A Fuzzy Set Theory Based Control of a Phase-Controlled Converter DC Machine Drive

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Abstract—Fuzzy logic or fuzzy set theory is recently getting increasing emphasis in process control applications. The paper describes application of fuzzy logic in a speed control system that uses a phase-controlled bridge converter and a separately excited dc machine. The fuzzy control is used to linearize the transfer characteristics of the converter in discontinuous conduction mode occurring at light load and/or high speed. The fuzzy control is then extended to the current and speed control loops, replacing the conventional proportional-integral (PI) control method. The compensation and control algorithms have been developed in detail and verified by digital simulation of a drive system. The simulation study indicates the superiority of fuzzy control over the conventional control methods. Fuzzy logic seems to have a lot of promise in the applications of power electronics.

I. INTRODUCTION

FUZZY LOGIC is recently finding wide popularity in various applications that include management, economics, medicine and process control systems. The theory was introduced by Zadeh [1] around twenty seven years ago, but only recently its application has received large momentum. Fuzzy logic, unlike the crisp logic in Boolean theory, deals with uncertain or imprecise situations. A variable in fuzzy logic has sets of values which are characterized by linguistic expressions, such as SMALL, MEDIUM, LARGE, etc. These linguistic expressions are represented numerically by fuzzy sets (sometimes referred to as fuzzy subsets). Every fuzzy set is characterized by a membership function, which varies from 0 to 1 (unlike 0 and 1 of a Boolean set). Although fuzzy theory deals with imprecise information, it is based on sound quantitative mathematical theory. A fuzzy control algorithm for a process control system embeds the intuition and experience of an operator, designer and researcher. The control does not need accurate mathematical model of a plant, and therefore, it suits well to a process where the model is unknown or ill-defined. Of course, fuzzy control algorithm can be refined by adaptation based on learning and fuzzy model of the plant. The fuzzy control also works well for complex nonlinear multi-dimensional system, system with parameter variation problem, or where the sensor signals are not precise. Recently, it has been applied to fast response linear servo drive [5] giving superior results. The fuzzy control is basically nonlinear and adaptive in nature, giving robust performance under parameter variation and load disturbance effect.

The application of fuzzy theory in power electronics is almost entirely new [6]. A power electronics system, in general, has complex nonlinear model with parameter variation problem, and the control needs to be very fast. In this paper, the application of fuzzy logic in a phase-controlled converter dc drive system is described. The fuzzy control linearizes the transfer characteristics of the converter in discontinuous conduction mode and controls the feedback current and speed loops as well.

II. REVIEW OF FUZZY CONTROL THEORY

Since the fuzzy control theory is somewhat new to the power electronics community, it is appropriate to review here some basics concepts of fuzzy logic and fuzzy control. The reader interested in a more comprehensive review of the subject will find refs. [13] and [14] very helpful.

A fuzzy set has a distinct feature of allowing partial membership. In fact, a given element can be a member of a fuzzy set, with degree of membership varying from 0 (non-member) to 1 (full member), in contrast to a "crisp" or conventional set, where an element can either be or not be part of the set. Fig. 1 illustrates the difference for the case of a hypothetical temperature control system. In Fig. 1(a), a crisp classification is provided, such that, the temperature value \( T = 67^\circ F \) is a member of the HOT set only. In contrast, in Fig. 1(b) temperature is considered a fuzzy variable, and \( T = 67^\circ F \) is a partial member of both MILD and HOT fuzzy sets. Because language is the primary means for conveying knowledge, fuzzy variables are usually referred to as linguistic variables, and the fuzzy sets are viewed as the mathematical representation of their linguistic values (e.g., COLD, MILD, and HOT in Fig. 1). The numerical interval, that is relevant for the description of a fuzzy variable, is commonly named Universe of Discourse (in Fig. 1, the real interval [20, 90]).

A few operations of Boolean theory are also valid in fuzzy set theory, which are given below.

Union: Given two fuzzy sets \( A \) and \( B \), defined on a universe of discourse \( X \), the union \( (A \cup B) \) is also a fuzzy set of \( X \), with membership function given as

\[
\mu_{A \cup B}(x) = \max \{ \mu_A(x), \mu_B(x) \} \quad (1)
\]

where \( x \) is any element of \( X \).

Intersection: The intersection of two fuzzy sets \( A \) and \( B \) of the universe of discourse \( X \), denoted by \( A \cap B \), has the
Fig. 1. Representation of temperature using: (a) Crisp set. (b) Fuzzy set.

