Fuzzy Logic Control of Food Frying Process: Optimization of DC Wingding Currents of Food Frying Process Control

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ABSTRACT

This paper demonstrates the application of fuzzy filtering to motor winding current estimation in permanent magnet synchronous motors. The optimization of DC winding currents of food frying process is very important since brushless motors are not self-commutating, and are more complicated to control. Brushless motors have three windings, rather than two. The currents and voltages applied to the motor windings must be controlled independently and correctly as a function of rotor position in order to produce useful torque, unlike the torque produced by a brush motor, which is fairly easy to control because the motor commutates itself. Torque is proportional to the DC current into the two terminals of the motor, irrespective of speed. Torque control can therefore be implemented by a P-I feedback loop, which adjusts the voltage applied to the motor in order to minimize the error between requested and measured motor currents. The knowledge of this P-I feedback loop is borrowed in order to develop a fuzzy logic optimization algorithm for DC winding currents of food frying process control. However, the electronics required to drive brushless motors is substantially more complex than that for brush motors used in industrial food frying process which fuzzy logic aims at solving.

It is shown via simulation that fuzzy techniques provide an attractive alternative to current estimation using analytic techniques [1,6]. It is further shown how the fuzzy membership functions can be tuned using gradient descent [2] and the ripple cancellation technique [3,5], which resulted in the optimization of the DC winding currents of food frying process control.

(Keywords: fuzzy logic, field orientation control, FOC, servomotor controls, DC wingding currents, brush and brushless motor)

INTRODUCTION

During the last decade or two, servomotors have evolved from largely brush types to brushless. This is due to lower maintenance and higher reliability of brushless motors. As brushless motors have become more prevalent during this period, the circuit and system techniques used to drive them have evolved as well. The variety of control schemes has led to a similar variety of buzzwords that describe them.

Torque is proportional to the DC current of the two terminals of the motor, irrespective of speed. Torque control can therefore be implemented by a P-I feedback loop which adjusts the voltage applied to the motor in order to minimize the error between requested and measured motor currents (Figure 1).

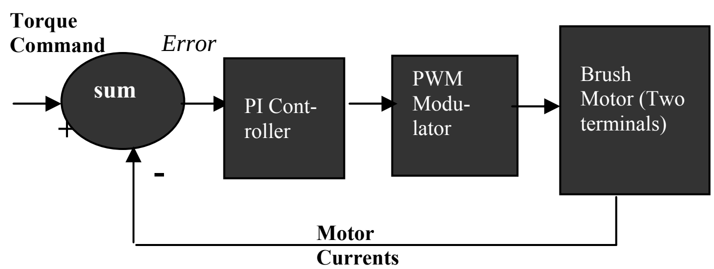


Figure 1: Torque Control.

Field Orientation Control (FOC), or vector control (Vas, 1990)[8], of an induction machine achieves decoupled torque and flux dynamics leading to independent control of the torque and flux for a separately excited DC motor. FOC methods are attractive but suffer from one major disadvantage: they are sensitive to motor parameter variations such as the rotor time constant and an incorrect flux measurement or estimation at low speeds (Trzynadlowski, 1994)

[7]. However, FOC is still more preferable to sinusoidal and trapezoidal commutation. Sinusoidal commutation produces smooth motion at slow speeds, but is inefficient at high speeds.

Trapezoidal commutation can be relatively efficient at high speeds, but causes torque ripple at slow speeds. Field Oriented Control provides the best of both commutation. Consequently, performance deteriorates and a conventional controller such as a PID is unable to maintain satisfactory performance under these conditions. Fuzzy Logic Control offers a satisfactory solution to this problem.

BRUSHLESS MOTOR BASICS

A brushless DC motor is an AC synchronous electric motor. In a conventional (brushed) DC motor, the brushes make mechanical contact with a set of electrical contacts on the rotor (called the commutator), forming an electrical circuit between the DC electrical source and the armature coil-windings. As the armature rotates on axis, the stationary brushes come into contact with different sections of the rotating commutator. The commutator and brush system form a set of electrical switches, each firing in sequence, such that electrical-power always flows through the armature coil closest to the stationary comutatator (permanent magnet).

