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Nonlinear Modeling of Complex Large-Scale Plants Using Neural Networks and Stochastic Approximation

A. Alessandri and T. Parisini

***Abstract*—This paper deals with a general methodology for system grey-box identification. As is well-known, the tuning of accurate models of real plants (obtained, for instance, by using the physical knowledge of the plants and the technicians' expertise), on the basis of the measures provided by the available sensors, remains a challenge. In this paper, a tuning methodology for complex large-scale models, is presented. The proposed technique is based on the suitable use of neural networks and specific stochastic-approximation algorithms. It is therefore possible to design a simulator that can be connected in parallel with a real plant, thus providing the plant technician with information about inaccessible variables that are useful for supervision purposes. The proposed methodology is applied to a section of a real 320 MW power plant. Simulation results on the tuning algorithm show the effectiveness of the approach.**

I. Introduction

For plants of high complexity and large dimensions, it is of major importance to develop as accurate models as possible. On the basis of a precise model, one can design a reliable simulator that makes it possible to define the modes of the plant functioning under different operating conditions. Such modes are significant for the tuning of the control system and, above all, for the plant supervision. Moreover, by using such models, one can also obtain estimates of the evolutions of both accessible and inaccessible state variables; these estimates are very useful, for instance, for fault detection.

However, as is well known, despite one has built a structurally accurate model, the strong nonlinearities and the variations in the dynamic characteristics of such systems over time generally do not allow one to identify accurate stationary models by using standard identification methods (see, for instance [1]). Actually, these methods assume a *black-box* model, which has not a structure that is necessarily compatible with the underlying physical reality of a plant. In this respect, a *grey-box* approach seems to be more appropriate, as it is possible to take into account different levels of knowledge about the several parts of the whole plant.

In the literature, one can find many works on *grey-box* identification techniques; however, in such works, the models used are linear (see, for instance, [2] and [3]), hence they are not suitable for the modeling of real complex physical processes. If models are nonlinear, the number of related papers is notable reduced and attention is mainly focused on the so-called multiple-hypotheses statistical identification techniques (see, [4]–[6]). According to these techniques, models of different nature and complexity are evaluated from a statistical point of view, and one resulting model is obtained that is acceptable in terms of a prefixed criterion. In any case, however, the *on-line adaptation* of the model remains in general rather difficult.

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As will be explained, our approach is substantially different form those cited above, as it considers a single model obtainable in two phases. In the first phase, a model is built that is as consistent as possible with the physical reality of the various components of the process under examination; this allows one to take into account different levels of knowledge of such components. In the second phase, a model-tuning process is defined that allows one to compensate for the unavoidable inaccuracies in the physical modeling developed in the first phase.

In the context of nonlinear plants, it is also worth recalling that the state estimation problem is by no means a simpler problem, as it can be solved analytically only under the assumptions of a linear dynamic system, of a linear observation channel, and of white Gaussian process and measurement noises. The most widely used method is the extended Kalman filter (EKF). This generalization of the Kalman filter involves successive linearizations of nonlinear dynamics around a previously deduced estimation point (see, for instance, [7]). The EKF performance is generally satisfactory only when the EKF is applied to nonlinear filtering problems in which such linearizations do not cause a large mismatch between the linear model and the nonlinear framework, and only for high signal-to-noise ratios.

In addition, it should be stressed that, in the case of plants of high complexity and large dimensions, the use of stationary linear models and the estimation of the state after linearization operations are in general unsuitable for supervision purposes, whereas they are sometimes sufficient for the design of reliable regulators. For instance, if one makes too simplifying assumptions on a model, fault detection may become infeasible [8], [9].

Some works have recently appeared in the literature that suggest using neural networks to solve identification, adaptive-control [10] and state-estimation problems for nonlinear systems [11], [12]. In particular, in [12], the state estimation problem is stated in a different, though approximate, way. The nonlinear filter is assigned a given structure in which the values of a certain number of parameters have to be determined via nonlinear programming so as to minimize the estimation cost function. The filter structure is implemented by means of multilayer feedforward neural networks in which the unknown parameters are the synaptic weights. Such an approach has yielded good results for different complex and strongly nonlinear problems but, like the EKF, cannot be applied if a plant model is characterized by nondifferentiable nonlinearities, and if the computation of the model Jacobian matrix $\frac{\partial \underline{f}}{\partial \underline{x}_t}$ ($\underline{x}_{t+1} = \underline{f}(\underline{x}_t, \underline{r}_t)$ being the discrete-time model state equation) is particularly complex or even impossible, as is the case with several types of real plants.

The above considerations have led to a general conceptual approach including the following basic steps.

- Building a plant model that is as accurate as possible. This model should be designed by using as much as possible the available a-priori knowledge on the dynamic behavior of a system and by exploiting the expertise of plant technicians.
- Validation of such a model with respect to the real plant.
- Tuning of the inaccessible internal parts of the model on the basis of the measures provided by the available sensors, using neural networks and stochastic approximation.

After the first step, i.e., the definition of the plant model (obviously, this step is specific for the particular plant considered), given the

approximations inherent in the model, and taking into account the fact that many quantities affecting the dynamics of the system are not stationary, the problem of on-line tuning the model on the basis of the measures provided by the available sensors should be faced. To this end, in the overall model, we define two distinct categories of approximate blocks: i) blocks characterized by approximate mathematical structures, and ii) blocks with structures that can be considered correct but with some partially unknown parameters. The former are replaced with multilayer feedforward neural networks, for which we have to determine the synaptic weights corresponding to the best tuning of the model to the real system's behavior. This leads to a very complex parametric identification problem, involving a large number of parameters. However, as mentioned earlier, most of available plant models are characterized by hard nonlinearities that do not allow the application of the well-known backpropagation technique for training neural networks [10], [13].

