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A multiobjective-optimal neuro-fuzzy extension to power plant co-ordinated control

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This paper presents an overall control scheme for wide-range multiobjective-optimal operation of a fossil-fuel power unit. The scheme provides the means to accommodate operating scenarios characterized by multiple operating requirements, and to attain optimal operation along any arbitrary unit load-demand pattern. The proposed strategy builds upon current co-ordinated control schemes, which typically account for simultaneous control of power and steam pressure. First, the scope of co-ordination over the internal processes of the unit is extended by including the control of the drum water level to achieve balanced overall plant operation at all loads. Then, a supervisory reference governor and a neuro-fuzzy feedforward control path are added to complement the already existing multiloop feedback control configuration. The reference governor implements a set-point scheduler based on unit load demand to set-point mappings, which are designed by solving a multiple objective optimization problem. The feedforward control path approximates the nonlinear multivariable inverse static behaviour of the power unit at the optimal operating conditions specified by the set-point mappings through a set of multi-input–single-output fuzzy inference systems, which are designed using a neuro-fuzzy learning paradigm. With this approach, the plant is driven by an arbitrary unit load-demand pattern from which the reference governor specifies the multiobjective-optimal operating conditions for the plant through set-point trajectories; the feedforward control path provides control signals to achieve wide-range manoeuvrability and the feedback control path compensates for uncertainties and disturbances, along and around the commanded set-point trajectories, respectively. Simulation results demonstrate the feasibility of the proposed control scheme.

Key words: co-ordinated control; multiobjective optimization; neuro-fuzzy control; power plant; process optimization.

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Nomenclature

\[ E_{uld} \quad \text{Unit load demand (MW)} \]
\[ E (E_d) \quad \text{Electric power (reference) (MW)} \]
\[ P (P_d) \quad \text{Steam pressure (reference) (kg/cm}^2\text{)} \]
\[ L (L_d) \quad \text{Drum water level deviation (reference) (m)} \]
\[ \rho_f \quad \text{Fluid (steam-water) density (kg/cm}^3\text{)} \]
\[ u_1 (u_{1ff}, u_{1fb}) \quad \text{Fuel control valve demand (feedforward, feedback) (p.u.)} \]
\[ u_2 (u_{2ff}, u_{2fb}) \quad \text{Steam control valve demand (feedforward, feedback) (p.u.)} \]
\[ u_3 (u_{3ff}, u_{3fb}) \quad \text{Feedwater control valve demand (feedforward, feedback) (p.u.)} \]
\[ \alpha_s \quad \text{Steam quality} \]
\[ q_e \quad \text{Evaporation rate (kg/s)} \]
\[ E_{spm} \quad \text{Unit load demand to electric power set-point mapping} \]
\[ P_{spm} \quad \text{Unit load demand to pressure set-point mapping} \]
\[ L_{spm} \quad \text{Unit load demand to level deviation set-point mapping} \]
\[ \Omega_i \quad \text{Feasibility region of } i\text{th decision variable} \]
\[ J(\cdot) \quad \text{k-dimensional vector of objective functions} \]
\[ J_i(\cdot) \quad \text{i\textsuperscript{th} objective function} \]
\[ f_i(\cdot) \quad \text{i\textsuperscript{th} function} \]
\[ \lambda \quad \text{Unconstrained scalar variable} \]
\[ w_i \quad \text{i\textsuperscript{th} weighting coefficients} \]
\[ J_i^* \quad \text{i\textsuperscript{th} optimization goal} \]
\[ \beta_i \quad \text{i\textsuperscript{th} relative preference value} \]
\[ SP \quad \text{Vector of set-points} \]
\[ M_{ss}(\cdot) \quad \text{Power unit steady-state model} \]
\[ LE_d \quad \text{Linguistic variable for power set-point} \]
\[ LP_d \quad \text{Linguistic variable for pressure set-point} \]
\[ LL_d \quad \text{Linguistic variable for level deviation set-point} \]
\[ K_{0,E,P,L} \quad \text{Rule consequent coefficients} \]
\[ E_{ss} \quad \text{Steady-state electric power} \]
\[ IAE_V \quad \text{Integral of absolute value of variable } V \text{ error} \]
\[ P_{uff} \quad \text{Power of feedforward control signal } u_{iff} \]
\[ P_{ufb} \quad \text{Power of feedback control signal } u_{ifb} \]

1. Introduction

In recent years, economical convenience has forced fossil-fuel power units (FFPUs), of all sizes, to participate in load-following duties, despite the fact that most of them were designed to operate at constant base-load, for the power systems to be able to match the power needs of consumers (Armor, 1985). Effective participation of an FFPU in load-following duties requires the ability to generate power in daily, weekly and seasonal cycles, as well as to follow random fluctuations about those patterns. Large power variations, from the minimum to the maximum generation level and vice versa, in short time periods are not rare any more. Thus, cycling
practice demands wide-range operation capability in both energy generation and energy rate of change. Additionally, competition among utilities and stringent regulations have increased the complexity of the operating context of FFPUs far beyond the already challenging wide-range load-tracking operation requirement. So, it is now necessary to satisfy simultaneously, in the best possible way, many competing needs and requirements for the generation companies to stay competitive, yet remain profitable, and consequently to survive. Among the most relevant objectives are those related to conservation and life extension of major equipment, and to reduce any adverse environmental impact (Divakaruni and Touchton, 1991). This includes minimization of fuel consumption, minimization of heat rate, minimization of thermal stress, minimization of pollutant emissions, and many others. Therefore, this situation may be synthesized as an essential requirement for a control system to provide the means to achieve the demanded power while attaining optimal process operation under multiple, generally conflicting, operating objectives throughout the operating range of the FFPU.

