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Design of neural predictor for noise analysis of passenger car's engines

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This paper presents noise analysis of passenger cars using artificial neural networks (ANNs). The research covers experimental analysis of car's engines and simulation analysis of noise parameters using ANNs. Radial Basis Neural Network (RBNN) type gives superior performance for predicting noise of cars.

Keywords: Artificial neural network, Engine noise, Learning algorithm

Introduction

Noise source identification in a diesel engine[1,2] has been analysed using acoustic signals and vibration signals measurement. Tokoro *et al*[3] investigated generating mechanism and reduction method of high frequency noise, generated by discontinuous slips and flow of holding air between belt and pulley of trial belts, for engine timing belt. Leclere *et al*[4] investigated low frequency amplitude modulation of noise generated by an engine operating at idle. Bartosch & Eggner[5] introduced a vibro-acoustic optimization algorithm, which was based on an analytical gradient computation of energy of a subsystem with respect to statistical energy analysis (SEA) coupling and internal loss factors. Behzad *et al*[6] presented both numerical and experimental investigation of noise emission level associated with two types of speed reducer for different dimensions and different speeds of vehicle and zero acceleration. Shu & Liang[7] presented an identification of complex diesel engine noise sources based on coherent power spectrum analysis. Kim & Lee[8] found pressure surge as one of main noise sources for intake stroke. Yildrim & Uzmay[9] investigated vertical vibration of vehicles using a radial basis neural network (NN). Simulations results[10] gave superior performance of suspension control system with neural controller. Slider-crank and cam-follower mechanisms[11] described noise effects on system.

This paper presents a novel experimental NN based approach for testing and evaluating noise level for passenger car's engines.

Materials and Methods

Feedforward Neural Networks (FFNNs)

In experimental investigation, an intelligent data acquisition, a microphone and PC were used (Fig. 1) to collect noise data during three different running speeds of car's engines. FFNNs type, used to analyse engine noise (Fig. 2), consists of input layer with one neuron, first and second hidden layers with 10 non-linear neurons, and output layer with two non-linear neurons.

$$z_j = g\left(\sum_{i=1}^{1}\sum_{j=1}^{10} W_{ij} f_i + b_j\right) \qquad ...(1)$$

where z_j are output of j^{th} neuron in first hidden layer, W_{ij} are weight of connection between input layer neuron and first hidden layer neurons, b_j are bias of j^{th} neuron in first hidden layer. b_j is weight of connection between a fixed input of unit value and neuron j in hidden layer. Function g(.) is called activation function of first hidden layer. Output signal of second hidden layer can be expressed as

$$z_k = g\left(\sum_{j=1}^{10}\sum_{k=1}^{10} W_{jk} z_j + b_k\right) \qquad ...(2)$$

where z_k are output of k^{th} neuron in second hidden layer, W_{jk} are weight of connection between neurons of first

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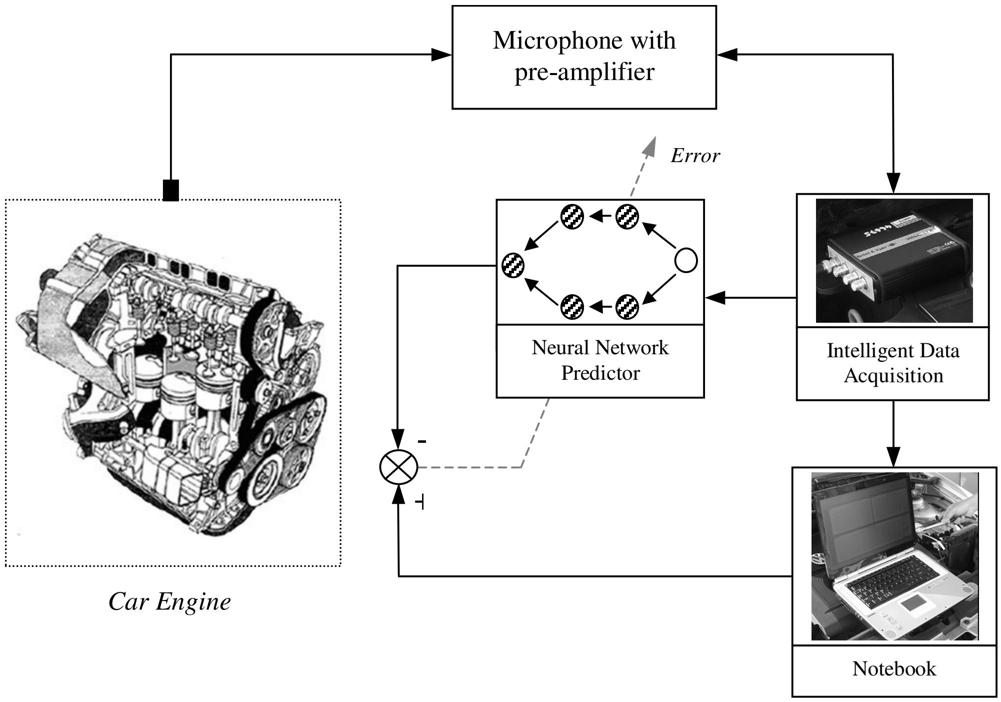


