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EFFICIENCY ESTIMATION OF INDUCTION MOTORS AT DIFFERENT SIZES WITH ARTIFICIAL NEURAL NETWORKS AND LINEAR ESTIMATION USING CATALOG VALUES

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ABSTRACT

Induction motors are the most preferred engines in industry because of their simple but robust structure. The efficiency of the preferred motor is crucial for the limitations of the loads to be pulled by the locomotive and the locomotive's suitability for the geographic conditions. For this reason, determining the energy efficiency and operating conditions of induction motors is crucial. It is often not possible to realize the efficiency of induction motors experimentally because it is necessary for the motor to be stopped during the experiment. This prevents the analysis of the efffects of the experiment on the energy efficiency of the motor.

The efficiency estimation of induction motors provides a significant contribution to operation and energy efficiency. There is a variety of studies in literature related to efficiency estimation. However, the future of this study is the realization of efficiency estimations of induction motors at 17 different power types with artificial neural networks and linear estimation by looking at the speed values, current and moment, listed in the manufacture's catalog in full load. Before obtaining the estimations, the statistical analysis of the correlations between efficiency and moment, efficiency and speed, efficiency and current of the motor were applied.

Keywords: Efficiency estimation, Neural networks, Linear estimation, Induction motors

1. INTRODUCTION

Induction motors can be designed for specific torque, rotation speed and drawn current parameters according to their use. Therefore, these different designs result in different efficiency percentages on the output of the motors. When the power of the motor is increased, the efficiency of the motor should also be increased, in order to avoid an undesired amount of lost power. However, how can we be sure that we reach the desired efficiency percentage without complex and time-consuming power measurements and calculations? Observations show that there are strong correlations between efficiency and three critical parameters of the motor: drawn current, moment and rotation speed.

In Section 2, a literature review is given about efficiency estimation in induction motors. There are six methods for efficiency estimation of induction machines.

In Section 3, information is given about the company named Gamak. The 17 induction motors' values which are used in this study are given in Table 1 from Gamak's catalog.

In Section 4, an efficiency estimation is performed with linear estimation for 17 induction motors. Firstly, the Linear Prediction (LP) model is introduced. Correlations of efficiency of motor with drawn current, output moment and rotation speed are given. The pearson correlation coefficient between efficiency and moment, efficiency and drawn current and efficiency and rotation speed; various data for the different sizes of induction motors are obtained. Lastly, the linear estimation model is created using these correlations. According to this model, estimation values are given in Table 3.

In Section 5, an efficiency estimation is performed with Artificial Neural Networks (ANN) for 17 induction motors. Firstly, the ANN model is introduced, the specifications for this are given in Figure

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1. The results of the simulation are given in Figure 2. According to this model, estimation values are given in Table 4.

In Section 6, the comparative efficiency results of the two methods, according to different input values, are given in Table 5. Root Mean Square Error (RMSE) Values are given in Table 6.

In Section 7, Tables 5 and 6 are interpreted and a decision is made about which model is more accurate.

2. LITERATURE REVIEW

The efficiency measurement of electric motors can be made in two ways, directly and indirectly. These methods can be called "experimental methods." IEEE 112-B and CSA-390 are direct methods and the following equation can be used:

$$\text{Efficiency } \% = \frac{\text{Mechanical Output Power}}{\text{Electrical Input Power}} x100 \tag{1}$$

For this reason, it is necessary to measure both the mechanical output power and the electrical input power. Electrical input power can be measured accurately with the simple installation of medium-priced equipment. The mechanical output power can be defined by multiplication torque by angular velocity. While it is possible to get accurate results with a relatively simple procedure (± 1 RPM), which requires inexpensive hardware for speed measurement. But it requires a more detailed setup and more expensive equipment to get accurate results in torque measurement.

IEC 34-2 and JEC 37 are indirect methods. To avoid the complexity and cost of torque measurements, the motor’s efficiency can be indirectly determined by the following equation:

$$\text{Efficiency } \% = \frac{\text{Electrical Input Power} - \text{Losses}}{\text{Electrical Input Power}} x100 \tag{2}$$

This calculation requires the measurement of motor losses. Many motor losses, (copper, iron, mechanical), can be measured quite accurately. But the remaining losses, (leakage losses), are not measurable.

Numerous methods are proposed in literature for in situ efficiency estimation of induction machines. These methods are as follows:

1) slip method;
2) current method;
3) simplified equivalent circuit method [1];
4) simplified loss segregation method [2];
5) nonintrusive air-gap torque (AGT) (NAGT) method [3];
6) optimization-based methods [4]–[14].