The many loops of the control system in an FFPU regulate all the energy transformations taking place within the unit to produce the required electric power. The overall unit control scheme (OUCS), embracing just a few control loops, commands the dominant behaviour of the power unit, while the remaining loops work to catch up. The OUCS implements the highest automatic operation mode in an FFPU by driving it as a single entity, and constitutes the interface to upper power system control levels. The OUCSs are typically classified as boiler follower, turbine follower and coordinated control (CC; Babcock and Wilcox, 1978), with CC schemes the most successful. Typically, current CCs embrace simultaneous control of electric power and main steam pressure by means of a multiloop configuration of single-input–single-output (SISO) PID feedback loops. Such approach has proved its value during normal operation at base-load, where the plant characteristics are almost constant, nearly linear and weakly coupled. Nevertheless, under wide-range operation, traditional control schemes, designed and tuned for regulation and disturbance rejection about a fixed operating point, but set-point tracking, may decrease the global performance of the unit due to the coupled nonlinear dynamics of the process, thus making them less acceptable for wide-range cyclic operation. To attain better performance, several compensations have been added to the basic CC to reduce the interaction effects among the control loops (Taft, 1987). Also, several approaches based on advanced control techniques have been proposed, including: decoupling theory (Ray and Majumder, 1985), generalized predictive control (Rossitier et al., 1991), model-based predictive control (Lu and Hogg, 1995), and robust control (Weng and Ray, 1997). However, since most FFPUs and their control systems were designed to operate at base-load conditions, their use for wide-range operation may impose strong physical demands on the equipment (Durrant and Vollmer, 1971). Except for a few of them (Nakamoto et al., 1993), most advanced designs are only valid for a narrow operation range about the design base operating point. Therefore, this state of the art calls for the development of effective control strategies to support the much required wide-range operation capability.

On the other hand, most research effort has focused in the development of better feedback control strategies, aimed to attain optimal dynamic process operation. Although the structure of power systems and power plants seems to favour super-
visory control of power units, little attention has been paid to the development of supervisory process optimization strategies through set-point scheduling; the literature on this topic is scarce (Dieck-Assad et al., 1987; Ben-Abdennour and Lee, 1996; Prasad et al., 1999). Most of the time, it is assumed that satisfactory set-point values are always available, without questioning their origin and adequacy, and the fact that feedback control alone cannot refine operation beyond what is established by the set-points is frequently overlooked. Most set-point values are provided by predefined characterizations valid for the original rated operating policy; there is no provision to take into account new operating policies and changes in the dynamic characteristics of the power unit. Currently, there are no established mechanisms to specify the requirements of the operating scenario being faced by the power unit to integrate them into a process optimization strategy. There is no provision for optimal operation under multiple objectives, as currently required at power units. Recently, interest in the interactions between power units and power systems is being rejuvenated (Lausterer, 1997). This may draw more attention to power plant process optimization within the power system operation. Therefore, effective participation in overall power system process optimization demands a revision of the methods used for process optimization at power units, and consequently the methods used for set-point generation.

Previous research by the authors has shown the feasibility of feedforward control to facilitate wide-range operation (Garduno and Lee, 1999), and pressure set-point scheduling to achieve process optimization (Garduno and Lee, 2000). Now, this paper presents a comprehensive OUCS that integrates both approaches to attain multiobjective optimal wide-range operation in a power unit. The proposed scheme builds upon current CC schemes. First, the scope of the CC is extended to include the drum water level control in the core of the co-ordination strategy. This tactic provides the means to achieve overall plant energy/mass balance at all loads along the whole operating range of the unit. Then, a supervisory reference governor and a reference feedforward control path are incorporated into the existing PID-based multiloop feedback control scheme. As will be shown, this approach allows for optimal wide-range operation along any unit load-demand pattern under a great diversity of operation scenarios characterized by multiple operating objectives.

After these introductory remarks, the next section describes, qualitatively and quantitatively, the fundamental dynamics taken into account to extend the scope of the CC system. The third section presents the extended CC system structure. The fourth section summarizes the details of the multiobjective optimal set-point scheduler in the reference governor. The fifth section provides the main features of the feedforward control path. The sixth section presents some simulation experiments that demonstrate the feasibility of the proposed control system. Finally, the last section concludes this work.

