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SPEED ESTIMATION OF ASYNCHRONOUS MOTOR USING FEED FORWARD NEURAL NETWORK

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Abstract
The main objective of this work is to develop speed estimator for an asynchronous motor using feed forward artificial neural network. A mathematical model has been developed for the asynchronous motor and has been implemented in Matlab. Then, a speed estimator has been designed using feed forward neural network and has been connected with the asynchronous motor for estimating its speed. Then simulations have been carried out to estimate the performance of the proposed speed estimator.
Keywords: Neural Network, Asynchronous Motor, Space Vector Modulation PWM

INTRODUCTION

AC motors are the most powerful motors in industrial applications Motion management and primary domestic appliances networks. The key benefits of AC induction engines include simple and robust construction, low cost, low maintenance and direct access to an AC power source. There are many varieties in the market of AC induction motors. For various uses, different motors are appropriate. Although the AC induction motors are simpler to build than DC motors, their design and their characteristics are much more clearly known in the speed and torque control of various AC induction motor types. The basics of an AC induction motor has its various forms, features, selection requirements for various applications and simple control technology are discussed in this implementation note.

1.2 Induction Motor Speed

The stator magnet field revolves synchronously at speed

(NS) $$N_s = 120 \times \frac{f}{P} \qquad (1)$$

where:
NS = the Stator Speed Synchronous magnetic field in RPM
P = The pole number on the stator
f = the supply frequency in Hertz
The magnetic field formed in the rotor alternates in nature due to the induced voltage. The rotor begins to move in the same way as the stator flux in order to maximise the relative speed and strives to keep up with the spinning flux. In reality, however, the rotor cannot "catch" the field of the stator. The rotor is lighter than the stator field speed. This is known as the base speed (Nb). The NS-NB gap is called the slip. The slip depends on the load. A load rise can delay or increase slip of the rotor. A load decrease will speed up or reduce the slip of a rotor. The slip is shown as a proportion and can be measured use the formula below

$$\%slip = \frac{N_S - N_b}{N_S} \times 100 \qquad (2)$$

where:
N_s= the speed synchronously in RPM
N_b= the base speed in RPM

1.3 Speed Control Methods

The following three groups are primarily defined by many speed modulation strategies applied in modern-day VFD:

- Vector Control (Indirect Drive Control)
- Direct Driving Drive Control (V/f Check) (DTC)
- Scalar Control (V/f Control)

1.3.1 Scalar Control

This method of control supplies the motor to the PWM control through the feature-rich PIC microcontroller using variable frequency signaux provided by an inverter. The V/f ratio here is kept constant such that the whole operating spectrum is torqued constantly. Since the input variables are only regulated in magnitude – frequency and voltage – this is called the "scalar power.". The drives are normally regulated free of feedback (open loop control) devices. Therefore, this kind of control offers low costs and is an easy solution to implement. In these controls, very little engine information is required to control frequency. This control is therefore used extensively..An inconvenience of such a control is that the produced torque depends on load because it is not strictly controlled. Furthermore, because of the preset switching pattern of the converter, the transient response of such a control is not easy. However, if the rotor rotation has a constant block then the motor will be heated, regardless of how to execute the overcurrent control loop.The problem with The load and the blocked rotor based speed can be solved with Usage of the speed/position sensor. This adds expense, scale and sophistication to the system. A variety of options exist to enforce scalar regulation. The following parts outline the common schemes.

1.3.2 Sinusoidal PWM

In this way, the weighted sinusoidal PICmicro microcontroller stores the values and can be used at given user intervals at the output port. This technique has the advantage of being very limited in estimation. Just one sine wave survey table is expected because all motor phases have been moved to 120 electric degrees. The downside of this approach is that the basic voltage is less than 90%. The harmonics on the frequencies of PWM switching are also very large.

1.3.3 Six-Step PWM

On the VFD inverter there are six different switching states. Double rotation of the three-phase AC induction motor when turned in a given order. The benefit of this procedure is that intermediate measurement is not necessary and is thus easy to use. In addition to the DC bus, the amplitude of the basic voltage is greater. The downside of the motor induction is higher lowering harmonics that cannot be filtered.This means increased losses in the engine, greater torque and a jerky low speed running.

1.3.4 Space Vector Modulation PWM (SVPWM)

This control strategy is founded on the assumption that the induction motor three-phase voltage vectors can be transformed into a single revolving vector. VFD can be used to rotate this space vector generating sine waves in three phases. The benefits of averaging, Lower memory requirements are less harmonic at the PWM switching frequency compared with sinusoidal pwm etc.. The drawbacks are not the complete use of the voltage of the DC bus and additional measurement is necessary etc.