In brushless DC motors, the electromagnets do not move, instead, the permanent magnets rotate and the armature remains static. In order to transfer current to a moving armature, the brush-system/commutator assembly is replaced by an intelligent electronic controller. The controller performs the same power distribution found in a brushed motor, but using a solid-state circuit rather than a commutator/brush system.

Brushless motor drive functions to minimize the direct component of the stator field and maximize the quadrature component.

For the purposes of control system modeling and analysis, it is the convention to work in terms of winding currents rather than stator magnetic field. This is because motor currents are easily measured externally while fields (actually flux) are not. In a brushless motor, the stator field is produced by current flow in three equally spaced stator windings. Because these windings are mechanically located 120 degrees apart, they each produce a field vector component that is oriented 120 degrees from the other two. These three components sum to produce the net magnetic field of the stator. In order to model the fields produced by the stator windings in terms of winding current, 'current space vectors' are used. The current space vector for a given winding has the direction of the field produced by that winding and a magnitude proportional to the current through the winding. This allows us to represent the total stator field as a current space vector that is the vector sum of three current space vector components, one for each of the stator windings.

An intuitive way to view the stator current space vector is as a fictitious current that would flow in a single fictitious winding that rotates so as to produce the same stator field direction and magnitude as the combination of three real currents through real stator windings.

The stator current space vector can be broken into orthogonal components in parallel with, and perpendicular to, the axis of the rotor magnet. The quadrature current component produces a field at right angles to the rotor magnet and therefore results in torque, while the direct current component produces a field that is aligned with the rotor magnet and therefore produces no torque. A good control algorithm will minimize the direct component of stator current since it only serves to produce waste heat and aggravate bearing wear.

Winding currents will be adjusted so as to produce a current space vector that lies exclusively in the quadrature direction. Torque will then be proportional to the magnitude of the current space vector. In order to efficiently produce constant smooth torque, the stator current space vector should ideally be constant in magnitude and should turn with the rotor so as to always be in the quadrature direction, irrespective of rotor angle and speed. While the stator current space vector may be constant in magnitude and direction. If viewed from the rotating frame of reference of the rotor, from the fixed frame of the stator, the current space vector describes a circle as the motor turns. Because the current space vector is produced by the vector sum of components from each of the motor windings, and because the three windings are physically oriented on axes that are 120 degrees apart from each other, the motor currents should ideally be three sinusoids, each phase shifted 120 degrees from the other two.

The sinusoidal winding currents should also be phased with respect to rotor angle so that the direct component of the stator current space vector is minimized (zero) and the quadrature component is maximized. This is the ideal case, and is achieved with varying degrees of success by different brushless motor control schemes.

FIELD ORIENTED CONTROL (FOC)

The fundamental weakness of sinusoidal commutation is that it attempts to control motor currents that are time variant in nature. This breaks down as speeds and frequencies go up due to the limited bandwidth of P-I controllers. Field Oriented Control solves this problem by controlling the current space vector directly in the d-q reference frame of the rotor. In the ideal case, the current space vector is fixed in magnitude and direction (quadrature) with respect to the rotor, irrespective of rotation. Because the current space vector in the d-q reference frame is static, the P-I controllers operate on DC, rather than sinusoidal signals. This isolates the controllers from the time variant winding currents and voltages, and therefore eliminates the limitation of controller frequency response and phase shift on motor torque and speed. Using Field Oriented Control, the quality of current control is largely unaffected by speed of rotation of the motor (Copley Control Corp., 2005).

In Field Oriented Control, motor currents and voltages are manipulated in the d-q reference frame of the rotor. This means that measured motor currents must be mathematically transformed from the three-phase static reference frame of the stator windings to the two-axis rotating d-q reference frame, prior to processing by the PI controllers (Figure 2).

Similarly, the voltages to be applied to the motor are mathematically transformed from the d-q frame of the rotor to the three-phase reference frame of the stator before they can be used for PWM output. It is these transformations, which generally require the fast mathematical capability of a Digital Signal Processing (DSP) or high performance processor, which are the heart of Field Oriented Control.