Fig. 2. Basic operations involving fuzzy sets. (a) Original fuzzy sets defined on x. (b) Union. (c) Intersection. (d) Negation.

membership function given by

\[ \mu_{A \cup B}(x) = \min(\mu_A(x), \mu_B(x)) \]  \hspace{1cm} (2)

Compliment: The compliment of a given set A of the universe of discourse X is denoted by \( \neg A \), and has the membership function

\[ \mu_{\neg A} = 1 - \mu_A(x) \]  \hspace{1cm} (3)

Fig. 2 illustrates these three basic properties. For fuzzy logic control, a few more concepts, such as fuzzy implication (fuzzy rules) and fuzzy composition (fuzzy inference) are important. A fuzzy rule typically has an IF-THEN format as follows:

\[
\text{IF} \ (x \text{ is } A \text{ AND } y \text{ is } B) \text{ THEN } (z \text{ is } C)
\]

where \( x, y \) and \( z \) are fuzzy variables and \( A, B \) and \( C \) are fuzzy subsets in the universe of discourses \( X, Y \) and \( Z \), respectively. If the conditions expressed in the antecedent (IF portion) are met, then the action(s) specified in the consequent (THEN portion) are taken. In order to design a fuzzy controller, a fuzzy rule base consisting of several rules must be constructed. For example, consider an hypothetical fuzzy speed control system for a dc motor, where the speed error (E) and change in error (CE) are used to determine changes in the control signal (DU), that in this case is the command armature current \( i_a \). A part of the rule base would be:

- Rule 1: IF E is Zero AND CE is Zero THEN DU is Zero;
- Rule 2: IF E is Zero AND CE is Negative Small THEN DU is Negative Small;
- Rule 3: IF E is Positive Small AND CE is Negative Small THEN DU is Zero;

Here, error (E), change in error (CE) and change in control (DU) are considered fuzzy variables, with possible values given by fuzzy sets such as Positive Small, Negative Small, and so on. As illustrated in Fig. 1, a given numerical value can be a member of more than one fuzzy set. This means that, for a particular input pair of values (E and CE), more than one rule could be activated or "fired". Therefore, there must be a way to combine the individual control actions of the fired rules, such that a single, meaningful action is taken. In fuzzy logic terms, the composition operation is the mechanism by which such task can be performed. Although several composition principles have been proposed in the literature, the most common one is the SUP-MIN (SUpremum-MINimum) composition. In a simplistic way, given a rule base, it is possible to construct a n-dimensional fuzzy relation \( R \) (lets consider it as a function of \( n \) variables). The simplest case is a single input \( x \), single output \( u \) system, resulting in a 2-dimensional fuzzy relation, represented by a membership function \( \mu_B(x, u) \). For this case, the composition operation can be expressed as:

\[ \mu_B(u) = \sup_x[\min(\mu_A(x), \mu_B(x, u))] \]  \hspace{1cm} (4)

where \( A \) is the known fuzzy set for the input \( x \) and \( B \) is the inferred fuzzy set for the output \( u \). In practice, the fuzzy relation \( R \) is seldom evaluated explicitly; instead, the SUP-MIN composition is applied to one rule at a time, and the individual control actions combined using the union operation. Fig. 3 illustrates the fuzzy composition by SUP-MIN principle for the two stated rules. Note that the output membership function of each rule is given by MIN operator whereas the combined fuzzy output is given by the SUP operator. This will be evident by numerical example in section 3.

The general structure of a fuzzy control system is given in Fig. 4. The control signal \( U \) is inferred from the two state variables error \( e \) and change in error \( \dot{e} \) (\( de/dt \) for the
sampling interval). The e and ce are per unit (pu) signals derived from the actual E and CE signals by dividing with the respective gain factors as shown. In a strict sense, the fuzzy controller is designed to process fuzzy quantities only. Therefore, all crisp input values must be converted to fuzzy sets before being used. This process is called fuzzification operation, and can be performed by considering the crisp input values as “singleton” (fuzzy sets that have membership value of 1 for the given input value and 0 for all other points in the universe of discourse). In Fig. 3, the given input values E and CE were “converted” to fuzzy sets by this process, before being compared to the other fuzzy sets. In a similar way, there is a need for converting the output of the fuzzy controller (a fuzzy set) to a crisp value required by the plant. This is called defuzzification operation, and can be performed by a number of methods of which the center-of-gravity (also known as centroid) and height methods are common. The centroid defuzzification method selects the output crisp value corresponding to the center of gravity of the output membership function which is given by the expression

\[ U_0 = \frac{\int u \mu(u) du}{\int \mu(u) du} \]  