1.3.5 SVPWM with Over modulation

The execution of SVPWM with overmodulation will create a basic sinus amplitude wave that is larger as the bus for DC. The drawback is complicated estimation, line to line waveforms are not "pure" and the THD rises yet lower than the THD of the 6-stage PWM approach.

1.4 Artificial Neural Networks (ANN)

An ANN scheme classification and how ANNs are trained according to their learning [18]. The classification comes from the form of information data management achieved by giving them the unknown input X. The object is to find the distribution of weights in the neighborhood of a new observation of X, Figure 3. shows the concept of a basic network. They are made up of multiple layers of neural arrangement and can have distinct architectures. You should even supervise or supervise the preparation [19].

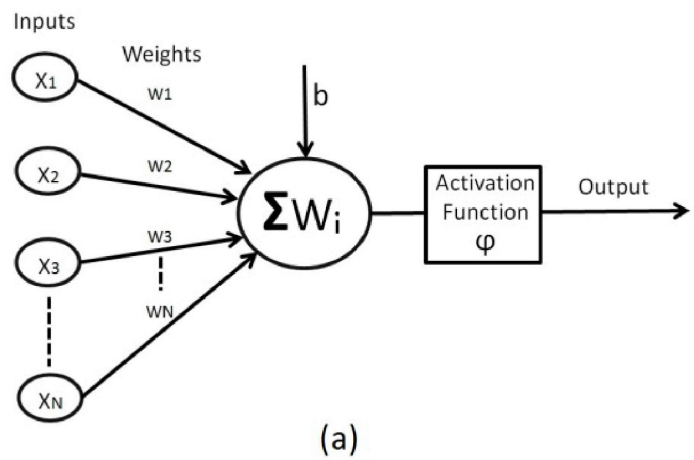


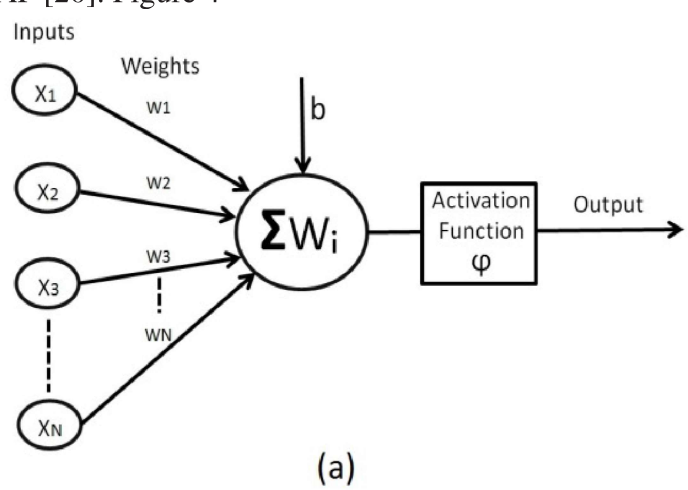
Figure 1 A fundamental system for the neural network

2.1 Perceptron model for ANN

The conceptions of NNs are distinct. The sensor is the simplest to begin with. It will determine whether an input is one of two potential categories and has separate activation functions (AFs). Its list of AFs usually includes: a hard limiter, a logic threshold (ramp), a linear one (sigmoid), and (the most frequent) a logistic feature of Sigmoidal. Fig. 1.4 (a) and (b) represent the AFs of the Perceptron. The model of mathematics is given:

$$y = \phi\left(\sum_{i=1}^{N} w_i x_i - b\right) \quad (3)$$

In which Inputs are provided by device signals, the appropriate weights, b is the neuronal bias, and is the AF [20]. Figure 4



