

Modeling and fault diagnosis sensor by multi-model approach

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Abstract—This work falls within the fault detection and sensor faults dedicated to monitoring climate data and or air pollution. The strategy discussed in this paper represents a contribution to the study of methods for detecting and locating defects by analytical redundancy.

Indeed, it is a network of sensors installed in an urban area, measuring and continuously observing climate change and pollution. The failure of one or more of these sensors at given moments will inevitably result in an erroneous analysis of the situation. The proposed technique is based on the nonlinear modeling using blind Multi-models, choosing the "Multi-model decoupled state" structure and at the same time we will give an idea about the multi-model in coupled state says Sugeno-Takagi; and hierarchical structure. The goal through using these models is the generation of residues for diagnosis.

Keywords—*Software sensors; nonlinear systems; Multi-model; Air pollution.*

Résumé— Ce travail relève de la détection de pannes et de défauts de capteurs dédiés à la surveillance des données climatiques et ou de pollution atmosphérique. La stratégie étudiée dans cet article représente une contribution à l'étude des méthodes de détection et de localisation de défauts par redondance analytique.

En effet, Il s'agit d'un réseau de capteurs installés dans une agglomération, mesurant et observant en permanence les changements climatique et de pollution. La défaillance ou la panne d'un ou de plusieurs de ces capteurs à des instants donnés va entraîner inévitablement une analyse erronée de la situation. La technique préconisée est basée sur la modélisation non linéaire en utilisant entre autres les Multi-modèles, on choisissant la structures « Multi-modèle à état découplé » et en même temps on va donner une idée sur les multi-modèles « à état couplé dit de Takagi-Sugeno ; et structure Hiérarchisée ». Il s'agit de trouver des modèles non linéaires en combinant plusieurs modèles linéaires. Ces modèles seront utilisés pour la génération

de résidus en vue du diagnostic.

Mots-clés— *Capteurs software ; Multi-modèles; Systèmes non-linéaires ; Pollution atmosphérique.*

I. INTRODUCTION

Considering the importance of climatic variations study, as for as the air pollution constitutes one of the environmental problems most complex and most difficult which arise for the world today. About any form of human activity is likely to deteriorate, in a way or of another, the clean air and the protective atmosphere of the Earth.

Every day, the human activities, either industrial, agricultural or residential, has as a result, the rejection of great quantities of natural and synthetic chemicals in the atmosphere.

In the case of the air pollution, one of the worst problems is due to the fact that, even if the primary causes of the toxic issuing are local or national, the released particles despise borders.

The dominant winds transport these polluting substances in the whole world, which causes serious environmental damage in distant places and contributes to the general degradation of the Earth's atmosphere [1].

Consequently, we will undertake a work which concerns the detection of failures and defects of sensors dedicated to the monitoring of the climatic data and or of air pollution.

The strategy studied in this memory represents a contribution to the methods engineering of Fault Detection and Isolation(FDI) per analytical redundancy. The issue of problem of failure diagnosis has been addressed by several authors such [2] where the paper presents a study with an emphasis on robustness and applications. Most work on fault detection and isolation in non-linear systems are based on non-linear observers [3]. Authors in [4] addressed the case of design of dynamic party relations by considering additive and

multiplicative faults, in [5] authors used local approach for FDI. In [6] authors focused on hybrid systems by using structural parity residuals, where these residuals may be used to detect continuous and discrete faults.

Works on FDI growth with challenges according to complex systems, where requirements increased. Authors in [7] proposed a methodology for modelling physical systems in the case of discrete-event approach. In order to achieve failure diagnosis in systems with limited sensor availability authors in [9] present a hybrid approach to failure diagnosis. This approach integrates the qualitative discrete event systems diagnostic methodology, and a variety of diagnostic technologies in one unified framework.

Indeed, it is about a virtual network of sensors installed in an agglomeration [10], measuring and permanently observing the climatic and pollution changes (NO_x et O_3). The failure or the stoppage of one or several of these sensors at moments given will automatically involve an erroneous analysis of the situation. The recommended technique is based on nonlinear modelling [11], using inter alia the Multi-models [8], one emphasizing on the appointed structure “structure multi-model at uncoupled state”. It concerns of to find nonlinear models by combining several linear models. Each linear model is active in a quite specific area of operation. The areas of operation of the linear models must be determined by classification. These models will be used for the generation of residues with a diagnosis view.

