

Three autoregressive-neural network hybrid models for energy efficiency estimation of induction motors

Energy
efficiency
estimation

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Received 14 February 2018
Revised 22 June 2018
11 September 2018
Accepted 24 September 2018

Abstract

Purpose – Improvements on the energy efficiency of the induction motors bear on not only these motors but also on the whole industry as a result of preference of these types of motors. In recent projects, energy efficiency of the induction motors is approaching to 90 per cent. The first necessary condition of the efficiency improvements is an accurate estimation of energy efficiency. This study aims to estimate the energy efficiency of induction motors by using three innovative estimation methods.

Design/methodology/approach – Data for 307 motors were taken from three different companies and their torque, power, power factor and speed data were used. Three hybrid models were created by estimating the error of three autoregressive (AR)-based efficiency estimation models with the back-propagation artificial neural network (ANN) structure. In these proposed hybrid models, the AR models were supported with artificial neural networks to obtain a minimum estimation error. These three hybrid models were called as AR1-ANN, AR4-ANN and residual-ANN.

Findings – Without hybridization of AR models by back-propagation ANNs, the best estimation result was obtained by residual model. On the other hand, for the proposed hybrid models, the best estimation was obtained by AR1-ANN, followed by AR4-ANN and finally the residual-ANN according to ME values.

Practical implications – Proposed AR-ANN hybrid models relieve of longtime experiments for the energy efficiency measurement of induction motors. Furthermore, these AR-ANN models give more accurate results than the available methods in the literature. Engineering value of this research is three different issues in finding energy efficiency. The first one is minimizing of the test cost, the second one is no requirement the test equipment and the third one is not interrupting the motor. Every company that needs motors can use these estimation methods due to the advantages.

Originality/value – Novel three AR-ANN hybrid models for energy efficiency estimation were studied. These novel methods give better response than the other methods which were used for estimation of induction motors in the literature.

Keywords Energy efficiency, Estimation, Autoregressive model, Back-propagation, Induction motors

Paper type Research paper

Nomenclature

TWh = Terawatt Hour;
Cov = Pearson's correlation coefficient;



COMPEL - The international
journal for computation and
mathematics in electrical and
electronic engineering
Vol. 38 No. 1, 2019
pp. 431-451
© Emerald Publishing Limited
0332-1649
DOI 10.1108/COMPEL-02-2018-0093

ρ	= Efficiency Correlations;
$E[XY]$	= Sum of the X and Y Variables;
$E[X]$	= Sum of the X Variables;
$E[Y]$	= Sum of the Y Variables;
n	= Number of the Variables;
α	= Coefficient;
ϵ	= Error of the Model;
o	= the output of the transfer function;
i	= the input of the transfer function;
Un	= the update function;
J	= the Jacobian matrix;
e	= the network error;
Eff	= Efficiency;
P	= Power;
PF	= Power Factor;
S	= Speed;
M	= Momentum;
ME	= Mean Error;
ME%	= Mean Error in terms of Percentage;
mse	= Mean Squared Error;
MAE	= Mean Absolute Error;
RMSE	= Root Mean Squared Error;
RMSE%	= Root Mean Squared Error in terms of Percentage;

1. Introduction

The total electricity use for electric motors represents 46 per cent of global electricity consumption in 2006; 38.3 per cent of electric consumption by motors is used by pumps, fans and compressors in heating, ventilation and air conditioning systems in the commercial sector; Motors in the industrial sector account for 68.9 per cent of electricity use, mostly in manufacturing use and production areas (Waide and Brunner, 2011).

Alternating current (AC) three-phase induction motors are widely used in commercial buildings and industrial applications in pumps, fans and compressors, where they are continuously operated because of their efficiency and low cost (DOE, 2008).

The energy-efficient use of induction motors is a significant contributor to both economic and environmental issues, especially as induction motors are believed to account for 90 per cent of the motors used in industry. Some models, especially in the motor drive systems, may allow to determine important additional data, where experimental tests may have some limitations (Baptista *et al.*, 2015). Some of existing methods generally use the experimental tests for to find accurate results in efficiency, but these tests are limited and very costly. Also, some existing methods use the circuit equations, but to get the circuit equation parameters is not possible sometimes because they need some devices. In this study, efficiency estimation was made by using estimation methods because of the limitation of experimental tests and circuit equations, but not for drive systems.

2. Methods of finding energy efficiency in induction motors

2.1 Experimental methods (site testing)

The efficiency measurement of electric motors can be calculated in two ways for experimental methods, directly and indirectly.

Experimental methods are generally more precise; however, they are not widely used due to the establishment and operation costs of test laboratories (Anibal *et al.*, 2008).

2.1.1 Direct methods. The efficiency of electric motors can be measured directly by using the following equation:

$$\text{Efficiency\%} = \frac{\text{Mechanical Output Power}}{\text{Electrical Input Power}} * 100 \quad (1)$$

For this reason, measurements for both mechanical output power and electrical input power are necessary. Electrical input power can be measured precisely with medium priced equipment that is easy to set up. Mechanical output power can be defined as the multiplication of the torque and angular velocity. While it is possible to obtain an accurate result with a relatively easy procedure that requires cheap equipment for the speed measurement (± 1 RPM), the torque measurement requires a more detailed setting up and more expensive equipment. The torque measurement generally requires a connection to a dynamometer, which is equipped with an accurate torque converter that allows the generation of a variable charge to control the motor. In North America, test methods depending on the direct measurement of efficiency are commonly used. The Institute of Electric and Electronic Engineers (IEEE) Standard 112 is a standard adopted both by the National Electric Manufacturers Association (NEMA Standard MG-1) and the US Ministry of Energy. In Canada, the Canadian Standards Association Standard 390 follows a procedure that is very similar to the IEEE 112 Standard.

2.1.2 Indirect methods. To avoid the complexity and expensive costs of the torque measurements, a motor's efficiency can be calculated by the following equation:

$$\text{Efficiency\%} = \frac{(\text{Electrical Inp.Power} - \text{Losses})}{\text{Electrical Input Power}} * 100 \quad (2)$$

Equation (2) requires the measurements of the motor's losses. Most of the motor's losses, (copper, iron, mechanical), can be measured quite precisely. However, the remaining losses, (stray charge losses), cannot be measured exactly. In indirect efficiency test methods, the stray charge losses at full charge are considered to be 0.5 per cent of the input power at full charge, as recommended by the International Electrotechnical Commission 34-2 Standard. This hypothesis does not take into account the stray charge losses, particularly in small motors. Not to consider these losses is a failure in energy efficiency calculations, which is greater in 60 Hz systems than 50 Hz systems. The failure is greater in Japan Industrial Standards 37, because the stray charge losses are completely ignored in the indirect measurement.

