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FUZZY LOGIC CONTROL APPLICATION IN A NUCLEAR POWER PLANT

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Abstract: A group of multi-input-single-output fuzzy logic controllers are designed for a nuclear power plant to control turbine power, reactor pressure, and reactor water level based on input-output data from plant simulations with conventional PI controllers. Simulations show that fuzzy logic control may result in faster reference signal tracking and final value holding. Milder control actions of fuzzy controllers may reduce challenges to safety systems during transients. *Copyright © 2002 IFAC*

Keywords: fuzzy logic control, nuclear power plant, boiling water reactor, reactor control

1. INTRODUCTION

Since Zadeh first introduced fuzzy set concept in 1965 (Zadeh, 1965), there has been growing interest in fuzzy techniques and in their applications to difficult control problems, from academy to industry. Due to its easy-to-use characteristics and its robustness in performance, the fuzzy logic control (FLC) technique has been widely applied in many areas (Driankov, 1996), including fossil power plants (Moon and Lee, 2001). In nuclear industry, however, application of FLC presents a tremendous challenge. The strict safety regulations prevent researchers from quickly introducing novel fuzzy-logic methods. On the other hand, the application of fuzzy logic has a number of very desirable advantages over classical methods, e.g., its robustness and the capability to include human experience. For this reason, researchers keep working in this area. Since 1980s, there have been some hundreds of articles found discussing fuzzy logic applications in nuclear industry (Ruan, 1996; Heger, et al. 1995). FLC application for a single system have been successfully designed and implemented in some cases. The application of FLC to the 5-MWth Massachusetts Institute of Technology (MIT) research reactor was reported to be generally more robust than its analytic counterparts (Bernard, 1988). Ramaswamy, et al. (1993) developed a fuzzy controller using Kalman filter algorithm to automatically generate fuzzy rules to control reactor power so that the temperature response is improved. Arslan and Lee (1997) also designed a fuzzy controller to control a reactor power. The distinguishing feature of their work is that the robust stability analysis of the designed fuzzy controller is carried out with a Lur’e problem based approach. Lin and Yang (1998) described a fuzzy logic controller design for an advanced boiling water reactor (ABWR) plant water level control, whose performance was comparable to the conventional controller. However, most previous studies in FLC design for nuclear systems focus on single system, for reactor power control or water level control, etc., and the interactions among systems were not taken into consideration. There are cases that the system under control behaves well but the performance of other systems may not be improved or even be degraded. There is no paper in the literature that studies fuzzy logic control application to nuclear power plant overall control system, which can deal with all plant main variables simultaneously. The study described in this paper intends to fill out this blank.

In this paper, a group of fuzzy logic controllers are designed to take care of reactor power control, reactor level control and pressure regulation simultaneously for an ABWR nuclear power plant. Although each controller is oriented toward one single system, performances of other systems are also taken into consideration during the parameter tuning of each controller. The controllers are designed on the basis of input-output data from plant simulation with conventional PI controllers. To simplify fuzzy rule design for multi-input fuzzy controller, a methodology to combine input variables into two is employed so that one single rule table is sufficient for each controller design. Simulation results show that the application of FLC technique to the nuclear power plant overall control is feasible. Generally fuzzy logic controllers have comparable or better performance as conventional controllers. Fuzzy controllers can improve the system performance with respect to faster reference signal tracking capability, less overshoot/undershoot, etc.

2. PLANT MODEL DESCRIPTION

To demonstrate the feasibility of fuzzy logic control (FLC) technique application in nuclear power plant overall control, a simplified advanced boiling water reactor (ABWR) model developed in MATLAB SIMULINK® environment is used in this study. This model is the same as was used to design a robust controller by Shyu (2001), and it is similar to the model used by Lin and Yang (1998) to design a fuzzy logic controller for reactor water level control.

