# Wide Range Operation of a Power Unit via Feedforward Fuzzy Control

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***Abstract*—A two-level hierarchical control scheme for wide-range operation of fossil fuel power units is presented. At the supervisory level, a fuzzy reference governor generates, according to a variable pressure operating policy, the set-point trajectories to command the unit along any load demand pattern. At the control level, a feedforward-feedback control strategy is implemented. The feedforward control path contains a set of multi-input single-output fuzzy inference systems, designed from steady-state input–output plant data. The feedback control path consists of PID controllers in a multi-loop configuration, as currently available at power units. With this strategy, the feedforward path provides most of the control signal for wide-range operation, diminishing the control effort on the PID controllers. The feedback path supplies the complementary control signal component for regulation and disturbance rejection in small neighborhoods about the commanded trajectories. Simulation results demonstrate the feasibility of the control scheme to attain cyclic load-following operation.**

***Index Terms*—Feedforward-feedback control, fossil-fuel power unit, fuzzy inference systems, set-point generation, wide-range operation.**

## I. Introduction

EFFECTIVE participation of a Fossil Fuel Power Unit (FFPU) in load-following duties, requires the ability to undertake large power variations in the form of daily, weekly, and seasonal cycles, as well as random fluctuations about those patterns [1], [2]. Hence, the main objective of an overall unit control scheme becomes to efficiently orchestrate all energy transformations taking place in the FFPU, throughout its whole operating range, to catch up with the load demand. Main transformations comprehend input fuel combustion, steam generation, development of rotational motion, electric power production, and steam condensation. All of them are nonlinear, multidimensional, and strongly coupled processes, which never happen to be at true steady-state conditions.

Currently, most control systems at FFPUs are multiloop configurations of PID controllers. Such approach has proved its value during normal operation at base load, where plant characteristics are almost constant, nearly linear and weakly coupled. Conversely, wide-range operation imposes strong physical demands on unit equipment, and leads inherently to conflicting operational and control situations, since FFPUs were designed to operate at constant load conditions. Under these circumstances, traditional control schemes, designed and tuned for regulation and disturbance rejection, but setpoint tracking, may decrease the global performance of the unit, thus making them less acceptable for cyclic operation.

Feedforward and feedback (FF/FB) control may be combined to attain wide-range operation. The main idea is to use open-loop feedforward control to achieve wide range maneuverability and closed-loop feedback control to regulate and to overcome uncertainties and disturbances around the commanded trajectory. A FF/FB control strategy has been applied successfully for wide-range load control of steam and gas turbine units in combined cycle power plants [3], [4]. In addition, some simulation-based studies have explored the FF/FB scheme using different approaches. In [5] a robust control approach for a steam power plant is reported, in [6] a scheme for optimal temperature tracking is presented, and a design based on genetic algorithms is presented in [7].

In this paper, a two-level hierarchical control scheme to attain wide-range operation is presented. The upper level contains a reference governor implemented with a fuzzy inference system (FIS). The lower level implements a FF/FB strategy using FISs in the FF path. Section II describes the overall control strategy. Section III presents the design of the FISs in the FF path. Section IV shows, through computer simulation, the performance of the control system. Finally, some comments and concluding remarks are drawn in Section V.

## II. Unit Control Scheme

### *A. Hierarchical Control Structure*

The FFPU is assumed to carry out load-following duties in a large power system operating under automatic generation control. The desired overall unit response is specified entirely by a unit load demand profile, which may be calculated by load forecast and economic dispatch programs, or provided directly by the operators at the power plant.

A two-level hierarchical structure is proposed for overall unit control (Fig. 1). The upper level, called supervisory control level, consists of a reference governor that provides the references, $y_d$, for the control loops at the lower level. The lower level, named direct control level, embodies both feedforward and feedback control processors, which provide the feedforward control signal, $u_{ff}$, and the feedback control signal, $u_{fb}$ respectively. Together, both processors realize a multivariable FF/FB control strategy to provide the demands to the control valves, $u$.

