Fuzzy Logic Application for Intelligent Control of a Variable Speed Drive

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Abstract- The slip power recovery configuration is an attractive scheme of variable speed drive, with high efficiency and low converter rating; however, high performance control has being difficult. In this paper, novel applications of fuzzy logic for the intelligent control of a slip power recovery system are presented. A direct fuzzy logic controller and an adaptive fuzzy controller, based on model reference adaptive control, are developed and simulated for the doubly-excited machine and converter system. Compared with the field orientation control, the intelligent control of the complex slip power recovery system reduces costs and enhances robust and desired performance.

Key Words: Fuzzy Logic Control, Adaptive Fuzzy Control, Slip Power Recovery System, Variable Speed Drive

I. Introduction

Slip power recovery systems composed of a doubly-excited wound-rotor induction machine and power electronic converters in the rotor circuit might become very attractive for variable speed drives and generators [1,2], exhibiting potentials to compete with more common high performance systems with their machine stators excited by power converters. The advantages of slip power recovery systems (SPRS) include higher efficiency and lower converter rating.

Doubly-excited machines were known to be inherently unstable, and classical controllers had been designed to achieve closed-loop stability. Advanced control of the SPRS has received attention recently. However, most of the advanced control schemes, including field orientation control [2], decoupled control [3] and possible application of modern nonlinear control, have the disadvantages of requiring excessive numbers of sensors and observers. Also, their performance is usually subject to parameter variations and disturbances.

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Fuzzy reasoning [4,5,6,7,8], as a promising AI technique, has found many industrial applications [9]. Interest has been shown recently in the applications in the fields of electric drives and power electronics [10,11]. Fuzzy logic control of the SPRS would provide a simple way of controlling the complex doubly-excited machine and converter system. A step further, by adding some capacity of adaptation to the fuzzy logic controller, the performance of the system would be even less dependent on changing operating environment and machine parameters, and less dependent on the ad hoc designing of the fuzzy controller parameters.

In this paper, building upon a progressive summary of the working principles and issues of fuzzy logic and fuzzy control, novel applications in motion control are presented, which include a direct fuzzy logic controller for a slip power recovery system and a model reference adaptive fuzzy controller for the same system. Computer simulation results will be given, and the new intelligent control techniques will be compared with other advanced controls, including the field orientation control method.

II. Fuzzy Logic and Fuzzy Control

A. Philosophy and Development of Fuzzy Logic

Human reasoning is fuzzy, or approximate, and so is the real world. Fuzzy logic is the logic underlying modes of reasoning which are approximate rather than exact, thus it is closer to human reasoning and the real world than formal logic. Like expert systems, a fuzzy system displays human intelligence, hence fuzzy logic is generally categorized into AI fields. It has rapidly become one of the most successful AI technologies that find applications in industries.

The greatest achievements of this technology are in fuzzy logic control, for which the basic philosophy underlies in the following common recognition:

- Often it is hard to get a good model for the plant;
- While often experts qualitatively know how to control the plant.

Research and applications of fuzzy logic are developing very rapidly, with promising impacts on electric drives and power electronics in the future. *Fuzzy Hardware Systems* have been developed, including fuzzy rule boards, fuzzy interface devices, and optical fuzzy inference devices. *Fuzzy Logic Chips* are in the market now, including fuzzy inference chips and fuzzy filp-flops. *Fuzzy Computers* using fuzzy memory and inference engines are new developments. *Fuzzy Expert System* shells are also in the market. *Fuzzy Computing* uses fuzzy associative memories for approximate intelligent computing. *Fuzzy Neuron* joins fuzzy systems with neural networks for the purpose of learning, especially for pattern recognition.

Fuzzy logic theory is also developing. One of the topics of interest is to develop *Fuzzy Dynamical Systems Theory* using well developed systems theory. The main problems to overcome in applications are the difficulty of expert knowledge acquisition, and the difficulty or uncertainty in fuzzy modelling of the linguistic structure for a process.

B. *Fuzzy System and Fuzzy Logic*

Shown in Fig. 1 is a block diagram of a fuzzy system, which includes a fuzzification block, a knowledge-base, a fuzzy inference engine and a defuzzification block. The functions of the blocks and working principles of the fuzzy system are explained in this section, by briefly summarizing the basic concepts of fuzzy sets and fuzzy logic.

