Multiobjective Optimal Power Plant Operation Through Coordinate Control with Pressure Set Point Scheduling

Raul Garduno-Ramirez, *Student Member, IEEE* and Kwang Y. Lee, *Senior Member, IEEE*

***Abstract*—Coordinated control schemes, at fossil fuel power plants, drive units as a whole through a variable pressure operating policy. Ordinarily, the pressure control loop set-point is obtained from the unit load demand through a fixed nonlinear mapping that does not allow for process optimization under operating conditions different from the originals. This paper presents a procedure to optimally design the power-pressure mapping by defining and solving a multiobjective optimization problem. Both, procedure and mapping are realized as a supervisory set-point scheduler. The optimization problem is solved with the nonlinear goal programming method, which provides a single solution from the set of all multiobjective optimal solutions based on the assignment of relative preference values to the objective functions. This approach provides a way to specify the operating policy to accommodate a great diversity of operating scenarios. The procedure is presented through a case study, and its feasibility is demonstrated via simulation experiments.**

***Index Terms*—Multiobjective process optimization, operating scenario accommodation, power plant coordinated control, pressure set-point scheduling, relative preference values.**

I. INTRODUCTION

THE CURRENT operating context of a fossil fuel power unit (FFPU) is characterized by many needs and requirements. Firstly, a FFPU must support the main objective of the power system, which is to meet the load demand for electric power at all times, at constant voltage and at constant frequency [1]. In addition, competition among utilities and other market driven forces have increased the usage of FFPUs in load following duties [2]. Moreover, stringent requirements on conservation and life extension of major equipment, and regulations on reduced environmental impact have to be fulfilled [3]. This situation may be synthesized as an essential requirement for FFPUs to achieve optimal operation under multiple operation objectives, such as minimization of load tracking error, minimization of fuel consumption and heat rate, maximization of duty life, minimization of pollutant emissions, etc.

From an automation point of view, attainment of optimal process operation considers two great avenues: supervisory steady-state optimization control and dynamic optimal feedback control. Supervisory controls determine process operating conditions to command the lower level automation functions. The hierarchical structure of power systems seems to favor supervisory optimization of power units via set-point scheduling. Unfortunately, little attention has been paid in this regard. Most research has focused to achieve better feedback control, sometimes assuming that satisfactory setpoint values are available, and most times ignoring that feedback control alone cannot refine operation beyond what is established by the set-points. In general, there is no questioning on the origin and adequacy of the set-points for optimal power unit operation.

There are only a few strategies for power plant supervisory optimization available in the literature. In [4], sub-optimal set-point values are calculated using the dynamic model of a power unit as a constraint for the optimization of a single objective function. In [5] a fuzzy inference system generates pressure set-points to minimize steam throttling losses during cyclic operation. In [6] the set-points are shifted according to the statistical behavior of selected output signals to improve economic performance. The use of power-pressure nonlinear relationships to accommodate up to three different predefined operating conditions is shown in [7], [8]. It is important to note that in all these cases, there is no established mechanism to specify the requirements of the operating scenario, and consequently it is not possible to incorporate them into the process optimization strategy. Neither is there a provision to satisfy multiple operation objectives simultaneously, as currently required at power units.

At fossil fuel power units, the coordinated control (CC) scheme constitutes the uppermost layer of the control system. The CC is responsible for driving the boiler-turbine-generator set as a single entity and is the primary means to achieve process optimization through control. The dominant behavior of the unit is governed through the power and steam pressure control loops. Given the unit load demand, the CC provides control signals to the boiler and to the steam turbine to match the responses of the boiler and the turbine-generator during load changes and load disturbances. Ordinarily, the set-point for the pressure control loop is obtained from the unit load demand through a power-pressure nonlinear mapping along the whole power operating-range of the unit. This mapping defines the unit's operating policy and stays fixed in most installations. Unfortunately, this approach does not allow for process optimization should the operating scenario changes from that considered in the original design. In view of the current operating context, it is of the highest practical interest to have the means to adjust the power-pressure mapping to optimally accommodate different operating scenarios.

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The authors are with the Department of Electrical Engineering, Pennsylvania State University, University Park, PA 16802.

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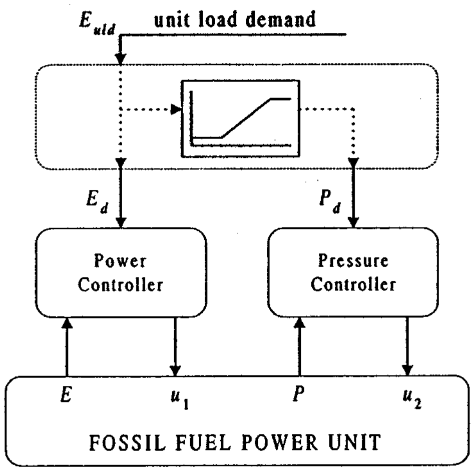

Fig. 1. Coordinated control.

