Neural Network Architectures for Fault Diagnosis and Parameter Recognition in Induction Machines


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Abstract - This paper presents a neural network that is able to give, together with the rotor fault diagnosis, the combined rotor-load inertia momentum of an induction machine. The inputs of the network are the spectral components of machine input currents, speed and torque. A specific neural network architecture containing new fast spline-based neurons with improved generalisation capabilities has been used. The training set is obtained by a faulted machine dynamical model as simulator.

I. INTRODUCTION

The trend of on-line diagnostic systems in recent years has been to automate the analysis of measured signals by incorporating artificial intelligence facilities into the monitoring scheme. Considering fault detection in induction machines, some proposals concern the introduction of neural networks to improve the fault diagnosis [1,2], or to learn the characteristics of healthy machines in order to discern different abnormal conditions [3]. In this paper rotor fault detection is deeply investigated from the point of view both of the variables, introduced by the fault, suitable to be used in the learning process of the neural network, and of the further information on the electric system that can be achieved as outputs of the neural network. Moreover the structure of the neural network itself is examined with the aim to obtain the more fit architecture for the neural strategy chosen.

In previous works the authors developed a diagnostic procedure to detect rotor faults based on the anomalous spectrum line at frequency (1-2sf) that arises in the stator current spectrum when a fault occurs. Using a steady-state faulted machine model, diagnostic indexes that link the spectrum line amplitude to the fault entity and to the machine operating conditions, can be computed and inserted in the rules of the knowledge base managed by an expert system [4,5]. The procedure gives quite acceptable results, that can be furtherly improved utilizing other spectrum lines.

It is a matter of fact that the electric rotor dissymmetries give rise, beside to the (1-2sf) component, to a sequence of frequencies (1±2ks)f in the current spectrum due to the subsequent torque and speed ripples. These current lines, clearly detected in the experimental spectrum of faulty machines, can be evaluated, together with the spectrum components of torque and speed, utilising a transient model of the faulty machine.

The analysis results show, as it can be expected, that the combined load-machine inertia momentum plays an important role, together with the broken bar number, on the amplitude of the different spectrum lines. The knowledge of the inertia momentum, not usually available, can be very useful in many applications. Therefore in this paper a study is presented to develop a neural network able to give, together with the fault diagnosis, the combined inertia momentum.

In this first approach the data for the learning process are obtained by simulation and are referred to a single machine. As input data the current, torque and speed spectra can be utilized and, the outputs will be the fault entity and the inertia momentum. Obviously some of these input data are impractical from the experimental point of view: the current instantaneous value can be easily achieved, but torque and speed signals are not usually at disposal. But the results are encouraging and the future development of the study will be the utilization only of the current signals. As neural network, a multilayer structure with generalised sigmoidal neurons containing an adaptive activation function is utilised [6]. The good generalisation capabilities of this network are depicted by a comparison with the traditional sigmoidal network.

II. FAULTED MACHINE MODEL

It is well known that a failure in the rotor cage of induction machine causes e.m.f.s at frequency (1-2sf) in the stator windings. If the effects due to the consequent currents (i.e. torque ripple and subsequent speed ripple) are disregarded, a steady state model can utilised to correlate the fault severity with the stator current component at frequency (1-2sf) [9].

The results obtained through this model are quite good, depending on the machine size and overall on the load characteristic. Better results can be obtained removing the above recalled assumption. But when the speed is assumed as variable, a transient state model must be used. By adopting the model developed in [10,11], the faulted machine is studied by a system of two voltage equations in the d-q variables, referred to the rotor, for stator windings, N+1 voltage equations for the rotor in the rotor loop currents, still referred to the rotor, and the motion equation that links the derivative of rotor speed to, the electromagnetic torque, to the load torque and to the combined load-rotor inertia momentum. The failures in the bars are simulated by increasing the resistance of the broken bars.
The solution of the system can be obtained only in numerical form, but from the results’ analysis several features can be deduced [5], in particular:

- in the stator currents the component $I_1$ at frequency $(1-2s)f$ causes a torque component $T_1$ at frequency $2sf$ that gives rise to a speed component $\omega_1$ at the same frequency
- the speed component $\omega_1$ induces e.m.f.s and the consequent current components $I_1'$ and $I_2$ at frequencies $(1-2sf)$ and $(1+2sf)$ in the stator windings
- the stator component $I_2$ causes rotor currents at frequencies $\pm 3sf$ that cause stator currents $I_2'$ and $I_3$ at frequencies $(1+2sf)$ and $(1-4sf)$
- the component $I_3$ causes a torque component $T_2'$ at frequency $4sf$ and therefore a speed component $\omega_2$ at the same frequency
- the speed component $\omega_2$ causes the current components $I_3'$ and $I_4$ at frequencies $(1-4sf)$ and $(1+4sf)$.

Obviously the slip $s$ is the relative difference between the speed of the fundamental magnetic field and the medium value of the rotor speed under the assumption that speed ripple is negligible with respect to the slip value.

The current-speed component sequence goes on with decreasing amplitude.