2.2 Estimation methods

Various efficiency estimation methods have been developed due to the difficulty and cost of doing site testing. It is not an efficiency way to test the motors by interrupting the operation of them. For this reason, methods have been developed for estimating of energy efficiency.

3. Literature survey

There are many methods in literature for estimating the energy efficiency of induction motors. These are as follows.

3.1 Slip methods

The sliding method is based on measuring the motor speed (Kueck *et al.*, 1996; Ontario Hydro Report, 1990; Lu *et al.*, 2008; Charette *et al.*, 2000; Aspalli *et al.*, 2008; Phumiphak and Chat-uthai, 2002). The clearest advantage is simplicity:

- Standard slip method.
- Ontario hydro modified slip method.
- Upper limit slip method.

3.2 Current method

The current method is similar to the slip methods, and productivity using simple measurements and the manufacturer's data is estimated. (Kueck *et al.*, 1996; Ontario Hydro Report, 1990; Lu *et al.*, 2008; Charette *et al.*, 2000; Aspalli *et al.*, 2008). It is a straightforward method:

- Standard current method.

3.3 Circuit equation methods

The efficiency of an induction motor can be calculated from electric circuit equations (Kueck *et al.*, 1996). The circuit equation methods can provide an efficiency estimate for a motor except load operating conditions:

- Standard circuit equation method (IEEE Std-112 Method F/F1).
- Ontario hydro modified method F.
- Plate circuit equation nameplate method.
- Rockwell motor efficiency wizard method.
- Locked rotor method.
- Stopping frequency answer method.

3.4 Loss separation method

These are the simplest methods because they can easily estimate each lost component because of stator resistance, rotor resistance, core, friction and windage and stray load (Ontario Hydro Report, 1990). This method is crucial because of basing on the empirical equations for to estimate some lost values:

- Standard loss separation method (IEEE Std-112 Method E1).
- Ontario hydro modified method E.

3.5 Torque method

This can be referred to in a previous study (Lu *et al.*, 2008):

- Air gap torque method.
- Shaft torque method.

3.6 Plate value method

The most inconvenient efficiency evaluation method is to obtain motor information from motor plate values. (Kueck *et al.*, 1996; Ontario Hydro Report, 1990; Lu *et al.*, 2008):

- Standard plate method.
- Volgelsang and benning (V and B) method I, II.

3.7 Optimization-based methods

These can be referred to in previous studies (Charette *et al.*, 2000; Phumiphak and Chat-uthai, 2008; Aspalli, *et al.*, 2008; Siraki and Pillay, 2012; Lu *et al.*, 2007; Phumiphak and Chat-uthai, 2002; Pillay *et al.*, 1998; Phumiphak and Chat-uthai, 2004; Gomez *et al.*, 2008; Cunkas and Sag, 2010; Sakthivel *et al.*, 2010).

Optimization-based methods for estimating efficiency in real industrial conditions are another alternative.

In these methods, the efficiency of the motor is acquired by an optimization-based search algorithm (such as artificial neural networks, genetic algorithm, bacterial feed algorithm and multi-object optimization).

Based on a literature review, some research provides optimization-based techniques for estimating efficiency in balanced resource conditions. In some cases, the equivalent circuit method is combined with genetic algorithm to deal with the problem of estimating the efficiency in unbalanced feeding conditions.

In summary, the motor current method and the slip method are more applicable than the other methods in the literature. However, the reliability of these two methods is relatively less. Torque measurement methods, air gap torque methods and loss separation methods are more accurate, but not practical in the field use. The circuit equation methods are useful when it is not possible to remove the running motors while in the operating. The performance of any overhead induction motor is determined by the six circuit parameters consisting of stator windings, rotor windings, core loss resistances and stator, rotor leakage and magnetic reactance in the circuit equations. (Hughes, 2006). Although each method has its own disadvantages, optimization-based methods are emerging as the most useful methods nowadays. However, the equivalent circuit parameters of the induction motors are not necessary for the proposed methods. Instead of equivalent circuit parameters, the catalogue data for the power, speed, torque and power factor are used in this study. It is also assumed that the estimation is under balanced source conditions. However, as every estimation method has its weaknesses, it has been tried to reach the best estimation result by using different estimation methods in this study.

4. Materials and methods

The power, speed, power factor, moment and efficiency values of 307 motors used in this study were taken from three motor catalogs AEG [XX], TECO [XXI] and GAMAK [XXII].

4.1 AR1 model

In the AR1 model, only one parameter is used to estimate motor efficiency. This should be the parameter with the highest correlation with the motor's efficiency.

As a result of the correlation analysis, it is observed that the motor efficiency is mostly closely related to the power factor. This correlation analysis is obtained by calculating the Pearson correlation coefficient between parameters. Pearson's correlation coefficient can be calculated as follows:

$$Cov(\vec{X}, \vec{Y}) = E[XY] - E[X]E[Y] \quad (1)$$

$$Cov(\vec{X}, \vec{Y}) = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n (x_i - E[X])(y_i - E[Y]) \quad (2)$$

$$\rho(\vec{X}, \vec{Y}) = \frac{Cov(X, Y)}{\sigma_X \sigma_Y} \quad (3)$$

Correlation results are given in [Table I](#).

The correlation analysis includes not only cross correlations of the four parameters but also the cross correlations with their inverses. The correlation of the yield in the positive direction is found highest with the power factor. When the correlation of yield with other

parameters is examined, it is seen that the absolute correlation of these parameters with the inverse is stronger. Therefore, after the power factor, the inverse of the full load motor (1/power), the inverse of the full load motor torque (1/Moment) and the inverse of the full load rotational speed (1/speed) must be calculated in the efficiency estimation.

If only the power factor information is used, the created model will be calculated as follows. The coefficient of this model (a_{AR1}) is the projection of the efficiency on the normalized power factor:

$$\vec{Eff}: \text{Motor Efficiency Vector}; \quad \widehat{PF}: \text{Normalized Power Factor}: \frac{\overrightarrow{PF} - \min(PF)}{\max(PF) - \min(PF)} \quad (4)$$

$$\vec{Eff} = a_{AR1} \cdot \widehat{PF} + \vec{\varepsilon}_{AR1} \quad (5)$$

$$a_{AR1} = \frac{[\vec{Eff}]^T \cdot \widehat{PF}}{[\widehat{PF}]^T \cdot \widehat{PF}} \quad (6)$$