This paper introduces a procedure to optimally design the CC power-pressure mapping by defining and solving a multiobjective optimization problem, for which any operating objective of interest may be expressed arbitrarily in terms of one or more objective functions. The formulation of the multiobjective optimization problem is based on the goal programming approach [9], for which a way to specify preferences among the objective functions, in the form of relative preference values, is also introduced. Both, the optimization procedure and the calculated power-pressure mapping are embedded as a set-point scheduler in the CC scheme. This approach provides a method to attain process optimization through set-point scheduling under different operating scenarios characterized by multiple competing operating requirements. The operating scenario at hand can be accommodated by specifying an operating policy in terms of several objective functions and their relative preference values. The proposed method is general, versatile, and simple enough to be attractive for practical application. In Section II the resultant CC scheme, process model, and some essential operation facts needed for process optimization are presented. Section III briefly describes the goal programming method used to solve the optimization problem. Section IV describes the pressure set-point scheduler in detail. Section V provides simulation results to demonstrate the viability of the proposed approach. Finally, in Section VI, some important issues are summarized and conclusions are drawn.

II. Coordinated Control Scheme

A. Coordinated Control

The configuration of a conventional CC scheme is shown in Fig. 1, as corresponds to the coordinated turbine-follower mode [8]. The power controller generates commands for the fuel/air valve positions, u_1, from the measured generated power, E, and power demand, E_d, which is equal to the unit load demand, E_{uld}. The pressure controller drives the throttle valve calculating the position demand, u_2, from the measured steam pressure, P, and the pressure set-point, P_d, which is obtained from the unit load demand, E_{uld}, through a nonlinear power-pressure mapping.

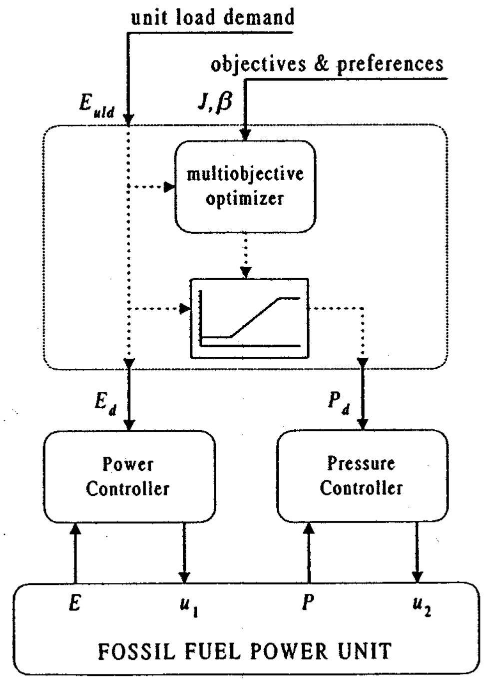

Fig. 2. Optimized coordinated control.

The structure of the proposed CC scheme is shown in Fig. 2, where the nonlinear mapping block has been replaced by a pressure set-point scheduler. From an input–output point of view, the set-point for the steam pressure control, P_d, is calculated from the unit load demand, E_{uld}, and the operating policy, which is specified by a vector of objective functions, J, and a corresponding vector of relative preference values, β. Although not shown, external disturbances, state variables, and control signals may be fed into the scheduler when required by the objective functions.

Inner details of the pressure set-point scheduler are also shown in Fig. 2. As will be shortly explained, the optimizer calculates the power-pressure mapping whenever there is a change in the operating policy. After the optimization has been carried out, updating the mapping can be done, upon request by the operator, either off-line or in parallel with the operation of the system. In this work only off-line updating is considered. Note that on-line updating will require a ramp function to be inserted in the P_d path for bumpless transition between the old and new set-point values.

In general, the proposed optimizer-mapping configuration adds versatility to the application of the pressure set-point scheduler. It isolates the optimizer preventing any numerical convergence problem having a negative effect on the unit, and makes it unnecessary to know the unit load demand for long periods ahead of time, as could be necessary with an optimizer providing the set-points directly on-line.

B. Power Unit Model

The essential dynamics of a FFPU have been remarkably captured for a 160 MW oil fired drum-type boiler-turbine-generator unit in a third order MIMO nonlinear model for overall wide-range simulations in [10]. The inputs are the positions of valve

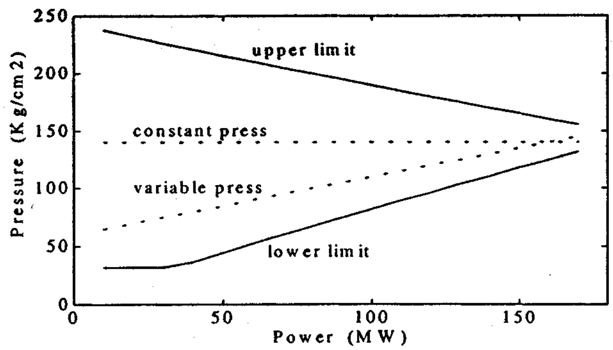

Fig. 3. Power-pressure operating window.