Although the reference frame transformations can be performed in a single step, they are best described as a two-step process.

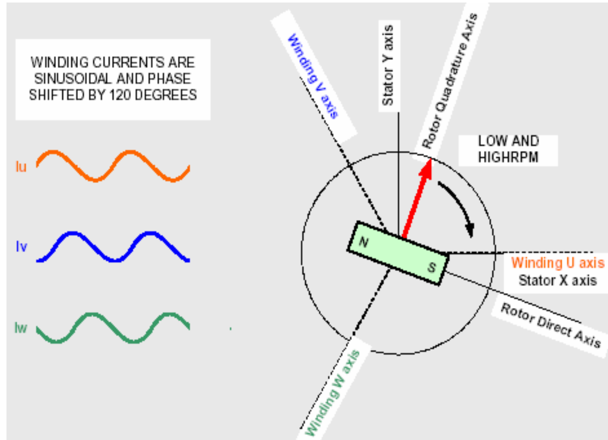


Figure 2: Field Oriented Control Results in a Current Space Vector which Rotates Smoothly with Rotor Position – Current Space Vector is in the Quadrature Direction And Torque [7].

The motor currents are first transformed from the 120-degree physical frame of the motor stator windings to a fixed orthogonal reference frame. They are then transformed from the fixed frame of the stator to the rotating frame of the rotor. This must be done at the update rate of the P-I controllers in order to insure valid results.

This process is reversed to transform voltage signals from the P-I controllers from the d-q frame of reference to the terminals of the stator windings. Once the motor currents are transformed to the d-q reference frame, control becomes rather straightforward. Two P-I controllers are used; one for the direct current component, and one for quadrature current.

The input to the controller for the direct current has zero input. This drives the direct current component to zero and therefore forces the current space vector to be exclusively in the quadrature direction. Since only the quadrature current produces useful torque, this maximizes the torque efficiency of the system. The second P-I controller operates on quadrature current and takes the requested torque as input. This causes the quadrature current to track the requested torque, as desired (Figure 3).