The next section addresses the problem statement. The third section addresses the multi-model approach with different structures. The section IV addresses the parametric optimization and the approach adopted for our problem. Finally, in the section (V) we describe the case study of our approach and we conclude in section (VI).

II. PROBLEM STATEMENT

The purpose of this paper is the fault detection of sensor dedicated to monitoring climate data and/or air pollution. The proposed technique is based on nonlinear modeling using the Multi-model approach [13]. The deployment of such approach needs a mathematical complexity of model and makes its use difficult and limited.

For this, we need to find nonlinear models by combining several linear models. Each linear model is active in a quite specific area of operation. The areas of operation of the linear models must be determined by classification. These models will be used for the generation of residues with a diagnosis view.

III. MULTI-MODEL APPROACH

The multi-model approach is a convex poly-topical representation; and was initiated by [14][15]. The idea of this approach is to understand the nonlinear behavior of a system by a set of local models (linear or affine) characterizing the operation of the system in different operating zones [15].

The motivation of this approach results from the fact that it is often difficult to design a model that takes into account the complexity of the system studied (Fig. 1).

Achieving a multi-model structure is to find a shape of interpolation between local linear models of a nonlinear structure. Each local model is a dynamic system LTI (Linear Time Invariant) valid around an operating point.

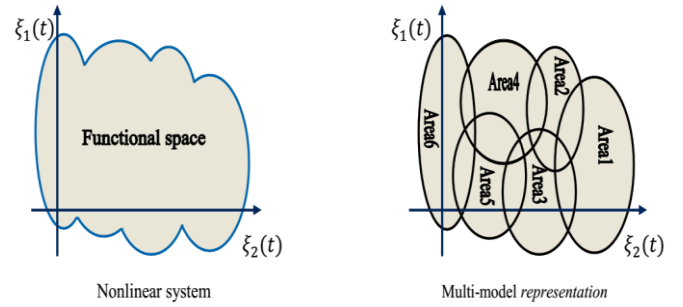


Fig. 1. Multi-model approach

If there are only measures of system inputs and outputs, we proceed by identifying, seeking or imposing multi-model structure. If, however, there is an explicit nonlinear model that need to be "simplified" or can be made more manipulable, we can proceed to linearization around different operating points. In this case, it is refined local models due to the presence of the constant from the linearization or poly-convex topical transformation [14].

According to the literature review, we can enumerated various forms of multi-model depending on the segmentation made on the input or output (i.e. the measurable state variables) and also according to the nature of the coupling between the local models associated with areas of operation. However, we note three multi-model structures: 1. Structure coupled, 2. Uncoupled Structure and 3. Hierarchical Structure.

A. Coupled structure (Fuzzy Model of Takagi-Sugeno)

The multi-model representation is obtained by linear interpolation of local models.

$$\begin{cases} \dot{x}_M(t) = \sum_{i=1}^M \mu_i(\xi(t))(A_i x_i(t) + B_i u(t) + D_i) \\ \hat{y}(t) = y_M(t) = \sum_{i=1}^M \mu_i(\xi(t))(C_i x_i(t) + E_i u(t) + N_i) \\ \xi(t) = \{u(t), x(t), y(t)\} \end{cases} \quad (1)$$

With $x_i \in \mathbb{R}^n$ represents the state vector, $u \in \mathbb{R}^m$ the control vector and $y \in \mathbb{R}^p$ the measurement vector. $A_i \in \mathbb{R}^{n \times n}$, $B_i \in \mathbb{R}^{n \times M}$, $C_i \in \mathbb{R}^{p \times n}$, $D_i \in \mathbb{R}^n$, $E_i \in \mathbb{R}^{p \times M}$ and $N_i \in \mathbb{R}^p$ are the matrixes associated to the sub models, and are constant and assumed to be known.

The quantities $\mu_i(\xi(t))$ represent the weighting functions that provide the transition between the sub-models that depend on the index variable $\xi(t)$. Also, this variable may correspond, for example, to a measurable variables of the system (the input or output signal of the system or non-measurable variables; the state of the system for example).