actuators that control the mass flow rates of fuel (u_1 in pu), steam to the turbine (u_2 in pu), and feedwater to the drum (u_3 in pu). The three outputs are electric power (E in MW), drum steam pressure (P in kg/cm^2), and drum water level deviation (L in m). The three state variables are electric power, drum steam pressure, and fluid (steam–water) density (ρ_f). The state equations are:

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2P^{9/8} - 0.15u_3 \tag{1.a}$$

$$\frac{dE}{dt} = ((0.73u_2 - 0.16)P^{9/8} - E)/10 \tag{1.b}$$

$$\frac{d\rho_f}{dt} = (141u_3 - (1.1u_2 - 0.19)P)/85. \tag{1.c}$$

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

$$q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09 \tag{2.a}$$

$$\alpha_s = (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015) \tag{2.b}$$

$$L = 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5) \tag{2.c}$$

where α_s is the steam quality, and q_e is the evaporation rate (kg/sec). Positions of valve actuators are constrained to [0,1], and their rates of change (pu/sec) are limited to:

$$-0.007 \le du_1/dt \le 0.007 \tag{3.a}$$

$$-2.0 \le du_2/dt \le 0.02 \tag{3.b}$$

$$-0.05 \le du_3/dt \le 0.05. \tag{3.c}$$

C. Power-Pressure Operating Window

The first step toward process optimization is to identify the power unit's power-pressure operating region, defined by the set of all permissible operating points. The feasible operating points lie between the upper and lower pressure limits shown in Fig. 3, which also shows mappings of a constant-pressure and a typical variable-pressure operating policies. The limits were determined through an iterative process using the power unit dynamic model along the whole power range, one power value at a time. At any given power value, the upper pressure limit is found as follows. Start from the value on the constant pressure mapping. Increase the pressure value. At the new power-pressure operating point so defined, calculate all other model variables to achieve equilibrium conditions, and verify them to get physically meaningful values. Keep increasing the pressure until physically reasonable equilibrium points cannot be obtained, the final value reached constitutes the upper limit. Then, the determination of the lower pressure limit follows a similar approach, but the iteration starts from pressure values in the variable-pressure mapping, and the pressure is decremented at each iteration. The process is repeated over the whole power range.

In addition to provide the unit's power-pressure operating window, the previous process clearly shows that any power demand can be generated with a pressure value anywhere between the upper and lower limits. A decision must be made regarding the adequate pressure value to use. Then, the next step toward process optimization is to optimally define a relation between the unit load demand and pressure values in the permissible operating region. A procedure to solve this problem under different operating scenarios facing multiple operating requirements is presented in the following sections.

III. Multiobjective Optimization

Basic multiobjective optimization concepts are presented. The material is rather standard and can be found in any text on the subject [9]. The formulation to be used is introduced.

A. Mathematical Formulation

A multiobjective optimization problem (MOOP) under a given set of constraints is usually stated as [9]:

Find x that minimizes:

$$J(x) = [J_1(x)\ J_2(x)\ \cdots\ J_k(x)]^T \tag{4}$$

subject to:

$$x \in X$$
$$g_i(x) \in G_i, \qquad i = 1, 2, \ldots, m$$

where

- x is an n-dimensional vector of decision variables,
- X is the set of feasible solutions,
- $J(x)$ is a k-dimensional vector of objective functions,
- g_i are the constraint functions and
- G_i are their corresponding allowable intervals.

In general, any MOOP deals inherently with conflicting objectives and none of the feasible solutions simultaneously minimizes all the objectives, since the individual solutions for each objective function determine different points in the space of decision variables. Because of this. the solution of a MOOP is a set of noninferior solutions (Pareto optimal set), for which improvement of any one objective can be achieved only at the expense of increasing at least another objective function. Normally, the MOOP is considered to be solved when the Pareto optimal set is determined. However, in a practical application, a unique solution usually needs to be selected through a decision making process, which most of the time is solved heuristically.

B. Nonlinear Goal Programming

There are several methods available to solve a MOOP, e.g., utility function, inverted utility function, global criterion, bounded objective function, and goal programming [9]. The utility function method, which composes a single objective function through the weighted sum of all objectives, is very attractive for practical applications due to the simplicity and intuitiveness of its formulation. Nevertheless, it is not used in this project because it does not always provides access to all solutions and the weights do not necessarily correlate to preference on the objectives [9]. It is not trivial to choose proper weights when the number of objectives is large and use different units. The nonlinear goal programming (NGP) method [9] is used to overcome these disadvantages, while preserving simplicity and intuitiveness in the formulation.

