Chapter 2

Identification of Equivalent Circuit Parameters, Life of the Motor and Methods of Prediction

2.1 INTRODUCTION

Advances in technology have made it possible to use AC drive in applications were high dynamic response, high speed accuracy is require. AC drives are light weight, less expensive and has low maintenance compared to DC drives.

AC motors require power converters and voltage controllers in order to control frequency, voltage and current. The three phase induction motor is work-horse of modern industry. Three phase induction motors are commonly used in constant speed application and adjustable–speed applications. Computer based Modeling and simulation of induction machine has opened new horizons for performance analysis. The realization of that analysis requires elaboration of mathematical models of motors under consideration. It requires solution of two basic problems:

- Formulation of a system of differential equations,
- Calculation of the values of coefficients (parameters), which are used in these equations.

A good mathematical model can help in predicting the behavior of induction machine under different operating conditions and in selecting the appropriate machine for specific operation.

In this chapter, the work proposes a method for estimation of parameter and prediction of steady state performance for induction motor based on equivalent circuit. The equivalent circuit parameters are find out by different tests of induction motor i.e. no load test, block rotor test, dc test etc, to evaluate the parameters of the IM equivalent circuit and draw the circle diagram, making it possible to deduce the IM characteristics, these tests are done in simulink and to facilitate the transition from tests to drawing the circle, the procedure was automated via a user friendly program written in the matlab environment for conventional and converter fed induction motor. This saves time and gives better accuracy.

Equivalent circuit parameters are modified or estimated using numerically optimization method (Newton-Raphson method-discussed in chapter 5), which is a fast local convergence method used to solve nonlinear equations. Programming is done matlab M-file, because differential equations are easily solved with jacobian in matlab.

Once the exact parameters are determined performance can be calculated algebraically as well as graphically and performance can be predicated using any one of the three methods given on page 12, 13, and 15.

2.2 BASIC THEORY OF INDUCTION MOTOR

Like any conventional electric machine, the induction motor has two active elements, a stator and a rotor, which interact via an air gap where the energy exchange take place. In normal operation, the stator is excited by alternating voltage. This creates a rotating magnetic field inducing currents in the rotor winding. These currents, in turn, interact with rotating field to produce torque. Under some assumptions regarding the operation (balanced currents, unsaturated circuits), the stator and rotor fluxes can be calculated. Because of symmetry of balanced three phase IM stator and rotor windings, it is sufficient to take only one phase into account. Each phase has a resistance R in series with a linkage inductance L, and windings are magnetically coupled through a mutual inductance Lm. Since the frequency of stator currents is f_1, the frequency of current induced in the rotor winding is equal to $f_2 = s*f_1$. Accordingly, the voltage and current equations for the stator (primary) and rotor (secondary) are expressed as follows:

$$V_s = R_s I_1 + j\omega L_s I_1 + j\omega L_m I_2 \text{\_\_}(2.1)$$

$$\frac{V_2}{s} = \frac{R_2}{s} I_2 + j\omega L_2 I_2 + j\omega L_m I_1 \text{\_\_\_\_}(2.2)$$

$$I_1 = I_m + I_2{}' \text{\_\_}(2.3)$$

Where I_1, I_2, I_2' and I_m are respectively the stator, the rotor, the rotor referred to the stator, and magnetizing currents and $X_L = \omega L$, where $\omega = 2\pi f$.

R_s : stator resistance, X_s : stator leakage reactance, R_{FE} : magnetizing resistance, X_m: magnetizing reactance, R_r : rotor resistance, X_r : rotor reactance, s : slip, V_s : supply voltage (V)

To take into account the iron losses, a resistance R_{FE} can be added in parallel with magnetizing reactance X_m. As there is an analogy between the IM and transformer, the per phase equivalent circuit T-diagram referred to the stator of the IM is depicted in fig.2.1. With this equivalent circuit, the operational performances of an

IM can be completely described. In normal operation, this diagram is used with constant voltage and frequency, therefore with a constant flux linkage.