The weights functions have the following properties:

$$\begin{cases} \sum_i^M \mu_i(\xi(t)) = 1 \\ 0 \leq \mu_i(\xi(t)) \leq 1 \end{cases} \quad (2)$$

Where $\mu_i(\xi(t)), i \in \{1, \dots, M\}$ are the activate functions and $\xi(t)$ is the vector of decision variables which is dependent on measurable state variables and / or of the order.

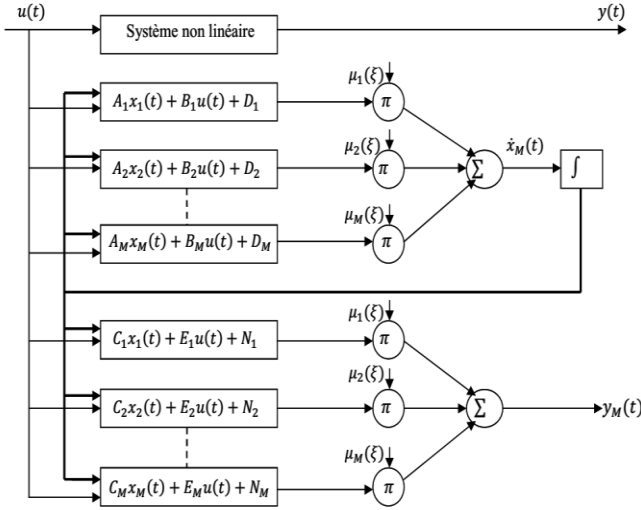


Fig. 2. Architecture of a multi-model coupled to local models

B. Decoupled structure

Another shape of multi-model approach is proposed by Filev[14], and results from the aggregation of local models described in a decoupled manner. The difference between this structure and the one presented in the previous paragraph is the fact that each local model is independent from others.

$$\begin{cases} \dot{x}_i(t) = A_i x_i(t) + B_i u(t) + D_i \\ y_i(t) = C_i x_i(t) \end{cases} \quad (3)$$

Hence the notion of local state corresponding to a prescribed operating region appears much clear in this structure.

The multi-model (global template) is given by:

$$\begin{cases} \dot{x}_i(t) = A_i x_i(t) + B_i u(t) + D_i \\ \hat{y}(t) = \sum_{i=1}^M \mu_i(\xi(t)) (C_i x_i(t)) \quad i \in \{1, \dots, M\} \\ \xi(t) = \{u(t), x(t), y(t)\} \end{cases} \quad (4)$$

Where $x_i \in \mathbb{R}^{n_i}$ and $y_i \in \mathbb{R}^{p_i}$ are respectively the state vector and the output vector of the i ème sub-model and where the parameters $u, y, \xi, A_i \in \mathbb{R}^{n_i \times n_i}, B_i \in \mathbb{R}^{n_i \times M}$ and $C_i \in \mathbb{R}^{p_i \times n_i}$ were defined in the previous section.

The overall output of the multi-model is the weighted sum of the sub-models outputs. Mixing between the sub-models is therefore carried out through the measurement equation.

Consequently, each sub-model has its own state space and there evolves independently according to the command and its initial state signal. The main advantage of multi-decoupled model is located in the fact that it allows the use of a vector dimension different state for each sub-model unlike to Takagi-Sugeno models. Thus, it becomes possible to adjust, during the identification phase, the complexity of each sub-model to the complexity of the dynamic behavior of the system in the various operating zones. The use of this structure will then allow avoiding saving a detailed and uniform description of the area of operation. This reduces the overall number of parameters to be identified. The introduction of such degree of flexibility promotes generality of decoupled multi-model, especially when modeling systems which structure or behavior may have changes according to the operating conditions[13].

We note that local variables $x_i(t)$ don't necessarily have a physical sense. The matrix A_i, B_i, D_i and the activation functions $\mu_i(x(t))$ are calculated in the same way as above (structure coupled). This structure can be seen as the parallel connection of M affine models weighted by their respective weights (Fig. 2).

