Fuzzy Predictive Supervisory Control Based on Genetic Algorithms for Gas Turbines of Combined Cycle Power Plants

Doris Sáez, *Senior Member, IEEE*, Freddy Milla, *Member, IEEE*, and Luis S. Vargas, *Senior Member, IEEE*

***Abstract*—This work presents a novel design and development of a fuzzy predictive supervisory controller, based on genetic algorithms (GA), for gas turbines of combined cycle units. The control design is based on an objective function that represents the economic and regulatory performance of a gas turbine by using a dynamic optimal set-point for the regulatory level. A fuzzy model is considered in order to characterize the nonlinear behavior of the gas turbine, which is used in two supervisory control systems. The first fuzzy supervisory control design includes a fuzzy model, where its parameters are held constant for the successive predictions. For the second fuzzy supervisory control design, its parameters are updated in each prediction and its nonlinear optimization problem is solved using GAs. The proposed fuzzy supervisory controllers are compared against a supervisory controller based on linear models and a regulatory controller with constant optimal set-points. Results indicate that the fuzzy GA predictive supervisory controller captures adequately the nonlinearities of the process, which, in turn, provides a promising approach to improve the performance of the combined cycle unit.**

***Index Terms*—Fuzzy systems, gas turbines, genetic algorithms (GA), predictive control.**

I. Introduction

TRADITIONALLY, plant controller designers have developed regulatory control strategies, based on proportional-integral-differential (PID) controllers in order to minimize costs [1]. However, more advanced control strategies, like fuzzy control, neural control, or predictive control, could improve the operational performance of the plants, especially under disturbances. As real power plants are faced with a wide range of perturbations, one of the most common being the unexpected environmental temperature fluctuations, the impact on the performance of the plant could be significant.

Modern combined cycle units have an optimal mix of gas and steam power production for a given output power (P). Usually, manufacturers supply this mix under nominal operating conditions. However, in practice, plants may deviate slightly from these points due to external and internal disturbances. In this work, a method for improving power plant operational efficiency, through the introduction of a fuzzy genetic algorithm (GA) supervisory controller; without modifying the lower regulatory level; is proposed. The objective function is designed to represent the whole complexity of the plant, including profit, operational costs, process energy consumption, and environmental impact [1].

The supervisory controller provides the regulatory level set-points, based on the optimization of the objective function. As a modification of the regulatory controller usually implies higher costs, it is a common practice in the industry to add a supervisory level instead. This alternative also improves the regulatory level by the dynamic set-points modification while process regulatory settings are kept constant.

Recently, some papers have dealt with supervisory control based on dynamic models. For example, de Prada [2] proposes a predictive control strategy based on the optimization of an economic index. This strategy is applied to a chemical reactor. Katebi [3] describes a decentralized control strategy, based on the optimization of a generalized predictive control objective function. The corresponding objective function has only regulatory objectives and the control strategy is applied to a thermal power plant simulator. Also, there are some industrial applications that give good economic results based on linear dynamic models. For example, in [4], a dynamic matrix control (DMC) supervisory controller is applied in a petrochemical process.

On the other hand, Bemporad [5] and Angeli [6] propose a reference governor at the supervisory level. In that approach, the objective function is given by the minimization of the reference trajectory error. A different approach for a reference governor based on a nonlinear prefilter, with the same objective function, is proposed by Gilbert [7].

Tadeo *et al.* [8] propose a constrained predictive supervisory controller dealing with the feedback loop of the PID controllers at regulatory level. In this case, the typical model-based predictive control (MBPC) objective function is considered.

Thermal power plants are nonlinear in nature; therefore, the supervisory control design has to include nonlinear models. In this work, we adopt fuzzy models, as these models are universal approximates for any nonlinear system.

Sáez *et al.* [9] implemented a fuzzy supervisory control strategy for the boiler of a combined cycle power plant, considering the fuzzy control design based on the linearized fuzzy model. However, due to the nonlinearity of the optimization problem, which arises from the nonlinear complete fuzzy predictive model, it becomes extremely complex to obtain a direct solution.

On the other hand, GAs have been used successfully in nonlinear optimization problems [10]. A main advantage is that the genetic optimization does not need the objective gradient

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The authors are with the Department of Electrical Engineering, Universidad de Chile, Santiago 412-3, Chile (e-mail: lvargasd@ing.uchile.cl).

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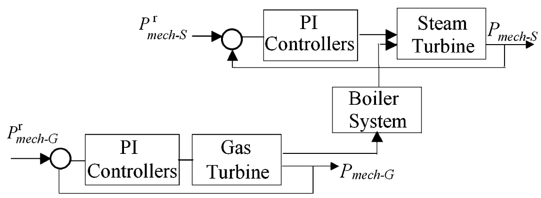

Fig. 1. Combined cycle power plant with control system.