Fig. 1—Schematic representation of experimental and neural networks analysis

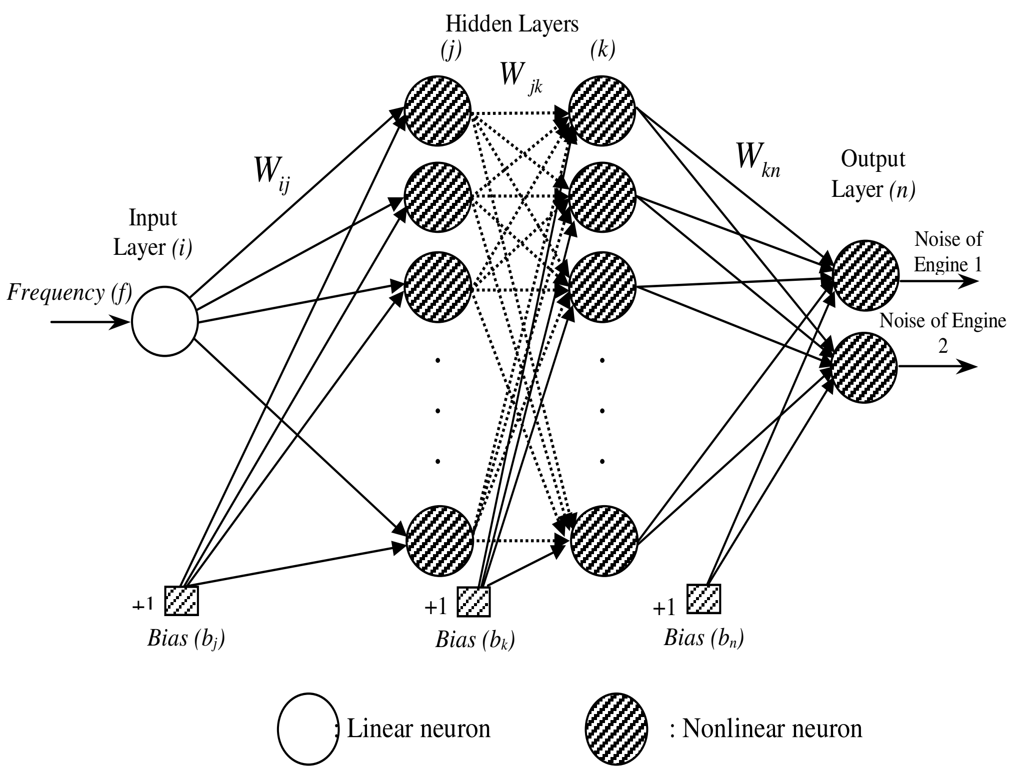