2. Power unit dynamics

2.1 Basic input–output behaviour

From the power system perspective, the overall input–output behaviour of an FFPU has noteworthy relevance. On one hand, long-term frequency stability
analysis, which assumes that all electromechanical oscillations have died out and that the system is operating at constant frequency, perhaps different from the nominal value, could be in a time frame of several to tens of minutes. On the other hand, the main boiler dynamics are relatively slow: steam pressure and temperature oscillations, and the effect of fuel flow variations on the generated power, are in the order of minutes. Therefore, the dynamics of FFPU's are considered a major factor in frequency stability analysis (Kundur, 1994). Accordingly, any FFPU participating in load-frequency control duties should be equipped with control systems that take into account the long-term overall input–output dynamic behaviour of the unit.

In a drum-type FFPU, the essential overall dynamics may be described in terms of the major inputs (fuel flow, air flow, steam flow into the turbine, feedwater flow, and spray flows into the superheater and reheater) and outputs (electric power, steam throttle pressure, drum water level, superheater outlet temperature, and reheater outlet temperature) (Maffezoni, 1997). Electric power and steam pressure are tightly coupled and are affected heavily by the fuel/air flow and the steam flow. Feedwater flow slightly affects power and pressure, but greatly affects the drum level, which in turn is considerably affected by the fuel and steam flows. Similarly, the spray flows have a minor effect on power and pressure, but greatly affect the heater's outlet temperatures, which are heavily influenced by the fuel flow. In summary, fuel and steam flow may be used to drive the unit to the desired values of power and pressure, this will disturb the drum water level and heater's outlet temperatures, which may then be manipulated with the feedwater and spray flows, respectively.

The interaction between fuel, steam and feedwater flows as inputs, and power, pressure and water level as outputs, obligates us to primarily take these variables into account to achieve wide-range operation. Spray flows and temperatures can be used for further improvement. This work concentrates on the former situation. Furthermore, the open-loop behaviour determines the input–output pairing to form the feedback control loops. Figure 1 shows the response to a step opening

![Figure 1](http://example.com/f1.png)

Figure 1  Open-loop response to steam valve step
in the steam valve with the fuel and feedwater valves kept constant. Power increases and decays back close to its original value, while pressure decreases to a new value and the level keeps decreasing. Figure 2 shows the response to a step opening in the fuel valve, with the steam and feedwater valves at a fixed position. Both throttle pressure and power increase to a new fixed higher value, while the level keeps decreasing again. From these tests it can be seen that for short-term purposes, a fast response to load variations may be attained using the throttle valve to control power and the fuel valve to regulate the steam pressure. Conversely, for long-term purposes, fuel flow should be used to control power, and the throttle valve to control the steam pressure. In both cases the level has to be regulated to balance plant operation.

2.2 Mathematical model

The essential dynamics of an FFPU have been remarkably captured for a 160-MW oil-fired drum-type boiler-turbine-generator unit in a third order multi-input–multi-output (MIMO) nonlinear model for overall wide-range simulations (Bell and Astrom, 1987). The inputs are the positions of the valve actuators that control the mass flow rates of fuel ($u_1$ in p.u.), steam to the turbine ($u_2$ in p.u.), and feedwater to the drum ($u_3$ in p.u.). The three outputs are the electrical 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 the electric power, drum steam pressure and the fluid (steam-water) density ($\rho_f$). The state equations are:

\[
\frac{dP}{dt} = 0.9u_1 - 0.0018u_2P^{9/8} - 0.15u_3 \quad (1a)
\]

\[
\frac{dE}{dt} = (((0.73u_2 - 0.16)P^{9/8} - E)/10 \quad (1b)
\]

Figure 2  Open-loop response to fuel valve step
\[
\frac{dP_f}{dt} = \frac{(141u_3 - (1.1u_2 - 0.19)P)}{85} \quad (1c)
\]

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

\[
q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09 \quad (2a)
\]

\[
\alpha_s = \frac{1}{\rho_f - 0.0015} / \left( \frac{1}{0.8P - 25.6} - 0.0015 \right) \quad (2b)
\]

\[
L = 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5) \quad (2c)
\]

where \(\alpha_s\) is the steam quality, and \(q_e\) is the evaporation rate (kg/s). The control valves have rate and position limits.

### 3. Control system

#### 3.1 Co-ordinated Control

Given a unit load demand, the CC provides the demands to the boiler and to the steam turbine to harmonize the slow response of the boiler with the faster response of the turbine-generator set, to provide a fast and stable unit response during load changes and load disturbances. Depending on the pairing of controlled and manipulated variables, there are two possible modes for CC: co-ordinated boiler-follower mode and co-ordinated turbine-follower mode (Landis and Wulfsohn, 1988). In co-ordinated boiler-follower mode, the power controller generates the demand to the steam throttle valve from the unit load demand and the measured generated power. The pressure controller generates the demand to the fuel/air valve subsystem from the measured throttle pressure and the pressure set-point. The pressure set-point is obtained from the unit load demand through a nonlinear characterization. In co-ordinated turbine-follower mode, the power controller generates the demand for the fuel/air valve subsystem from the unit load demand and the measured generated power. The pressure controller generates the demand to the throttle valve from the measured throttle steam pressure and the pressure set-point. Again, the pressure set-point is obtained from the unit load demand through a nonlinear characterization (Figure 3). Thus, based on the unit step responses shown in the first section, the boiler-follower CC should be preferred for fast transient response, while the turbine-follower CC should be chosen to achieve long-term process optimization objectives.

