Estimating Electrical Parameters of the Induction Motor by Measuring the Components Temperatures

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ABSTRACT:
In this article the electrical parameters of the induction motor are estimated by measuring temperature of its components. This process consists of four sections: 1-Thermal resistance model 2- Electrical parameters 3- Electrical model and 4- Neural network which presents motor parameters and operational status compatible with corresponding learning data. In thermal resistance model, we use physical and geometrical properties of motor components to formulate thermal resistance of each component of the motor. In electrical model, electrical losses are calculated by electrical variables, by relationship between electrical losses and thermal resistance ,these modelesgives us corresponding temperatures as output. These temperatures were used for training network (temperatures as input data, stator current and maximum torque as target data) in the neural network. After measuring temperatures of the components and using them as inputs to neural network, the corresponding stator current and maximum torque (target data) are estimated. All the stator currents referred to this paper were validated by experimental measurements.

KEYWORDS: Induction motor, Thermal resistance model, parameter estimation.

1. INTRODUCTION

Induction motors are commonly used in industries worldwide because they are cheap and easy to use and control. They do not have the compotator (mechanical instrument to control rotor speed) in their structure. They also**,**do not need additional winding for starting motor in the three-phase model. There are many methods for estimating the parameters in the inductionmotor. In one of these methods, transient statorcurrents were used to identify the parameters of an electromechanical model of the induction motor [1]. But parameters are obtained from a relatively poor initial guess, depending on magnitude of the physicalparameters, using a two-step strategy based on nonlinear least-squares regression techniques. The model also requiers a set of observed voltages and currents and an approximate of initial values. In another method a set of data (voltage, current, speed, power factor or torque) obtained from the field test of the motor (instead of the no load and blocked rotor tests), were coupled with the genetic algorithm to evaluate the parameters of equivalent circuit [2]. Measuring torque in this method is not easy in many cases. This method using genetic algorithm, which is based on natural selection and natural genetics by random numbers, to solve a system of nonlinear equations. Initial guesses play an important role in this method. In the next method, induction motor parameters were resulted from transient stator currents [3]. This method consisted of three sub-methods, estimating the parameters of lumped model using startup transient data. Stator currents and voltages were required for the parameter estimates, but no measurements from the motor shaft were needed. In the first sub-method a good initial guess were obtained from a conventional iterative maximum-likelihood or least-squares estimator. The second sub-method minimizes equation errors of the induction motor in the least-square sense by a Levenburg–Marquardt iteration. The third sub-method is a continuation of the Levenburg–Marquardt method,
motivated by observed properties of some pathological loss functions. This method minimizes observations error in the least-squared sense and is, therefore, a maximum likelihood estimator under appropriate conditions of normality. These three series of sub-methods will change the final results. Estimation of state and parameters by kalman filter is the common method that presents an on-line estimation algorithm [4]. Computation of the stator currents is not always needed in practice and we have to include these variables to the state vector for completeness of the algorithm and to check the results.

All of these methods require data in addition to knowledge of the stator electrical excitation and may even require disassembly of the machine. Many of these methods are focused on tracking the rotor resistance or time constant for field orientedcontrol applications. A common thread among these induction machine parameter and state estimation problems is the need for either a good initial guess or accurate knowledge of machine parameters.

2. THERMAL RESISTANCE MODEL

In order to describe the thermal analysis of the induction motor, there are some usual models like the exact analytical calculation and the numerical analysis lumped parameter or the nodal method. But the lumped parameter thermal model is simple and has accurate results among the others. In this model, the electrical machine is divided geometrically into a number of lumped components, each one having a heat generation and interconnections to neighboring components through the thermal resistances. The lumped parameters are derived from entirely dimensional information, the thermal properties of the materials used in the design, and constant heat transfer coefficients .The lumped parameter thermal model is allowed to include all the major components and heat transfer mechanisms within the machine [5]. The geometry of a totally enclosed fan cooled (*TEFC*) induction motor can be divided into ten components which are shown in Fig. 1.