(5)

In the height method, the centroid of each output membership function for each rule is first evaluated. The final output is then calculated as the average of the individual centroids, weighted by their heights (degree of membership) as follows:

\[ U_0 = \frac{\sum_{i=1}^{n} u_i \mu(u_i)}{\sum_{i=1}^{n} \mu(u_i)} \]  

(6)

Finally, the data base provides the operational definitions of the fuzzy subsets used in the control rules, fuzzification and defuzzification operations. Further details of fuzzy control will be discussed in Section 3.

In spite of the advantages in fuzzy control, the main limitation is the lack of a systematic procedure for design and analysis of the control system. Generally, a trial-and-error iterative approach is taken which may be time-consuming. A few other difficulties in fuzzy control are: (1) Lack of completeness of the rule base. The controller must be able to give a meaningful control action for every condition of the process. (2) There is no definite criteria for selection of the shape of membership functions, degree of overlapping of the subsets and the levels of data quantization.

III. DC MACHINE DRIVE WITH PHASE-CONTROLLED CONVERTER

The speed control system under consideration is shown in Fig. 5. The power circuit consists of a phase-controlled bridge converter that drives a separately excited dc motor. For simplicity, the converter is used in motoring mode only with fixed field excitation. The speed control loop has inner current control loop to provide fast transient response as well as to limit the armature current. The current loop output \( V_a' \) is added with the feedforward counter emf signal \( V_c' \), to generate the control signal \( V_c \), which then generates the firing angle \( \alpha \) by cosine wave crossing method. The feedforward addition of counter emf gives faster loop response. The fuzzy control blocks are indicated in Fig. 5.

The converter may operate in either continuous or discontinuous conduction mode. At low speed when the counter emf is small, the conduction will be continuous. However, at high speed, the conduction will tend to be discontinuous. In continuous conduction mode, the normalized armature circuit equations [7] can be given as follows:

\[ I_a(pu) = \frac{I_a}{3V_m/\pi} = \frac{X}{R} \left[ \cos \alpha - \frac{\pi V_c}{3V_m} \right] \]  

(7)

\[ V_d(pu) = \frac{V_d}{V_m} = \frac{3}{\pi} \cos \alpha \]  

(8)

where

- \( I_a \) = armature current (average)
- \( V_m \) = peak ac line voltage
- \( X \) = armature reactance (\( \omega L \))
- \( R \) = armature resistance
- \( \alpha \) = converter firing angle
- \( V_c \) = armature counter emf

and

- \( V_d \) = converter output voltage (average)

The line voltage \( V_m \) can essentially be considered as constant, and therefore, \( V_d \) can be controlled linearly by \( V_c \) with cosine wave crossing technique as indicated in the figure. In discontinuous conduction mode, the following armature circuit equations are valid [7]:

\[ I_a(pu) = \frac{I_a}{3V_m/\pi} = \frac{X}{R} \left[ \cos \left( \frac{\pi}{3} + \alpha \right) \right. \\
\left. - \cos \left( \frac{\pi}{3} + \alpha + \theta_1 \right) - \frac{V_c}{V_m} \theta_1 \right] \]  

(9)

\[ V_d(pu) = \frac{V_d}{V_m} = \frac{3}{\pi} \left[ \cos \left( \frac{\pi}{3} + \alpha \right) \right. \\
\left. - \cos \left( \frac{\pi}{3} + \alpha + \theta_1 \right) - \frac{V_c}{V_m} \theta_1 \right] + \frac{V_c}{V_m} \]  