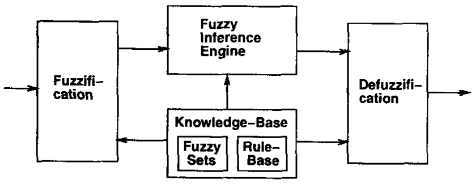

Fig. 1 Fuzzy System Structure

- *Universe of Discourse* $\mathcal{A}_i$
  The range of values or collection of elements over which we will reason. The subscript i denotes the object of interest.
- *Linguistic Variable* $\tilde{a}_i$
  A symbolic description of an element, which for example may stand for *speed.*
- *Linguistic Value* $\tilde{A}_i^j \in \tilde{A}_i$
  A symbolic description of a value that an element can take on, which for example may stand for *PS* or *positive small.* The superscript j denotes the particular linguistic value.
- *Fuzzy Set* $A_i^j = \{(a_i, \mu_{A_i^j}(a_i)) : a_i \in \mathcal{A}_i\} \in A_i$
  Representing a linguistic value, a fuzzy set A_i^j allows its members to have grades of membership, $\mu_{A_i^j}(a_i)$, in the interval [0,1].
- *Membership Function* $\mu_{A_i^j}(a_i)$
  The mapping that associates each member a_i with its grade of membership in the set A_i^j.
- *Fuzzy Inference*
  Mapping from input fuzzy sets to output fuzzy sets based on the fuzzy IF-THEN rules and the compositional rule of inference.
- *Knowledge Base*
  Contains information on fuzzy sets and a rule base with a set of linguistic conditional statements based on expert knowledge.
- *Fuzzification*
  Mapping of a crisp point a_i into a fuzzy set A_i^j.
- *Defuzzification*
  Mapping of fuzzy sets into a crisp point.

Therefore, in Fig. 1, the fuzzification process maps a crisp point of real meaning, such as measured data, into fuzzy sets, by the knowledge of the input membership functions. The fuzzy inference engine then uses the rules in the rule base to produce fuzzy sets at its output, corresponding to its input fuzzy sets. Finally the defuzzification process uses the knowledge of the output membership functions to map the output fuzzy sets into a crisp value that is usable. One of the many types of membership functions is shown in Fig. 2.

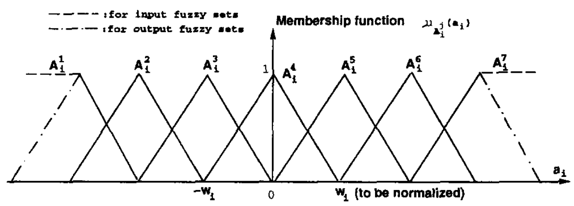

Fig. 2 Triangular Membership Functions

Based on this simple outline, further necessary concepts are summarized in the following.

- *Singleton Fuzzification*
  Interprets an input a_0 as a fuzzy set with the membership function $\mu_A(a)$ equal to zero except at the point a_0, where $\mu_A(a_0)$ equals one.
- *Fuzzy Set Operations*
  -Product $\mu_{A \star A'}(a) = \mu_A(a)\mu_{A'}(a), a \in \mathcal{A}$
  -Min $\mu_{A \star A'}(a) = min\{\mu_A(a), \mu_{A'}(a) : a \in \mathcal{A}\}$
  Alternative definitions and operations are possible.

- *Cartesian Product*
  It is a fuzzy set A with $\mu_A(a_1, a_2, ...) = \mu_{A_1^j \times A_2^k \times ...}(a_1, a_2, ...) = \mu_{A_1^j}(a_1) \star \mu_{A_2^k}(a_2) \star ...$
  "$\star$" can represent the minimum operator or the product operator. For the premises of a fuzzy rule, it is an inherent representation of "AND".

- *Fuzzy Implication*
  It is a fuzzy set S with $\mu_S(x, y) = \mu_{A \to B}(x, y) = \mu_A(x) \star \mu_B(y)$ where A, B are fuzzy sets on X, Y respectively. When "$\star$" represents the minimum operator, it implies that the conclusion is no more certain than the premise.

