Direct Torque Control of Induction Motor by Active Learning Method

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Abstract-This paper presents a high performance direct torque control (DTC) theme for the induction motor (IM). To solve those problems associated with conventional DTC, such as flux and torque ripple, variable switching frequency, inaccuracy in motor model and other parts of system. The Active Learning Method (ALM) is implemented on the DTC. In the Active Learning Method for information modeling, a method known as Ink Drop Spread (IDS) is used. The simulation results of DTC system based on ALM and the comparison of motor performance under the proposed control system with respect to those obtained under conventional DTC confirms its effectiveness and accuracy.

Keywords: active learning method, direct torque control, fuzzy modeling, induction motor, reinforcement learning.

I. Introduction

Induction motors are replacing DC motors in the industry applications, even in the applications where a fast speed and torque response in four quadrants is required, at present in Europe the electrical drives business is worth approximately \$1.0 Billion/Annual.

Direct Torque Control (DTC) has been actively investigated during the last decade in the area of AC drives for induction motors. This control strategy was first introduced by Takahashi in 1986 [1] and at the same time Depenbrock developed a similar idea in 1988 under the name of Direct Self Control [2]. The main advantage of DTC is the high performance achieved (decoupled control of torque and stator flux, fast torque response and robustness) together with the simplicity of the scheme (no need for coordinate transformation, modulation block and current regulation), Although, some disadvantages are present such as non accuracy of torque and flux estimators, and an inherent torque and flux ripples because of non optimal switching [3], [4]. Lots of papers published on solving DTC drawbacks. Some of these papers fuzzified the DTC system inputs and improve its characteristics [5],[6]. Some else tried to improve the torque and flux estimators [7], [8].

This paper introduces Active Learning Method (ALM) to overcome the above mentioned disadvantages. ALM can adapt itself with torque and flux estimators and estimate the outputs with regards to errors in torque and flux estimations. Also proposed method avoids mathematical complexities of fuzzy like's methods and so it is faster than conventional methods.

The active learning method (ALM) has been proposed as a new approach to soft computing. The concept of the ALM is based on the hypothesis that humans interpret information in the form of pattern-like images rather than in numerical or logical forms. The ALM is algorithmically modeled on the intelligent information-handling processes of the human brain, and it is characterized by computing on the basis of intuitive pattern information [9]-[11].

The ALM uses its own modeling technique called the ink drop spread (IDS) method. The IDS method is able to deal with various modeling targets, ranging from logic operations to complex nonlinear systems [12]. The IDS method possesses stable fast convergence, and its modeling process, which is based on computing that uses pattern information instead of complex formulas, is simple and efficient.

The paper is organized as follows: in section II, a review of conventional DTC is presented; then, in section III, Active Learning Method (ALM) is introduced and its modeling technique (IDS) is explained in section IV, in section V the DTC system is modeled by ALM, simulation results of DTC by ALM are available in section VI. Finally, the conclusions are exposed in section VII.

II. Direct Torque Control Principles

Fig.1 shows the schematic of Direct Torque Control. As it can be seen there are two different loops corresponding to the magnitude of the stator flux modules and torque. The reference values for the stator flux and torque are compared with the calculated ones. The output of both stator flux and torque comparators together with the position of the stator flux are used as the input of the control block.

Flux and torque estimations are performed by means of mathematical model of induction motor using other magnitudes such as stator current and mechanical speed.

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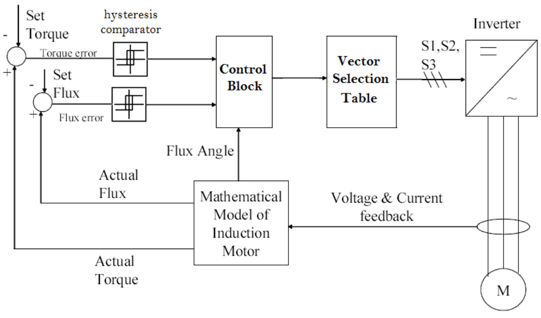

Figure 1.Block scheme of DTC

As shown in Fig.2, the position of the stator flux is divided into six sectors, highlighted by dashed line and the flux position is determined with this sectors.