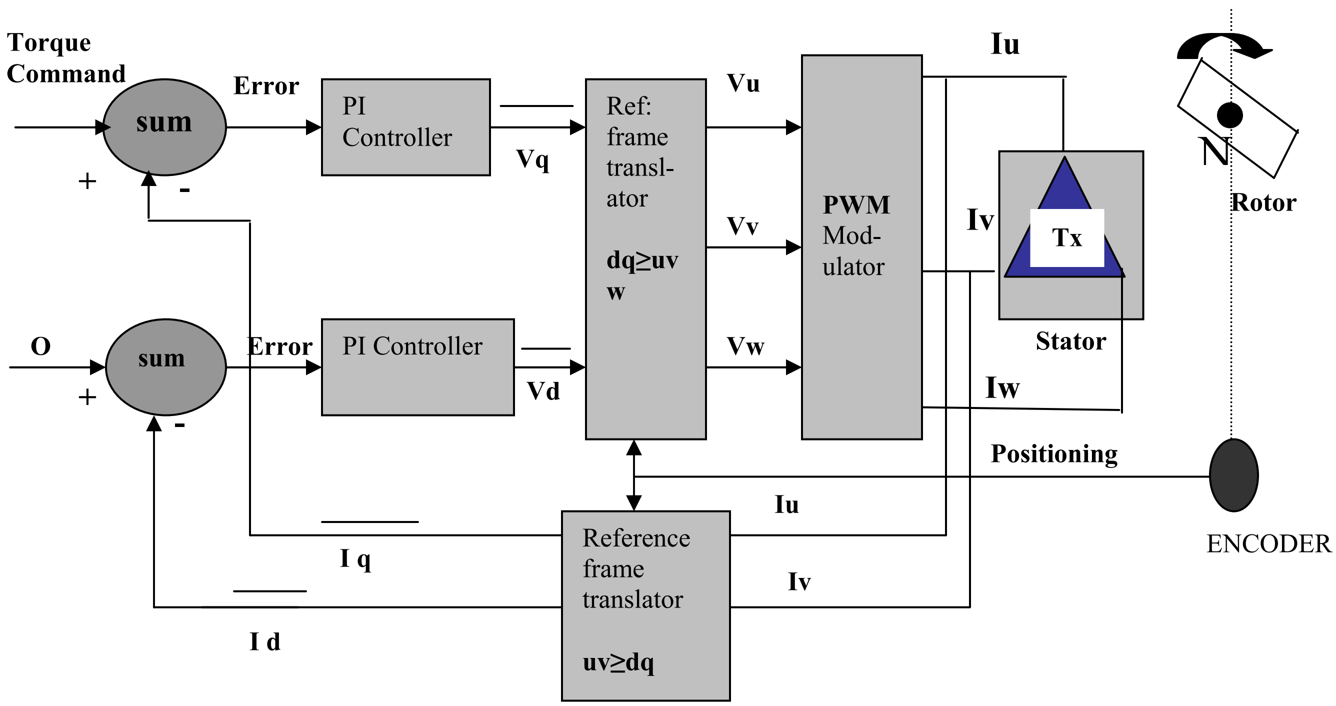


Figure 3: Field Oriented Controller (FOC) for Brushless Motors [7].

"PI controllers operate in the d-q reference frame of the rotor, they are isolated from the sinusoidal variation of motor currents and voltages and therefore perform equally well at low and high speeds".

The outputs from the two P-I controllers represent a voltage space vector with respect to the rotor. Mirroring the transformation performed on motor currents, these static signals are processed by a series of reference frame transformations to produce voltage control signals for the output bridge. They are first transformed from the rotating d-q frame of the rotor to the fixed x-y frame of the stator. The voltage signals are then converted from an orthogonal frame to the 120 degree physical frame of the U, V and W motor windings. This results in three voltage signals appropriate for control of the PWM output modulator.

OPTIMIZATION OF DC MOTOR WINDING CURRENTS

The electrical windings of permanent magnet synchronous motors are spaced on the stator at regular angles. When excited with current, the windings produce magnetic fluxes that add vectorially to produce the stator flux. The controlling variables are the proportions of currents in the motor windings. This torque is maximum when the rotor flux is 90^0 behind the stator flux in the direction of motion. At this point the flux vectors are said to be field-oriented for maximum torque at a given current. This is also the most efficient operating region of the motor, because in this mode the power input to the mechanical side of the motor is maximized. For continuous rotation at the highest torque and efficiency, the stator flux is rotated in the desired direction of motion, keeping 90 ahead of the rotor flux. Controlling the current in the stator windings produces the stator flux [4].

The motor's winding currents are generally shaped like a sinusoid. Knowing this, we can formulate common-sense fuzzy membership functions for use in a predictor-corrector type of estimator. These initial membership functions are constructed on the basis of experience, and trial and error. The fuzzy system is a recursive nonlinear estimator. Its inputs are comprised of past estimates, and present and past measurements. From this starting point we gather experimental data from a motor and fine-tune the fuzzy membership functions using gradient-descent[2]. The fuzzy estimator is applied to actual motor winding currents. The results presented in this paper establish fuzzy estimation as a viable alternative for stator winding current estimation.

An appropriate initial knowledge base is critical, because without an initial knowledge we cannot proceed any further with any optimization schemes. In spite of its importance (according to Dan Simon), the generation of initial knowledge remains as a difficult and ill-defined task in the construction of fuzzy logic systems. In general, we denote the centroid and half-width of the i-th fuzzy membership function of the j-th input by c_{ij} and b_{ij}. So the degree of membership of a crisp input x in the i-th category of the j-th input is given by [9]:

$$f_{ij}(x) = \{1 - |x - c_{ij}| / b_{ij} \quad |x - c_{ij}| \le b_{ij}/2 \qquad \textbf{(1)}$$

Otherwise:

The fuzzy output is mapped into a crisp numerical value using centroid defuzzification.

$$g(zk, \hat{x}_k) = \frac{\sum_{i=1}^{n} m(y_j) y_j J_j}{\sum_{j=1}^{n} m(y_j) J_j} \qquad \textbf{(2)}$$

where y_j and J_j are the centroid and area of the j-th output fuzzy membership function and n is the umber of fuzzy output sets. (Note that in the case of symmetric triangular membership functions, J_j equal to the half-width of the j-th output fuzzy membership function.) The fuzzy output function $m(_y)$ is computed as:

$m(y)$ = fuzzy output function = $\Sigma\, m_{ik}(y)$ **(3)**

m_{ik} (y) = fuzzy output function when (input 1 Є class i) and (input 2 Є class k)

If the fuzzy membership functions are triangular, gradient descent can be used to optimize the centroids and the widths of the input membership functions, and the centroids of the output membership functions. Consider an error function given by:

$$E = \frac{1}{2N} \sum_{q=1}^{N} E_q^2 \qquad \textbf{(4)}$$

$$E_q \equiv \hat{x}_q - x_q \qquad \textbf{(5)}$$

Where N is the number of training samples. We can optimize E by using the partial derivatives of E with respect to: (a) the centroids of the input fuzzy membership functions; (b) the half-widths of the input fuzzy membership functions; and (c) the centroids of the output fuzzy membership functions.

(i) Input Centroids

Using the relationships of equation (1) and following, we obtain [9]:

$$\frac{\partial E}{\partial c_{ij}} = \frac{1}{N} \sum_{q=1}^{N} E_q \frac{\partial \hat{x}_q}{\partial c_{ij}} \qquad \textbf{(6)}$$

$$\frac{\partial \hat{x}_q}{\partial c_{ij}} = \sum_{p=1}^{n} \frac{\partial \hat{x}_q}{\partial m_p} \frac{\partial m_p}{\partial c_{ij}} [m_p \equiv m(y_p)] \qquad \textbf{(7)}$$

$$\frac{\partial \hat{x}_q}{\partial m_j} = \frac{J_j (y_j - \hat{x}_q)}{\sum_{i=1}^{n} m_i J_i} \qquad \textbf{(8)}$$

$$\frac{\partial m_p}{\partial c_{ij}} = \sum_{k,1} rklp \frac{\partial w_{kl}}{\partial c_{ij}} \qquad \textbf{(9)}$$

where rklp = 1 if [(input 1) Є class k and (input 2) Є class l] ⇒ (output Є class p), and 0 otherwise,

$\partial w_{kl} / \partial c_{ij}$ is given as follows:

$$\frac{\partial w_{kl}}{\partial c_{ij}} = \begin{cases} \partial f_{k1} / \partial c_{ij} : f_k i(input1) \le f_{l2}(input2) \\ \partial f_{l2} / \partial c_{ij} \quad \text{otherwise} \end{cases}$$

(10)

The partials of the membership grades f (.) with respect to the input centroids are [9]:

$$\frac{\partial f_{k1}(.)}{\partial c_{i2}} = \frac{\partial f_{l2}(.)}{\partial c_{i1}} = 0 \quad \textbf{(11)}$$

$$\frac{\partial f_{k1}(.)}{\partial c_{i1}} = 2\delta_{ik} \sin g\left[(.) - c_{i1}\right]/ b_{i1} \quad \textbf{(12)}$$

$$\frac{\partial f l2(.)}{\partial ci2} = 2\delta_{il} \sin g\left[(.) - c_{i2}\right]/ b_{12} \quad \textbf{(13)}$$

Where δ_{ik} is the Kronecker delta function ($\delta_{ik} = 1$ for i = k, 0 otherwise).

ii. Input Half-Widths
Again using (1) and following, it can be shown that [9]

$$\frac{\partial E}{\partial b_{ij}} = \frac{1}{N}\sum_{q=1}^{N} Eq \frac{\partial \hat{x}_q}{\partial bi_j} \quad \textbf{(14)}$$

$$\frac{\partial \hat{x}_q}{\partial bi_j} = \sum_{p=1}^{n} \frac{\partial \hat{x}_q}{\partial m_p}\frac{\partial m_p}{\partial bi_j}\left[m_p \equiv m(y_p)\right] \quad \textbf{(15)}$$

$$\frac{\partial \hat{x}_q}{\partial m_j} = \frac{J_j(y_j - \hat{x}_q)}{\sum_{i=1}^{n} m_i J_i} \quad \textbf{(16)}$$