- *Sup-star Compositional Rule of Inference*
  Let R and S be fuzzy sets defined on X and $X \times Y$ respectively, then the sup-star composition is a fuzzy set denoted by $R \circ S$ with
  $\mu_{R \circ S}(y) = sup\{\mu_R(x) \star \mu_S(x, y) : x \in X\}$

- *Center of Gravity Defuzzification Method for Sup-Min*
  After the Sup-min inference generates, for each fired rule, the areas of possibility distribution for the output, the gravity center of the overall area is calculated to be the output crisp value. Other defuzzification methods include Max-criterion and Centroid [5].

- *Normalization*
  Keeping all the universes of discourse fixed, the fuzzy system can be tuned at its input and output with normalizing gains, making design easier and more flexible.

A practical illustration of the operation of a fuzzy system is then given in Fig. 3, for a multiple-input single-output fuzzy system with 2 inputs, e_1 and e_2, and 1 output, u. For each input or output, two fuzzy sets are shown, though usually there are more. e_1, e_2 and u are numerical variables associated with linguistic variables such as speed and torque, etc. ZE (zero), PS (positive small) and PL (positive large) are linguistic values of the linguistic variables. Given the values for e_1 and e_2 as shown, *Singleton* fuzzification process maps them to associated fuzzy sets with membership values: e_1 is mapped into the fuzzy set representing "ZE" with a membership value of 0.75, and mapped into the fuzzy set representing "PS" with a membership value of 0.25; e_2 is mapped into the fuzzy set representing "PS" with a membership value of 0.5. Then the following rules (assumed exist in the rule base) fire to find the output fuzzy sets that contains the output:

- If $\tilde{e}_1$ is ZE and $\tilde{e}_2$ is PS, then $\tilde{u}$ is PS;
- If $\tilde{e}_1$ is PS and $\tilde{e}_2$ is PS, then $\tilde{u}$ is PL.

By using the *Sup-Min* inference method for both the premises and the fuzzy implication, as illustrated, and by using *Center of Gravity* defuzzification method for the shaded area, the desired output value is then found.

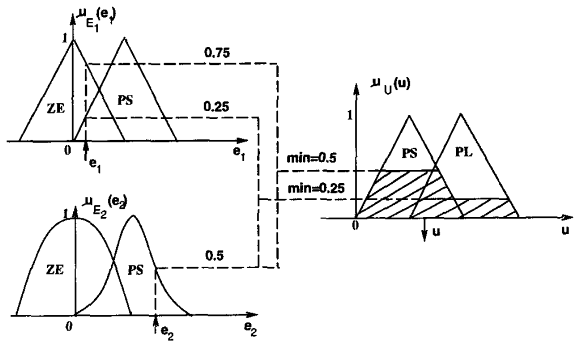

Fig. 3 A Practical Illustration

C. Fuzzy Logic Control

A typical fuzzy control system is shown in Fig. 4, with the fuzzy system replacing a usual compensator in the loop.

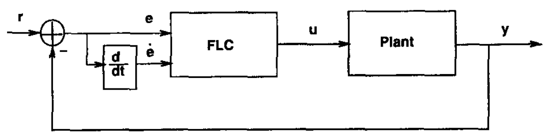

Fig. 4 Fuzzy Control System

The knowledge base of the fuzzy system stores the expert knowledge on how to control the plant, while the inference engine stores the information on how a human operator "in the loop" would use this knowledge to control the plant. Advantages of the fuzzy controller over conventional controllers include: it has nonlinear control actions; less dependence on mathematical models; could better reject noise, disturbances and parameter variations. The hard (and important) part of designing the fuzzy control system is the designing of the knowledge base, as illustrated in Fig. 5.