(10)
\[
\frac{V_c}{V_m} = \frac{\sqrt{1 + (X/R)^2}}{[1 - \exp(-R\theta_1/X)]} \\
\left\{ \sin \left( \frac{\pi}{3} + \alpha + \theta_1 - \phi \right) - \sin \left( \frac{\pi}{3} + \alpha - \phi \right) \right\} \\
\exp \left( -\frac{R\theta_1}{X} \right) \tag{11}
\]

where \( \theta_1 \) = conduction angle of current pulse \( (0 < \theta_1 < \pi/3) \) (see Fig. 11(a)) and \( \tan \phi = X/R \). For a fixed \( X/R \) parameter, the equations (7) – (11) are plotted in Fig. 6 for different \( \alpha \) angles, which also indicates the boundary between continuous and discontinuous conduction modes. For example, at \( \alpha = 80^\circ \), the conduction is continuous at the point A. As the machine counter emf is increased, the \( V_d(pu) \) remains constant at decreasing \( I_a(pu) \) until the point B when the conduction becomes discontinuous. Further increase of counter emf will cause increase of \( V_d(pu) \) until it reaches the point at which \( I_a(pu) = 0 \). The nonlinear \( V_d(pu) - I_a(pu) \) relation adversely affects the gain characteristics of the current control loop. If, for example, the loop gain is made optimum at continuous conduction mode, the lower gain at discontinuous conduction will make the loop response sluggish. On the other hand, if the gain is optimized for discontinuous mode at a certain operating point, the loop will tend to be unstable at continuous conduction. Among the number of methods suggested to linearize the converter transfer characteristics at discontinuous conduction mode, the look-up table method suggested by Ohmoe et al. [7] appears to be very attractive. In this method, an auxiliary compensating \( \Delta\alpha \) angle is generated as a function of main \( \alpha \) angle and armature current \( I_a \) and then added with the \( \alpha \) angle to generate the \( \alpha_n \) angle as indicated in Fig. 5. As a consequence, \( V_d(pu) - I_a(pu) \) relation for each \( \alpha \) angle becomes horizontal at discontinuous mode (Fig. 6), and therefore, the gain value becomes the same as in continuous conduction. The two-dimensional relation of \( \Delta\alpha \) can be pre-computed for each \( X/R \) parameter and stored in the form of a look-up table for microcomputer implementation. If the parameter \( X/R \) variation is considered, and the compensating angle is needed with good accuracy, then the look-up tables memory tends to be very large.

### A. Fuzzy Linearization of Converter at Discontinuous Conduction

It was mentioned before that fuzzy control is well-suited in a non-linear system, especially where parameter variation problem exists. Therefore, we will attempt here fuzzy method of \( \Delta\alpha \) angle compensation, in order to linearize the converter...
transfer characteristics in discontinuous conduction mode. The special feature in fuzzy control is that the \( \Delta \alpha \) angle is expressed as a fuzzy relation of the variables \( I_a \) and \( \alpha \) angle. The set of rules for fuzzy compensation is given in the matrix form in Table I where all the symbols are defined in the usual fuzzy logic terminology. A typical rule has the following structure:

If \( I_a \) is small negative (NS) AND \( \alpha \) is small positive (PS) THEN \( \Delta \alpha \) is small negative (NS)

The rule base is developed by heuristics from the viewpoint of practical system operation. The current \( I_a \) is treated as normalized value. Fig. 7 shows the membership function plots of the variables \( \alpha \), \( I_a(\text{pu}) \) and \( \Delta \alpha \). The universe of discourse of the variables cover the whole discontinuous conduction region. The sensitivity of a variable determines the number of fuzzy subsets. The universe of discourse of \( \alpha \) is described by five fuzzy subsets, whereas \( I_a(\text{pu}) \) and \( \Delta \alpha \) are described by nine and eleven subsets, respectively. The linguistic terms used for the subsets are for convenience only and must be interpreted in “context free” grammar, since their conventional meaning does not correspond to the sign and numerical values of the variables. In Fig. 7, 50% overlap has been provided for the neighboring fuzzy subsets. Therefore, at any given point of the universe of discourse, no more than two fuzzy subsets will have non-zero degree of membership. This choice of fuzzy partitioning along with the SUP-MIN composition method as described before, results in simplification of fuzzy linearization algorithm. It is evident that for any input data of \( I_a(\text{pu}) \) and \( \alpha \), only four rules will be valid in the entire rule base given in Table I. The algorithm for fuzzy linearization can then be summarized as follows. A numerical example is also included for clarity.

1. Sample the dc current \( I_a \) and firing angle \( \alpha \) from the current control loop. Convert \( I_a \) to \( I_a(\text{pu}) \).

