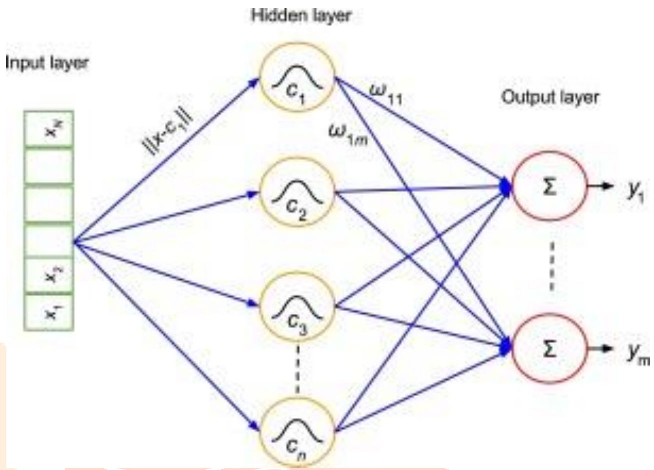
To detect faults, some methods for obtaining information fusion from different sensor sources have recently been developed. For example, MS Safizadeh and SK Latifi6 detected bearing failure using an accelerometer and a loading cell, and Z Li et al.7 fused the information from the vibration and wear particle analysis to enhance early fault detection. However, for practical application of fault detection, the device is costly, and it is not easy to achieve online detection in a vehicle; hence, it is difficult to collect wear particle information. W Cao et al.8 proposed an online visual ferrograph (OLVF) and performance monitoring sensors to evaluate engine wear, but the weight of the different sensors is difficult to determine, and the condition factor may influence the monitoring results.

In fusion methods, some researchers have proposed using an SVDD (support vector data description)-based algorithm for the fault diagnosis of a mechanical equipment system. Z Jiang et al.9 focused on one-class classification of mechanical faults, and it is unnecessary for their method to pre-process the signals to extract their features. Y Zhang et al.10 presented a classifier combining SVDD with kernel possibilistic C-means clustering for the fault diagnosis of rolling machinery. XL Zhang et al.11 proposed combining SVDD with support vector machine (SVM) to solve the data description problem with negative samples. L Duan et al.12 presented an SVDD model by applying a binary tree structure from top to bottom for classification of machinery fault diagnoses because samples under faulty conditions are usually far fewer than samples under normal conditions. G Yin et al.13 combined incremental support vector data description (ISVDD) with incremental output extreme learning machine (IOELM) structure to find a new failure mode quickly in the continuous condition monitoring of the equipment. Some researchers have proposed the use of Dempster–Shafer (D-S) evidence theory to resolve conflicting results generated from each diagnosis model and thus increase classification accuracy. KH Hui et al.14 proposed an SVM–D-S model to detect multi bearing faults. A Moosavian metal.15 developed a fault diagnosis for a spark plug in an internal combustion (IC) engine based on acoustic and vibrational signals using sensor fusion and classifier combination from D-S evidence theory. Basir et al. fused data obtained from four different sensors using D-S evidence theory for fault diagnosis of an IC engine. They mentioned that the simultaneous usage of several information sources and D-S evidence theory can substantially increase fault detection accuracy.16 Y Wang et al.17 developed a decision-level data fusion technique using D-S evidence theory for fault diagnosis in electronically controlled engines, which could process non-commensurate data but had low fusion accuracy.

3. METHODOLOGY

- Radial Basis Function Networks

  Radial basis function (RBF) networks are a commonly used type of artificial neural network for function approximation problems. Radial basis function networks are distinguished from other neural networks due to their universal approximation and faster learning speed. An RBF network is a type of feed forward neural network composed of three layers, namely the input layer, the hidden layer and the output layer. Each of these layers has different tasks. An RBF network with a specific number of nodes (i.e. 10) in its hidden layer is chosen. A Gaussian function is used as the transfer function in computational units. Depending on the case, it is typically observed that the RBF network required less time to reach the end of training compared to MLP. These chosen MLP and RBF networks are later examined in the next chapters under new test conditions. The agreement between the model predictions and the experimental observations will be investigated and the results of the two models will be compared. The final model is then chosen based on the least computed error.



The output of the ith activation function phi(i) in the Hidden layer of the network can be calculated based on the distance between the input pattern x and the center i.

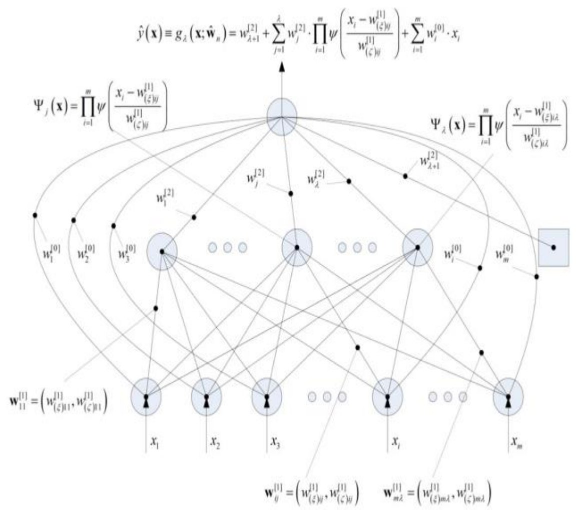
$$\phi_i(||x - c_i||) = \exp\left(-\frac{||x-c_i||^2}{2\sigma_j^2}\right)$$

The output of node k of the output layer is:

$$y_k = \sum_{j=1}^{n} \omega_{jk}\phi_j(x)$$

- Wavelet Neural Networks

A wavelet network has the form of a three layer network. The lower layer represents the input layer, the middle layer is the hidden layer and the upper layer is the output layer. Input Layer of the wavelet network is introduced with explanatory variables. The hidden layer consists of the hidden units. In the hidden layer the input variables are transformed. Finally, in the output layer the approximation of the target values is estimated. The idea of wavelet network is to use wavelet basis to the training data. Hence, the wavelet estimator is expected to be more efficient. In this structure, the activation function is a linear combination of wavelet basis instead of the wavelet function. During the training phase, the weights of all wavelets are updated. In order for the model to perform well in the presence of linearity, we use direct connections from the input layer to the output layer. Hence, a network with zero hidden units is reduced to the linear model.