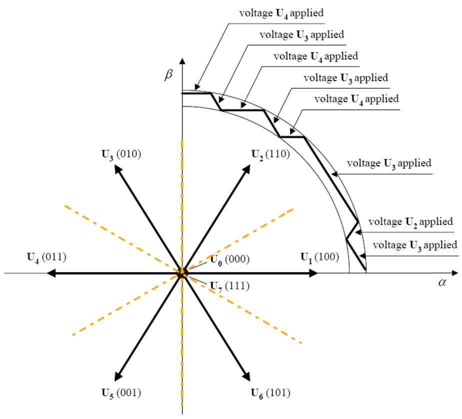

Figure 2.Stator voltage vectors and flux position sectors

There are also 8 voltage vectors which correspond to possible inverter states. These vectors are shown in Fig 2. There are six active vectors U_1-U_6 and two zero vectors U_7, U_0.

The stator flux linkage and the electromagnetic torque are controlled directly by the selection of optimal switching pattern. The selection is made to limit the flux and torque errors within respective flux and torque hysteresis bands. The outputs of the optimal voltage switching vector look-up table, are used to control the inverter. The Voltage vector U_2 increases both the magnitude of torque and stator flux and the vector U_3 increases the magnitude of stator flux and decreases the torque. The vector U_5 decreases both the magnitude of the stator flux and the torque, and the vector U_6 increases the magnitude of stator flux and decreases the torque. The Voltage vectors U_0 and U_7 decrease the magnitude of stator flux and the torque, U_1 increases the magnitude of stator flux, and U_4 decreases the magnitude of stator flux. Also, U_1 and U_4 maintain the torque [13].

The above considerations allow construction of the selection table as presented in Table 1.

Table 1.Optimum switching Table

e_ψ	e_T	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6
1	1	U_2	U_3	U_4	U_5	U_6	U_1
	0	U_7	U_0	U_7	U_0	U_7	U_0
	-1	U_6	U_1	U_2	U_3	U_4	U_5
0	1	U_3	U_4	U_5	U_6	U_1	U_2
	0	U_0	U_7	U_0	U_7	U_0	U_7
	-1	U_5	U_6	U_1	U_2	U_3	U_4

III. Active Learning Method (ALM)

Active Learning Method (ALM) is a new fuzzy modeling method which has been developed by Bagheri Shouraki and Honda (1997a).

Active Learning Method is the learning mode in which the learner improves the performance by acquiring information from the behavior of his own. The concept of the ALM is based on the hypothesis that humans interpret information in the form of pattern-like images rather than in numerical or logical forms. The ALM is algorithmically modeled on the intelligent information-handling processes of the human brain, and it is characterized by computing on the basis of intuitive pattern information.

ALM considers the behavior of complicated MIMO systems as collection of simple systems which are single input single output (SISO) systems and the system is expressed by combining them(Fig.3). This modeling method not only is similar to human logical thinking but also avoids mathematical complexity.

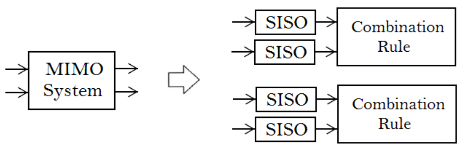

Figure 3. Division and combination of system

In Active Learning Method (ALM), the control knowledge is acquired actively by trial and error. In this method, the input-output data is gathered from the control object by the method of trial and error, and the controller is constructed based on the gathered information. This process is repeated.

In this method, the learning is done by mutual action with the environment (Fig.4) and promoted by reinforcement learning. The reinforcement learning originated from animal learning psychology and the optimization method like dynamic programming. In this method, the action is reinforced by giving reward or punishment according to the behavior taken in a certain state.

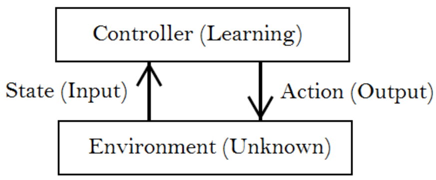

Figure 4.Learning from environment.

ALM starts with gathering data and projecting them on different data planes. The horizontal axis of each data plane is one of the inputs and the vertical axis is the output. IDS (Ink Drop Spread) processing engine will look for a behavior curve, hereafter narrow line, on each data plane. The heart of this learning algorithm is a fuzzy interpolation method which is used to derive a smooth curve among data points [14], [15].

IV. Ink Drop Spread (IDS)

The basic concept of IDS is to extract the system properties from the input-output data by using fuzzy process. This method searches for continuous possible paths on the interpolated data points on each plane. In this method, we assume that each data point on each data plane is a light source (Fig.5), which has a cone shape illumination pattern. As the distance from these light sources increases, their illumination pattern will interfere and generate new bright areas. The lights interfere with each other and the illuminated pattern appears to show light and darkness. That is, the part where many lights fall is lighter than other part. By combining the light parts continuously, a kind of narrow path expressing the input-output relations can be obtained [16].