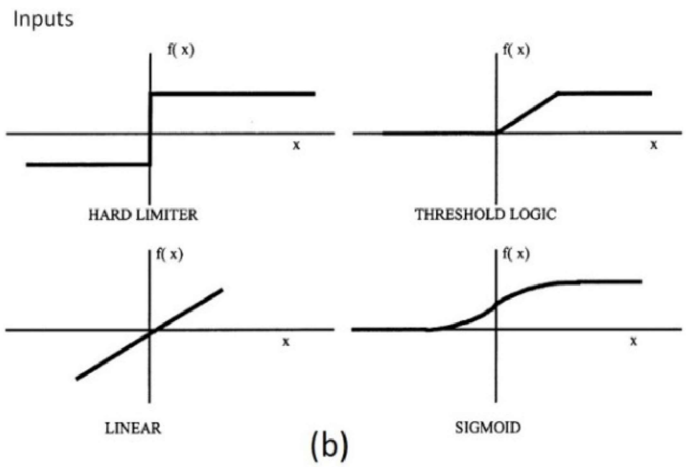


Fig 2 A perceptron and its activation functions, (a) and (b) respectively

3. Speed Estimation using ANN

ANNs owe their popularity to nonlinear function approximation ability. They are widely used to solve problems that can be characterized as black-box. The design procedure assumes that we know input signals and output signals but, we don't know the mathematical description of the process happening inside the black-box. There are many attempts to solve various estimation problems that occur in drives as black-box ones. Some remarks on ANN-based flux estimation can be found in [25]. As far as mechanical speed is considered, a very straightforward choice is to use ANN as a function f1 approximator where is defined as follows

$$\omega_r^{(k)} = f_1\left(u_{-s}^{(k)}, i_{-s}^{(k)}, u_{-s}^{(k-1)}, i_{f_1}^{(k-1)}, \ldots\right) \qquad (4)$$

Practical realization requires limited length of tapped delay lines (TDLs, number of delayed signals in (4). For example, it was assumed and partially proved in [24] that a single delayed signal is enough. It occurs in some control systems for AC motors that this relation can be function-like even for zero-length TDL [27]. This implies that a static system

$$\omega_r^{(k)} = f_2\left(u_{-s}^{(k)}, i_{-s}^{(k)}\right) \qquad (5)$$

can serve as a speed estimator. Of course, it is impossible to model dynamical system, e.g. like this one

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \qquad (6)$$

using static mapping

$$y = f_3(u) \qquad (7)$$

Nevertheless, it can occur that for

$$\begin{cases} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + Bu \\ y = C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{cases} \qquad (8)$$

where x1 denotes measurable part of state vector and x2 is a part of the state vector to be estimated, a relation between (u, x1) and y can be successfully approximated as a function $y = f_4(u, x_1)$ (9)

And this is in the case of speed estimation in selected AC drives. The presence of a control system can additionally simplify this task. Note that management loops are also too established that dominating time constants of the plant are compensated. This in turn implies that relation between (u, x, x_c, u_c) and y, where x state variables introduced by control system, uc - input functions (incl. reference signals), is usually more function-like then the one between (u, x_1) and . The single biggest problem with (4) is that there exists a serious mismatch between frequency spectra of input and output signals of the ANN. In certain commercial uses, asynchronous motors are generally found in electrical machinery. Various parameters of an asynchronous motor vary with time and operating condition. Despite much study, the speed has been calculated of asynchronous motors and estimated some of the parameters like flux and torque yet not much work has gone into speed estimation of asynchronous motors using ANN. Thus, in this thesis the use of a feed forward ANN has been explored to estimate the speed of an asynchronous motor.

4. Results and Discussions

As studied in previous chapters, ANN be indebted their popularity for estimation of nonlinear equations. ANN are generally used to solve a wide variety of black-box estimation problems. In black-box estimation problems only input and output signals are known and their mathematical relation is unknown. But real estimation problems are mostly Gray-box estimation problems and ANN can be modeled for these Gray-box estimation problems by using some form of mathematical description. The rotor speed of an asynchronous motor does not have a singular function and contains numerator and denominator functions, so ANN directly can't be used for its speed estimation. So, in the job at hand we have developed six speed signals by transforming voltages and currents. The parameters of the asynchronous motor used in following Table 1.

Table 1 Parameters of Asynchronous Motor

Parameter	Value
Stator Inductance	0.1010
Rotor Inductance	0.0978
Magnetizing Inductance	0.0926
Rotor Resistance	1.264 Ω
Sampling Frequency	100 KHz

MATLAB implements the whole framework and Simulink software. A feedforward ANN has been used for speed estimation. Figure 1 shows the block diagram of the Simulink model.