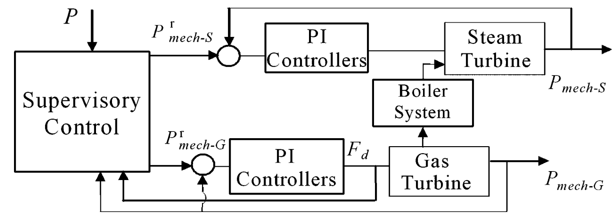

Fig. 2. Supervisory control diagram for a combined cycle power plant.

calculation, that could represent significant savings in computational effort.

There are few works about nonlinear predictive control design, based on GA. For example, Al-Duwaish [11] proposes a nonlinear model predictive control using GAs where the predictor is based on Hammerstein and Wiener models. Fabro [12] describes a fuzzy predictive control using GAs where the optimization variables are given by the fuzzy set parameters of the controller.

This work proposes the design and development of a new fuzzy GA predictive supervisory control strategy for gas turbines based on nonlinear predictions using the fuzzy model. Also, in order to solve the nonlinear optimization problem and as a new contribution, GAs are used as a very good tool.

The paper is organized in five sections. In Section II, the gas turbine process with its corresponding control system is described. Section III analyzes the proposed supervisory controllers for gas turbines. Section IV explains the fuzzy supervisory predictive control based on GAs. Next, in Section V, applications to a gas turbine are presented. Finally, in Section VI, the work conclusions are presented.

II. Gas and Steam Turbine Models of Combined Cycle Thermal Power Plants

A. Combined Cycle Power Plant

Combined cycle power plants have high efficiencies and require comparatively lower investment costs than other technologies. These plants consist of a gas turbine, a boiler, and a steam turbine to generate electricity [1]. The exhaust gases from the gas turbine are used to provide the necessary heat for the boiler steam production. Finally, this steam is fed to the steam turbine.

Although the generated power of the plant is assigned by the economic dispatch, the generation share of each turbine can be modified within the space of the technical constraints of the thermodynamic process. The challenge for plant operators is to deliver the assigned power by the central economic dispatch (P) by satisfying the constraints and minimizing the total cost.

In Fig. 1, the traditional control configuration for a combined cycle power plant is presented. In this diagram, the set-points for the gas turbine power $P^r_{\mathrm{mech}-G}$ and the steam turbine power $P^r_{\mathrm{mech}-S}$ satisfy $P^r_{\mathrm{mech}-G} + P^r_{\mathrm{mech}-S} = P$. Both turbines have a regulatory level given by proportional-integral (PI) controllers.

This work deals with the optimization of the economical cost of the combined cycle power plant, i.e., minimization of gas turbine cost as well as steam turbine cost. The mathematical formulation of this problem is very complex, and a decoupling of the steam and gas stages is adopted in this work. We use the fact that the most important economical cost of the combined cycle power plant is given by the production cost of the gas turbine power, i.e., the cost of the fuel (natural gas or diesel). Thus, the combined cycle power plant is economically optimized by using the dynamical set-point for the gas turbine power $P^r_{\mathrm{mech}-G}$. The corresponding set-point for the steam turbine $P^r_{\mathrm{mech}-S}$ is given by the difference between the dispatched power (P from the system operator) and the optimal dynamic set-point for the gas turbine, i.e., $P^r_{\mathrm{mech}-S} = P - P^r_{\mathrm{mech}-G}$. The proposed supervisory scheme is shown in Fig. 2.

In order to accommodate the resulting power in the steam turbine ($P^r_{\mathrm{mech}-S}$), it may be necessary that additional fired burners be available for the boiler. As these actions may impose an additional cost given by the fuel in the steam burners, we limit the allowed deviation by imposing the minimization of the set-point trajectory error. Finally, from the efficiency point of view, it is always desirable to get the maximization of the gas turbine power production by using the least amount of fuel.

As a consequence, the objective function used in this work is a combination of three components: 1) minimization of gas fuel consumption, 2) minimization of the regulatory criterion associated to the trajectory error and control action effort, and 3) maximization of gas turbine power. For simplicity, the objectives 1) and 3) are treated together in an economic criterion. On the other hand, objective 2) is treated as a standard regulatory criterion. A detailed formulation of the objective function is presented in Section III.

B. Gas Turbine

The works by Cohen *et al.* [13] and Shobeiri [14] present very detailed models of the gas turbine. These are distributed parameter models, where the gas flow dynamics is described for different sections of the turbine. Hung [15] and Biss *et al.* [16] present simpler models, using steady-state equations derived experimentally. Undrill [17], [18] present models for grid dynamic studies based on a set of thermodynamic curve fits. Similarly, Agüero *et al.* [19] present dynamic models for gas turbines. Pourbeik [20] describes gas turbine models for power system studies based mainly on linear models. On the other hand, Ordys *et al.* [1] describe an intermediate model for the gas turbine that permits supervisory control strategy design. This model includes the main dynamics of the gas turbine for a wide range of operating conditions.