Qualitatively speaking, the reference governor specifies and coordinates the desired responses of the boiler, steam turbine,

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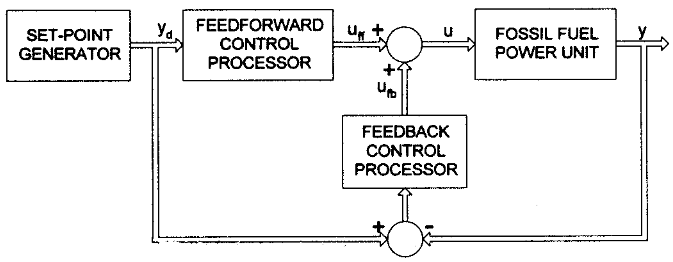


Fig. 1. Hierarchical control scheme.

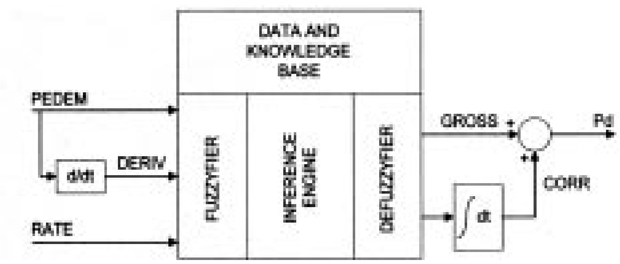


Fig. 2. Fuzzy pressure set-point generator.

TABLE I
RULES TO GENERATE GROSS TERM

| | | | |
|---|---|---|---|
| PEDEM | low | medium | high |
| GROSS | very_low | medium | very_high |

TABLE II
RULES TO GENERATE CORRECTION TERM RATE

| | CORR | RATE: negative | no change | positive |
|---|---|---|---|---|
| DERIV | positive | neg | no_change | large_pos |
| | no change | neg | neg | pos |
| | negative | large_neg | no_change | pos |

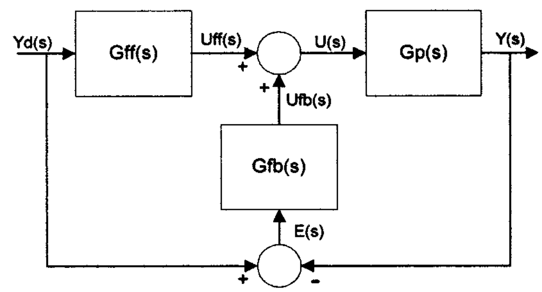


Fig. 3. Two degrees of freedom control configuration.

and electric generator. The feedforward control path should provide the main contribution to the control valve demands to achieve wide-range operation. The role of the feedback control path is meant to be complementary, that is, it should supply the control signal component necessary for regulation and disturbance rejection in small neighborhoods about the commanded trajectories.

### B. Supervisory Set-Point Generation [8]

The set points for electric power, steam pressure, and drum water level, $y_d = [E_d \; P_d \; L_d]^T$, are generated at the supervisory level. The power set-point, $E_d$, is the same as the unit load demand provided by the operator or AGC. The drum water level deviation set-point, $L_d$, is always set to zero. The steam pressure set point, $P_d$, is obtained by adding a gross (GROSS) and a correction term (CORR), which are inferred by the Fuzzy Pressure Set-Point Generator (FPSPG) (Fig. 2). The set of rules that generates GROSS constitutes a nonlinear mapping of the current unit load demand (PEDEM) that implements a variable-pressure operating policy. In addition, CORR is provided by a set of rules that command additional pressure variation depending on the current derivative (DERIV) and the near future rate of change (RATE) of the unit load demand.

The FPSPGs input variables are fuzzified using Gaussian, $N$(mean, variance), membership functions. Input PEDEM spans 0 to 160 MW with $low = N(0, 40)$, $medium = N(80, 25)$, and $high = N(160, 40)$. Both DERIV and RATE span $-5.0$ to 5.0 %load/minute with $negative = N(-5, 1.5)$, $no\text{-}change = N(0, 1.5)$, and $positive = N(5, 1.5)$. Outputs GROSS and CORK have 5 evenly distributed triangular membership functions, $\{very\_low,\ low,\ medium,\ high,\ very\_high\}$ and $\{large\_neg,\ negative,\ no\_change,\ positive,\ large\_pos\}$, respectively. The knowledge base has 12 rules (Table I and Table II) with min and max methods for the logic "*and*" and "*or*" connectives, respectively. Inference was done by Mamdani combination. Implication and aggregation used the min and max methods, respectively. Defuzzification was carried out by the center of gravity method. More details on the FPSPG can be found in [8].

