ON-LINE OPTIMIZATION OF EFFICIENCY AND EMISSIONS OF ENERGETIC PROCESSES: AN INDUSTRIAL CASE APPLICATION OF THE EVOLUTIONARY CONTROL METHODOLOGY

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Introduction

The extensive use of energy presents a severe challenge to the environment and makes indispensable to focus the research on the maximisation of the energy efficiency and minimisation of environmental impact (in particular the reduction of NO_x and CO emissions). In this context the combustion process control assumes an importance much more relevant with respect to the past, especially for the combustion plants where the pollutants emissions, the environmental impact and the energy efficiency are strictly related to the modality of the process management.

The proposed methodology ([3]) is based on dynamics-based classification and evolutionary optimisation. The principal features of the approach are: *dynamics based*, *no intensive modelling* (progressive training directly from the measurements), able to follow the *plant evolution*. In our proposal the process knowledge is developed directly by the system through the observation of the effects that the regulation actions (acted by the operators or any other existing control systems) have on the plant performance.

The main processes which we are looking at for application of the evolutionary control in the context of combustion plants are: eco-sustainable energy processes, gas turbines, industrial combustion chambers, engines. Actually, we are using this methodology in order to develop a prototypal control system for a real waste incinerator plant.

1. The Dynamic State Identification

The innovative approaches to the plant control are generally based on a model which is able to describe the plant reaction to the changes in the regulation in term of induced variation on the plant performance. The main problem in real industrial applications is that it's very difficult to build a model which can take into account all the variables, especially in complex processes like the plant for energy production or transformation. In most of the cases some variables are impossible to measure or some ageing effect can push the original model towards the obsolescence. A good chance to achieve this kind of information is the non-linear dynamic analysis of signals connected with the plant dynamics. The plant dynamic state can very well integrate the process measurement supplying the missing information. In the following a way to obtain theses description is illustrated.

The plant is monitored with *process measurements* (process parameters averaged on the time interval which defines the period of the plant monitoring) and *dynamic measurements* (sensors with dynamic response following the process dynamics fluctuations). The dynamical measurements are elaborated on the time interval and the chaos invariants are computed. These discriminants describe the *plant state*. In 1996, [1] a new methodology for the classification problems based on the attractor morphology using few discriminant parameters has been outlined. This methodology has been successfully applied to different areas (multiphase flow regime recognition, gas turbine characterisation, pollutant predictions in conventional combustion chambers ([1],[4] et al.). The basic idea is to compute a series of "moments of inertia" for the attractor, extending in order and dimensions, which characterise the morphology of attractor and identify a current dynamics of the process. We build a series of shape descriptors, named *dynamic moments*. The technique consists of specifying certain points or axes or planes with respect to which the distances to every point of the attractor are computed.

Generally, the dimension of the space in which we compute the dynamic moments should be equal to the number of the dimensions of the chaotic process. However, if the chaotic process has high dimension, for classification purposes it is possible to extract discriminant characteristics by computing the dynamics moments in a lower dimension space, provided that the classes are well enough separated. Obviously, for dimensions 2 and 3 we have easily visualizable geometric interpretation, while for higher dimensions we lose visual representation and reduce the procedure to an algorithmic selection. As example here we describe the 2D dynamic moments. When we work in two dimensions we are projecting the attractor on the plane, so we consider only two components of the signal: $x_i=s(it)$ and $y_i=s(it+T)$ where t is the acquisition time, T is the time lag ranging from 0 to a high value making the components totally independent. We compute the distances between every point on the attractor and two axes, the bisector of first-third quadrant (called *principal axis*) and second-fourth quadrant, and the origin:

$$d_{1,i} = \frac{\sqrt{2}}{2}\left|x_i - y_i\right| \qquad (1)$$

$$d_{2,i} = \frac{\sqrt{2}}{2}\left|x_i + y_i\right| \qquad (2)$$

$$d_{3,i} = \sqrt{x_i^2 + y_i^2} \qquad (3)$$

Using these distances we are able to define moments of order j

$$M_{m,j}(T) = \frac{\sum_{i=1}^{N} d_{m,i}{}^{j}}{N} \qquad (4)$$

where N is the number of samples and m=1,2,3 the considered distance.