The basic idea of the NGP method is to look for a solution x to produce an objective vector, $J(x)$, as close as possible to a target objective vector, J_t. This is equivalent to minimize the distance, $d(J(x), J_t)$, from the candidate solution to the target vector, which may be expressed as a function of the deviation $\delta = J_t - J(x)$, called an achievement function, $h(\delta)$. Furthermore, if the deviation is expressed as the difference of two positive-valued vectors, $\delta = \delta_n - \delta_p$, then the achievement function can be expressed as a monotonically increasing p-norm in terms of δ_n and δ_p. Hence, a MOOP can be stated as:

Find x which minimizes the achievement function:

$$h(\delta_p, \delta_n) = \left[\sum_{i=1}^{k}(w_{pi}\delta_{pi} + w_{ni}\delta_{ni})^p\right]^{1/p}, \qquad p \geq 1 \quad (5)$$

subject to:

$$\begin{array}{ll} x \in X & \\ g_i(x) \in G_i & i = 1, 2, \ldots, m \\ J_i(x) + \delta_{ni} - \delta_{pi} = J_{t_i} & i = 1, 2, \ldots, k \\ \delta_{pi} \geq 0, \quad \delta_{ni} \geq 0 & i = 1, 2, \ldots, k \end{array}$$

where δ_{pi} and δ_{ni} are the positive and negative deviation terms of the ith objective, and w_{pi} and w_{ni} are their corresponding weighting factors. For each objective function, only one of the two deviation terms is nonzero, that is $\delta_{ni}\delta_{pi} = 0$ always holds; therefore δ_{ni} measures the underachievement, $J_i(x) < J_{ti}$, and δ_{pi} the overachievement, $J_i(x) > J_{ti}$, of a goal.

The NGP method minimizes a metric of the deviations from the target objectives, instead of directly minimizing the objective functions of the general formulation in (4). As the utility function method, the NGP formulation is in the form of a single-objective problem, constrained by all the objective functions stated as goals, and can be solved numerically with any appropriate scalar optimization algorithm. The solution will inherently include the decision making process to select a unique solution from the Pareto optimal set.

C. Optimization Algorithm

Central to the design of the power-pressure mapping will be the formulation of a MOOP following the nonlinear goal programming approach. To that aim, some particularities are taken into account to obtain a working algorithm from (5). First, the achievement function is made an l_1-norm setting $p = 1$. Second, all objective functions will be subject only to minimization, none to maximization, thus only the measures of overachievement will be useful, that is only the positive deviation terms and their weighting factors are to be utilized. Third, only the worst (maximum) positive deviation term (overachievement) is necessary to be minimized. Application of these measures to (5) yields the following working NGP formulation:

Find u that minimizes:

$$\delta_m = \max_{i=1, \ldots, k} \delta_{pi} \quad (6)$$

subject to:

$$(J(u) - J^*)) - w\delta_m \leq 0$$

where J^* is the k-dimensional vector of target objectives, and w is a k-dimensional vector of weights, $w_i \geq 0$, to be defined as follows.

Generally, the objective function target values are obtained by solving the k single-objective optimization problems:

$$J_i^* = \min\{J_i(u) \colon u \in \Omega\} \qquad i = 1, 2, \ldots, k. \quad (7)$$

The weighting coefficients, w_i, may be chosen arbitrarily to reflect preference on the objectives. To ease this task and make it intuitive, it is proposed to set them using:

$$w_i = (1 - \beta_i)J_i^* \quad (8)$$

where the $\beta_i \in [0, 1]$ are introduced as normalized nondimensional values to specify arbitrary relative preferences among the objectives. Intuitively, a lowest relative preference is indicated with $\beta_i = 0$, and a highest relative preference with $\beta_i = 1$. Note that $\beta_i = 1$ makes $w_i = 0$ and causes the associated constraint in (6) to be a hard constraint, $J_i(u) = J_i^*$, that must be satisfied. Intermediate values may be used to assign a degree of slackness in the achievement of the objective, and equal values can be assigned to indicate objectives with the same preference.

IV. Set-Point Scheduler

The essence of the problem is that of designing a nonlinear mapping to transform any given unit load demand profile to the set-point trajectory for the steam pressure control loop:

$$SP \colon (E_{uld}, t) \rightarrow (P_d, t) \quad (9)$$

where

E_{uld} is the unit load demand (MW),
P_d is the steam pressure demand (Kg/sec^2), and
t is time (sec).

The mapping SP is designed by solving a multiobjective optimization problem that takes into account the specified objectives, their relative preferences, and the steady-state model of the plant. The design process develops in three steps along the unit load demand range (Fig. 4):

- Determination of the feasibility regions for the decision variables.
- Solution of the multiobjective optimization problem to find optimal steady-state control signals.

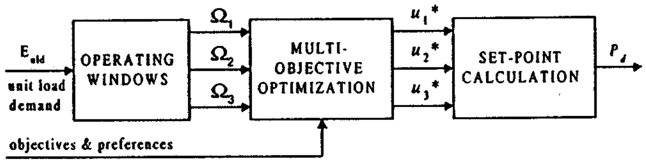

Fig. 4. Three step set-point generation process.