4.2 AR4 model

The AR4 model is essentially a model that can be applied to a time series generally. However, in this model, assuming that the inverse of speed, inverse of moment, inverse of power, power factor and efficiency data are successive examples, the AR4 model, which estimates the efficiency using the previous four examples, is constructed as follows:

$$\widehat{P^{-1}}: \text{Normalized Inverse of Full Load Power}: \frac{\overrightarrow{P^{-1}} - \min(P^{-1})}{\max(P^{-1}) - \min(P^{-1})} \quad (7)$$

$$\widehat{M^{-1}}: \text{Normalized Inverse of Full Load Moment}: \frac{\overrightarrow{M^{-1}} - \min(M^{-1})}{\max(M^{-1}) - \min(M^{-1})} \quad (8)$$

$$\widehat{S^{-1}}: \text{Normalized Inverse of Full Load Speed}: \frac{\overrightarrow{S^{-1}} - \min(S^{-1})}{\max(S^{-1}) - \min(S^{-1})} \quad (9)$$

$$\vec{Eff} = a_{AR4,1} \cdot \widehat{PF} + a_{AR4,2} \cdot \widehat{P^{-1}} + a_{AR4,3} \cdot \widehat{M^{-1}} + a_{AR4,4} \cdot \widehat{S^{-1}} + \vec{\varepsilon}_{AR4} \quad (10)$$

Table I.
Efficiency
correlations of
various parameters
and their reverses

$\rho(\vec{X}, \vec{Y})$	Power	Speed	Power factor	Moment	Efficiency
Power	1	0.034652	0.368991	0.884498	0.387115
1/Power	-0.16515	-0.24081	-0.63404	-0.12815	-0.79619
Speed	0.034652	1	0.401842	-0.02734	0.34054
1/Speed	-0.05089	-0.99825	-0.43417	0.012405	-0.38489
P.F.	0.368991	0.401842	1	0.282859	0.802703
1/P.F.	-0.33721	-0.39116	-0.99066	-0.25891	-0.81993
Moment	0.884498	-0.02734	0.282859	1	0.2935
1/Moment	-0.13752	-0.2619	-0.61685	-0.10751	-0.78197

$$\begin{bmatrix} a_{AR4,1} \\ a_{AR4,2} \\ a_{AR4,3} \\ a_{AR4,4} \end{bmatrix} = \begin{bmatrix} \rho(\overrightarrow{Eff}, \overrightarrow{Eff}) & \rho(\overrightarrow{Eff}, \widehat{PF}) & \rho(\overrightarrow{Eff}, \widehat{P^{-1}}) & \rho(\overrightarrow{Eff}, \widehat{M^{-1}}) \\ \rho(\overrightarrow{Eff}, \widehat{PF}) & \rho(\overrightarrow{Eff}, \overrightarrow{Eff}) & \rho(\overrightarrow{Eff}, \widehat{PF}) & \rho(\overrightarrow{Eff}, \widehat{P^{-1}}) \\ \rho(\overrightarrow{Eff}, \widehat{P^{-1}}) & \rho(\overrightarrow{Eff}, \widehat{PF}) & \rho(\overrightarrow{Eff}, \overrightarrow{Eff}) & \rho(\overrightarrow{Eff}, \widehat{PF}) \\ \rho(\overrightarrow{Eff}, \widehat{M^{-1}}) & \rho(\overrightarrow{Eff}, \widehat{P^{-1}}) & \rho(\overrightarrow{Eff}, \widehat{PF}) & \rho(\overrightarrow{Eff}, \overrightarrow{Eff}) \end{bmatrix}^{-1} \times \begin{bmatrix} \rho(\overrightarrow{Eff}, \widehat{PF}) \\ \rho(\overrightarrow{Eff}, \widehat{P^{-1}}) \\ \rho(\overrightarrow{Eff}, \widehat{M^{-1}}) \\ \rho(\overrightarrow{Eff}, \widehat{S^{-1}}) \end{bmatrix} \quad (11)$$

4.3 Residual model

In the residual estimation model, four coefficients such as in AR4 are found. However, when these coefficients are found, the AR1 model is applied successively instead of as in the AR4 model. First, the AR1 model is created with the power factor data of efficiency. Later, a new AR1 model is modeled with the opposite of full load power for the error of the previous model.

The error of the second AR1 model is modeled by the inverse of the moment and the error of the third AR1 is modeled with the inverse of the speed.

The modeling process is described in detail by the following equations:

$$\overrightarrow{Eff} = a_{RES,1} \cdot \widehat{PF} + a_{RES,2} \cdot \widehat{P^{-1}} + a_{RES,3} \cdot \widehat{M^{-1}} + a_{RES,4} \cdot \widehat{S^{-1}} + \overrightarrow{\varepsilon}_{RES} \quad (12)$$

$$a_{RES,1} = \frac{[\overrightarrow{Eff}]^T \cdot \widehat{PF}}{[\widehat{PF}]^T \cdot \widehat{PF}} \quad (13)$$

$$\overrightarrow{\varepsilon}_1 = \overrightarrow{Eff} - a_{RES,1} \cdot \widehat{PF} \quad (14)$$

$$a_{RES,2} = \frac{[\overrightarrow{\varepsilon}_1]^T \cdot \widehat{P^{-1}}}{[\widehat{P^{-1}}]^T \cdot \widehat{P^{-1}}} \quad (15)$$

$$\overrightarrow{\varepsilon}_2 = \overrightarrow{\varepsilon}_1 - a_{RES,2} \cdot \widehat{P^{-1}} \quad (16)$$

$$a_{RES,3} = \frac{[\overrightarrow{\varepsilon}_2]^T \cdot \widehat{M^{-1}}}{[\widehat{M^{-1}}]^T \cdot \widehat{M^{-1}}} \quad (17)$$

$$\overrightarrow{\varepsilon}_3 = \overrightarrow{\varepsilon}_2 - a_{RES,3} \cdot \widehat{M^{-1}} \quad (18)$$

$$a_{RES,4} = \frac{[\vec{\varepsilon}_3]^T \cdot \widehat{S}^{-1}}{[\widehat{S}^{-1}]^T \cdot \widehat{S}^{-1}} \quad (19)$$

$$\vec{\varepsilon}_{RES} = \vec{\varepsilon}_3 - a_{RES,4} \cdot \widehat{S}^{-1} \quad (20)$$

As a result of this analysis, error estimates are made with artificial neural networks using inputs which have achieved the highest correlation. These errors are added to the estimates of these three estimation methods to reach new forecast values. Finally, the error between these hybrid estimates and the motor efficiency is fixed. The properties of artificial neural networks will be given before the results of these models are given.