Based on the National Electrical Manufacturers Association (NEMA) MG1 standard, induction motors can operate with up to 5% unbalanced voltages [15]. Also, up to ±10% over/under voltage supply conditions are commonly seen in industrial facilities.

In real industrial conditions and, specifically, in weak power systems, the voltage unbalanced factor (VUF) or the over/under voltage rate can be even more severe. An unbalanced power supply occurring with a combination of over/under voltage conditions can significantly affect the machine's efficiency [15], [16]. Thus, a method which is compatible with these conditions should be employed to have a reliable estimation of the efficiency under real industrial situations.

Only the last two methods are applicable in real industrial conditions where some level of unbalanced and over/under voltage conditions exist. Unbalanced supplies can be present due to many reasons, such as incomplete transposition of transmission lines, open delta transformers, blown fuses on three-phase capacitor banks, unequal distribution of single-phase loads, or defective transformers in power systems [15], [16].

In the NAGT method [3], the AGT is calculated based on the voltage and current signals as well as the magnitude of the stator's resistance at the operating temperature. In this method, the effect of the unbalanced voltages is considered on the net produced torque. However, the accuracy of this method is impaired due to the fixed assumption of the no-load losses as well as stray load loss at different loading and supply voltage conditions.

Optimization-based methods are another alternatives for the efficiency estimation under real industrial conditions. In these methods, the machine's efficiency is calculated based on the estimation of parameters for the equivalent circuit in the machine with the help of an optimization-based search algorithm, (such as genetic algorithm, bacterial foraging algorithm, and multiobjective optimization).

Some studies present the optimization-based techniques for efficiency estimation under balanced supply conditions. In some, the equivalent circuit method is combined with the Genetic Algorithm (GA) to deal with the efficiency estimation problem under unbalanced supply conditions. In [7], the authors of this paper reported a new evolutionary-based (EVB) efficiency estimation algorithm which works with balanced and unbalanced supplies.

3. GAMAK MOTORS

The company Gamak was founded in 1961 and it is the domestic product of "Electric Motor" which is one of the most important products that Turkish industry needs for production. In a short period, Gamak started production of the first electric motor to be produced in Turkey. Gamak contributed to national production with cheaper spare parts instead of the cost of using expensively imported engines.

Gamak is one of the most important producers of electric motors in the world, not just in Turkey. With electric motors produced in the power range of 0,06 kW to 1000 kW, it can meet almost all the engine needs of industry. Gamak can almost provide all the parts required for electric motor production at its own facility, and collect the entire production under one roof. The company has one of the most distinguished laboratories in Europe.

In this study, 17 different asynchronous power motors using the full load efficiency values given in Gamak's catalog are estimated with LP and ANN using nominal speed, current and torque values.

Table 1. Induction Motor Parameters for Different Sizes (4 poles, 1500 rpm, 3 phases and 400 V) as listed in Gamak's catalog [17]

Motor kW	Speed (RPM)	Current (Ampere)	Moment (Nm)	Full Load Efficiency (%)
5,50	1465	11,2	35,9	87.9
7,5	1465	15,4	48,9	89
11	1465	21,3	71,7	90
15	1465	29,4	97,8	90.6
18,5	1470	34,5	120	91.3
22	1470	42,5	143	91.7
30	1470	55	195	92.5
37	1470	67	240	92.7
45	1470	80	292	93.3
55	1475	96	356	93.7
75	1480	133	484	94
90	1480	158	581	94.3
110	1485	195	707	94.5
132	1485	230	849	94.7
160	1485	280	1029	94.9
185	1485	323	1190	94.9
200	1485	350	1286	95

4. EFFICIENCY ESTIMATION WITH LINEAR ESTIMATION

4.1. Correlations of Efficiency of Motor with Drawn Current, Output Moment and Rotation Speed

The main parameter which gives a numerical magnitude for the correlation of two phenomena would be covariance [18], if these phenomena are thought as random variables as shown in (3).

$$Cov(X,Y) = E[XY] - E[X]E[Y] \tag{3}$$

In (3), $E[\cdot]$ denotes the expected or mean value of the phenomenon. In discrete variables, covariance can be calculated by (4) from the samples measured for these two variables.

$$Cov(X,Y) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - E[X])\left(y_j - E[Y]\right) \tag{4}$$

According to Eq-4, some idea can be obtained from the relation of events *X* and *Y*. However, this covariance value is dependent on the magnitude of the standard deviations of *X* and *Y*. This dependency prevents the determination of the value. To discard the effects of the standard deviations of *X* and *Y* and to normalize the value between 1 and -1, the covariance value should be divided by the standard deviations of *X* and *Y*. According to this division, the Pearson Correlation Coefficient [19] is obtained as (5).