Our work considers a phenomenological gas turbine model proposed by Ordys *et al.* [1], [21], which is used a base for a

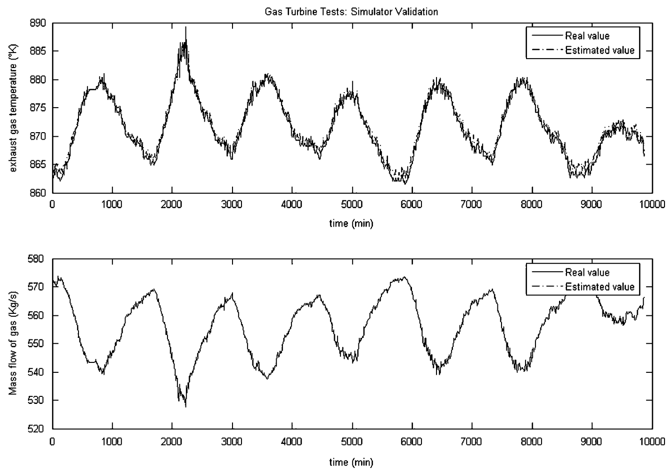

Fig. 3. Validation tests for the simulator model.

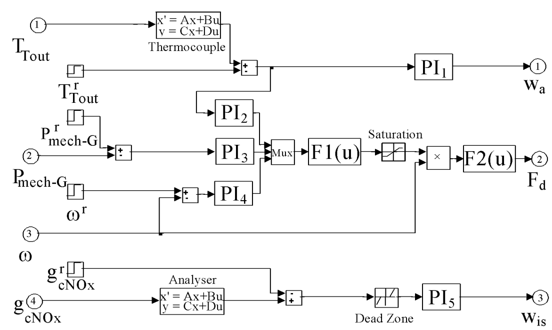

Fig. 4. Gas turbine control system.

Matlab-Simulink simulator. This simulator has been tested by using practical and experimental verification in a 350-MW combined cycle thermal power plant, named Nueva Renca, located in Santiago, Chile. In Fig. 3, theoretical and experimental results are shown for the gas turbine. Mass flow and exhaust gas temperature have been selected as critical variables to show the performance of the simulator used in this paper.

From the tests in Fig. 3, the error calculated for mass flow is in the range of 2%, whereas, for the temperature, it is less than 1%. Similar results for other variables were also verified.

C. Control System Strategy

For a gas turbine, controlled variables are exhaust gas temperature (T_{Tout}), the power of the gas turbine ($P_{\mathrm{mech}-G}$), the frequency (ω), and the NO_x concentration in the exhaust gases ($g_{\mathrm{cNO}x}$). The manipulated variables are the air flow to the compressor (w_a), the fuel flow (F_d), and the steam flow injected into the combustion chamber (w_{is}). A detailed diagram, showing the control for the gas turbine, is shown in Fig. 4.

This work deals mainly with the power control (the governor) through F_d. This control system, which includes the switching controllers [F1(u)], uses the minimum signal of PI controllers (PI_2, PI_3, and PI_4) in order to calculate the fuel flow control action (F_d).

III. Supervisory Predictive Control Design for Gas Turbines

The supervisory control level is given by a predictive controller that provides the optimal dynamic set-points of the regulatory level (control system) of a process. The supervisory level allows to improve the power plant efficiency without modifying the control strategy at lower regulatory level.

Particularly, as shown in Fig. 2, the supervisory level gives the optimal set-points for the gas turbine power ($P^r_{\mathrm{mech}-G}$) in order to optimize an objective function. In this application, the proposed objective function contains two terms. The first term is related to the economical performance, in this case, the plant profit (J_{Cp}). The second term is a regulatory criterion (J_{Cr}), which takes into account the set-point trajectory error and the control action effort. The regulatory criterion ensures that the solution is stable within technical constraints. Then, the total objective function to be optimized at the supervisory level is given by

$$\mathrm{Max} \quad J = J_{Cp} - \eta J_{Cr} \tag{1}$$

where η is a practical weighting factor.

The proposed economic objective function (J_{Cp}) is

$$\mathrm{J}_{Cp} = \sum_{i=1}^{N} C_p \hat{P}_{\mathrm{mech}-G}(t+i-1) - \sum_{i=1}^{N} C_f F_d(t+i-1) - C_F \tag{2}$$

where C_f is the fuel price, C_p is the power price factor, C_F stands for fixed costs, and N is the number of intervals of the prediction horizon (typically less than a minute).

The proposed regulatory-level objective function (J_{Cr}) is

$$\mathrm{J}_{\mathrm{Cr}} = \sum_{j=1}^{N} \left(\hat{P}_{\mathrm{mech}-G}(t+j) - P^*_{\mathrm{mech}-G}\right)^2 + \lambda \sum_{i=1}^{N} \Delta F_d^2(t+i-1) \tag{3}$$

where $\hat{P}_{\mathrm{mech}-G}(t+j)$ is the j-step ahead prediction for the gas turbine power and λ is a weighting factor for the fuel-flow deviation. The reference trajectory $P^*_{\mathrm{mech}-G}$ for the gas turbine power is a constant value in order to ensure that this power will be within the space of the technical constraints of the thermodynamic process.