#### 3.2 Extended Co-ordinated Control

The general structure of the extended CC system, shown in Figure 4, includes three major components: reference governor, feedback and feedforward controls. The set-points for electric power, steam pressure and drum water level, \(y_d = [E_d P_d L_d]\), control loops are calculated at the reference governor. The feedforward and feedback blocks provide the feedforward control signal, \(u_{ff} = [u_{1ff} u_{2ff} u_{3ff}]\), and
Figure 3 Turbine-following Co-ordinated Control

the feedback control signal, $u_{fb} = [u_{1fb}, u_{2fb}, u_{3fb}]$, respectively. Both control signal vectors are added to provide the control signals, $u = [u_1, u_2, u_3]$, to the fuel, steam and feedwater control valves.

At the reference governor, the set-points are obtained from the unit load demand while optimally satisfying the operating policy, which is specified in terms of an arbitrary number of objective functions and relative preferences, which in turn are dictated by the operating scenario at hand. The feedforward control approximates the inverse nonlinear input–output steady-state behaviour of the FFPU. It is implemented as an MIMO fuzzy system that provides smooth control signals over the whole operating range of the FFPU. The feedback control block is implemented as a multiloop configuration of three independent SISO control loops based on PID control algorithms, as currently available at power units. As was previously concluded for long-term operation purposes, the process input–output pairing for the feedback loops is made between the fuel valve and the electric power, the throttle valve and the steam pressure, and the feedwater valve and the drum water level deviation.

From a global perspective, the set-point scheduler specifies and co-ordinates the desired response of the power unit through the optimal set-point trajectories. The feedforward and feedback paths implement a two degrees-of-freedom nonlinear multivariable controller. 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 now complementary, in that it supplies the component of the control signal that is necessary for regulation and disturbance rejection about the specified set-point trajectories.
Additionally, it should be highlighted that the drum water level control became fully integrated in the CC scheme. This approach allows balanced unit operation at any load, which is a major requirement to achieve wide-range operation. Furthermore, the proposed control structure seems well suited for upgrading actual control systems, since it may preserve the existing feedback control configuration and facilitate implementation of automation functions, such as manual–automatic-co-ordinated operation modes, and transfer between them. Finally, as will be shortly shown, all required optimization functions are performed offline and out-of-the-loop, avoiding the algorithm convergence problems at run-time faced by other approaches (Nakamura and Uchida, 1989; Weng and Ray, 1997).

4. Reference governor

The reference governor consists of a one-to-many nonlinear mapping and a supervisory mapping designer. The one-to-many mapping is implemented as three separate one-to-one set-point mappings, from the unit load demand to each one of the set-points (Figure 5):

\[ E_{spm}: E_{uld} \rightarrow E_d \]  
\[ P_{spm}: E_{uld} \rightarrow P_d \]  

(Figure 4 Extended Co-ordinated Control)
where $E_{uld}$ is the unit load demand (MW), $E_d$ is the power set-point (MW), $P_d$ is the steam pressure set-point (kg/s$^2$), and $L_d$ is the drum water level deviation set-point (m).

The design of the three one-to-one mappings is carried out simultaneously by the supervisory designer 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 follows three major steps:

1) determination of the feasibility regions for the control signals at every pre-specified unit load demand value;
2) solution of the multiobjective optimization problem to find the optimal steady-state control signals;
3) calculation of set-points through direct evaluation of the steady-state model of the unit.

4.1 Feasibility regions of control signals

The determination of the feasibility regions, $\Omega_u$ for the control signals, $u_i$, $i = 1, 2, 3$, may be done experimentally, or set manually to impose operating constraints. In this paper, the nonlinear mathematical model of the FFPU was used for this purpose. Computationally intensive simulations are carried out to find the upper and lower limits of the feasible regions along the whole unit load operating range.

Once the windows are determined, they are programmed as look-up tables that provide the feasible regions, $\Omega_u$ of the inputs as functions of the unit load demand value:

$$\Omega_i = f_i(E_{uld}), \; i = 1, 2, 3$$  \hspace{1cm} (4)
4.2 Optimal steady-state control signals

At several values of the unit load demand, the following multiobjective optimization problem is solved:

$$\min J(u)$$ (5)

subject to:

$$u_i \in \Omega_i(E_{uld}), i = 1,2,3$$

where $$J(u) = [J_1(u) J_2(u) \ldots J_k(u)]^T$$ is a $$k$$-dimensional vector of objective functions, and $$u = [u_1 u_2 u_3]^T$$ is the three-dimensional vector of control signals, whose optimal values are to be determined.

The objective functions may represent cost functions for evaluating load-tracking error, thermal stress, heat rate, pollution or whatever performance function needs to be optimized as a function of the control inputs, state variables or any other system variables.

