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Online Optimal Neuro-Fuzzy Flux Controller for DTC Based Induction Motor Drives

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***Abstract*- In this paper a fast flux search controller based on the Neuro-fuzzy systems is proposed to achieve the best efficiency of a direct torque controlled induction motor at light load. In this method the reference flux value is determined through a minimization algorithm with stator current as objective function. This paper discusses and demonstrates the application of Neuro-fuzzy filtering to stator current estimation. Simulation and experimental results are presented to show the fast response of proposed controller.**

I. INTRODUCTION

It is estimated that more than 50% of the generated electric energy in the world is consumed by electric machines [l]. Improving efficiency in electric drives is important, mainly, for two reasons: economic saving and reduction of environmental pollution [1]. This is why considerable effort is done to improve their efficiency. More than 60% of industrial electricity is consumed by the induction motors (IM). IM have a high efficiency at rated speed and torque [2]. However, at light loads, iron loss increases drastically which reduces considerable efficiency [1].

To improve motor efficiency, the flux must be reduced with an expert control algorithm. That tries to obtain a balance between copper and iron loss when torque is constant [3].

Vector control (FOC) and Direct torque control (sensorless vector control) are the two most popular techniques for induction motor torque control [4]. Unlike Vector control, direct torque control (DTC) does not require coordinate transformation and any current regulator and encoder. It controls flux and torque directly based on their instantaneous errors [5]. In spite of its implicitly, direct torque control is capable of generating fast torque response. In addition, direct torque control minimizes the use of machine parameters; hence it is much less sensible to parameter variation [6].

For such reasons, DTC has become one of the most popular methods for induction motor drive system control. However, there are many disadvantages with this control method.

The most significant problem with DTC is that the nominal value of flux is optimized for nominal motor operating point. But at light load, using the same flux value decreases the power factor and efficiency of the drive [7].

Among the flux controllers used to set the flux amplitude in light loads, the loss search controller is the best method adapted for DTC drives. That is because other flux controller categories eliminate the independence of DTC from machine parameters [8]. In past researches, this controller has been imposed on the DTC loop. It was shown that the stator current is better than input power to be used as the objective function [9]. But classic minimum loss search controller produces divergence problem and steady state flux ripple; this problem is referred to the existence of the noise in the measurements.

In order to find the minimum stator current we need to accurately estimate the current. It is a challenging problem because the measurements are strongly affected by the noise.

In the proposed method, from some point in steady state we gather experimental data for given flux values. We change the flux value in small steps starting from flux nominal value. Then we apply a neuro-fuzzy estimator to obtained data. Based on the result of this estimator, we decide either to gather a new data or calculate the optimal flux value.

In the next section, a brief introduction to the DTC of induction motors is presented. Various methods for optimizing the motor flux are reviewed in Section III. The classic flux search controller is described in Section IV. ANFIS is reviewed in Sections V and VI. The proposed control algorithm is presented in Section VII. Experimental results are presented to show the performance of proposed controller.

II. DIRECT TORQUE CONTROL

The basic idea of the DTC concept, which its block diagram is shown in Fig. 1, is to choose the best vector of the voltage, which makes the flux rotate and produce the desired torque. During this rotation, the amplitude of the flux remains inside a pre-defined band. The stator flux vector can be calculated using the measured current and voltage vectors:

$$\bar{\psi}_s = \int (\bar{v}_s - R_s \bar{i}_s)dt \qquad (1)$$

Where ψ_s is stator flux space vector, v_s stator voltage space vector, i_s stator current space vector, and R_s stator resistance. For calculation, in a stationary d–q reference frame, the electromagnetic torque of an induction machine is usually estimated as follows:

$$T_e = \frac{3}{2} P(\psi_{ds} i_{qs} - \psi_{qs} i_{ds}) \qquad (2)$$

Where P is the number of pole pairs, ψ_{ds} and ψ_{qs} are d and q-axis components of ψ_s, i_{ds} and i_{qs} are d- and q-axis components of i_s.

Circular trajectory of the stator flux is divided to six symmetrical sections referred to inverter voltage vectors. For each section, a proper vector set is proposed. Voltage vectors are applied to motor to make amplitudes of the flux and torque remains constant [10].