4.4 Structure of artificial neural network

Artificial neural network (ANN) is a method used in many fields of technology for estimation purposes that have been introduced in recent years. The ANN imitates the process of the human brain learning in the simplest way. It tries to reach the solution of the problem based on what it knows, even if there is a problem that they have not encountered before, by connecting similar subjects as human brain does. ANN basically has two layers (hidden and output) and a great number of neurons. The counts and layers of these neurons can be set as desired. In ANN, transfer functions can be decided according to whether the problem is linear or non-linear. In this study, the hyperbolic sigmoid transfer function, which is non-linear transfer function, is used because motor efficiency is not linear with respect to the input parameters. The back-propagation of the network type has been chosen because it simply means that the amount of errors found in the network leads back to the neurons in the hidden layer and increases the success of the training. The *trainlm* learning function is used because it is the fastest responsive learning function in backpropagation. The disadvantage of *trainlm* is that it slows down the program toward the end of the experiments because it requires a great deal of storage. However, it is not possible to arrive at a judgment for layer number, number of neurons and weight for all these decisions, which is similar to ANN's black box analogy. It is not always possible to estimate the outputs when the inputs are known. Therefore, this study was carried out with different numbers of neurons and layers, and the best of them were chosen. The following transfer function (hyperbolic tangent sigmoid transfer function), network type (backpropagation), is given:

$$o = \frac{2}{1 + e^{-2i}} - 1 \quad (21)$$

Here, O and i are the outputs and inputs of the transfer function, respectively. Here, (i) the input is obtained as a linear weighted combination of the outputs from the neurons of the previous layer. In back-propagation, the update function Un can be computed as:

$$Un = - [J^T \times J + \mu I]^{-1} \times J^T \times e \quad (22)$$

Here, J is the Jacobian matrix containing the first derivatives of the network errors according to weight and deviation, and e is the network error. Typically, the μ value should be dropped after each successful step and only after a temporary step the error term (or when the performance function increased) should be increased. Therefore, the performance function is decremented or constrained at each iteration (Hagan and Menhaj, 1994). This is a feature of ANN because it is an optimization-based estimation method.

Artificial neural network toolbox of Matlab has been used for network training and testing. Performance is calculated with mean error (ME). The training parameters are as follows.

In this study, the test values and the simulation values were the same because it has a hybrid structure. The goal of the hybrid structure is to observe whether there is an improvement in the estimation values obtained by other estimation methods when hybridized with ANN.

In addition, the input values were normalized for all tests, but the values obtained from the previous estimation method and the error values requiring estimated for the hybrid models are not normalized. The aim is to estimate the efficiency values given in the catalogue in the most accurate way.

4.5 Hybrid models

The goal in the hybrid model is to estimate the error of the three AR-based models with the back-propagation ANN structure. Thus, AR models will be supported with artificial neural networks and the minimum error will be obtained.

The hybrid model for AR1 was constructed as follows. Here, we tested constructs with a different number of neurons for the ANN with two hidden layers.

Figure 1 shows that the best estimation was made with 22 neurons in each two hidden layers, and the hybrid model was built according to this estimation.

Best validation performance is 9.2317 at epoch 257 in Figure 2:

$$Eff_{AR1} = a_{AR1} \cdot \widehat{PF} \tag{23}$$

$$NN_{AR1}(\widehat{PF}, \widehat{PF}^{-1}, \widehat{M}^{-1}, \widehat{P}^{-1}, S, Eff_{AR1}) = \widetilde{\varepsilon}_{AR1} \tag{24}$$

$$\overrightarrow{Eff} = \widetilde{Eff}_{AR1} + \widetilde{\varepsilon}_{AR1} + \overrightarrow{\varepsilon}_{Hybl} \tag{25}$$

The results are given in Table III and Figures 4-8.

As seen in the table, the hybrid model response is better for all error calculations.

The hybrid model for AR4 was constructed as follows. Here, we tested constructs with a different number of neurons for the ANN with two hidden layers.

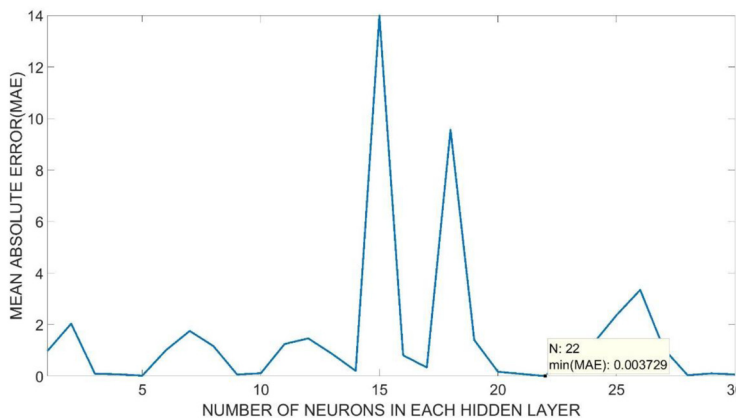


Figure 1.
AR1-ANN estimation
error results for
different number of
neurons in two
hidden layers

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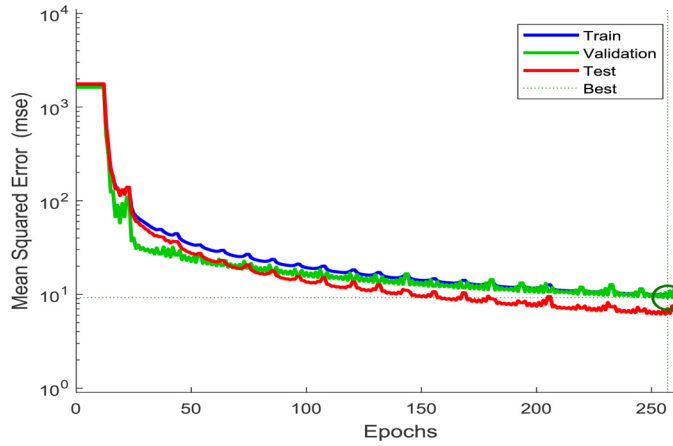


Figure 2.
Best estimation
epochs value of the
AR1-ANN

Table II.	Epochs	1000
Training parameters	Error Goal	0
of neural networks	max_fail	6
	Momentum update	0.001

	*RMSE	RMSE (%)	** ME	ME (%)
Table III. Comparison of AR1 and AR1-ANN efficiency estimate error	5.8324	6.5472	0.5612	0.6360
	4.4056	4.9676	-0.0372	0.0042