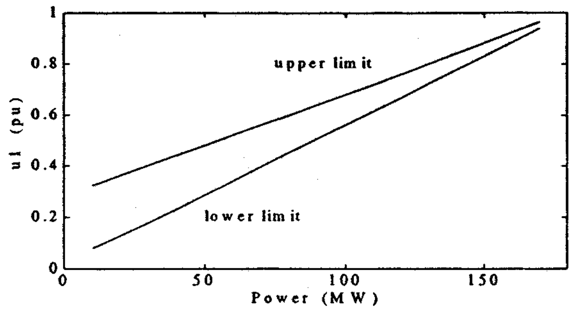

Fig. 5. Fuel valve demand operating window.

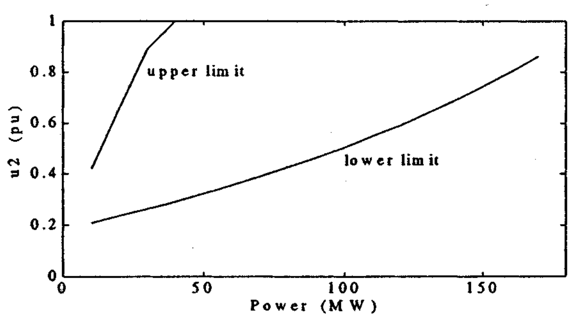

Fig. 6. Steam valve demand operating window.

- Calculation of the pressure set-points through direct evaluation of the steady-state model of the unit.

Without loss of generality and to ease the presentation, the powerpressure mapping is developed as a case study where the objective functions depend only on the control signals. Extension to objective functions involving state variables, or any other system signal, will follow a similar approach.

A. Feasibility Regions of Control Signals

The feasibility regions, Ω_i, $i = 1, 2, 3$, of the decision variables u_1, u_2, and u_3, may be determined experimentally, or set manually to impose operating constraints. In this case, the nonlinear mathematical model of the FFPU was used in a way similar to that explained in Section II to obtain the pressure operating region. The regions for the control signals u_1, u_2, and u_3 are shown in Figs. 5–7, respectively. Once the regions are determined, the envelops are programmed as look-up tables that provide the feasible regions as functions of the unit load demand value:

$$\Omega_i = f_i(E_{uld}), \qquad i = 1, 2, 3. \tag{10}$$

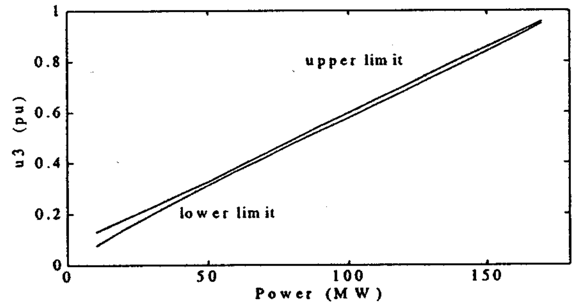

Fig. 7. Feedwater valve demand operating window.

B. Optimal Steady-State Control Signals

In this stage, a MOOP in the form of (6), subject to (10), is solved to find a vector of feasible inputs $u = [u_1 u_2 u_3]^T$ that minimizes the objective functions, $J(u) = [J_1(u) J_2(u) \cdots J_k(u)]^T$ with preferences $\beta = [\beta_1 \beta_2 \cdots \beta_k]^T$. The objective functions may account for load-tracking error, thermal stress, heat rate, pollution, or any other operating objective of interest to be optimized. One operating objective may be represented by more than one objective function. The result of this stage is a vector of optimal control signals, u^*, for each unit load demand value considered.

C. Calculation of Set-Points

Finally, every vector of optimal control signals, u^*, is used to generate a pressure set-point through the steady-state model of the power unit:

$$P_d = M_{ss}(u^*) \tag{11}$$

where M_{ss} is the power unit steady-state model solved with u as input and the controlled variables as outputs. The steady-state model is obtained by equating the dynamic state equations (1.a)–(1.c) to zero. The pressure set-point can be calculated with any equation; using (1.c) for simplicity:

$$P_d = \frac{141 u_3^*}{1.1 u_2^* - 0.19}. \tag{12}$$

D. Unit Responsiveness

Unit responsiveness refers to the capacity of the power unit to undertake sudden changes in power generation based on the amount of steam energy stored in the boiler that can be released for that purpose. Then, for any given power value, operation at higher drum pressure is said to be more responsive because there is more steam available for a rapid release, than at lower pressure. The working power-pressure characteristic specifies the unit responsiveness.

The previous three-step optimization procedure can be started from any initial condition, but in doing so, the ability to establish a desired unit responsiveness can be lost, since the outcome of the optimization procedure will depend entirely on the subsequent evolution of the optimization algorithm. To avoid this situation, the initial conditions can be given values corresponding to an expected power-pressure characteristic with the desired unit responsiveness. The constant and variable pressure characteristics previously shown in Fig. 3 are reasonable choices. This approach makes the optimization procedure to be more that of a refinement process to get the optimal power-pressure relationship around the desired responsiveness requirement.