### C. Feedforward/Feedback Control Strategy

The initial idea of the FF/FB control strategy comes from the two-degrees-of-freedom linear control system in Fig. 3. The output to set-point transfer function is given by (1). If $G_{ff}(s) = [G_p(s)]^{-1}$, perfect tracking, $Y(s) = Y_d(s)$, can be attained. Besides, in the absence of uncertainty and disturbances the feedback element is unnecessary.

$$Y(s) = [I + G_p(s)G_{fb}(s)]^{-1} \cdot [G_p(s)G_{ff}(s) + G_p(s)G_{fb}(s)]\, Y_d(s) \qquad (1)$$

The FFPUs are large complex systems for which $G_p(s)$, if known, is only valid around a single operating point, and its inverse is not guaranteed to exist. Hence, the ideal FF/FB strategy is inadequate to attain wide-range operation. Requirements on $G_{ff}(s)$ can be lessened to only approximate the inverse dynamics, and let the FB path compensate for uncertainty to track the demand. However, there is still the need for a plant model, which is a particularly difficult issue for control with distributed systems.

To overcome these problems we proposed for the FF path to approximate the inverse steady-state behavior using inputoutput process data along the whole operating range of the FFPU, that is, to solve a kind of inverse kinematic problem.

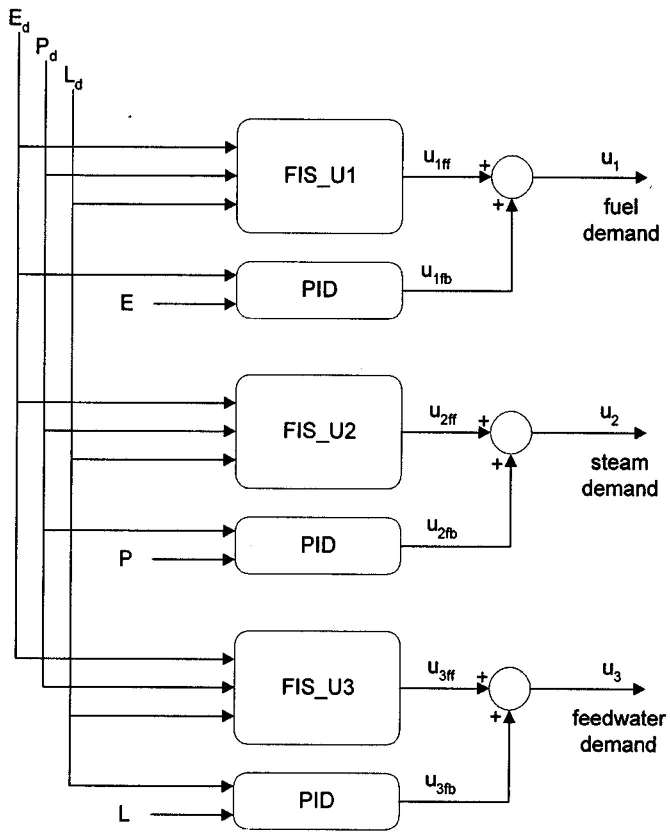


Fig. 4. Feedforward/feedback control configuration.

The feedforward control processor is implemented as a fuzzy system that approximates the inverse nonlinear inputoutput steady-state behavior of the FFPU. It contains three FISs, one for each individual control valve demand, which provide the feedforward control signal component, $u_{ff} = [u_{1ff}\ u_{2ff}\ u_{3ff}]^T$. The FISs provide smooth control signal contributions over the whole operating range of the FFPU, with no process model required at all.

The feedback control processor is a multi-loop control configuration based on conventional PID control algorithms, as currently available at power units. In this case, the FB path was implemented with three independent single-input–single-output control loops, which provide the complementary control signal $u_{fb} = [u_{1fb}\ u_{2fb}\ u_{3fb}]^T$. Note that no attempt was done to compensate for interaction effects, leaving that task implicitly to the feedforward control. Process input–output pairing for the feedback loops was made between the fuel valve and the electric power, the throttle valve and the main steam pressure, and the feedwater valve and the drum water level deviation. Fig. 4 shows the direct control level configuration including both the RID based feedback controllers and the feedforward controllers based on fuzzy inference system.

