

APPLICATION NOTES

Using Fuzzy Logic in Control Applications: Beyond Fuzzy PID Control

Stephen Chiu

A substantial amount of literature on fuzzy control deals with the use of fuzzy rules to implement nonlinear proportional-integral-derivative (PID) type control. As a result, many control engineers are led to believe that using fuzzy rules to implement nonlinear PID control is the prime use of fuzzy logic for control. However, when we examine commercial products in which fuzzy control is said to be incorporated, we rarely see fuzzy logic being used to implement nonlinear PID control; fuzzy logic is used mostly to handle high-level control functions that traditional control methods do not address.

This article discusses different ways that fuzzy logic can be used in high-level control functions. Specifically, we examine the use of fuzzy logic for supervisory control, for selecting discrete control actions, for identifying the operating environment, and for evaluating controller performance. The purpose of this article is to stimulate the use of fuzzy logic to provide new control functions that are outside the domain of traditional control — where fuzzy control is likely to provide the greatest payoff.

Introduction

Much of fuzzy control research is focused on the set-point regulation problem, where the control objective is to drive a process variable (e.g., motor shaft position, oven temperature) to a commanded set-point. If one reads a paper on fuzzy control, chances are the paper will describe a fuzzy controller with set-point error and error change as its inputs, and the output is an actuator command or a change in actuator command. The fuzzy controller would

execute control rules of the form: “if set-point error is positive big and error change is positive small, then actuator output is negative big.” When used in this way, fuzzy control is not much different from conventional PID (proportional-integral-derivative) control — it is solving the same set-point regulation problem addressed by PID control and solving it in essentially the same way as PID control, except that fuzzy control provides a nonlinear input/output mapping. Hence, fuzzy control is often viewed as a form of nonlinear PID control, and comparisons of fuzzy control versus conventional PID control abound in literature. Many engineers lose interest in fuzzy control after finding the performance improvement offered by fuzzy PID control cannot offset the increased complexity in computation and controller tuning, or after finding nonlinear PID control can be more efficiently implemented through other mechanisms (e.g., gain scheduling or look-up table) than through fuzzy rules. Conventional PID control is well-established and can satisfy the performance requirements of most set-point regulation problems at minimal cost; there is little incentive to switch from conventional PID control to a more complex, nonlinear form of PID control unless the conventional controller is doing an unsatisfactory job. Hence, the fuzzy PID controller that is ubiquitous in technical literature rarely appears in actual commercial applications; commercial applications of fuzzy control are largely focused on high-level, task-oriented control rather than set-point regulation.

The misconception in equating fuzzy control with nonlinear PID control has

steered many engineers away from exploiting the full potential of fuzzy logic in control applications. The purpose of this article is to point out the many ways that fuzzy logic can be used in control applications beyond fuzzy PID control. In particular, the emphasis here is on the use of fuzzy logic to perform high-level control functions that fall outside the domain of conventional control methods. We will examine industrial applications where fuzzy logic was employed for supervisory control, for selecting discrete control actions, for identifying the operating environment, and for evaluating controller performance.

Supervisory Control

Fuzzy control in the form of nonlinear PID control has not found much acceptance in industry, because conventional PID control is well entrenched, simpler, low cost, and works satisfactorily for most applications. For the instances where fuzzy logic is applied to set-point regulation, it is typically used in a high-level module that supervises a conventional PID controller. Here we give several examples to illustrate different forms of fuzzy supervisory control.