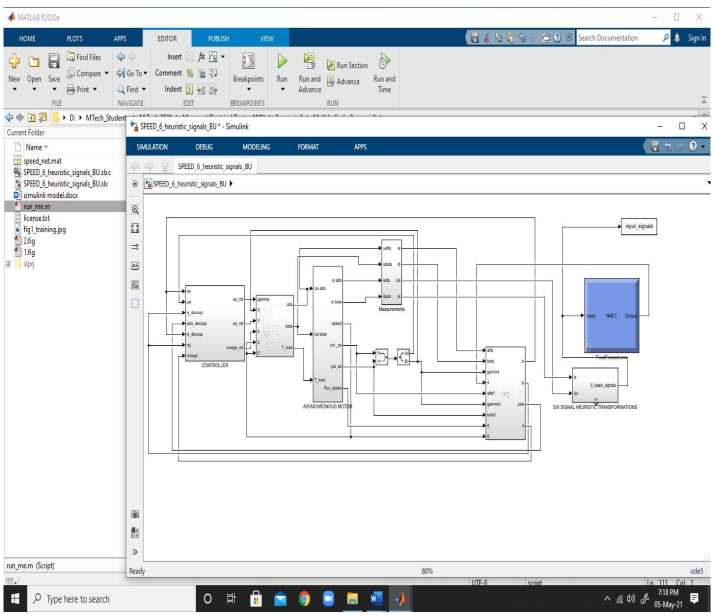
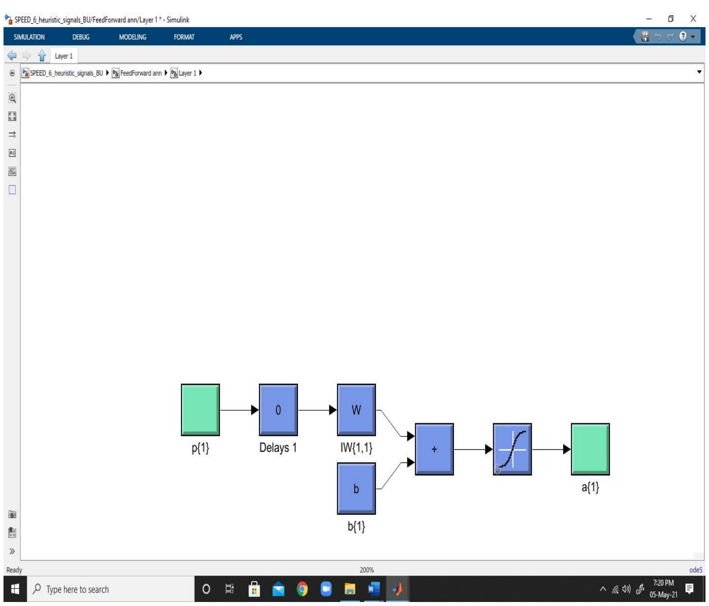
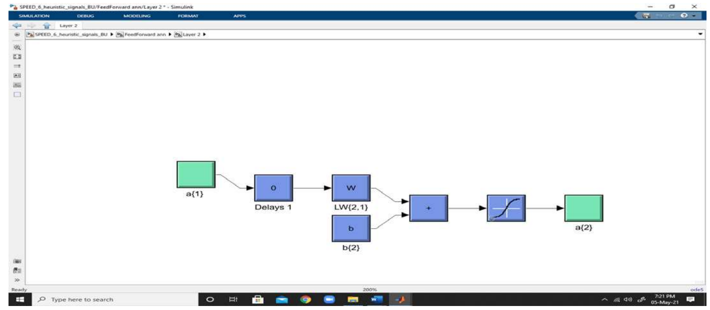


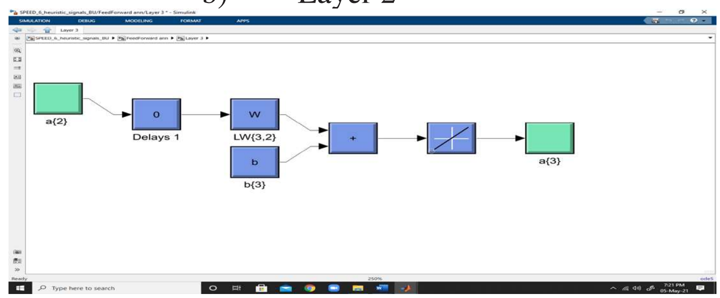
Figure 3 Block Diagram of Model Implemented in Simulink



a) Layer 1



b) Layer 2



c) Layer 3

Figure 4 Architecture of Each Layer of Feedforward ANN

The feedforward Network of neural nets is made up of 3 layers. Layer 1 and 2 use Sigmoid function and Layer 3 uses linear function

5. Conclusion

In this paper, it has been concluded that the model suggested as it is fairly accurate in estimating the speed rapidity of the Asynchronous motor. From results, it has also been concluded that as the load torque increasing the speed of the motor decreases, which confirms the inverse torque-speed relationship of an asynchronous motor as generally, Asynchronou motors are used in many commercial applications as electrical devices. In future the use of backpropagation ANN or deep neural network can be done for estimating the characteristics of the motor.

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