FUZZY EFFICIENCY OPTIMIZATION OF AC INDUCTION MOTORS

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This paper describes the early states of work to implement a fuzzy logic controller to optimize the efficiency of AC induction motor/adjustable speed drive (ASD) systems running at less than optimal speed and torque conditions. In this paper, the process by which the membership functions of the controller were tuned is discussed and a controller which operates on frequency as well as voltage is proposed. The membership functions for this dual-variable controller are sketched. Additional topics include an approach for fuzzy logic to motor current control which can be used with vector-controlled drives. Incorporation of a fuzzy controller as an application-specific integrated circuit (ASIC) microchip is planned.

FUZZY LOGIC CONTROL OF AC INDUCTION MOTORS

In research funded by the U.S. Environmental Protection Agency (EPA), the authors have been pursuing the development of energy optimizer algorithms for ac induction motors driven by adjustable speed drives (ASDs). Our goals are:

1) increase the efficiency of ASD/motor combinations, especially when operating off of rated torque/speed conditions. ASDs using V/Hz control, which is the current predominant industry standard, still do not gain maximum efficiency from motors operating at less than rated loads and speeds;

2) develop a generic energy efficiency optimizing controller (EEOC) which can be applied to a wide range of ac induction motors, regardless of their size and corresponding equivalent circuit values;

3) develop an energy efficiency optimizing controller (EEOC) which can eliminate the requirement for tachometer or encoder feedback, and still maintain the stability of closed-loop control; and

4) develop an energy efficiency optimizing controller (EEOC) which is self-tuning, thus eliminating the need for extensive operator/manufacturer involvement in the installation of the energy optimizer into ASDs.

Fuzzy logic approaches to these goals are attractive for two reasons:

1) the use of fuzzy logic promises to simplify the energy efficiency optimizing controler (EEOC) control problem, which is highly nonlinear;

2) fuzzy logic offers a way to develop an energy efficiency optimizing controller (EEOC) controller which will offer the stability of closed loop control without the need for speed feedback, thus eliminating the cost of tachometers and encoders.

Fuzzy Efficiency Optimization for Steady State Motor Operation

Our main interest has been to solve the problems above for large horsepower motors (>10 hp) running at steady state conditions in industrial applications (e.g. pump and fan motors).

An induction motor simulator has been developed based on the equivalent circuit representation of a motor. As a starting point, the simulation values which are produced correspond to those which would be produced by a V/Hz controller. The simulator computes the values of the motor state variables (currents, voltages, power, frequency, etc.) in response to changes in the value of the stator voltage, V_s. The values of V_s are

provided to the simulator by a fuzzy energy optimizer. (This energy optimizer was discussed in a previous paper delivered at FUZZ-IEEE '92 in San Diego in March.) This energy optimizer, referred to as the Single Variable Fuzzy Logic Motor Controller, and illustrated in the accompanying block diagram, alters the value of stator voltage (V_s) and then measures the input power P_{In} to see if it has changed.
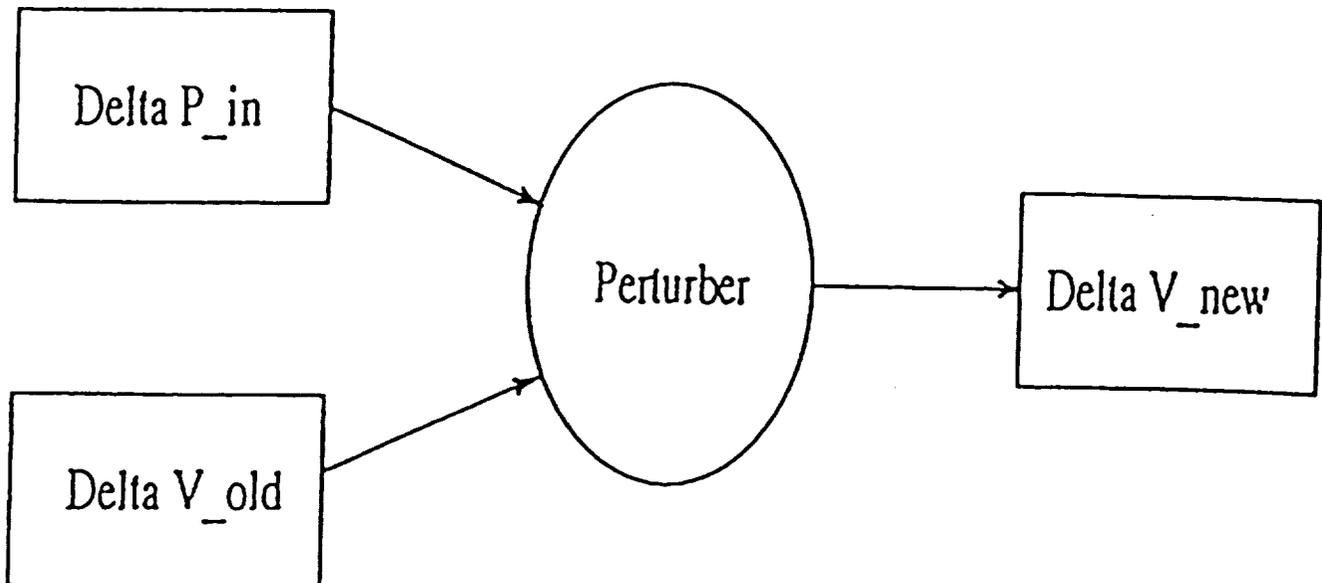
Figure 1. Block Diagram of the Fuzzy Logic Energy Optimizer

Dependent on the magnitude and direction of the change in P_{In}, a set of fuzzy rules, represented here by the section labeled 'Perturber' in the block diagram and using ΔP_{In} and the last change in V_s, ΔV_{s_old}, as inputs, computes an incremental change in the stator voltage ΔV_{s_new} which is then applied to the simulator. A new set of state variables is computed and the process is repeated until either a minimum input power is obtained, characterized by the return of a value of 0 for ΔV_s from the fuzzy controller, or, if tolerance limits on the output torque or the shaft speed of the motor have been exceeded. After some testing, the max-dot inference method and centroid defuzzification were employed.