The temperature controller produced by Yokogawa Electric [1] is a good example of how fuzzy logic can be used for supervisory control. Temperature control usually involves processes that have a long time delay; for many processes, it is also imperative that the temperature does not overshoot the desired set-point. However, it is difficult to avoid overshoot when a process has a long time delay, except by using low feedback gains, which results in slow system response. In Yokogawa

Electric's temperature controller, fuzzy logic is used to determine artificial set-points that are fed to a conventional PID controller. The control architecture is shown in Figure 1. The PID controller is allowed to have high feedback gains for fast system response. As the fuzzy supervisory module detects impending overshoot, it "fools" the PID controller by commanding the PID controller to aim for a temperature value that is somewhat lower than the actual set-point. As the temperature rises to (and overshoots) the artificial set-point, the fuzzy module gradually raises the artificial set-point toward the actual set-point. In this way, the fuzzy supervisory module leads the PID controller along a temperature trajectory that can quickly reach the actual set-point without overshoot.

In a motion controller produced by Allen-Bradley, fuzzy logic is used to supervise the automatic tuner of a conventional PID controller [2]. The tuner observes the system response and automatically adjusts the PID controller feedback gains during successive tuning cycles to obtain desired system response characteristics. To facilitate fast convergence to the optimal gain values, and to protect the system against incorrect gain changes, a fuzzy supervisory module scales the output of the tuner (the gain adjustment

commands) based on the resultant system performance (see Figure 2). The fuzzy module adaptively scales the tuner's output based on the amount of performance improvement after each tuning cycle and the consistency of the performance improvement over the past few tuning cycles. The tuner's output is scaled up if the system performance is consistently improving, and scaled down if the tuner becomes ineffective in further improving performance or if the performance vacillates.

In a steam turbine control application at General Electric, a fuzzy supervisory module is used to combine the output of several conventional PID controllers [3]. The turbine control system employs three PID controllers for regulating the turbine temperature, speed, and stress, respectively. However, there is only one control actuator (the bypass valve) for regulating these three parameters. Therefore, the different, often conflicting actuator commands from the three PID controllers must be resolved into a single command. The fuzzy supervisory module assigns weights to the different PID controller outputs based on the high-level control objective specified by an operator and on the current system state (temperature, speed, and stress). For example, if the objective is to prewarm the turbine as fast as possible, then temperature control would be given higher priority than speed and stress control unless the speed or stress are significantly misbehaving. This control architecture is shown in Figure 3.

In most process control applications, a human operator must determine the set-points for numerous PID controllers and periodically adjust the set-points to adapt to changing process conditions. Another type of fuzzy supervisory control involves converting the human operator's knowledge into a set of fuzzy rules, and thus creating a high level controller that automatically determines the set-points for the low-level PID controllers. Froese et al. [4] describes an example of this type of fuzzy supervisory control applied to slurry treatment.

The capability of a control system can be greatly enhanced by adding a supervisory module to complement conventional control algorithms. The implementation of intelligent supervisory functions is usually straightforward using fuzzy logic. The examples described above provide only a glimpse of the possibilities; other examples of fuzzy supervisory control can be found in [5].

Selection of Discrete Control Actions

Control problems that require the selection of discrete control actions, such as choosing to turn left or right, are not addressed by control theory. This type of control problem is surprisingly common, and each application is open to novel solutions simply because there is no standard method for handling these problems. In other words, they are ripe for the application of fuzzy logic. The control of automatic transmission in automobiles is one such problem (i.e., choosing to shift up, shift down, or stay in the current gear).

Conventional automatic transmission selects shift action based on only the vehicle speed and throttle opening. Figure 4 shows a typical shift pattern for the gears as a function of the vehicle speed and throttle opening. In general, increasing speed and/or decreasing throttle opening lead to higher gears, while decreasing speed and/or increasing throttle opening lead to lower gears. This simple shift selection function does not consider the many other factors that affect a human driver's shift action (e.g., type of road and the road incline) and therefore the behavior of the automatic transmission often does not match the driver's intention. For example, if the driver releases the gas pedal (decreases throttle opening) to coast down a steep hill, the automatic transmissions will typically shift to a higher gear instead of lowering the gear to provide engine braking torque. To address this deficiency, Nissan Motors has developed a fuzzy automatic transmission controller that provides more intelligent selection of the shift action [6].

