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Multi Neural Network Based Approach for Fault Detection and Diagnosis of A Dc Motor

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Abstract: Recently, neural networks have emerged as potential tools in the area of fault detection and diagnosis. This study explores a multi neural network based fault detection and diagnosis approach. The network architecture adopted is an RBF. The approach has been applied for detection and diagnosis of suitable parameters failures on a dc motor. The simulation results illustrated that after training of the neural networks, the system is able to detect the different failures.

Key words: Fault detection and diagnosis, multi neural network, Radial Basis Function (RBF) neural network, dc motor

INTRODUCTION

In the recent years and in the context of competitiveness there is an increasing demand for modern industry systems to become safer and more reliable. Process failure can potentially result not only on the loss of productivity but also o the loss of equipments and human lives. For these reasons, there is a growing need the development of procedure for fault detection and diagnosis in order to increase reliability and the availability of the installations in the aim of reduce the costs of maintenance of the production equipments, also that an early detection and diagnosis can help to avoid system breakdown and material damage.

Many investigations have been done to develop fault diagnosis methods. In some of these approaches the artificial neural networks are used to examine the presence of faults in the process and give a fault classification signal to declare whether or not the process is faulty. Neural network can be used to overcome the difficulties to deal with nonlinear behaviour. Let us note that a suitable choice of the database of the training allows the network to learn and generalise for operating with future input data.

In the present work, we propose a serial multi neural network homogeneous configuration including a set of a radial basis function network to solve this problem. The results of diagnosis obtained on a dc Motor (often used in the literature as being a model of validation) are presented.

NEURAL NETWORK

One defines an artificial neural network as being a parallel processor of distributed information processing. Its structure puts back on a massive interconnection of called basic cells neurons of which the representation is a directed graph.

Neural networks is entirely characterized by its architecture in other words the number of neurons constitute them and their diagram of interconnection, their functions of activation (which are fixed according to the task that the network must fill) and finally their coefficients which are generally determined by an algorithmic process called training.

Three classes of network architecture are generally considered:

- The multi-layer networks which are very much used because of their relevance in classification, they are appeared as neurons organized in successive layers.
- The recurrent networks which are presented in the form of a multi-layer network equipped with loop of internal reaction within a layer.
- The topological networks which refer to a space organization of neurons determining a measurement of proximity particular obey metric between neurons.

The Figure summarizes the various types of networks according to various architectures. Once fixed architecture, we proceed to the training in which the aim is to estimate the coefficients of the network so that this last as well as possible filled the task to which it is dedicated.

Let us note that as the neural network is an universal approximator they have the advantage by their parsimonies (obtaining the approximations with less parameters). Such as the parallelism of