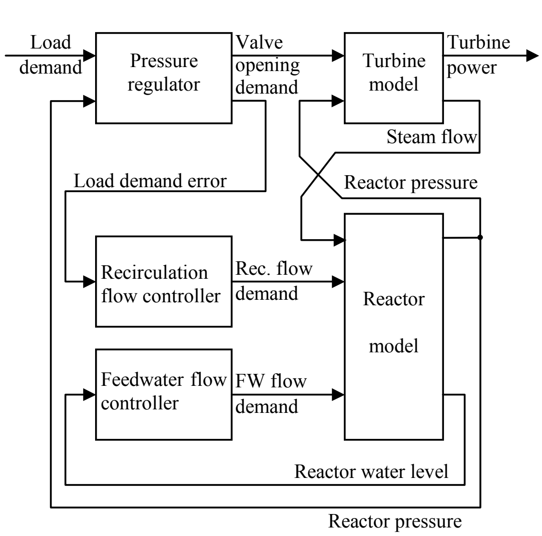

Fig. 1. Interconnections among ABWR model components.

Three main parts are contained in the model: 1) reactor model, which includes neutron and thermal hydraulic dynamics, 2) turbine dynamics, and 3) control system. The control system consists of three main subsystems: reactor power control, reactor water level control and pressure regulation. The interactions among these components are shown in Fig. 1. For a boiling water reactor, power control is implemented through reactor recirculation flow adjustment or control rod movement. In the 70-100% rated power range, which is of the interest in this study, the reactor is controlled only by recirculation flow adjustment on the basis of load demand error, which is sent from the pressure regulator block. Similar to fossil power plants, reactor water level control is controlled by adjusting feedwater flow rate and pressure control is carried out by adjusting the turbine throttle valve opening. All parameters in the model are normalized to rated conditions on a per unit basis.

3. FUZZY LOGIC CONTROLLER DESIGN

The objective of fuzzy logic controller design is to control the turbine power, reactor pressure and reactor water level simultaneously. The performance of these controllers is set to be comparable to or better than the existing conventional PI controllers in terms of reference signal tracking and final signal holding time, overshooting (undershooting) during transients, and control signal smoothness, etc.

Each of these controllers is a multi-input-single-output controller. However, during the design of each controller, the interactions of all these three controllers are considered. The overall structure of the controllers is a multi-input-multi-output controller as depicted in Fig. 2, which shows the connection of FLC with the plant.

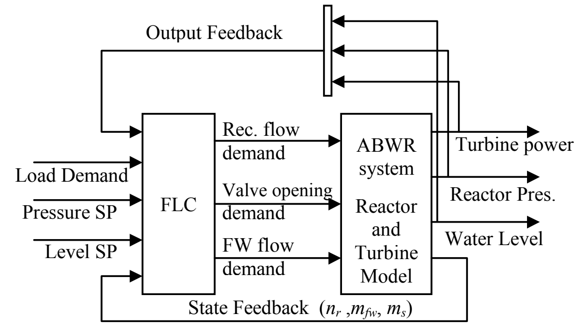

Fig. 2. Connection of fuzzy logic controller into the ABWR system. States fed back to the FLC are: n_r—neutron density; m_{fw}—feedwater flow; m_s—steam flow. SP: setpoint; FW: feedwater

3.1 General Issues

Data Acquisition. Knowledge acquisition is a very important step for fuzzy rule generation and for a successful design of an FLC. In this study, knowledge is obtained from plant simulation results with traditional PI controller, instead of from experienced operator. Simulation of the plant model is run with existing PI controllers and with appropriate perturbations to generate data. The coverage of data must be as complete as possible so that the obtained knowledge is meaningful and useful. Most importantly the maximum region of variables need to be reflected in the generated data. Usually bi-directional simulation is needed, for example, if simulation with a step change in load demand from 100% to 90% of rated power is performed, another simulation with step change from 90% to 100% in load demand also needs to be performed. Acquiring data from running existing PI controller mainly provides guidelines for FLC design and the generated fuzzy rules and control parameters are subject to be tuned for desired performance.

FLC structure. By introducing a methodology to combine FLC input variables into two variables, all three controllers share the same final structure: each FLC is a two-input-one-output PI-like controller, i.e., two inputs, namely, the error (e) and change of error (ce) of the main input over a time period of T, are the inputs to an FLC. T=0.5 second in this study for all three fuzzy controllers. Therefore, the fuzzy rule base is a two-dimensional rule table for each FLC.