$$\frac{\partial m_p}{\partial b_{ij}} = \sum_{k,1} r_{klp} \frac{\partial w_{kl}}{\partial b_{ij}} \quad \textbf{(17)}$$

where r_{klp} is given following (21) and $\partial w_{kl} / \partial b_{ij}$ is given by:

$$\frac{\partial w_{kl}}{\partial b_{ij}} = \begin{cases} \partial f_{k1} / \partial b_{ij} & f_{k1}(input1) \le f_{l2}(input2) \\ \partial f_{l2} / \partial b_{ij} & otherwise \end{cases} \quad \textbf{(18)}$$

The partials of the membership grades with respect to the half-widths of the input fuzzy membership functions are given as:

$$\frac{\partial f_{k1}(.)}{\partial b_{i2}} = \frac{\partial f_{l2}(.)}{\partial b_{i1}} = 0 \quad \textbf{(19)}$$

$$\frac{\partial f_{k1}(.)}{\partial b_{i1}} = \delta_{ik}\left[1 - (.)\right]/ b_{i1} \quad \textbf{(20)}$$

$$\frac{\partial f_{l2}(.)}{\partial b_{i2}} = \delta_{il}\left[1 - (.)\right]/ b_{i2} \quad \textbf{(21)}$$

(iii) Output Centroids
The partials of the objective function E with respect to the centroids of the output fuzzy membership functions are given as [9]:

$$\frac{\partial E}{\partial y_j} = \frac{1}{N}\sum_{q=1}^{N} Eq \frac{\partial \hat{x}_q}{\partial y_j} \quad \textbf{(22)}$$

$$\frac{\partial \hat{x}_q}{\partial y_j} = \frac{m_j J_j}{\sum_{i=1}^{n} m_i J_i} \quad \textbf{(23)}$$

The gradient descent rule is then used to update the independent variables from one iteration to the next as follows:

$$c_{ij}(k+1) = c_{ij}(k) - \eta_c \frac{\partial E(k)}{\partial ci_j} \quad \textbf{(24)}$$

$$b_{ij}(k+1) = b_{ij} - \eta_b \frac{\partial E(k)}{\partial b_{ij}} \quad \textbf{(25)}$$

$$y_j(k+1) = y_j(k) - \eta_y \frac{\partial E(k)}{\partial y_j} \quad \textbf{(26)}$$

Where η_c, η_b and η_y are gradient descent step sizes.

RESULTS

Figure 4 shows the measured maximum torque and power versus speed. The maximum torque is 210 Nm. For speeds up to 6000 rpm, operation at a constant power of 25 kW was achieved readily.

Figure 5 shows the torque as a function of stator phase current at different speeds.

Below the base speed, the torque is proportional to the current for high currents because of saturation of the magnetic circuit, whilst for low currents the torque is approximately proportional to the current squared. Above the base speed, the torque per ampere decreases due to the phase advancing control.

Figure 6 shows the phase current waveforms for a high torque output at low speed and a low torque at high speed. The efficiencies at different speeds are shown in Figure 7. The efficiency for a 25 kW output at 2400 rpm was 89.0%, which was 3% lower than the predicted 92.3 %.