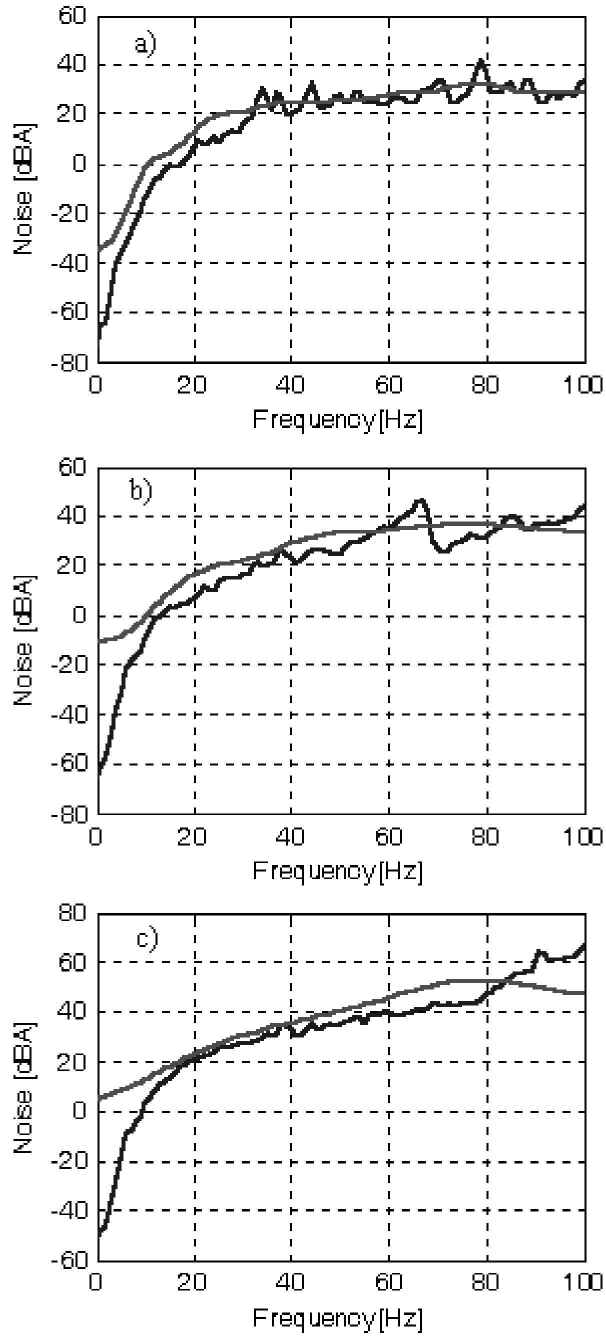
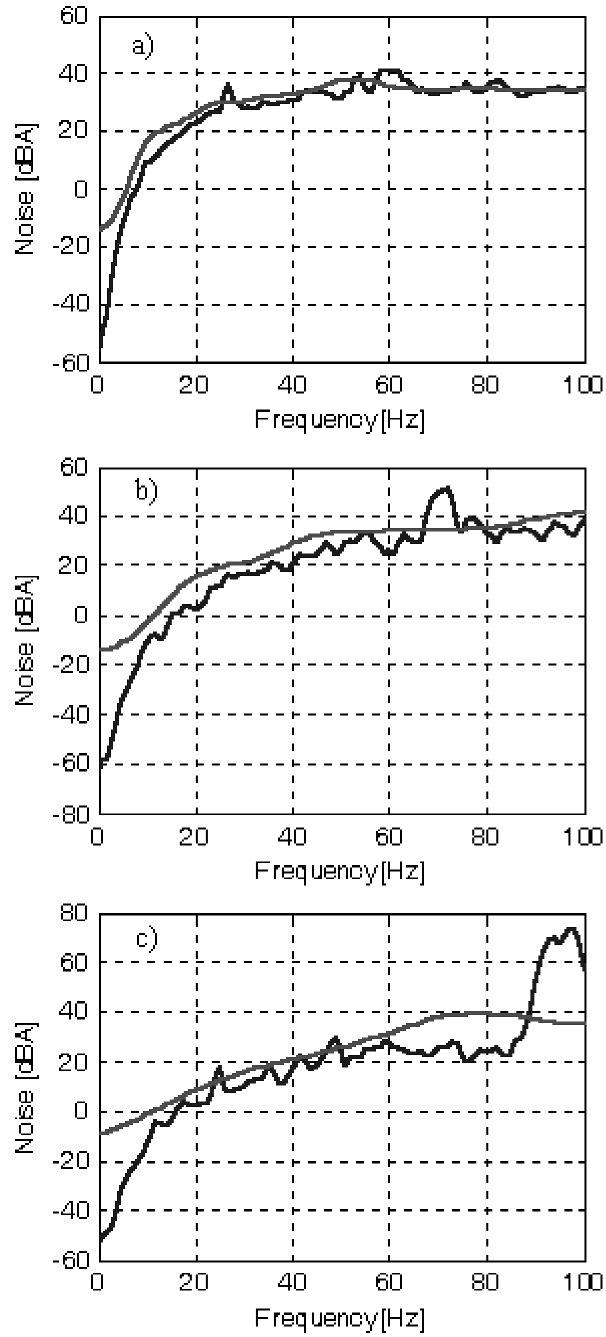