Membership Function Selection. For computational efficiency, efficient use of memory, and performance analysis, a uniform representation of membership functions is required. In this study, the triangular-shaped function is employed. A typical diagram of membership functions of a term set of a fuzzy variable x, whose term set has seven elements {NB, NM, NS, ZE, PS, PM, PB}, is shown in Fig. 3, where p_1, p_2, ……, p_7 are peak points of corresponding membership functions. Since membership functions in the form as depicted in Fig. 3 are comprehensively used throughout this paper, a convention is used to simplify membership function expressions.

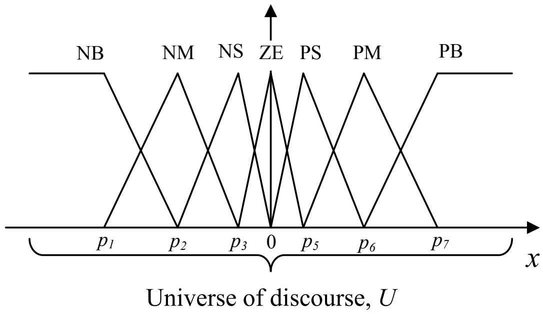

Fig. 3. Triangular membership functions of a fuzzy variable.

Observing Fig. 3, it is found that the membership function can be completely represented with three terms: 1) variable name x, 2) term set {NB, NM, NS, ZE, PS, PM, PB}, and 3) the peak value set $\{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}$—a set of peak values corresponding to fuzzy labels in the term set with the same order, where $p_4 = 0$ is not shown in the figure. Therefore, Fig. 3 can be simply expressed by the following convention, which will be used in the following text to represent membership functions without diagrams:

$$\begin{array}{cccccccc} x: & \text{NB} & \text{NM} & \text{NS} & \text{ZE} & \text{PS} & \text{PM} & \text{PB} \\ & p_1 & p_2 & p_3 & p_4 & p_5 & p_6 & p_7 \end{array} \tag{1}$$

Input-output mapping. In this study singleton fuzzification and centroid defuzzification method are used. Based on these methods and the selection of membership functions, the input-output relationship of a controller may be expressed as follows:

$$u^* = \frac{\Sigma_{l=1}^{M} \overline{u}^l (\mu_{B^l}(\overline{u}^l))}{\Sigma_{l=1}^{M} \mu_{B^l}(\overline{u}^l)} \tag{2}$$

where u^* is the FLC output; $\overline{u}^l$ is the center of the fuzzy set G^l, that is, the point in U at which the maximum membership function is given; $\mu_{B^l}(\overline{u}^l)$ is degree with which the l^{th} fuzzy rule is applicable; G^l is the fuzzy output from the l^{th} fuzzy rule base; and M is the number of fuzzy rules.

3.2 Feedwater Controller (FWC)

In this study, the basic method to collect data to generate fuzzy rules is to run simulations to get input-output data of a fuzzy controller. Lin and Yang (1998) developed a fuzzy controller to control reactor water level with a very similar method. In their study, the data required for generating fuzzy rules were the results of various instances of satisfactory manual control of an ABWR simulation model using trial-and-error method. This method was reported to be superior to that in their previous research. Since the ABWR model used by Lin and Yang is very close to the model used in this study, some of the results presented in their paper are used as the basis of the current FW FLC design.

In Lin and Yang's study, four variables are used as FLC inputs: water level error $e_l(kT)$ that is defined as the current water level minus the level setpoint, change in water level error $ce_l(kT)$, change in pressure $cp(kT)$ over a period of T, and flow mismatch between steam and feedwater flow $dfs(KT)$. The output is the change of feedwater flow $cu_{FW}(kT)$. The signals are generated at discrete time point kT, where k is the serial number. To generate input-output data, both water level setpoint change and load demand change were simulated. Physical domains of each variable are: $e_l(kT)$: [-0.6, 0.6]; $ce_l(kT)$: [-0.05, 0.05]; $cp(kT)$: [-0.04, 0.04]; $dfs(kT)$: [-0.06, 0.06]; cu_{FW} (kT): [-0.04, 0.04]. To make the fuzzy rule base better match the generated data, partition of physical domain of each variable to generate a term set is performed with the help of C-mean clustering method. A 4-dimensional fuzzy rule base that consists of five highly incomplete rule tables is generated.

