Approaching the Analysis of Linear Machines via Artificial Neural Networks

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Abstract

Artificial neural networks are used in this study for the analysis of a sector motor with the purpose of obtaining its thrust. The sector motor is a type of rotary induction machine, which owing to its particular shape, present the end-effects usually found in the linear machines. The analysis of a sector motor via the machine equations is not convenient because the equations do not easily lead to a model that can be applied to different operating situations. This problem arises from the difficulties in incorporating the end-effects into the machine equations. On the other hand, as the artificial neural networks are convenient tools for managing the situations of difficult modeling, they can be applied as an alternative approach for the analysis of this kind of machine. In order to generate the data required by the neural network learning process, the machine is tested in the laboratory under various driving situations, which comprise transient and steady state conditions. The main purpose of this work is to obtain an artificial neural network architecture that represents the sector motor under the required operating conditions.

1 Introduction

The sector motor shape and the relation of its topology with the conventional rotating induction machine are shown in figure 1(a). The topology of the actual linear machine topology is shown in figure 1(b) for comparison.

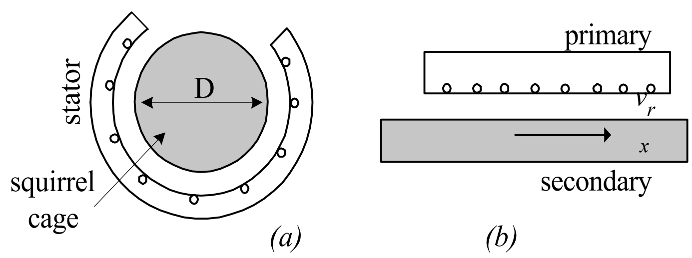

Figure 1- (a) The evolution of a sector motor from the rotating induction machine, (b) The actual topology of a typical linear induction machine.

The presence of entry and exit end-effects in the sector motor is clear in figure 1(a) because of the similarities of its topology to the actual linear counterpart, where these effects are commonplace. It is also well known that whenever the machine equations are derived from the rotary induction machine, appropriate factors are required for considering the end-effects [1]. Otherwise, the simulated thrust (or torque) does not agree with the corresponding actual value that can be measured in the laboratory.

2 Deriving the thrust developed by the linear machine

The analysis of the thrust developed by the linear machine is often based on first writing an equation for the wave of air-gap flux density that is established by the primary and secondary currents. Then the interaction of this flux with the wave representing the stator linear current density is considered. An equation for the thrust is derived from this interaction. For this calculation, the primary current can be considered as an equivalent current layer. The stator current linear density j_S as a function of the time t and the longitudinal position x is given by the wave:

$$j_S(x,t) = J_{\max} e^{j(wt - p\frac{x}{t_p})} \quad (1)$$

where t_p is the polar pitch and w is the stator angular frequency.

As a result of applying the one-dimensional analysis to the sector motor topology, the wave of air-gap flux density is obtained by:

$$b(x,t) = B_S + B_e = B_{S\max} \cos\left(wt - p\frac{x}{t_p + d_S} \right) + B_{e\max} e^{(\frac{-x}{a})} \cos\left(wt - p\frac{x}{t_{pe} + d_e} \right) \quad (2)$$

where B_S is referred as the fundamental part of the flux density wave whereas B_e accounts for its end-effect component. In equation (2) δ_S is the angle between the axes of the waves J_S and B_S (see figure (2)). J_S is the stator linear current density wave and δ_e is the end-effect angle.

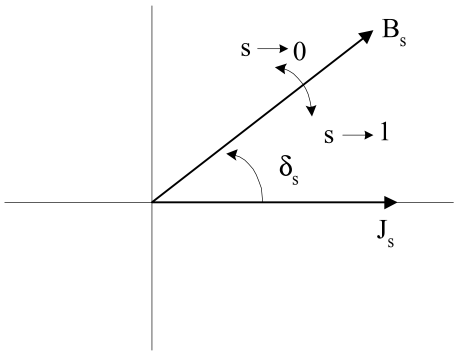

Figure 2 – Phasor diagram between the functions $b_S(x,t)$ and $j_S(x,t)$.