   [Let’s assume: \( I_a = 5.6 \text{pu}, \alpha = 55^\circ \), \( I_{\text{base}} = 98.5 \text{pu} \) (see Table II) \( I_a(\text{pu}) = 5.6/98.5 = 0.057 \]

2. Calculate the interval indices \( I \) and \( J \) (that identify the interval number in the fuzzy subsets) for \( \alpha \) and \( I_a(\text{pu}) \), respectively as follows:

   \[
   I = \text{INT} \left( \frac{(\alpha + 10)}{20} \right) \\
   J = \text{INT} \left( \frac{(I_a(\text{pu}) + 0.01)}{0.01} \right) \\
   \begin{align*}
   I = 3, & \quad J = 6 
   \end{align*}

3. Calculate the degree of membership of \( \alpha \) and \( I_a(\text{pu}) \) for the leftmost fuzzy subset using \( I \) and \( J \), respectively as follows:

   \[
   \mu_Z(\alpha) = (20I + 10 - \alpha)/20 \\
   \mu_{PS}(I_a(\text{pu})) = (0.01I - I_a(\text{pu}))/0.01 \\
   [\mu_Z(55^\circ) = 0.75, \mu_{PS}(0.057) = 0.3]
   
4. Evaluate degree of membership for other subsets by complement relation

   \[
   \mu_{PS}(\alpha) = 1 - \mu_Z(\alpha) \\
   \mu_{PM}(I_a(\text{pu})) = 1 - \mu_{PS}(I_a(\text{pu})) \\
   [\mu_{PS}(55^\circ) = 0.25, \mu_{PM}(0.057) = 0.7]
   
5. Identify the four valid rules in Table I (stored as look-up table) and calculate the degree of membership \( \mu_{RI} \) contributed by each rule \( R_i[i = 1, 2, 3, 4] \), using MIN operator

   \[
   \begin{align*}
   [\mu_{R1}] &= \text{MIN} \{ \mu_Z(\alpha), \mu_{PS}(I_a(\text{pu})) \} \\
   &= \text{MIN} \{0.75, 0.3\} = 0.3 \\
   [\mu_{R2}] &= \text{MIN} \{ \mu_{PS}(\alpha), \mu_{PS}(I_a(\text{pu})) \} \\
   &= \text{MIN} \{0.25, 0.3\} = 0.25 \\
   [\mu_{R3}] &= \text{MIN} \{ \mu_Z(\alpha), \mu_{PM}(I_a(\text{pu})) \} \\
   &= \text{MIN} \{0.75, 0.7\} = 0.7 \\
   [\mu_{R4}] &= \text{MIN} \{ \mu_{PS}(\alpha), \mu_{PM}(I_a(\text{pu})) \} \\
   &= \text{MIN} \{0.25, 0.7\} = 0.25
   \end{align*}
   
6. Retrieve the amount of correction \( \Delta \alpha_i, i = 1, 2, 3, 4 \) corresponding to each rule, from Table I

   \[
   \begin{align*}
   \Delta \alpha_1 &= (\alpha = Z, I_a(\text{pu}) = PS) \rightarrow \Delta \alpha_1 = NB = 3^\circ \\
   \Delta \alpha_2 &= (\alpha = PS, I_a(\text{pu}) = PS) \rightarrow \Delta \alpha_2 = NM = 6^\circ \\
   \Delta \alpha_3 &= (\alpha = Z, I_a(\text{pu}) = PM) \rightarrow \Delta \alpha_3 = NB = 3^\circ \\
   \Delta \alpha_4 &= (\alpha = PS, I_a(\text{pu}) = PM) \rightarrow \Delta \alpha_4 = NB = 3^\circ
   \end{align*}
   
- Table I

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>NB</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_a )</td>
<td>NB</td>
<td>NS</td>
<td>Z</td>
<td>PS</td>
<td>PB</td>
</tr>
<tr>
<td>( \Delta \alpha )</td>
<td>NB</td>
<td>NS</td>
<td>Z</td>
<td>PS</td>
<td>PB</td>
</tr>
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- Fig. 6: Theoretical \( V_d - I_a(\text{pu}) \) phase plot without compensation.
7. Calculate the crisp value of $\Delta \alpha$ by height defuzzification method as follows:

$$\Delta \alpha = \frac{(0.30 \times 3 + 0.25 \times 6 + 0.70 \times 3 + 0.25 \times 3)}{(0.30 + 0.25 + 0.70 + 0.25)} = 3.5$$

The strength of fuzzy compensation is that the number of rules required to express the fuzzy relation is fairly small and memory requirement is low compared to large look-up table needed in conventional method. The compensation algorithm will accommodate reasonable variation of $X/R$ parameter, and therefore, this effect need not be considered separately.