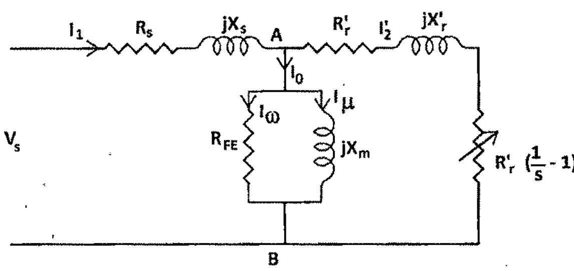
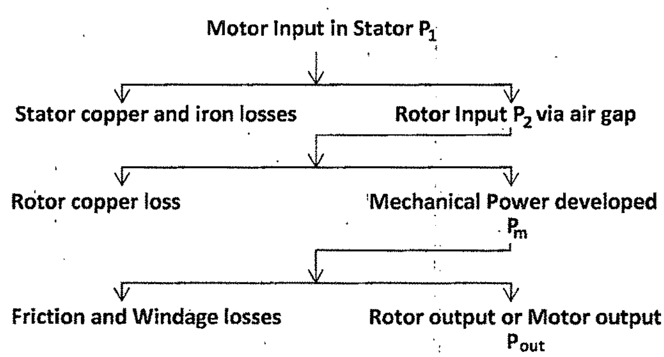


Figure 2.1 Equivalent circuit of an Induction Motor

2.3 STEADY STATE PERFORMANCE OF INDUCTION MOTOR

Steady state performances of induction motor are found out algebraically as well as graphically.

Power stages in an induction motor are as below



Power Stages in an Induction Motor

Performances are determined from following equations from equivalent circuit (Figure 2.1):

Stator input = Stator output + Stator losses

The stator output is transferred entirely inductively to the rotor circuit.

Obviously, Rotor input = Stator output

Rotor gross output = Rotor input – Rotor Cu losses

This Rotor output is converted into mechanical energy and gives rise to gross torque T_g.

Let N r.p.s. be the actual speed of the rotor and if T_g is an N-m, Then

$2\pi N * T_g$= Rotor gross output in watts

$$R_L = R_r\left(\frac{1}{s} - 1\right)\_\_(2.4)$$

$$Z_r = \frac{R_r}{s} + jX_r\_\_(2.5)$$

$$\frac{1}{Z_0} = \frac{1}{R_{FE}} + \frac{1}{jX_r}\_\_(2.6)$$

$$\frac{1}{Z_{co}} = \frac{1}{Z_2} + \frac{1}{Z_0}\_\_(2.7)$$

$$Z_{eq} = Z_{co} + Z_s\_\_(2.8)$$

$$I_1 = {}^{V}/_{Z_{eq}} = I_0 + I_2\_\_(2.9)$$

$$I_2 = I_2 * \frac{Z_0}{Z_0 + Z_r}\_\_(2.10)$$

$$P_{out} = 3I_2^2R_L\_\_(2.11)$$

$$T_g = P_{out}/\omega_m\_\_(2.12)$$

$$Rotor\ input = T_g * 2\pi N_s\_\_(2.13)$$

$$Rotor\ cu\ loss = T_g * 2\pi(N_s - N)\_\_(2.14)$$

$$\emptyset = \left[\tan^{-1}\left\{\frac{Im(Z_{eq})}{Re(Z_{eq})}\right\}\right]\_\_(2.15)$$

$$Power\ factor = \cos\emptyset\_\_(2.16)$$

$$Power\ Input\ P_{in} = 3VI_{eq}\cos\emptyset \_\_(2.17)$$

$$Efficiency = \frac{P_{out}}{P_{in}} * 100\_\_(2.18)$$

2.4 LIFE OF THE MOTOR:

Life of the motor means the period of time for which motor is available for doing specified work or is able to deliver the rated power starting from the time from which motor is put in to the service. Normally the life of the motor is decided by the healthiness of insulation system and bearing.

Induction motors are widely used in industry, and usually have a long life. To predict the life and reliability of the motors within a reasonable time, a simple and available accelerated degradation testing method is presented by Deqiang Zheng [9]. To simulate the unbalanced load on the motor, the lamina with circular holes is mounted on the shaft of the motor eccentrically, and different unbalanced loads are obtained by changing the mounted places of the lamina. A motor accelerated test with three kinds of stress is applied, and the Orbit Areas are used to reveal the performance degradation index of motor. The life and reliability of the motor is finally predicted and evaluated with a balanced lamina mounted on the shaft as its normal working condition. The accelerated degradation testing approach has been proven to be practical to predict the life of the motors.