This technique is essentially a search scheme for the minimum input power point, which occurs in a motor driven by a pulse-width-modulation (PWM) ASD when the copper losses and core losses of the motor are equivalent, as shown in the following figure.
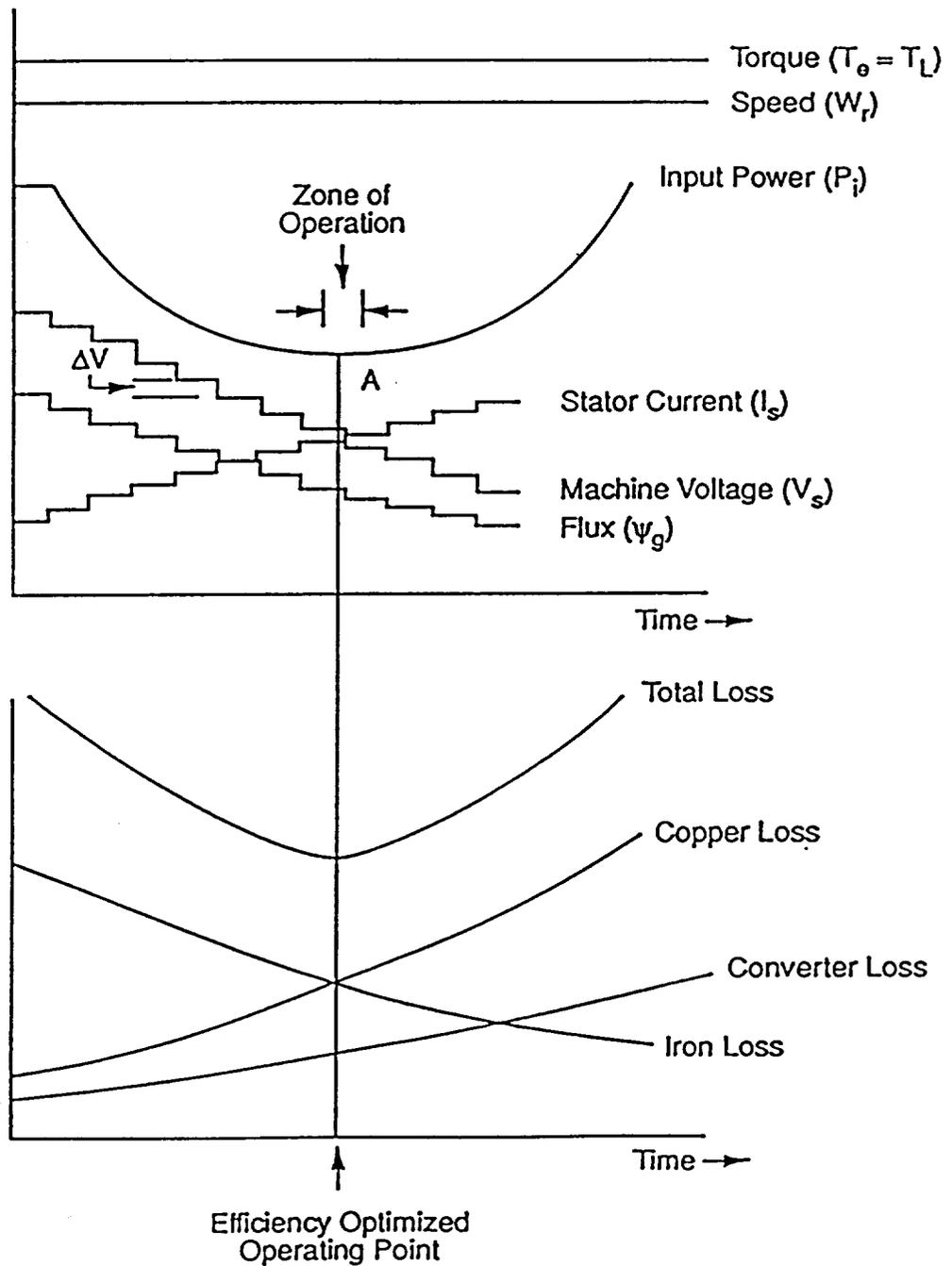
Figure 2. Efficiency Optimization Control based on Real-time Search.

Note that the prediction in the search scheme is that the stator voltage will decrease and the stator current will increase. This prediction has been borne out by the simulator results. The simulator also predicts efficiency improvements by the energy efficiency optimizing controller (EEOC) over standard V/Hz control, as shown in Figure 3.

After the controller rules were refined from simulation of motors of various sizes, a set of 13 fuzzy rules were developed, shown in Table 1.