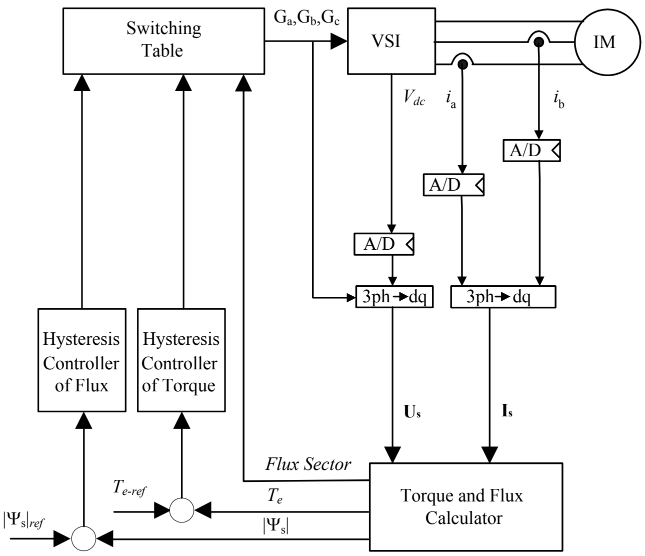


Fig 1. Block diagram of the DTC method

III. CLASSIC FLUX SEARCH CONTROLLER

In this family of flux controllers, the input power of drive is minimized by adjusting the flux value in consecutive steps. The stator flux is decreased from its initial value (ψ_{o}) to (ψ_{opt}), the optimal value of flux that results in minimum input power. The input power of motor is calculated using Eq. (3):

$$P_{active} = V_d I_d + V_q I_q \tag{3}$$

where d and q represent the Concordia transformation components of the current and voltage.

The flux reference value is varied in consequent steps to minimize the active power. It can be expected that the value of flux step determines the flux ripple at the steady-state. To achieve a low flux ripple, the flux step should be as small as possible. But, if the objective function is merged with some noise ($\Delta n>0$), if the flux step value is small enough, as it was mentioned in [11], [12], the control algorithm will have convergence problem and the flux controller does not tend to the optimum value of flux. In the classic search controller, the samples of motor input power which are obtained from Eq. (3) pass through an averaging operator to yield the average value of motor input power to attenuate the effect of noise. But the experimental results have shown that this method response is not satisfying enough and the convergence time is too long. Hence we need other noise cancellation algorithms (not averaging method).

In next sections the anfis concepts and its application in noise canceling is described and base on it a flux search controller proposed.

IV. NOVEL ADAPTIVE NOISE CANCELLATION METHOD

Widrow and Glover first approached adaptive noise cancellation (ANC) [19]. The schematic diagram of their method is shown in Fig. 2.

Here an information signal *s(t)* is unmeasurable and a noise source signal $v_1(t)$ is measurable. The noise source goes through an unknown nonlinear function to generate a distorted noise $v_0(t)$ which is unmeasurable. It is then added to an information signal *s(t)* to compose an output signal *x(t)* which is measurable. The goal is to recover the information signal *s(t)* from the compound output signal *x(t)*. The detected output signal is presented as:

$$x(t) = s(t) + v_0(t) = s(t) + f\,(v_1(t),\ v_1(t-1),\ldots), \tag{4}$$

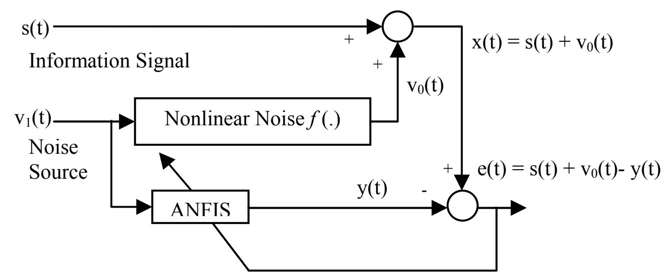


Fig. 2. The architecture of ANFIS for noise cancellation

where the function *f (.)* denotes the nonlinear function that the noise source signal v_1 goes through. If we know the function *f (.)* exactly, we can easily retrieve the original information signal by subtracting $v_1(t)$ from *x(t)* directly. However, *f (.)* is usually unknown in advance and may change with time. In this method Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to implement *f (.)*.

The ANFIS applied in this paper uses Takagi and Sugeno's fuzzy if-then rules [13] [14]. The basic learning rule to identify the parameters is based on gradient descent, which was proposed by Werbos [15]. but the method is generally slow and likely to become trapped in local minima. Here a hybrid learning rule [16], which combines the gradient method and the least squares estimate (LSE) is used[17][18].