V. Simulation Results

In what follows, the design and evaluation of the pressure set-point scheduler are presented for an operating scenario where improved load-tracking and heat-rate are the major operating objectives for process optimization.

A. Multiobjective Optimal Mappings

As previously stated, an operating policy can be specified by objective functions and their relative preference values, both of which define a multiobjective optimal power-pressure mapping. To achieve optimal load-tracking and heat-rate, the load-tracking error, fuel usage, and throttling losses in the main steam and feedwater control valves, should be taken into account. For this purpose, the following objective functions can be considered for minimization:

$$J_1(u) = |E_{uld} - E_{ss}| \tag{13.a}$$

$$J_2(u) = u_1 \tag{13.b}$$

$$J_3(u) = -u_2 \tag{13.c}$$

$$J_4(u) = -u_3 \tag{13.d}$$

where E_{uld} is the unit load demand (MW), and E_{ss} is the corresponding generation (MW) as provided by the steady-state model:

$$E_{ss} = \frac{0.73u_2 - 0.16}{0.0018u_2}(0.9u_1 - 0.15u_3). \tag{14}$$

Regarding the objective functions, $J_1(u)$ accounts for the power generation error, thus minimizing it will improve load-tracking. $J_2(u)$ directly accounts for fuel consumption through the fuel valve position; minimizing u_1 will reduce fuel usage. $J_3(u)$ accounts for losses due to pressure drop across the steam valve. Since the pressure drop increases as the valve closes, it is desired to keep it as wide open as possible, thus maximizing u_2, or equivalently minimizing $-u_2$, will reduce losses in the steam valve. A similar reasoning applies to $J_4(u)$ which accounts for pressure drop losses in the feedwater control valve. In general, more complex objective functions can be used to account for more specific requirements.

Next, the desired operating policy is built in three stages to show the effect of multiple objectives being considered. In the first stage, only the minimization of the load-tracking error is considered. Thus, only the objective function $J_1(u)$ is to be optimized with its relative preference value arbitrarily set for the highest priority, that is $\beta_1 = 1$. The resultant power-pressure mapping is shown in Fig. 8. This mapping matches the variable pressure policy (V Press) of a conventional coordinated control, which was provided as the typical variable pressure mapping in Fig. 3. In the second stage, fuel usage $J_2(u)$ with relative preference $\beta_2 = 0.5$ is considered in addition to $J_1(u)$ with $\beta_1 = 1$. The resultant mapping is also shown in Fig. 8.

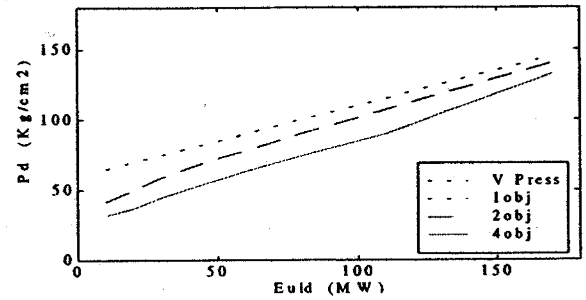

Fig. 8. Multiobjective optimal $E_{uld} - P_d$ relationships.

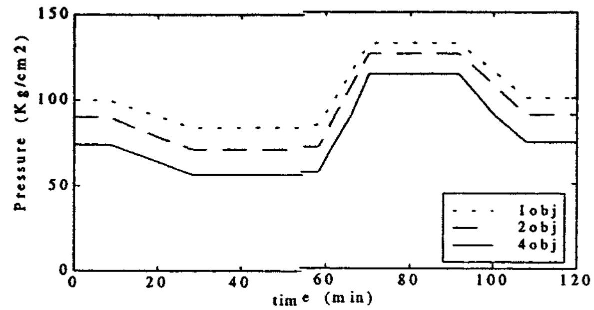

Fig. 9. Steam pressure set-point trajectories.

Finally, in the third stage and in addition to $J_1(u)$ and $J_2(u)$, the throttling losses in the steam valve, $J_3(u)$, and in the feedwater valve, $J_4(u)$, are also taken into account, with relative preference values set to $\beta_3 = 1$ and $\beta_4 = 0$. These values set the relevance of steam throttling losses at the same level as load-tracking since losses at the steam valve may be large due to its wide operating range (Fig. 6), and indicates that any amount of feedwater losses can be tolerated since the operating window for u_3 is narrow (Fig. 7). The resultant mapping is also plotted in Fig. 8.

Comparison of these results shows a trend to lower the pressure setpoint along the whole power range. Interestingly, the first decrease in pressure, from the 1-objective to the 2-objective case, was obtained without the intervention of $J_3(u) = -u_2$; further downward shifting was obtained by considering $J_3(u)$ explicitly in the 4-objective case. This behavior confirms quantitatively that process optimization can be achieved, in general, by opening the throttling valve as wide as possible for the given operating conditions. While operators do this intuitively in actual plants, this method provides a specific value for the pressure setpoint such that all operating constraints are optimally satisfied.