Nissan's fuzzy automatic transmission controller selects shift action based on more input information than a conventional automatic transmission controller. The inputs to the fuzzy controller are the vehicle speed, throttle opening, change in speed during the last 2 seconds, change in speed during the last 5 seconds, change in throttle during the last clock period, change in throttle during the last 2 clock periods, and an estimate of the vehicle's running resistance. For each possible gear, a set of fuzzy membership functions is defined for these input variables; the membership functions describe the specific condition under which the particular gear should be used. For example, the set of membership functions for gear 2 would describe the range of speed, throttle opening, change

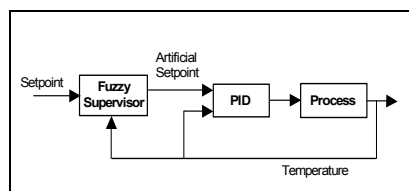


Fig. 1. Conventional PID control is assisted by a fuzzy supervisor to prevent overshoot.

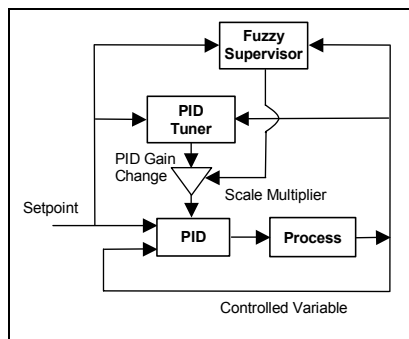


Fig. 2. A fuzzy supervisor scales the output of a PID tuner based on the effectiveness and consistency of the tuner in improving PID controller performance.

in speed, change in throttle opening, etc., that is appropriate for gear 2. The fuzzy controller evaluates the degree to which the present driving condition matches the condition defined for each gear, and thus obtains a measure between 0 and 1 that indicates the suitability of each gear for the present condition.

Two additional sets of fuzzy membership functions are defined to describe suitable conditions for upshift and downshift, respectively. The fuzzy controller also evaluates, according to these membership functions, the degree to which the present driving condition calls for upshifting and downshifting. Let the degree of suitability for using the i 'th gear be denoted by G_i , the degree of suitability for upshift be denoted by G_{up} , and the degree of suitability for downshift be denoted by G_{down} ; the fuzzy controller determines whether to perform an upshift or a downshift by evaluating the following function:

$$S = \frac{G_i * i + G_{up} * G_{i+1} - G_{down} * G_{i-1}}{G_i * i}$$

where i is the present gear number. The controller commands an upshift if S is greater than 1 by some threshold, and commands a downshift if S is less than 1 by some threshold. Thus, in order to command an upshift, the suitability of the higher gear and the suitability of upshift must both be high. The gear number i is cleverly included in the evaluation function to induce a preference to remain in the same gear as the gear becomes higher.

In addition to the key point that this control application requires the selection of discrete control actions, another notable point is that this fuzzy controller does not use any fuzzy "if-then" rules. In this application we see that only fuzzy membership functions are employed to obtain a measure of the degree of matching between conditions; and the degrees of matching are used as parameters in an analytical criterion function for decision making. Hence, fuzzy control does not necessarily involve explicit "if-then" rules; however, the analytical criterion function may be viewed as an implicit rule.

Identification of Operating Environment

Typically a simple control law can provide good performance within only a limited range of operating conditions. Thus, many control systems require switching between different control laws as the operating condition changes. Gain

scheduling, whereby the controller feedback gains are switched to different values as the plant state moves from one operating region to another, is commonly used in conventional control systems to compensate for the limitations of linear control laws.

For set-point regulation problems, switching between different control laws is usually a straightforward function of the measured plant states (e.g., speed, altitude, temperature). However, at higher levels of control, switching between different control laws, or control strategies, is based on high level characterizations of the operating environment (e.g., driving on a highway or city street, cooling a room full of people or an empty room). Because the high level characteristics of interest are often not directly measurable, the characteristics often need to be inferred from indirect sensor measurements. In such cases, fuzzy logic is extremely useful for encoding the heuristics to infer the characteristics.