This justifies our choice of using a suitable stochastic approximation technique to estimate the unknown parameters. The application of the so-called *simultaneous perturbation stochastic approximation* (SPSA) [14] turns out to be particularly effective. Such a technique is somewhat similar to the classic stochastic approximation using a finite-difference approximation for the gradients, but is much simpler and more efficient from a computational standpoint, while preserving the same convergence characteristics.

This paper is organized as follows: in Section II, the identification problem is stated in its general form and the transformation of the learning problem into a parametric estimation one is described. In Section III, the salient features of the smoothed SPSA technique used are discussed. Finally, in Section IV, the proposed methodology is applied to a specific real plant (the four heaters of a feedwater high-pressure line of a 320 MW power plant located at Piombino, Italy). Extensive simulation results are reported that show the effectiveness of the neural-parametric technique in estimating the approximate parts of a complex model of the plant, previously obtained by using suitable physical and thermodynamical laws.

II. Statement of the Identification Problem

Consider a discrete-time global model of the plant whose dynamics can be described by

$$\Sigma : \begin{cases} \underline{x}_{t+1} = \underline{f}(\underline{x}_t, \underline{r}_t) \\ \underline{y}_t = \underline{h}(\underline{x}_t) \end{cases} \tag{1}$$

where $\underline{x}_t$ represents the state vector, $\underline{r}_t$ represents the input vector, and $\underline{y}_t$ represents the vector of the measurable variables.

Unfortunately, when large complex plants are considered, the above model generally includes a significant number of simplifying hypotheses about both the mathematical structures of some blocks and the values of different parameters. In many cases, the large variations in the plant over time may give rise to nonnegligible errors on some model sections.

Therefore, despite the intrinsic complexity of the plant, it would be useful to employ suitable techniques that make it possible to reduce the aforementioned approximation errors during the plant operation. Such techniques would allow the development of an accurate model that might be simulated in parallel with the plant, with obvious advantages for supervision tasks. For instance, inaccessible state variables might be visualized.

Consistently with the grey-box approach, we consider two main types of uncertainties affecting the model:

- uncertainties in the mathematical structure;
- uncertainties in parameter values.

The uncertainties in the mathematical structure can be modeled by using a set of unknown functions $\underline{\gamma}^j(\bar{\underline{x}}^j),\ j = 1, \ldots, M$, where M represents the number of sections of the global model characterized by a partially/totally unknown structure, and $\bar{\underline{x}}^j$ is the part of the state vector corresponding to the jth section. Moreover, we collect in the vector $\underline{\theta}$ all the unknown mathematical and physical parameters representing parametric uncertainties. Then, we obtain the following approximate model to be identified:

$$\tilde{\Sigma} : \begin{cases} \tilde{\underline{x}}_{t+1} = \tilde{\underline{f}}(\tilde{\underline{x}}_t, \underline{r}_t, \underline{\theta}) \\ \tilde{\underline{y}}_t = \tilde{\underline{h}}(\tilde{\underline{x}}_t, \underline{\theta}) \end{cases} \tag{2}$$

where $\tilde{\underline{f}}$ and $\tilde{\underline{h}}$ implicitly depend on $\underline{\gamma}^j(\bar{\underline{x}}^j),\ j = 1, \ldots, M$, $\tilde{\underline{x}}_t \triangleq \mathrm{col}(\bar{\underline{x}}_t^1, \ldots, \bar{\underline{x}}_t^M)$. Now, in order to identify the model (2) (which, in terms of classical identification theory, is a prediction model), for a given initial state and a given time-instant t, we define the following cost function

$$J(\underline{\gamma}^1, \ldots, \underline{\gamma}^M, \underline{\theta}) = \sum_{i=t-N}^{t} \|\underline{y}_i - \tilde{\underline{y}}_i\|_P^2 \tag{3}$$

where N is a suitable time-window and P is a suitable positive definite matrix. Then, the identification problem can be stated as the following parametric-functional optimization problem.

Problem 1: At time t, find the optimal functions $\underline{\gamma}^{1^\circ}, \ldots, \underline{\gamma}^{M^\circ}$ and the optimal value of the parameter $\underline{\theta}^\circ$, such that the cost function (3) is minimized for every possible set of measures $\underline{y}_{t-N}, \ldots, \underline{y}_t$.

Clearly, the general assumptions under which Problem 1 has been stated prevent us from solving it in an analytical way. Actually, Problem 1 entails the solution of nonlinear (and nonquadratic) functional optimization problems. The approximating method that constitutes the basis for our approach consists in assigning the unknown functions defined in Problem 1 given structures in which a certain number of parameters have to be determined in order to minimize the above cost. In particular, the functions $\underline{\gamma}^j(\bar{\underline{x}}^j)$ are approximated by parametrized functions of the form $\hat{\underline{\gamma}}^j(\bar{\underline{x}}^j, \underline{w}^j),\ j = 1, \ldots, M$, where $\hat{\underline{\gamma}}^j$ is the input/output mapping of a multilayer feedforward neural network and $\underline{w}^j$ is a vector of parameters to be tuned. Among various possible approximating functions, we choose nonlinear approximators based on feedforward neural networks, as these approximators are computationally easy to handle, and, above all, exhibit powerful approximating capabilities [15].

Now, the vector $\underline{w} \triangleq \mathrm{col}(\underline{w}^j,\ j = 1, \ldots, M)$ represents all the weight vectors of the neural networks approximating the unknown functional parts of the model. As a result, denoting by $\underline{\beta} \triangleq \mathrm{col}(\underline{w}, \underline{\theta})$ the total parameter vector, we obtain the following approximate parametric model to be identified:

$$\hat{\Sigma} : \begin{cases} \hat{\underline{x}}_{t+1} = \hat{\underline{f}}(\hat{\underline{x}}_t, \underline{r}_t, \underline{\beta}) \\ \hat{\underline{y}}_t = \hat{\underline{h}}(\hat{\underline{x}}_t, \underline{\beta}) \end{cases}. \tag{4}$$

Accordingly, the cost function takes on the form

$$\hat{J}(\underline{\beta}) = \sum_{i=t-N}^{t} \|\underline{y}_i - \hat{\underline{y}}_i\|_P^2. \tag{5}$$

Hence, we have the following.