In this case, the set-points $g^r_{\mathrm{cNO}_x}$ and T^r_{Tout} for the controlled variables $g_{\mathrm{cNO}x}$ and T_{Tout}, respectively, will be constant, because they do not affect the economic objective function J_{Cp} (2).

In order to solve the optimization problem at the supervisory level, the gas turbine can be modeled as a linear model or as a nonlinear fuzzy model. The regulatory level is typically composed of linear PI controllers.

A. Linear Model

The dynamic of the gas turbine power was identified using the "autoregressive integrated with exogenous variable" (ARIX) discrete models [22].

The ARIX discrete model for the gas turbine ($P_{\mathrm{mech}-G}$ [in megawatt]), was obtained with data generated by a fuel-flow excitation signal (F_d [in kilogram per second]) applied to a gas turbine simulator. The sampling time was $T_s = 1$ [in second]. Thus, the ARIX model is given by the following expression:

$$A(z^{-1})P_{\text{mech}-G}(t) = B(z^{-1})F_d(t) + \frac{e(t)}{\Delta} \quad (4)$$

where $e(t)$ is the white noise, $A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2}$, and

$$B(z^{-1}) = b_1 z^{-1} + b_2 z^{-2}.$$

B. Takagi and Sugeno Models

Fuzzy models have been used successfully for the identification of nonlinear systems [23]. This paper considers the use of the Takagi and Sugeno fuzzy models. In this case, the assumptions are based on fuzzy sets and the consequences are linear models for different operating points.

The Takagi and Sugeno fuzzy model for the gas turbine power ($P_{\text{mech}-G}$ [in megawatt]) using the same data set as for linear modeling, generated by a fuel-flow excitation signal (F_d [in kilogram per second]) applied to a gas turbine simulator is considered. Therefore, the fuzzy model is given by the following rules:

R^1 : If $P_{\text{mech}-G}(t-1)$ is A_1^1 and $P_{\text{mech}-G}(t-2)$ is A_2^1 and $F_d(t-1)$ is A_3^1 and $F_d(t-2)$ is A_4^1

$$\text{then } P_{\text{mech}-G}(t) = \gamma_{11}P_{\text{mech}-G}(t-1) + \gamma_{12}P_{\text{mech}-G}(t-2) + \gamma_{13}F_d(t-1) + \gamma_{14}F_d(t-2) + \gamma_{10} \quad (5)$$

R^2 : If $\mathrm{P}_{\mathrm{mech-G}}(t-1)$ is A_1^2 and $\mathrm{P}_{\text{mech}-G}(t-2)$ is A_2^2 and $\mathrm{F_d}(t-1)$ is A_3^2 and $F_{\mathrm{d}}(t-2)$ is A_4^2.

$$\text{then } \mathrm{P}_{\text{mech}-G}(t) = \gamma_{21}\mathrm{P}_{\text{mech}-G}(t-1) + \gamma_{22}\mathrm{P}_{\text{mech}-G}(t-2) + \gamma_{23}F_d(t-1) + \gamma_{24}F_d(t-2) + \gamma_{20}$$

Fig. 5 presents the corresponding membership functions for fuzzy model inputs $P_{\text{mech}-G}(t-1), P_{\text{mech}-G}(t-2), F_d(t-1)$ and $F_d(t-2)$. In this work, the *premise* (A_i^r in Fig. 5) parameters for the fuzzy modeling are obtained by using fuzzy clustering, and the *consequence* [γ_{ri} in (5)] parameters are obtained by the Takagi and Sugeno method based on least squares [23], [24].

The output of the fuzzy model presented in (5) is

$$\hat{P}_{\text{mech}-G}(t) = \left(\sum_{r=1}^{2} w_r(t)\gamma_{r1}\right) P_{\text{mech}-G}(t-1) + \left(\sum_{r=1}^{2} w_r(t)\gamma_{\text{rn}}\right) P_{\text{mech}-G}(t-2) + \left(\sum_{r=1}^{2} w_r(t)\gamma_{\text{rn}}\right) F_d(t-1) + \left(\sum_{r=1}^{2} w_r(t)\gamma_{\text{rn}}\right) F_d(t-2) + \left(\sum_{r=1}^{2} w_r(t)\gamma_{r0}\right) \quad (6)$$

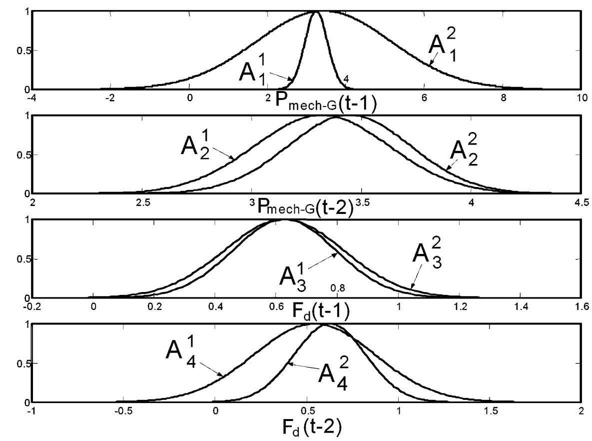

Fig. 5. Membership functions.