The fuzzy controller described above results in comparable performance as the existing conventional PI controller for some cases. However, if the plant operating condition is different from what were used in the original paper, the controller may not perform smoothly, mainly due to the incompleteness of the fuzzy rule base, even though some fuzzy rules were added to the table with the intention to cover more operation domain. To solve this problem, one possible solution is to fill out all the blanks in the original table with intuition and common sense. But this would bring computational inefficiency, especially in real-time case, since the fuzzy rule is a 4-dimensional table, and the resulted controller is hard to tune.

In the current design, the same variables are employed and the physical domains of these variables are kept unchanged. All these variables are normalized by the upper boundaries of their corresponding physical domains. Normalized variables are denoted as e_{lr}, ce_{lr}, dfs_r, cp_r and cu_{fwr} for e_l, ce_l, dfs, cp and cu_{fw}, respectively.

In order to avoid designing a high-dimension, hard-to-tune controller, a simple 2-dimensional rule table is employed based on level error (e_l) and change of error (ce_l). The rationale for this simplification is: both reactor pressure change (cp) and feedwater/steam mismatch (dfs) are responsible for the trend in level change: if the reactor pressure is going down (cp<0) or more feedwater is entering the reactor than the amount of steam leaving the reactor (dfs>0), the water level tends to increase (ce_l>0) even though such a trend has not been observed (due to system delay), and vice versa. Therefore both cp and dfs can be used to predict the future behavior of water level change. Based on this observation, cp and dfs are combined into ce_l (change of water level). For the two-dimensional fuzzy rule table including error and change of error, change of error has the similar effect as the error on control actions, so the following algorithm is used in programming:

$$\overline{e}_{lr} = e_{lr} + a \cdot dfs_r - b \cdot cp_r, \quad \text{a>0 and b>0} \qquad (3)$$

where $\overline{e}_{lr}$ is the revised level error (normalized) that is used in the new rule base. Coefficients *a* and *b* are optimized for best combination of water level response during load-demand or setpoint change with respect to settling time and overshoot/undershoot (Huang, 2001). Optimized values are *a*=0.2 and *b*=0.1.

The membership functions of $\overline{e}_{lr}$, ce_{lr} and cu_{fwr} are:

$\overline{e}_{lr}$:	NB	NM	NS	NZ	ZE	PZ	PS	PM	PB
	-1.00	-0.45	-0.28	-0.14	0.00	0.14	0.28	0.45	1.00

ce_{lr}:	NB	NM	NS	ZE	PS	PM	PB
	-1.00	-0.36	-0.15	0.00	0.15	0.36	1.00

cu_{fwr}:	NB	NM	NS	NZ	ZE	PZ	PS	PM	PB
	-1.00	-0.30	-0.10	-0.04	0.00	0.04	0.10	0.30	1.00

Generation of fuzzy rules starts from the first part of the fuzzy rules generated by Lin and Yang (1998) where fuzzy rules are given for control action based on e_l and ce_l when *cp*=0 and *dfs*=0. The table is expanded to cover all combinations of e_l and ce_l by filling out the blanks in the form with intuition. Even though the completeness of fuzzy table is not mandatory for FLC design, the completeness does remove any possible problem during implementation without bringing too much additional computational burden. The final two-dimensional fuzzy rule table is listed in Table 1.

3.3 Recirculation flow control (RFC)

The input variables used for RFC design are load demand error $e_w(kT)$ that is defined as the difference between the load demand $W_{sp}(kT)$ and the current power $W(kT)$ < $e_W(kT) = W_{sp}(kT) - W(kT)$ >, change of load demand error over sampling period T < $ce_W(kT) = e_W(kT) - e_W([k-1]T)$ >; the output variable is the change of recirculation flow over T < $cu_{RF}(kT) = u_{RF}(kT) - u_{RF}([k-1]T)$ >. It is noted that the current power in the definition of load demand error is defined as $W = W_t \cdot \lambda + n_r \cdot (1-\lambda)$, which is the weighted average of turbine power (W_t) and reactor power (n_r) so that the time delay between these two variables can be taken into account for better turbine power dynamic response (Huang, 2001). The above λ is the weighting factor, $0 \le \lambda \le 1$. The value λ=0.15 yields an optimal result with respect to rising time, settling time and overshoot/undershoot.