Notes: *RMSE: root mean square error; **ME: mean square error

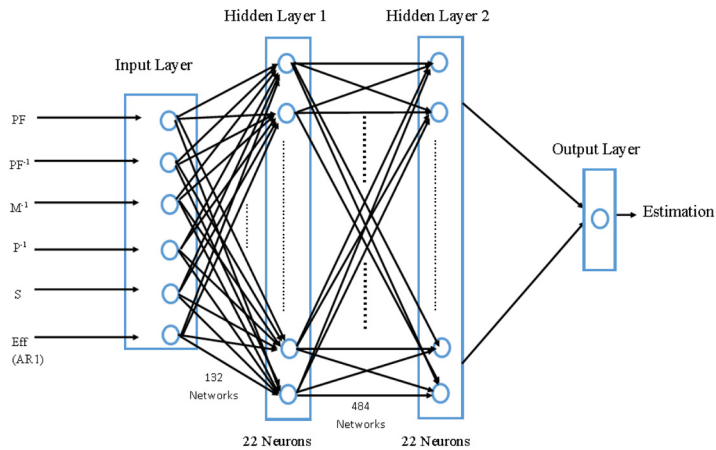


Figure 3.
Block diagram of the
AR1-ANN

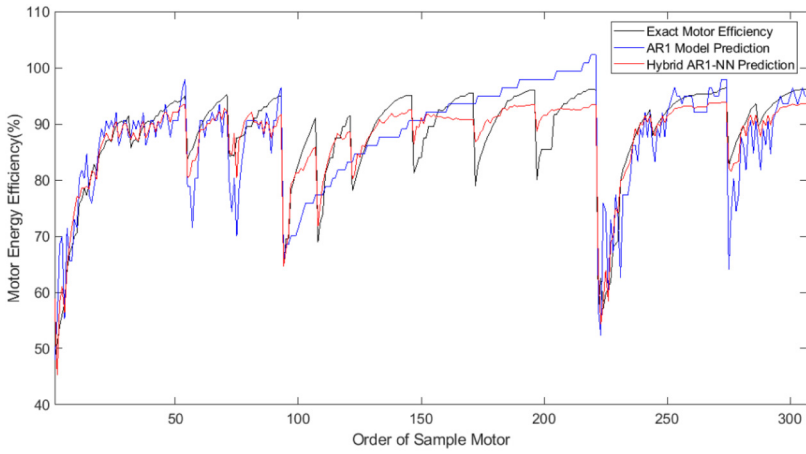


Figure 4.
Estimation for all
motors of AR1 and
AR1-ANN models

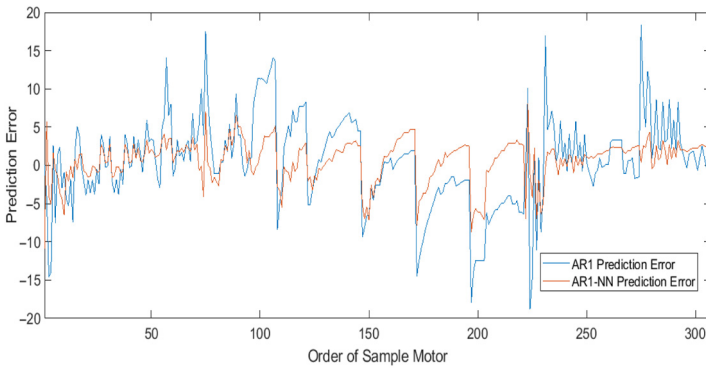


Figure 5.
Estimation errors for
all motors of AR1 and
AR1-ANN models

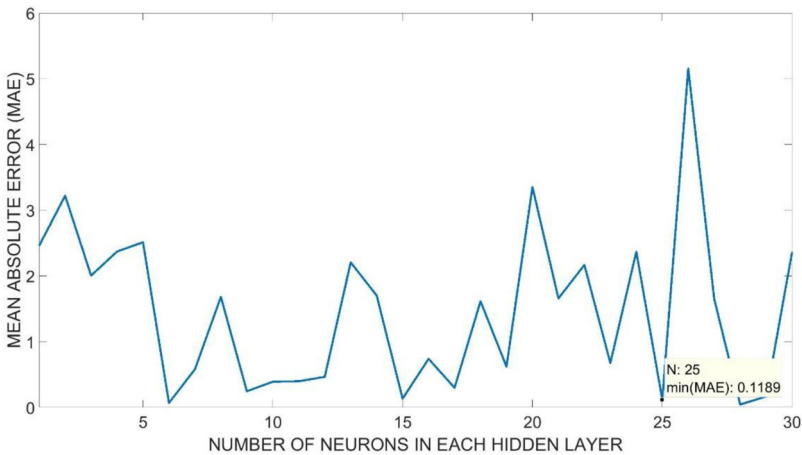


Figure 6.
AR4-ANN estimation
error results for
different number of
neurons in two
hidden layers

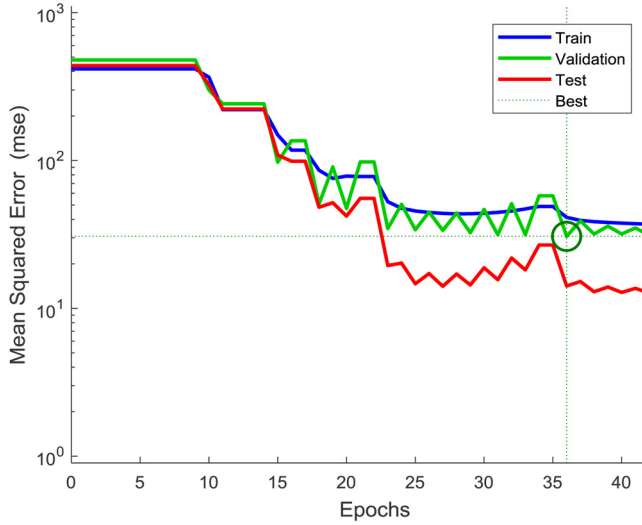


Figure 7.
Best estimation
epochs value of the
AR4-ANN

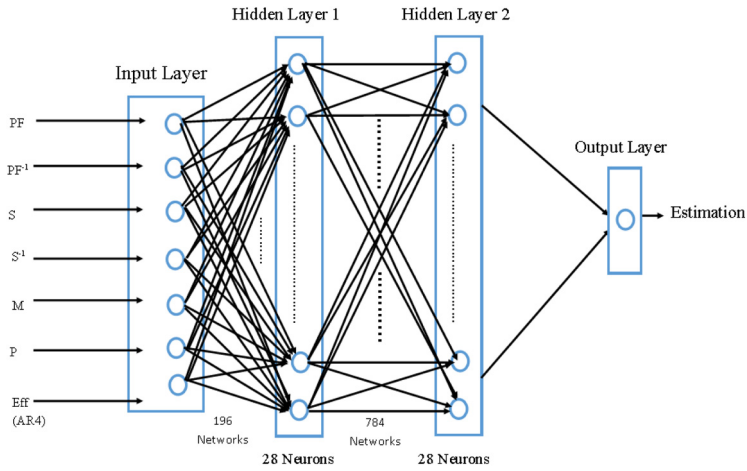


Figure 8.
Block diagram of the
AR4-ANN

Figure 6 shows that the best estimation was made with 28 neurons in each two hidden layers and the hybrid model was built according to this estimation.