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \tag{5}$$

For obtaining the Pearson Correlation Coefficient between efficiency and moment, efficiency and drawn current and efficiency and rotation speed, various data for the various sizes of induction motors are needed. For this purpose, the parameters listed in GAMAK's catalog, which are given in Table 1 of Section 3, is used.

If (5) is applied on Eq-3, the Pearson Correlation Coefficients are found as shown in Table-2.

Table 2. Pearson Correlation Coefficients

$\boldsymbol{\rho(E,S)}$	$\boldsymbol{\rho(E,C)}$	$\boldsymbol{\rho(E,M)}$
0.8993	0.8234	0.8241

Note: E, S, C, M denotes Efficiency, Speed, Current and Moment respectively.

According to Table 2, it can be said that the most correlated parameter with efficiency is rotation speed and the parameter least correlated with efficiency is drawn current. However, both parameters have strong correlations with efficiency, which provides the opportunity to construct a linear predictor for efficiency.

4.2. Linear Estimation Model

Assuming that $\widehat{E_{\mathrm{i}}}$ is the estimation value of efficiency. Then there are four linear predictors proposed as (6), (7), (8) and (9) respectively.

$$\widehat{E_{\mathrm{i},all}} = a_M M_{i,Norm} + a_C C_{i,Norm} + a_S S_{i,Norm} + \min(E) \tag{6}$$

$$\widehat{E_{\mathrm{i},MC}} = b_M M_{i,Norm} + b_C C_{i,Norm} + \min(E) \tag{7}$$

$$\widehat{E_{\mathrm{i},CS}} = c_C C_{i,Norm} + c_S S_{i,Norm} + \min(E) \tag{8}$$

$$\widehat{E_{\mathrm{i},MS}} = d_M M_{i,Norm} + d_S C_{i,Norm} + \min(E) \tag{9}$$

For a successive estimation, input parameters of the predictors were normalized as in (10)

$$X_{i,Norm} = \frac{X_i - \min(X)}{max(X_i - min(X))} \tag{10}$$

The coefficients of the predictor $\widehat{E_{\mathrm{i},all}}$ was calculated by the correlation matrix as in (11).

$$\begin{bmatrix} a_M \\ a_C \\ a_S \end{bmatrix} = K \cdot \begin{bmatrix} \rho(E,E) & \rho(E,M) & \rho(E,C) \\ \rho(E,M) & \rho(E,E) & \rho(E,S) \\ \rho(E,C) & \rho(E,S) & \rho(E,E) \end{bmatrix}^{-1} \cdot \begin{bmatrix} \rho(E,M) \\ \rho(E,C) \\ \rho(E,S) \end{bmatrix} \qquad K = max\big(E_i - min(E)\big) \tag{11}$$

The coefficients of the predictor $\widehat{E_{\mathrm{i},MC}}$ was calculated by the correlation matrix as in (12).

$$\begin{bmatrix} b_M \\ b_C \end{bmatrix} = K \cdot \begin{bmatrix} \rho(E,E) & \rho(E,M) \\ \rho(E,C) & \rho(E,E) \end{bmatrix}^{-1} \cdot \begin{bmatrix} \rho(E,M) \\ \rho(E,C) \end{bmatrix} \qquad K = max\big(E_i - min(E)\big) \tag{12}$$

The coefficients of the predictor $\widehat{E_{\mathrm{i},CS}}$ was calculated by the correlation matrix as in (13).

$$\begin{bmatrix} c_C \\ c_S \end{bmatrix} = K \cdot \begin{bmatrix} \rho(E,E) & \rho(E,C) \\ \rho(E,S) & \rho(E,E) \end{bmatrix}^{-1} \cdot \begin{bmatrix} \rho(E,C) \\ \rho(E,S) \end{bmatrix} \qquad K = max\big(E_i - min(E)\big) \tag{13}$$

The coefficients of the predictor $\widehat{E_{\mathrm{i},MS}}$ is calculated by the correlation matrix as in (14).