The use of fuzzy logic to characterize the operating environment is illustrated by another automatic transmission controller developed by Nissan Motors

[7]. This alternative automatic transmission controller holds a set of conventional shift patterns that are optimized for different driving environments (e.g., highway driving, mountain driving, city driving), and selects the appropriate shift pattern according to the driving environment. For example, human drivers prefer to maintain a constant gear when driving on a winding road, although the throttle must change constantly. Therefore, driving on a winding road calls for a shift pattern that is less sensitive to throttle change than a shift pattern designed for highway driving. In this automatic transmission controller, fuzzy logic is not used to directly control shifting, but to identify the driving environment so that the appropriate conventional shift pattern can be selected to control shifting.

Because there are no suitable sensors for identifying the driving environment, Nissan engineers used fuzzy logic to infer the driving environment from the driver's accelerator input. For example, the accelerator input tends to be small and constant when driving on a highway, while the accelerator input fluctuates

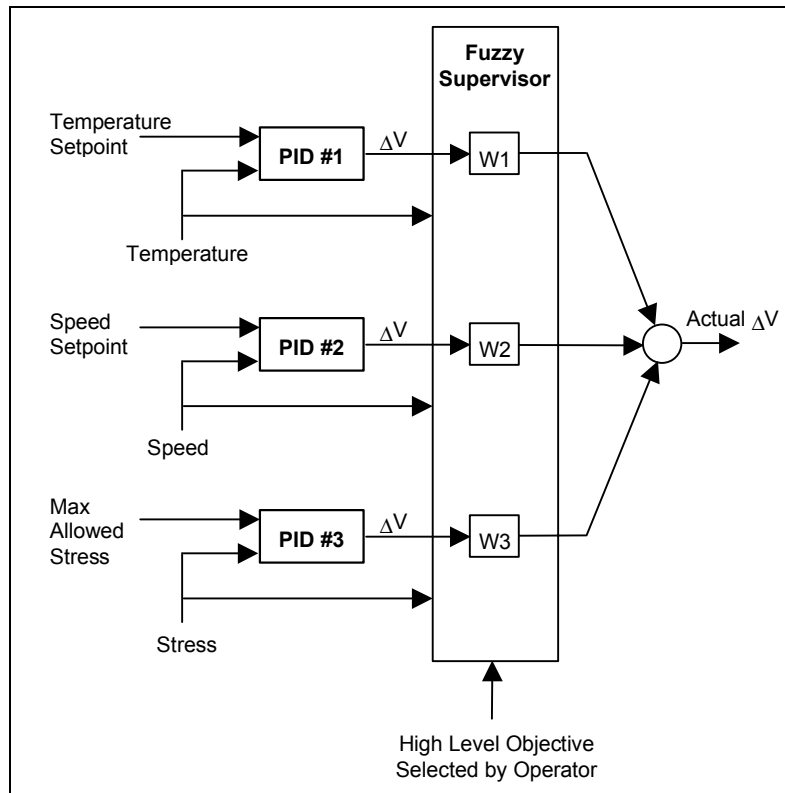


Fig. 3. A fuzzy supervisor assigns weights to the output of different PID controllers according to the current system state and the control objective specified by a human operator

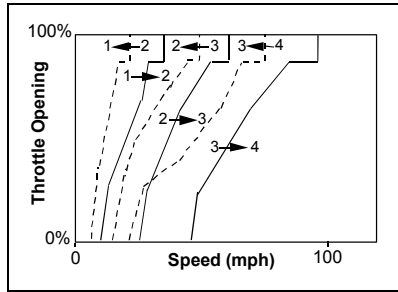


Fig. 4. Typical shift pattern for conventional automatic transmissions. The notation 2→3, for example, indicates shifting from gear 2 to gear 3.