Fig. 2—Schematic presentation of neural network predictor (Engine 1: Old brand car engine, Engine 2: Nearly new brand car engine)



(___) Experimental; (.....) GRNN

Fig. 3—Experimental and GRNN values of engine 1 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm

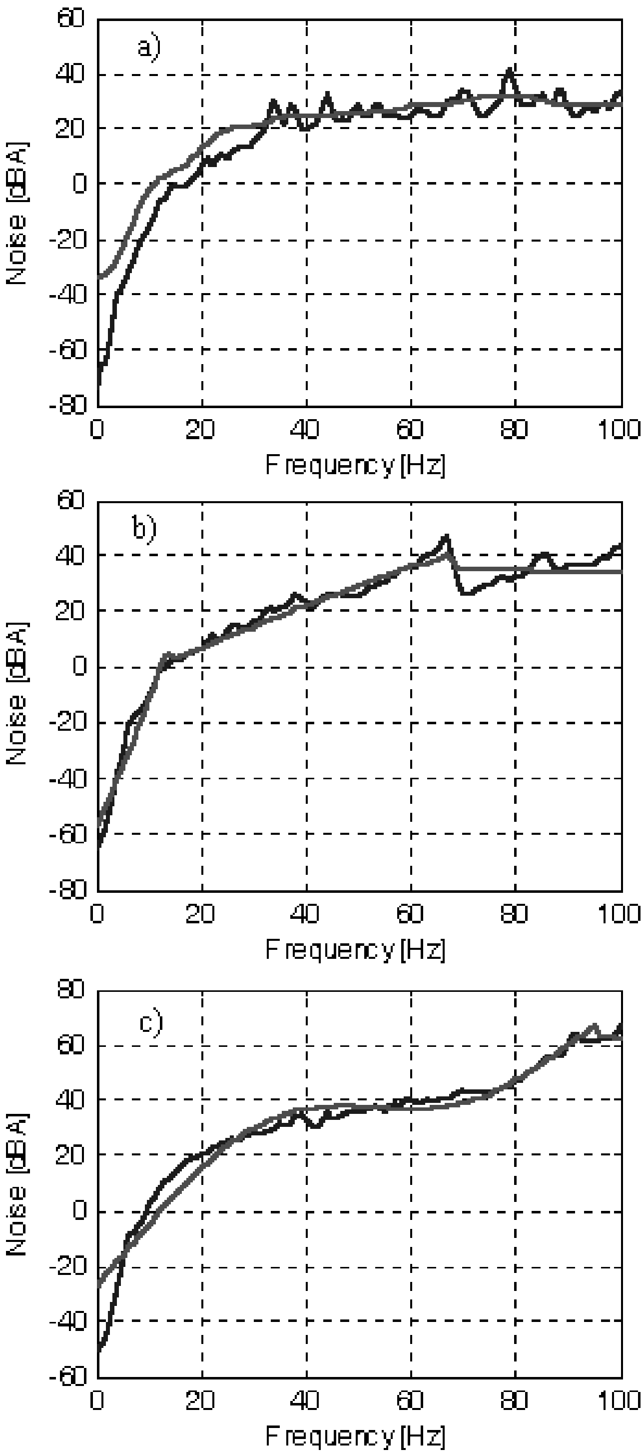


(___) Experimental; (.....) GRNN

Fig. 4—Experimental and GRNN values of engine 2 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm

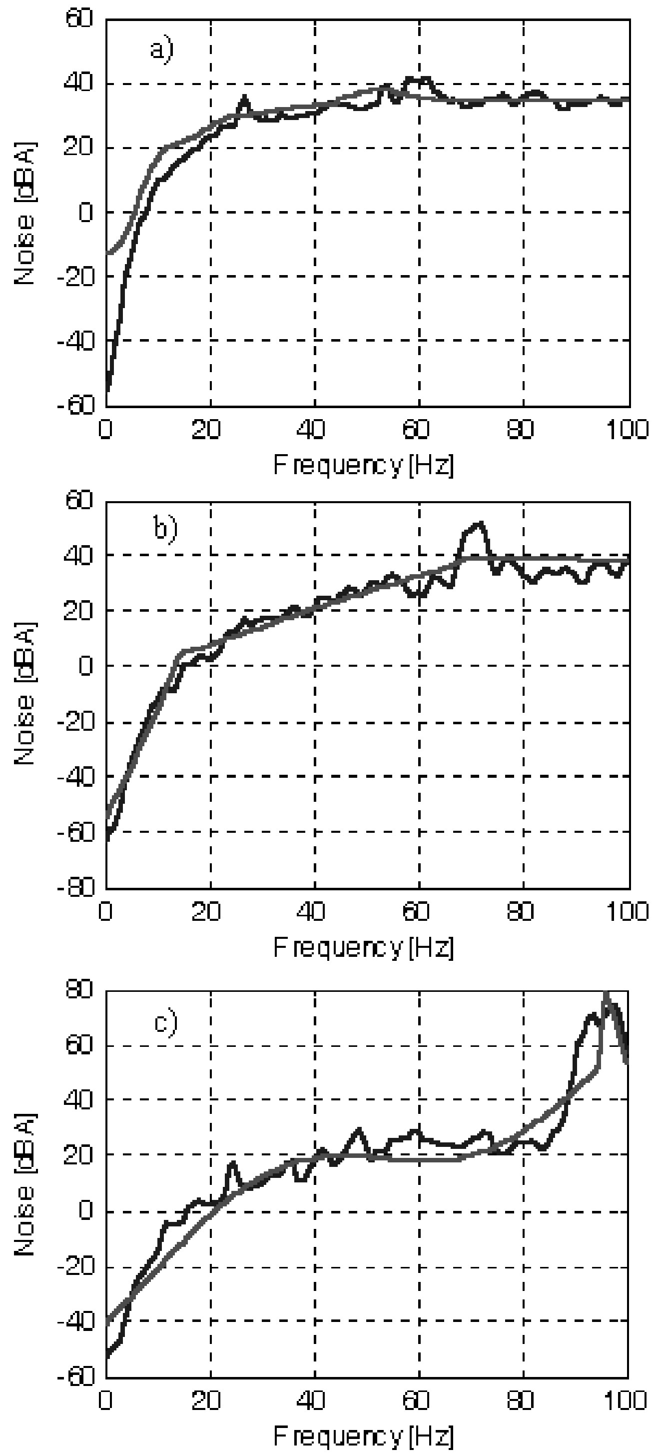
hidden layer and second hidden layer, b_k are bias of k^{th} neuron in second hidden layer, b_k is weight of connection between a fixed input of unit value and neuron k in second hidden layer. Function g(.) is called activation function of second hidden layer. Output signal of NN can be expressed as

$$y_n = g\left(\sum_{k=1}^{10}\sum_{n=1}^{2} W_{kn} z_k + b_n\right) \quad ...(3)$$



(___) Experimental; (.....) GRNN

Fig. 5—Experimental and MNN values of engine 1 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm



(___) Experimental; (.....) GRNN

Fig. 6—Experimental and MNN values of engine 2 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm

where W_{kn} are weights between k^{th} neurons the second hidden layer and n^{th} neurons output layer and b_n are bias of n^{th} neurons in output layer.

General Regression Neural Network (GRNN)

GRNN (Figs 3&4) are paradigms of Probabilistic and Radial Basis Function used in functional approximation.

To apply GRNN to analyze, a vector f_j and f_k are formed. Output y is weighted average of target values t_n of training cases *fn* close to a given case f_j and f_k, as

$$y_n = \frac{\sum_{k=1}^{10}\sum_{n=1}^{2} z_k W_{kn}}{\sum_{k=1}^{10}\sum_{n=1}^{2} W_{kn}} \quad ...(4)$$

where,

$$W_{kn} = exp\frac{\left[-\left|f_k - f_n\right|^2\right]}{2h^2}$$

and

$$W_{jk} = exp\frac{\left[-\left|f_j - f_k\right|^2\right]}{2h^2}$$

Only weights to be learned are smoothing parameters, h of RBF units, which are set using a simple grid search method. Distance between computed value n and each value in the set of target values T is given by;

$$T = \{1,2\} \quad ...(5)$$

Values 1 and 2 correspond to training class and all other classes respectively. Class corresponding to target value with minimum distance is chosen. GRNN exhibits a strong bias towards target value nearest to the mean value μ of T. Therefore, target values 1 and 2 were used because both have the same absolute distance from μ.