B. Fuzzy Control of Current and Speed Loops

In addition to converter linearization, fuzzy logic control was applied to the speed and current loops as well, replacing the conventional $PI$ controllers. The objective was to explore the control robustness in the presence of parameter variation and load disturbance effect. However, both loops must satisfy the needs of fast transient response with minimum overshoot. With converter linearization, both speed and current loops have essentially first order characteristics. Therefore, intuitively the same fuzzy control strategy should be valid for both loops.

The fuzzy speed and current control are equally effective in ac drives with vector control, since the transient response is similar to that of a dc machine.

The general input variables considered in the fuzzy rule base are:

$$E(K) = R(K) - C(K)$$
$$CE(K) = E(K) - E(K - 1)$$

where

$E(K)$ = loop error
$CE(K)$ = change in loop error
$R(K)$ = reference signal
$C(K)$ = output signal
$K$ = sampling interval

The structure of a general rule can be given as

IF $E(K)$ is $X$ AND $CE(K)$ is $Y$ THEN $DU(K)$ is $Z$

where $DU(K)$ is the change in the control setting. $X$, $Y$ and $Z$ are the fuzzy subsets defined in the universe of discourse of $E$, $CE$ and $DE$, respectively. The variables can be expressed as per unit quantities as follows:

$$e(pu) = E(K)/GE$$
$$ce(pu) = CE(K)/GCE$$
$$du(pu) = DU(K)/GU$$

where $GE$, $GCE$ and $GU$ are the respective gain factors of the controller. The gain factors are normally different in speed and current control loops. The representation of the variables in terms of per unit values permits flexibility in the design and tuning of the controller. Fig. 8 shows the membership functions of $e(pu)$, $ce(pu)$ and $du(pu)$ variables. Note that the fuzzy subsets for each variable have asymmetrical shape causing more crowding near the origin. This permits precision control near the steady state operating point, without unduly increasing the number of subsets. However, a finer partitioning for $du(pu)$ was necessary considering the sensitivity of this variable. As fuzzy controller design is based on intuition and experience, instead of the system model, the following considerations were given in the beginning:

1. If both $e(pu)$ and $ce(pu)$ are zero, then maintain the present control setting $U(K)$ (i.e., $du(pu) = 0$)

2. If $e(pu)$ is not zero, but is approaching this value at satisfactory rate, then maintain the present control setting $U(K)$.

3. If $e(pu)$ is growing, then change in the control signal $du(pu)$ is not zero and its value depends on the magnitude and sign of $e(pu)$ and $ce(pu)$ signals [9].

Table II gives the rule base matrix for current and speed controllers. A close look at the rule base indicates that the auxiliary diagonal consists of $Z$ elements which conform to the second consideration as given above. Note that the value assigned to $du(pu)$ depends on the distance from the auxiliary diagonal. The parameters $e_1, e_2, \ldots, c_1, c_2, \ldots, u_1, u_2, \ldots$ in Fig. 8 are iterated to tune the controller performance. The control procedure is essentially identical to that of $\Delta \alpha$ compensation scheme. The steps for speed control can be summarized as follows:
Fig. 8. Membership functions of speed and current controllers. (a) Error. (b) Change in error. (c) Change in control.

1. Sample $\omega^*_r$ and $\omega^r_c$.
2. Compute error ($E$), change in error ($CE$) and their per unit values as follows:
   
   \[
   E(K) = \omega^*_r(K) - \omega^r_c(K)
   \]
   
   \[
   CE(K) = E(K) - E(K - 1)
   \]
   
   \[
   e(pu) = E(K)/GE
   \]
   
   \[
   ce(pu) = CE(K)/GCE
   \]

3. Identify the interval index I and J for $e(pu)$ and $ce(pu)$, respectively by comparison method.
4. Compute the degree of membership of $e(pu)$ and $ce(pu)$ for the relevant fuzzy subsets.
5. Identify the four valid rules in Table II and calculate the degree of membership $\mu_{RI}$ using MIN operator.
6. Retrieve $du$ for each rule from Table II.
7. Calculate the resultant crispy value of $du(pu)$ by height defuzzification method.
8. Compute the next control signal as
   
   \[
   U(K) = U(K - 1) + GU + du(pu)
   \]

The control for the current loop is same as above except here the gain factors $GE$, $GCE$ and $GU$ are different.