RULES

1. IF ΔP_{in} IS N AND ΔV_{s_old} IS N, THEN ΔV_{s_new} = N.

2. IF ΔP_{in} IS N AND ΔV_{s_old} IS P, THEN ΔV_{s_new} = P.

3. IF ΔP_{in} IS N AND ΔV_{s_old} IS NM, THEN ΔV_{s_new} = NM.

4. IF ΔP_{in} IS N AND ΔV_{s_old} IS PM, THEN ΔV_{s_new} = PM.

5. IF ΔP_{in} IS NM AND (ΔV_{s_old} IS NM OR ΔV_{s_old} IS N), THEN ΔV_{s_new} = NM.

6. IF ΔP_{in} IS NM AND (ΔV_{s_old} IS PM OR ΔV_{s_old} IS P), THEN ΔV_{s_new} = PM.

7. IF ΔP_{in} IS PM AND (ΔV_{s_old} IS NM OR ΔV_{s_old} IS N), THEN ΔV_{s_new} = PM.

8. IF ΔP_{in} IS PM AND (ΔV_{s_old} IS PM OR ΔV_{s_old} IS P), THEN ΔV_{s_new} = NM.

9. IF ΔP_{in} IS P AND ΔV_{s_old} IS NM, THEN ΔV_{s_new} = PM.

10. IF ΔP_{in} IS P AND ΔV_{s_old} IS PM, THEN ΔV_{s_new} = NM.

11. IF ΔP_{in} IS P AND ΔV_{s_old} IS N, THEN ΔV_{s_new} = P.

12. IF ΔP_{in} IS P AND ΔV_{s_old} IS P, THEN ΔV_{s_new} = N.

13. IF ΔP_{in} IS Z AND ΔV_{s_old} IS ANY, THEN ΔV_{s_new} = Z.
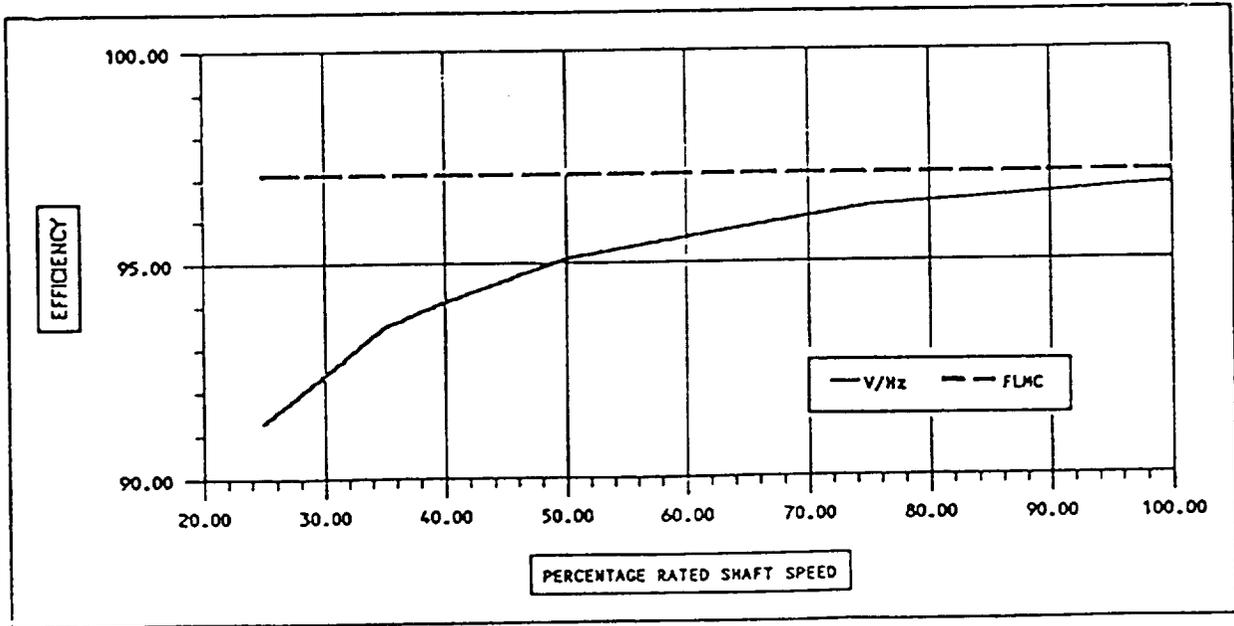
Table 1. Single Variable Controller Rules

Figure 3. Energy Efficiency Optimizing Control (EEOC) versus V/Hz Control for a 100 HP Motor with Torque $\propto$ Speed^2.

The variable values, N, NM, P, PM, and Z stand respectively for negative, negative medium, positive, positive medium, and zero. Data gathered from the motor simulator led to development of limits for membership functions for the fuzzy variables voltage and power. Figure 4 illustrates this for the linguistic variable ΔP_{in}.
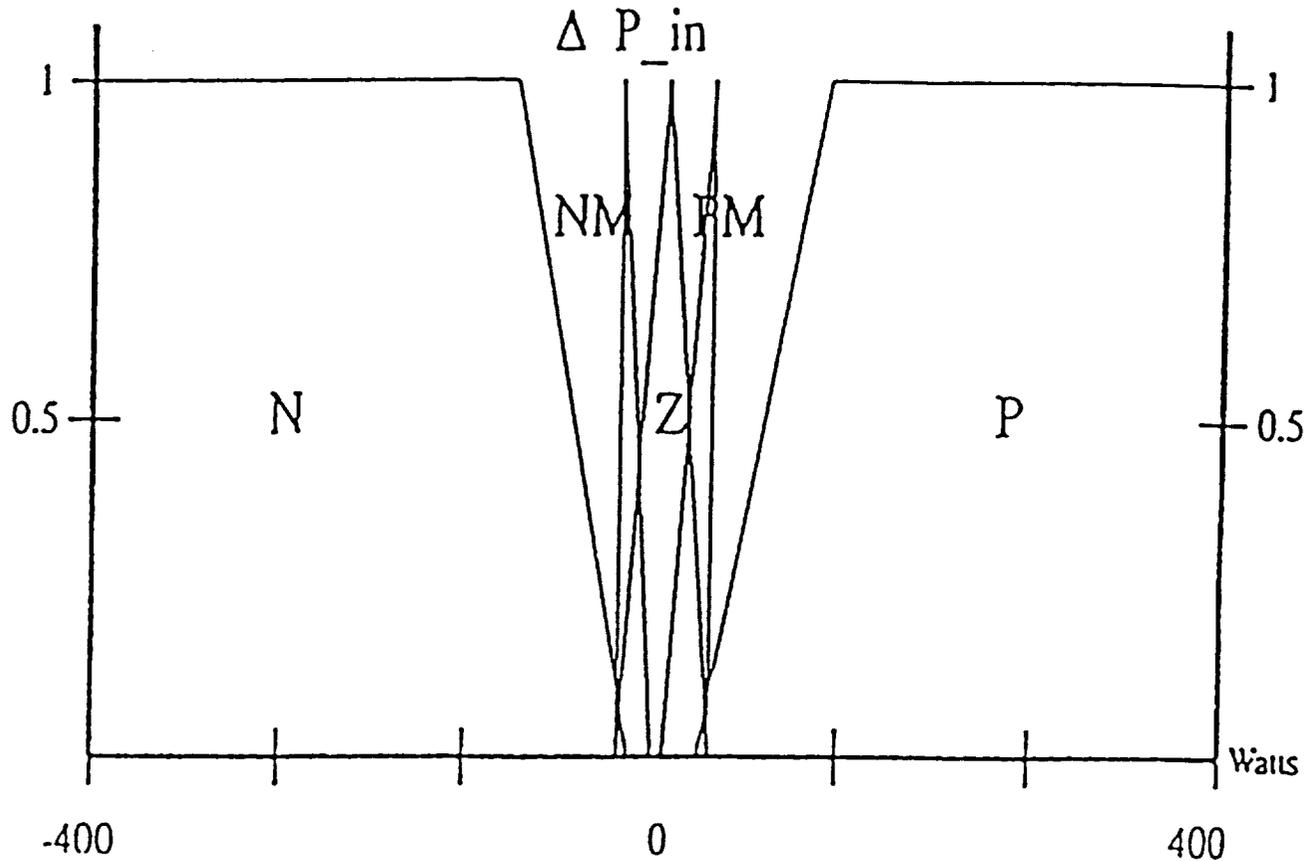

Figure 4. Final Membership Functions for the Fuzzy Variable ΔP_{in}.

