An Adaptive Fuzzy Current Controller with Neural Network For Field-Oriented Controller Induction Machine

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Abstract

Recently, the development of novel control methodology enables us to improve the performance of AC-machine drives by using pulse width modulation (PWM) technique. Usually, the dynamic characteristic of induction motor (IM) has been represented by the 5-th order nonlinear differential equation. This dynamics, however, can be reduced to 3-rd order dynamics by applying direct control of IM input current. This methodology concludes that it is much easier to control IM by means of the field-oriented methods employing the current controller. Therefore a precise current control is crucial to achieve a high control performance both in dynamic and steady state operations.

This paper presents an adaptive fuzzy current controller with artificial neural network (ANN) for field-oriented controlled IM. This new control structure is able to adaptively minimize a current ripple while maintaining constant switching frequency. Especially the proposed controller employs neuro-computing philosophy as well as adaptive learning pattern recognizing principles with respect to variations of the system parameters. The proposed approach is applied to the IM drive system, and its performance is tested through various simulations. Simulation results show that the proposed system, compared among several known classical methods, has a superb performance.

1. INTRODUCTION

The field-oriented control approach to the application of IM drive system has achieved high control performance, which could be available through only DC motor drive system. The dynamic characteristic of IM has been represented by the 5-th order nonlinear differential equation. This dynamics, however, can be reduced to 3-rd order dynamics by applying direct control of IM input current.[1] Therefore, a precise current control is crucial for the high control performance.

Recently, fuzzy theory and artificial neural network technology has been applied to the motor current control system.[2] For instance, application of ANN to IM current control system is proposed by Song, J. W., et. al.[3] where neural network generates optimal switching pattern and control PWM signals directly while being continuously trained to update a certain knowledge represented by the specific characteristic features of IM drive system. This system, however, should employs the off-line learning method with respect to the specific pattern of IM drive system at initial control stage. This is because ANN could not sufficiently learn the characteristics of IM at initial stage, by which the control system can neither control nor learn simultaneously. This prompts us to develop fuzzy current controller[4] which is able to achieve control objective from initial stage. Fuzzy current controller has the following advantages: 1) it does not require modeling and analysis of IM, 2) it is applicable to the nonlinear system, and 3) it can exploit expert's knowledge. Even though it has several advantages over conventional controllers, there still remains unresolved problem of the general methodology for choosing optimal scaling factor and designing proper membership function.

As a conventional control approach, the hysteresis current controlled voltage source inverter (CC-VSI) was proposed by Plunkett [5]. This approach has been rapidly spread out in AC motor drive systems because it can reduce the order of system dynamics as mentioned above. From CC-VSI, many control schemes have also been developed [6]. The control goal of CC-VSI is first to achieve the high control performance, secondly to reduce losses due to the harmonic from load side by minimizing the current ripple, thirdly to reduce the switching losses of power component device. Hysteresis current controllers use some type of hysteresis in the comparison of the line currents to the current references. A current controller with hysteresis band [7] has a simple control structure and has the capability to limit peak current in which, however, the switching frequency to enforce current within the hysteresis band can not be maintained constant; it is varied in accordance with load and speed variation. This incurs excessive harmonics. In order to achieve a constant switching frequency, the ramp comparison controller [8] has been proposed. The ramp comparison controller compares the current errors to a triangle waveform to generate the inverter firing signals. This method, however, generates a possible phase delay which deteriorates the system performance. In addition, if the motor time constant is smaller than slope of the ramp wave, multiple modulation would be generated in the one period of reference ramp signal. Predictive controllers calculate the inverter voltages required to force the currents to follow the current reference. Two types of predictive current controllers on the basis of space vector have been developed: one put emphasis on the constant switching frequency [9], and the other on the minimum switching frequency [10]. Both types of predictive current controllers require an excessive computation time to obtain the next switching state.

This paper extends the previous fuzzy current controller[4] to a novel adaptive fuzzy current controller by combining ANN technology principle.[11] The proposed approach in this paper is able to not only improve the control performance but also resolve the problems remained in the current controller for field oriented IM drive system. Moreover, the proposed current controller is able to reduce the current ripple adaptively while maintaining a constant switching frequency even under the parameter variation and abrupt load changes.