Input-output data are collected from plant transient from ±10% load demand step inputs. The physical domain of e_w, ce_w and cu_{RF} are [-0.1, 0.1], [-0.003, 0.003] and [-0.005, 0.005], respectively. Similar to FWC design, normalization is performed before the rule base generation.

The fuzzy C-means clustering method is also used to determine membership functions of input/output variables and to generate fuzzy rule table. It is used in two steps: 1) to find clustering centers for individual variable, and then use these centers as the peak values of the corresponding membership functions; 2) to obtain multi-dimensional cluster centers and use these centers to generate fuzzy rules. In this case the cluster centers are 3-dimensional points, each of which belongs to one rule to some degree. From step 1), the membership functions for e_{Wr}, ce_{Wr} and cu_{RFr} are preliminarily obtained and from step 2, preliminary fuzzy rules are generated. However, this rule table is neither complete nor consistent. Basic knowledge about the plant and intuition are used to fill out blanks of the table and to modify the table to remove inconsistencies. Further trial-and-error methods are used to tune the parameters of membership functions of fuzzy variables and to adjust fuzzy rules. Final fuzzy rules are listed in Table 2 and membership functions are listed as follows:

e_{Wr}:	NB	NM	NS	ZE	PS	PM	PB
	-0.90	-0.52	-0.07	0.00	0.07	052	0.90

ce_{Wr}:	NB	NM	NS	ZE	PS	PM	PB
	-0.96	-0.61	-0.28	0.00	0.28	0.61	0.96

cu_{RFr}:	NB	NM	NS	NZ	ZE	PZ	PS	PM	PB
	-0.98	-0.73	-0.40	-0.12	0.00	0.12	0.40	0.73	0.98

3.4 Pressure Regulation (PR)

Pressure regulator controls the system pressure by adjusting the turbine throttle valve opening. Pressure error (e_p) and the change of pressure error (ce_p) are used as the controller inputs and the change of valve opening (cu_{cv}) is used as the controller output. These variables are defined as: $e_p(kT) = p_{sp}(kT) - p(kT)$, where $p_{sp}(kT)$ and $p(kT)$ are the pressure setpoint and

Table 1 Fuzzy rules of FWC output (cu_{FWr})

ce_{lr} \ $\overline{e}_{lr}$	*NB*	*NM*	*NS*	*NZ*	*ZE*	*PZ*	*PS*	*PM*	*PB*
NB	PB	PB	PB	PB	PM	PS	PZ	ZE	ZE
NM	PB	PB	PB	PM	PS	PZ	ZE	NZ	NS
NS	PB	PB	PM	PS	PZ	ZE	NZ	NS	NM
ZE	PB	PM	PS	PZ	ZE	NZ	NS	NM	NB
PS	PM	PS	PZ	ZE	NZ	NS	NM	NB	NB
PM	PS	PZ	ZE	NZ	NS	NM	NB	NB	NB
PB	PZ	ZE	NZ	NS	NM	NB	NB	NB	NB

Table 2 Fuzzy rules of RFC for control action cu_{RFr}

ce_{wr} \ e_{wr}	*NB*	*NM*	*NS*	*ZE*	*PS*	*PM*	*PB*
NB	NB	NM	NS	NZ	ZE	PM	PB
NM	NB	NM	NS	NZ	PZ	PM	PB
NS	NB	NM	NZ	NZ	PZ	PM	PB
ZE	NB	NM	NZ	ZE	PZ	PM	PB
PS	NB	NM	NZ	PZ	PZ	PM	PB
PM	NB	NM	NZ	PZ	PS	PM	PB
PB	NB	NM	ZE	PZ	PS	PM	PB

the current pressure, respectively; $ce_p(kT) = e_p(kT) - e_p([k-1]T)$ and $cu_{cv}(kT) = u_{cv}(kT) - u_{cv}([k-1]T)$.