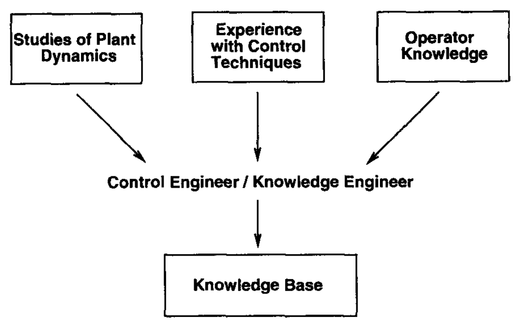

Fig. 5 Knowledge Base Construction

III. Direct Fuzzy Logic Control of SPRS

A. System Structure and Fuzzy Logic Controller

With a direct fuzzy logic controller (FLC), the slip power recovery variable speed drive system is shown in Fig. 6. A current regulated PWM (CRPWM) converter regulates rotor currents. The other converter connecting the dc link to the power line can also be a PWM converter for more flexibility and better waveforms [2].

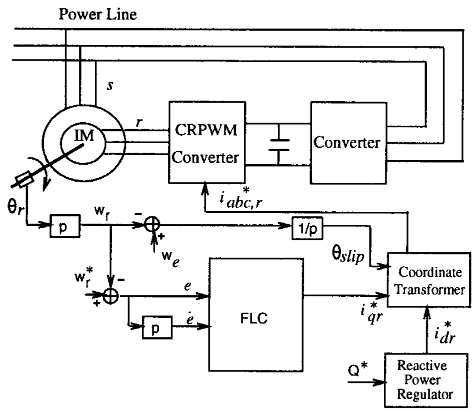

Fig.6 SPRS with Fuzzy Logic Controller

The FLC generates q-axis rotor current command to compensate for any speed error, while the reactive power regulator generates d-axis rotor current command. The dq dynamic reference frame of the machine rotates synchronously with respect to the stator flux, with its d-axis overlaps the instantaneous axis of the stator flux. In such a reference frame, we had shown that the stator active power (or the torque) and the reactive power can be controlled separately by the two rotor current components i_{qr} and i_{dr}, respectively [2]. Reactive power flow of the system can be flexibly controlled; for example, unity power factor operation can be maintained, or the machine copper losses can be minimized [2].

Compared with the field orientation control method for the SPRS [1,2], the numbers of sensors and observers have been reduced; for example, stator current sensors, torque observer and flux observer are eliminated. Torque and flux PID regulators are also eliminated. The number of coordinate transformers is reduced to only one, with the stator flux position being sensed.

For the FLC, the linguistic valuables are its inputs speed error and change of speed error, and its output q-axis rotor current, for which the fuzzy sets are denoted as E_1^j, E_2^j and U^j respectively, with $j = 1, ..., 7$. The linguistic values, in the order from 1 to 7, are NL(negative large), NM(negative medium), NS(negative small), ZE(zero), PS(positive small), PM(positive medium), PL(positive large). Fuzzy control rules are shown in Table 1. For example, the first entry in the table has the following equivalent meaning

Table 1. Fuzzy Rules

u	E_2^1	E_2^2	E_2^3	E_2^4	E_2^5	E_2^6	E_2^7
E_1^1	7	7	7	6	6	5	4
E_1^2	7	7	6	6	5	4	3
E_1^3	7	6	6	5	4	3	2
E_1^4	6	6	5	4	3	2	2
E_1^5	6	5	4	3	2	2	1
E_1^6	5	4	3	2	2	1	1
E_1^7	4	3	2	2	1	1	1

- If E_1^1 and E_2^1, then U^7; or
- If $\tilde{e}_1$ is NL and $\tilde{e}_2$ is NL, then $\tilde{u}$ is PL.

All the inputs and the output are normalized with tuning. Standard triangular membership functions as shown in Fig. 2 are used for both the input fuzzy sets and the output fuzzy sets. *Singleton* fuzzification and *Center of Gravity* defuzzification are used. ***Sup-Product*** inference method is used for premises and ***Sup-Min*** inference method is used for fuzzy implications.

B. Simulation

Simulation is conducted for a variable speed drive with a 50hp doubly-excited wound rotor induction machine [2,12]. Full 5th order dynamical model of the system, in stator flux dq reference frame [1,2], is used in the simulation, as well as power converter actual high-frequency switching.

Performance specifications can be met by adjusting the normalizing gains of the fuzzy logic controller, with considerations of the limiting factors related with the machine and power converters, such as torque limit, current limits, sampling time, maximum converter switching frequency, etc. Soft and nonlinear control actions resulted from the fuzzy rules practically eliminate overshoots in speed tracking.