Best validation performance is 30.6943 at epoch 36 in Figure 7:

$$Eff_{AR4} = a_{AR4,1} \cdot PF + a_{AR4,2} \cdot P^{-1} + a_{AR4,3} \cdot M^{-1} + a_{AR4,4} \cdot S^{-1} \quad (26)$$

$$NN_{AR4}(\widehat{PF}, \widehat{PF}^{-1}, \widehat{S}, \widehat{S}^{-1}, \widehat{M}, \widehat{P}, Eff_{AR4}) = \widehat{\varepsilon}_{AR4} \quad (27)$$

$$\overrightarrow{Eff} = \overrightarrow{Eff}_{AR4} + \overrightarrow{\varepsilon}_{AR4} + \overrightarrow{\varepsilon}_{Hyb2} \quad (28)$$

$$NN_{AR4}(\widehat{PF}, \widehat{P}, \widehat{M}, \widehat{S}) = \widetilde{\varepsilon}_{AR4} \quad (29)$$

$$\begin{aligned} \overrightarrow{Eff} &= a_{AR4,1} \cdot \widehat{PF} + a_{AR4,2} \cdot \widehat{P}^{-1} + a_{AR4,3} \cdot \widehat{M}^{-1} + a_{AR4,4} \cdot \widehat{S}^{-1} \\ &+ NN_{AR4}(\widehat{PF}, \widehat{P}, \widehat{M}, \widehat{S}) + \overrightarrow{\varepsilon}_{Hyb2} \end{aligned} \quad (30)$$

The results are given in Table IV and Figures 9-13.

As seen in the table, the hybrid model response better for all error calculations.

The hybrid model for residual was constructed as follows. Here, we tested constructs with a different number of neurons for ANN with two hidden layers.

Figure 11 shows that the best estimation was made with 14 neurons in each two hidden layers, and the hybrid model was built according to this estimation.

Best validation performance is 20.3919 at epoch 50 in Figure 12:

$$Eff_{RES} = a_{RES,1} \cdot \widehat{PF} + a_{RES,2} \cdot \widehat{P}^{-1} + a_{RES,3} \cdot \widehat{M}^{-1} + a_{RES,4} \cdot \widehat{S}^{-1} \quad (31)$$

$$NN_{RES}(\widehat{PF}, \widehat{PF}^{-1}, \widehat{S}, \widehat{S}^{-1}, \widehat{M}, \widehat{P}, Eff_{RES}) = \widetilde{\varepsilon}_{RES} \quad (32)$$

$$\overrightarrow{Eff} = Eff_{RES} + \widetilde{\varepsilon}_{RES} + \overrightarrow{\varepsilon}_{Hyb3} \quad (33)$$

The results are given in Table V and Figures 14 and 15.

As can be seen in the table, the hybrid model response is worse for ME but better for RMSE values.

	RMSE	RMSE (%)	ME	ME (%)
AR4	6.9547	7.8419	1.1575	1.3112
AR4-ANN	4.8077	5.4211	-0.0448	0.0508

Table IV.
Comparison of AR1
and AR1_hybrid
efficiency estimate
error

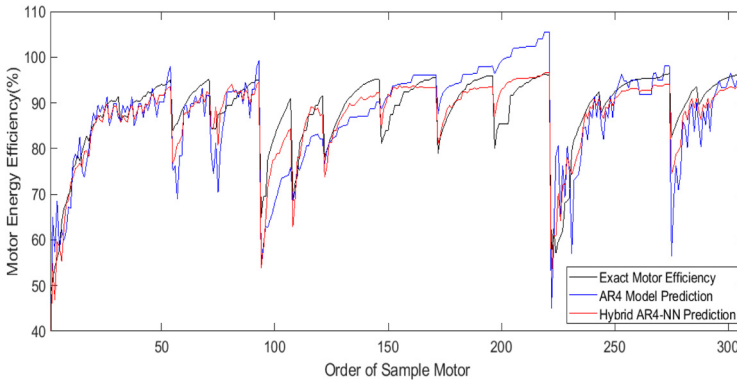


Figure 9.
Estimation for all
motors of AR4 and
AR4-ANN models

Figure 10.
Estimation errors for
all motors of AR4 and
AR4-ANN models

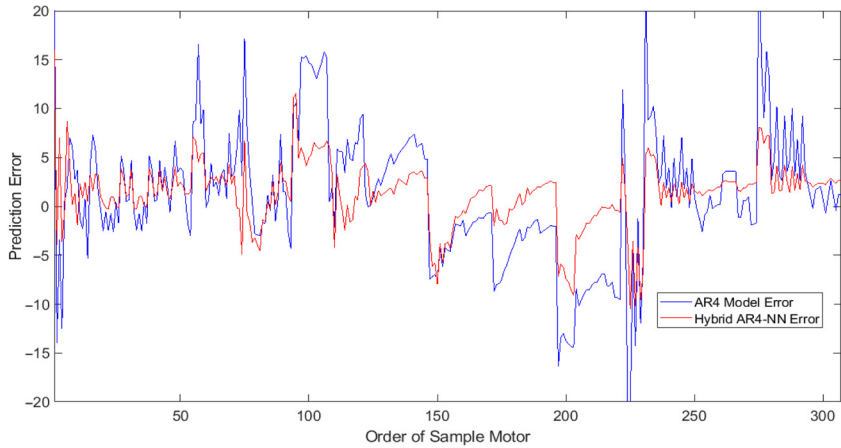
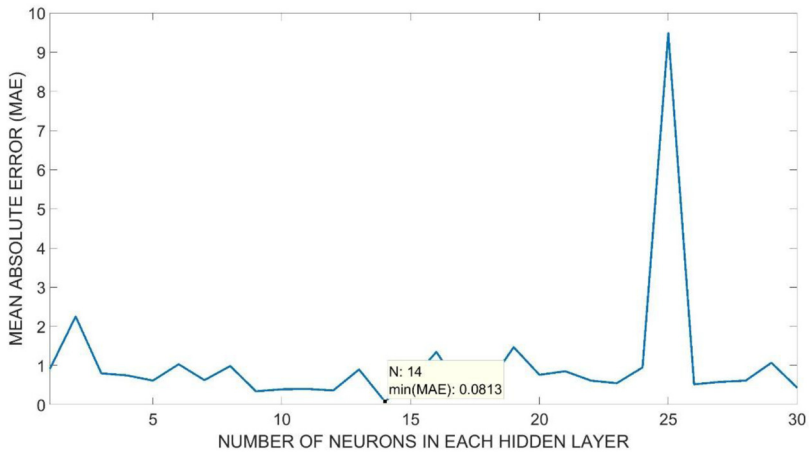


Figure 11.
Residual-ANN
estimation error
results for different
number of neurons in
two hidden layers