For T=0, $x_i=y_i$, and the attractor is compressed on the principal axis; when T increases, these moments describe the morphological evolution during the unfolding process of the attractor. The moments evolve from the linear value (for T=0) to non-linear one. Finally we can outline that the even moments are always positive and describe the scatter of the attractor, while the odd moments are symmetry descriptors. Although 2D moments can be accurate enough to characterize chaotic processes, sometimes it can be necessary to extend moment calculation to higher dimensions in order to have parameters more sensitive to the fine characteristics of the attractor. The reader interested in detail in this topic can refer to [Annunziato and Abarbanel, 1999].

2. The artificial life environment for on-line optimization

In complex processes, one of the basic problem we have to face for control is the continuous evolution of the plant along the life (aging, mantainance, upgrading, etc..). This is a big problem for traditional control methods: being based on fixed optimisation rules, they don't take care of the evolution of the process during its life. In order to try to overpass this difficulty we developed an adaptive technique, named *evolutionary control*, oriented to optimisation and control of complex systems. The basic features of the methodology we propose are:

?? *no intensive modelling* (progressive training and updating directly from measurements);
?? capability to follow the *process evolution.*

The essence could be synthesised by the sentence: "not *control rules* but autonomous *structures able to dynamically generate optimised-control rules"*. In our proposal, the process knowledge is obtained directly by the system through measurements observation, and it's used to update a dynamic model of the process itself, which we call *performance model*.
The implementation of this idea is described in figure 1.

The basic concept consists in the realisation of an artificial environment that *lives* in parallel with the process and that asynchronously communicate with it, in order to dynamically control and optimise it. We suppose to always measure from the process its current regulations and the related value of an observable quantity which we call performance and which represents the objective function of our optimisation. In this way measurements are composed by both process variables and performance. The system continuously gets measurements and the dynamic state description from the process and provides the process back with the control actions.

The main blocks of the evolutionary control (fig. 1) are the alife environment and the performance model. The first one is an artificial environment composed by individuals able to find the optimal solutions. The second one is a model of the process performance used by the alife environment in order to provide its individuals with a fitness value. The final control actions are the average between the best solution achieved by the alife environment and the current regulations. This is because we wish smooth transitions among different states. Each time a new measurement is acquired the performance model is updated with it (*continuous learning*) and a new individual, representing the new experimented/observed process condition, is inserted in the artificial environment. Thus the system is continuously updated, it follows the process not-monitored changes and drives the evolution towards better performances. Of course, at the beginning the system is not able to give any suggestion but it only learns from the process measurements. The artificial environment starts being active and giving right suggestions when the performance model is trained.

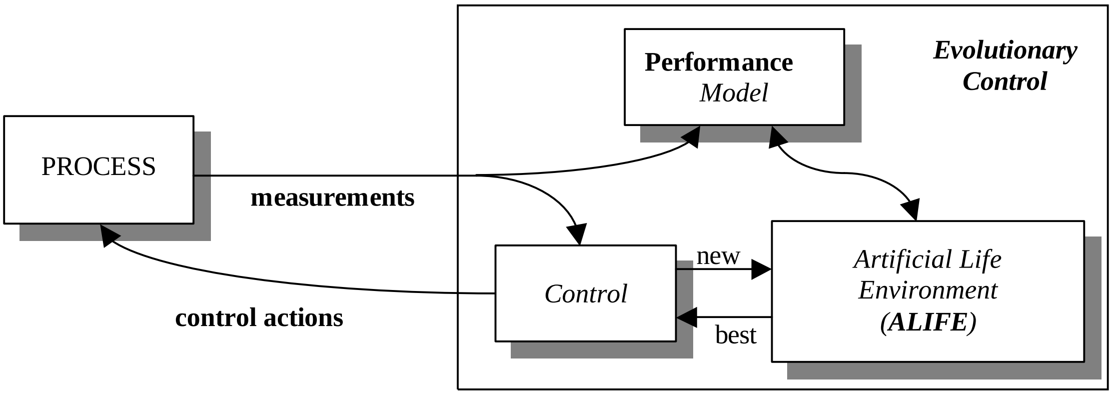

Fig 1: the scheme of the evolutionary control

The artificial environment implemented derives from the *Artificial* *So*ciety approach illustrated in Annunziato et al. [4]. This approach has been tested for the optimisation of a static well known problem, the Travelling Salesman Problem, where it has reached the optimal value for the 30, 50 and 75 towns [4]. The alife context is a two-dimensional lattice (*life space*) representing a flat physical space where the artificial individuals (or *autonomous agents*) can move around. Every iteration (*life cycle*), the individual moves in the life space and, in case of meeting with other individuals, interaction occurs. Each agent has a particular set of rules that determines its interactions with other agents basically based on a competition for energy in relation to the performance value. Agents can also self-reproduce via haploid mutation.