It was found from the simulator that the P_{in} can vary by as much as ±400W. Surfaces were constructed from curves relating the various changes in ΔV_{new} to changes in ΔP_{in} and ΔV_{old}. An example of such a surface, generated from data collected with the simulator, is shown in Figure 5.
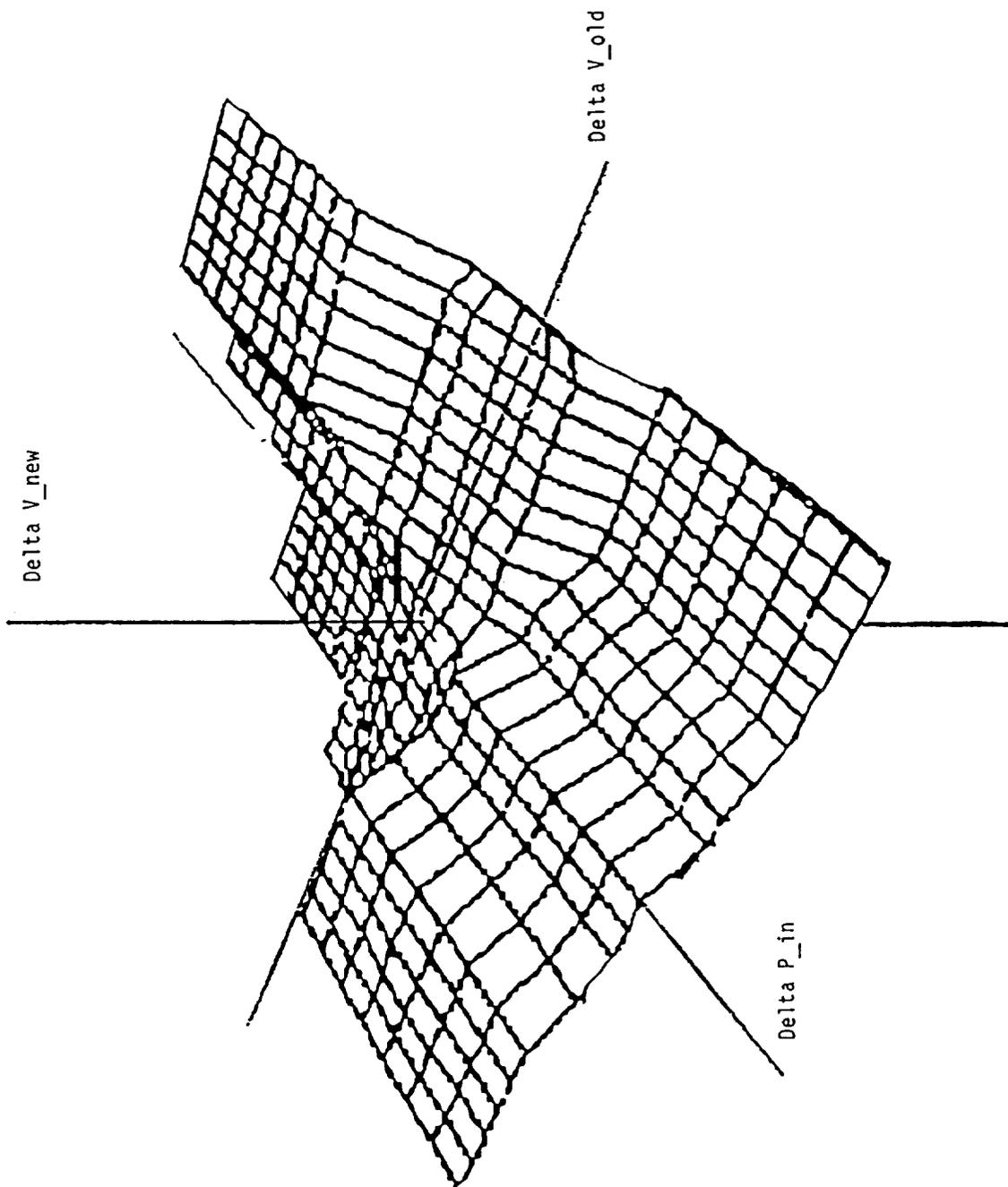
Delta V_new

Delta V_old

Delta P_in

Figure 4.   Surface Generated from Simulator Data Relating Changes in ΔV_{new} to Changes in ΔP_{in}.

These surfaces can be used to optimize the membership functions by examining the surfaces for abrupt or discontinuous changes in the output variable ΔV_s at various values of the input variables ΔP_{in} and ΔV_{s_old}. Based on the magnitude of the discontinuity either the input membership functions' overlaps could be changed or the width of the output membership functions could be changed.

As this initial controller was used to simulate, from equivalent circuit data, several different motors, several features of the controller became clear as this data was analyzed. For example, any change in stator voltage produced a drop in the output shaft speed ω_r, which is generally undesirable. Also, for a given set of equivalent circuit values, maximum efficiency is closely related to total circuit impedance, Z_{in} , regardless of the torque/speed condition.