Problem 2: At time t, find the optimal value of the parameter $\underline{\beta}^\circ$, such that the cost function (5) is minimized for every possible set of measures $\underline{y}_{t-N}, \ldots, \underline{y}_t$.

Problem 1 has been reduced to the parametric optimization Problem 2, and, in the next section, we present an algorithm to solve it.

III. Solution of Problem 2 via the Simultaneous Perturbation Stochastic Approximation Algorithm

It is now necessary to estimate the optimal parameter vector solving Problem 2. To this end, it is worth noting that

- in general, real systems exhibit strong nonlinearities, hence it is not possible to apply classical estimation algorithms such as the Kalman filter or the least-squares method;

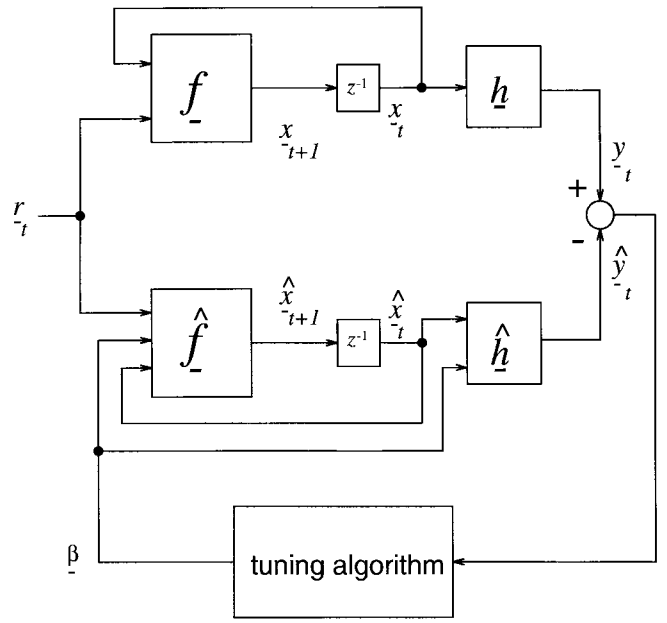

Fig. 1. General scheme of the tuning algorithm.

- the presence of nondifferentiable nonlinearities and the on-line inaccessabilities of some internal model variables prevent one from using techniques based on some linearization method, like the EKF or other algorithms based on the computations of the gradients of cost functions (e.g., the backpropagation technique [13]). (For a nonlinear filtering technique based on neural networks and on backpropagation, see, for instance, [12].)

Refer to the general scheme depicted in Fig. 1.

As can be noticed, the samples of the measures provided by the available sensors and of the other accessible signals of the plant are used for the on-line estimation of the vector $\underline{\beta}$. This can be done by applying some descent algorithm. However, for the aforementioned reasons, the exact gradient of the expected cost cannot be computed, and hence a stochastic approximation approach has to be followed. We choose the *smoothed simultaneous perturbation stochastic approximation* [16]. In the following, the most significant features of this algorithm will be summarized for the reader's convenience. They are detailed in [16], from which we have taken most of the notation.

The algorithm can be written as

$$\underline{\hat{\beta}}_k = \underline{\hat{\beta}}_{k-1} - a_k \underline{G}_k, \quad k = 0, 1, \ldots \tag{6}$$

where $\underline{G}_k$ is a smoothed approximation to $\underline{g}_k(\underline{\hat{\beta}}_k) \triangleq \nabla_{\underline{\beta}_k} E(\hat{J})$ of the form

$$\underline{G}_k = \rho_k \underline{G}_{k-1} + (1-\rho_k)\underline{\hat{g}}_k(\underline{\hat{\beta}}_{k-1}), \quad \underline{G}_0 = \underline{0} \tag{7}$$

where $\underline{\hat{g}}_k$ is the so-called simultaneous perturbation approximation to $\underline{g}_k$ (see [14] for the original definition of the unsmoothed simultaneous perturbation technique). More specifically, the lth component of $\underline{\hat{g}}_k(\underline{\hat{\beta}}_{k-1})$ is given by

$$g_{kl}(\underline{\hat{\beta}}_{k-1}) = \frac{\hat{J}^{(+)}_{k-1} - \hat{J}^{(-)}_{k-1}}{2c_k \Delta_{kl}} \tag{8}$$

where $\hat{J}^{(-)}_k$ and $\hat{J}^{(+)}_k$ are two observations corresponding to the parameter perturbations $\underline{\hat{\beta}}_k - c_k \underline{\Delta}_k \alpha_k$ and $\underline{\hat{\beta}}_k + c_k \underline{\Delta}_k \alpha_k$, respectively. Δ_{kl} are suitable random variables and $\{c_k\}$ is a sequence of positive scalars that satisfy some regularity conditions (see [14] and [16] for a detailed discussion on the algorithm and on the characteristics of the above quantities in terms of convergence properties).

The use of the smoothed SPSA algorithm instead of standard finite-difference stochastic approximation (FDSA) techniques is motivated by the fact that only two perturbations are needed, instead of the $2p$ ones necessary for the computation of the approximation to $\underline{g}_k (p = \dim(\underline{\beta}))$. Analogous convergence properties are however maintained. The above computational advantage is of basic importance, given the large number of necessary parameters to be estimated, which represents a common characteristic of neural-network training.

In the remaining part of the paper, we focus on a specific complex real plant in order to better point out the characteristics and potentialities of the proposed methodology.