TABLE I
PREDICTION ERROR $\bar{E}$

Prediction error	Linear model	Fuzzy model
One-step ahead	1.40 %	0.64 %
10-step ahead	3.86 %	1.78 %

where $w_r(t)$ is the normalized activation degree for rule r. Equation (6) may be written as

$$\hat{P}_{\text{mech}-G}(t) = d_1(t)P_{\text{mech}-G}(t-1) + d_2(t)P_{\text{mech}-G}(t-2) + d_3(t)F_d(t-1) + d_4(t)F_d(t-2) + d_0(t) \quad (7)$$

where all d_i are a function of the activation degree $w_r(t)$ and correspond to the fuzzy model factors of (6).

C. Model Analysis

For the gas turbine power, Table I presents the one-step ahead and 10-step ahead prediction errors using the linear model, obtained in Section III-A, and the fuzzy model, obtained in Section III-B. The prediction error corresponds to the mean value of the instant error according to

$$\bar{E} = \text{Avg}\left[E(t)\right] = \text{Avg}\left[100 \cdot \frac{\hat{P}_{\text{mech}-G}(t) - P_{\text{mech}-G}(t)}{P_{\text{mech}-G}(t)}\%\right]. \quad (8)$$

From Table I, the fuzzy model exhibits better results than the linear model.

The control strategy proposed in this work uses the 10-step ahead prediction. For this strategy, Table I shows that the gas turbine fuzzy model error is less than half of the linear model error. Thus, the Takagi and Sugeno fuzzy models are chosen to represent the nonlinearities of the gas turbine.

D. Regulatory Level

In Fig. 4, the PI_3 controller has gas turbine power ($P_{\text{mech}-G}$) as input, which is assumed to be in ON state to avoid the need for switching. This assumption is based on empirical experience from the real operation of combined cycle units.

The PI_3 for fuel-flow controller, as a function of gas turbine power, is given by

$$F_d(s) = \left(k_p + \frac{k_i}{s}\right)\left(P^r_{\text{mech}-G}(s) - P_{\text{mech}-G}(s)\right) \tag{9}$$

where k_p is the proportional gain and k_i is the integrator gain. The corresponding PI_3 discrete model, using sampling time $T_s = 1$ [in second], is

$$\left(1 - z^{-1}\right) F_d(t) = \left(\alpha + \beta z^{-1}\right)\left(P^r_{\text{mech}-G}(t) - P_{\text{mech}-G}(t)\right) \tag{10}$$

where $\alpha = \frac{T_s k_i}{2} + k_p$ and $\beta = \frac{T_s k_i}{2} - k_p$.

E. Linear Supervisory Controller

The linear supervisory controller for gas turbines is based on the optimization of the objective function (1) by using the linear models (4) and the regulatory level (9).

Constraints associated to the predictions for gas turbine power, by using the ARIX model (4), are

$$\begin{aligned}
&\hat{P}_{\text{mech}-G}(t+j) + (a_1 - 1)\hat{P}_{\text{mech}-G}(t+j-1)\\
&+ (a_2 - a_1)\hat{P}_{\text{mech}-G}(t+j-2) - a_2\hat{P}_{\text{mech}-G}(t+j-3)\\
&- b_1\Delta F_d(t+j-1) - b_2\Delta F_d(t+j-2) = 0\\
&\text{for}\quad j = 1,\ldots,10 \quad \text{and} \quad \Delta \equiv 1 - z^{-1}
\end{aligned} \tag{11}$$

From (10), the fuel-flow increments for the prediction horizon (N) satisfy the following constraints:

$$\begin{aligned}
&\Delta F_d(t+i-1) - \alpha P^r_{\text{mech}-G}(t+i-1) - \beta P^r_{\text{mech}-G}(t+i-2)\\
&+ \alpha\hat{P}_{\text{mech}-G}(t+i-1) + \beta\,\hat{P}_{\text{mech}-G}(t+i-2) = 0\\
&\text{for}\quad i = 1,\ldots,10.
\end{aligned} \tag{12}$$

Finally, the optimization problem of the linear supervisory controller has a quadratic objective function (1) and linear constraints, given by the process model (11) and PI_3 discrete controller model (12). The resulting optimization problem is solved by using quadratic programming [25].

IV. Fuzzy Supervisory Predictive Control Based on GAs

A. Fuzzy Supervisory Controller

For the fuzzy supervisory control strategy, the same objective function (1) and the same linear model of PI_3 controller (9) are used. However, for the gas turbine, the fuzzy model of (7) is used.