$$\begin{bmatrix} d_M \\ d_S \end{bmatrix} = K \cdot \begin{bmatrix} \rho(E,E) & \rho(E,M) \\ \rho(E,S) & \rho(E,E) \end{bmatrix}^{-1} \cdot \begin{bmatrix} \rho(E,M) \\ \rho(E,S) \end{bmatrix} \qquad K = max\big(E_i - min(E)\big) \tag{14}$$

For Table 1, the predictor equations are found as in (15), (16), (17) and (18) respectively.

$$\widehat{E_{\mathrm{i},all}} = 1.92 M_{i,Norm} - 0.30 C_{i,Norm} + 5.07 S_{i,Norm} + 87.9 \tag{15}$$

$$\widehat{E_{\mathrm{i},MC}} = 3.21 M_{i,Norm} + 3.20 C_{i,Norm} + 87.9 \tag{16}$$

$$\widehat{E_{\mathrm{i},CS}} = 2.27 C_{i,Norm} + 4.35 S_{i,Norm} + 87.9 \tag{17}$$

$$\widehat{E_{\mathrm{i},MS}} = 2.28 M_{i,Norm} + 4.34 C_{i,Norm} + 87.9 \tag{18}$$

$\widehat{E_{\mathrm{i},CS}}$ and $\widehat{E_{\mathrm{i},MS}}$ have close coefficients because the normalized current data and normalized moment data are so close to each other because of linear dependency.

According to the predictor equations, the predicted current values are found as in Table 3.

Table 3. Estimation Values of Proposed Predictors

Full Load Efficiency	$\widehat{E_{i,all}}$	$\widehat{E_{i,MC}}$	$\widehat{E_{i,CS}}$	$\widehat{E_{i,MS}}$
87.9	87.9	87.9	87.9	87.9
89	87.916	87.973	87.928	87.924
90	87.946	88.087	87.968	87.865
90.6	87.979	88.231	88.022	88.013
91.3	89.277	88.336	89.142	89.138
91.7	89.305	88.471	89.196	89.180
92.5	89.374	88.723	89.280	89.274
92.7	89.432	88.952	89.360	89.356
93.3	89.5	89.208	89.447	89.451
93.7	90.853	89.524	90.640	90.652
94	92.285	90.202	91.974	91.970
94.3	93.412	90.688	92.142	92.146
94.5	93.841	91.361	93.476	93.461
94.7	94.028	92.057	93.710	93.719
94.9	94.261	92.992	94.045	94.047
94.9	94.471	93.812	94.333	94.340
95	94.595	94.314	94.514	94.514

5. EFFICIENCY ESTIMATION WITH ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANN), created by imitating human brain function, can perform a process of learning through experimentation just as the human brain does. Perhaps the most important place where ANN is being used is in estimation. ANN intends to reveal the relationships between data which is sometimes easy to understand but sometimes nonlinear.

Without any assumption, ANN can provide modeling without any additional information between input and output. Therefore, ANN can easily provide nonlinear modeling [20]. Network training is provided by input and output information according to these inputs.

Back Propagation Networks (BPN), also used in this study, is a network structure that is frequently used. The standard back propagation algorithm is a gradient descent algorithm in which the net weights advance in the negative gradient of the performance function. Many types of back propagation algorithms are based on standard optimization techniques such as gradient descent and the Newton method. [20] The backpropagation algorithmwas first proposed by Werbos [21] and later by Rumelhart [22], independently of each other. In 1986, Rumelhart and his colleagues rediscovered the backpropagation algorithm, making the algorithm known and widely used.

In many previous studies it has been shown that artificial neural networks (ANN) give better results than conventional methods of estimation, [23-25]. The reason for the use of ANN is its success, especially for nonlinear input data. [26] And the Back Propagation Networks (BPN), which is a type of ANN and also used in this study, is the most commonly used learning algorithm.

In this study, the values of speed, current and torque, which are given in Table 1, are used. In the first experiment, all of these three parameters were applied as the input vector of the NN. In the following three experiments, each parameter is applied as a single input value. At this stage, inputs are normalized first. A forward feed back propagation network is used, as can be seen in Figure 1. The remarkable point is Mean Square Error (MSE) as a performance function, 1 as the number of layers and 30 as the number of neurons. There is no hidden layer because hidden layers cause the exponent of the equation. In this study there is a logistic regression need for to compare with LP.Later, the network is trained to make estimations. The results can be seen in Figure 2 and Tablo 4.