IV. Application of the Methodology to a Power Plant Model

In this section, an application of the method previously described is presented. In the first subsection, for the reader's convenience, brief descriptions of the power plant considered and of its global model are reported. The reader interested in more details is referred to [9], where a fault-diagnosis method for the same plant is addressed, and to [17], where some specific modeling issues are addressed. However, some technical details of the model development, based on the physical characteristics of the system, are reported in order to define the advantages of the *grey-box* approach to the identification problem, in terms of the consistency of the identified model with the physical parts of the plant, and to identify the model parts that are structurally and/or parametrically unknown. This will make it possible to design a system that can be on-line tuned to the plant behavior, and that allows the monitoring of significant state variables, both for a possible tuning of control components and for supervision and fault-detection purposes.

A. Description of the Power Plant

This subsection describes a section of the 320 MW power plant located at Piombino, Italy (see Fig. 2). In particular, one of the two feedwater high-pressure heater lines electronically controlled is considered. This line is devoted to the regeneration process, i.e., a technique that improves the plant efficiency. More specifically, the thermodynamic cycle involves the problem that the energy spent by the boiler to transform the water from the liquid phase into the aeriform phase is not completely used in the turbine. This occurs not only because of the intrinsic losses in the turbine, in the boiler, and in the pump, but mainly because it is necessary to condense the steam coming from the turbine at the same temperature and pressure values as those at the beginning of the process. This completes the thermic cycle, so it is possible to heat the liquid once again.

The regeneration process aims to limit energy losses inside the cold source. It follows the scheme shown in Fig. 2: the heaters inserted in the thermic cycle bleed steam from the high-pressure and medium-pressure turbine stages in order to preheat the liquid feedwater coming from the feed pumps and going into the boiler. This process is basic to a high overall plant efficiency, as the water needs less energy from the boiler and decreases the heat given to the cold source.

The high-pressure heater line is depicted in Fig. 3 and is composed of four heaters, denoted by HPHX1, HPHX2, HPHX3, and HPHX4. The feedwater comes from the feed pump, flows through the four heaters, and goes into the boiler. After leaving the turbine, the superheated steam exchanges heat with the feedwater and then condenses. Each heater (see Fig. 4) consists of a vertical-axis cylindrical hollow, divided into halves by a vertical septum and including a $\cap$-shaped tube-bundle where the feedwater flows.

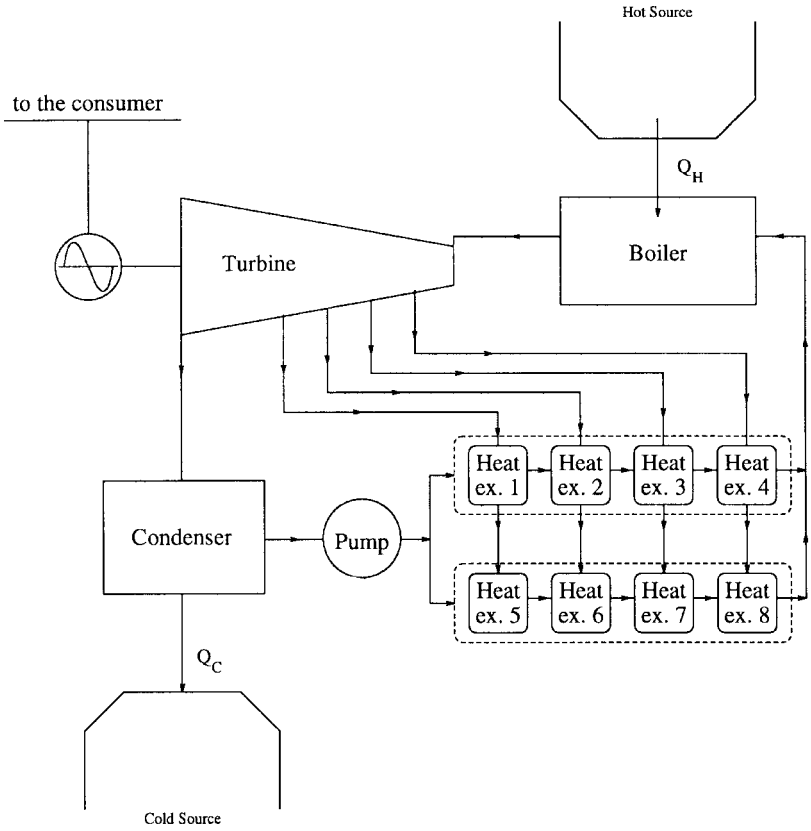

Fig. 2. Scheme of the regeneration process.