5. Result and discussion

5.1 Model verification and comparison methods

Four error indicators were used to check the error rates of the models. These were mean error (ME), root mean square error (RMSE), mean error percentage and RMSE percentage. Their formulas are as follows:

$$\text{Mean Error} = \text{Mean}(\text{Efficiency} - \text{Prediction}) \quad (34)$$

$$\text{RMSE} = \sqrt{\text{Mean}[(\text{Efficiency} - \text{Prediction})^2]} \quad (35)$$

$$\text{Mean Error}\% = [(100 \cdot \text{Mean}(\text{Efficiency} - \text{Prediction}) / \text{Mean}(\text{Efficiency}))]\% \quad (36)$$

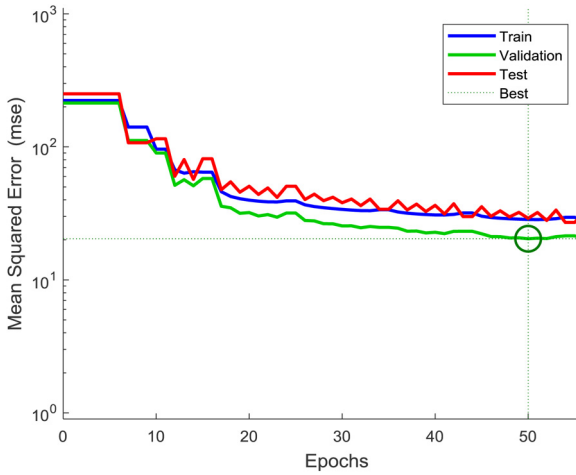


Figure 12. Best estimation epochs value of the residual-ANN

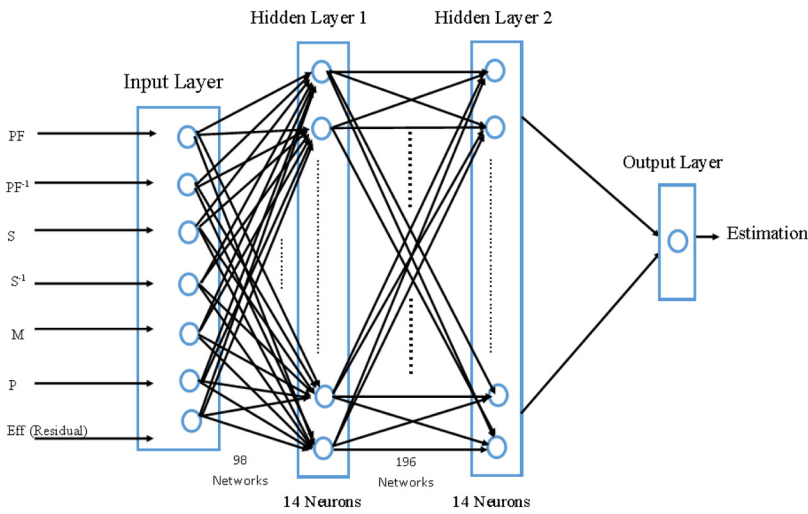


Figure 13. Block diagram of the residual-ANN

$$RMSE\% = \left[\left(100 \cdot \sqrt{\text{Mean}[(\text{Efficiency} - \text{Prediction})^2]} / \sqrt{\text{Mean}(\text{Efficiency}^2)} \right) \right] \% \quad (37)$$

5.2 Model error results

The performances of the generated AR models were obtained as errors in Table VI.

As seen in the Table VI, the best result is the AR1-ANN model and the worst result is in the residual-ANN model according to ME. The best result is the residual-ANN model and the worst result is in the AR4-ANN model according to RMSE. The main reason for the low performance of AR4-ANN compared to AR1-ANN is the inverse of speed, inverse

of moment, inverse of power, power factor and power efficiency data. Their validity as the assumption of a false time sequence is questionable. However, with the residual model, the time series condition was run and a higher value was obtained in the estimation.

Another result that was obtained with these experiments was the acceptance of the inverse relationship of efficiency with power, moment and speed. There is actually a non-linear relationship here. It is estimated that the generated residual model can be further

Table V.
Estimation for all motors of residual and hybrid residual-ANN models

	RMSE	RMSE%	ME	ME%
<i>Residual</i>	5.6019	6.3165	-0.0425	0.0481
<i>Residual-ANN</i>	3.4290	3.8665	-0.0812	0.0921

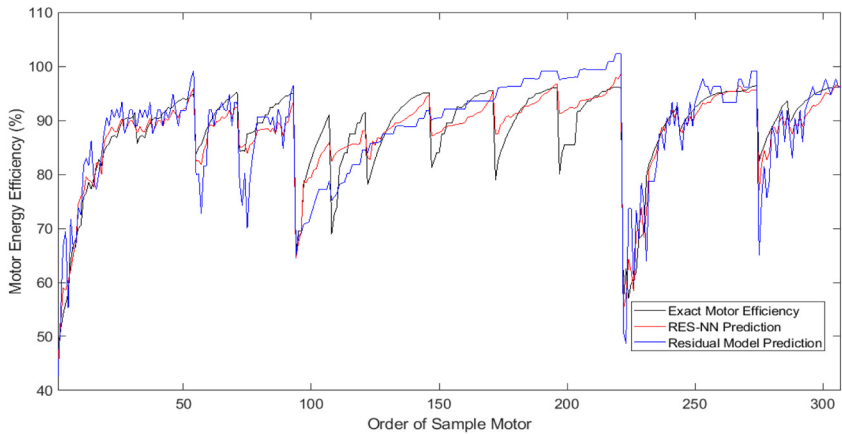


Figure 14.
Estimation for all motors of residual and hybrid RES-ANN

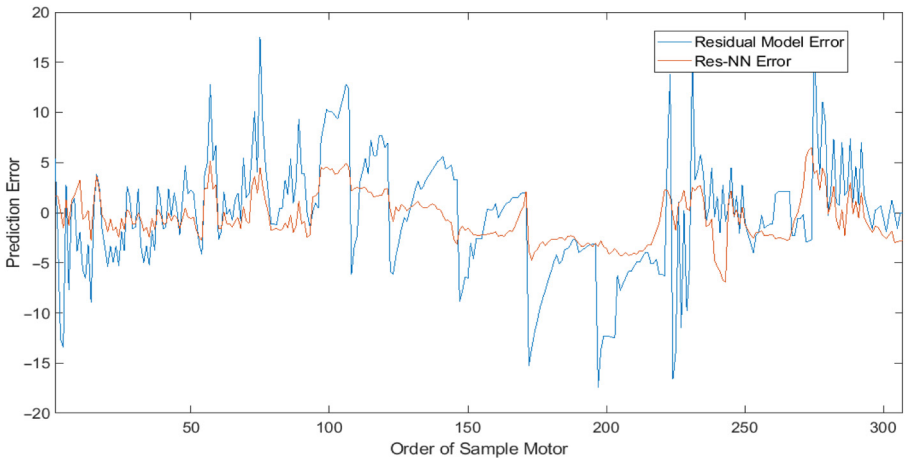


Figure 15.
Estimation errors for all motors of residual vs hybrid RES-ANN

strengthened by nonlinear regression models that can be developed for these three models.