2. PROPOSED CURRENT CONTROLLER

In general, the requirements for the high performance current control system are : 1) fast tracking performance, 2) minimum current ripple, 3) robustness to parameter variation, and 4) zero steady-state error in both reference tracking and load regulation. This paper employs fuzzy control approach in order to achieve a robust control structure to the parameter variation. This is because the fuzzy current controller does not require the exact dynamics of IM to be controlled. Hence, the performance of the fuzzy controller might be more insensitive to the parameter variation than conventional controllers based on exact mathematical model.[12] There is, however, no concrete design methodology for fuzzy rule based control algorithm. In many cases, there is difficulty in tuning parameters used in fuzzy controller (i.e., scale factor, shape of membership function, etc.). Moreover, when the variation of motor parameters occurs, the current error is no longer minimized. Therefore it is required for additional adaptation mechanism.

The proposed current controller consists of an adaptive fuzzy current controller using ANN estimation unit of which structure diagram is shown in Fig. 1. The fuzzy current controller has two input components : errors modified by ANN estimation outputs, and the change of errors of three phase at each sampling time. In order to minimize output current ripple, the fuzzy controller generates

PWM pattern signals which will be fed to inverter drive. The ANN estimation unit learns the characteristic of IM based on current error and train of past error, and it predicts next error which modify input of the fuzzy current controller. The proposed controller determines the PWM signals which can adaptively minimize the output current ripple, under unexpected variation of IM parameters and/or controller parameters. The proposed current control architecture improves performance of the previous fuzzy controller.

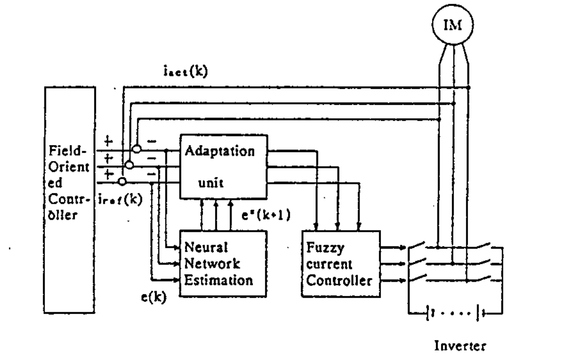


Figure 1. Block diagram of proposed current controller

3. THE FUZZY CURRENT CONTROLLER

This section details the development of the fuzzy current controller for field oriented IM drive system. For convenience of incorporating the intuition and experience of human expert into fuzzy control algorithms, the behavior of the dynamic current response is first investigated. The current error between the reference and actual values of current controller corresponding to one phase e(k), and its error change $\Delta e(k)$ of IM drive system are defined as follows:

$$e(k) = i_{ref}(k) - i_{act}(k) \quad (1)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (2)$$

where $i_{ref}(k)$ represents the reference current of one phase, $i_{act}(k)$ represents the actual current of one phase in k-th sampling interval. The general current response in one arm is shown in Fig. 2. where one represents the current response which has multiple switching states affected by switching states in other arms and the other represents a switching state in one arm.

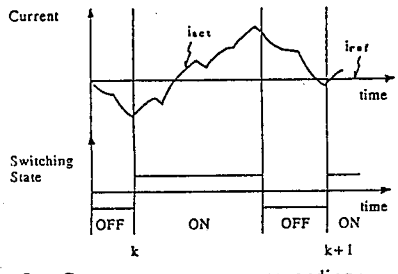


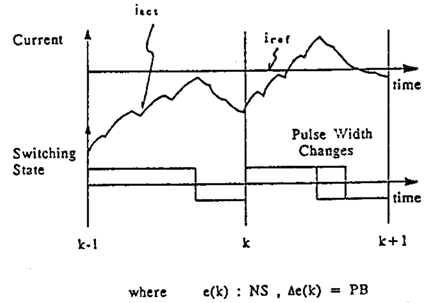
Figure 2. Current response corresponding to switching state

In accordance with the magnitude and sign of $\Delta e(k)$, actual current is classified into seven cases. For each case, error e(k) is also classified as the same way. The linguistic variables used for identifying the each case are defined as follows:

case I : Δe = PB
case II : Δe = PM
case III : Δe = PS
case IV : Δe = ZE
case V : Δe = NS
case VI : Δe = NM
case VII : Δe = NB

where N, P, B, M, S and ZE represent negative, positive, big, small, medium, and zero.

In the case I, the magnitude of e(k) is much greater than that of e(k-1). For each case of e(k), the output of fuzzy current controller (the change of the inverter on-time width) should be determined based on expert's intuition and experience in such a way e(k+1) will become zero. For instance, if e(k) is NS and $\Delta e(k)$ is PB, then the change of on-time width should be NM. NM means that (k+1)th on-time width decreases to some extent compared with k-th width. This case is illustrated in Fig. 3. By applying the same procedure to each case, control output is determined appropriately. The linguistic control rules obtained by above procedure are listed in Table 1.



where e(k) : NS , $\Delta e(k)$ = PB

Figure 3. Determination of fuzzy control rules

After determination of fuzzy control rules, the next step is to define the membership functions corresponding to each element in the linguistic set. Even though many types of membership functions have been already developed, for simplicity, triangular membership function are used in this paper. The universe of discourse of the error and error change ranges from -3[A] to +3[A] respectively. The membership functions are shown in Fig. 4. Finally for synthesis of the final control action, the center of gravity is used.