Equation (2) shows that the sector motor air-gap flux density is composed by two terms B_S and B_e which represent waves that are traveling in opposite directions each other. Conventional asynchronous machines have only the usual term Bs because they do not present longitudinal end-effects. The end-effects require another term (B_e) to present in equation (2). Besides, the terms B_S and B_e have different polar pitches, respectively t_p and tp_e. They also attenuate differently with the position x. The machine developed thrust can be calculated by considering the interaction of the waves $b(x,t)$ and $j_S(x,t)$ [2]:

$$f = \frac{D}{2}\int_0^C \Re e\left(j_S(x,t).b^*(x,t)\right)dx = f_S + f_e \qquad (3)$$

where $b^*(x,t)$ is the complex conjugate of $b(x,t)$, D is the rotor diameter and C is the primary length.

The thrust f in equation (3) can be written as the sum of two terms, as a result of the end-effects which affects its magnitude and require the appropriate correction. For the specific case of the sector motor and its operating conditions, it is quite difficult to make the correction of the machine equations in order that the end-effects are taken into account as required. Therefore, the results that are obtained in the laboratory do not agree with the corresponding results from the simulations. An example of this fact is shown in figure (3).

Even if the corrections are considered in the simulations, the results presented in figure (3) show no agreement of the simulated thrust with the corresponding values that were measured in the laboratory. This means that modelling the sector motor via the machine equations is possible but adjusting the proper correcting factors, which account for the end-effects, is not an easy task.

Like the conventional rotating induction machine, an equivalent electric circuit can also be used as a simulation tool for steady-state operation considerations. However, if the conventional rotating machine equivalent circuit is used, an impedance parameter Z_e must be incorporated to it so that the end-effects are accounted for in the model [3].

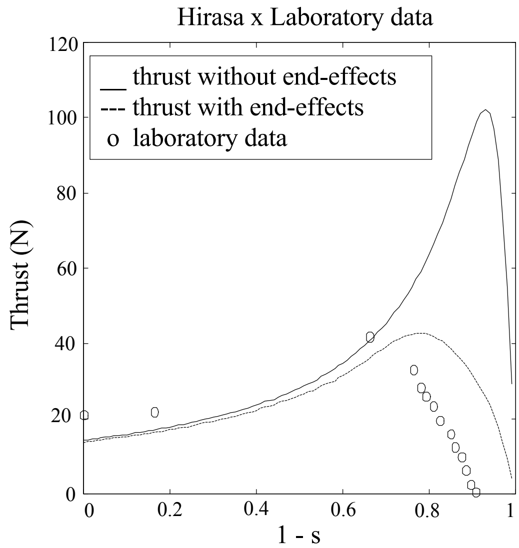

Figure 3 – Sector motor developed thrust using Hirasa equations and laboratory data.

Although there are other linear machine topologies for which the use of correction factors may lead to good results, this is not the case for the sector motor. Therefore, the use of the machine equations is not the preferable approach in this study. As the conditions relating the different machine variables are of difficult determination, the use of artificial neural networks for the analysis is very convenient because this particular tool applies very well.

3 Neural network architecture

The artificial neural network (ANN) ability to identify the solutions (mapping property) made this tool very interesting for solving complex problems. The learning algorithm allows the neural network synaptic weights to be properly adjusted (ability of learning and generalizing the solutions) so that the input and output variables of a given process can be mapped. Some kinds of problems have complex relationships between its variables, which are not well defined [4]. This is the case of the sector motor where the conventional modeling techniques may not work for all the cases. The multilayer perceptron artificial neural network of figure (4) was used in this work for mapping the sector motor thrust under various operating conditions.

A typical perceptron network is depicted in figure (4), with m inputs and p outputs, where each circle represents a single neuron. The name feedforward implies that the flow is one way and there are not feedback paths between neurons. The output of each neuron from one layer is an input to each neuron of the next layer. The initial layer where the inputs come into the ANN is called the input layer, and the last layer, i.e., where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layer.

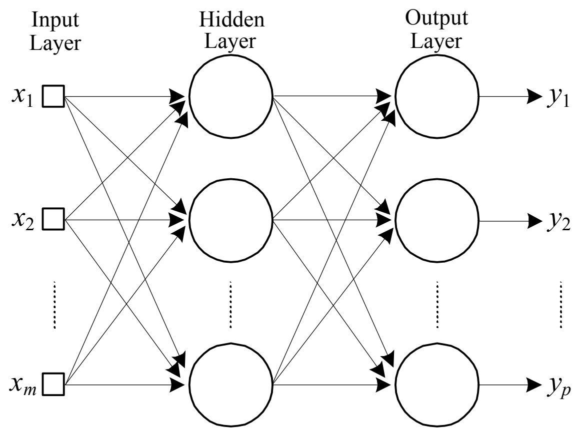

Figure 4 – Typical multilayer perceptron neural network.