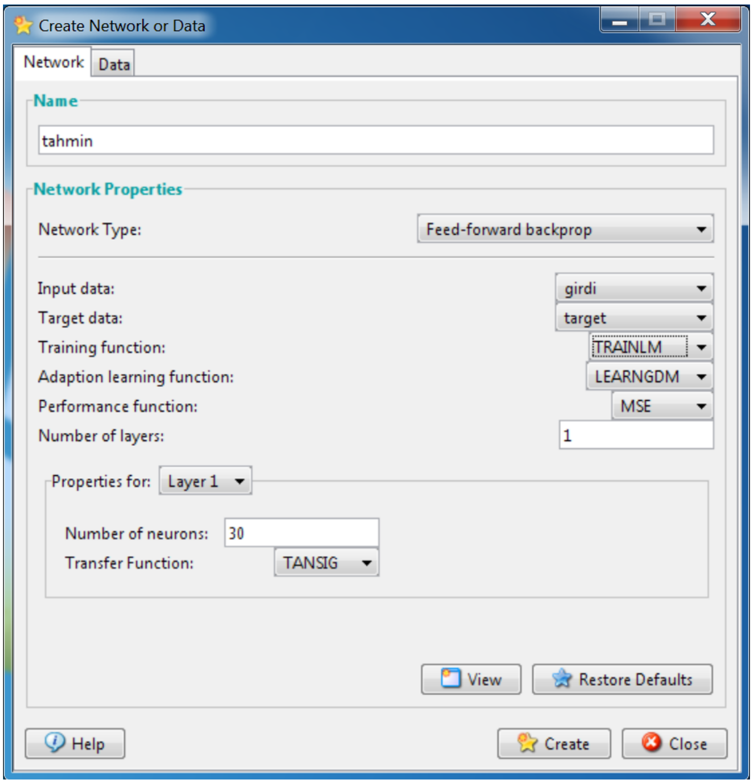

Figure 1. Specifications of the Network

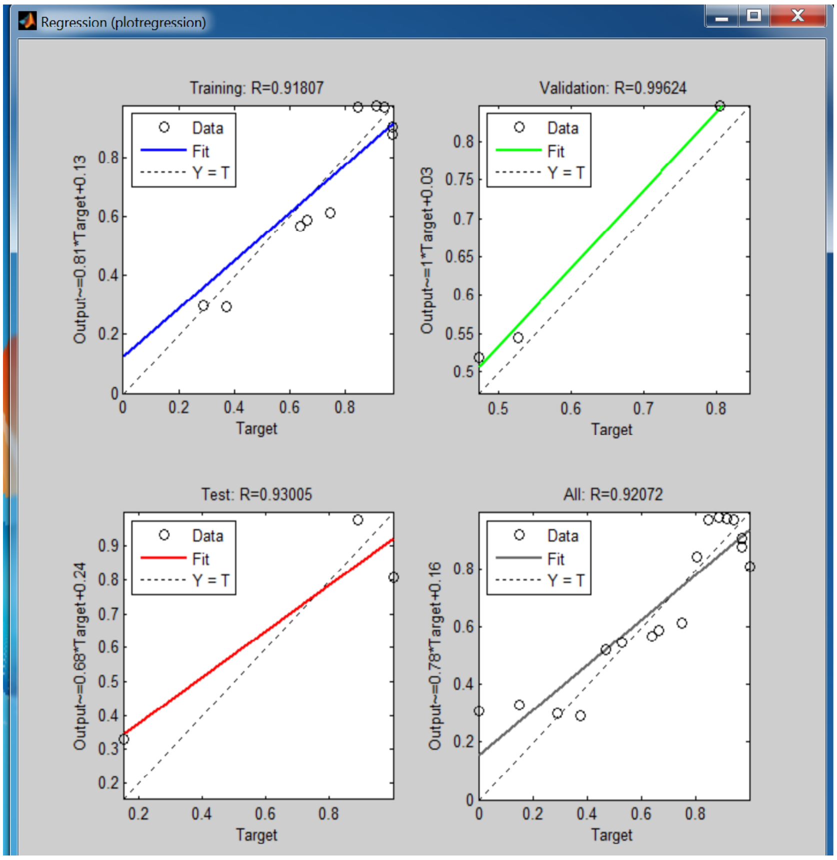

Figure 2. Simulations Results (According to three inputs)