The noise signal $v_1(t)$ and the distorted noise signal $v_0(t)$ do not relate to the information signal *s(t)*. However, it cannot be measured directly because it is a part of the overall measurable signal *x(t)*. The detected signal *x(t)* can be measured as the expected output of ANFIS training only if the information signal *s(t)* is not correlated with the noise signal $v_1(t)$.

But according to the previous sections, we know that the motor's input power signal is a smooth function of flux and this property of motor enables us to obtain another Adaptive noise cancellation method that is used in this paper. In this method unlike the Widrow's method, it is assumed that instead of the noise signal, the information signal is correlated in some unknown way with a primary signal, the schematic diagram of this method is shown in Fig.3.

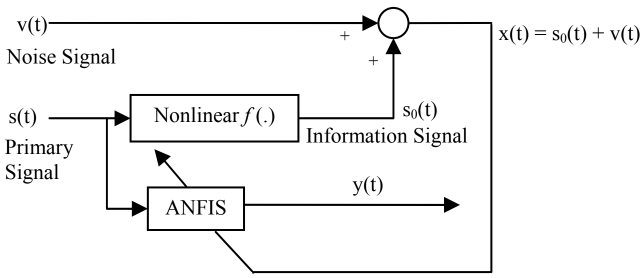


Fig.3. The new architecture of ANFIS for noise cancellation

In Fig. 3, signal $s_0(t)$ is the information signal (input power signal) and *v(t)* is the unmeasurable noise signal and *s(t)* is the primary function ,the information signal $s_0(t)$ is added to *v(t)* to form the measurable output signal *x(t)* . Here *y(t)* denotes the output of ANFIS and it is the output of the whole system which is the estimation of information signal .
The detected signal is:

$$X(t) = s_0(t) + v(t) = f(s(t), s(t-1), ...) + v(t) \qquad (5)$$

The function *f (.)* denotes the nonlinear function that the primary signal goes through. The noise signal *v(t)* is not related to the information signal $s_0(t)$ and the primary signal *s(t)*. if the information signal *s(t)* is not correlated with the noise signal *v(t)* shown in Fig.7,The detected signal *x(t)* can be the expected output of ANFIS training .
Adaptive noise canceller has two inputs: the detected output signal, and the primary function. The information signal $s_0(t)$ is correlated to the distorted primary function and not correlated to the noise signal *v(t)*. ANFIS accepts the error signal *e* to control and adjust the weights *W* which make the output of ANFIS, denoted as *y(t)*, to approximate the information signal $s_0(t)$.

$$e(t) = x(t) - y(t) = s_0(t) + v(t) - y(t) \qquad (6)$$

we square the above equation and obtain :

$$e(t)^2 = (s_0(t) + v(t) - f(s(t), s(t-1), s(t-2), ...))^2 \qquad (7)$$

where *f* is the function implemented by ANFIS. *v(t)* is not related to *s(t)* and its previous values, Eq.(10) can be expanded to

$$e(t)^2 = (v(t))^2 + (s_0(t) - y(t))^2 + 2v(t)s_0(t) - 2v(t)y(t) \qquad (8)$$

Taking means of both sides of Eq. (11) yields

$$E[e^2] = E[v^2] + E[(s_0 - y)^2] + 2E[s_0 v] - 2E[vy] \qquad (9)$$

It is assumed that *v(t)* is not correlated to $s_0(t)$ and *y(t)*, then $E[sv_0]$ and $E[sy]$ are equal to zero,

$$E[e^2] = E[v^2] + E[(s_0 - y)^2] \qquad (10)$$

Here $E[v^2]$ does not change when ANFIS adjusts its MFs to minimize $E[e^2]$ because it is not related to weight W :

$$E[e2]_{\min} \Leftrightarrow E[(s0 - y)2]_{\min} \qquad (11)$$

Therefore, training ANFIS to minimize the total error $E[e^2]$ is equivalent to minimize $E[(s_0 - y)^2]$. The filter output Y(t) is the best squares estimate of the information signal and the function $f(\cdot)$ achieved by ANFIS can be as close as the passage dynamics $f(\cdot)$ in a least squares sense.