In order to solve this problem, two approaches are considered. In the first case, the fuzzy model factors (7) are assumed constant for next predictions, i.e., the fuzzy model is linearized for the current instant. In the second alternative, the prediction of gas turbine power is obtained by using the complete fuzzy model, i.e., the fuzzy model factors are updated at each prediction. The corresponding equations are as follows:

1) For the linearized fuzzy model, the fuzzy model predictions of (7) are

$$\begin{aligned}
&\hat{P}_{\text{mech}-G}(t+j) - (d_1(t) - 1)\hat{P}_{\text{mech}-G}(t+j-1)\\
&+ (d_1(t) - d_2(t))\hat{P}_{\text{mech}-G}(t+j-2)\\
&+ d_2(t)\hat{P}_{\text{mech}-G}(t+j-3)\\
&- d_3(t)\Delta F_d(t+j-1) - d_4(t)\Delta F_d(t+j-2) = 0\\
&\text{for}\quad j = 1,\ldots,10
\end{aligned} \tag{13}$$

Note that as the activation degree $w_r(t)$ are assumed constant for the prediction horizon, it follows that $d_i(t) = d_i(t+j)$.
The resulting optimization problem is solved again by quadratic programming.

2) In the second alternative, predictions of gas turbine power are established from (7) as follows:

$$\begin{aligned}
&\hat{P}_{\text{mech}-G}(t+j) - (d_1(t+j-1) - 1)\hat{P}_{\text{mech}-G}(t+j-1)\\
&+ (d_1(t+j-2) - d_2(t+j-2))\hat{P}_{\text{mech}-G}(t+j-2)\\
&+ d_2(t+j-3)\hat{P}_{\text{mech}-G}(t+j-3)\\
&- d_3(t+j-1)\Delta F_d(t+j-1)\\
&- d_4(t+j-2)\Delta F_d(t+j-2) = 0\\
&\text{for}\quad j = 1,\ldots,10
\end{aligned} \tag{14}$$

Note that as the activation degree $w_r(t)$ are updated at each prediction, it follows that

$$\begin{aligned}
&d_i(t+j) = d_i(\hat{P}_{\text{mech}-G}(t+j-1), \quad \hat{P}_{\text{mech}-G}(t+j-2),\\
&\times F_d(t+j-1), \quad F_d(t+j-2))\\
&\text{for} j = 1,\ldots,10 \text{ and } i = 1,2,3,4.
\end{aligned} \tag{15}$$

In order to solve this nonlinear optimization problem, we propose GAs [10].

B. Fuzzy GA Supervisory Controller

GAs are typically considered for nonlinear optimization problems [10]. The classic GAs start by encoding the proposed solutions (or initial population) into a binary or a real string (codification).

Convergence of the GAs depends mainly on a right formulation of the fitness function The fitness function could be given by the objective function, which is ordered by linear scaling or ranking.

Typical recombination techniques are crossover and mutation. The crossover is given by the cross (or reciprocal interchange of a part of the string) between two parents or individuals from the current population. For the mutation, the individuals interchange bits, or genes of the encoded string with a low probability, in order to create two new offspring. The offspring performance is evaluated in the next iteration or generation using the fitness function.

Once the new generation is obtained through a recombination process, all individuals are evaluated using the fitness function. A criterion is defined in order to select the next parent generation. The better individuals for the next generation are selected from parents and offspring, or the parents are selected with a defined high percentage (60–80%) of the better individuals from parents and offspring. The remaining percentage is selected from the other individuals with a probabilistic method as roulette wheeled selection (RWS) or stochastic universal sampling (SUS).

The solution of fuzzy predictive control requires a nonlinear optimization algorithm [26]. In summary, the proposed algorithm for solving the fuzzy predictive control (14)–(15) based on GAs has two main steps:

1) Codify the vector of manipulated variables into a binary string.
2) Apply the GA algorithm to solve the nonlinear optimization problem.

V. Simulation Tests

A. Evaluation Basis

The proposed supervisory controllers of Sections III and Sections IV are compared with a standard control strategy based on constant optimal set-points. The corresponding set-points are obtained from static optimization of the objective function defined in (1). Then, the static set-points are

$$P^r_{\mathrm{mech}-G} = P^*_{\mathrm{mech}-G} - \frac{C_p K_{\mathrm{Pg}} - C_f}{2\eta K_{\mathrm{Pg}}} \tag{16}$$

where K_{pg} is the static gain for the gas turbine power, which, in turn, is a function of fuel flow.

In order to produce different operating conditions, a disturbance in the temperature of the air-mass flow into the compressor is introduced. The values for the disturbance move between 276 and 294 [in Kelvin] considering a time span of 450 s. As we recollect from the field experience of plant operators, this is a very common event as the environment of the plant experiences temperature fluctuations hourly, which, in turn, affect the combustion mix and efficiency.

In order to quantify the improvement of the proposed strategy, a standard profit indicator, based on the comparison of the control strategy with constant set-point, is used as follows [9], [27]:

$$\text{Profit} = 100 \times \left(1 - \frac{J_{Cp}\text{with supervisory level}}{J_{Cp}\text{with constant set-points}}\right)\% \tag{17}$$

where J_{Cp} is given by the economic objective function in (2).

B. Supervisory Controllers

Fig. 6 shows the closed-loop responses of the gas turbine system, for the four controllers under analysis, namely the regulatory controller with constant set-point, the linear supervisory controller, the linearized fuzzy supervisory controller, and the fuzzy GA supervisory controller. All the tests were carried out considering $\eta = 1$in (1).