The error and error change should be appropriately mapped onto the predefined universe of discourse. The performance of fuzzy control system depends on this scaling mapping. Usually, the procedure for determining the optimal value of these scale factors, however, does not have unique solution. Therefore, optimal performance can not be guaranteed with arbitrary scale factors. Moreover, parameter variation of IM may incur poor dynamic response with this fixed scale factors. In this paper, in order to overcome these drawbacks, the concept of ANN estimation methodology is developed with fuzzy control.

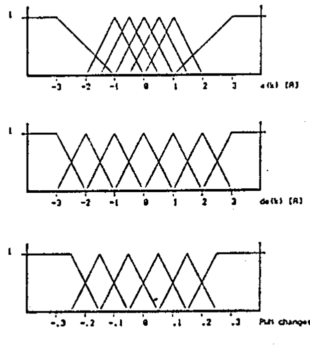


Figure 4. Membership functions

4. NEURAL NETWORK ESTIMATION UNIT

ANN has very useful properties. For instance, when the training set contains noisy or inconsistent examples, during the learning phase ANN extracts the characteristics of IM. After learning, ANN can generalize, giving correct responses even in the presence of patterns that are not included in the training set. Furthermore, when the input-output mapping can be obtained by applying some type of rule, the network tends to discover the rule instead of memorizing the input-output pattern pairs. In this paper, we focus our effort on the learning ability of ANN for the enhancement of control performance. Up to date there have been many kinds of learning methodologies of ANN for practical application and new methods are now still under elaboration. This paper employs a multilayer perceptron model (PDP-model) with error back propagation (EBP) which is one of the adaptive learning models, and also one of the most powerful tools in the area of ANN technologies until now. [13]

The EBP algorithm uses an objective function, which is defined as the summation of square errors between the desired outputs and the network outputs. It then employs a steepest-descent search algorithm to find the minimum of the objective function. The equations to change the weights of output-layer and hidden-layer, are as follows:

$$\Delta W_{pq,k}(n+1) = \eta \cdot \delta_{q,k} \cdot OUT_{p,j} + \alpha \cdot \Delta W_{pq,k}(n) \quad (3)$$

$$W_{pq,k}(n+1) = W_{pq,k}(n) + \Delta W_{pq,k}(n+1) \quad (4)$$

$$\delta_{q,k} = error_{q,k} \cdot f'(NET_{q,k}) \quad (5)$$

where,

α = momentum factor

η = learning rate

$W_{pq,k}(n)$ = interconnection weights between p'th neuron of output - layer and q'th neuron of hidden-layer (subscript k means by the target-layer)

$W_{pq,k}(n+1)$ = weight values at step (n+1)

$error_q$ = the difference between the desired or target value and the actual output at q'th neuron of output layer

$\delta_{q,k}$ = backpropagated error at q'th neuron of k'th-layer.

$OUT_{p,j}$ = output value of neuron p at j'th-layer.

$NET_{q,k}$ = NET(Summation) value of q'th neuron at k'th-layer.

$f'(NET_{q,k})$ = the differential value of activation function

Note that above subscripts, "p" and "q" correspond to specified neuron in each-layer. The symbol "j" and "k" represent each-layer. In the case of hidden-layer, error $\delta_{q,k}$ is obtained by equ. (6).

$$\delta_{p,j} = \left(\Sigma\ \delta_{q,k} \cdot W_{pq,k}\right) f'(NET_{p,j}) \quad (6)$$

at hidden layer

Fig. 5 shows the proposed architecture of ANN, where ANN consist of 15 neurons in input layer, 30 neurons in two hidden layer respectively, and 3 neurons in output layer. Table 2 shows parameters and their values of the developed ANN used for estimation unit.

In the learning phase, the inputs of the ANN for error estimation unit are composed of e(k-1), ... ,e(k-5) at each sampling time.[14] The outputs of ANN unit are the estimated present errors, $e^*(k)$, of each phase current. The ANN is learned or trained in such a way that outputs of ANN converge to actual errors. In this paper, the differences between the desired or target values and the actual outputs at first, second, and third neuron of output layer are as follows:

$$error1 = e_u(k) - e^*_u(k) \quad (7)$$

$$error2 = e_v(k) - e^*_v(k) \quad (8)$$

$$error3 = e_w(k) - e^*_w(k) \quad (9)$$

When the learning is accomplished with these training samples, the proposed ANN is changed in the recall phase and predicts the next step errors $e^*(k+1)$ of 3 phase with inputs consisting of e(k), ... , e(k-4). This predicted error is used to compensate the input of the fuzzy controller, which determine the PWM on time width.