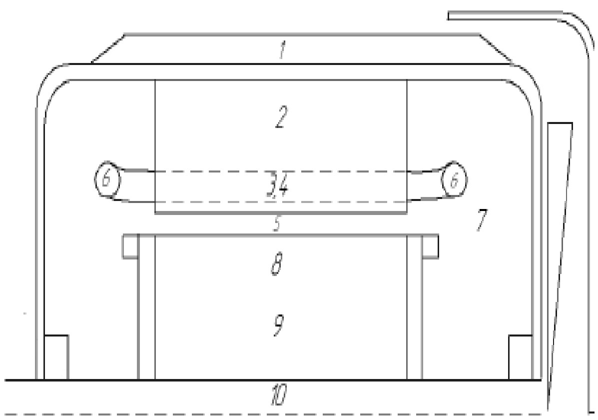

Fig. 1.The motor components sections according to physical properties

1. Frame 2. stator iron 3. stator teeth 4. Stator winding 5. airgap 6. endwinding 7. endcap air 8. rotor winding 9. rotor iron 10. shaft

Generally, the *Rth* thermal resistance describing the conductive heat transfer in one dimension is [5]:

$$\mathrm{Rth} = \frac{l}{\lambda . s} \tag{1}$$

Where l is the length of the body, λ is thermal conductivity, and s is the cross-section area. The present section gives details of the geometries and it formulas for each of the ten networks of thermal resistances. These networks are combined to form the total mesh for the entire machine presented in Fig. 2.

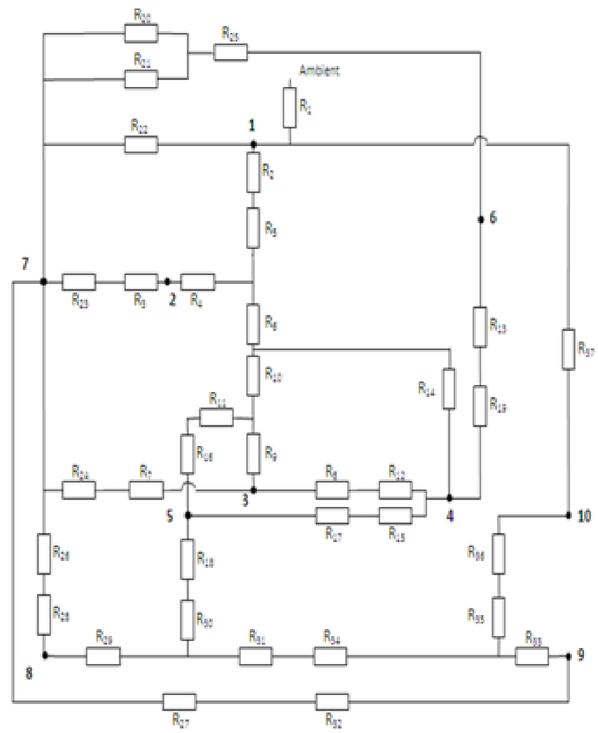

Fig. 2. The thermal resistance network of induction motor

3. ELECTRICAL PARAMETERS OF THE MOTOR

An induction motor works by inducing voltages and currents in the rotor of the machine and so**,** it sometimes**,** called a rotating transformer. Like a transformer, the primary (stator) induces a voltage in the secondary (rotor), but unlike a transformer, the secondary frequency is not necessarily the same as the primary frequency. Induction motor (IM) is a quite complex, non-linear system. The set of differential equations are mostly used for this mathematical description [6].