The development of high-frequency pulse width-modulation-based adjustable-speed drives (ASDs) has increased the efficiency, performance, and controllability in induction motor applications [10]. However, the high switching frequencies and the faster switching times of insulated gate bipolar transistors (the device of choice in these ASDs) introduce disadvantages like over voltages at the motor terminals when long cables are used between the drive and the motor. Another industry-wide concern is the generation of rotor shaft voltage and the resulting bearing current. The grease film in a bearing act as a capacitor that charges due to the transitions in the common-mode voltage imposed at the motor terminals by the drive. The breakdown of the film causes a spike of current to flow that can damage the bearing and reduce life. A significant amount of effort has been directed at understanding the shaft voltage phenomenon and the associated bearing current. This paper attempts to develop circuit models to predict the level of the shaft voltage. The circuit models can then be used to predict the shaft voltage levels at different installations, using simulation software like PSpice. Circuit models for two specific motors are developed. The predicted shaft voltage is very close to the actual voltage levels seen on the shaft when the motors are operated by ASDs.

Researchers have presented a various methods for determining the effect of bearing currents on life of the bearings [11 to 17].

2.5 PREDICTION TECHNIQUES:

2.5.1 INTRODUCTION

In decision making, one deal with devising future plans. The data describing the decision situation must thus be representative of what occurs in the future. For example, in inventory control, we base our decisions on the nature of demand for the controlled item during specified planning horizon. Also, in financial planning, we need to predict the pattern of cash flow over time.

In electrical drive system sometimes one comes across a situation where he/she is require to predict the behaviour of the motor or predict the performance of the motor ahead of the time. For example we are interested in knowing the behaviour of motor when magnitude of supply voltage will change or frequency will change or waveform will change or load pattern will change. We are not only interested in knowing the steady state performance of motor but we are also keen to the dynamic performance of the drive. During the operation drive occasionally comes across the unforeseen disturbances. If this happens then, how drive will behave? Hence it is necessary predict the behaviour of the drive ahead of time.

Generalized predictive control (GPC) is nowadays, widely, spread in control theory as well as in the industrial world. Generalized predictive control (GPC) belong to this family has been demonstrated as a powerful controlling process plants, In this work [18] a polynomial approach of generalized predictive control is proposed whose aim to find optimal values for the tuning control and application of predictive control with polynomial form RST and application of induction motor and developed prediction optimal equation with cost function and resolved of the Diophantine equations this application is reserved in our work for the induction motor with example of a dynamic system and non linear multivariable with load torque.

This chapter presents three techniques for forecasting future changes in the level of a desired variable as a function of time:

1) Moving average

2) Exponential smoothing

3) Regression

The main symbols used in this chapter are:

Y_t = Actual (or observed) value of the random variable in period *t*.

Y_t^*= Estimated value of the random variable in period *t*.

ϵ_t = Random component (or noise) in period

2.5.2 MOVING AVERAGE TECHNIQUE

The underlying assumption for this technique is that the time series is stable, in the sense that its data are generated by the following constant process;

$$Y_t = b + \epsilon_t \quad \text{\_\_\_\_(2.19)}$$

Where b is an unknown constant parameter estimated from the historical data. The random error ϵ_t is assumed to have a zero expected value and a constant variance. Additionally, the data for the different periods are not correlated.

The moving average technique assumes that the most recent n observations are equally important in estimating the parameter b. Thus, at a current period t, if the data for the most recent n periods are

$$Y_{t-n+1}, \quad Y_{t-n+2}, \quad Y_{t-n+3}, \text{\_\_\_\_\_\_} Y_n \text{\_\_\_\_\_}(2.20)$$

then the estimated value for period t+1 is computed as

$$Y_{t+1}^* = \frac{Y_{t-n+1} + Y_{t-n+2} + \_\_Y_n}{n} \text{\_\_\_\_\_}(2.21)$$

There is no exact rule for selecting the moving average base, n. if the variations in the variable remain reasonably constant over time, a large n is recommended. Otherwise, a small value of n is advisable if the variable exhibits changing patterns. In practice, the value of n ranges between 2 and 10.