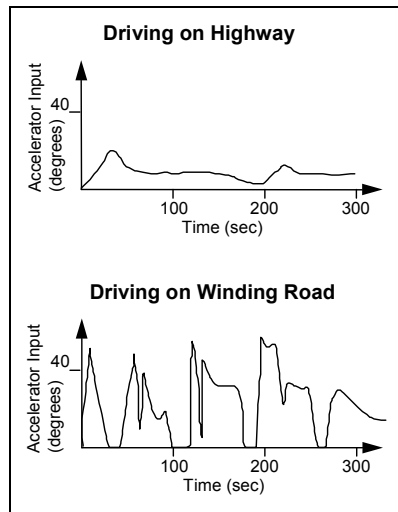


Fig. 5. A driver produces distinctive accelerator input behaviors when driving on a highway versus driving on a winding road.

wildly when driving on a winding road (see Figure 5). Fuzzy membership functions were defined to characterize the accelerator input, variance in accelerator input, and vehicle speed that the driver produces in each driving environment (see Figure 6). The controller evaluates the degree to which the accelerator and speed data match the condition associated with each driving environment. Based on the driving environment with the highest degree of match, the appropriate shift pattern is applied to control shifting.

In addition to using fuzzy logic to infer the operating environment, another interesting aspect of this application is the use of the human driver as the environment sensor. Creatively inferring information from indirect sensors (often sensors that seem unrelated to the characteristic that we want to measure) is

at the heart of many successful fuzzy control applications.

The fuzzy controlled vacuum cleaner and washing machine from Matsushita Electric both incorporate creative use of sensors to infer characteristics of the environment. The Matsushita vacuum cleaner automatically adjusts suction power and beater bar speed based on the amount of dust and floor type. An infrared LED sensor in the vacuum cleaner counts the number of dust particles that pass through the air tube. The floor type is inferred from the rate of change in the number of dust particles counted; the number of dust particles tends to decrease slowly when vacuuming on a thick carpet (more difficult to pick up dust), decrease faster on a normal carpet, and decrease rapidly when vacuuming on a wood floor (see Figure 7).

The fuzzy controlled washing machine from Matsushita has an infrared LED sensor that measures the turbidity of the exiting water. If the turbidity increases rapidly as a function of time, then it is inferred that the clothes were soiled by mud (which washes off easily). If the turbidity increases slowly, then it is inferred that the clothes were soiled by oil.

The “intelligence” of a controller is dependent on the amount of information available to the controller. When there is a lack of directly measurable information, our tendency is to try to design a robust controller that provides acceptable performance under all variations of the unknown (e.g., an automatic transmission shift pattern that works adequately for all driving environments). Instead of accepting merely adequate performance, we should challenge ourselves to find ways to obtain the information needed for optimal performance. In many cases, the information needed to optimize control choices can be inferred from indirect sensor measurements. Creativity of the system designer in inferring information from indirect sources, coupled with the power of fuzzy logic for easily encoding the heuristics, plays an important role in implementing truly intelligent controllers.

Define Optimality Measure

How do we compare two system behaviors and judge which one is better? This issue arises when a control engineer must specify an optimality measure from which to search for the “best” control law. The optimality measure defines the ideal system behavior and provides a

quantitative measure of the closeness to the ideal behavior. Analytic optimality measures, such as the quadratic cost function, give the human designer a very limited language for expressing how to judge which system behavior is closer to the ideal. As an example, consider the common use of the root-mean-square (RMS) error as an optimality measure in system modeling. The ideal system behavior is one that produces zero error; however, in judging which system behavior is closer to the ideal, a designer may want to consider not only the RMS error, but also the maximum error, the average percentage error, and whether the errors occur on the conservative side. Complex trade-offs between these error types may be involved in selecting the “best” system behavior. The RMS error is only a rough approximation of how the human designer judges optimality.