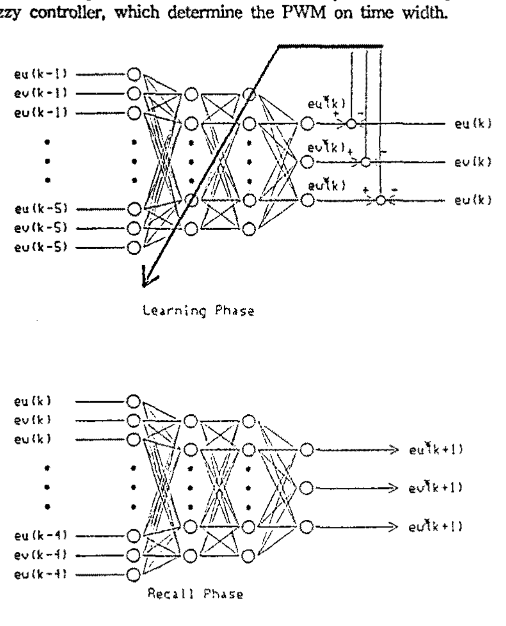


Figure 5. The architecture of ANN

5. SIMULATION RESULTS

In order to test the performance of the proposed control system and compare with other conventional control system, performance index is defined as follows :

$$I = \sqrt{\frac{\Sigma\ \left((i^*u(k)-iu(k))^2+(i^*v(k)-iv(k))^2+(i^*w(k)-iw(k))^2\right)}{N}} \quad (10)$$

where $i^*u(k)$, $i^*v(k)$, and $i^*w(k)$ represent the reference current of u, v, and w phase respectively, iu(k), iv(k), and iw(k) represent the actual current, and N represents the sampling number in one period.

For comparison, we used hysteresis band, ramp comparison current control system, which are applied to many commercial industrial drive systems. In addition, the fuzzy controller which has the membership function in Fig. 4 and proposed controller using completely learned neural network which has same membership function, are also compared. The specification of 3 phase 5Hp IM for the simulation is shown in Table 3. In this paper, average inverter frequency of each controller is 4KHz. In general hysteresis controller has better characteristics due to the shorter band. It, however, is to obtain proper switching operation with shorter band as claimed at [6]. This is because the inverter has some periods of high switching frequency. In this paper , the average switching frequency of the hysteresis controller is approximately 4 KHz by setting the hysteresis band to 1[A]. Fig. 6 shows the performance index I of each control system with respect to various motor speed ω_r[rad/s] at no load operation. As clearly shown in Fig. 6, the fuzzy controller has better performance compared with other control systems. Furthermore, the proposed system, the fuzzy controller with pre-learned for the one-step ahead error prediction, has the best performance among others. Even though the hysteresis control system has poor performance compared to other systems, its rms error value remains constant through all operating speed range. As opposed to the hysteresis control system, the rms error value of other control systems tend to increase as operating speed increases. The proposed control system, however, significantly reduce the current ripple through all operating speed range.

For detail analysis of control performance on time domain, the current response of each control system (under no load condition with speed reference, 100[rad/s]) is provided in Fig. 7, 8, 9, and 10. Fig. 7, Fig. 8, Fig. 9, and Fig. 10 show the responses of the inverter output current for hysteresis, ramp comparison, fuzzy, and proposed current controller respectively at no load condition. Fig. 7 shows the current response of hysteresis controller with hysteresis band 1[A]. As shown in this figure, quite a large current ripple can be observed. Fig. 8 shows the current response of ramp comparison controller where current ripple is significantly reduced compared with hysteresis controller. But this control system incurs time-delay which deteriorates overall control performance of Field-Oriented Controller for IM. The current response of fuzzy control system is shown in Fig. 9. Compared to hysteresis controller and ramp comparison controller, this control system a little bit reduces the current ripple as well as time-delay. The current ripple remains still large. The control performance of proposed control system is illustrated in Fig. 10. Compared with Fig. 7 ~ Fig. 9, the proposed system successfully suppresses current ripple and significantly improves control performance in term of performance index value.