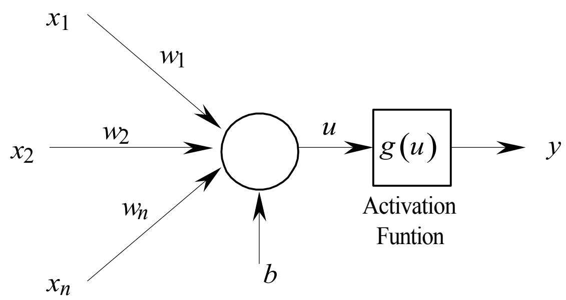

Figure 5 - Single artificial neuron.

Each neuron can be modeled as shown in figure (5), with n being the number of inputs to the neuron. Associated with each of the n inputs x_i is some adjustable scalar weight, w_i ($i=1,2,...,n$), which multiplies that input. In addition, an adjustable bias value, b, can be added to the summed-scaled inputs. These combined inputs are then fed into an activation function, which produces the output y of the neuron, that is:

$$y = g\left(\sum_{i=1}^{m} w_i x_i + b\right) \tag{4}$$

where g is generally specified by a sigmoid function or hyperbolic tangent function.

The training process of the neural network consists of successive presentations of input-output data pairs. The basic structure having one hidden layer has been shown to be powerful enough to produce an arbitrary mapping among variables. During the training, the data are propagated forward through the network, which adjusts its internal weights to minimize the function cost (average squared error between the true output and that output produced by the network) by using the back-propagation technique. The details of the back-propagation algorithm are well known in literature and its steps can be found in [4].

A review of the main steps of this algorithm is presented here. The function to be minimized is the sum of the average squared error (E_{AV}) of the output vector,

$$E_{AV} = \frac{1}{N}\left(\sum_{k=1}^{N} E(k)\right) \tag{5}$$

where N is the number of training vectors and $E(k)$ is the sum of squared errors over all neurons in the output layer, i.e.,

$$E(k) = \frac{1}{2}\left(\sum_{j=1}^{p}\left(d_j(k) - y_j(k)\right)\right)^2 \tag{6}$$

For an optimum weight configuration, $E(k)$ is minimized in relation to synaptic weight, so that for each data set,

$$\frac{\partial E(k)}{\partial w^{l}_{ji}} = 0 \tag{7}$$

where w is the weight connecting the neuron j of the l-layer to neuron i of the $(l-1)$-layer.

Finally, the weights of the network are updated using the following relationship:

$$w^{l}_{ji}(k+1) = w^{l}_{ji}(k) - h\,\frac{\partial E(k)}{\partial w_{ji}(k)} \tag{8}$$

where η is a constant that determines the learning rate of the back-propagation algorithm.

4 Acquiring data in the laboratory

Several tests were carried out in the laboratory to get the data for the determination of the sector motor thrust. Different situations regarding the way the sector motor is driven were considered. For all the tests, the sector motor is connected to the inverter and the required machine input variables (stator current, voltage and machine speed) are acquired in the set-up for different mechanical load conditions. A schematic view of the experimental set-up that was used for getting the measured quantities in the laboratory is presented in figure (6).

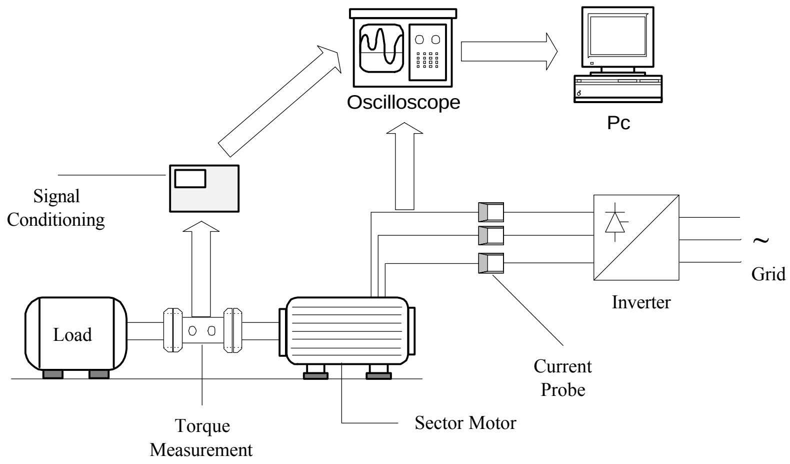

Figure 6 - Experimental setup.