The key point here is that a system considered optimal according to an analytic measure is not necessarily optimal according to human judgment. It is also important to keep in mind that analytic optimality measures are only mathematical tools for expressing what a designer wants a system to do; the true judge of optimality is the human designer, not the numerical value produced by the analytic measure. Unfortunately, we tend to choose an optimality measure based on whether it

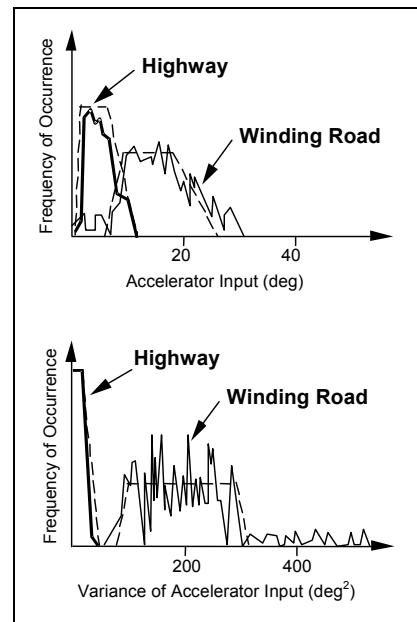


Fig. 6. Fuzzy membership functions characterize the accelerator input and variance in accelerator input produced by the driver in different driving environments.

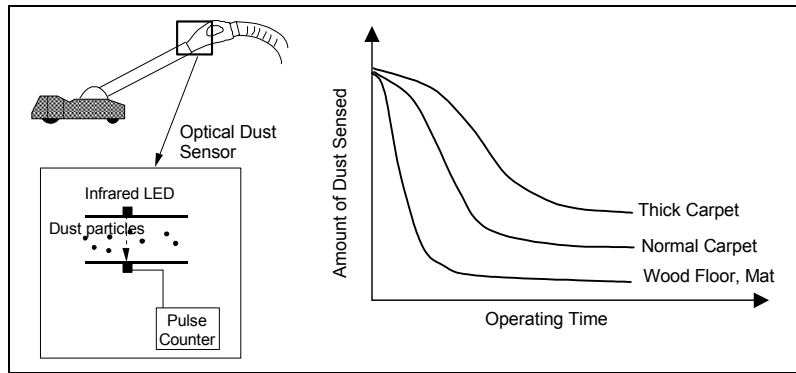


Fig. 7. The fuzzy vacuum cleaner from Matsushita infers the floor type from the rate of decrease of dust.

has nice mathematical properties, not based on whether it can express what is in the designer's mind.

The use of fuzzy logic to express optimality measures is perhaps the most valuable benefit that fuzzy logic brings to control applications. Fuzzy membership function is a natural framework for expressing the human designer's conception of the ideal system behavior and of how to measure closeness to the ideal behavior. Fuzzy logic can also provide smooth transitions in the optimality measure to emphasize certain control objectives as the operating condition changes.

The subway train control system developed by Hitachi [8] is an example where fuzzy logic was applied to evaluate the optimality of control actions. For this particular system, the train's acceleration/deceleration is controlled by setting a power lever and a brake lever at different notch positions. Changing the notch position frequently

or in large increments creates an uncomfortable ride. In addition to riding comfort, the controller must consider safety, on-time arrival, energy consumption, and stopping the train accurately at a specified position along the station platform. Optimizing train control requires trade-off between these multiple, often conflicting objectives.

The control method is based on predicting the outcome of each possible control action and then choosing the action that corresponds to the optimal outcome. A simple simulation of the train dynamics is used to predict the resultant speed, stopping position, and time of arrival for each possible choice of notch position. The optimality of each predicted outcome is then rated by a set of fuzzy rules, taking into account factors such as the degree to which the train is on schedule, the degree of safety of the predicted speed, closeness of the predicted stopping position to the desired stopping position, amount of

notch change, and the elapsed time since the last notch change. Here fuzzy rules rate the different control outcomes by balancing multiple objectives in a way that reflects human's sensibility of "optimal". The notch position associated with the optimal outcome is then selected as the notch command.