In quasi-steady state condition, i.e. when the speed and current transient is over, and therefore the speed oscillates around its mean value and the currents are an expansion of sinusoidal functions, the instantaneous values of torque, speed and currents can be processed by a FFT algorithm and their spectra will show:

- resultant components $I_1$ (freq. $(1-2sf)$), $I_2$ (freq. $(1+2sf)$), $I_3$ (freq. $(1-4sf)$), $I_4$ (freq. $(1+4sf)$), ....
- resultant components $T_1$ (freq. $2sf$), $T_2$ (freq. $4sf$), ....
- resultant components $\omega_1$ (freq. $2sf$), $\omega_2$ (freq. $4sf$), ....

The amplitude of torque, speed and current components increases with the number of contiguous broken bars, while the main parameter that influences the speed ripple for a given broken bar number is the combined load-rotor inertia momentum.

The shapes of the instantaneous torque, speed and stator current are reported in Figs. 1 and 2 for one broken bar for two values of i.m. for a machine of 450 W, whose main plate and parameters are reported in Tab 1.

**Tab. I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated Power (kW)</td>
<td>0.450</td>
</tr>
<tr>
<td>Rated Voltage (V)</td>
<td>127</td>
</tr>
<tr>
<td>Rated Current (A)</td>
<td>1.5</td>
</tr>
<tr>
<td>Rated Slip</td>
<td>0.045</td>
</tr>
<tr>
<td>Supply Frequency (Hz)</td>
<td>50</td>
</tr>
<tr>
<td>Rotor Inertia Momentum (Nms²)</td>
<td>0.00225</td>
</tr>
<tr>
<td>Number of Bars</td>
<td>27</td>
</tr>
</tbody>
</table>

The figures report also the variables’ spectra and are referred to the quasi-steady state condition and to the rated load.

The simulation has been repeated for different i.m. values and loads. In Fig. 3 the shape of the first two current component $I_1$ and $I_2$, for one and two broken bars and in correspondence of 0.5, 0.75, 1 times the rated load, are reported in function of the inertia momentum. Fig 4 shows the shapes of $T_1$ and $\omega_1$.

As it can be expected, the shapes of $I_1$ and $I_2$ are increasing with the i.m., on the contrary the shapes of $I_2$ and $\omega_1$ are decreasing. Therefore it is possible to use these signals to define both the broken bar number and the inertia momentum value. These variables are assumed as outputs of the neural network, while as inputs we use the current components at frequencies $(1\pm 2sf)$ and $(1\pm 4sf)$, and the torque and speed component at frequency $2sf$.

The machine operating conditions are put into account introducing the further inputs:

- Current fundamental component
- Torque fundamental component
- Slip (in practice speed fundamental component).

The neural network will have nine inputs and two outputs, whose values will be properly normalized.
Fig. 1 - Quasi-steady state variables' example (rated torque) for one broken bar and J=0.00225 Nms²
a - instantaneous e.m. torque [Nm] b - instantaneous speed [rad/s] c - instantaneous stator current [A] d - e.m. torque spectrum [Hz] e - speed spectrum [Hz] f - current spectrum [Hz]

Fig. 2 - Quasi-steady state variables' example (rated torque) for one roken bar and J=0.009 Nms²

III. THE GENERALIZED SIGMOIDAL NEURAL NETWORK (SGNN) ARCHITECTURE

The neural network chosen has a multilayer structure with adaptive activation function. This NN is designed using a neuron, called generalized sigmoidal (SG) neuron, containing an adaptive parametric spline activation function [6]. This function has several interesting features: 1) is easy to adapt, 2) retains the squashing property of the sigmoid, 3) has the necessary smoothing characteristics, 4) is easy to implement both in hardware and as software simulation. The multilayer networks built with such neurons are still universal approximators and have usually a smaller structural complexity, maintaining good generalization capabilities.

The spline activation functions are smooth parametric curves, divided in multiple tracts. The i-th tract of the curve \( F_i(u) \) is represented by

\[
F_i(u) = [F_{x_i}(u), F_{y_i}(u)]^T : 0 \leq u \leq 1
\]

where \( u \) is the parameter, \( T \) is the transpose operator and \( F_{x_i}(), F_{y_i}() \) are two polynomial functions describing the curve in the two coordinates \( x \) and \( y \).

In particular due to the continuous first derivative, which allows to develop a back-propagation-style learning algorithm, we use the Catmull-Rom-based spline [7,8].

The expression (1) is simply rewritten as

\[
F_i(u) = \begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 3 & 0 & 0 \\ 1 & -1 & 0 & 0 \end{bmatrix} \begin{bmatrix} Q_i \\ Q_{i+1} \\ Q_{i+2} \\ Q_{i+3} \end{bmatrix}
\]

where \( u \in [0, 1] \) and \( Q_{j+m} \ (m=0, \ldots, 3) \) are the four control points for each curve tract. Such spline schemes are called local schemes, as the shape of the curve in the i-th tract is affected only by its four control points, so that the curve can be modified locally without influencing distant tracts. Eq. (2) represents the neuron output for the i-th tract.

The proposed neuron is composed of a classical linear combiner, which performs the weighted sum of the inputs, and, as Fig. 5 shows, of two blocks (SG1 and SG2) which realize the spline adaptive activation function.