Due to void reactivity feedback that is sensitive to the system pressure change, special attention needs to be paid in FLC design for pressure regulation. Two steps are followed to design the fuzzy pressure regulator: 1) design a base fuzzy controller for pressure control during mild transients, i.e., both pressure deviation from steady state (pressure error) and pressure error does not change sharply, 2) extend the base controller to cover all possible operation space, i.e., to consider all possible transients, such as load demand change, or pressure setpoint change. In addition, a setpoint change rate limiter has been added to the system.

During the base fuzzy controller design step, sinusoidal signal with a period of 70 seconds and magnitude of 0.01 is introduced to the pressure setpoint. This combination of magnitude and period is selected to make the coverage of the generated pressure error, and change of error matches those of the response under ±1% pressure setpoint step input. However, the fuzzy rules generated in this step only cover a small part of the rule table and some combinations of e_p and ce_p encountered during the load-demand-change transient are not covered. To overcome this problem, both fuzzy rules and membership functions are modified dramatically in the second step. The main change is to strengthen the control action for big pressure error signals, for which the control action obtained in the first step is mild. This modification makes the controller adapt to the load demand change perturbation, which requires stronger control action than that for pressure setpoint change. To cope with pressure setpoint change transient, a rate limiter is applied to the pressure setpoint input to the FLC to avoid too strong control actions during pressure setpoint change transients. In this study, the pressure setpoint change rate is limited to 0.1% per second, i.e., for a ±1% setpoint change, it takes at least 10 seconds for the system to respond, no matter whether it is a step input or a ramp input.

The final fuzzy rules are listed in Table 3 and the membership functions of each variable are as follows:

e_{pr}:	NL	NB	NM	NS	ZE	PS	PM	PB	PL
	-1.0	-0.5	–0.2	–0.1	0	0.1	0.2	0.5	1.0

ce_{pr}:	NG	NL	NB	NM	NS	ZE
	-1.0	-0.8	-0.6	-0.4	-0.25	0.0
	PS	PM	PB	PL	PG	
	0.25	0.4	0.6	0.8	1.0	

cu_{cvr}:	NH	NG	NL	NB	NM	NS	ZE
	-4.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0
	PS	PM	PB	PL	PG	PH	
	0.2	0.4	0.6	0.8	1.0	4.0	

Table 3 Final fuzzy rules of pressure regulator for control action cu_{cvr}

e_{pr} \ ce_{pr}	*NG*	*NB*	*NM*	*NS*	*NZ*	*ZE*	*PZ*	*PS*	*PM*	*PB*	*PG*
NL	PH	PH	PH	PH	PH	PH	PH	PG	PL	PB	PM
NB	PH	PH	PH	PH	PG	PL	PB	PM	PS	ZE	NS
NM	PG	PG	PG	PL	PB	PM	PS	ZE	NS	NM	NB
NS	PG	PG	PL	PB	PM	PS	ZE	NS	NM	NB	NL
ZE	PG	PL	PB	PM	PS	ZE	NS	NM	NB	NL	NG
PS	PL	PB	PM	PS	ZE	NS	NM	NB	NL	NG	NG
PM	PB	PM	PS	ZE	NS	NM	NB	NL	NG	NG	NG
PB	PS	ZE	NS	NM	NB	NL	NG	NH	NH	NH	NH
PL	NM	NB	NL	NG	NH	NH	NH	NH	NH	NH	NH

4. SIMULATION RESULTS

The fuzzy logic controllers designed above have been implemented on the simplified ABWR model in MATLAB Simulink environment. Simulations have been performed with step inputs of load demand change, reactor water level setpoint change and pressure setpoint change at different power levels (≥70% rated power). Generally the simulation results show that the fuzzy logic controllers' performance is comparable to or better than that of the existing PI controllers with respect to reference signal tracking and final value holding time, overshot/undershoot, etc., during the transients. Due to space limit, only partial simulation results are presented.