Table 4. Estimation Values of ANN

Motor kW	Efficiency Estim. (%) (speed, current and moment)	Efficiency Estim. (%) (speed)	Efficiency Estim. (%) (current)	Efficiency Estim. (%) (moment)
5,5	88,869	89,508	88,16	88,287
7,5	89,130	89,508	88,273	88,336
11	89,601	89,508	88,722	88,489
15	90,426	89,508	91,060	90,534
18,5	91,732	91,945	91,995	91,324
22	92,034	91,945	92,802	91,521
30	92,364	91,945	92,980	94,288
37	92,863	91,945	93,440	93,056
45	93,293	91,945	92,773	93,115
55	92,757	93,699	94,568	93,712
75	94,021	93,979	93,918	94,812
90	94,751	93,979	94,240	94,302
110	94,402	94,810	94,483	94,514
132	94,834	94,810	94,458	94,755
160	95,086	94,810	94,767	94,884
185	95,099	94,810	94,750	94,959
200	95,099	94,810	94,631	95,003

6. COMPARATIVE RESULTS

The comparative efficiency results of the two methods according to different input values are given in Table 5. Root Mean Square Error (RMSE) values are given in Table 6. One thing to note is that while LP requires at least two types of inputs, NN requires only single type of input.

Table 5. Estimation Values of LP and ANN

Full Load Efficiency	$\widehat{E_{i,all}}$ LP	$\widehat{E_{i,MC}}$ LP	$\widehat{E_{i,CS}}$ LP	$\widehat{E_{i,MS}}$ LP	$\widehat{E_{i,all}}$ ANN	$\widehat{E_{i,S}}$ ANN	$\widehat{E_{i,C}}$ ANN	$\widehat{E_{i,M}}$ ANN
87.9	87.9	87.9	87.9	87.9	88,869	89,508	88,16	88,287
89	87.916	87.973	87.928	87.924	89,13	89,508	88,273	88,336
90	87.946	88.087	87.968	87.865	89,601	89,508	88,722	88,489
90.6	87.979	88.231	88.022	88.013	90,426	89,508	91,06	90,534
91.3	89.277	88.336	89.142	89.138	91,732	91,945	91,995	91,324
91.7	89.305	88.471	89.196	89.180	92,034	91,945	92,802	91,521
92.5	89.374	88.723	89.280	89.274	92,364	91,945	92,98	94,288
92.7	89.432	88.952	89.360	89.356	92,863	91,945	93,44	93,056
93.3	89.5	89.208	89.447	89.451	93,293	91,945	92,773	93,115
93.7	90.853	89.524	90.640	90.652	92,757	93,699	94,568	93,712
94	92.285	90.202	91.974	91.970	94,021	93,979	93,918	94,812
94.3	93.412	90.688	92.142	92.146	94,751	93,979	94,24	94,302
94.5	93.841	91.361	93.476	93.461	94,402	94,81	94,483	94,514
94.7	94.028	92.057	93.710	93.719	94,834	94,81	94,458	94,755
94.9	94.261	92.992	94.045	94.047	95,086	94,81	94,767	94,884
94.9	94.471	93.812	94.333	94.340	95,099	94,81	94,75	94,959
95	94.595	94.314	94.514	94.514	95,099	94,81	94,631	95,003

Table 6. RMSE of Estimation Values LP and ANN

Linear Estimation				Artificial Neural Networks			
$\widehat{E_{i,all}}$	$\widehat{E_{i,MC}}$	$\widehat{E_{i,CS}}$	$\widehat{E_{i,MS}}$	$\widehat{E_{i,all}}$	$\widehat{E_{i,S}}$	$\widehat{E_{i,C}}$	$\widehat{E_{i,M}}$
2,076	2,089	2,178	2,18	0,311	0,552	0,534	0,403

7. CONCLUSION

In this study, Artificial Neural Network (ANN) and Linear Estimation (LP) which are considered as optimization techniques were used for the efficiency estimation of 17 induction motors. Subsequently, two different methods were compared according to the efficiency values given in the manufacturer's catalog in Table 5 and 6. According to these Tables, as expected, the combination of speed and current and torque values are the most accurate results. With these three inputs, the model performs quite well.

Also, using moment and drawn current data in a single estimation model is inappropriate because they have the same information according to linear dependency for LP. However, if the speed data is used in any predictor, the predictor gives better results because of the strong correlation with efficiency.

For ANN, another noteworthy point is that the closest value is obtained from current input excepting three inputs. The other finding is that it is not possible to use speed alone as an input in the estimation of efficiency.

To understand which model is more accurate the RMSE values can be studied. In Table 6, ANN's RMSE values are less than LP. As shown in previous studies, this research provides evidence that ANNs give better results than conventional methods of estimation.

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