In this stage of research, we consider the following assumptions:

- Balanced symmetrical and stable three-phase power supply
- Constant load
- Healthy rotor and mechanical parts of motor

Figure 3 shows the equivalent circuit model of the Induction Motor

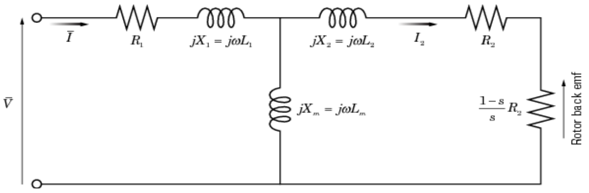

Fig. 3. Equivalent circuit model of the Induction Motor

In the figure: R1 is the stator resistance.R2 is therotor resistance with respect to the stator.*L1* is the stator inductance.*L2* is the rotor inductance with respect to the stator. *Lm* is magnetizing inductance of stator, Its value is hard to estimate from motor parameters, but the effect is usually small. This value is 25 times the Stator inductance *(L1)*value also is very large compared to *L1* and *L2*.S is the rotor slip.$\bar{V}$ and $\bar{I}$ are the sinusoidal supply voltage and current phasors. Rotor slip *S* is defined in terms of the mechanical rotational speed ω_m, the number of pole pairs*p*, and the electrical supply frequency ω by:

$$s = 1 - \frac{p\omega_m}{\omega} \qquad (2)$$

This means that the slip is one when starting, and zero when running synchronously with the supply frequency.For an n-phase induction motor the torque-speed relationship is given by:

$$T = \frac{npR_2}{\omega S}\frac{V_{rms}^2}{R_1+R_2+\frac{1-S}{S}R_2+(X_1+X_2)^2} \qquad (3)$$

Where V_{rms} is the line-neutral supply voltage for a star-configuration induction motor, and the line-to-line voltage for a delta-configuration induction motor.*n* is the number of phases.*R1* and *R2* are the resistance of the statorandrotor windings.*S is the* Rotor slip defined by equation (8).X_1 (*ω. L1*) andX_2(*ω. L2*) are thestator and rotor impedances. *p* is the number of pole pairs.electrical parameters of the induction motor were divided into three sections, the parameters that were defined by no load test , the parameters that were defined by full load test (blocked rotor test) and thevenin equivalent circuit parameters.

3.1. No load test parameters

Some of the important electrical parameters that resulted from no load test were listed below:

- phase voltage for per phase circuit(*Vp*)
- magnetising reactance(*Xm*)
- No-load Impedance (*Znl = X1+Xm*)
- Stator copper losses(*P_scl*)
- Rotational Losses(*P_rot*)
- No load power factor(*PF_nl*)
- core resistance(*Rc*)

3.2. Full load test parameters -blocked rotor

- Full load phase voltage(*Vfl*)
- Rotor resistance(*R2*)
- Full load equivalent impedence(*Zfl*)
- Full load power factor(*PF_fl*)
- Full load equivalent resistance(*Rfl*)
- Full load equivalent reactance(*Xfl*)

3.3. Thevenin equivalent circuit parameters

- Thevenin equivalent voltage(*Vth*)
- Thevenin resistance(*Rth*)
- Starting torque of motor(*T_start*)
- Slip for maximum torque(*S-max*)
- Maximum torque(*T-max*)

Through these electrical parameters, the maximum torque (T-max) and stator &rotor currents are the more important from the others because by estimating these parameters we can define motor operational states (fault or normal) .For example there are many methods for short circuit fault detecting by measuring the stator currents.

4. ELECTRICAL MODEL

This model consists of electrical parameters like maximum torque, rotor speed, and stator and rotor currents. The only output of this model is losses but in different types that would happen in the induction motor, copper and iron losses in stator and rotor plus additional losses are the model output. These losses have a heat generation role in the lumped parameter thermal model.

4.1. Iron losses

The iron losses are obtained by dividing the magnetic circuit of the machine into n sections with approximately constant flux density by:

$$\mathrm{PFe,n} = \sum_n \mathrm{kFe,n.P15\,.mFe,n.}\left(\frac{\mathrm{Bn}}{\mathrm{1.5T}}\right)^2 \qquad (4)$$

Where *m Fe ,n* is the mass of the magnetic circuit's section, *P15*is the variation flux density factor,*Bn* is the flux density, and *T* is constant which shows iron properties in the motor [7]. The *k Fe, n* correction coefficients define the iron losses in different sections of different machine types. In present work the 17 magnetic circuits are divided into stator yoke and stator teeth.