Because of the loss of shaft speed, it was clear that even the optimized controller would never perform adequately working alone. Therefore attention was turned to a controller which could both compensate for the loss in shaft speed resulting from the voltage perturbations and still allow a minimum input power point to be reached. It was recognized that the loss of rotor speed could be corrected by increasing the frequency of the stator voltages and currents, while the minimum power input point can be obtained by perturbing the voltage. Furthermore, a correlation of ω_r impedance suggested that if the change in input impedance were known for a particular change in synchronous frequency ω_e and voltage V_s, then approaching an optimum impedance as rapidly as possible should achieve both the minimum input power and the correction of the drop in ω_r. This led us to develop a preliminary controller concept for a frequency perturber, shown here in block diagram form in conjunction with the existing voltage perturber.
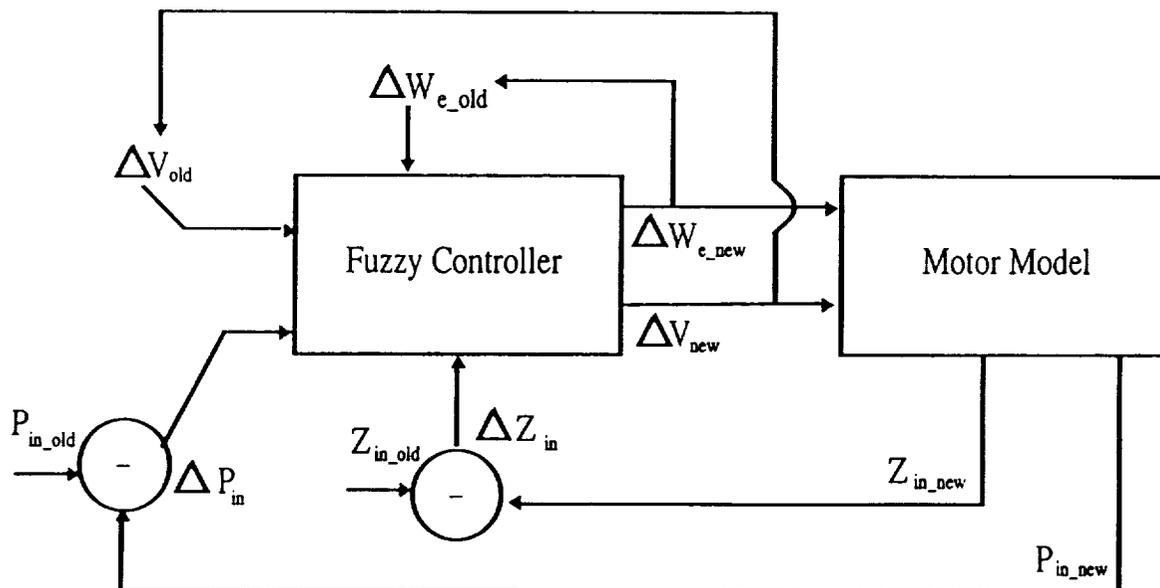

Figure 6. Dual Variable Fuzzy Logic Controller for AC Induction Motor

Thus the set of rules which perturbed the voltage were augmented by another set of rules which perturbed ω_e using the previous value of $\Delta\omega_e$, $\Delta\omega_{e\text{-old}}$, and ΔZ_{in}. This new fuzzy rulebase, which has 9 rules, fires simultaneously with the 13 rules of the SVFLC. The rule-base for inference of the synchronous frequency is shown in the following table.