We suppose to periodically acquire a set of measurements on the real process (*measurement cycle)*, to calculate the current value of the actual *performance* and to provide such information to the control system. The performance is the target of the optimisation and it is derived from measurements. At every cycle of measurement, a *new* individual is built on the base of the measured values and inserted in the environment.

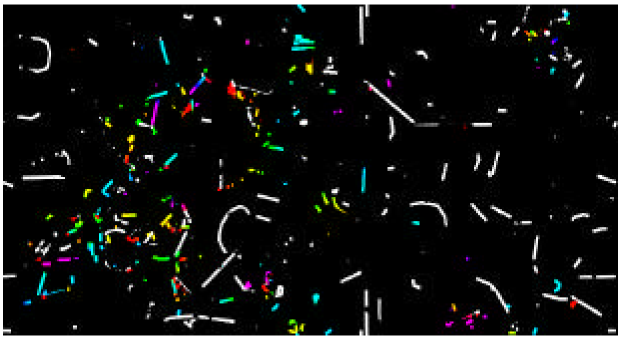

Figure 2 - The Artificial Life environment

Three blocks compose the data structure of each individual: the *genotype*, the *information* and the *status*. The first one includes a collection of behavioural parameters regarding dynamics, reproduction and interaction. The *information* block includes a series of parameters related to the process to control: the regulation and measurement values; both the information and the genotype don't change during the individual life. The *status* parameters include dynamics and structural parameters (position, direction, curvature, wire description), age, energy and performance values. These parameters change during the individual life.

An important feature that makes us think of this strategy as the right one is the finiteness of the individual life. The optimisation, in fact, succeeds in keeping itself updated on the evolution of the process by continuously renewing the population on line. This is allowed by an *ageing* mechanism, according to which each individual dies after a fixed number of life cycles (*average life*).
The performance is updated using an external problem-specific model. This is due to the possible changes in the unknown variables of the process not represented in the genotype. For this reason the performance variable is located in the status block. We can summarise the main issues of alife approach as follows:

?? ***biodiversity*** – the periodic introduction of new individuals lets the algorithm not to converge towards a local optimum, but several search path remain active in order to allow a deeper exploration of the regulations space;

?? ***evolution*** – the artificial environment is able to evolve in parallel with the process, continuously renewing the whole configurations among which the proposed optimal control set is chosen;

?? ***adaptivity*** – owing to the above-mentioned evolution and biodiversity, the system is able to quickly react whenever an unforeseen change in fitness landscape occurs.

A detailed description of the method and artificial life environment is reported in [5].

As a first step, the evolutionary control has been tested on the Kuramoto-Shrivashinsky [4] differential equation system The model describes the propagation of unstable flame front in uniform combustible mixtures [2]. Subsequently the method has been tested on the well known chaotic Chua electronic circuit (in software and hardware). In both these experiences we use some (two or three) parameters to control the system and an external parameter as a unknown noise continuously varying. Finally we leave the control system to manage the regulation parameters in order to continuously optimise a performance function. In [4] and [5] detailed results about the on-line optimisation capability of the system are reported.

As a short example, the fig. 3 shows the results of the control of Chua system that is characterised by 4 control parameters. In this experiment we try to regulate three parameters in order to recovery the performance of the circuit which is continuously disturbed by external changes on the fourth parameters. The curve of the performance (blue) obtained with the evolutionary control is compared with the curve of the performance (red) in absence of any sort of control.

Finally the experimental qualification on large scale plant have been started in the frame of the EcoTherm 5FP-EU project (2002-2004: “Evolutionary Control for Thermal sustainable processes”). Two plants for thermo-valorisation of solid urban waste are considered (Ferrara plant in Italy and Rotterdam plant in Netherlands). The first results are reported in next paragraph.