The output variable that is expected to be estimated by the neural network is the thrust available in the machine shaft. Possible signal interference from measurement errors and instrument output inaccuracies are possible and need to be eliminated because the neural network must be immune to errors in the input variables. Some of the results that the ANN produced from the data acquired in the laboratory follows as examples.

The example presented in figure (7) corresponds to starting the sector motor directly from the inverter and 60Hz. No mechanical load is connected to the machine shaft as the data is acquired. The thrust obtained from the ANN output is presented as a function of the speed.

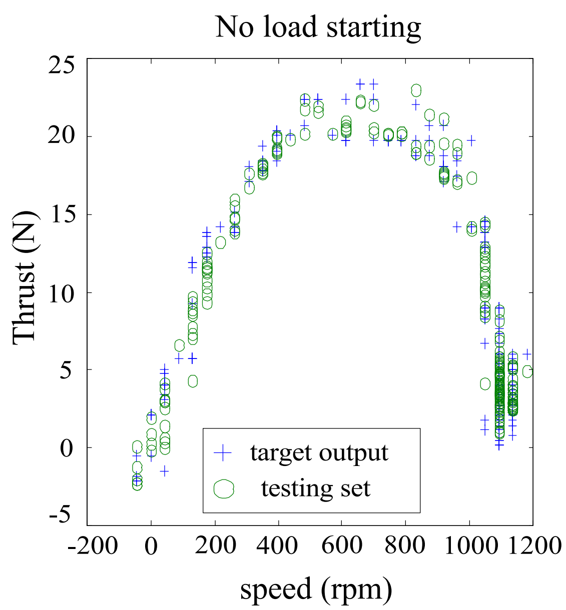

Figure 7 - Starting the sector motor with no load. The thrust given by the neural network learning algorithm.

For the case shown in figure (7), a two-hidden-layer artificial neural network architecture with *5-4-1* neurons was used. The learning function which best dealt with the input data was *trainbr*. Its process is known as *Bayesian regularization*.

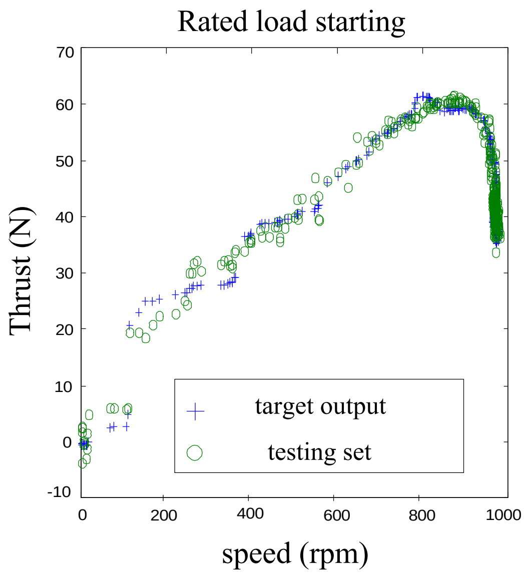

Figure 8 - Starting the sector motor under full load: the thrust as given by the neural network learning algorithm.

Figure (8) shows another example where the sector motor is started under full mechanical load and rated stator voltage (220V).

After feeding the laboratory data to the neural network learning process and performing the tests for validation, the target output for the case shown in figure (8) is obtained. For this specific case, the neural network architecture which best cope with the data was a two-hidden-layer configuration with *6-5-1* neurons. The learning function which best managed the input data was *trainbr*.

The result shown in figure (9) corresponds to the situation where the sector motor is being started with an overload of 30 per cent of its rated value.

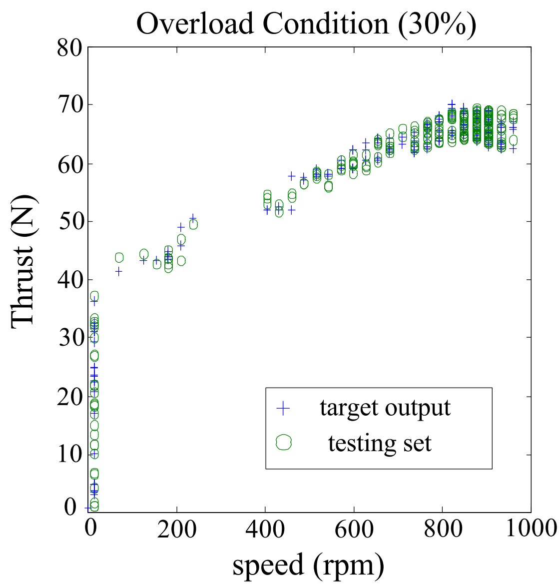

Figure 9 - Starting the sector motor under an overload of 30% load. The curve shows the thrust that is given by the artificial neural network learning algorithm.