V. Neuro-Fuzzy search controller

In order to find the minimum of the input power signal ,in motor's steady state , We change the flux value in small steps starting from flux nominal value and we gather experimental data for given flux values and Then we apply a neuro-fuzzy estimator to obtained data. After estimation, if the noise cancelled piece of signal is descending it means that we should gather more data, and if it is ascending it means that the minimum is in the obtained data and we can find it. The derivate of the piece has been used to find out if the corresponding piece of function is descending or ascending

VI. Simulation Results

In order to evaluate the performance of the method the DTC control system with neuro-fuzzy estimator is performed by Matlab simulation. Fig.s 4 to 7 show the basic operation of controller. In this simulation, the flux period for each data gathering epoch is 0.1 wb and every input has two membership functions with bell shape. Table 1 shows the motor parameters. These fig.s have three parts: A is the corrupted information signal but only shows the required data for finding the minimum, B is the estimation of A, that contains the minimum and C shows the variation of flux while finding the minimum.
Fig.s 4 and 5 show a comparison between two different initial functions: parabolistic and ramp. It can be seen that operation of ramp function is more acceptable and the estimated stator current has a distinct minimum point with this function. This result is also shown in figs. 6 and 7.
Comparison between figs 4 and 6 and figs 5 and 7 shows that variation of sampling point numbers has not obvious effect on the convergence time because less number of sampling points leads to more time interval required for ANFIS analysis.

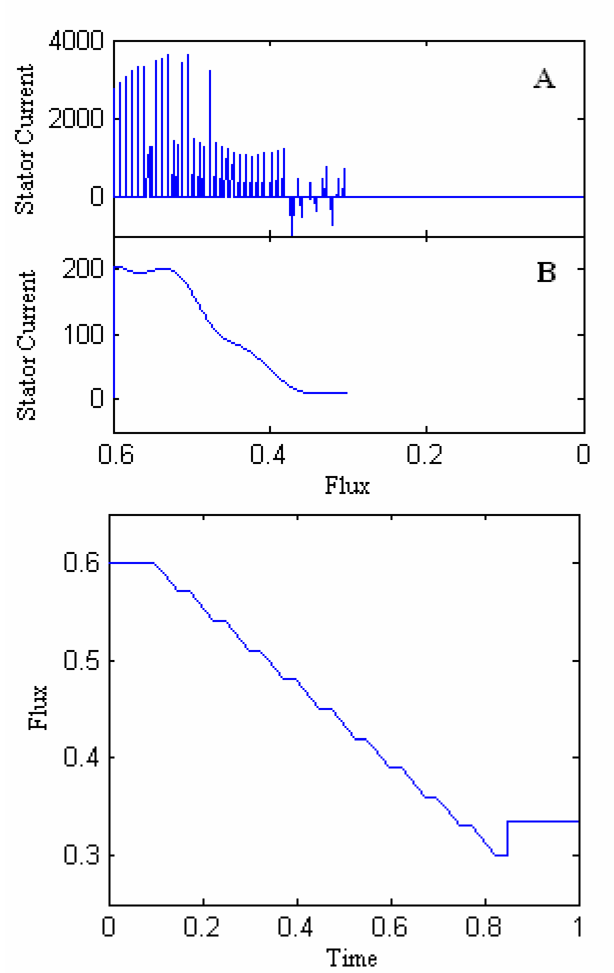
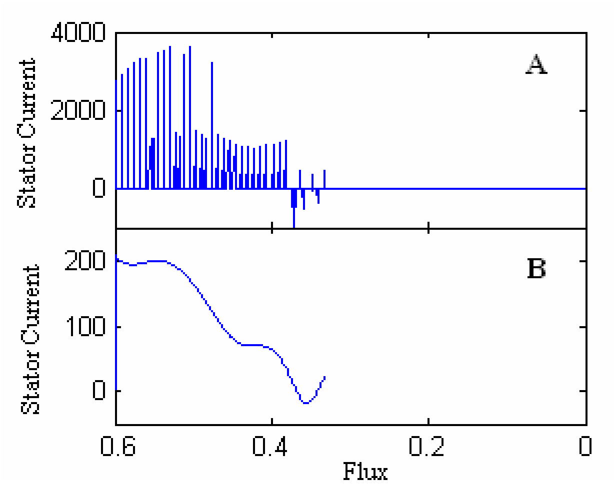