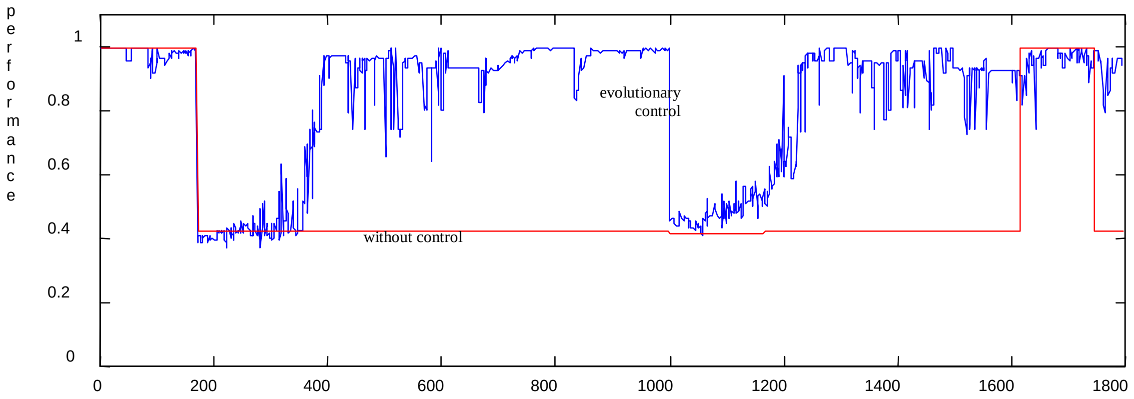

Fig. 3: Typical result of the performance recovery of the evolutionary control.

3. The application to urban waste thermo-valorisation plant

The proposed approach has been applied at a real scale waste incinerator of a multi-services special company of Ferrara Municipality (Italy), the Azienda Gas Energia Ambiente (AGEA), which has as principal scope the management of energy-environmental services on the territory. The plant of Canal Grande (located close to the city) in connection with a geothermal power plant provides the heating of part of the civil habitations and produces the 37.5% of the annual requirements of the users. The plant, designed in 1988, is working since the end of 1993 and can be considered a modern plant. It actually respects all the EU directives and imposed limits. The technology used for the thermal destruction is classified as grid furnace, which has a wide use in the waste combustion area, particularly three steps grid with alternate mechanic movement. The combustion chamber is characterized by the following parameter: feed flow rate 400000-800000 Kcal/(m^2*h), specific mechanic charge 200-400 Kg/(m^2*h), specific thermal charge 60000-200000 Kcal/(m^3*h). Due to the previous Italian regulation the plant is provided with post-combustion chamber in order to guarantee a controlled permanence of the gas produced by the combustion before the out of the chimney. The plant can treat 40000 tons/year of urban solid waste, which have a PCI average of 2500 Kcal/kg and a capacity of 6tons/hour. See fig. 4 for the plant layout.

The plant is monitored by several different equipment: the Flame Dynamic Detection system in order to identify the flame dynamics through “dynamic moment” analysis (see par. 1 and next paragraph) of the of the signals obtained by image sequences acquired inside of the combustion chambers; the real-time data acquisition system in order to acquire all regulations variable of the plant; a chemical species commercial analyser and chemical species predictor (developed by ENEA) in order to measure the plant performance.