IV. SIMULATION STUDY

In order to validate the control strategies as discussed above, digital simulation studies were made using PC-SIMNON language (developed by Lund Institute of Technology, Sweden). Table III shows the parameters of the drive system used for simulation study. The speed and current loops of the drive were also designed and simulated with PI control, in order to compare performance with the respective fuzzy control loop. The compensation and feedback control algorithms were iterated until best simulation results were obtained.

In the beginning, the performance of the fuzzy compensation scheme was tested keeping both the speed and current loops open. Fig. 9 shows the voltage and current responses without
compensation. Initially, $V_a$ was set such that $\alpha = 70^\circ$, and then the drive simulation was enabled. With inertia load, the machine speed builds up freely with the developed torque. Initially, the conduction is continuous and $V_d = V_d^* = KV_a$. As speed builds up, the drive enters into discontinuous conduction with higher counter emf, and $V_d$ rises above the reference value $V_d^*$ as shown. Fig. 10 shows the same response with fuzzy $\Delta \alpha$ compensation, indicating that $V_d = V_d^*$ in both continuous and discontinuous regions. Fig. 11 shows the corresponding time domain plot of converter dc voltage ($v_d$) and armature current ($i_a$) waves with $\Delta \alpha$ compensation, where time starts at 0.46 sec. The above test procedure was repeated with different values of $\alpha$ angle, and the corresponding $V_d(pu)$ - $I_a(pu)$ phase plots are given in Fig. 10. It is evident that with fuzzy $\Delta \alpha$ compensation, $V_d(pu)$ at a certain angle essentially remains constant for the whole region of $I_a(pu)$.

The current control loop is then tested with the fuzzy controller with the speed loop remaining open, but the speed is locked to a fixed value so as to establish the discontinuous conduction mode. Fig. 12 (a) shows the current loop response with $\Delta \alpha$ compensation which can be compared with Fig. 12 (b) that gives response without compensation. The boost of transient response due to converter linearization is evident. The responses of the current loop with PI control, but with and without $\Delta \alpha$ compensation, are also given in Fig. 13 for comparison purpose. The response improvement in Fig. 12 for either condition indicates the superiority of fuzzy control. Next, the speed loop was closed, and transient response was tested with both fuzzy current and speed control at linearized converter condition. Fig. 14 shows the speed and current response that covers both continuous and discontinuous regions. The figure also shows the effect of 40% step load torque applied at 0.8 sec. Fig. 15 shows the corresponding system response under PI control in both the loops. Table IV summarizes the response improvement under fuzzy control.

Finally, the drive system was tested with $\omega^*_e$ step at the same condition as before but with four times the effective inertia load. Fig. 16 shows the response with fuzzy control, and Fig. 17 gives the response with PI control, for comparison. Although the major portion of the rise time occurs with the current loop saturated, some improvement in rise time and overshoot under fuzzy control is evident. The reason for superior performance of fuzzy controlled system is that basically it is adaptive in nature and the controller is able to realize different control law for each input state ($E$ and $CE$). The response of PI controlled system, on the other hand, is sensitive to model change that occurs with parameter variation.

V. DISCUSSION ON REAL TIME IMPLEMENTATION

Although the drive system control was not implemented in real time, some discussion on fuzzy control implementation
Fig. 15. PI control system response to a \( \omega_c \) step and \( T_L \) step. (Top) Speed. (Bottom) Currents.

**TABLE IV**

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<th>Performance Comparison of Fuzzy and PI Controlled Drive System</th>
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<tbody>
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<td>Fuzzy</td>
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<td>Rise Time (s)</td>
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<td>Overshoot (rpm)</td>
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<td>Speed drop with TL (rpm)</td>
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<td>Recovery time with TL (s)</td>
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Fig. 16. Fuzzy control system response to a \( \omega_c \) step with a new inertia of four times the original value. (a) Speed. (b) Currents.