Fig. 4. (A) Corrupted information signal. (B) Estimation of A. (C) Variation of flux while finding the minimum. Sampling period size = 500, Reference function=x^2, Calculated optimal flux = 0.3351, Final sampled flux = 0.3000



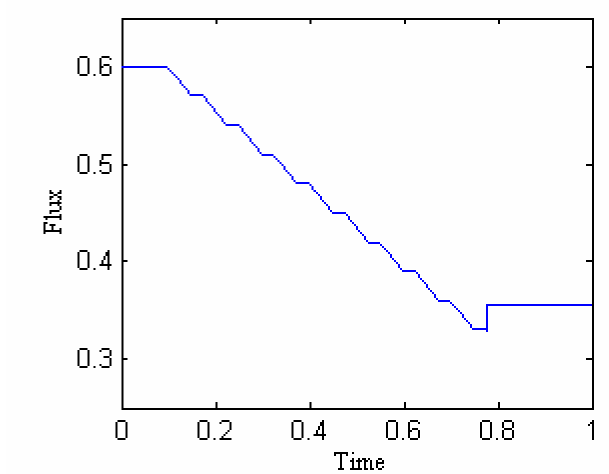
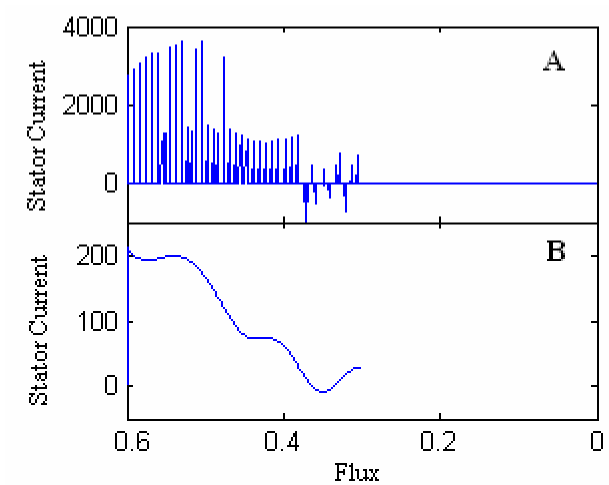


Fig. 5. (A) Corrupted information signal. (B) Estimation of A. (C) Variation of flux while finding the minimum. Sampling period size = 500, Reference function=ramp, Calculated optimal flux = 0.3547, Final sampled flux = 0.3300



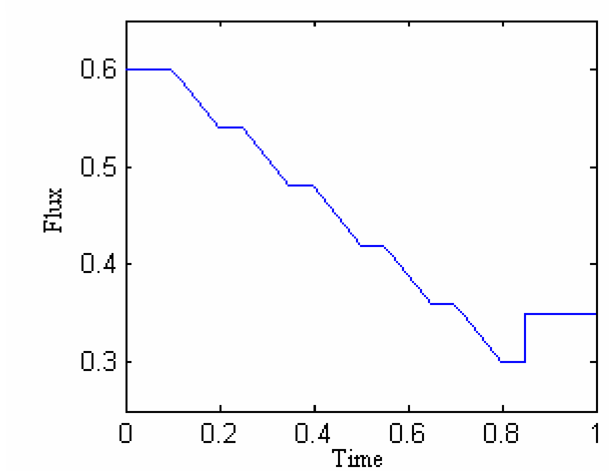


Fig. 6. (A) Corrupted information signal. (B) Estimation of A. (C) Variation of flux while finding the minimum. Sampling period size = 1000, Reference function=ramp, Calculated optimal flux = 0.3493, Final sampled flux = 0.3000