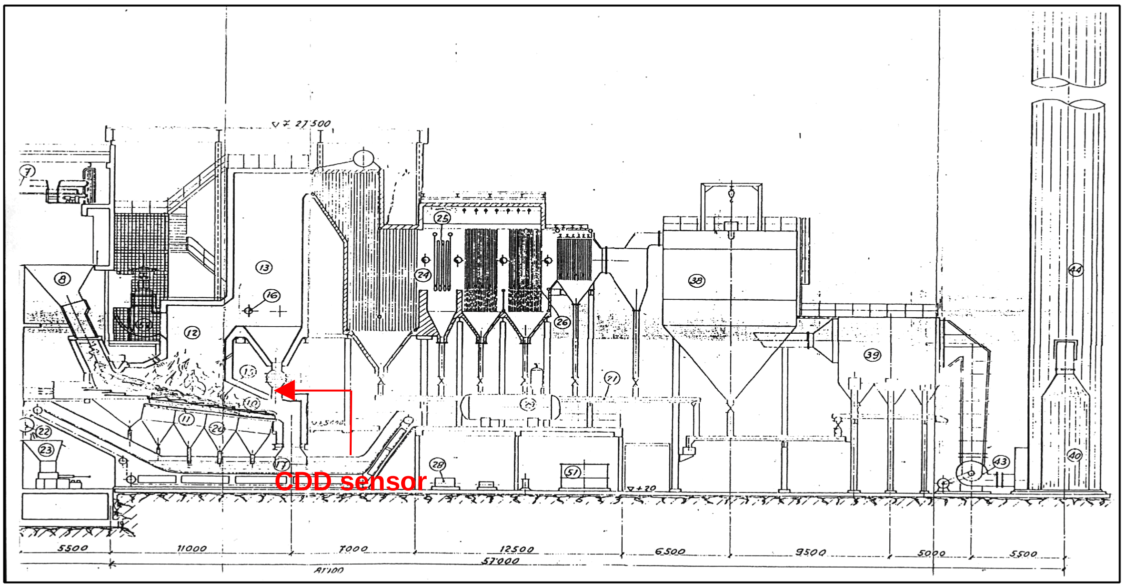

Fig. 4: The AGEA-Ferrara waste incinerator

4. The Flame Dynamics Detection system and the prediction of the NOx

This instrumentation is composed by a PC with a fast image acquisition board and a CDD sensor 64x64 pixels of dimension. The developed software allows to capture the flame dynamics with a frequency of 213 fps. The CDD sensor is located in front of an optical window on the wall of the combustion chamber (Figure 4).

The sequences of images (about 30000 frames), of 256 levels of grey, are elaborated through a specific filter in order to clean the noise due to the presence of dust, produced by the waste combustion, which causes the darkening of the camera's view. The signal representing the light intensity fluctuation in time for each pixel is used to calculate the dynamic moments. The set of the output is composed by 30 values (for each pixel of the frame) of dynamic moments different for order and dimensions. The acquisition and calculation is completely automatic and it doesn't need any action by the operator. Previous and present experiences point out the robustness and the reliability of the FDD system, either from the point of view of the hardware or for the software, in critical and hard environments and then it shows optimal features for the industrial use.

In fig. 5 a scheme of the analysis procedure is illustrated. Starting from the brightness signal of the generic pixel we compute, for all the frames, the related attractor and then the dynamic moments. Iterating this for all the pixels we get the image of the values of a moment, we extract the probability distribution of such a 'moment image' and then we get the value of the most probable value of such distribution as representative, for that moment, of the dynamics. We apply such process to the most significant moments selected with a features selection procedure described in [6].

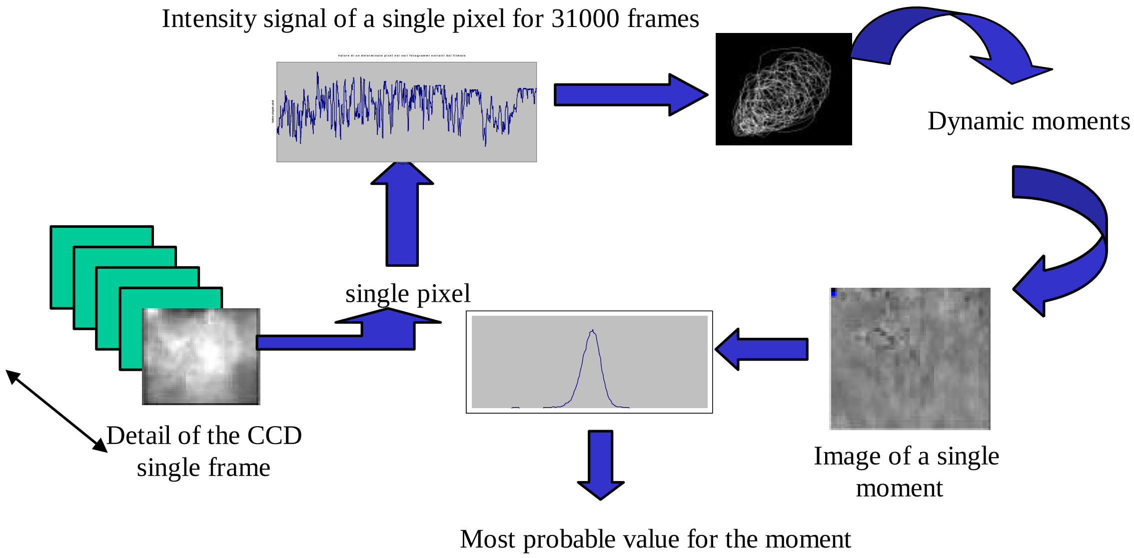

Fig 5: Steps of the Flame Dynamic Detection (FDD) system analysis procedure

In order to check the correlation of the dynamic moments with the plant performance we try to develop a neural model to correlate the process measurements and the dynamic decription with a typical output of the plant: the NOx release at the outlet the plant.