4.2. Additional losses

Additional losses include all the electromagnetic losses which are not taking intoaccount the resistive and iron losses. These losses are difficult to estimate andmeasure. In the IEC standards, the additional loss(Pad)is assumed to be 0.5 % of theinput power(Pin) in the induction motors:

$$\mathrm{Pad} = 0.5.10^{-2}.\mathrm{Pin} \tag{5}$$

4.3. Resistive losses

The proportion of the resistive losses in the machine total losses is high. The resistive losses (Pcu) ina winding with m phases, current (I), and resistance (R) are generated according toOhm's law:

$$\mathrm{Pcu} = \mathrm{m.R.I}^2 \tag{6}$$

Losses that we used in this case consist of the resistive losses in the rotor and the stator of motor[8]. The final output of this model is losses matrix that is shown below

$$P := \begin{bmatrix} 0 \\ \frac{P_{Feys}}{2} \\ \frac{P_{Feds} + 0.3 \cdot P_{ad_{1474}}}{2} \\ \frac{(P_{Cus_{1474}}) \cdot 0.48 + 0.4 \cdot P_{ad_{1474}}}{2} \\ 0 \\ \frac{(P_{Cus_{1474}}) \cdot 0.52}{2} \\ 0 \\ \frac{(P_{Cur_{1474}})}{2} \\ \frac{0.3 \cdot P_{ad_{1474}}}{2} \\ 0 \end{bmatrix} \tag{7}$$

Where index *1474* means that all losses are measuring in the *1474* rpm rotor speed. In order to calculate temperaturefrom the electrical and thermal resistance model, we should convert the thermal resistance to a thermal reactance matrix. For this purpose, we define G as:

$$\mathbf{G} = \begin{bmatrix} \sum_{i=1}^{n} \frac{1}{R_{1,i}} & -\frac{1}{R_{1,2}} & \cdots & -\frac{1}{R_{1,n}} \\ -\frac{1}{R_{2,1}} & \sum_{i=1}^{n} \frac{1}{R_{2,i}} & \cdots & -\frac{1}{R_{2,n}} \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{1}{R_{n,1}} & -\frac{1}{R_{n,2}} & \cdots & \sum_{i=1}^{n} \frac{1}{R_{n,1}} \end{bmatrix}, \tag{8}$$

The temperature rise is obtained from matrix multiply G

And P as [9]:

$$\Delta\mathrm{T} = \mathrm{G}^{-1}.\mathrm{P} \tag{9}$$

5. NEURAL NETWORK

We use artificial neural network as detecting fault system in our plan [10]. At the beginning, we should have enough data for training and testing network. According to the stator current variation in three operational status (normal, inner phase short circuit, and phase to phase short circuit), the temperatures of ten components have been changed. These ten temperaturesare used as input data and thestator current as target data in neural network. In thiscase, we considered *100* samples for each of three status. On the other hand, we had *300* samples in total as input data for training the network. We used a two-layer feed forward back propagation neural network with *TRAINLM* training function, *LEARNGDM* as adaption learning function ,*TANSIG* for transfer function and *MEAN SQUARE ERROR* as defined performance function. This type of neural network with these properties is so strong for parameter estimates of the system. Algorithm iterations with minimum error were *50*. All these propertieshave been checked experimentally and they're been showed the best result.

6. RESULTS AND DISCUSSION

The temperatures of the components obtained from the procedure (Matlabm-files) were compared with professional software for thermal analysis in electrical motors (Motorcad v3.1) [11]. To confirm the results, we adapted the parameter of Matlab m-files into the Motorcad inputs options by an expert engineer. This input data adaptation between the Matlab and Motorcad was done in two sections. The first section consisted of electrical data (such as stator and rotor currents, rotor speed, maximum torque and electrical resistance). The other section was consisted of physical and geometrical properties of the motor components (such as mass, shape, heat transfer coefficient in motor iron and different alloys).