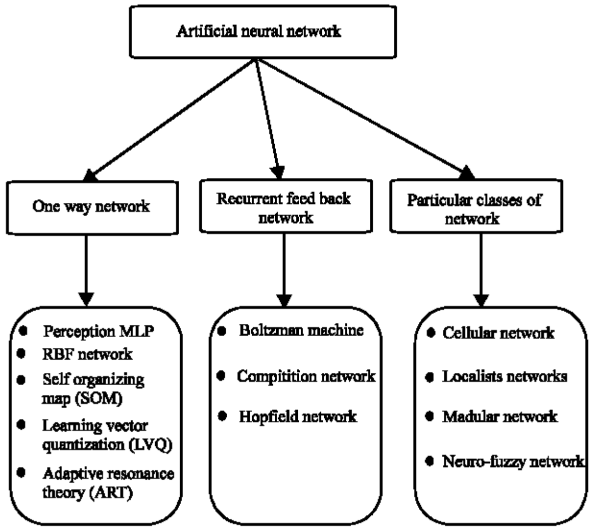

Fig. 1: Taxonomy of principal neuronal architectures

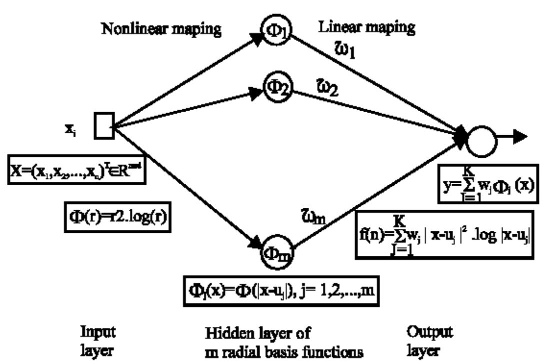

Fig. 2: Radial basis function network

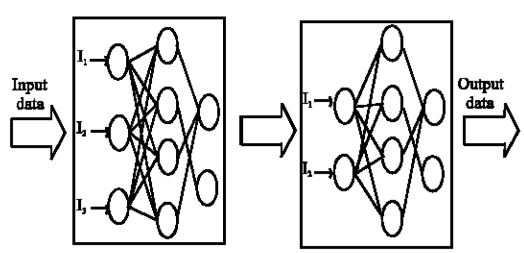

Fig. 3: Serial architecture of multi neural network

Table 1: Scale of the parameters intervals

Prarmeters	Min	Max	Step
R_a	7.56	10.16	0.1
L_a	0.057	0.095	0.001
J	0.070	0.092	0.001

Table 2: Test r esults

	R_a	L_a	J
Not classified vectors	25	24	26
Error of generalization	0.0268	0.0268	0.0290
(%) of classification	97.2(%)	97.3(%)	7.1(%)

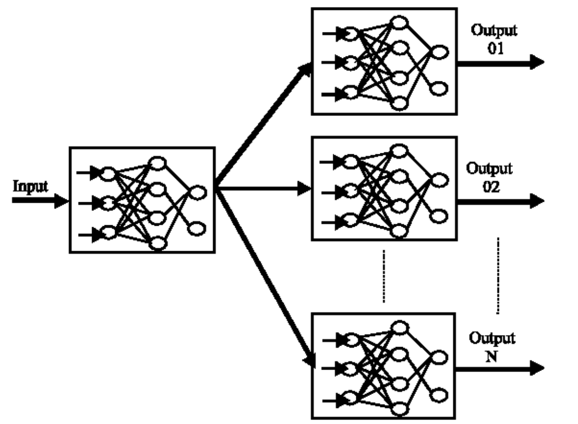

Fig. 4: Serial/parallel architecture of multi neural network

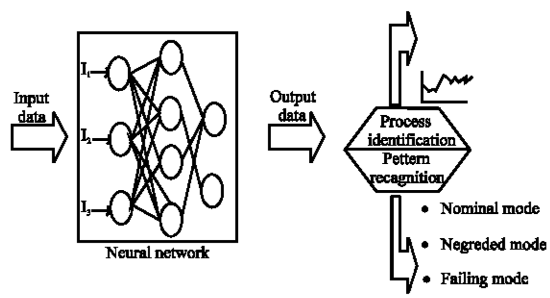

Fig. 5: Application of the neural network in monitoring of industrial plants

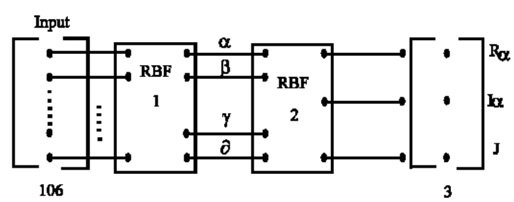

Fig. 6: Nominal speed and the failing modes

their structure, their capacity of adaptation and generalization.

We are interested in the problem of detection and diagnosis of the failures, of this fact the principal task will be that of classification. We thus proposed an architecture multi neuronal containing network with radial basic functions for their flexibilities of use like their capacity of classification.