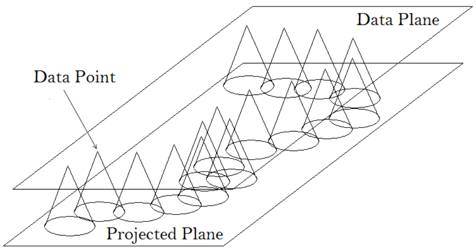

Figure 5. Concept of IDS (Ink Drop Spread)

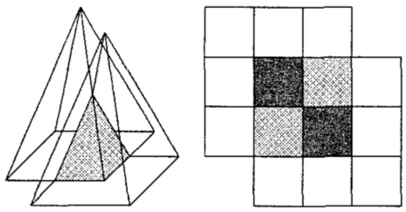

Figure 6.irradiation pyramid

By applying IDS method on each data plane, two different types of information would be extracted. One is the narrow path and the other is the deviation of the data points around each narrow path (Fig.6). Each narrow path shows the behavior of output relative to an input and spread of the data points around this path shows the importance degree of that input in overall system behavior.

Less deviation of data points around the path presents higher degree of importance and vice versa.

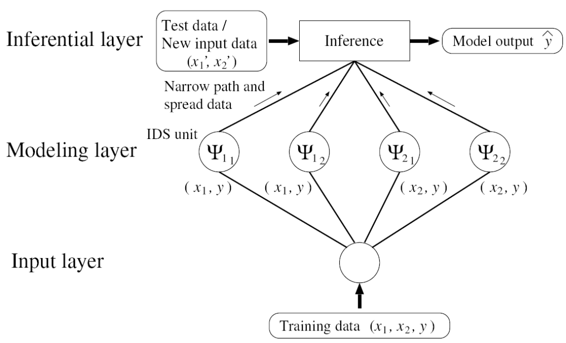

Figure 7.Structure of IDS model

Fig.7 illustrates the architecture of an IDS model with two-input, two-partition structure. The IDS model comprises three processing layers. The bottom input layer breaks down input-output data into SISO data, and transfers them to the upper modeling layer. The top inferential layer computes the prediction with the learning data transferred from IDS units. With the exception of the case where a particularly high accuracy is required for an IDS model, the upper layer does not intervene the learning process of IDS units [17].

The spread functions, which show the amount of spread of data on each plane resulting from the effects of other variables, can be calculated using a method presented in [10] by S.B.Shouraki and N.Honda. Then the output of the system can be calculated by equation 1.

$$y=\frac{\left[\frac{1}{a_1}f_1(x_1)+\frac{1}{a_2}f_2(x_2)+\ldots+\frac{1}{a_n}f_n(x_n)\right]}{\left(\frac{1}{a_1}+\frac{1}{a_2}+\ldots+\frac{1}{a_n}\right)} \qquad (1)$$

Where

y = the output of system (function)

$x_1, x_2,\ldots, x_n$ = inputs of the system (variables)

$f_1, f_2,\ldots f_n$ = the narrow path functions for plane x-y for each variable

$a_1, a_2,\ldots, a_n$ = spread values.

V. Modeling DTC by ALM

In this section Direct Torque Control of induction motor is modeled using Active Learning Method.

In ALM the input-output information is collected from the control object by the method of trial and error, and controller is constructed by the fuzzy-like processing of these data. In the other word some trial inputs are applied to control object and this action is reinforced by giving reward or punishment according to the result. These trial and error inputs should be selected so that covers all possible system inputs. Obviously, as the number of this trial and error actions increases, the system model improves.

Regarding the DTC system diagram, represented in Fig.1, the input-output structure of the DTC system control block is shown in Fig.8. The DTC system is a multi input-single output system and according to the ALM basis should be divided into systems with single input and single output (SISO) systems. The DTC control block inputs consist of Torque error, Flux error and Stator Flux angle (position). The stator Flux angle is not considered as an independent input in SISO systems because there is not any direct relationship between stator flux angle and inverter state (Fig.1). So as mentioned above, the stator flux is divided into six sectors and this modeling procedure is done for each sector. In the other word, there are 6 couple SISO systems and every couple is for a sector.