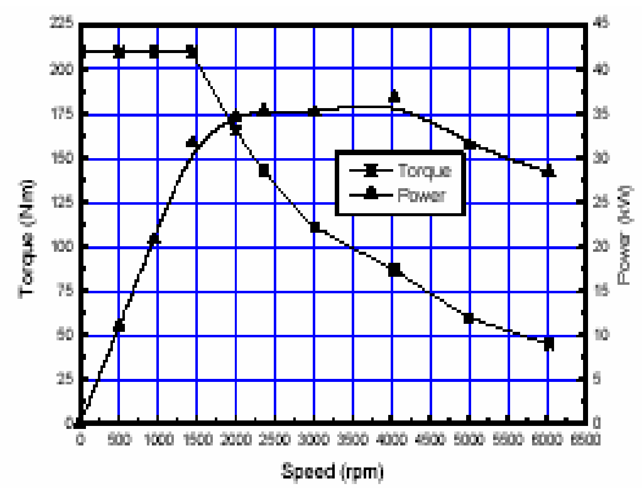
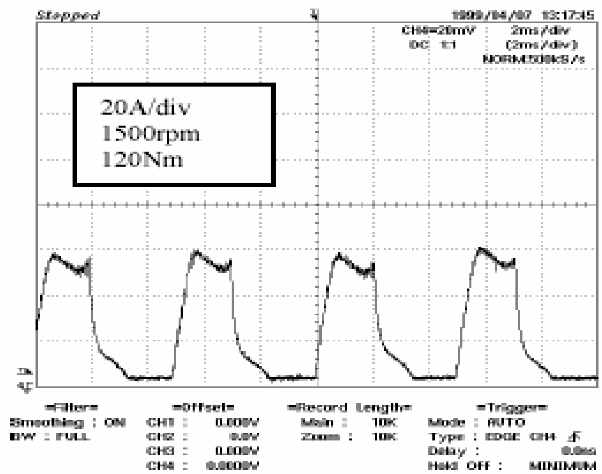


Figure 4: Measured Maximum Torque and Power Versus Speed.



(a) At low speed.

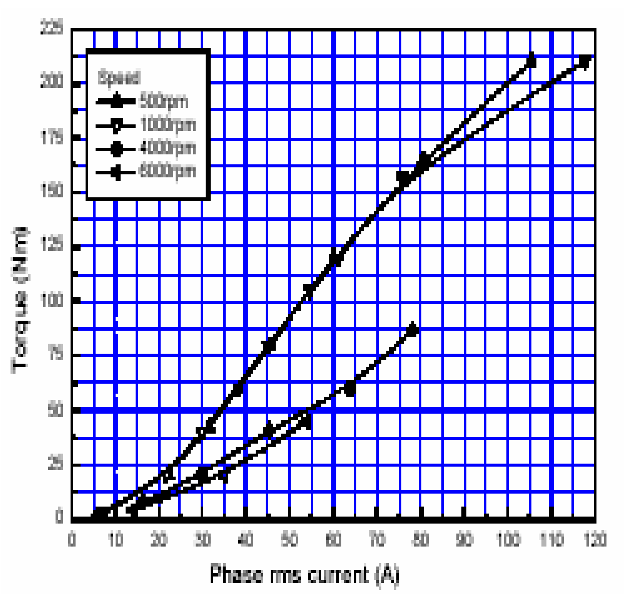
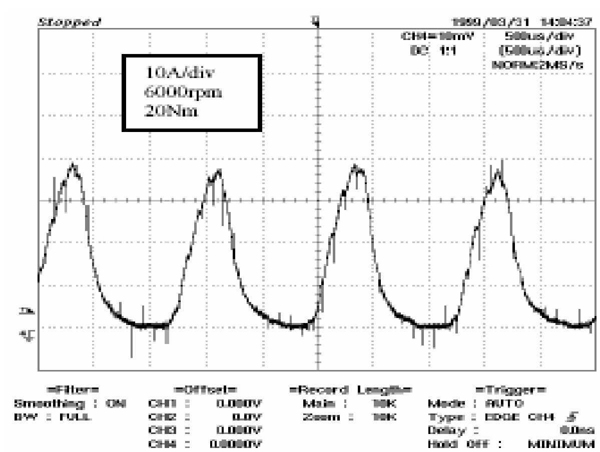


Figure 5: Torques Against Stator Phase Current at Different Speeds.



(b) At high speed

Figure 6: Phase Current Waveforms.

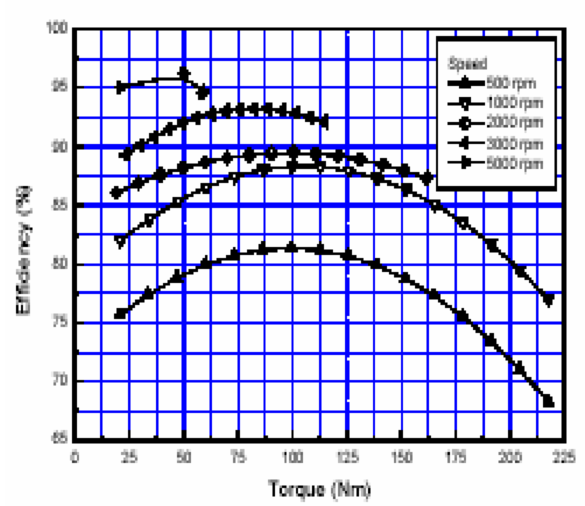


Figure 7: Efficiency at Different Speeds.