RULES

1)   IF $\Delta\omega_{e\_old}$ IS P AND ΔZ_{in} IS N THEN $\Delta\omega_e$ = P

2)   IF $\Delta\omega_{e\_old}$ IS Z AND ΔZ_{in} IS N THEN $\Delta\omega_e$ = P

3)   IF $\Delta\omega_{e\_old}$ IS N AND ΔZ_{in} IS N THEN $\Delta\omega_e$ = N

4)   IF $\Delta\omega_{e\_old}$ IS P AND ΔZ_{in} IS Z THEN $\Delta\omega_e$ = Z

5)   IF $\Delta\omega_{e\_old}$ IS Z AND ΔZ_{in} IS Z THEN $\Delta\omega_e$ = Z

6)   IF $\Delta\omega_{e\_old}$ IS N AND ΔZ_{in} IS Z THEN $\Delta\omega_e$ = Z

7)   IF $\Delta\omega_{e\_old}$ IS P AND ΔZ_{in} IS P THEN $\Delta\omega_e$ = N

8)   IF $\Delta\omega_{e\_old}$ IS Z AND ΔZ_{in} IS P THEN $\Delta\omega_e$ = N

9)   IF $\Delta\omega_{e\_old}$ IS N AND ΔZ_{in} IS P THEN $\Delta\omega_e$ = P

Table 2. Added Rules for Control Frequency

The symbols P, N, and Z stand respectively for positive, negative and zero. Limits on the membership functions were developed as before by analyzing output data from the simulator and setting the limits. The preliminary output membership functions for $\Delta\omega_e$ are illustrated in the following figure.
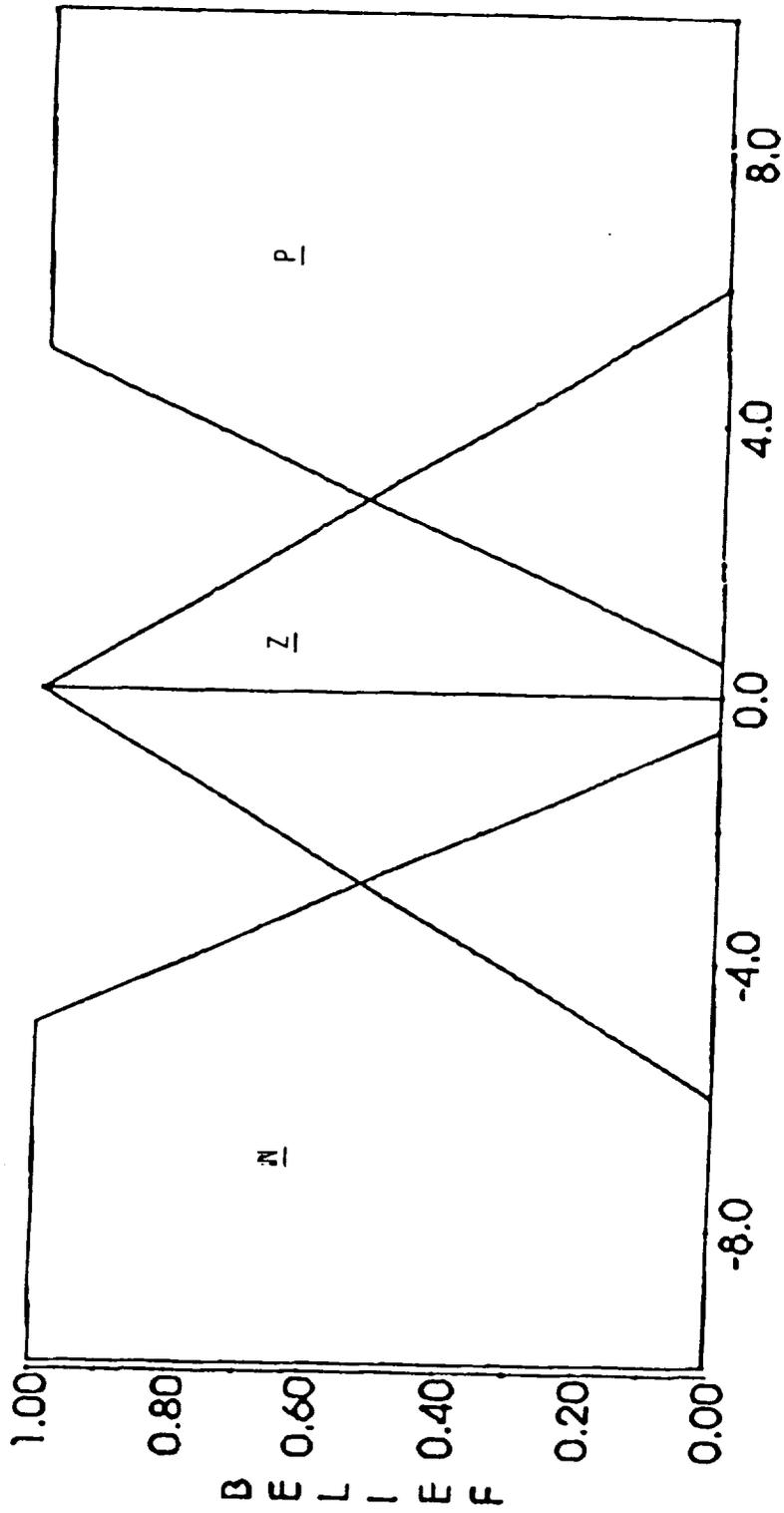
Figure 7. Membership Functions for ΔW_e

Hz x 10^3

As in the previous work, a control surface was generated and could be used to tune the membership functions. Note in the control surface graph that there are certainly abrupt changes in $\Delta\omega_e$ for certain values of ΔZ_{in} and $\Delta\omega_{e\ old}$.
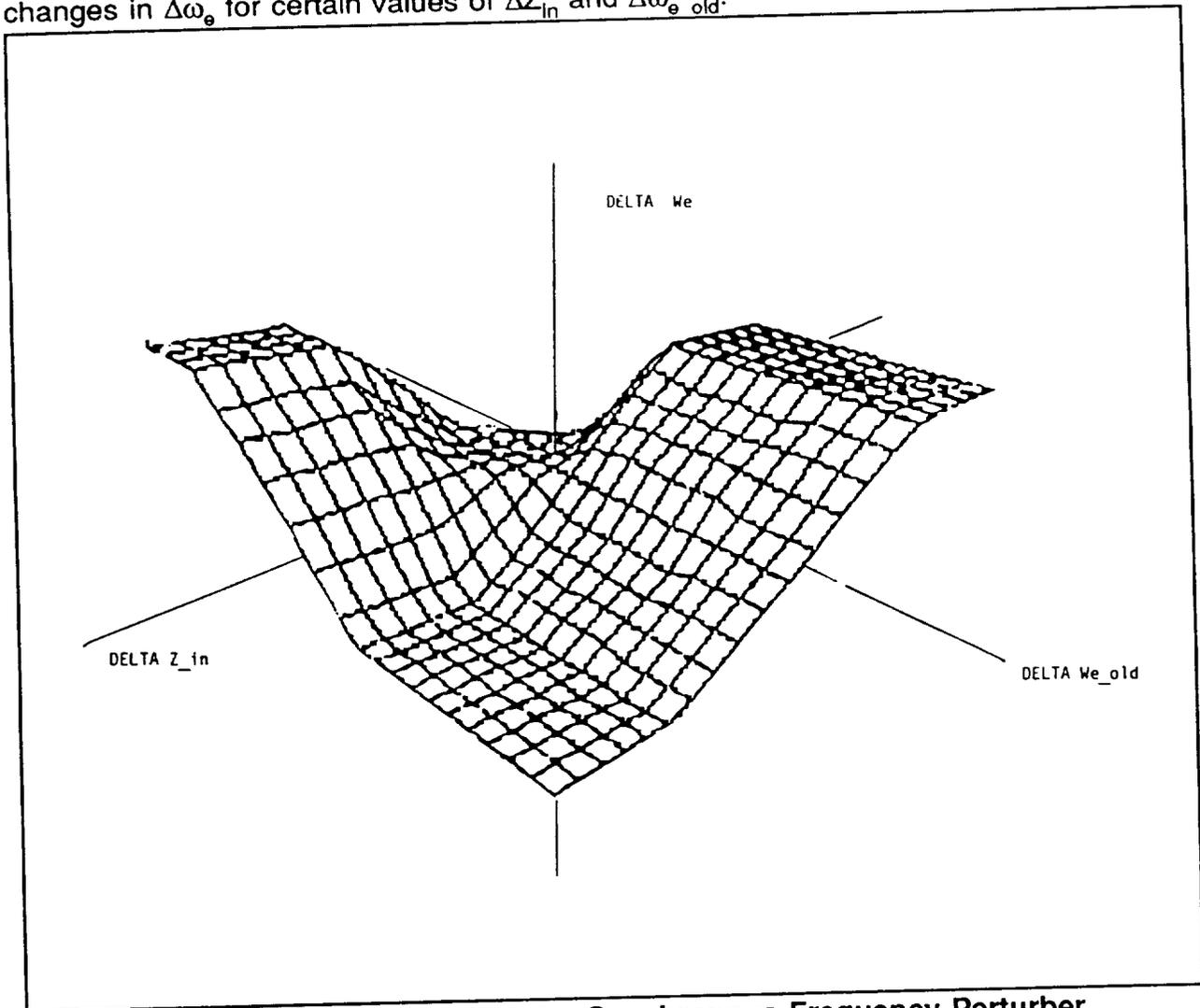
Figure 8. Control Surface for Synchronous Frequency Perturber

Fuzzy Efficiency Optimization using Indirect Vector Control

A parallel effort is taking place to provide fuzzy efficiency optimization for induction motors which use indirect vector or field-oriented control of induction motors rather than PWM. Indirect vector control is another approach to the control of ASD/motor combinations which controls current rather than voltage. This type of energy optimizer emphasizes the suppression of transient phenomena in the motor, and is focused more on dynamic process control applications (lathe motors, steel mill rolling, etc) than the steady state controller. The controller is illustrated in Figure 9.