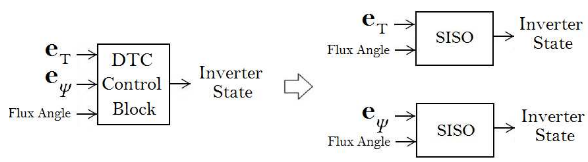

Figure 8.Inputs and outputs of DTC and DTC SISO models

MATLAB’s DTC block is used for applying trial and error inputs. Sampling frequency and inverter switching frequency justified on 20 kHz. Trial and error inputs applied to the DTC model which its torque set value is a random function in order to experience different possible errors. Some of the sample data obtained by 25000 repetitions are presented in Table 2.

As the Table 2 samples show, some inputs lead to improvement in result and some of them worsen the results. The inputs which lead to decrease in torque or flux errors should be rewarded and the others should be punished.

Table 2.Some sample trials

e_T (NM)	e_ψ (wb)	Flux Sector	Inverter vector
16.58525	0.005745	3	5
15.73732	0.012678	3	4
14.88131	0.019592	3	4
5.350821	0.019328	3	4
-5.1948	0.018405	3	2
-15.7194	0.017401	3	2
-16.0108	0.011697	3	2
-14.0427	0.0056	3	2
-12.074	-0.00051	3	2
-10.1047	-0.00664	3	2
-8.13501	-0.01279	3	1
-6.16497	-0.01894	3	1
4.300601	-0.01817	3	7
15.82101	-0.01691	3	5
18.01083	-0.01651	3	5

These 25000 samples are plotted in a three dimensional space (Fig.9) and the following formula is used to determine the efficiency of each trial action:

$$d_{T_i} = e_{T_i} - e_{T_{i+1}} \quad \text{If} \quad e_{T_i} \geq 0 \qquad (2)$$

$$d_{T_i} = e_{T_{i+1}} - e_{T_i} \quad \text{If} \quad e_{T_i} \leq 0 \qquad (3)$$

$$M = MAX(d_{T_i}) \qquad (4)$$

$$E_i = \frac{d_{T_i}}{M} \qquad (5)$$

The flux equations are the same as torque equations.

The efficiency of each applied inverter vector is calculated by equation (5), E_i determine the magnitude (reward) of each trial and error and its popularity. Any inverter vector with bigger E_i, which leads to more improve in decreasing error, is reinforced and so its relevant vector magnitude in Fig.9 will be bigger. Fig.9 shows the result of 25000 trial and error repetition which is the projected plane for SISO system of sector 1 with the input of torque error and the output of inverter state.

In Fig.9 the plane of trial actions with reward and punishment of data is shown from four different angle of view. The top view of projected plane (last part of Fig.9) confirms the conventional lookup table represented in Table.1. As Table 1 shows, only active vector U_2, U_3, U_5, U_6 are applied for the flux position of sector one and the results of ALM confirms the classical DTC lookup table (Table 1).

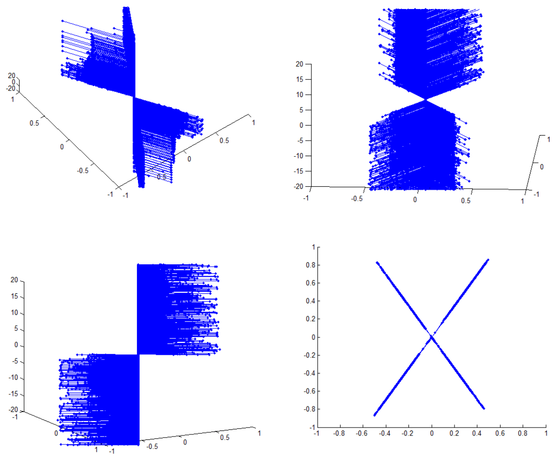

Figure 9.IDS irradiation pattern for SISO system with torque error as input and inverter vector as output

In Fig.9 the horizontal plane expresses the inverter voltage state and the vertical axis determines the error. The respective correct inverter state of any torque error can be calculated based on these three dimensional plots and the control rules are acquired by these plots, also rules obtained by ALM are similar to classic ones with some minor differences. The rules format is as:

If e_T is e_{T1} and flux sector is α then inverter state is V_m

If e_Ψ is $e_{\Psi 1}$ and flux sector is β then inverter state is V_n

The ALM output in each sector will be achieved by combining SISO models of sector torque and flux errors. DTC total system model is achieved by combining 12 SISO models of six sectors and this combination is based on the sum of adaptability of each SISO model. The equation 6 is used for calculating output by combining SISO outputs.

$$y = \alpha_T \times y_T + \alpha_\psi \times y_\psi \qquad (6)$$

Where α is the adaptability of each SISO, determined by the efficiency (E_i) of each case. By this equation the output of a case in sector one will be a compromise of sector one torque and flux error SISO systems outputs.