Fig. 7 shows the speed tracking dynamics of the system for one torque limit. Fig. 8 shows corresponding q-axis and d-axis rotor currents. The d-axis rotor current is controlled separately to maintain a specific amount of stator reactive power flow, such that the machine copper losses are minimized [2]. Fig. 9 shows the speed tracking dynamics for a higher torque limit, such that speed tracking is faster. For this relatively large machine, speed tracking performance is satisfactory with servo quality.

Simulation results show that the performance of the system is comparable with that of the field orientation controlled system, with fewer sensors and observers, and without PID regulators. Furthermore, rejection of parameter variations is achieved, as simulated in Fig. 10 when the rotor resistance increases 10 times at t=0.01 second. Similarly, since a mathematical model is not used and the system end-results are the direct goals of any control action, disturbances and certain fault conditions can be easily tolerated.

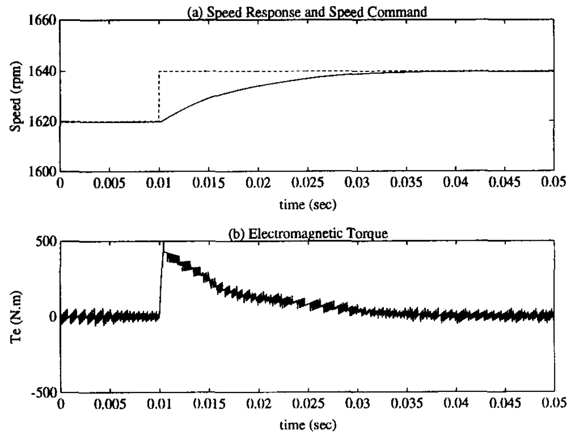

Fig. 7 Direct Fuzzy Control Simulation

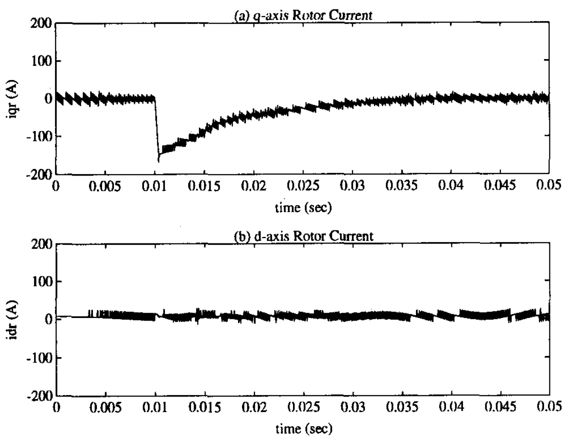

Fig. 8 Rotor Currents (PWM Switchings Simulated)

IV. Adaptive Fuzzy Control of SPRS

A. System Structure and Learning/Adaptation Mechanism

With adaptive fuzzy control, the slip power recovery variable speed drive system is shown in Fig. 11. Based on the previous system with direct fuzzy logic control, a reference model and a fuzzy learner/adaptor are added.

The principle of model reference adaptive control is employed in the system. The performance specifications are stored in the reference model, which uses the speed command, ω_r^*, to produce a reference speed ω_r^{ref} that meets the desired performance specifications. Note that the performance specifications, including speed overshoot, rise time, settling time, etc, should be reasonable so that machine capabilities are considered. The reference speed ω_r^{ref} is compared with the actual speed ω_r,

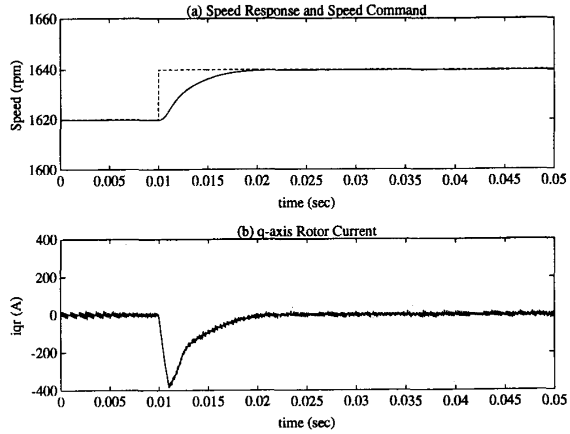

Fig. 9 Direct Fuzzy Control (Higher Torque Limit)