B. System Simulations

System tests presented here are intended to expose the behavior of the power unit to achieve process optimization during wide-range cyclic operation using the mappings just obtained. The desired unit load demand, E_{uld}, consists of a cycle with small, medium, and large load changes at slow, medium, and fast rates, respectively. The corresponding pressure set-point patterns for the cases with 1, 2, and 4 objectives are shown in Fig. 9. These plots are obtained from the desired unit load demand through the power-pressure mappings in Fig. 8.

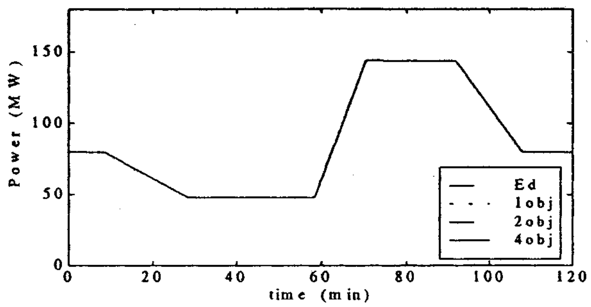

Fig. 10. Electric power response.

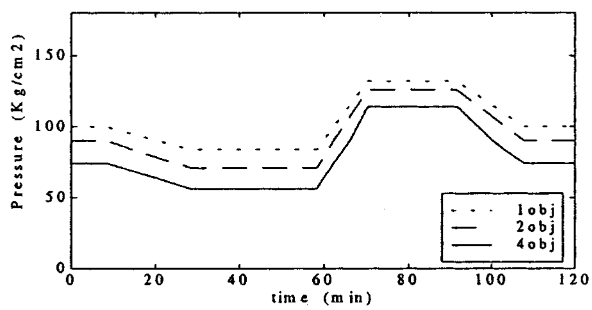

Fig. 11. Steam pressure response.

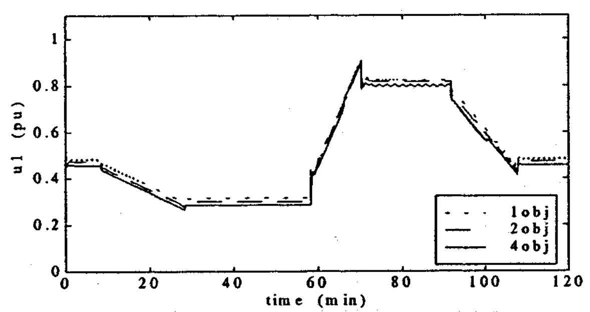

Fig. 12. Behavior of fuel valve, u_1.

The power and pressure responses for the cases with 1, 2, and 4 objectives are shown in Figs. 10 and 11, respectively. The corresponding behavior of the control signals u_1, u_2, and u_3, is shown in Figs. 12–14, respectively, which relate directly to the respective objective functions J_2, J_3, and J_4. To have a better appreciation of these results, the values accumulated during the simulation for each one of the four objective functions are provided in Table I, where as is usual for minimization problems, a smaller value indicates better performance, including the negative values for J_3 and J_4, where the negative values reflect the definition of the objective functions (13.c) and (13.d). Objectives which were not subject to optimization are provided within parentheses for each case; their values are presented so that all cases can be compared back to back. Unlikely, all objectives improved as the number of objectives increased. In general, results show agreement with the expected behavior. In addition, note that chattering in Fig. 12 is mainly due to operation far from the controllers' tuning-point and it calls for improvement on the feedback control strategy. Conventional fixed-gain PID

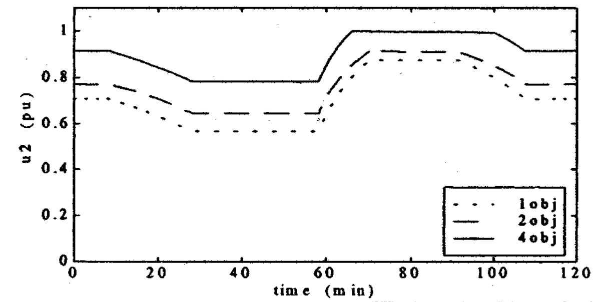

Fig. 13. Behavior of steam valve, u_2.

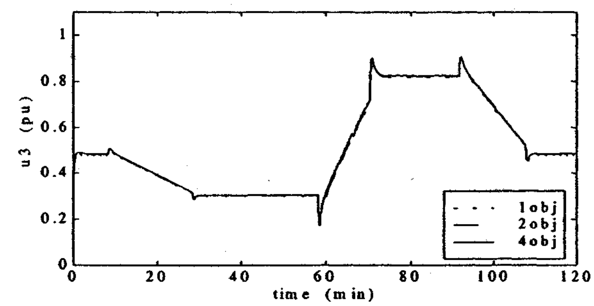

Fig. 14. Behavior of feedwater valve, u_3.