VI. Simulation Results and Comparison with Classic Methods

All of the coeds for ALM modeling have been programmed in MATLAB software. A 460 v, 150 kVA and 60 Hz squirrel cage motor with 2 pairs of poles is used in simulations.

The target of DTC control is to limit the torque magnitude in a predefined band. In simulations the control rule of DTC system is modeled by ALM based on the data obtained 25000 trials repetitions. Control rules achieved by applying IDS method on the trial actions results. Fig.10 shows the change of the number of control rules obtained by the simulations with increasing trial actions number. Obviously, number of rules increases as number of trials increase. Number of trial action could be determined regards to the specified required accuracy.

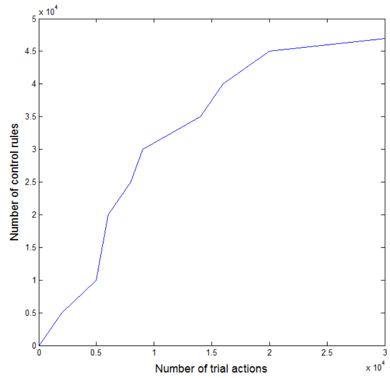

Figure 10.Change in number of control rules

The result of torque control for both classical DTC and the proposed method is presented in Fig.11-13 (the x axis (time) is ranged from 0 to 0.07 (s) and the y axis (torque) from -100 to 500 (NM)).

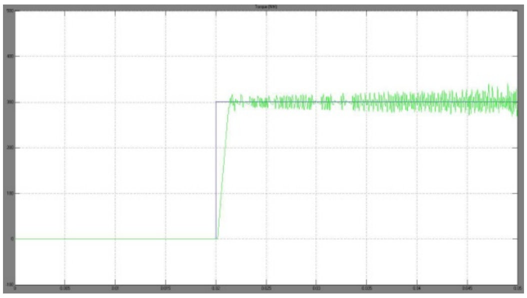

Figure 11.Output torque of conventional DTC

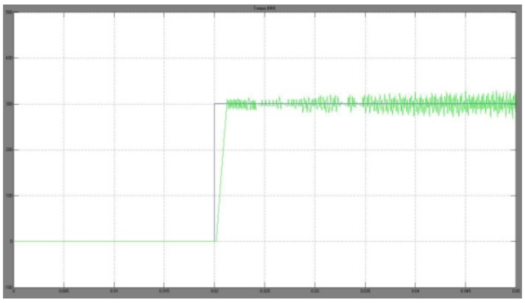

Figure 12.Output torque of ALM based DTC with rule base result from 5000 trial actions

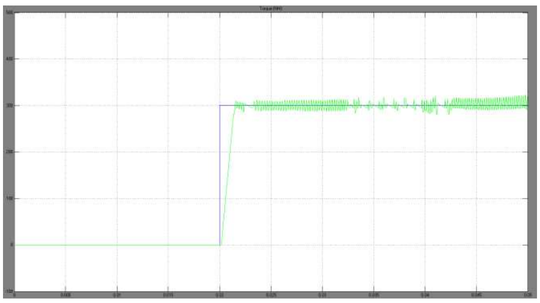

Figure 13.Output torque of ALM based DTC with rule base result from 25000 trial actions

As can be seen, the ALM leads to less deviation from the set value of torque (desired torque) rather than the conventional DTC; this is due to its adaptability with motor model and the total system. The ALM accuracy increases as the number of trial and error actions increase, also switching frequency is decreased. Fig.12 and Fig.13 shows this improvement (around 30%) in ALM based DTC system by decreasing torque error.

VII. Conclusions

Direct Torque Control is an important alternative method for the induction motor drive control system. This paper implements ALM to model the DTC system control block, which solves some major drawbacks of DTC scheme. The proposed method adapts itself with the total environment of the system, so impact of induction motor model uncertainties and other inaccuracies in the control system will be omitted.

The proposed method models the DTC system actively by repetition. The trial data is memorized and evaluated in ALM by IDS method. Finally the different SISO systems IDS are combined and the DTC model is achieved. The new model of DTC replaced with the conventional one and the achieved results of simulations confirm the effectiveness of the proposed method..

Flux linkage and torque ripples are dramatically reduced under ALM based DTC. Fast response performance which is DTC inherent advantage is also improved regarding the simplicity of the proposed method comparing with previous models.

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