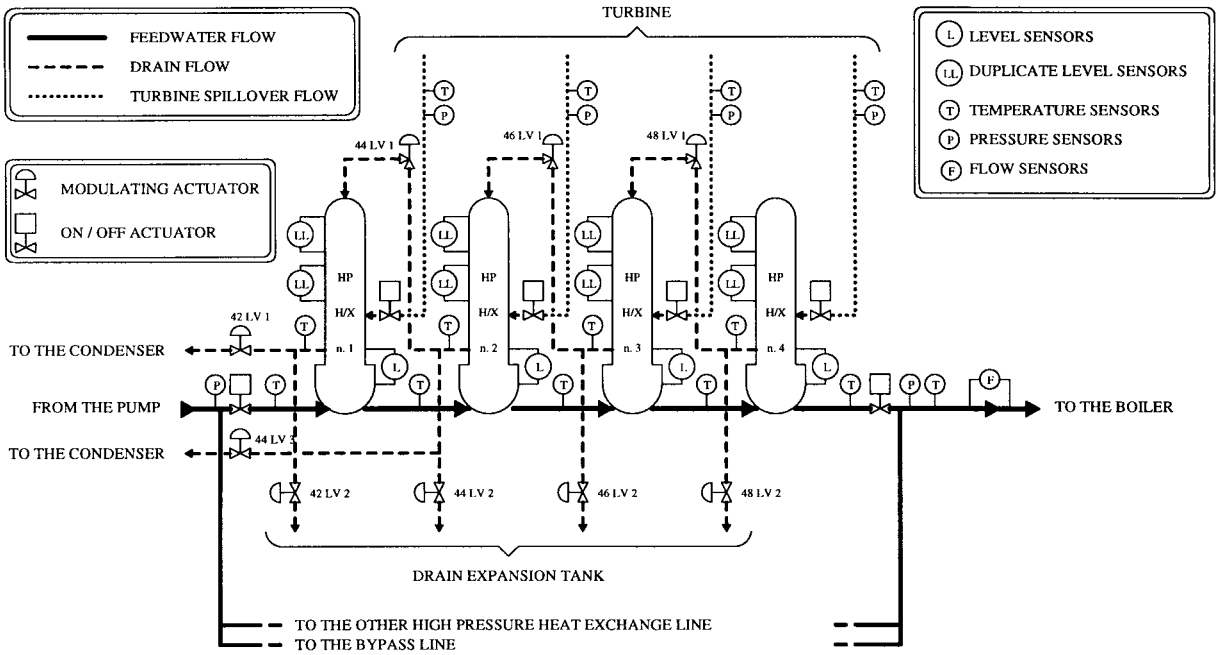

Fig. 3. The high-pressure heater line.

The hollow is made up of three areas for the different types of steam:

A: desuperheating area, where the superheated steam cools down until it reaches the saturated steam condition through the heat exchange with the feedwater flowing in the tube-bundle;

B: condensing area, where the saturated steam condenses (vapor-liquid transition);

C: subcooling area, where the condensed steam and the drain coming from the downstream heaters undergo a process of heat exchange with the feedwater.

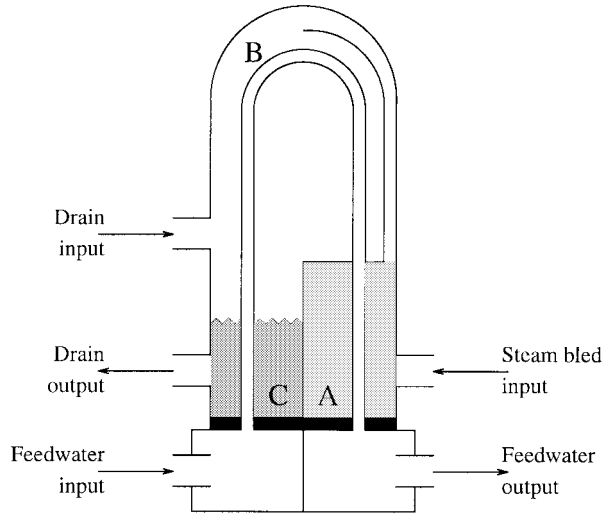

Fig. 4. A heater.

The model of the plant has been built on the basis of the models of the single heaters that make up the high-pressure line, of the sensors, of the actuators and of the controller elements. The model of each heater (see Fig. 4), has been obtained by a "physical" approach according to the grey-box identification concept. The equations describing each heater have been derived from the mass, energy and momentum conservation laws. In particular, an analysis has been made of i) the behavior of the fluid inside the hollow by using the equations for the conservation of the mass of drain water, for the conservation of the mass of water and steam, and for the conservation of the energy of subcooled water; and ii) the behavior of the fluid in the tube-bundle by using the equations for the heat exchange in the desuperheating, drainage, and condensation areas, and the equations for the loss of pressure in the tube-bundles due to the metal friction. Regarding the fluid inside the hollow, the following assumptions have been made:

- —negligible heat exchange between the hollow and the external environment;
- —negligible exchanges of energy and mass, due to surface phenomena at the interface between the condensing and subcooling areas;
- —the heat-exchange surface between the hollow fluid and the tube-bundle is fixed in the desuperheating area and the level of the heat exchange depends on the condensing and subcooling areas;
- —uniform pressure distribution inside the hollow;
- —uniform enthalpy distribution inside each area (A, B, and C);
- —negligible density variations inside the subcooling area.

Moreover, the following assumptions have been made about the feedwater:

- —feedwater in liquid state and in subcooling condition;
- —constant fluid pressure in the tube-bundle and equal to the input pressure in the heater;
- —uniform physical properties of the tube-bundle metal;
- —negligible longitudinal heat conduction in both the pipe metals and the fluid.

From the above assumptions, a set of nonlinear state equations can be derived to define the behavior of the thermodynamic coordinates of the thermotransformation in each heater [17]. The global system can be described by 71 state variables (to the exclusion of those related to the regulation system) and 29 measurable variables.

The models of the heaters have an identical structure and differ only in constants such as geometric coefficients (tank height, inside tank diameter, pipe length, inside and outside pipe diameters, desuperheating area), thermal coefficients (pipe-metal specific heat, pipe-metal thermal conductivity, steam thermal-exchange coefficient, water thermal-exchange coefficient), number of tubes in the tube-bundle, etc.

The complex nonlinear model of the power plant considered has first been extensively simulated, and the behaviors of the accessible system variables have then been analyzed by plant experts. Subsequently, the system has been tested on the real plant. The reader is referred to [9] for more details on the validation phase. As can be noticed from the figures in [9] (not shown here) the results are satisfactory, thus proving the reliability of the model developed, especially in the light of the fact that it has been connected to the real plant in an adequate way. Suffice it to say that the differences between simulated and real variables have always been of a percent order not exceeding the accuracy limits of the available sensors.

However, the validation of the described model allows one to confirm only that the behavior of the model is satisfactory in terms of accessible variables. By contrast, nothing can be said on the modeling of the parts related to inaccessible state variables, which are very important for the supervision, as previously mentioned. Therefore, in the next subsection, we shall show, on the basis of simulation results, that the model tuning by the methodology described in Sections II and III allows one to estimate also such inaccessible model parts.

B. Tuning of the Power Plant Model

The complex model briefly described in the subsection includes a large number of simplifying hypotheses about both the mathematical structures of some blocks and the values of different parameters. In many cases, the large variations in the plant over time may give rise to nonnegligible errors on some model sections that cannot be accessed by the available sensors.

Therefore, it would be very useful to employ the technique presented in Sections II and III in order to reduce the aforementioned approximation errors during the plant operation.