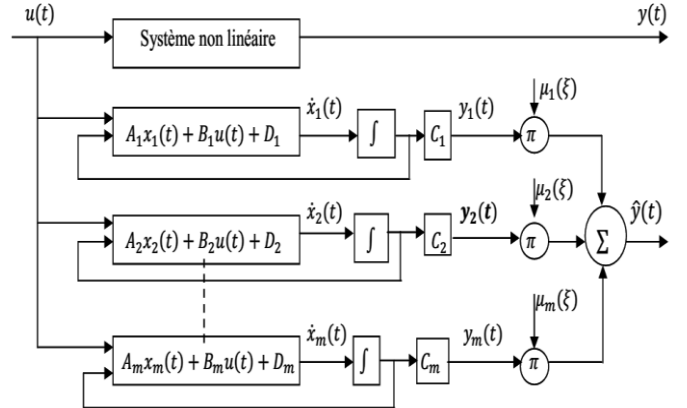


Fig. 3. Architecture of a multi-model with decoupled local models

C. hierarchical structure

Although the multi-model approach has been very successful in many fields (control, diagnostics), its application is limited to systems with few variables (reduced size). The number of local models increases exponentially with increasing number of variables. For example, a multi-single-output model variables and activation with defined functions for each variable consists of local models. Researchers, such (Frie, 1981) (Brei, 1984) and (Hube, 1985) investigated this problem by using different approaches.

To overcome this problem, (Raju et al, 1991) proposed a model for multi-hierarchical structure to reduce the number of local models. (Figure 4) shows a typical example of a hierarchical multi-model having inputs and outputs; in this

structure, each local models have two inputs; the global model is then composed of local models [14].

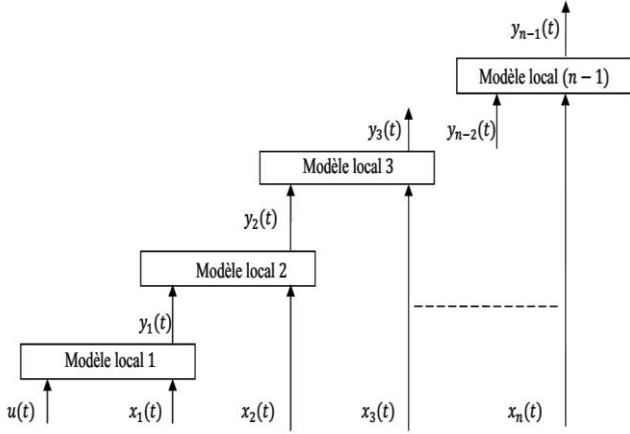


Fig. 4. Architecture of a multi-hierarchical model

Where the local model is described as:

$$\begin{cases} \dot{x}_1(t) = (A_1 x_1(t) + B_1 u(t) + D_1) \\ y_1(t) = \mu_1(\xi(t))(C_1 x_1(t) + E_1 u(t) + N_1) \\ \xi(t) = \{u(t), x(t), y(t)\} \end{cases} \quad (5)$$

And the n th local model is described as:

$$\begin{cases} \dot{x}_n(t) = (A_n x_n(t) + B_n y_{n-2}(t) + D_n) \\ y_{n-1}(t) = \mu_n(\xi(t))(C_n x_n(t) + E_n y_{n-2}(t) + N_n) \\ \xi(t) = \{u(t), x(t), y(t)\} \end{cases} \quad (6)$$

IV. PARAMETRIC OPTIMIZATION

When the model of the system is not linear according to the parameters, there is no analytical solution to estimate these parameters. In this case we use iterative nonlinear optimization techniques. In this section, we focus on the parametric optimization of a multi-model structure.

Several optimization methods can be used, according to information available. If knowledge on the parameters of activation functions and those of local models are not available, these parameters should be optimized using an iterative procedure due to nonlinearities of the global model (multi-model) compared to its parameters.

The identification methods of the set of all parameters must satisfy a number of constraints in terms of operating context. For this purpose, the following three criteria: global, local or combined, are used to perform the parametric optimization.

A. The global criterion

The global criterion is defined through the following equation:

$$J_G(\theta) = \frac{1}{N} \sum_{t=1}^N \varepsilon(t, \theta)^2 = \frac{1}{N} \sum_{t=1}^N (\hat{y}(t) - y(t))^2 \quad (7)$$

Where (N) is the horizon of observation and (θ) is the parameter vector of the local models and those of activation functions.