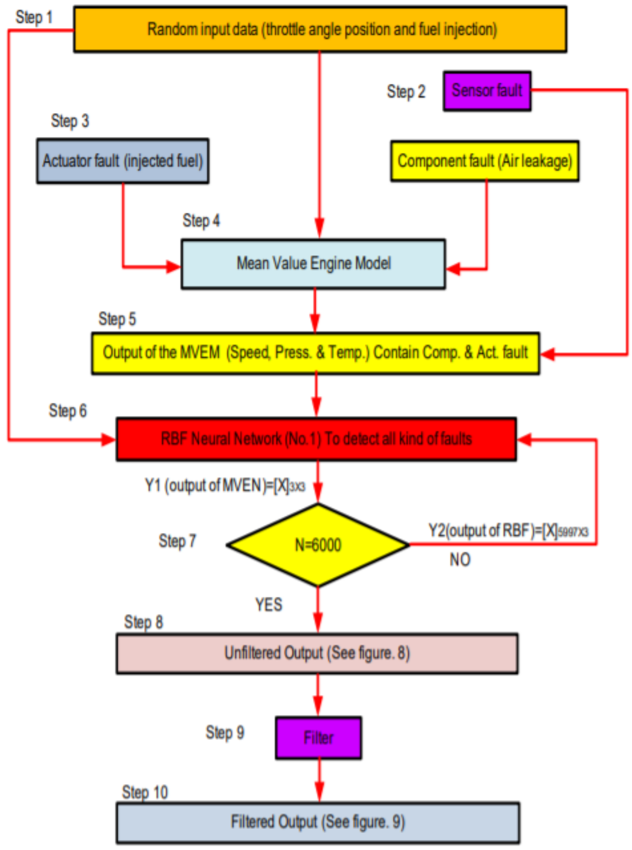


The structure of a single hidden-layer feedforward WN is given .The network output is given by the following expression:

$$g_\lambda(\mathbf{x};\mathbf{w}) = \hat{y}(\mathbf{x}) = w_{\lambda+1}^{[2]} + \sum_{j=1}^{\lambda} w_j^{[2]} \cdot \Psi_j(\mathbf{x}) + \sum_{i=1}^{m} w_i^{[0]} \cdot x_i.$$

In the above expression, Ψj(x) is a multidimensional wavelet which is constructed by the product of m scalar wavelets, x is the input vector, m is the number of network inputs, λ is the number of hidden units, and w stands for a network weight.

4. PROPOSED SYSTEM



The Figure shows the flow chart of fault detection. The RBF neural network receives five inputs signals, the first three inputs signals are manifold pressure, temperature and crankshaft speed which containing fault information, and the second two inputs signals are the throttle angle and the fuel mass flow and has three outputs with each indicating one of the investigated states in Amplitude. This neural network will use at the beginning only the first three rows of the MVEM output matrix which consists of signals values of manifold pressure, manifold temperature and crankshaft speed, all these three inputs contain sensor, component and actuator faults, after that the output of the neural network will be used as a target matrix, that means this neural network is an independent model. The hidden nodes which are chosen by k-means method are 12, this is because the test result is very good and the size of neural network will be small, consequently the train and test time will be small. Width and weights are trained using ρ -nearest neighbours algorithms and the same data of μ, w(0), P(0) which were used to train neural network engine model are used here. The trained network is then tested for all faults occurring.

5. CONCLUSION

In this study a complete statistical framework for constructing and using WNs in various applications was presented. Although a vast literature about WNs exists, to our knowledge this is the first study that presents a step by step guide for model identification for WNs. More precisely, the following subjects were examined: the structure of a WN, training methods, initialization algorithms, model selection methods, variable significance and variable selection methods and finally methods to construct confidence and prediction intervals. Finally the partial derivatives with respect to the weights of the network, to the dilation and translation parameters as well as the derivative with respect to each input variable are presented.

The MVEM developed by Hendricks and et al (2000) is used for simulations during the research period after small modification. Expansion work has been done to the existing MVEM simulation by including air fuel ratio sensor time delay, temperature sensor dynamics etc. Three sensor faults (intake manifold pressure, temperature and speed), one component fault (leakage in the intake manifold) and one actuator fault (injected fuel mass flow) have been simulated when the simulation model is subjected to disturbances and noise. An independent RBF neural network model was used to model engine dynamics and the training algorithms are reviewed and derived. By using ρ – Nearest Neighbours method and K-means algorithm the width in hidden layer nodes of the RBF neural network σ and the centres c are calculated for RBFNN. The recursive least square algorithm was applied for training the weights w of the RBFNN. Fault detection for engine studied in this paper is using neural network modelling method, this method can detect dynamic faults, and this is because the modelling is for dynamic system, so can detect the faults in dynamic condition and for other simulated three types of fault (sensor, actuator and component). From The simulation results it can be seen that the independent RBF neural networks were able to detect sensor, actuator and component faults clearly.

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