The optimization problem can be solved by many different methods. In this paper, it was solved using the nonlinear goal programming method (Miettinen, 1999). In this formulation a goal and a priority is assigned to each objective function. Then, the solution algorithm tries to satisfy as many of the goals as possible starting with the highest priority goal. To do this, the multiobjective optimization problem (5) is reformulated as (Garduno and Lee, 2000):

$$\min_{\lambda, u \in \Omega}$$ (6)

subject to:

$$J_i(u) - w_i \lambda \leq J_i^* \quad i = 1,2,\ldots,k$$

where $$\lambda$$ is an unconstrained scalar variable, $$J^*$$ are the goals to be realized, and $$w_i \geq 0$$ are weighting coefficients that may be chosen arbitrarily to reflect preference on the objectives. Values assigned to the weighting coefficients serve also to select a unique solution from the set of Pareto optimal solutions. It is proposed to set them as

$$w_i = (1 - \beta_i)J_i^* \quad i = 1,2,\ldots,k$$ (7)

where $$\beta_i \in [0,1]$$ is introduced to specify a relative preference value among objectives. The lowest preference is indicated with 0 and the highest with 1. Intermediate values may be used to prioritize among different objectives.

4.3 Calculation of set-points

Once the optimal control signals, $$u^*$$, are found at each selected unit load demand, they are used to calculate the optimal set-points through the steady-state power unit model:

$$SP = M_{ss}(U^*)$$ (8)
where $SP = [E_d \ P_d \ L_d]^T$ is a vector of set-points, $M_{ss}$ 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 setting the derivatives of the dynamic state equations (1a,b,c) to zero. Then, the set-points are given by:

$$E_d = \frac{0.73u_1^* - 0.16}{0.0018u_2^*} - (0.9u_1^* - 0.15u_2^*)$$  
(9a)

$$P_d = \frac{141u_3^*}{1.1u_2^* - 0.19}$$  
(9b)

$$L_d = 0$$  
(9c)

Finally, the set of optimal set-points is arranged to form the desired set-point mappings (3a, b, c).

As said before, with this approach the set-point scheduler will command the plant only through operating points that are optimal in a multiobjective sense – optimizing the overall operation of the power unit in the way defined by the objectives and their preferences. Basic concepts about multiobjective optimization, as well as more details on the mathematical formulation of the multiobjective optimization problem used here, can be found in Garduno and Lee (2000).

5. Neuro-fuzzy feedforward control

It has been shown that reference feedforward control, through a group of multi-input–single-output (MISO) fuzzy systems, may ease achievement of wide-range operation (Garduno and Lee, 1999). The fuzzy systems were designed from the input–output plant data under a typical power-pressure operating policy. Now, a neuro-fuzzy paradigm exploits the learning capabilities of neural networks to update the MISO fuzzy systems in the feedforward control path whenever the operating policy changes. This approach provides the control system with learning capabilities that allow it to accommodate different operating scenarios.

5.1 Feedforward fuzzy control path

Ideally, the reference feedforward control path should be, or approximate, the inverse dynamic model of the power unit. However, this approach comes with no guarantee of being well defined, besides being prone to inaccuracies since accurate wide-range modelling is a difficult issue for complex processes such as power units. To overcome this problem, it has been proposed that the feedforward path should only be required to approximate the nonlinear inverse input–output steady-state behaviour of the unit (Garduno and Lee, 1999). Proceeding in the same way, and using the intermediate results of the already discussed set-point mapping design problem, the feedforward path can be designed to be a vehicle to
provide the control signals necessary to achieve wide-range multiobjective optimal process operation.

The inverse static model approximation is realized through an MIMO fuzzy system which is composed of three MISO fuzzy subsystems: FIS_U1, FIS_U2 and FIS_U3 (Figure 6). Each MISO fuzzy subsystem implements a nonlinear multivariable function of the form:

\[ u_{iff} = f(E_{dr}, P_{dr}, L_{d}), \quad i = 1, 2, 3 \]  

(10)

that is, all subsystems are supplied with the same set-points \((E_{dr}, P_{dr} \text{ and } L_{d})\), as calculated by (9), and each one of them provides one of the feedforward control signals \((u_{1ff}, u_{2ff} \text{ and } u_{3ff})\).

The design of the MIMO fuzzy feedforward path is carried out using steady-state input–output data of the unit along its whole power operating range. This information is available from the intermediate results of the set-point mapping design problem, or alternatively from actual plant data, in which case the selected input variables would be the fuel valve demand, \(u_1\), the steam throttle valve demand, \(u_2\), and the feedwater valve demand, \(u_3\), and the power generation, \(E\), steam throttle pressure, \(P\), and drum water level deviation, \(L\), as output variables.

Then, each MISO fuzzy system is built using the process outputs as inputs, and one process input as output. At this point, a neuro-fuzzy paradigm can automate the design process, avoiding the cumbersome tasks normally involved in the design of fuzzy systems by the traditional trial and error or expert-assisted methods. To this aim, the neuro-fuzzy paradigm is considered next.

Figure 6  Neuro-fuzzy feedforward controller
5.2 Neuro-fuzzy paradigm

In a hybrid neuro-fuzzy system (NFS), a neural network and a fuzzy system are combined into one homogeneous structure. NFSs are intended to synthesize the advantages of both neural networks and fuzzy systems in a complementary way to overcome their disadvantages. There are several approaches for the integration of neural networks and fuzzy systems.