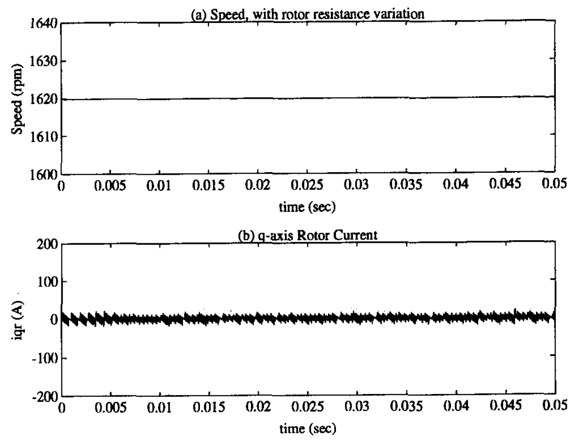

Fig. 10 Rejection of Rotor Resistance Variation

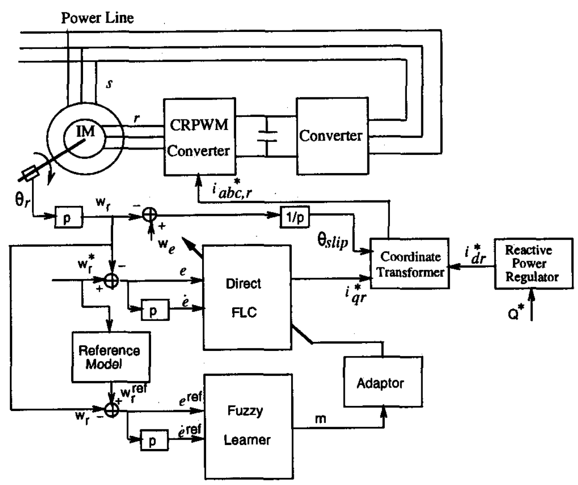

Fig.11 SPRS with Adaptive Fuzzy Controller

and the error e^{ref} and change of error $\dot{e}^{ref}$ are inputs to the fuzzy learner, which outputs the instruction m to adapt the direct fuzzy logic controller.

The design of the fuzzy learner is very similar to the FLC in the previous system, with the same fuzzy sets, rule base (which is quite universal), and methods of fuzzification, inferences and defuzzification.

The design of the direct FLC also follows the one in the previous system, except that the membership functions for the output fuzzy sets now have triangular shape with fixed width but flexible centers. All of these membership functions are initially centered at zero, representing the fact that the direct FLC initially does not know how to control the machine. These centers are shifted, or adapted, by the fuzzy learner/adaptor such that the output of the direct FLC will control the machine to follow the reference speed response. In each time-step, all of the previously activated fuzzy sets U^j have the centers c^j of their membership functions shifted by the amount of the adapation variable, output of the fuzzy learner m:

$$c^j(t) = c^j(t - dt) + m(t) \tag{1}$$

while the membership functions for the previously unactivated fuzzy sets remain unchanged to have local memory of any previously learned response.

B. Simulation

Simulation is conducted for the same drive. Performance specifications are stored in the second-order reference model with the dynamical equation:

$$\ddot{\omega}_r^{ref} + K_1\dot{\omega}_r^{ref} + K_2\omega_r^{ref} = K_2\omega_r^* \tag{2}$$

With $K_1 = 1000, K_2 = 250000$, Fig. 12 shows the step speed response of the system with the learning/adaptive fuzzy controller. Fig. 13 is for another reference model with $K_1 = 600, K_2 = 90000$. In both cases, initially all the membership functions for the output fuzzy sets U^j are centered at zero, while later those for some of U^j related with positive then zero speed errors are automatically positioned. Note that the desired speed tracking specifications are met excellently, with the solid lines closely match the dotted lines. With moderately fast sampling and high-frequency PWM switching, learning/adaptation is almost instantaneous during speed transients. Rejection of machine parameter variations and disturbances is also achieved.