Another important issue is to try to find out the efficiency values which already are in the catalogue with the estimation methods. In fact, the empirical efficiency values situated in the catalogue are used for testing purposes, so the innovative estimation models can estimate whether these efficiency values give accurate results, because with changing operating conditions or years, efficiency value is needed to be calculated again. This reliable estimation methods can find the efficiency value without the requirement of difficult tests. Also, efficiency value is obtained without interrupting the motor.

Engineering value of this research is three different issues in the finding energy efficiency. The first one is minimizing of the test cost, the second one is there is no need of lot of test equipment and the third one is not to interrupt the motor.

Companies which need motors can use these estimation methods due to the advantages mentioned in the previous section. Further, the obtained results can be useful in the estimating efficiency of induction motors which will be designed.

5.3 Comparison with the other studies

In this article, it was attempted to reach the efficiency values of 307 motors in the most accurate way by using six different methods (AR1, AR4, residual, AR1-ANN, AR4-ANN, residual-ANN hybrid). The values found in the previous studies, and in this study, are as follows according to the ME value:

- The results show the validity of the proposed method, as the error in efficiency determination was less than 1 point for all load points (Lu *et al.*, 2008).
- According to the full load, it was attempted to estimate 86 per cent efficiency according to IEEE test results. Results were 86 per cent according to current

Table VI.
Error comparison of
AR1, AR4 and
residual hybrid
efficiency
estimations

	AR1-ANN	AR4-ANN	Residual-ANN
ME	-0.0372	-0.0448	-0.0812
ME %	0.0042	0.0508	0.0921
RMSE	4.4056	4.8077	3.4290
RMSE %	4.9676	5.4211	3.8665

Table VII.
A Comparison of the
estimated and
measured efficiency
for ten selected
induction motors

AR1-ANN	ESTIMATION AR4-ANN	Residual-ANN	MEASURED
50.5123	37.9135	39.2749717	48
52.6759	39.0452	45.330253	51
65.8174	50.2571	52.9631472	54
68.482	49.9367	55.3520941	56
54.5414	47.0471	53.7304882	58
71.4856	59.5744	63.19969	64
62.6718	62.4203	66.892121	67
61.0007	63.2899	67.9178293	68
68.4048	66.9688	68.1838513	70
65.5729	67.4914	69.0903148	70.6

method, 67 per cent according to slip method and 81 per cent according to operating point test (OPT). So briefly, there was a two-point error in the best estimation (Phumiphak and Chat-uthai, 2008).

- The errors of estimated efficiency, input current and torque vary only slightly, five points over the actual motors operating at range of half load to full load (Lu *et al.*, 2007).
- There were many tests completed in this study, but the best result is Method 1. For Method 1, only full load input parameters were used for motor parameter determination. Then efficiency for each load point was determined based on the calculated parameters. The process ran five times and the average values of efficiency were taken. Results of genetic algorithm using different equivalent circuits, two input parameters and Method 1 was -0.32 point according to full load. The other results were worse than this result (Phumiphak and Chat-uthai, 2002).
- There are many tests here, but only the best responses have been selected. If IEEE 112 B test was taken as reference, 0.6 point was determined with TPT method (OPT) and 0.1 point with two OPT method (Pillay *et al.*, 1998).
- There are many tests here, but only the best responses have been selected. Best responses were found to have 2.13 points according to nondominated sorting genetic algorithm method and 2.04 points according to strength pareto evolutionary algorithm method (Gomez *et al.*, 2008).
- In this study, the error was found as 1.1 points by using bacterial foraging algorithm (Cunkas and Sag, 2010).
- NNs were developed using three-layer feed forward networks structure, and the average error was reduced to 0.6890 points at best for different motor types (Karnavas and Chasiotis, 2016).
- This study indicates that the calculated motor efficiencies for both types of motors with design power from 0.75 to 225 kW at four given load conditions have relative errors of ± 5 per cent, except for only one point with a little higher error of 7 per cent (Li *et al.*, 2015).
- There are many tests here, an optimization-based algorithm has been proposed for in situ efficiency estimation of induction machines operating with over-/undervoltage and unbalanced supplies. Best error is 0.4 per cent for 50 per cent of rated load, 7.5-hp machine with 10 per cent undervoltage and 6 per cent voltage unbalanced factor (undervoltage unbalanced) (Siraki and Pillay, 2012).

In this study, without hybridization of AR models by back-propagation ANNs, the best estimation result was obtained by the residual model. On the other hand, for the proposed hybrid models, the best estimation was obtained by AR1-ANN, followed by AR4-ANN and residual-ANN according to ME values. But hybridization values always gave more accurate results than without hybridization according to error values (ME, ME percentage, RMSE and RMSE percentage).

After all, ME values were found as 0.0372, 0.0448 and 0.0812 points for three different methods.

There are two questions to ask about the use of ANNs. Why are these combinations giving the best response and is it possible to achieve better result? Although it cannot be explained completely because of the black box analogy, which is a general feature of

artificial neural networks, the reason why this combination gives the best results is that it shows that the inputs have a non-linear relationship between them, and so there must be more than one layer (multi layers are used for non-linear problems). In all experiments, two layers gave better results than one layer. The number of neurons was determined between 0 and 30 because after 30 neurons, it was determined that the error did not decrease. Other preferred parameters for forming ANNs have been described in detail in previous sections.

The answer to the second question is, yes, perhaps better response results can be found with other hybrid methods. This is possible with the infinite combination of many factors, such as the number of inputs, input sequences, weights and changing the network type. But the goal here is to find the combination that gives the acceptable error until you find the best combination. The values reported herein are the best results of all the experiments which were done in this study, and also these results are also very good when compared to other results in literature.

6. Conclusion

For this study, 1,535 motor data – energy efficiency, torque, power, power factor and speed data of 307 motors – were used. The energy efficiency of induction motors was estimated with two steps. First step is that three models (AR1, AR4 and residual) are used to estimate for the motor efficiency. Second step is that three hybrid models were created by estimating the error of three autoregressive-based efficiency estimation models with the back-propagation ANN structure. Before hybridization ME values were found as absolutely 0.5612 (AR1), 1.1575 (AR4) and 0.0425 (residual). After hybridization, ME values were found as absolutely 0.0372 (AR1-ANN), 0.0448 (AR4-ANN) and 0.0812 (residual-ANN) for three different methods. Hybridization values always gave more accurate results than without hybridization according to error values ME, except for residual. ME values are chosen to compare with preview studies. The results are very sufficient according to previous studies (the lowest ME value of -0.32 points according to above literature), but the best estimation is obtained from AR1-ANN. Further, it is estimated that the generated residual model can be further strengthened by nonlinear regression models that can be developed for these three models.

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