The kind of NFSs of interest for this work have several common defining characteristics. The NFS approximates an $n$-dimensional, usually unknown, function that is partially defined by a set of input–output data. The NFS is a fuzzy system whose knowledge rules represent the relation among samples of the given data. The components of the NFS are determined using neural network learning algorithms applied to the given data. For the purpose of learning, the fuzzy system may be represented by a feedforward neural network. In one of the simplest possible representations, at least three layers are required: the first layer would represent the input variables, the middle layer would represent the fuzzy rules and the third layer would represent the output variables. The connection weights would be specified with fuzzy sets. The neuron units would evaluate $t$-norm and $t$-co-norm operators as activation functions (Wang, 1997). Models with more than three layers and fuzzy sets as activation functions are also possible (Ghezelayagh and Lee, 1999). What is relevant here is that the neural network representation may vividly illustrate the parallel nature of fuzzy systems.

The learning procedure is a data-driven process. The learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system. The learning procedure takes into account the properties of the associated fuzzy system, thus constraining the possible modifications of the system’s parameters. Since the NFS is always a fuzzy system at any stage of the learning process, the learning procedure can be initialized specifying the components of a fuzzy system. Consequently, the NFS paradigm may be used to build a fuzzy system from data or to enhance an existing one by learning from examples.

5.3 Synthesis of the NFSs

There is currently available several methods to synthesize an NFS: GARIC, NEFCON, FuNe, ANFIS, etc. (Nauck et al., 1997). In this work, the NFSs are synthesized using the general purpose adaptive neuro-fuzzy inference system (ANFIS) technique (Jang, 1993). The MISO fuzzy systems required for the feedforward control path are implemented as first-order Sugeno-type fuzzy systems, with knowledge rules, $R_j$, of the form:

$$IF : E_d \text{ is } LE_d \text{ and } P_d \text{ is } LP_d \text{ and } L_d \text{ is } LL_d$$

$$THEN : u^j_i = K^0_j + K^E_j E_d + K^P_j P_d + K^L_j L_d$$

(11)

where $j = 1,\ldots,N$ is the rule number, $i=1,2,3$ is the output number, $LE_d$, $LP_d$ and $LL_d$ are linguistic variables with values low, medium and high, and $K^0, K^P, K^E$ and $K^L$ are coefficients to be determined for each rule. Using the ANFIS method, the
fuzzy system is represented by a three-input–one-output five-layer feedforward neural network as shown in Figure 7. The neurons in each layer implement different functions of the fuzzy system. Layer 0, $L_0$, not always considered a layer, is the input layer that transmits the input signals to the next layer. Layer 1, $L_1$, performs input fuzzification. In this case, there are nine neuron units, each one implementing the bell-shaped membership functions of a linguistic variable (low, medium or high) to fuzzify the coming input. Layers 2 ($L_2$), 3 ($L_3$), and 4 ($L_4$) implement the 27-rule knowledge base, where each rule is represented by three neuron units aligned horizontally across the three layers. Each neuron unit in $L_2$ forms the antecedent of a rule as in (11): receives input from only three units in the previous layer, and evaluates the antecedent into a value of the degree of fulfillment for that rule. Then in every neuron unit of $L_3$ the degree of fulfillment for each rule is normalized with respect to the values for all the rules. Thus, each unit in $L_3$ is connected to all units in $L_2$, and provides the normalized degree of fulfillment value to units in $L_4$. The neuron units in $L_4$ are directly connected to

**Figure 7** Neural network structure of fuzzy system
all input units in $L_0$ and to one unit in $L_3$. Each unit computes the consequent of a rule weighted by the relative degree of fulfillment. Finally, $L_5$ performs defuzzification by adding all the inputs coming from $L_4$ and provides the desired feedforward control signal value.

Given an initial fuzzy system, the ANFIS method allows tuning the input membership functions of the linguistic variables in $L_1$, and determination of the coefficients in the knowledge rule consequents in $L_4$. The learning process is carried out iteratively in two phases. First, the input patterns are propagated, and the optimal consequent parameters are estimated by a least mean square procedure keeping the antecedent parameters constant. Second, the patterns are propagated again and the antecedent parameters are modified by back-propagation keeping the consequent parameters constant. The use of differentiable membership functions and consequent functions enables the method and guarantees convergence for a given set of training data.

6. Simulation results

Several simulation experiments were carried out to show the performance of the proposed extended CC scheme. In what follows, the design results of the set-point scheduler and the neuro-fuzzy feedforward systems are presented, as well as simulation results on the performance of the whole system that includes the already existing multiloop feedback configuration with conventional PI controllers.

6.1 Set-point scheduler

With the aim of implementing an operating policy to attain minimum load-tracking error and improved heat rate, the following objective functions can be considered:

\[
\begin{align*}
J_1(u) &= |E_{uld} - E_{ss}| \quad (12a) \\
J_2(u) &= u_1 \quad (12b) \\
J_3(u) &= -u_2 \quad (12c) \\
J_4(u) &= -u_3 \quad (12d)
\end{align*}
\]

where $E_{uld}$ is the unit load demand or desired power generation in MW, and $E_{ss}$ is the corresponding steady-state power generation as provided by the static model.