This criterion favors a good characterization of the global behavior of the nonlinear system with the multi-model.

B. The local criterion

The local criterion is defined through the following equation:

$$J_L = \frac{1}{2} \sum_{i=1}^L \sum_{t=1}^N \mu_i(\xi(t)) (\hat{y}_i(t) - y(t))^2 \quad (8)$$

It promotes a good matching between the local behavior of the sub-models and the local behavior of the nonlinear system provided, however, that little μ_i are mixed. It is very well suited for obtaining a multi-phenomenological model and / or explanatory.

C. The combined criterion

Finally, the combined or mixed criterion defined by equation (8) represents a compromise between the previous two criteria:

$$J_C = \alpha J_G + (1 - \alpha) J_L \quad \leq \alpha \leq 1, \quad (9)$$

D. Parametric estimation with a global criterion

The parametric estimation with a global criterion is described by the following equation:

$$\varepsilon(k) = \hat{y}(k) - y(k) \quad (10)$$

Where $\varepsilon(k)$ is the error between the full output of the MM and the output of SNL.

1) The gradient vector

Note that the criterion of the derivatives with respect to parameters can be evaluated from σ sensitivity functions defined by:

$$\sigma_\theta = \frac{\partial y}{\partial \theta} \quad (11)$$

$$\begin{aligned} G_G &= \frac{\partial J}{\partial \theta} = \frac{\partial}{\partial \theta} \sum_{k=1}^N (\hat{y}(k) - y(k))^2 \\ &= \sum_{k=1}^N (\hat{y}(k) - y(k)) \frac{\partial y(k)}{\partial \theta} \end{aligned} \quad (12)$$

2) The Hessian matrix

The second derivative of J is given by:

$$H_G = \frac{\partial^2 J}{\partial \theta \partial \theta^T} = \sum_{k=1}^N \sigma_\theta \sigma_\theta^T + 2 \sum_{k=1}^N \frac{\partial \sigma_\theta}{\partial \theta^T} (\hat{y}(k) - y(k)) \quad (13)$$

Digital inversion difficulties can appear if the matrix is not well conditioned. In this case, we can change the Hessian to another form:

$$H_{Ga} = \frac{\partial^2 J}{\partial \theta \partial \theta^T} = \sum_{k=1}^N \sigma_{\theta} \sigma_{\theta}^T + 10^{-3} I(N), \quad (14)$$

With $I(N)$ the identity matrix.

V. CASE STUDY

For our approach we used data from [12] which provides a description of the kinetics of formation of ozone in the atmosphere as a function of changes in reactant concentrations (Fig. 5)

We have chosen here to use a global criterion to perform the identification of multi-model. It wants a multi-model prediction, not explanation of local behaviors. The parametric estimation is performed with considering the gradient vector $G(\theta(k))$ and the Hessian matrix $H(k)$ defined by relations (11, 12, 13).

The multi-model is made arbitrarily by $L = 2$ sub-models. The A_i, B_i, D_i and C_i parameters and sub-models are scalar type.

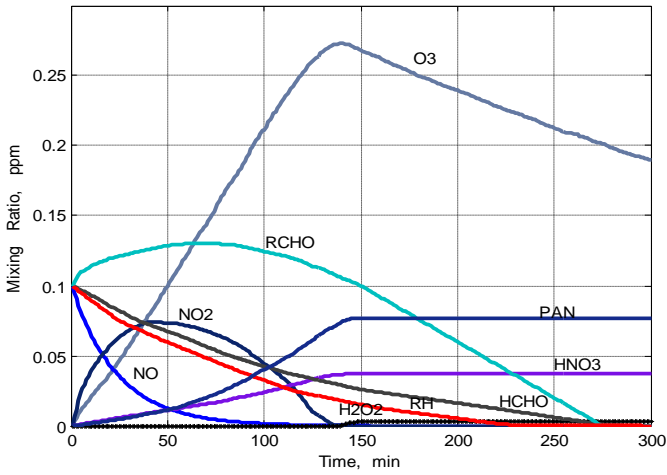


Fig. 5. Kinetics of compounds involved in the formation of atmospheric ozone, inspired from [12]

The parameters involved in the formation of ozone are: $NO_2, HNO_3, NO, HCHO, RCHO, PAN, RH, H_2O_2$, we will consider that these parameters are inputs, and ozone as the output of our proposed system (paragraph VI).