## III. Feedforward Fuzzy Inference Systems

### *A. Design of Feedforward FIS*

Several design methods may be used to design the fuzzy inference systems in the feedforward control processor from

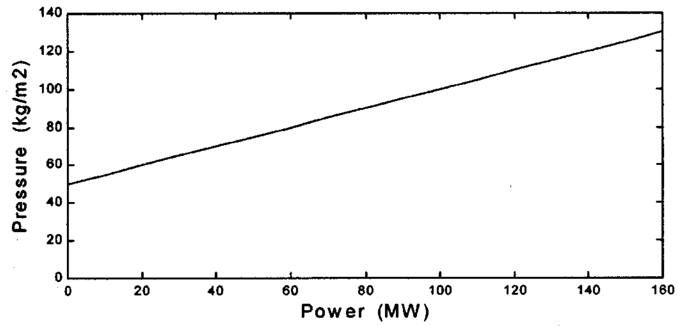


Fig. 5. Power and pressure steady-state values.

input–output data. Common methods are the table look-up scheme, gradient descent training, recursive least squares, and clustering [9], [10]. The method known as adaptive neuro-fuzzy inference system (ANFIS) [11], [12] was used here. This technique allows the implementation of multi-input–single-output (MISO) first-order Sugeno-type FIS with weighted average defuzzification.

This approach provides off-line learning capability to the control system. Here, learning is understood as the process of tuning the input membership functions, building the fuzzy inference rules of the knowledge base, and identifying the consequent parameters of the feedforward FIS, necessary to reproduce the input–output behavior of system. The learning process is of the training type. It could take place prior to the operation of the control system, or upon demand during operation. Only the former case is considered in this project.

The learning process develops through the following stages. First, a set of input–output data, to be used as training data, needs to be generated or obtained from the process. Another optional data set can be used as checking data after training. Second, the initial FIS structures need to be created. For each input, the range of operation, number of membership functions, as well as their shape, must be defined. Finally, the learning process is carried out using the training data to adjust the membership functions, to create the inference rules, and to determine their consequent parameters. The resultant FIS is verified using the checking data set.

### *B. Feedforward FIS*

Steady-state data along the whole operating range was used to design the feedforward FISs. Power and pressure data, reflecting the variable pressure operating policy, are shown in Fig. 5. The drum level deviation in steady state is zero and is not shown. The corresponding control valve demands ($u_1$ for fuel, $u_2$ for steam, and $u_3$ for feedwater) are given in Fig. 6.

To obtain the inverse kinematic model, the inputs to each FIS are given by the current outputs (electric power, drum steam pressure, and drum water level) of the power unit, and the outputs of the FIS are given by the current demands to the control valves (fuel, steam, and water). Once imbedded in the control system, the inputs to the FIS are supplied with the setpoints to obtain the feedforward contribution to the control valve demands.

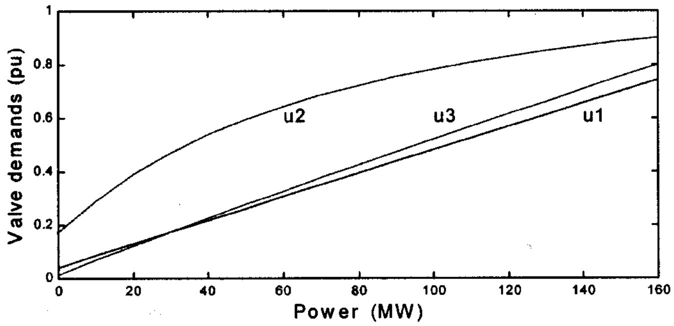


Fig. 6. Control valve demands steady-state values.

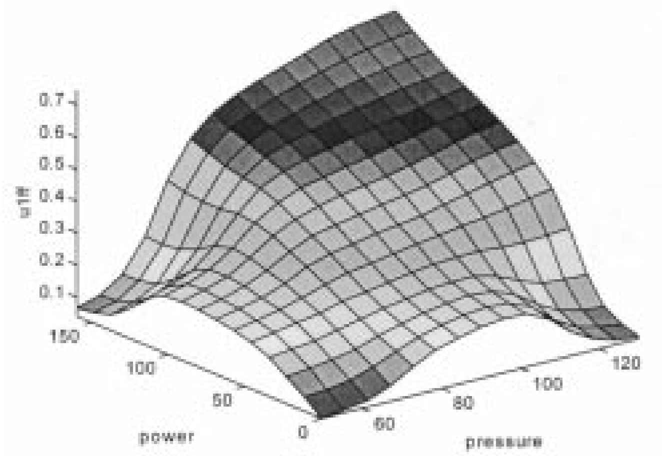


Fig. 7. Fuzzy surface for $u_{1ff}$.