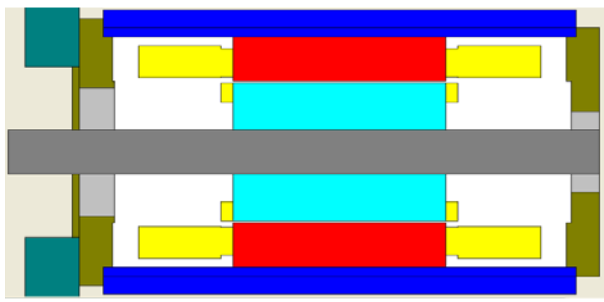

Fig. 4. The IM components specified by colors in MOTORCAD

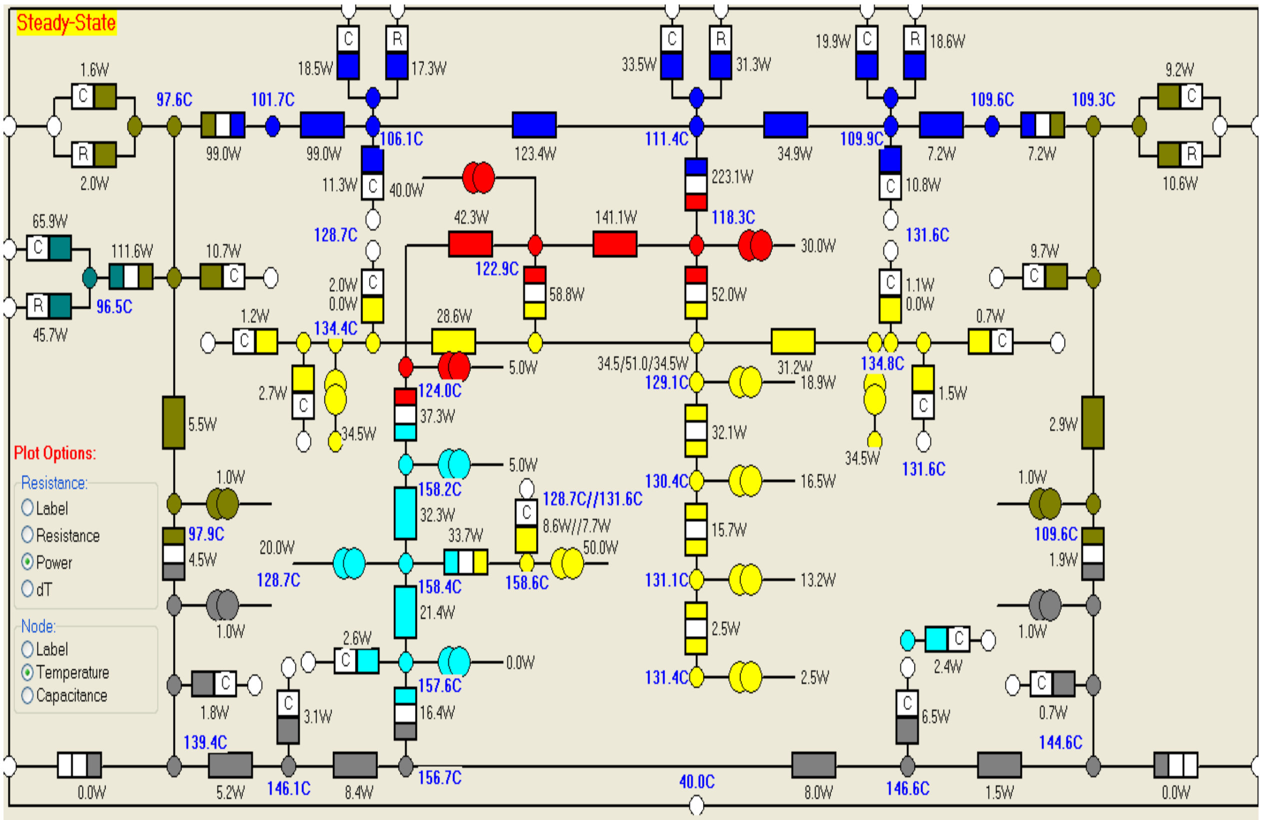

Fig. 5. The components temperatures and losses in MOTORCAD according to fig.4colores

The rise of temperatures components in transition state is shown in Fig 6.