To show the effect of the multiobjective optimization approach, and for later comparison, the operating policy is implemented in three successive cases. In the first case, only the load-tracking error, $J_1(u)$, is minimized with a relative preference value $\beta_1=1$ for top priority. The second case also minimizes the fuel usage, $J_2(u)$, with preference $\beta_2=0.5$. The third case adds minimization of throttling losses in the steam valve $J_3(u)$ and in the feedwater valve $J_4(u)$, with preference values $\beta_3=1$ and $\beta_4=0$, respectively. The resulting set-point mappings show that $E_d = E_{uld}$ and $L_d = 0$ for all cases, and the steam pressure set-point mappings provide lower values for the cases with more objectives (Figure 8).
6.2 Feedforward control

The MISO neuro-fuzzy systems in the feedforward control path were designed for the three process optimization cases being considered using the power unit's steady-state input–output data resulting from the multiobjective optimization process. Input–output patterns were taken every 10 MW in the unit load demand, spanning the whole power operating range of the unit, that is from 10 to 180 MW.

For the neuro-fuzzy systems to represent the inverse static model of the power unit, the input training patterns are given by the triads \((E, P, L)\), and the output training patterns are given by each one of control signals \(u_1, u_2\) and \(u_3\). Once embedded in the control system, all the MISO systems will be fed with the same optimal set-points \((E_d, P_d, L_d)\), and each one will provide a feedforward control signal: \(u_{1\text{ff}}, u_{2\text{ff}}\) and \(u_{3\text{ff}}\).

6.3 System simulations

The performance of the whole system is demonstrated through wide-range load-tracking simulations. An ad hoc unit load-demand pattern, \(E_{u\text{ld}}\), with characteristics similar to those of a typical daily load cycle is employed. The load-demand profile includes a small load change at small rate, a large load change at fast rate and a medium load change at medium rate, with constant load at the intermediate periods.

Tests are conducted for all optimization cases (one-, two- and four-objective). The set-point trajectories are obtained online from the unit load-demand pattern, through the multiobjective-optimal set-point mappings already designed. The power set-point trajectory is, in all cases, equal to the unit load-demand pattern, \(E_d(t) = E_{u\text{ld}}(t)\). Also, for all cases \(L_d(t) = 0\). The pressure set-points follow the shape of \(E_{u\text{ld}}(t)\) but at different levels. The power, pressure and level responses for the
A multiobjective-optimal neuro-fuzzy extension to power plant co-ordinated control

three process optimization cases are shown in Figures 9, 10 and 11, respectively. All cases show very good load-tracking results. Differences between the power set-point trajectory and the generated power are almost indistinguishable. Also, tracking of the pressure trajectory and regulation about zero drum level deviation are very good, with minor oscillations after the sharp changes in the set-point.

Figure 9  Power response to optimal set-points

Figure 10  Pressure response to optimal set-points
trajectory. To have a better appreciation of these results, Table 1 provides the values of the \( IAE \) performance index:

\[
IAE_V = \int_0^t \left| V_d - V \right| dt
\]  

where \( V = E, P, L \). From these values the average power tracking errors are 0.30, 0.33 and 0.35 MW, equivalent to 0.19, 0.21 and 0.22%, for the cases with one, two, and four objectives, respectively. The cumulative tracking errors for the pressure and level set-points also correspond to very small average tracking errors. It should be noted that in all cases, the primary objective of power tracking, represented by the first objective \( f_1(u) \), is achieved while the unit is following different pressure set-point trajectories.

The behaviour of the control signals \( u_1, u_2 \) and \( u_3 \) is shown in Figures 12, 13

<table>
<thead>
<tr>
<th>Variable</th>
<th>1-objective</th>
<th>2-objectives</th>
<th>4-objectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E )</td>
<td>2.4162e3</td>
<td>2.6328e3</td>
<td>2.7918e3</td>
</tr>
<tr>
<td>( P )</td>
<td>1.6805e2</td>
<td>3.1950e2</td>
<td>4.0953e2</td>
</tr>
<tr>
<td>( L )</td>
<td>2.3156e4</td>
<td>2.3018e4</td>
<td>2.1421e4</td>
</tr>
</tbody>
</table>

Table 1 Tracking IAE performance
and 14, respectively, for all optimization cases (one-, two- and four-objectives). Also, Figure 15 shows the feedforward, $u_{1,ff}$ and feedback, $u_{1,fb}$ components of the fuel valve control signal, $u_1$, for the case with four objectives. These results confirm that in the two-degrees-of-freedom control system configuration, the feedforward control provides the main contribution to the total control signal to achieve wide-
range operation, while the feedback control supplies the control action component needed to eliminate the tracking error along the commanded trajectories. From another perspective, it can be said that the feedforward control diminishes the control effort required from the feedback control, as shown in Table 2, which summarizes the power:

**Figure 14** Behaviour of feedwater valve demand

**Figure 15** Feedback and feedforward control signals
Table 2  Contribution of control signal components

<table>
<thead>
<tr>
<th>Component</th>
<th>1-objective</th>
<th>2-objectives</th>
<th>4-objectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1^{ff}$</td>
<td>2.5491e3</td>
<td>2.4767e3</td>
<td>2.3642e3</td>
</tr>
<tr>
<td>$u_1^{fb}$</td>
<td>8.9664e0</td>
<td>1.2561e1</td>
<td>1.5552e1</td>
</tr>
<tr>
<td>$u_2^{ff}$</td>
<td>4.0775e3</td>
<td>4.7544e3</td>
<td>6.3751e3</td>
</tr>
<tr>
<td>$u_2^{fb}$</td>
<td>9.1312e-2</td>
<td>1.7076e-1</td>
<td>5.0433e-1</td>
</tr>
<tr>
<td>$u_3^{ff}$</td>
<td>2.2681e3</td>
<td>2.2864e3</td>
<td>2.3170e3</td>
</tr>
<tr>
<td>$u_3^{fb}$</td>
<td>1.2558e1</td>
<td>1.2145e1</td>
<td>1.1305e1</td>
</tr>
</tbody>
</table>

of each control signal component for all optimization cases.

Finally, Table 3 provides the values of the objective functions, $J_1$ through $J_4$, accumulated during the whole simulation for all three optimization cases. The objectives which were not subject to minimization for a given case are parenthesized; their values are provided to allow comparison among all cases, and the negative values reflect the definition of $J_3$ and $J_4$. As stated before, cumulative values of $J_1$, despite increasing when more objectives were considered, correspond to very small average load-tracking errors of the same order of magnitude. Concurrently, all the remaining objectives improved as more objectives were taken into account. Since $J_2$, $J_3$ and $J_4$ directly relate to the plant heat rate, their minimization corresponds to a betterment of the overall operation of the power plant.

The previous results clearly show the advantages of the multiobjective optimization approach. In all cases the generated power is approximately the same, i.e., consideration of more objectives does not degrade the power response of the unit, which is the single most important objective to be satisfied. In the second place, results show that when more objectives were considered the overall performance of the unit was improved because less fuel was required to generate the same

Table 3  Cumulative objective function values

<table>
<thead>
<tr>
<th>Objective</th>
<th>1-objective</th>
<th>2-objectives</th>
<th>4-objectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_1$</td>
<td>2.4163e3</td>
<td>2.6329e3</td>
<td>2.7919e3</td>
</tr>
<tr>
<td>$J_2$</td>
<td>(4.1530e3)</td>
<td>4.0698e3</td>
<td>3.9562e3</td>
</tr>
<tr>
<td>$J_3$</td>
<td>(–5.6017e3)</td>
<td>(–6.0964e3)</td>
<td>(–7.0833e3)</td>
</tr>
<tr>
<td>$J_4$</td>
<td>(–3.8928e3)</td>
<td>(–3.9081e3)</td>
<td>(–3.9437e3)</td>
</tr>
</tbody>
</table>
amount of power, without compromising the speed of response. Clearly, better-
ment is possible because of the reduced pressure drop losses in the steam throt-
tling valve and feedwater valve, which are commanded to be as open as possible
when the corresponding objectives are considered.

7. Summary and conclusions

This paper presented an extended CC scheme for fossil-fuel power units. A multi-
objective-optimal set-point scheduler and a neuro-fuzzy feedforward control path,
both including the drum level control, were added to a conventional multiloop
CC scheme.

The scheduler provides the set-points to the control loops through mappings
designed by solving a multiobjective optimization problem along the power
operating range of the unit. For optimization, the number and form of the
objectives can be set arbitrarily, and their priorities assigned intuitively, to
accommodate the operating scenario at hand. The feedforward and feedback
control structure constitutes a two-degrees-of-freedom nonlinear multivariable
controller. The feedforward path, implemented with neuro-fuzzy systems, pro-
vides the control signal contributions corresponding to the optimization sol-
ution, and the feedback control path provides the control signal contributions
necessary to overcome uncertainties and perturbations along the optimal set-
point trajectories. The nonlinear neuro-fuzzy systems are learned offline after
the solution of the optimization problem, to approximate the inverse static
model of the power unit, and they are updated each time the operating scenario
changes in an automated learning procedure. Therefore, the extended neuro-
fuzzy feedforward–feedback CC scheme provides the means to optimize the
overall operation of the unit under arbitrary operation scenarios, and facilitates
wide-range operation with good regulation about the commanded trajectories.

Perhaps the main disadvantage of the proposed approach is the dependency of
the solutions on the mathematical model of the process. Nevertheless, it should
be noted that the methodology involved is general enough to be particularized
on demand for a given plant. General fixed solutions are not pursued since plants,
and their models, are not standard, nor are the operating scenarios fixed. Also,
the model used in this paper is good enough to illustrate the principles of the
proposed approach, and general enough to guide the realization using other mod-
els. Certainly, the development of a model-independent version would add even
more versatility for application to any plant and would increase the chances of
implementation in an actual plant.

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References