The gradient descent method was also used to optimize the fuzzy membership functions. The training data consisted of real motor winding currents collected with a digital oscilloscope at a rate of one sample every 200μs which were run through a simple symmetric non-causal moving average filter consisting of a total of 51 points. The gradient descent learning parameters η_c , η_b and η_y were all initialized to 1. Figure 8 shows 2500 samples of raw current. Figure 9 shows the same current after being passed through a fuzzy filter that was optimized via gradient descent. The improved smoothness of the filtered current is evident from a comparison of the figures. This results in an improvement of the current control scheme for the DC motor.

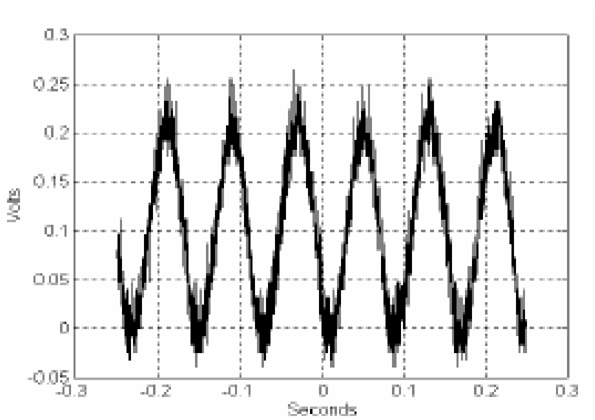


Figure 8: Unfiltered Currents.

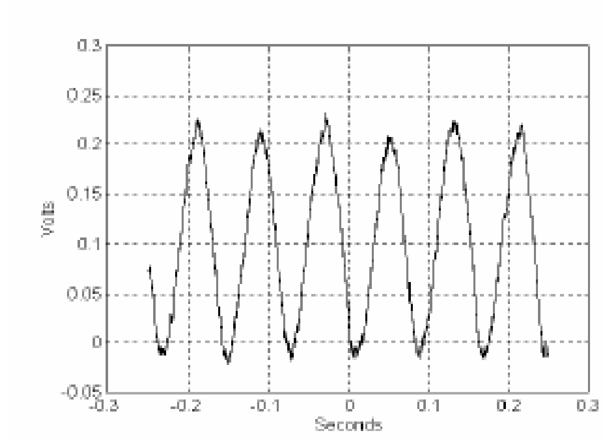


Figure 9: Filtered Currents.

CONCLUSION

Results shown that the goal of optimizing the DC winding currents in brushless motors of food frying industrial machines was achieved, the fuzzy logic optimization routine validated, and the partial ripple cancellation was experienced. The knowledge borrowed from P-I controller was used to further optimize the controller.

A fuzzy estimator was applied to the estimation of DC motor winding currents. This approach offers the benefits of fuzzy logic while providing performance on par with analytic methods. The fuzzy estimator also offers the possibility of training if a nominal current history is known a *priori*. The system proved the flexibility of implementing a real time fuzzy logic servomotor control.

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APPENDIX

Iq, Id frame	Vector current in q and d reference of the rotor.
Vq, Vd frame	Vector voltage in q and d reference of the rotor.
Iu, Iv, Iw	Winding currents in u, v, w-axis respectively.
Vu, Vv, Vw	Winding voltages in u, v, w-axis respectively.
U,v,w	are motor windings in u-, v-, w- axis respectively
q	Torque

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SUGGESTED CITATION

Osofisan, P.B. and M.O. Falodun. 2007. "Fuzzy Logic Control of Food Frying Process: A Conception of Frying Process Control". *Pacific Journal of Science and Technology*. 8(2):313-321.