Modular Neural Network (MNN)

MNN (Figs 5 & 6) refers to adaptive mixtures of local experts. A gating network determines contribution of each local network to total output as well as what range of input space each network should learn. Back propagation algorithm is used to train gating and local networks. The outputs of local networks are combined to give the network output as

$$y_n = \sum_{k=1}^{10}\sum_{n=1}^{2} g_{kn} y_{kn} \quad ...(6)$$

where y_{kn} are output of k^{th} local network and y_{kn} are normalized output vector elements of gating network given as

$$y_{kn} = \frac{e^{u_{kn}}}{\sum_{j=1}^{10}\sum_{n=1}^{2} e^{u_{jn}}} \quad ...(7)$$

where u_{kn} are weighted input received by k^{th} output unit of gating network. In Eq. (6), $\sum y_{kn} = 1$ and 0d”y_{kn}d”1. Gating and local experts are trained to maximize following function using back propagation learning rule

$$L = ln\left[\sum_{k=1}^{10}\sum_{n=1}^{2} y_{kn} e^{-\frac{1}{2}\left|N_f - N_{fn}\right|^2}\right] \quad ...(8)$$

where N_f are experimentally obtained number of cycles to failure and N_{fn} are corresponding output given by NN. The NN simultaneously adjusts connection and threshold of local networks as well as connection weights and thresholds of gating networks. Error for k^{th} output of gating network is calculated as

$$\frac{\partial L}{\partial u_{kn}} = h_{kn} - y_{kn} \quad ...(9)$$

where h_{kn} are a posterior probability that k^{th} local network is responsible for current output as

...(10)

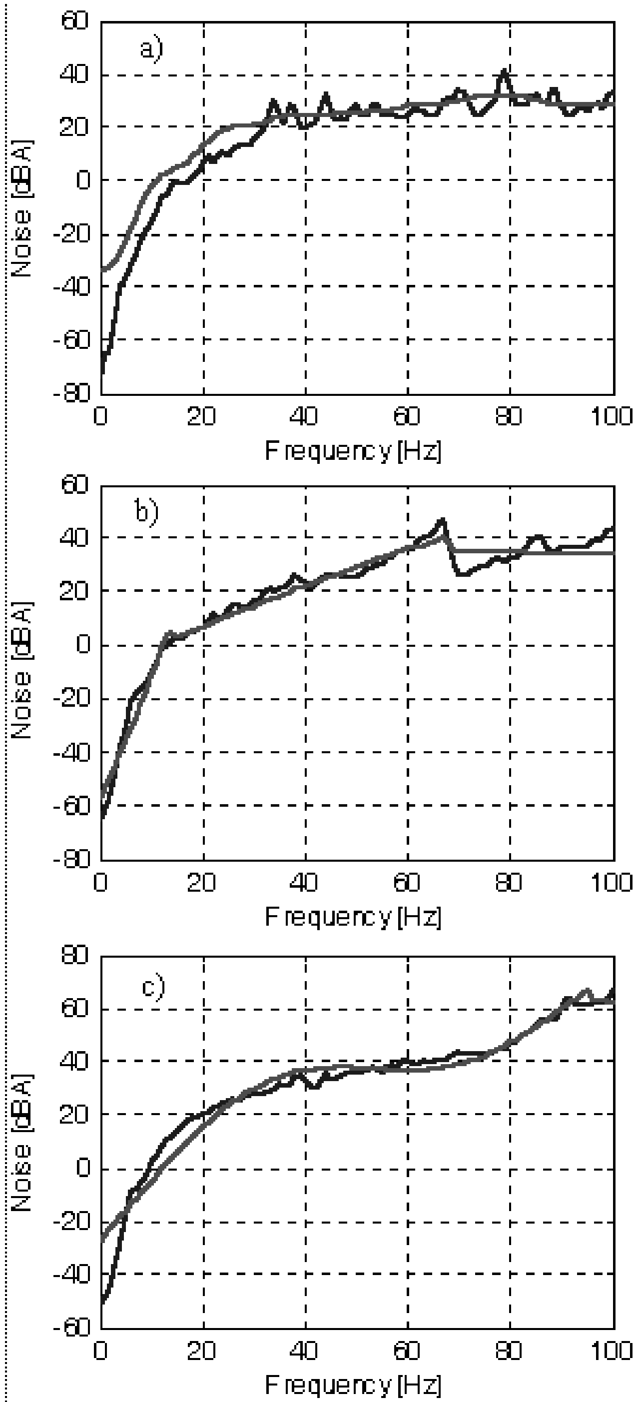
while error for k^{th} local network is calculated as