Figure 8. Fuzzy Efficiency Optimization for Indirect Vector Control.

In indirect vector control, the motor is modeled using a change of variables which represents the state variables of the motor in terms of two magnetically decoupled equivalent circuits, generally referred to as the d-q representation of a motor. When vector control is employed the currents i_{ds} and i_{qs} control the flux and the torque of the machine, respectively.

Fuzzy efficiency optimization for indirect vector control utilizes the same type of minimum input power search scheme outline above, however rather than perturbing the stator

voltage, the rotor flux λ_r is changed by perturbing the current i_{ds}. Then P_{In} is measured to see if the input power has changed. In the event that it has, a set of fuzzy rules computes a new value of Δi_{ds}, based on ΔP_{In} and the previous value of Δi_{ds}, referred to as $L\Delta i_{ds}$. Then P_{In} is measured again and the process is repeated. A table showing the preliminary rules relating Δi_{ds} to ΔP_{In} and $L\Delta i_{ds}$ is shown in the following table.

RULES

1. If LDids is N and ΔPi is PB, then LDids is PB.

2. If LDids is N and ΔPi is PM, then LDids is PM.

3. If LDids is N and ΔPi is PS, then LDids is PS.

4. If LDids is N and ΔPi is ZE, then LDids is ZE.

5. If LDids is N and ΔPi is NS, then LDids is NS.

6. If LDids is N and ΔPi is NM, then LDids is NM.

7. If LDids is N and ΔPi is NB, then LDids is NB.

8. If LDids is P and ΔPi is PB, then LDids is NB.

9. If LDids is P and ΔPi is PM, then LDids is NM.

10. If LDids is P and ΔPi is PS, then LDids is NS.

11. If LDids is P and ΔPi is ZE, then LDids is ZE.

12. If LDids is P and ΔPi is NS, then LDids is PS.

13. If LDids is P and ΔPi is NM, then LDids is PM.

14. If LDids is P and ΔPi is NB, then LDids is PB.

Table 3. Fuzzy Rules for Efficiency Optimization with Indirect Vector Control.

A total of 14 IF-THEN rules are defined for the energy optimizer utilizing indirect vector control.

Figure 10 illustrates the preliminary membership functions derived from observation of results obtained from computer simulations.
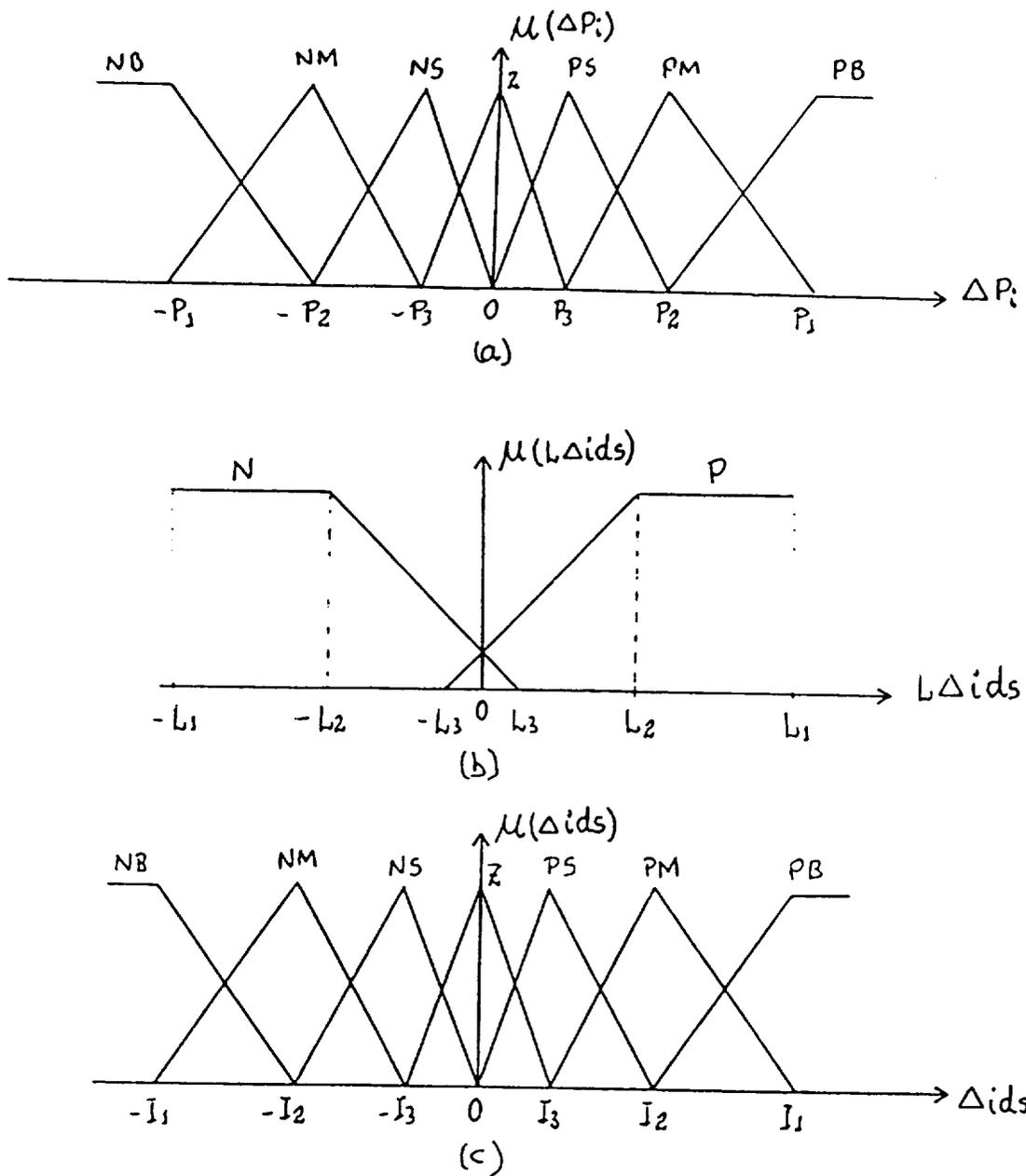
Figure 10. Preliminary membership functions for fuzzy efficiency controller: (a) change in input power; (b) last change in current i_{ds}; (c) new change in current i_{ds}.