Shown in Fig. 4 are the plant responses under a step change of +10% in load demand at 90% rated power condition. Transients of turbine power, reactor power, turbine throttle pressure and reactor water level are presented. The reason that the reactor power is also presented is because it is a very important index for reactor safety. From the figure it is seen that the turbine power response from FLCs is very close to that from PI controllers, showing a small improvement in final value holding time. The reactor power response has a comparable overshoot and a little better settling time. Significant improvement is achieved in settling time of turbine pressure and reactor water level responses. The water level surge amplitude is also smaller for FLCs.

Shown in Fig. 5 are plant responses under pressure setpoint and reactor water level setpoint changes. From the pressure setpoint change responses it is clear that the fuzzy controllers performs better in that the reactor power surges in a much smaller (about ¼) magnitude. This difference is because of the control action difference—the control valve responses dramatically for PI controller while it responses mildly and smoothly for fuzzy controllers. The reactor pressure responses for fuzzy and PI controllers are comparable, even though the FLC behaves slower at beginning of the transient due to the rate limiter, eventually they converge to their final values almost at the same time. The water level setpoint change responses also show that the FLCs performs better in that the level transient with FLCs has a much shorter settling time. Results with power response and pressure responses also show a better performance of FLCs (not shown in the figure).

5. CONCLUSIONS

Fuzzy logic controllers are designed for an advanced boiling water reactor nuclear power plant overall control for high power range to control turbine power, pressure and reactor water level simultaneously, with the consideration of interactions among plant subsystems. Simulations show that these controllers have a comparable or better performance compared with the existing PI controllers, showing that the fuzzy logic control application in nuclear power plant overall control is feasible.

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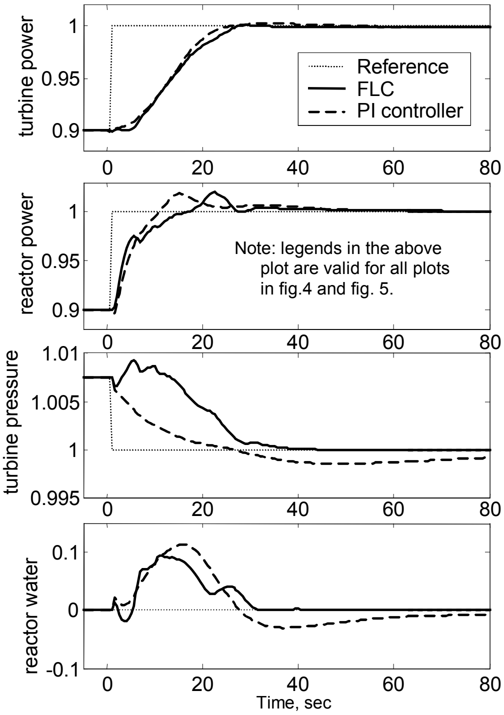

Fig. 4. Plant responses under +10% step change in load demand at 90% rated power condition.

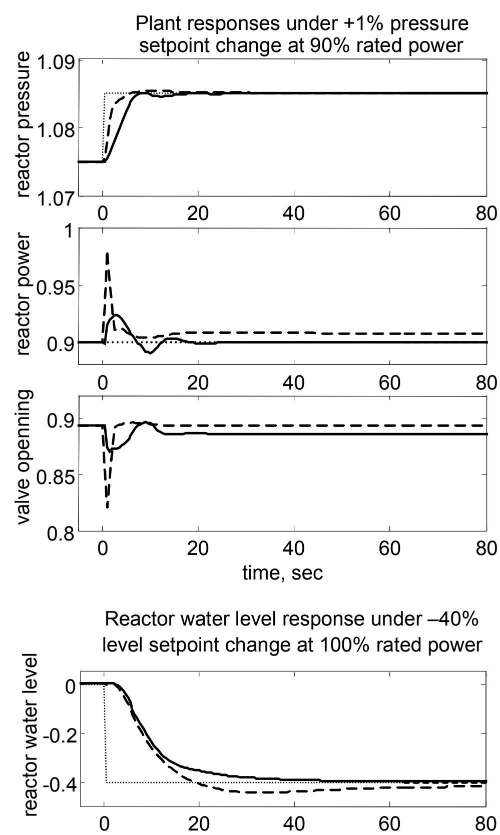

Fig. 5. Plant responses under changes in pressure and water level setpoint change.