For the specific case of figure (9), the selected neural network was also a two-hidden-layer configuration with *6-5-1* neurons. The learning function which best managed the input data was *trainbr*.

Another example is shown in figure (10). In this case the machine was tested in steady-state. An inverter is driving the machine with 60 Hz, under rated load. A one-hidden-layer neural network architecture with *6-1* neurons was now used. The learning function was *trainlm* in this case.

Figure (10) shows that, for the case of steady-state operation, the generalization of results which was produced by the neural network allows to anticipate with success the measured thrust.

As a final application example, an inverter is used to drive the machine with rated voltage (220V) under steady-state condition. The inverter frequency was 50Hz. A one-hidden-layer neural network architecture with *6-1* neurons was now used. The learning function was *trainlm* in this case. The results are shown in figure (11).

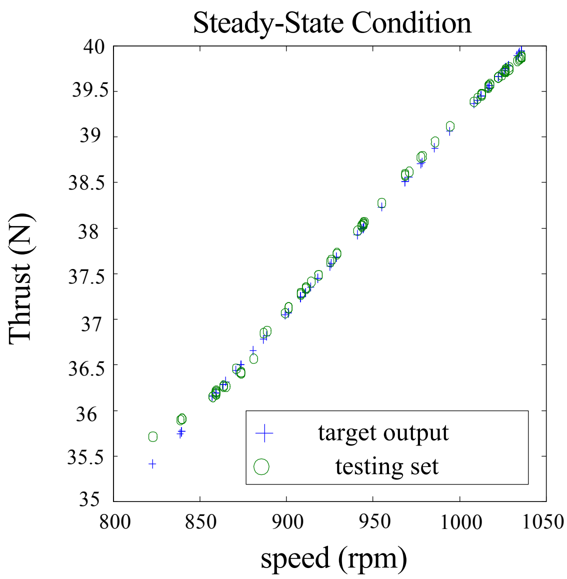

Figure 10 - Learning algorithm results corresponding to steady-state operation, full load and 60Hz.

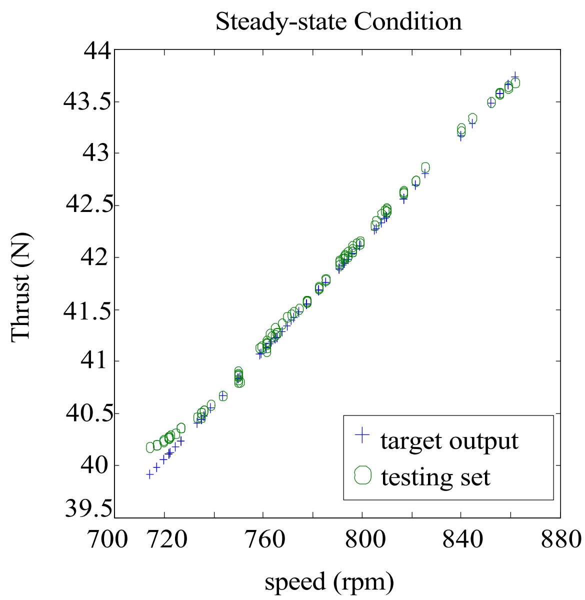

Figure 11 - Learning algorithm results: the machine is driven through an inverter, 50Hz and full load.

5 Concluding remarks

The application of artificial neural networks to characterize the thrust developed by a sector motor is the purpose of this work. This motor has a particular shape which makes its modeling difficult when the usual machine equations are intended to be applied for it. Another difficulty is that the machine parameters are not all known and are not easy to be obtained in the laboratory. Besides, if the machine equations are used, they must be corrected for the end-effects presented by this kind of machine. The required correcting factors are not of easy determination for all the situations.

Therefore, the research had to be aimed at using an alternative approach in order to get a good estimate for the machine thrust available in the shaft. As the results of figures (7) to (11) clearly show, the determination of the thrust by means of the artificial neural networks approach was very satisfactory. Notice that no machine parameters were required for the analysis, which is very interesting, as they are not all available for the machine modelling by other means. In this specific research, when fed with the data acquired in the laboratory, the neural network learning process was able to produce the appropriate network topology so that the results from it were in good agreement with the actual data for all the cases which were considered in the analysis.

6 Acknowledgments

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