Notice that there are no significant differences between the curves representing the responses to the linear supervisory controller and the linearized fuzzy supervisory controller. This is due to the fact that the linearization process in both approaches renders a similar model. Thus, the fuzzy model linearization diminishes the nonlinear prediction scope of the algorithm.

Also, from Fig. 6, it is clear that the fuel flow (F_d) for the three supervisory controllers is almost constant. Therefore, the supervisory control is the cause for the gas turbine power changes in order to optimize the response of the plant, which is done mainly by changing the air flow (w_a). Thus, the control strategy achieves the regulatory objective of minimization of the control effort on the fuel flow.

A third element from Fig. 6, is that for all supervisory controllers the resulting turbine power ($P_{\mathrm{mech}-G}$) is slightly bigger than the values obtained from the standard control strategy. In fact, according to Fig. 6, the differences are around 1% for the linear and the linearized fuzzy supervisory controllers, and around 2% for the fuzzy GA supervisory controller. Thus, the supervisory controllers maximize the power output while, at the same time, they minimize the use of fuel, as dictated by (2).

Notice that the fuzzy GA controller has more power than the other control strategies. This is because the GA controller represents with more accuracy the nonlinear behavior of the gas turbine, as shown previously in Table I.

C. Comparative Analysis

In Table II, the mean values of the objective functions (2)–(3) and profit (17), for $\eta = 1$ and $\eta = 0.5$ are shown.

From Table II, simulation results show that the linear supervisory controller gives a profit increment ranging from 0.83 to 2.1% as compared to a control strategy with optimum constant set-points.

For the fuzzy linearized supervisory controller, which keeps its parameters constant for the prediction horizon, a profit increment ranging from 0.87 to 2.15% was obtained when compared with the standard control strategy. When a fuzzy GA supervisory control was used, a profit increment ranging from 1.25 to 3.13% was obtained as compared with a standard control strategy. This is the best result of Table II. A rough estimation, by using typical economical data from combined cycle units, shows that for operational costs of US$15 per megawatthour in units of 350 MW, plant factor 0.8 (average power/maximum power), the 3% of improvement in profit results in nearly US$1-million saving, yearly.

Table II shows clearly that the fuzzy GA approach renders the highest profit for a given η [see (1)]. This stems from the fact that the nonlinearities of the process are captured in a more efficient form by fuzzy methods as compared to simplified linear expressions. This also confirms the results shown in Fig. 6.

Finally, from Table II, the profits increase when η is reduced. This is expected as a smaller η implies a greater weight of the economic criterion. However, under these conditions, the operating point deviates with respect to the nominal operating point and, according to our simulation results, it may compromise the stability of the algorithm. Therefore, there is a tradeoff between the economic criteria J_{Cp} and the regulatory objective function J_{Cr}, which has to be taken into account depending on the aim of the plant control strategy.