In this respect, consider the global scheme in Fig. 5. Such a scheme includes some parts that are specific for the plant model considered, but that do not affect the generality of the proposed methodology, as previously stressed.

Such a scheme points out the two main types of uncertainties affecting the developed model:

1) *Uncertainties in the mathematical structure*. For instance, the quantities related to the other parts of the power plant have been assumed to be proportional to the load. This assumption may turn out to be very simplistic. Other approximations about the mathematical structure are inherent in the use of steam tables and in the various discretized transformation functions. In Fig. 5, we refer to completely unknown and approximately known structures. The former are really black-box models, while the latter are made of known and unknown sub-blocks. This schematization is very useful in the application considered here, and may turn out to be of some utility also in general.
2) *Uncertainties in parameter values*. For instance, we have used thermodynamic constants and geometrical parameters that are not known with precision and that may vary during the plant operation (e.g., pipe diameters, thermal capacities of the various metals used, etc.).

Furthermore, the model includes several hard nondifferentiable nonlinearities placed in the different blocks depicted in Fig. 5, which make it necessary to use the tuning algorithm presented in Sections II and III. The list of the above nonlinearities for each block is the following:

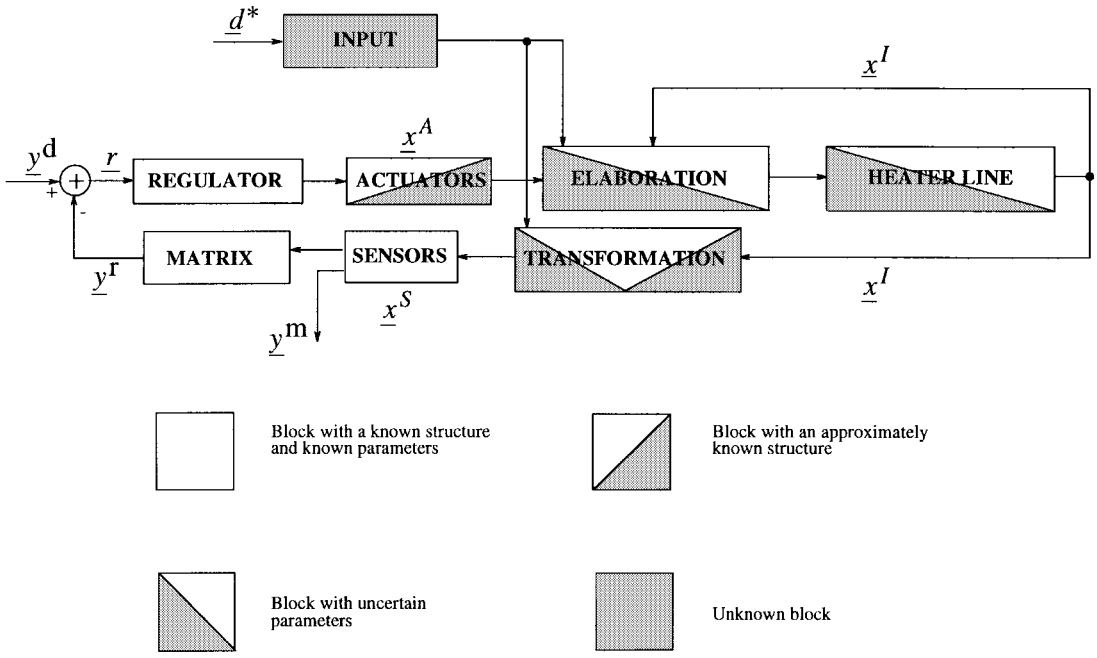

Fig. 5. Scheme of the global model. The parts with uncertain structures and/or uncertain parameters are clearly indicated.

Input block	load saturation.
Sensors block	water level saturation.
Regulator block	anti-wind-up actions and control saturations.
Actuators block	rate limiters and saturations.
Elaboration block	square-root functions in the output feedwater sections.
Transformation block	steam-tables and square-root functions in the output feedwater sections.

By replacing all the parts affected by uncertain functioning (see Fig. 5) with neural networks, one obtains the model (4) (see Section II), where $\underline{x} \triangleq \mathrm{col}(\underline{x}^I, \underline{x}^A, \underline{x}^S)$ represents the state vector $(\dim(\underline{x}) = 71)$, $\underline{y} \triangleq \mathrm{col}(\underline{y}^m, \underline{y}^r)$ represents the vector of the measurable variables $(\dim(\underline{y}) = 34)$, $\underline{w}$ is the total vector of the synaptic weights of the neural networks, and $\underline{\theta}$ is the vector of the unknown mathematical and physical parameters. For notation simplicity, here and in the following, we drop the index t. In [9], the list of parameters to be estimated (i.e., the components of the vector $\underline{\theta}$) is given, together with their approximate values based on the expertise of plant technicians.

As clearly stated in Section II, two distinct types of quantities have been identified, which have to be estimated on the basis of the measures provided by the available sensors of the plant: i) parameters of the model parts whose mathematical structures are assumed to be accurate enough, and ii) synaptic weights of the neural networks that describe the model parts whose mathematical structures are very approximate.

As mentioned in [9], the simulator on which the global model (including the neural networks) has been implemented can be connected to the FIP automation system of the power plant. This allows the on-line tuning of the model to the real plant. Clearly, one can verify that even the inaccessible model parts can be estimated to a reasonable accuracy by the proposed tuning method only via simulation. Therefore, we have developed an emulator of the described accurate model validated on the real plant. Such a simulated model has then been regarded as a real system, thus allowing one to measure even the inaccessible internal model parts. In parallel, we

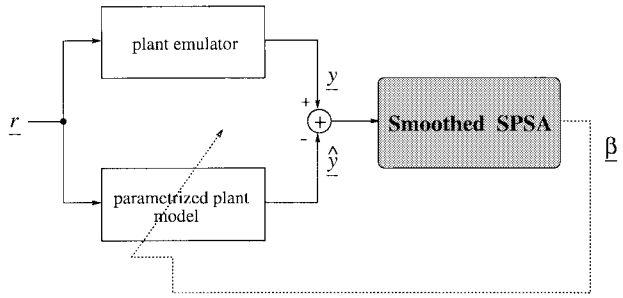

Fig. 6. Scheme of the simulation framework to verify the effectiveness of the tuning method.

have developed an analogous model whose parameters had yet to be tuned. We aimed to ascertain if the proposed methodology makes it possible to tune the model parameters to real values, and if the internal parts are estimated correctly. We refer the reader to Fig. 6, which is only a simplified version of Fig. 1, but which is useful within the context of the present section.