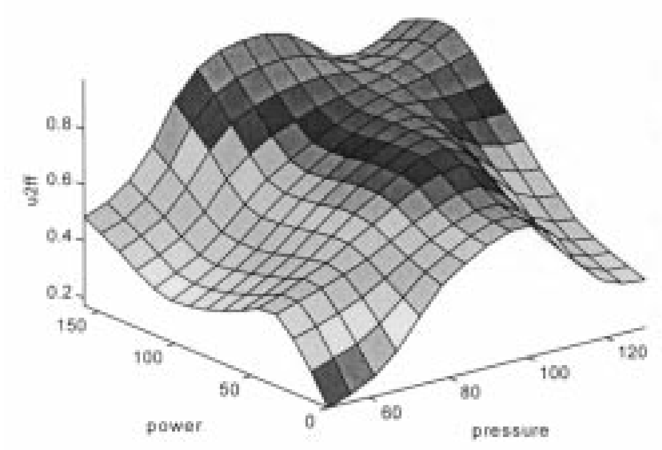


Fig. 8. Fuzzy surface for $u_{2ff}$.

All three feedforward elements, FIS_U1, FIS_U2, and FIS_U3, receive the same inputs. Sets of three and more membership functions per input were tested. The case with three membership functions is reported in this work. A total of 27 fuzzy inference rules were generated for each FIS. Surfaces in Figs. 7–9 graphically represent the rules to generate the control signals $u_{1ff}$, $u_{2ff}$, and $u_{3ff}$, in terms of the power and pressure set-points. The water level set-point does not affect the surfaces since it is always set to zero. Indeed, the surfaces represent the inverse static model of the FFPU, and they allow an approximate and quick visualization of the control signal values. As an advantage, the surfaces remain almost the same, with negligible differences, when the number of membership functions increases, in contrast to the amount of rules that grows geometrically.

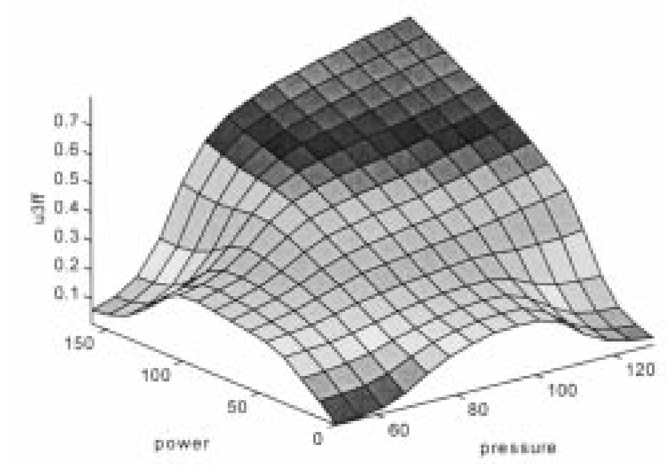


Fig. 9. Fuzzy surface for $u_{3ff}$.

Performance of the FF path to reproduce the inverse static behavior of the process was verified by reproducing the steady-state data of Figs. 5 and 6. This confirms the universal approximation properties of fuzzy systems. Differences in precision obtained with 3, 5, or more input membership functions were negligible.

## IV. Simulation Results

### *A. Model of Power Unit*

The power unit is simulated with the nonlinear dynamic model of a 160 MW oil fired drum boiler-turbine-generator unit, intended for overall wide range simulations [13]. The model is a three input, three output, third order nonlinear system. The inputs are the positions of the valve actuators that control the mass flow rates of fuel ($u_1$ in pu), steam to the turbine ($u_2$ in pu), and water to the drum ($u_3$ in pu). The three major outputs are the electrical power ($P_e$ in MW), drum steam pressure ($P$ in kg/cm$^2$), and drum water level ($L$ in m). The three state variables are the electric power, drum steam pressure, and the fluid (steam-water) density ($\rho_f$). The model state equations are