$$\frac{\partial L}{\partial I_{kn}} = h_{kn}\left[(N_f - y_{kn})\frac{\partial y_{kn}}{\partial I_{kn}}\right] \quad ...(11)$$

Training process is terminated either when mean square error between observed data and NN outcomes for all elements in training set has reached a pre-specified threshold or after completion of a pre-specified number of learning epochs.

Radial Basis Neural Network (RBNN)

Traditionally, RBNN (Figs.7 & 8), which model functions y(x) mapping x R^n to y R have two hidden layers such as

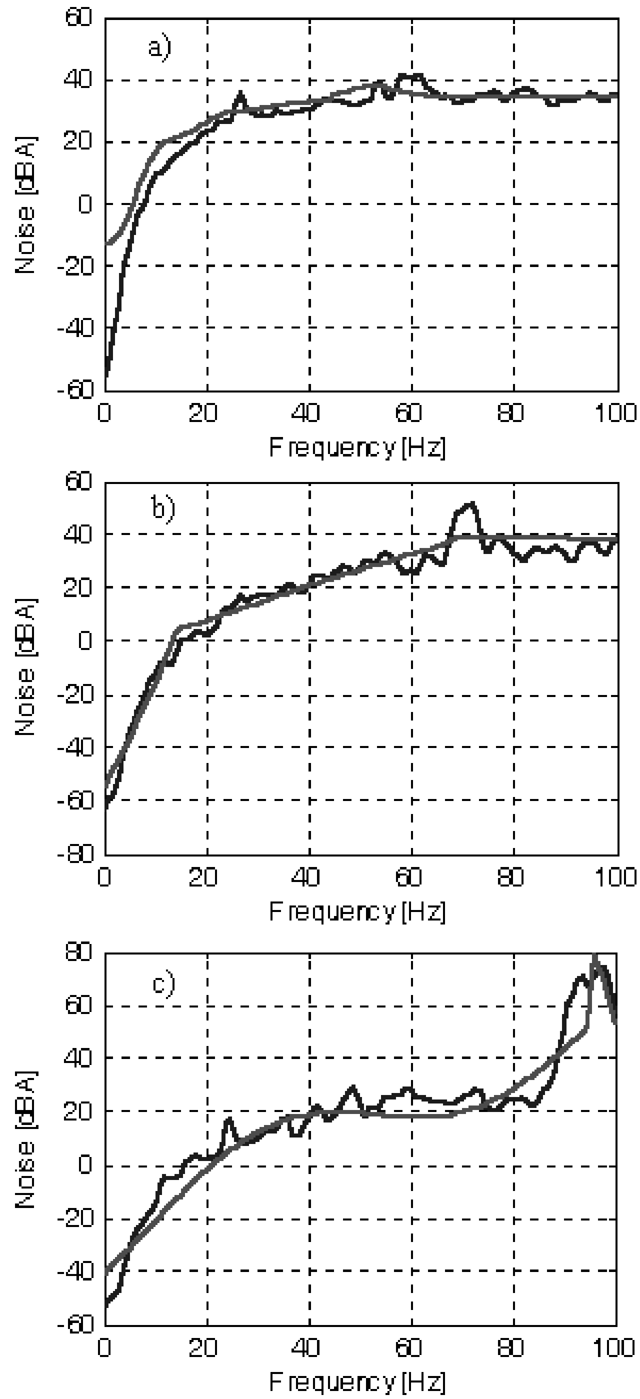


(___) Experimental; (.....) GRNN

Fig. 7—Experimental and RBNN values of engine 1 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm

$$f_j(x) = \sum_{i=1}^{1}\sum_{j=1}^{10} W_{ij} h_{ij}(x) \qquad ...(12)$$

and the second hidden layer output such as



(___) Experimental; (.....) GRNN

Fig. 8—Experimental and RBNN values of engine 2 with running speed of: a) 1000 rpm; b) 2000 rpm; c) 3000 rpm