Now, we describe the just introduced *simulation-based validation*. The model parts modeled by the neural networks are the modulating actuators, the steam table and the table of the enthalphy-into-temperature conversion; the parameters to be estimated are the water levels in the desuperheating areas. For the actuators, we used neural networks with two input units, four hidden units and one output unit; for the steam table, we used neural networks with ten input units, 20 hidden units, and ten output units; for the table of the enthalphy-into-temperature conversion, we used neural networks with eight input units, 15 hidden units and four output units. As to the cost function (5), we chose experimentally $N = 1000$, $t = N$ fixed, and $P = 0.1 \cdot I$, where I is the identity matrix. For the parameters of the Smoothed SPSA algorithm, we chose $a_k = 0.004/k^{0.602}$, $c_k = 0.6/k^{0.101}$, and $\rho_k = 0.5/k^{0.603}$; the scalars α_k were suitably chosen according to the magnitudes of the *a priori* estimated values of the corresponding parameters. We took the perturbations Δ_{kl} to

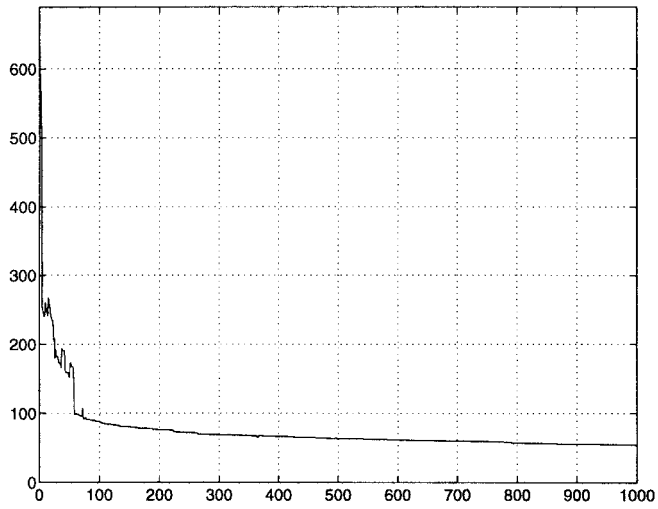

Fig. 7. Behavior of the estimation cost function during the learning procedure.

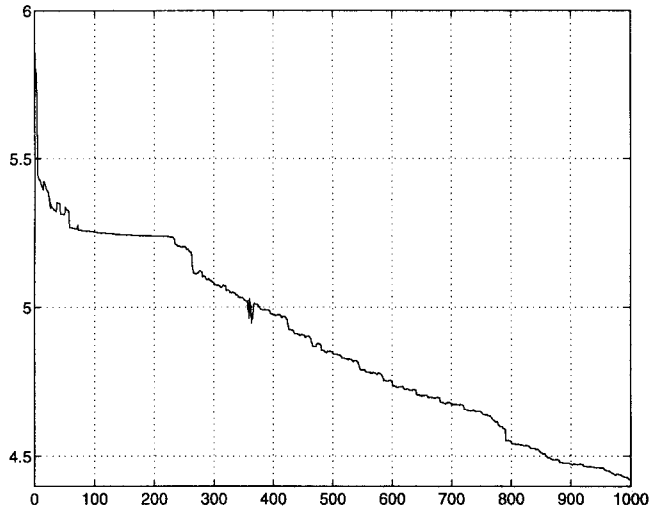

Fig. 8. Behavior of the RSS error during the learning procedure.

be Bernoulli ± 0.5 distributed, so guaranteeing the fulfillment of the main regularity assumptions made in [16].

The convergence of the learning procedure was satisfactory, as shown in Fig. 7. Note that the estimation cost function, whose behavior is shown in Fig. 7, may not be a reliable indicator as to whether the state variables generated by the model during the plant operation actually represent the real variables to a good approximation. Such a cost takes into account only the input–output behavior of the model, as compared with the behavior previously determined and parallel-simulated. Moreover, according to the scheme shown in Fig. 6, during the simulation phase, it is possible to build also an indicator of the goodness of the state-variable estimation, e.g., the root sum square (RSS) error of the state vector

$$\mathrm{RSS}(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|x_i(t) - \hat{x}_i(t)\|^2}$$

where $x_i(t)$ and $\hat{x}_i(t)$ are the ith components of $\underline{x}_t$ and $\hat{x}_t$, respectively, and $n = dim(\underline{x}_t)$.

Obviously, such an indicator can be computed only via simulation, not in real time; nevertheless, it is useful to assess the reliability of the approach in terms of estimation of the inaccessible state variables. Fig. 8 shows the good behavior of the RSS error.

In confirmation of the satisfactory estimates of the state variables, Fig. 9 shows a comparison between the real behavior of the water level in the condensing area and the estimated value in HPHX1, after 1000 training steps. It is easy to deduce that the deviation between the two behaviors is very small.

Furthermore, Fig. 10 gives the behaviors of four estimated parameters, i.e., the water levels in the desuperheating areas in the four heaters. As can be noticed, for all four heaters, satisfactory convergences of the parameters to their true values were obtained after a reasonable number of iterations.