Designing of the normalizing gains of the direct FLC and the fuzzy learner takes into consideration approximate performance requirements and limiting factors related with the machine and power converters. For the FLC in the previous system, the normalizing gains are designed for certain situations, which would then prohibit the machine to achieve desired performance in case of large changes in machine parameters or disturbances, or large changes in command signals. This problem is solved by the adaptive fuzzy controller, which is able to shift the FLC output to any allowable value as necessary; in other words, performance of the system is no longer sensitive to the selection of these normalizing gains and designing of the FLC. However, it should be stressed that the reference model must be reasonable.

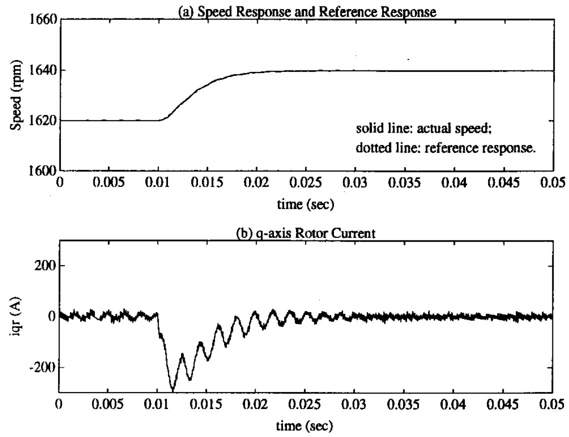

Fig. 12 Adaptive Fuzzy Control Simulation

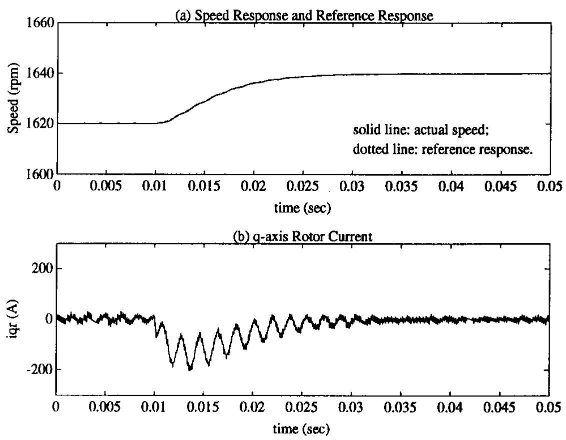

Fig. 13 Adaptive Fuzzy Control Simulation with Another Reference Model

Note that the learned knowledge is stored in the membership functions for the output fuzzy sets of the FLC, such that later adaptation is faster with less oscillations if the drive is used for repeated tasks. These automatically synthesized membership functions serve as local memory units, analogous to the learning weights connecting layered nodes in a neural network [7,8].

V. Conclusions

In this paper, principles and usefulness of fuzzy logic and fuzzy control have been illustrated, particularly through applications for the intelligent control of a complex variable speed drive system.

A. *Intelligent Motion Control*

The outlook for the applications of AI techniques in electric drives and power electronics is very promising. Such AI techniques as fuzzy logic, expert systems, neural networks, qualitative reasoning, qualitative modelling and simulation, constraint propagation programming, automating simulation and design, and so on, can all find challenging problems to solve in the vast fields of motion control, as demonstrated by the implementations of fuzzy control in this paper. Indeed, the combination of AI, the "brain", and motion control, the "muscle", will be most beneficial for our progressively automated civilization.

B. *Fuzzy Control of Variable Speed Drive*

A direct fuzzy logic controller has been designed and simulated for the speed control of a variable speed drive with slip power recovery configuration. Compared with conventional high performance controllers, the features of the system include:

- Less dependent on a mathematical model of the machine and the converter
- Reduced numbers of sensors and observers
- No need for PID type regulators
- Rejection of parameter variations, disturbances and some faults

Furthermore, for the same slip power recovery system, an adaptive fuzzy controller has been designed and simulated. In addition to the features listed above, further features of the system include:

- Learning and adaptation ability is achieved
- Less sensitive to the design of the direct fuzzy logic controller
- Less sensitive to changing environment

Broader spectrum of research and further developments are possible; for instance, the demonstrated control structures and strategies may also be applied in variable speed generating systems.

Acknowledgment

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Biography

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