$$f_k(x) = \sum_{j=1}^{10}\sum_{k=1}^{10} W_{jk} h_{jk}(x) \qquad ...(13)$$

where first hidden layer to output weight W_{ij} and second hidden layer to output weight W_{jk}. Characteristic feature of RBNN is radial nature of hidden unit transfer functions, h_{ij} and h_{jk}, which depend only on distance between input x and centre c_{ij} of each hidden unit, scaled by a metric R_j,

$$h_{ij}(x) = \varphi\left[(x - c_{ij})^T R_j^{-1}(x - c_{ij})\right]$$

and

$$h_{jk}(x) = \varphi\left[(x - c_{jk})^T R_j^{-1}(x - c_{jk})\right]$$

where φ is some function, which is monotonic for non negative numbers. Gaussian basis function so that the transfer functions can be written as

$$h_{jk}(x) = exp\left(-\sum_{n=1}^{2}\frac{(x_n - c_{kn})^2}{r_{kn}^2}\right) \quad ...(14)$$

A direct approach to the model complexity issue is to select a subset of centres from a larger set, which, if used in its entirety, would over fit the data (produce a model, which is too complex).

Experimental Set up

Experimental set up demonstrates feasibility of sensor system to determine in real-time fault detection of car's engines. Experimental aspects and assumptions are as follows: i) The desired responses of car's engine are made available at each instant from a noise analysing system; ii) Actual response of car's engine is measured by an intelligent data acquisition (IDA) set with microphone (Brüel & Kjaer 3560-L type IDA and 2671 type microphone with preamplifier) for 1000, 2000 and 3000 rpm running speed of engine; iii) NNs used in all cases are size of 1x10x10x2, with hidden and output layers totally nonlinear; iv) Network weights are initialized to values +100 and -100 in all cases; and v) Step size and learning rate determine the time constant of network and are critical parameters for the stable operation of overall system.

Results and Discussion

In simulation, three types of NNs are employed to analyze noise of car's engines for comparison. Experimental noise values were used as desired value of NNs. Frequency values (200) of cars as inputs were employed for training stage of the network. Moreover, 100 frequency values were used for testing stage of the network. On the other hand, noises of engines were employed as outputs desired values of the networks for both training and testing stages. In order to specify network accuracy in predicting system outputs, designed network was tested in responses to input, which were not used in the training step. For two engines with 1000, 2000 and 3000 rpm running speeds, results are plotted under GRNN (Figs 3 & 4), MNN (Figs 5 & 6) and RBNN (Figs 7 & 8).

In comparison to GRNN and MNN approaches, RBNN showed better performance because computation nodes in hidden layer of RBNN are quite different and serve a different purpose from those in output layer of the network. Activation function of each hidden unit in a RBNN computes distance between input vector and the center of that unit. RBNN using exponentially decaying localized nonlinearities (Gaussian function) construct local approximations to nonlinear input-output mapping. RBNN results exactly match to experimental results for all running speeds. Table 1 shows structural,

Table 1—Structural, training parameters and RMSE performance of the feedforward neural networks with different learning algorithms

NN Type	Learning rate η	Momentum term α	Iteration number N	Neuron number: Input n_I	Hidden 1 n_{H1}	Hidden 2 n_{H2}	Output n_O	Crank shaft speed rpm	RMSEs
GRNN	0.25	0.4	$5x10^7$	1	10	10	2	1000	0.0759
								2000	0.0768
								3000	0.0979
MNN	0.25	0.4	$5x10^7$	1	10	10	2	1000	0.0782
								2000	0.0213
								3000	0.0314
RBNN	0.25	0.4	$5x10^7$	1	10	10	2	1000	0.0023
								2000	0.0047
								3000	0.0053

training parameters and root mean square errors (RMSEs) of NNs.

Conclusions

Among different networks (GRNN, MNN and RBNN) proposed to predict noise of two types of car engines, RBNN has superior prediction. Besides, structure of an RBNN is unusual in that the constitution of its hidden units is entirely different from that of its output units. With radial basis functions providing foundation for design of hidden units, theory of RBNN is linked closely with that of radial-basis functions. RBNN with radial-basis function and fast convergence properties has great possibility in real-time prediction and analyse noise of passenger car engines.

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