We have added to our output (reagent concentrations of O_3) noise and outliers.

The weighting functions μ_i depend on the input signals « $NO_2, HNO_3, NO, HCHO, RCHO, PAN, RH, H_2O_2$ », the centers are given by " c_i " and the dispersion " σ_i ".

$$\begin{bmatrix} c_1 \\ \sigma_1 \end{bmatrix} = \begin{bmatrix} 0.04015 \\ 0.228 \end{bmatrix} \text{ et } \begin{bmatrix} c_2 \\ \sigma_2 \end{bmatrix} = \begin{bmatrix} 0.04015 \\ 0.325 \end{bmatrix}; \quad (15)$$

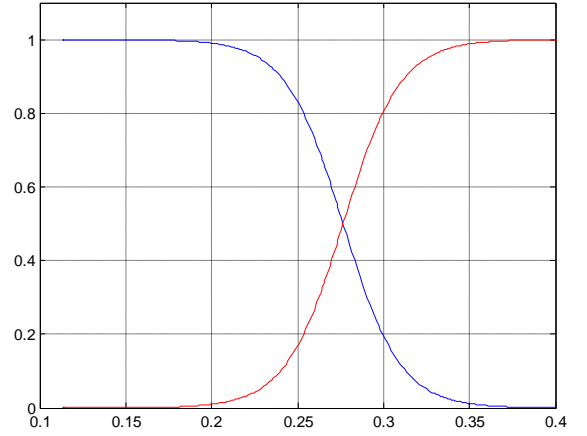


Fig. 6. Functions on ponderation μ_i

(Figure 6) shows functions on ponderation (μ_i) presented in figure 7 and described in the section of Coupled structure through the (Fuzzy Model of Takagi-Sugeno).

The development of our multi-model is based on the software sensor modeling according to real sensors readings. The development of our multi-model follows these three main steps: (1) Decomposition of the operating space into a number of operating areas; (2) Aggregation of sub-models; (3) Determination of parameters of each sub-model.

The model used in our approach is described in the following (figure 7).

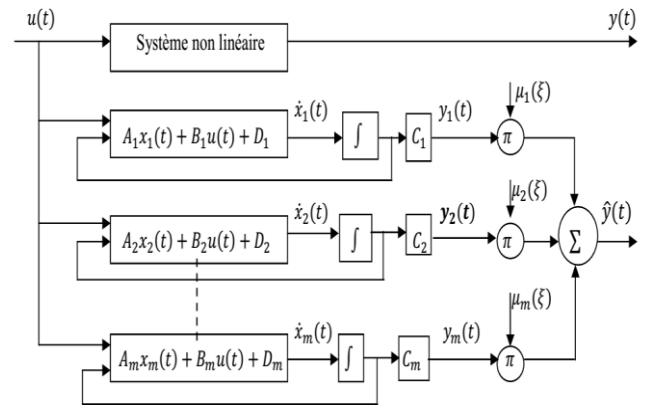


Fig. 7. Architecture of a multi-model: local models decoupled

Concerning the identification of the parameters of our model, if only provides measures of system inputs and outputs, the procedure will be through identification. This is the case study of this paper. If, however, we have an explicit nonlinear model that needs to be "simplified" or make it more manipulate it may proceed by linearization around different operating points or convex poly-topical transformation.

The chosen algorithm of identification is the improved Gauss-Newton algorithm:

The vector of parameters with particular iteration is:

$$\theta^+ = \theta - \Delta(H + \lambda I)^{-1}G; \quad (16)$$

Avec :

θ Vecteur de paramètres à une itération particulière.

θ^+ Cette même valeur à l'itération suivante.

$H = \frac{\partial^2 J}{\partial \theta \partial \theta^T}$ is the Hessienne matrix.

$G = \frac{\partial J}{\partial \theta}$ is the gradient vector.

Δ is the Relaxation coefficient.

λ is the Regularization parameter (Marquardt algorithm) [10].

I is the identity matrix.

The right choice of the initial parameters A_i, B_i, D_i et C_i of sub-models plays an important role in achieving good results; unfortunately there has not been a definite method for the initial selection of these parameters. In addition the choice of the number of local models is arbitrary.