![Diagram](image)

**Fig. 5.** Generalized sigmoidal neuron (SG-neuron) based on the Catmull-Rom spline adaptive activation function with the internal structure of the SG2 block

The block SG1 performs the mapping of the linear combiner output to the parametric domain, while the block SG2 computes the neuron output by using the activation function's control points, stored in a look-up table (LUT), and the polynomial coefficients of Eq. (2).

The learning algorithm for the SGNN is based on the classical back-propagation [8] where both the NN weights and the local activation function free parameters \( Q^{(i)}_n \) are adapted (see for detail [6]).

IV. NUMERICAL RESULTS

In order to show the improvement obtaining by using the SG-based NN in a system for on-line induction machines diagnostic and parameters estimation, we tested different network architectures trained by faulted machine simulator described in Sec. II.

Two network architecture were considered: the traditional sigmoid (here called MLP network) and the SG-based one. In particular three network are used: the first is a static MLP 9-2-2 (9 inputs, 3 hidden neurons and 2 outputs), the second is a SG 9-2-2 while the third is a simple SG 9-2-2 without hidden layer.

The training set is composed by 29 patterns: the input set is composed by 9 machine data (see Table I); while the output set contains the electric motor asymmetry severity and the inertia momentum, according to the consideration developed in Sec. II.

The inputs and outputs are referred to prefixed values for normalization purpose. Rated torque and current are chosen, the spectral components are referred to fundamental components, while a maximum of four broken bars and a maximum equal to eight times the rotor inertia value are fixed.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>NN TRAINING SET.</th>
</tr>
</thead>
<tbody>
<tr>
<td>INPUT PARAMETERS</td>
<td></td>
</tr>
<tr>
<td>( T/T _r )</td>
<td>Torque /Rated Torque</td>
</tr>
<tr>
<td>( s )</td>
<td>Slip</td>
</tr>
<tr>
<td>( I_s /I_s )</td>
<td>Supply Current Component/Rated Current</td>
</tr>
<tr>
<td>( I_{1s} ), ..., ( I_{6s} )</td>
<td>Current Components/Supply Current Comp.</td>
</tr>
<tr>
<td>( \alpha /\alpha )</td>
<td>First Speed Component/Mean Speed Value</td>
</tr>
<tr>
<td>( T/T )</td>
<td>First Torque Component/Mean Torque Value</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OUTPUT PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( n/4 )</td>
</tr>
<tr>
<td>( J/J _r )</td>
</tr>
</tbody>
</table>

The learning rate is \( \mu = 0.1 \) for the MLP 9-2-2 and the SG 9-2-2, and \( \mu = 0.05 \) for the single layer network. For all the SG-based NNs, the activation function adaptation parameter is \( \mu_s = 0.01 \). A momentum [8] \( \alpha = 0.3 \) is fixed for all the networks.

The performances are expressed in term Mean-Square-Error (MSE) computed using five networks, initialized with different weights, for each experiment. Moreover, Table 2 reports the number of free adaptable parameters and the average MSE \( \langle -MSE \rangle \) computed at the end of the learning.
Table II Fault Detection and Inertia Momentum NN Estimation Performance.

<table>
<thead>
<tr>
<th>Network</th>
<th>Free adaptable parameters</th>
<th>Training Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP9_3_2</td>
<td>38</td>
<td>-16.2</td>
</tr>
<tr>
<td>SG9_2_2</td>
<td>34</td>
<td>-17.4</td>
</tr>
<tr>
<td>SG9_2</td>
<td>28</td>
<td>-17.2</td>
</tr>
</tbody>
</table>

Fig. 6 shows the average MSE during the first 500 epochs. Five different initial conditions are used for each network architecture: (a) MLP9_3_2; (b) SG9_2_2; (c) SG9_2.

![Graph showing average MSE during learning phase for three networks](image)

The typical shape of the SG activation function obtained at the end of this learning is reported in Fig. 7.

![Activation functions for Layer 2](image)

The improvement of a rotor fault diagnostic system based on input current components has been presented. To the usual spectral component at frequency (1-2)f, other variables have been added: further current components, torque and speed spectral components. In this way not only a more effective diagnosis of broken bars can be obtained, but also a usually unknown parameters, the combined rotor-load inertia momentum, can be identified.

In this first approach the physical system has been simulated by a dynamical faulted machine model and the results have been used to train a neural network.

A specific NN architecture with adaptive activation function, has been presented. The SG-based networks are proved to be very effective, also with a small number of free parameters. Moreover, due to the implicit local nature of the spline curves, the number of parameters effectively adapted on-line, i.e. at each iteration, is much smaller than the total number of free parameters of the network.

V. CONCLUSION

REFERENCES


Tab. III

<table>
<thead>
<tr>
<th>Case</th>
<th>n/4</th>
<th>Target</th>
<th>NN</th>
<th>Target</th>
<th>J/J,</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.75</td>
<td>0.69</td>
<td>0.2</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>0.52</td>
<td>0.31</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1.03</td>
<td>0.31</td>
<td>0.32</td>
<td></td>
</tr>
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</table>

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