TABLE I
CUMULATIVE VALUES OF OBJECTIVE FUNCTIONS

Optimization criteria	1-objective	2-objectives	4-objectives
$J_1(u)$	118.87	110.97	100.00
$J_2(u)$	(4119.2)	4034.2	3907.1
$J_3(u)$	(-5654.2)	(-6151.2)	-7188.2
$J_4(u)$	(-4058.8)	(-4080.0)	-4120.3

(proportional-integral-derivative) control algorithms were used in the power and pressure controllers shown in Fig. 2.

C. Multiobjective Process Optimization

The previous case study shows the methodology to achieve process optimization in a multiobjective sense in a power plant, and the way to translate verbal operation requirements into mathematically tractable descriptions in terms of simple objective functions and their relative preferences. Tackling more complex operating objectives (i.e., life extension, and reduction of pollutant emissions) may require a more complete model of the process. In the case presented it should be noted that the objective function J_1 accounts for load tracking, while the objective functions J_2, J_3, and J_4 may be related directly to the unit's heat rate. Thus, the case study included two of the most important operation requirements currently faced by power units. In this regard, Fig. 15 shows side to side the electric power output, E, and the fuel power input, E_f, during a ramp increase in load for the cases with 1, 2, and 4 objectives. In general, the plots show that the ratio from the output power to the input fuel energy decreases as more objectives were considered. Since the output energy pattern is fixed, this behavior indicates a net improvement on the power generation process, that is a reduction in the unit's heat rate. Nevertheless, one should be aware that due to the model uncertainties, the trend in

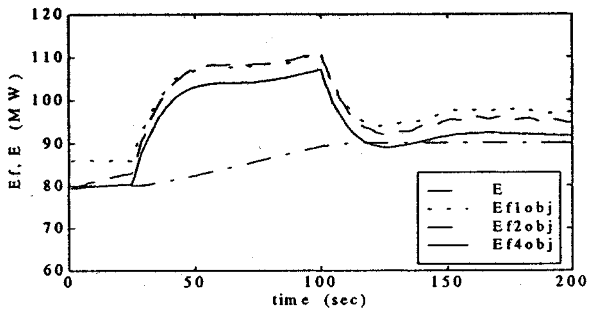

Fig. 15. Fuel input, E_f, and electric, E, power.

reducing the heat rate should only be considered qualitatively, since it is known that overall efficiencies for actual power plants are much lower.

VI. Summary and Conclusions

This paper presented a procedure to design multiobjective optimal power-pressure mappings for coordinated control of FFPUs. The set formed by the design procedure and mapping was realized as a supervisory pressure set-point scheduler. This approach allows overall process optimization, through set-point scheduling, for a great variety of operating scenarios characterized by multiple competing operating requirements. The scenario is accommodated through an operating policy that is specified in terms of objective functions and their preferences. The objective functions can be arbitrarily and directly proposed from the operating requirements, and the preference values are set in the range [0,1] to indicate the relative priority of the objectives. Then the power-pressure mapping is designed by solving a multiobjective optimization problem.

The optimization problem was formulated as a nonlinear goal programming problem, which provides a single design from the set of all possible multiobjective optimal designs by minimizing a scalar achievement function constrained by all the objective functions in the form of goals. The method is presented through a case study, and its viability is proved through simulation experiments. Results showed the method is suitable to achieve process optimization.

The proposed method is general, versatile, and simple enough for practical application. Interest has been expressed by a third party to incorporate the proposed method in training simulators to assist operators in assessing the pressure set-point under, diverse conditions. Perhaps, the main drawback of the proposed method is its dependency on the process model. In a next research stage, a fuzzy-based evolutionary strategy will be undertaken to deal with the uncertainty issues of the model.

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Raul Garduno-Ramirez received the B.S. degree in electrical engineering from the National Polytechnic Institute (IPN), Mexico, in 1985, and the M.S. degree in electrical engineering from Advanced Research Centre of the IPN, Mexico, in 1987. As a Fulbright Fellow, he is currently pursuing the Ph.D. degree in electrical engineering at the Pennsylvania State University. During 1986, he stayed at the National Mechanical Laboratory, Tsukuba, Japan, and during 1987–1995 at the Electric Research Institute, Mexico, where he was involved in the development of control systems for power plants. His current interest is in control software development and intelligent control.

Kwang Y. Lee received the B.S. degree in electrical engineering from Seoul National University, Seoul, Korea, in 1964, the M.S. degree in electrical engineering from North Dakota State University, Fargo, in 1968, and the Ph.D. degree in System Science from Michigan State University, East Lansing, in 1971. He has been on the faculties of Michigan State, Oregon State, Houston, and the Pennsylvania State University, where he is now Professor of Electrical Engineering. He is currently in charge of the Power Engineering Program and the Power System Control Laboratory at Penn State. His interests are power systems control, operation and planning, and intelligent power plant control. Dr. Lee has been a senior member of IEEE Control System Society, Power Engineering Society, and Systems, Man and Cybernetics Society. He is also a registered Professional Designer.