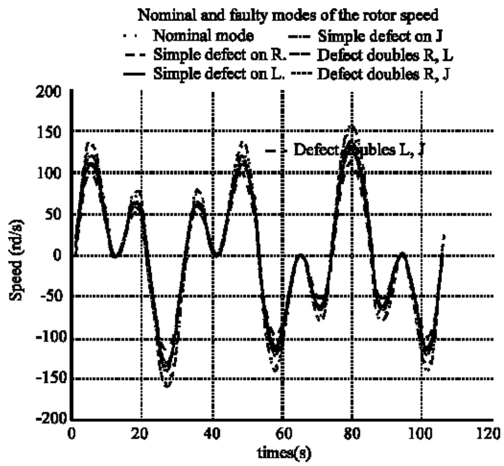

Fig. 7: Multi neural network architecture adopted

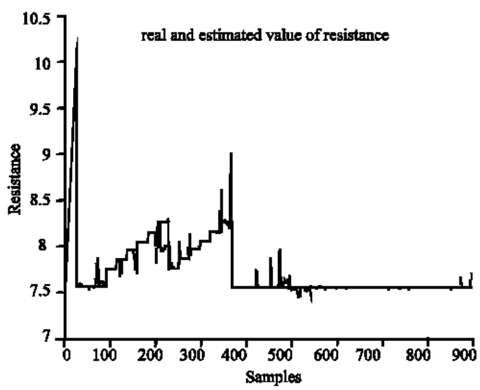

Fig. 8: Real and estimated resistance

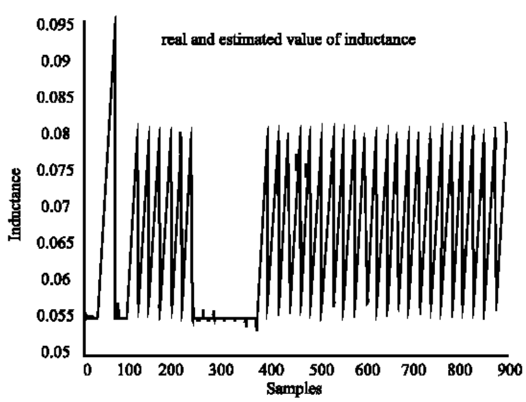

Fig. 9: Real and estimated inductance

RBF network: The radial basis function which were first introduce to solve the problem of multivariate interpolation have been employed in many different problems, in the literature the number of application covered by the RBFN is quite high, as an example one can

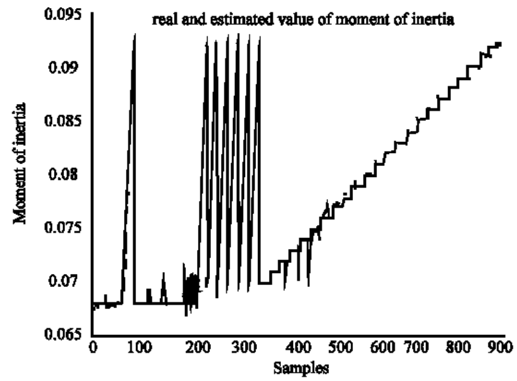

Fig. 10: Real and estimated inertia

quote: image processing, speech recognition, process fault detection and diagnosis, pattern recognition.

The design of a RBF network consists of three separate layers. The figure shows such architecture

- The input layer: Each neurons of this layer records the value of a characteristic describing an event of entry.
- The second layer is the hidden layer it forms a set of functions witch are called activation functions that provides a best fit to training data.
- The output layer gives the responses of the network to the activation pattern applied to the input layer.

A class of samples can be comparable with a group of dots of a space with N dimensions (N is the number of cell of the layer of entry). This last can be represented by areas having arbitrary forms. The learning procedure allocates networks resources in a meaningful way by placing the centre of the RBFN in only the regions of the input space were important data exist. Many learning strategies in the design of an RBFN exist depending on how the centre of the network is determined. The most used of them is that use of the standard K-nearest-neighbour rule for the selection of the hidden layer centres. This classifies an input vector by assigning the label of most frequently represented class among the K nearest samples. After that the Least-Mean-Square (LMS) algorithm is employed to calculate the weights of the output layer.

The recursive algorithm can be shown as bellow:

- Initialization of the centres Cj (0) 1 =? j =?N_h N_h: numbers applicant centres.
- At the moment K one assigns sample X with the one of K fields by using the relation: X ∈_Sj (k) if:

$$\left\| x - C_j \right\| \triangleleft \left\| x - C_i \right\| \quad (1)$$

For $i = 1,2 .... N_h$ such as $j \neq i$

Where Sj (k): Indicate the whole of the samples whose centres is Cj (k)

- By using the results of stage 2, one recomputed the centres of groups Cj (k+1) j= 1,2...... N_h with the formula:

$$C_j(k+1) = \frac{1}{N_j} \Sigma_{x \in Sj(k)} x \quad (2)$$

Nj: Indicate the number of the samples in Sj (k)

- If Cj (k+1) = Cj (k) f or j=1,2........ N_h the algorithm converges
  Else go at stage b.