In many control applications we know how we want a system to behave but find it difficult to express the desired behavior in an analytic formula. Fuzzy logic is a powerful tool for expressing human preferences and making the control system behavior accurately reflect these preferences.

Conclusion

There are many ways that fuzzy logic can be used in a control system to enhance capabilities and reduce operating cost. The high payoff applications are usually not in replacing a conventional PID controller with a fuzzy PID controller, but in using fuzzy logic at higher levels of control. The previous application examples illustrate the wide range of opportunities that exist and the many different ways that fuzzy logic can be used to complement conventional controllers. A designer who wishes to exploit the full potential of fuzzy logic must maintain a broad view of the different aspects of a control problem and be creative in applying fuzzy logic where appropriate.

The essence of fuzzy logic is that *it lets you express what's on your mind*. It is not surprising that most commercial applications of fuzzy control has been for high level, task-oriented control, where there are no standard analytic solutions but ample human intuition.

References

- [1] Yokogawa UT15/UT14 Digital Indicating Controllers, technical information publication # TI 5B4A7-01E, Yokogawa Electric, Tokyo, Japan, 1990.
- [2] S. Chand, "On-line, self-monitoring tuner for proportional integral derivative controllers," *Proc. IEEE Conf. on Decision and Control*, Brighton, England, Dec. 1991.
- [3] P. Bonissone, V. Badami, K. Chiang, P. Khedkar, K. Marcelle, and M. Schutten, "Industrial applications of fuzzy logic at General Electric," *Proceedings of the IEEE*, vol. 83, no. 3, pp. 450-465, March 1995.



Stephen L. Chiu is a Research Scientist at Rockwell Science Center. He received the B.S. degree in mechanical engineering and nuclear engineering from U.C. Berkeley in 1983 and the S.M. degree in mechanical engineering from M.I.T. in 1985. He has conducted research in robotics, fuzzy control, and neuro-fuzzy systems. His current work is focused on neuro-fuzzy systems and on managing a "smart" motor development project. He is presently an associate editor of the *Journal of Intelligent and Fuzzy Systems* and a member of the board of the North American Fuzzy Information Processing Society. He served previously as an associate editor of the *Control Systems Magazine* and as a co-guest editor of the *Proceedings of IEEE* in a special issue on fuzzy logic.

The author is with Rockwell Science Center, 1049 Camino Dos Rios, Thousand Oaks, CA 91360 (slchiu@rsc.rockwell.com). Portions of this article were published in the proceedings of the IEEE/IFIP International Conference on Information Technology for Balanced Automation Systems, Prague, August 1998. These portions are used with permission from Kluwer Academic Press.

- [4] T. Froese, C. von Altrock, and S. Franke, "Optimization of a water-treatment system with fuzzy logic control," *Proc. 3rd IEEE Int'l Conf. on Fuzzy Systems*, Orlando, USA, 1614–1619, June 1994.
- [5] K. Passino and S. Yurkovich, *Fuzzy Control*, Addison-Wesley Longman, 1998.
- [6] H. Takahashi, "Fuzzy control system for automatic transmission," U.S. Patent #4,841,815, issued June 27, 1989.
- [7] H. Takahashi, "A method for predicting the driving environment using fuzzy reasoning," *Proc. IEEE Round Table Discussion on Fuzzy and Neural Systems, and Vehicle Applications*, Tokyo, Japan, Nov. 1991.
- [8] S. Yasunobu and S. Miyamoto, "Automatic train operation system by predictive fuzzy control," in *Industrial Applications of Fuzzy Control*, ed. M. Sugeno, North-Holland, Amsterdam, pp. 1-18, 1985.