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2P^{9/8} - 0.15u_3 \quad (2a)$$

$$\frac{dP_e}{dt} = \left((0.73u_2 - 0.16)P^{9/8} - P_e\right)\Big/ 10 \quad (2b)$$

$$\frac{d\rho_f}{dt} = (141u_3 - (1.1u_2 - 0.19)P)/85 \quad (2c)$$

The drum water level is calculated using the following algebraic equations:

$$q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09 \quad (3a)$$

$$\alpha_s = (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015) \quad (3b)$$

$$L = 0.05(0.13\rho_f + 100\alpha_s + 0.11q_e - 68.3) \quad (3c)$$

where $\alpha_s$ is the steam quality, and $q_e$ is the evaporation rate (kg/sec). Positions of valve actuators are constrained to lie in

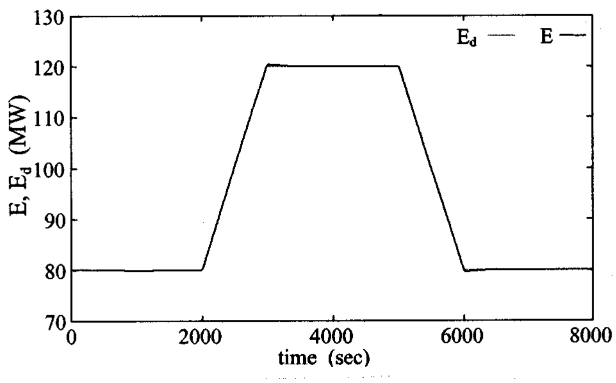


Fig. 10. Load tracking.

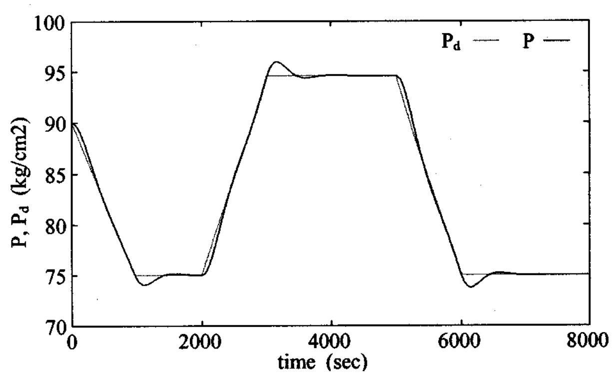


Fig. 11. Variable pressure operation.

the interval [0, 1], while their rate of change (pu/sec) is limited as follows:

$$-0.007 \leq \frac{du_1}{dt} \leq 0.007 \tag{4a}$$

$$-2.0 \leq \frac{du_2}{dt} \leq 0.02 \tag{4b}$$

$$-0.05 \leq \frac{du_3}{dt} \leq 0.05 \tag{4c}$$

*B. Simulation of Cyclic Operation*

The control system is embedded in a simulation shell for the analysis of overall unit control strategies. The shell was developed in a personal computer platform using the MATLAB/SIMULINK programming environment. A set of 50+ tests is available to characterize the process and to tune and analyze the control system.

Tests can be executed at various levels: 1) At the unit model level to verify the open-loop model responses. 2) At the direct level to include the models of valve actuators. 3) At the master level to include the control algorithms at the direct control level, in this case the feedforward and feedback components. 4) At the supervisory level to include the setpoint generator, and 5) At the system level to perform cyclic operation tests with the whole control system and process model.

In this project, most tests were conducted at the master level and at the system level. Master level tests were carried out to tune the PID algorithms of the feedback path. Results presented here show cyclic tests conducted at the system level. Figs. 10–15

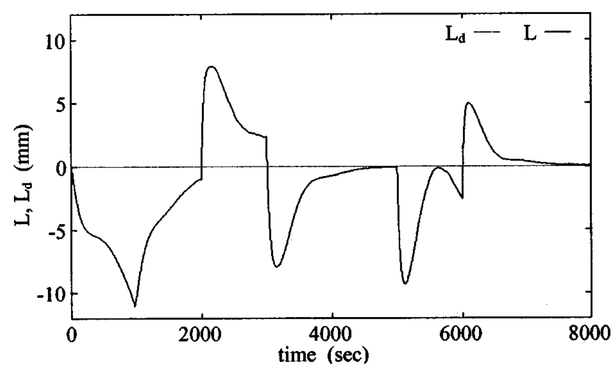


Fig. 12. Drum water level regulation.