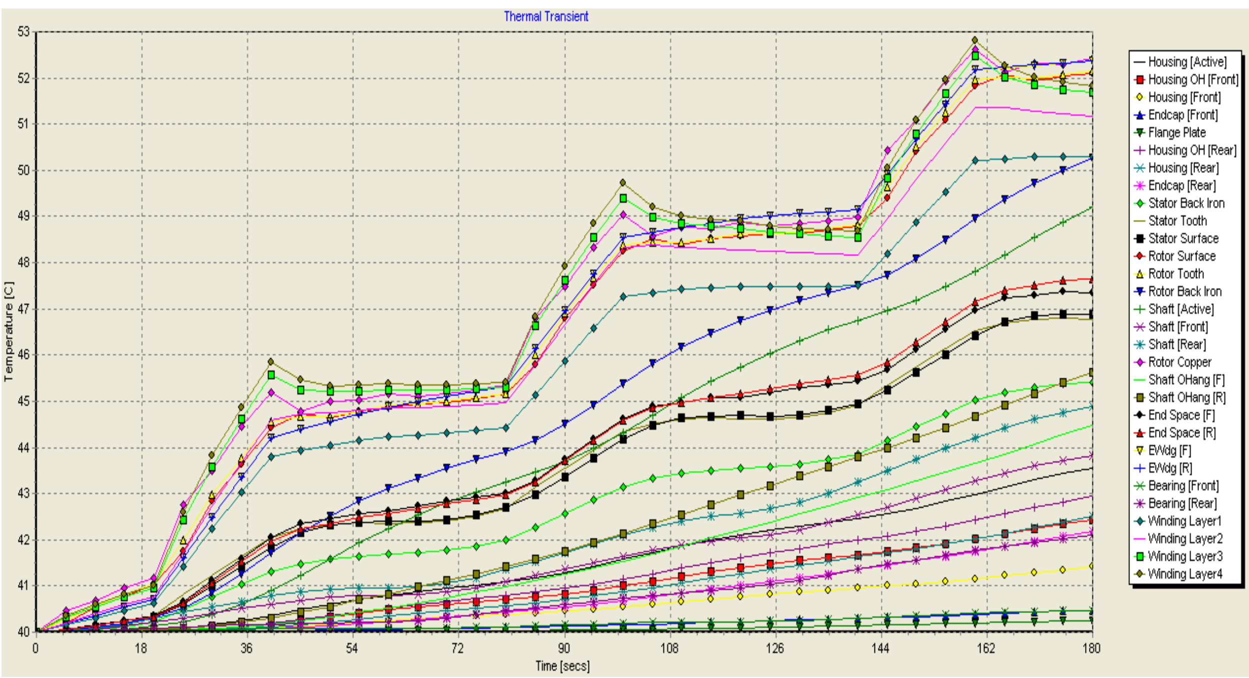

Fig. 6. The rise of components temperatures in transition state (60s)

Time period of transition state was set to 60 seconds, time period is a variable parameter and can increase or decrease manually. Comparison of the Matlab and Motorcad operations is shown in Fig. 7. Differences between our results and the standard values (Motorcad software) in frame and end cap were so close and in the rest of the components were rather large.

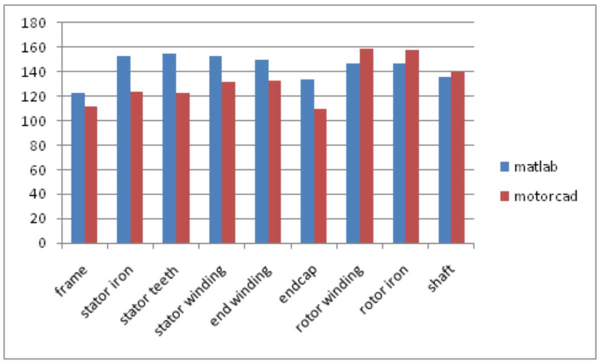

Fig.7. Temperatures Comparison between MATLAB and MOTORCAD

The final mean error was only *7.3%*.Our results were achieved in robustness conditions because we used low power motor (*250* Watts)led to temperature of the components close together.Test, train, and the best validation of neural network in the 21th epochs is shown in Fig. 8.