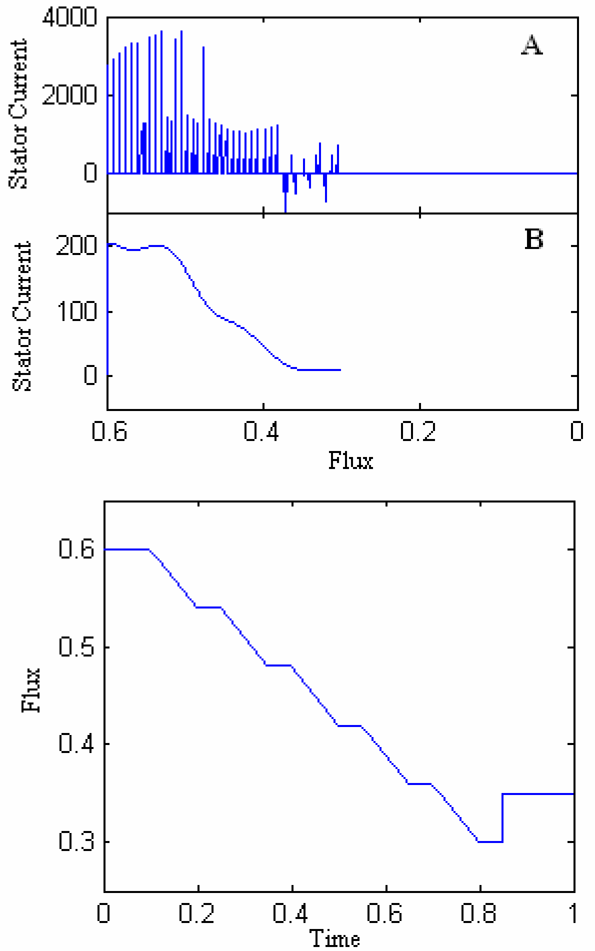


Fig. 7. (A) Corrupted information signal. (B) Estimation of A. (C) Variation of flux while finding the minimum. Sampling period size = 1000, Reference function=x^2, Calculated optimal flux = 0.3351, Final sampled flux = 0.3000

TABLE I
CHARACTERISTICS OF INDUCTION MOTOR

Parameter	Value
Rated Power	5.5 KW
Number of Poles	4
Stator Resistance	0.277 Ω
Stator Inductance	0.0553 H
Magnetizing Inductance	0.0538 H
Rotor Resistance	0.183 Ω
Rotor Inductance	0.0560 H

VII. EXPERIMENTAL RESULTS

To verify the simulation results, the proposed control method has been applied to a DTC experimental test setup. The experimental setup, shown in Fig. 8 consists of an induction motor, insulated gate bipolar transistor (IGBT) based inverter, and digital signal processor (DSP) (TMS320C) based controller. Detailed characteristics of DSP controlled inverter are presented in tables 3. The machine currents i_a and i_b and the dc bus voltage were interfaced into the controller through an analog to digital (A/D) converter built into the DSP board. The sampling time and motor speed are 133 μsec and 300 RPM, respectively.

Fig. 9 shoes the time response of proposed method for a torque step from T_n to $T_n/4$. It can be seen that the search controller finds the optimal flux value rapidly and has a smooth behavior in steady state.

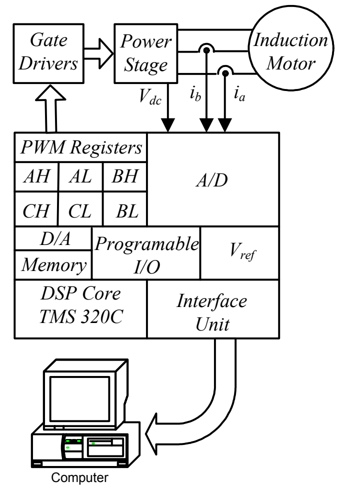


Fig. 8. Block diagram of experimental setup

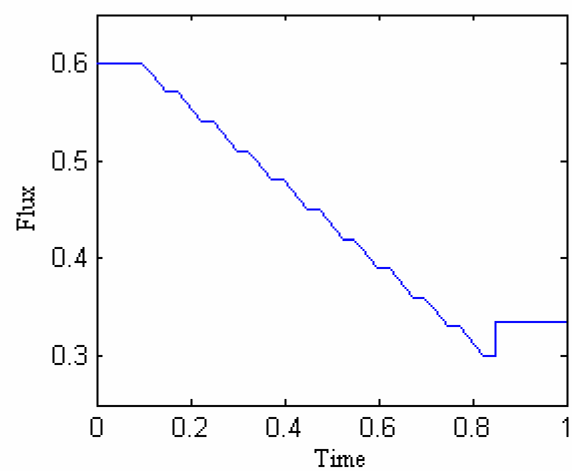


Fig. 9. Response of proposed search controller

VIII. CONCLUSION

An online flux search controller has been used to determine the reference value of stator flux according to load in DTC. A neuro-fuzzy noise cancellation algorithm is proposed to optimize the process to achieve fast dynamics and good steady state response. Simulation and experimental results show that this new controller can determine the optimum value of stator flux rapidly without considerable ripple in steady state.

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