If we use n=3, the estimated demand for next time (t=6) will equal the average of the demands for time 3 to 5- that is,

$$Y_6^* = \frac{Y_3 + Y_4 + Y_5}{3} \text{\_\_\_\_\_}(2.22)$$

2.5.3 EXPONENTIAL SMOOTHING

The exponential smoothing technique assumes that the process is constant, the same assumption used in the development of the moving average method. However it is designed to alleviate a drawback in the moving average method, where the same weight on all the data is used in computing the average. Specifically, exponential smoothing places a larger weight on the most recent observation.

Define α ($0 < \alpha < 1$) as the smoothing constant, and assume that the time series points for the past t periods are y_1, y_2, y_3........, y_n. Then y_{t+1} *, the estimate for period $t + 1$ is computed as

$$y^*_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} \dots \dots \text{\_\_\_\_}(2.23)$$

Because the respective coefficients of y_t, y_{t-1}, y_{t-2} ..... are progressively smaller, the new procedure puts more weight on the more recent data points.

The formula for computing y^*_{t+1} can be simplified as follows:

$$y^*_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} \dots \dots \text{\_\_\_\_}(2.24)$$

$$y^*_{t+1} = \alpha y_t + (1-\alpha)[\alpha y_{t-1} + \alpha(1-\alpha)y_{t-2} \dots \dots] \text{\_\_\_\_}(2.25)$$

$$y^*_{t+1} = \alpha y_t + (1-\alpha)y^*_t \text{\_\_\_\_}(2.26)$$

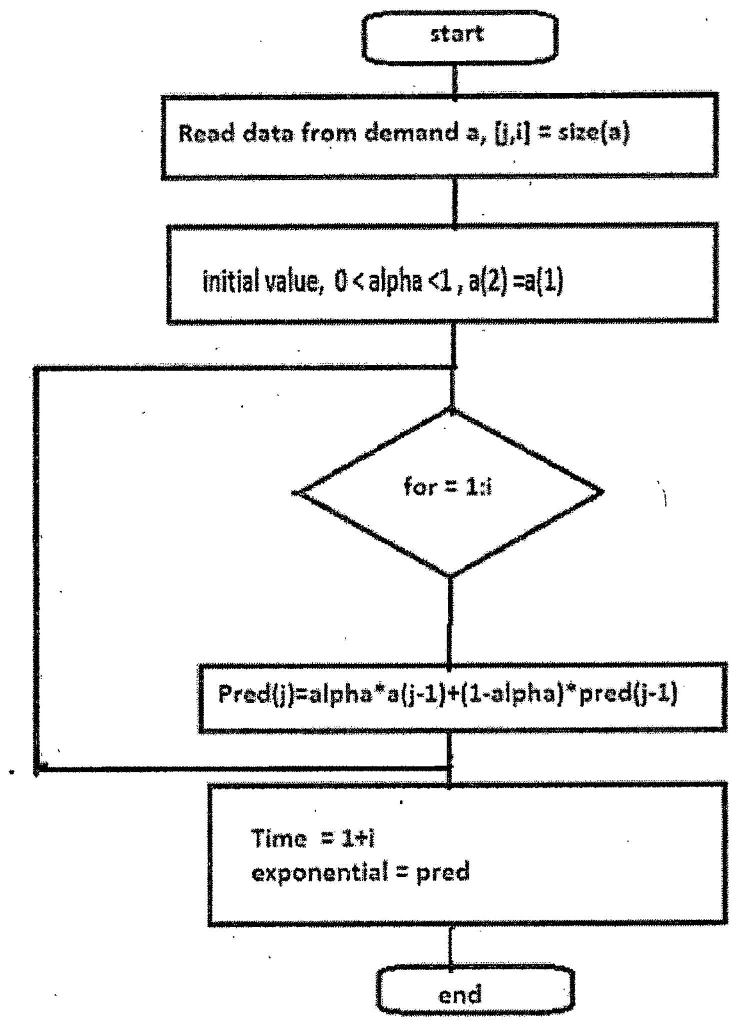
In this manner, y_{t+1}* can be computed recursively from y_t*. The recursive equation is started by skipping the estimate y_1* at t = 1 and assuming that the estimate for t = 2 is taken equal to the actual data value for t = 1, that is y_2* = y_1. Actually, any reasonable procedure can be used to start the computations. For example, some suggest estimating y_o* as the average of a "reasonable" number of periods at the start of the time series.