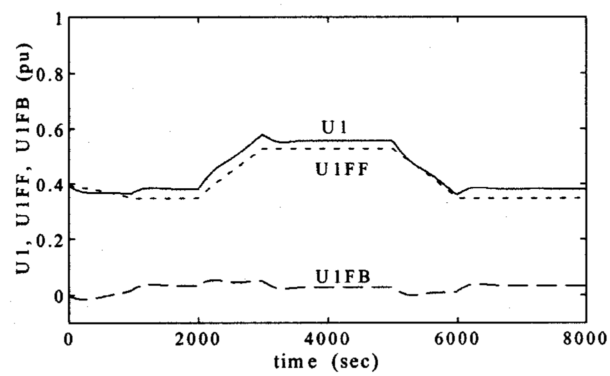


Fig. 13. Demand to fuel valve.

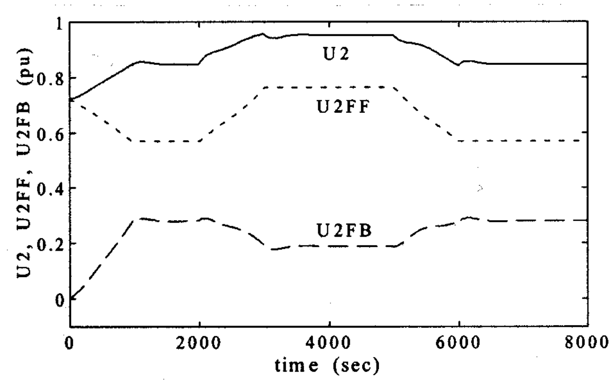


Fig. 14. Demand to steam throttling valve.

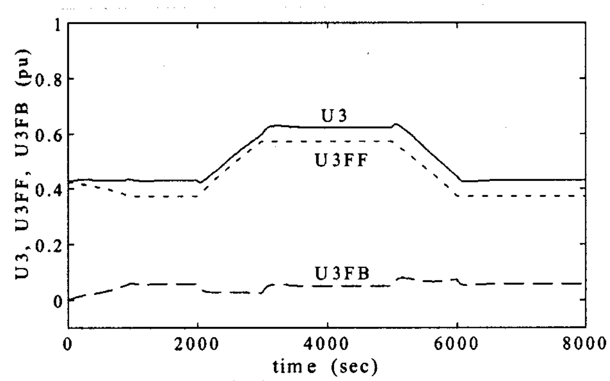


Fig. 15. Demand to feedwater valve.

show the system performance during a simple cycle. Fig. 10 demonstrates that load tracking is very good. Fig. 11 shows good tracking of the variable pressure pattern, and Fig. 12 shows good regulation about zero drum level deviation. Behavior of the control signal total demand Ui, feedforward contribution UiFF, and feedback contribution UiFB, for $i = 1, 2, 3$, are shown in Figs. 13–15 for the fuel valve, the main steam throttle valve, and the feedwater valve, respectively. Plots show agreement with the expected behavior. The feedforward contribution is the main component of the final control signal, while the feedback contributions are working to regulate the controlled variables about the commanded trajectories. Note that the contribution of U2FB is larger than that of U1FB and U3FB. This is due to the correction made to the pressure set-point at the FPSPG, and to the greater nonlinearity of the fuzzy surface for $u_{2ff}$ in the 80–120 MW operating region, compared to that of $u_{1ff}$ and $u_{3ff}$ (Figs. 7–9).

## V. Conclusion

In this paper, a general control system scheme for widerange cyclic operation of a FFPU was presented. The minimum necessary components were identified as the setpoint generator, the feedforward control element, and the feedback control element. These components were placed naturally in a two level hierarchical structure. The set-point generator and the feedforward components were designed using fuzzy inference systems, in the latter as nonlinear approximators to the inverse steady-state behavior of the unit. Input–output process data was used to build the FF controller with no process model requirement at all.

Results showed that the feedforward/feedback control strategy can be used successfully to attain dynamic wide-range load-following operation. The feedforward control signal drives the process through wide-range operating maneuvers, placing it close to the desired state. Meanwhile, the feedback control signal compensates for uncertainties and disturbances about the commanded trajectories.

After the feasibility demonstration of the proposed control scheme, reported in this paper, further improvement is sought through the following research activities: development of an optimal strategy for set-point generation, scope extension using a more detailed power unit model, and an analysis of performance robustness, which includes comparison to other existing control schemes.

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