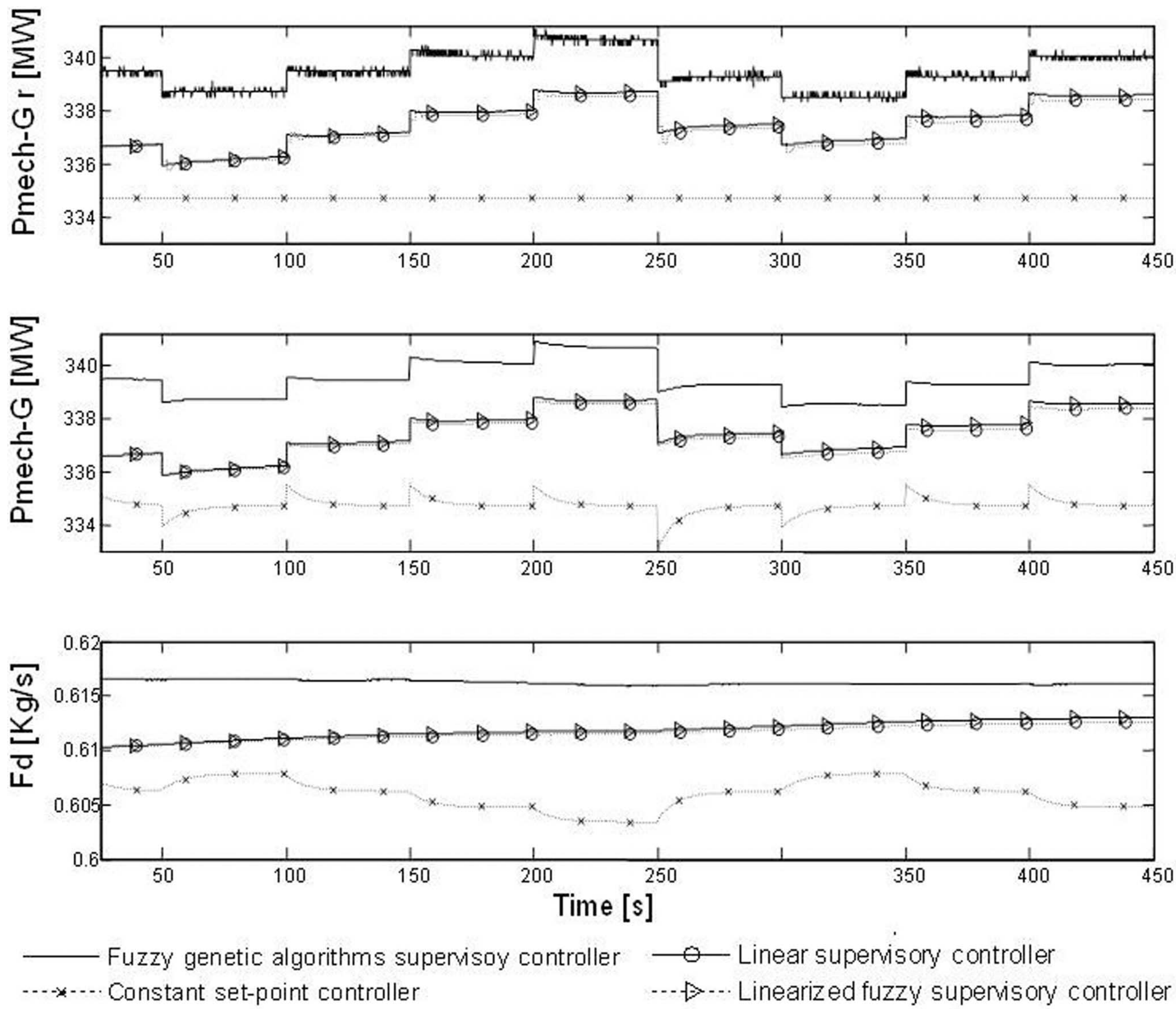

Fig. 6. Closed-loop response ($\eta = 1$).

TABLE II
SIMULATION RESULTS

	Supervisory predictive controllers			Regulatory level with constant set-point
	Linear	Linearized fuzzy	Fuzzy GA	
J_{Cp} ($\eta = 1$)	3314.2	3315.7	3328.2	3287
J_{Cr} ($\eta = 1$)	4.1126	4.5384	0.3038	15.148
Profit	0.8270%	0.8731%	1.2534%	
J_{Cp} ($\eta = 0.5$)	3316.3	3317.9	3349.7	3248
J_{Cr} ($\eta = 0.5$)	4.9694	4.9040	7.1479	60.142
Profit	2.1028%	2.1520%	3.1311%	

VI. CONCLUSION

In this work, a novel fuzzy GA supervisory controller for a gas turbine of a combined cycle power plant is proposed. The design of the controller is based on an objective function that combines an economic criterion, given by the plant profit, and a regulatory criterion, based on turbine power and fuel flow.

In order to represent the nonlinearities of the plant, a novel fuzzy model for gas turbine is proposed. The comparison with conventional linear models of gas turbines indicates that the fuzzy model exhibits the best performance.

Regarding the supervisory control, the fuzzy GA supervisory control strategy is able to improve the performance of the plant by nearly 3%.

Finally, future work will study the conditions for closed loop stability and robustness of the proposed supervisory controller.

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Doris Sáez (SM'06) received the M.Sc. and Ph.D. degrees in electrical engineering from the Pontificia Universidad Católica de Chile, Santiago, Chile, in 1995 and 2000, respectively.

She is currently an Assistant Professor in the Department of Electrical Engineering, Universidad de Chile, Santiago. She is the author or coauthor of more than 40 papers published in international journals and is the author of *Advanced Control of Solar Plants* (New York: Springer-Verlag, 2001). Her current research interests include fuzzy systems control design, fuzzy identification, predictive control, control of power generation plants, and control of transport systems.

Dr. Sáez is the President of the IEEE Chilean Section and a Co-Founder of the Chilean chapter of the IEEE Neural Networks Society. She has served as a Reviewer for the IEEE TRANSACTIONS ON POWER SYSTEMS, the IEEE TRANSACTIONS ON POWER DELIVERY, the IEEE TRANSACTIONS ON ENERGY CONVERSION, and the IEEE TRANSACTIONS ON NEURAL NETWORKS.

Freddy Milla (M'06) received the Diploma in electrical engineering and the M.Sc degree from the Department of Electrical Engineering, Universidad de Chile, Santiago, Chile, in 2004 and 2007, respectively. His current research interests include fuzzy systems control design, predictive control, multiparametric programming, and control of power generation plants.

Luis S. Vargas (M'97–SM'04) received the Diploma in electrical engineering and the M.Sc. degree from Universidad de Chile, Santiago, Chile, in 1985 and 1987, respectively, and the Ph.D. degree in electrical engineering from the University of Waterloo, Waterloo, ON, Canada.

He is currently an Associate Professor in the Department of Electrical Engineering, Universidad de Chile, which he joined in 1994.

His current research interests include voltage stability links between market and security in power system operation and planning, and impact of distributed generation (DG) in power networks.