Each node of exit has its own recursive estimator (RLS algorithm). If one defines the vector of exit of the layer hidden in T like

$\Phi(t) = [\ \Phi_1(.)\ \Phi_2(.) .... \Phi_{Nh}(.)\ ]^T =$
$[\ \Phi(d_1(t), B)\ \Phi(d_2(t), B.) .... \Phi(d_{Nh}(t), B)\ ]^T$
where di (t) = ||x(t)-Cj (t)|| $1 < i < N_h$

The vector of the weight of the i[th] neuron of left after adaptation at the moment (t) like:

$\theta_i(t) = [A_{1i}(t)\ A_{2i}(t) ..... A_{Nh}(t)]^T, 1 \leq i \leq m$

The i[th] recursive estimator fear being writes as follows:

$$\xi_i(t) = y_i(t) - \theta_i(t-1)\Phi(t) \quad (3)$$

$$P(t) = \frac{1}{\lambda(t)}\left[P(t-1) - \frac{P(t-1)\Phi(t)\Phi(t)' P(t-1)}{\lambda(t) + \Phi(t)' P(t-1)\Phi(t)}\right] \quad (4)$$

$$\theta_i(t) = \theta_i(t-1) + P(t)\Phi(t)\xi_i(t) \quad (5)$$

$1 \leq i \leq m$

The factor of lapse of memory is often calculated by:

$$\lambda(t) = \lambda_0 * \lambda(t-1) + 1 - \lambda_0 \quad (6)$$

With:

$\lambda 0 = 0.99$ $\lambda(0) = 0.95$.

The RBFN are employed mostly in classification problems. Many studies show that this kind of network is a superior over other neural network approaches in the following senses[2].

- RBFN are effectively capable of nonlinear mapping.
- The training time or the RBFN is quite low compared with the other neural network approaches.
- RBFN produce better classification accuracies than the other algorithms.

For these reasons, the RBF approach has been selected to solve the problem of detection and diagnosis.

Multi neural network architecture: Through the preceding sections we have shown that the approach of neural network is one of the very powerful tools that have been explored for fault detection and diagnosis problems because of their properties previously quoted. However they present in some cases, a limited successes because of their complexity (large number of neurons and long learning process)[3]. In order to deal with these disadvantages we propose to study and implement a new approach known as multi neural network approach which take advantage simultaneously from each neuron structure and having the advantage to permits us to limit classification errors.

Multi neural network is an effective method in parameters-varying and nonlinear process[4].The basic idea is to represent a non linear dynamical system by a set of locally valid sub model.

Two typical structures of a multi models are shown in Fig 3 and 4. Where the first is a serial multi MNN homogenous composed by two stages combining a RBF based classifier with a second RBF decision classification stage. In this case we train the first RBF and then its outputs constitute the learning database of the second one.

Figure 4 represents the serial/parallel multi neural network homogenous structure. Where the RBF disposed in parallel is used as decision stage. The first network is used as preliminary stage of classification or assignment for each new vector arising at the entry with the one networks structured in parallel. Also in this case we train the first classifier and its outputs constitute the learning database of each RBF network.

FAULT DETECTION AND DIAGNOSIS USING NEURAL NETWORKS

The techniques of monitoring containing neural network are founded on the existence of a database of training and not on the existence of a formal model of the equipment. The idea of such approach is summarized as follows: having a whole of data at the entry of the network let us seek an answer whose parameters are only the estimated parameters of the variables of monitoring, or a representation of the operating condition of the equipment. In is interested in the second description and in this case the problem of monitoring will be regarded as a problem of pattern recognition, such as the classes correspond to the various modes of failures of the system and the forms represent the whole of the measured observations.