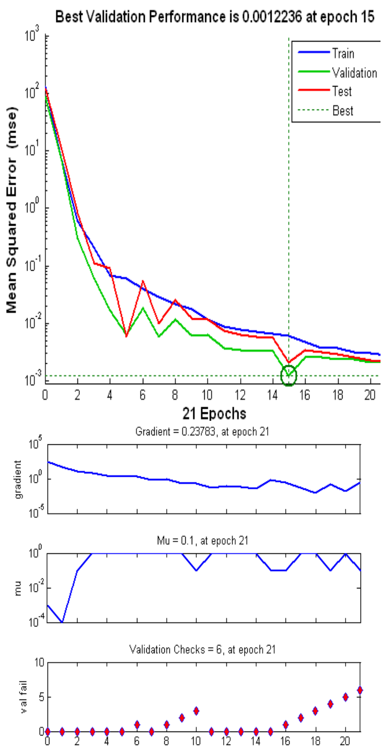

Fig. 8. The chart of the training 'nn'

The relation between the test, train, and validation data in neural network was *70%* of the data used for testing (*15%* for training and the remaining *15%* used for validationcheck). This is a standard model being used for parameterestimates by neural network. Fig. 9 shows how this system works.

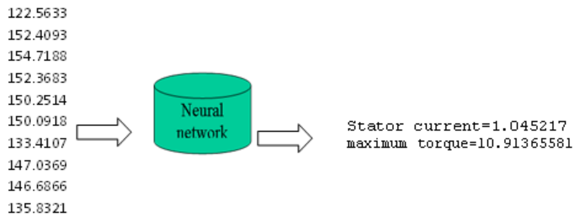

Fig. 9. The process of the system working

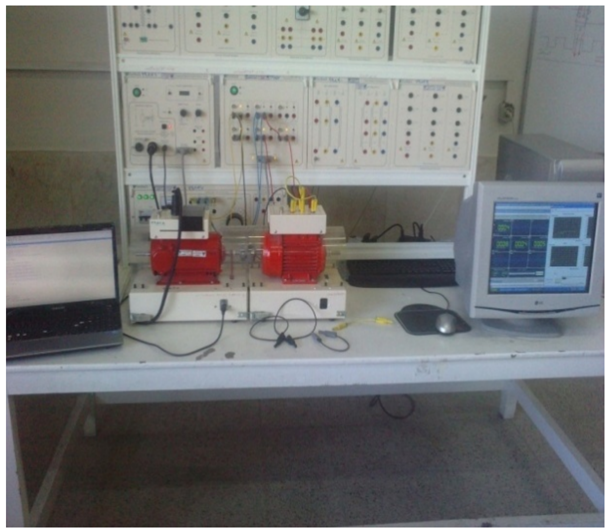

Fig. 10. The induction motor under test

7. CONCLUSION

This parameters estimating procedure in the induction motor is a novel process whichhas notbeen used before.The neural network was used as an instrument for detecting stator current and maximum torque in the motor because it has perfect properties such as self tuning, clustering, real time operations, stability, flexibility and adaptation training. These conditions help us to detect the motor status. All the other tools like fuzzy logic, genetic algorithm, and anfis (as a combined tool) have been earlier tested for this purpose [12]. But in this case best results were obtained in 'nn' operations. Our procedure was able to reliably detect healthy status. All we needed as a measurement instrument was a thermometer which recorded the temperature of the motor components and brought them to the neural network. This showed us the motor in which status was working.In future studies, we may improve this process by adding other parameters of the motor (like rotor current, rotor speed and etc) to stator current as target data in the neural network. Then, we will confirm the output results by electrical motor parameters (such as speed of rotor, stator and rotor currents, and electrical losses in the motor) just by measuring the motor components temperatures.

8. ACKNOWLEDGMENT

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