in real time is relevant. A high speed microcontroller (such as Intel 80C961) or digital signal processor (such as Texas Instruments TMS320C25) is needed for the control, which can also incorporate other control software. Recently, user-friendly software and hardware tools have been developed for fast development of controller codes. For example, Togai Infralogic, Inc. [22] has introduced fuzzy expert system development shell (TIL SHELL), where fuzzy production rules and membership functions can be written in user-friendly Fuzzy Programming Language (FPL). The FPL source codes are then compiled into portable C source code (re-entrant ANSI or K & R). The development system includes configurable Fuzzy C inference engine and Fuzzy C debugger. The inference engine supports MAX-PRODUCT and SUP-MIN inference methods, and centroid, height and alpha defuzzification methods. The inference engine is emitted in-line with C codes that can either be in fixed or floating point. The C-compiler then generates the machine codes for target application. The object codes can be loaded to an IBM PC/AT (or compatible) slot mounted Accelerator Board (manufactured by TIL) or other microcomputer for real time control. Dedicated hardware type programmable fuzzy controllers are also available.
VI. CONCLUSION

The project is intended to demonstrate the successful application of fuzzy logic control to a phase-controlled converter dc machine drive system. Fuzzy logic was used to linearize the transfer characteristics of the converter under discontinuous conduction, indicating that it is simpler than the conventional look-up table method, which needs a large memory. Fuzzy logic was also used in the design of current and speed controllers of the drive system, and the performance was compared with that of conventional PI-controlled system. The same speed and current control algorithm are also applicable for vector controlled ac drives. The simulation study clearly indicates the superior performance of fuzzy control, because it is inherently adaptive in nature. Of course, a high speed microprocessor is needed to implement the control, but the control law is simpler than model referencing adaptive control (MRAC), expert system and neural network techniques.

VII. GLOSSARY

Degree of Membership ($\mu$) : A number between 0 and 1 that expresses the confidence that a given element belongs to a fuzzy set.
Defuzzification: the process of determining the best numerical value to represent (replace) a given fuzzy set.
Expert System: A computer program that embeds the expertise of a human being in a certain domain.
Fuzzification: the process of converting non-fuzzy input variables into fuzzy variables.
Fuzzy Composition: A method of deriving fuzzy control output from given fuzzy control inputs.
Fuzzy Control: A process control that is based on fuzzy logic and is normally characterized by "IF—THEN" rules.
Fuzzy Logic: A branch of logic that admits infinite logic levels (from 0 to 1), to solve a problem that has uncertainties. This is in contrast to crisp logic that uses only two logic levels (0 and 1).
Fuzzy Implication: Same as fuzzy rule.
Fuzzy Model: The fuzzy rules and membership functions that describe the model of a plant which cannot be described by clear mathematical model.
Fuzzy Programming Language (FPL): A programming language (developed by Togai Infralogic Inc.) that is used to program the membership functions and rule base.
Fuzzy Rules: IF - THEN rules relating input (conditions) fuzzy variables to output (actions) fuzzy variables.
Fuzzy Rule Base: A set of rules that define a fuzzy control algorithm.
Fuzzy Set (or Fuzzy Subset): A set consisting of elements having degrees of membership varying between 0 (non-member) to 1 (full member). It is usually characterized by a membership function, and associated with linguistic values, such as SMALL, MEDIUM, LARGE, etc.
Fuzzy Set Theory: A set theory that is based on fuzzy logic.
Fuzzy Variable: A variable that can be defined by fuzzy subsets.
Fuzzy-C Debugger: A software in TILSHELL that helps in debugging the object program compiled from fuzzy C source codes.
Fuzzy-C Inference Engine: An inference engine (rule validation software) in TILSHELL (Togai Infralogic software development SHELL) that works with the C source codes of the fuzzy control program.
Height Defuzzification Method: A method of calculating a crisp output from a composed fuzzy value, by performing a weighted average of individual fuzzy subsets. The heights of each fuzzy subset is used as weighting factors in the procedure.
Linguistic Variable: Any variable (such as temperature, speed, etc) whose values are defined by language, such as LARGE, SMALL, etc. In this work, it is used as a synonym for fuzzy variable.
Max-Dot Inference Method: One that applies the product operator in the evaluation of each fuzzy rule, and the max operator to obtain the resultant fuzzy set.
Membership Function: A function that defines a fuzzy subset, by associating every element in the set with a number between 0 and 1.
Neural Network: A computational network that mimics the nervous system of human brain.
Singleton: A special fuzzy set that has the membership value of 1 at particular point and 0 elsewhere.
SUP-MIN Composition Method: A composition (or inference) method for constructing the output membership function by using maximum and minimum principle.
Universe of Discourse: The range of values associated with a fuzzy variable.

REFERENCES


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