SIMULATION AND EXPERIMENTAL RESULTS

In order to illustrate the method suggested in this work, a model of a dc motor is considered[5].

Dc motor model: The dc motor dynamics are given by the following two equations

$$Kwp(t) = -R_a i_a(t) - L_a\left[di_a(t)/d(t)\right] + V(t) \qquad (7)$$

$$Ki_a(t) = J\left[dw_p(t)/d(t)\right] + Dw_p(t) + C_c(t) \qquad (8)$$

Where:

W_p (t): rotor speed rad/s.
V (t): terminal voltage v.
Ia (t): armature current A.
C_c (t): load torque Nm.
J: rotor inertia Nm^2.
K: torque constant NmA^{-1}.
D: damping constant Nms.
Ra: armature resistance .
La: armature inductance H.

The load torque can be expressed as:

$$C_c(t) = \mu.w^2_p(t).[sign(w_p(t))] \qquad (9)$$

Where:

μ:is a constant

Finally the discrete time model is derived by first combining eq. 7, 8 and 9 and the replacing all continuous differentials with finite differences. The resulting model is

$$w_p(k+1) = \alpha.w_p(k) + \beta.w_p(k-1) + \gamma.[sign(w_p(k))].w_p^2(k) + \delta.[sign(w_p(k-1))].w_p^2(k-1) + \xi.V(k) \qquad (10)$$

Where:

$\alpha = [K+(1/K) + ((D-(J/T)) * (R_a+(L_a/T)) - (L_a*J)/T*T]/d$
$\beta = -[(1/K) * (L_a/T) * (D-(J/T)] / d$
$\gamma = -[-(\mu /K) * ((L_a/T) +R_a)] / d$
$\delta = -[(\mu /K) * (L_a/T)] / d$
$\xi = -1 / (K*d)$
$d = -(1/K) * ((L_a/T) +R_a) * (J/T)$

The dc motor used for simulation is described by the characteristics of 1h.p, 220v and 550rpm. Following parameter values are associated with:

J = 0.068 Kg m^2
K = 3.475 Nm A^{-1}
R_a = 7.56 Ω
L_a = 0.055 H
D = 0.03475 Nm s
μ = 0.0039 Nm s^2
T = 0.04 ms

Database construction: In order to generate the data for the training of the networks as well as the test of their capacities of generalization we simulated our system for duration of (479.52 ms) with a step of sampling of (4.52ms).

The training base let us include the simple and the doubles defect of the parameters which we considered to be significant on the modification of the dynamics of the system to knowing: R_a, L_a and J as that are indicated on (Fig. 6).

All the other parameters of the system will be considered invariants and the database was generated in the following way:

For each parameter (R_a, L_a and J) one simulates the system for intervals of data described by the table.

One obtains (106×89) points given case of simple fault. For the double faults (two parameters at fault simultaneously one combined the variations of the parameters in question for each couple (R_a, L_a), (R_a, J) and (L_a, J). The total database includes 894 vectors then (106 components for each one, corresponding to the values of samplings). This base is distributed in the following way 89 simple defects of which 27 vectors in the case of resistance fault, 34 for inductance fault and 23 for the case of inertia fault. The 805 others vectors are for the case of double defects.

RESULTS

The Adopted architecture is a multi homogeneous neural network; which consists of two RBF networks in serial as the figure indicates it.

The first network receives in output the (106) samples the speed of the rotor and delivers in output the estimated parameters (α,β,γ and d).While the second network its input is the output of the first network and its output is the physical estimated parameters (R_a, L_a and J).

Figures (8, 9 and 10) present the estimated values of R_a, L and J parameters.

After training, the error of generalization as well as the percentage of classification of the total base made up (894) vectors is presented in the bellow table.

CONCLUSIONS

This study presents a multi neural network system based fault detection and diagnosis scheme for parameters failures in a dc motor. This system synthesizes the merits of the RBF networks to produce good accuracies for classification and obtains good results for the fault diagnosis. Simulation results have shown that the capacity of classification of the systems multi networks is rather excellent. In our case a percentage of 97% of vectors of the total base are classified in a correct way.

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