The membership functions were developed using variables normalized in the interval [-1,1], hence the magnitudes of the endpoint variables (+/- P_1, +/- L_1, +/- I_1)across the domain of the membership functions is 1. The values of the interior limits on the membership functions have not at present been arrived at.

The max-min method of inference is being applied to obtain truth values of any particular rule, hence the design of the fuzzy membership functions for $L\Delta i_{ds}$ provides a degree of limitation for the truth value of a rule when $L\Delta i_{ds}$ is "negative small" or "positive small", even though there is no membership function specifically for those fuzzy values. This avoids using multiple membership functions in a place where fewer will perform the same job, and thereby reduces the size of the fuzzy rulebase. The overlap between the positive and negative membership functions assure that division by 0 will not occur in the height defuzzification method used by UT, since even if $L\Delta i_{ds}$ is 0, it will have a non-zero degree of belief in either the 'P' or 'N' region.

Reducing the flux to achieve minimum input power has an effect similar to that of reducing voltage in the previous controller. The shaft speed will drop. We have found that this can be compensated for by a change in the torque component of current i_{qs}. This is a function of the change in i_{ds}. After a change in the value of i_{qs} is made (which is not a fuzzy operation) fuzzy efficiency optimization is not reapplied until the machine has returned to steady-state condition, which is determined by comparing the sum of the absolute values of the last three rotor speed errors ($\Delta\omega_r$) to a tolerance value of 1 rad/sec. At that time a new value of Δi_{ds} is computed by the fuzzy efficiency optimizer and the cycle repeats. Even after optimum efficiency has been reached, this steady-state condition is checked for periodically in order to determine that no process disturbance has taken place which would require the controller to act in order to produce the required torque output or required speed.

All rules and membership functions are being tuned using computer simulation and by testing the controller in a laboratory setting. The following diagram shows the overall scheme of the laboratory setup.

Microprocessor
(or Programmable Microchip)
* Efficiency Optimization Control
* Fuzzy Logic
* Data Acquisition
* Motor Simulation

Chip

Developed Torque

Motor Load Signal

Stator Temperature

Dynamometer Controller

Feedback
* Voltage
* Current
* Frequency
* Power

Control Signals
* Voltage/Current
* Frequency

DC Power

Line Power (230 VAC)

Adjustable Speed Drive

Adjusted AC Voltage,

Current, Frequency

AC Induction Motor

Optical Shaft Encoder

Flexible Coupling

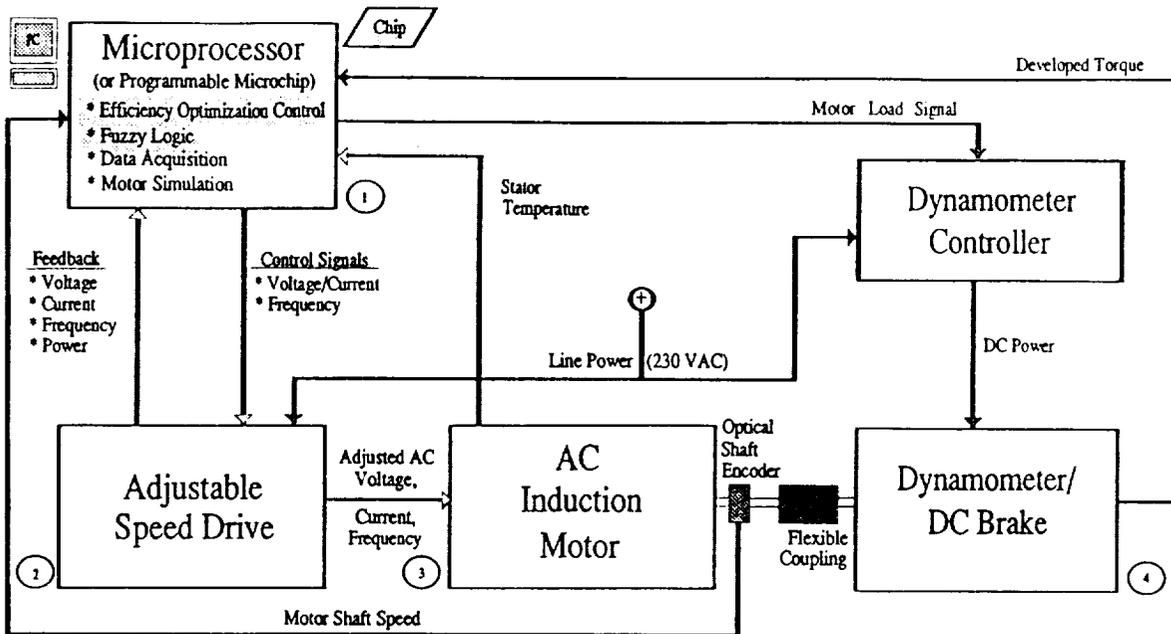**Dynamometer/ DC Brake**

Motor Shaft Speed

Figure 11. Motor Laboratory System

The fuzzy rules are executed in a 486/33 MHz from code compiled with other C routines, which also monitor system information via a data acquisition board, and communicate with the ASD to alter the ASD voltage and frequency output. The same code also directs an analog output on the data acquisition board to vary the strength of the field in the DC brake via the dynamometer controller, thus simulating various degrees of load on the motor.

Summary

Computer simulations have shown that a fuzzy controller which optimizes the use of energy by a motor/ASD combination can be developed. To be truly effective, the controller should alter both the stator voltage and stator frequency while maintaining the output power required of the motor/ASD system for the drive at hand. Energy efficiency optimization can be applied not only to drives which produce sinusoidal PWM output, but to indirect-vector controlled drives as well.