Finally, we report the results of some simulations of a plant malfunction only to stress, once again, the usefulness of a grey-box approach to the identification problem, based on the development of a model strictly consistent with the physical parts of the plant (more details on such a model-based fault-detection problem can be found in [17]). In particular, we simulated a feedwater leak in the tube-bundle in the condensing area. More specifically, the leakage flow from the tube-bundle can be expressed as $\gamma\sqrt{\Delta}$, where Δ is the difference in pressure existing between the hollow of the heater and

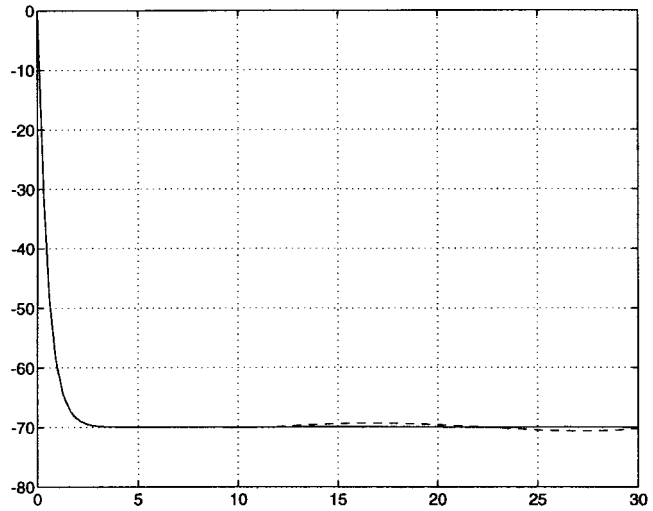

Fig. 9. Comparison between the estimated (dashed line) and true (continuous line) behaviors of the condensate level in Heater 1, after 1000 training steps.

the feedwater (such a difference of course depends on the operating conditions of the system) and $\gamma \geq 0$ is a scalar that models the leak in the tube-bundle (i.e., $\gamma = 0$ means absence of leaks, and an increase in γ, under the same operating conditions, means an increase in the leakage flow). In particular, one leak speed with $\gamma = 0.05$ was simulated. Fig. 11 shows the behaviors of the heaters' condensate levels during the plant malfunction. As can be seen, the feedwater leak in the tube-bundle of HPHX3 causes a decrease in the levels in the downstream heaters and an increase in the levels in the same heater and in the upstream ones.

Fig. 11 shows that one can model the aforementioned fault by observing the behaviors of the condensate levels. It is worth noting that the simulation and hence the input–output modeling of the fault (very frequent in heater lines) were possible only thanks to the fact that the developed model is consistent with the physical parts of the plant and to the fact that an effective tuning technique has been devised.

V. Conclusion

In this paper, a methodology for the grey-box identification of complex models of real plants has been proposed. More specifically,

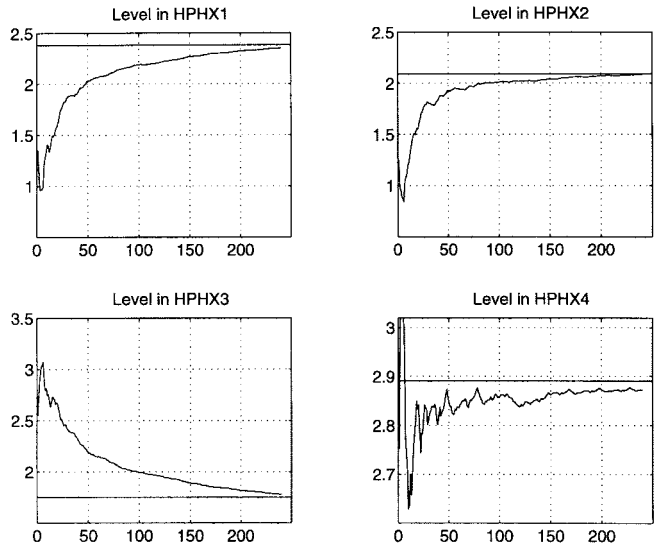

Fig. 10. Convergences of the estimated water levels in the desuperheating areas to their true values.

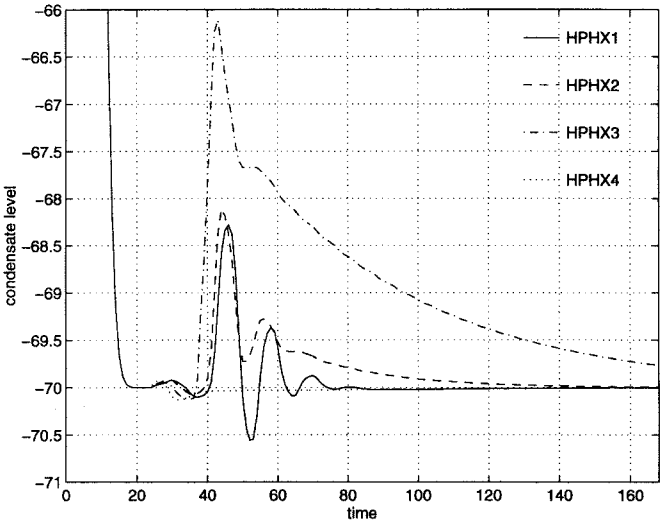

Fig. 11. Condensate levels in HPHX1, HPHX2, HPHX3, and HPHX4 during a plant malfunction in HPHX3 with $\gamma = 0.05$.

the tuning of the model parts, whose structures and/or parameters were approximately known, has been accomplished by using the measures provided by the available sensors.

The replacement of the structurally unknown parts with suitable multilayer feedforward neural networks makes it possible to reduce the model-tuning problem to a parametric-identification problem, which in general involves a large number of parameters to be tuned. The numerical solution of this problem can be obtained by a stochastic approximation technique, i.e., the SPSA, which allows, at the same time, the training of the neural networks and the estimation of the model parameters. The proposed method was applied to a real 320 MW power plant. Simulation results confirm the validity of the described approach, which is much more efficient than standard finite-difference methods for this application.

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