For the neural model we used a multilayer feed forward neural networks with the back propagation error training algorithm. We compared the results with an independent model that had as input only process measurements (Figure 5). The experimental results confirmed the usefulness of informations about the dynamic state, for the study of real processes, obtaining a considerable reduction of the relative error committed for the NOx estimation (see table 1).

	Process meas.	Process meas. + moments
Max relative error	17.65%	1.38%
Aver. Relative error	3.1%	0.2%

Table 1. NOx estimation results

The interpretation is that the flame dynamics are highly sensible to the kind of waste-material present in various instants and that only process variables are not able to extrapolate the information related to the process. As result we had the confirmation of the great capability of these discriminants as *needed* support for the plant's state identification. The non-linear dynamic analysis of the process adds a great quantity of information compared to more conventional approaches based only on statistic variables.

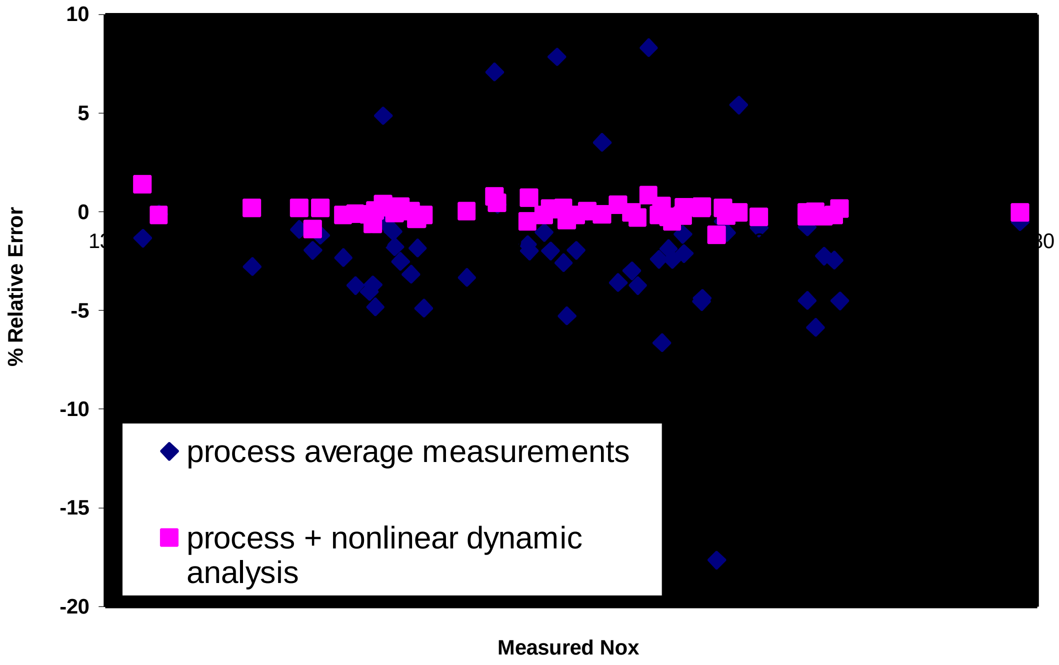

Fig. 6: Results about the NOx estimation with and without the plant dynamic state description

5. CONCLUSIONS

A new approach for the control and on-line optimisation has been described in its main components. This approach is based on dynamic state identification of the system and evolutionary optimisation on the process regulations. Good results have been obtained for dynamic analysis using the dynamic moment technique based on detection of attractor morphology. The results obtained for flame dynamics characterisation are resulted better than the more classical non-linear discriminants.

The powerful of optimisation have been shown by artificial life. A scheme of the overall implementation of the control strategy has been described. Software control simulators (Kuramoto-Sivashinsky equation and Chua electronic circuit) have been utilised to point out the control ability of the whole architecture.

Finally it has started the application of the proposed strategy on real scale waste incinerator in the framework of the EU Ecotherm project. First results show very encouraging confirmation about usefulness of dynamic description in order to improve the modelling of plant performances. More detailed studies are in progress to evaluate the performances of the control methodology in terms of a) which is the response time of intervention of the system, b) which disturbances can be recovered, c) which kind of new optimised configurations can be generated.

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