Fig. 11 and Fig. 12 show the control performance of fuzzy and proposed control system under variation of rotor resistance. In this simulation, we used 200% variation of rated rotor resistance. From these figure, we can conclude that the control system implemented based on fuzzy theory are insensitive to the variation of rotor resistance of IM. Fig. 13 shows the current tracking performance of the proposed control system under abrupt load change. As clearly shown in the figure, the tracking error is invariant even under abrupt load variation.

From the above simulations, we show that fuzzy current controller with neural network has outstanding better performance through all operating speed range. Especially, under the parameter variation and abrupt load changes, the proposed control system has good adaptability.

6. CONCLUSION

In this paper, a novel adaptive fuzzy current controller using ANN is proposed. ANN learns the characteristics of IM and modifies the error applied to fuzzy current controller. The proposed control system is applied to the field-oriented controlled IM drive system. This paper aims at establishing a completely new control system which shows a superb performance compared with conventional IM drive systems even under parameter variations and abrupt load changes. Through the simulations, we verified that the proposed controller has a good adaptability due to ANN learning ability.

For further elaborations related to this research work, we will develop the better estimation methodology based on ANN and better adaptation mechanism in order to reduce effects of the system parameter variation on the control performance.

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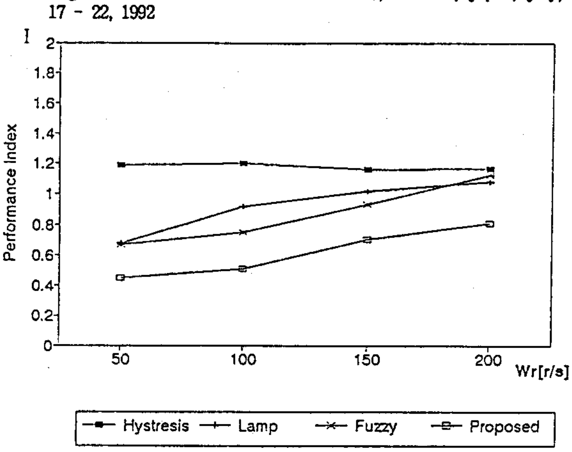

Figure 6. Performance of various controllers

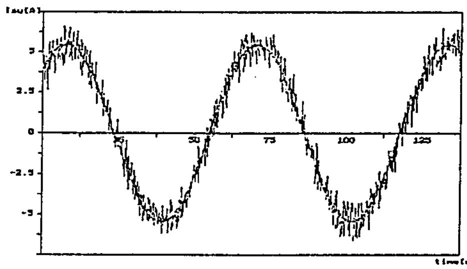

Figure 7. Current response of hysteresis controller

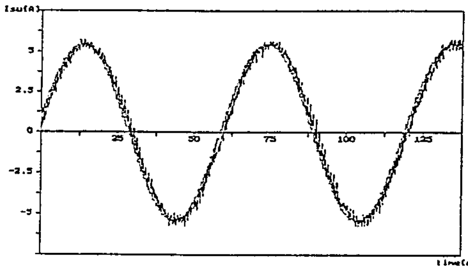

Figure 8. Current response of ramp comparison controller

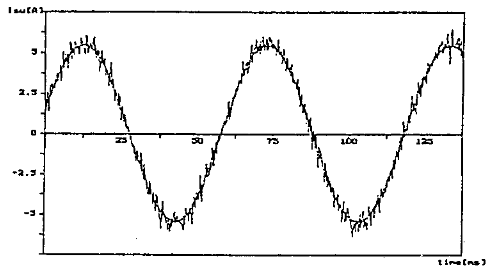

Figure 9. Current response of fuzzy controller

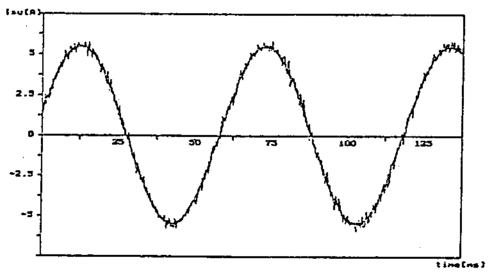

Figure 10. Current response of proposed controller

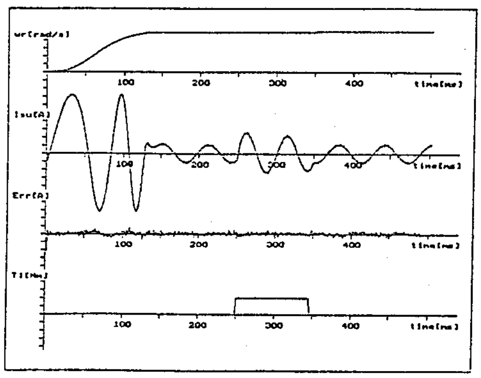

Figure 13. Current tracking performance under abrupt load changes