The selection of the smoothing constant α is crucial in estimating future forecasts. A large value of α implies that recent observations carry heavier weights.

For the given computations, the estimate for t = 6 is computed as

y_6* = αy_5 + (1-α) y_4*____(2.27)

Flow chart for exponential smoothing method



2.5.4 REGRESSION

Regression analysis determines the relationship between a dependent variable (e.g., performance for a drive) and an independent variable (e.g., load/situation/time). The general regression formula between the dependent variable Y and the independent variable X is given as

$$y = b_o + b_1X_1 + b_2X_2 + \cdots + b_nX_n + \epsilon \_\_\_\_(2.28)$$

Where $b_0, b_1 \ldots\ldots b_n$ are unknown parameters. The random error ϵ has a zero mean and a constant standard deviation.

The simplest form of the regression model assumes that the dependent variable varies linearly with time-that is,

$$Y^* = a + bX \_\_\_\_(2.28)$$

The constants a and b are determined from the time series data based on the least square criterion that seeks to minimize the sum of the square of the differences between the observed and the estimated values. Let (Y_i, X_i) represent the i^{th} point of the raw data representing the time series, i = 1,2,........,n, and define

$$S = \sum_{i=1}^{n}(Y_i - a - bX_i)^2 \_\_\_\_(2.29)$$

as the sum of the square of the deviations between the observed and estimated values. The values of a and b are determined by solving the following necessary conditions for the minimizations of S – that is,

$$\frac{\partial S}{\partial a} = -2\sum_{i=1}^{n}(Y_i - a - bX_i) = 0 \_\_\_\_(2.30)$$

$$\frac{\partial S}{\partial b} = -2\sum_{i=1}^{n}(Y_i - a - bX_i)X_i = 0 \_\_\_\_(2.31)$$

After some algebraic manipulations, we obtain the following solution:

$$b = \frac{\sum_{i=1}^{n} y_i x_i - n\bar{y}\bar{x}}{\sum_{i=1}^{n} {x_i}^2 - n\bar{x}^2} \_\_(2.32)$$

$$a = \overline{y} - b\overline{x} \_\_\_\_(2.33)$$

$$\overline{x} = \frac{\sum_{i=1}^{n} xi}{n} \_\_\_\_(2.34)$$

$$\overline{y} = \frac{\sum_{i=1}^{n} yi}{n} \_\_\_\_(2.35)$$

The equations show that we need to compute b first, from which the value of a can be computed.

The estimates of a and b are valid for any probabilistic distribution of Y_i. However, if Y_i is normally distributed with a constant standard deviation, a confidence interval can be established on the mean value of the estimator at $X = X_0$ (i.e, Y_0 = a + bX_0) as

$$(a + bx) \pm t_{\frac{\alpha}{2},n-2}\sqrt{\frac{\sum_{i=1}^{n}(y_i - y_i^*)^2}{n-2}} * \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{\sum_{i=1}^{n}(x_i^2 - n\bar{x}^2)}} \_\_\_\_(2.36)$$

The expression (Y_i – Y_i*) represents the deviation between the i^{th} observed and estimated values of the dependent variable.

For future predicted values of the dependent variable, Y, we are interested in determining its prediction interval (rather than the confidence interval on its mean value). As would be expected, the prediction interval of a future value is wider than the confidence interval on the mean value. Indeed, the formula for the prediction interval is the same as that of the confidence interval except that the term $\frac{1}{n}$ under the second square root is replaced with $\frac{(n+1)}{n}$.

Flow chart for regression method