We have chosen here to use a global criterion to perform the identification of multi-model. It wants a multi-model prediction, not explanation of local behaviors.

$$J_G(\theta) = \frac{1}{N} \sum_{t=1}^N \varepsilon(t, \theta)^2 = \frac{1}{N} \sum_{t=1}^N (\hat{y}(t) - y(t))^2 \quad (15)$$

The criterion of the minimization methods is based on a Taylor expansion around the test for a particular value of the parameter vector and an iterative process of gradual change of the solution. If we denote the iteration index of the search method and the value of the solution at the iteration, the update of the estimation is carried out as follows:

$$D(k) = H^{-1}(k)G(\theta(k)) \quad (16)$$

VI. RESULTS :

The obtained model is described through the following functions:

$$\hat{y}(k) = \mu_1(\xi(k))\hat{y}_1(k) + \mu_2(\xi(k))\hat{y}_2(k) \quad (17)$$

With:

$$\begin{aligned} u_1(k) &= NO(k); u_5(k) = HCHO(k); \\ u_2(k) &= NO_2(k); u_6(k) = RCHO(k); \\ u_3(k) &= HNO_3(k); u_7(k) = RH(k); \\ u_4(k) &= PAN(k); u_8(k) = H_2O_2(k); \end{aligned} \quad (18)$$

$$y(k) = O_3(k); \quad (19)$$

$$\begin{aligned} \xi(k) = u_9(k) &= u_1(k) + u_2(k) + u_3(k) + u_4(k) \\ &+ u_5(k) + u_6(k) + u_7(k) \\ &+ u_8(k); \quad (20) \end{aligned}$$

$\mu(\xi(k))$: follows a gaussian rule.

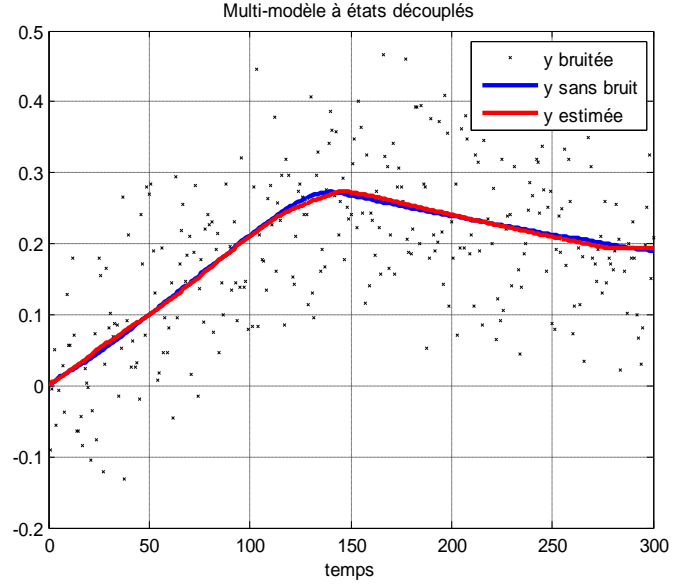


Fig. 8. Theoretical and estimated output function of $y = O_3$ in ppm

Based on [12] where authors show the kinetics of compounds involved in the formation of atmospheric ozone, we have chosen the case of O_3 (Ozone).

The (Fig. 8) represents the theoretical and estimated output function. In blue we have the output without noise, knowing the noise is represented through the cloud of dots.

In red we have the estimated output, which converges to the theoretical one in blue.

VII. CONCLUSION

In this paper we tried to analytically develop a Software redundancy sensor able to follow the kinetic evolution of Ozone, from databases of kinetic elements.

To achieve this goal we chosen a technique based on the nonlinear modeling using Multi-models, with the structure of "multi-model decoupled state."

We identified non-linear models by combining multiple linear models. Each linear model is active in a very specific area of operation. Linear models operating areas are determined by classification. Once the multi-model was developed, a method of diagnosis, detection and fault location was generated from a data bank. Then we used a method of comparison with the actual data collected. Through these results, it can be concluded if there is a defect or not, and to determine the sensor in question.

As future work we envisage to use a data bank, and method of comparison with the actual data collected. Also we envisage taking into account other parameters such UV ray.

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