COMPLEXITY AND CONTROL OF COMBUSTION PROCESSES IN INDUSTRY

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ABSTRACT

This paper reports some applications of artificial life environments for the development of solutions based on the evolutionary properties. We show how this approach is able to create complex structures and how they can be used to solve optimization problems and applied to the process control and optimization.

1 INTRODUCTION

The ideas of evolution, complexity, intelligence and life reproduction have long been stimulating the collective thinking. Scientific approaches then become predominant on the formation of hypothesis and practices to answer to these basic questions. Research and development, carried out around mathematical and physical models of intelligence (Artificial Intelligence) and more recently of life itself (Artificial Life), are developing new tools and ideas for the solution of complex problems which require evolving structures.
In problems ranging from traffic regulation to energy process control and optimization, the approaches that are based on model adaptation are not sufficient to solve the problem for long time. The not-controlled variables, the process aging, the irrational components caused by human intervention, the evolution of the process, in most of the cases require the change of the basic model or the objectives, or even the whole strategy. These difficulties expose the limitations of the systems based on the *artificial intelligence* or expert systems. In the expert systems, the intelligence of the human expert is formalized in a *knowledge base* and then transferred to the system. The *artificial neural networks* and *fuzzy logic* (Annunziato 1998) have been developed on the base of the emulation of the human reasoning (Hopfield 1983) and they have achieved large success in nonlinear modeling or control problems. If the knowledge base of the expert is not-optimal, the knowledge model is not accurate, the knowledge base or the neural network (in example the training data set) are not continuously updated following the process variations (*continuous learning*), then the system will not be able to drive/interpret the process for long time. Unfortunately, today it is quite clear that the idea of being able to *transfer* our intelligence to a machine is very difficult to realize in practice. To reach the goal of evolving structures, continuos learning of the system from the environment is necessary but not sufficient, and the ability of the system to change its internal structure is required. In short, we need information structures, which are able to *evolve* in parallel to the process we are modeling. Since late 70's a new branch of theory has been open in the evolutionary systems research: the genetic algorithms, starting from (Holland 1975) and developed in different directions (Goldberg 1989). In these approaches the algorithm structure is able to maximize an optimization function, or to optimize a winning strategy simulating some mechanisms of the genetic dynamics of chromosomes (reproduction, recombination, mutation, selection). These algorithms have been successful applied in many technological and engineering problems, in order to solve optimization (Oliver 1987) or design problems (Soddu 1993). The limitation of these approaches is that the internal structure of the information is generally static and defined/controlled by the author of the algorithm. In such a way these algorithms have been demonstrated to be very efficient to solve certain specific problems, but they are not really able to develop the necessary intelligence to evolve their internal structure. For instance they cannot produce a part of itself (*autopoiesis* (Maturana 1973)). A specific concept was introduced in 1960's and 1970's to take into account the evolving structures: the *self-organization.* This concept, introduced by (Ashby 1962), refers to the complex systems composed by a multitude of independent entities characterized by autonomous chaotic behavior. The self-organization is represented by the onset of a global organized structure (order) in the system. This concept has been studied by several authors (Prigogine 1971,1984) and (Kaufmann 1993) and applied to explain living and not-living systems. Lately, the self-organization concept has been adopted in many contexts of biological, physical and human sciences (fluidynamics, turbulence, laser theory (Haker 1977), social systems, economics, psychology) and it starts to be used for industrial applications (granular materials, optimization problems, process control and dynamics) through the modeling based on *cellular automata* [7,8]. The fusion of the concepts of genetics algorithms and the self-organization brought about the concept of the *artificial life* [9,10] started in the 80's.

For the first time, it has really opened the possibility to build evolving structures able to develop a completely new organization of the internal information. Artificial life is generally applied to study biological and social systems using software simulators (Langton 1989), (Rocha 1997), (Sims 1994), (Sommerer 1997), and the basic concept is to leave the system with the necessary degree of freedom to develop an *emergent behavior*, combining the genetics with other life aspects (interaction, competition, cooperation, food network, etc..). At the present, artificial life (or *alife*) is used mainly to study evolution problems, but we think that it has the potential to generate information structures that are able to develop a *local intelligence*. With the term *local intelligence* we refer to an intelligence very different from the human one, but much more connected to the environmental context (*the problem*) we need to solve. We are involved in the development of this kind of structures, which we call *artificial societies* (Annunziato 1999d). The goal of these structures is the solution of a specific class of complex problems (design and engineering (Annunziato 1999c)) which require evolving structures. The basic idea is: instead of *transferring intelligence through a top-down process* we want to *develop intelligence trough a bottom-up procedure*.

2 THE EVOLUTIONARY CONTROL AND OPTIMIZATION OF ENERGY PRODUCTION PROCESSES

The main social requirements about the management of energy plants are focussed on the maximization of the energy efficiency and minimization of environment impact (particularly as regards the reduction of NO_x and CO emissions). In this context the process control is highly relevant with respect to the past, especially for the combustion plants where the pollutants emissions are strictly related to the modality of the process management. Also the complexity of this function is widely increased because of it has to take into account many targets, like economic management, low environmental impact, plant stability and design constraints, energy efficiency. These aspects constitute a strong stimulus to develop more advanced strategies for the process control and optimization. Today, the methodologies for advanced control and optimization (expert systems, ARM or neural predictors, process on-line simulators) are surely useful for a wide fraction of the industrial requirements, but they have serious limitations in many real field applications. These limitations could be summarized in the following items:

- need of strong modeling (simulators, ARM predictors)
- need of long training (ARM-Neural predictors)
- need of heavy knowledge from operators (expert systems)
- fixed rules for all plant life (off-line, no dynamics, heuristics on critical measures)

Rarely these requirements are fulfilled for industrial combustion plants like waste incinerators or chambers for gas turbines. One of the most serious problems for some innovative methods based on learning (like neural or fuzzy control, (Annunziato 1998)) is that they are based on fixed optimization rules and do not take into account the evolution of the plant during its life (i.e. not controlled variables or constraints). The learning phase is generally difficult for data lacking and the development activities for process optimization require deep knowledge of the specific process. Generally, these methodologies are not extensible to other processes. New advances in the contexts of chaos and complexity (Takens 1980), (Lorenz 1963) (particularly in the analysis of real chaotic systems and complexity), stimulate the research in this direction in order to explore new approaches to the process control. In particular, nonlinear dynamics allows the possibility to describe the state of the process (and therefore the related performance like efficiency, emissions, etc.) on the basis of the characterization of its dynamics. Recent achievements in the field of nonlinear data analysis (dynamics invariants), make it more sensible and robust (Abarbanel 1996). The complexity description opens the possibility of the development of continuos learning during the plant life and the continuous redefinition of the optimization strategy. In spite all these promising scientific developments, at present only few studies have been done in order to apply them to the plant optimization and control (Rhode 1995). We would emphasize that the term *optimization* here is utilized in the sense of a *continuous on-line adaptation of the management of an existing plant*. The goal is to drive the process towards the optimal compromise between the management targets deriving the rules directly from the measurements. The ideas proposed in this paper are aimed to developing a new approach to the optimization and control of complex processes for energy production/consumption. This methodology is based on evolutionary optimization and it started from some successful experiences in the dynamic characterization (for diagnostics and control) for at least two industrial applications (oil field diagnostics and combustion dynamic characterization) (Annunziato 1999) (Annunziato 1999b) (Annunziato 2000). Furthermore an optimization study has shown very interesting features of artificial life environment with respect to more classical genetics techniques. The basic features of the proposed approach are:

- *dynamics based*
- *no intensive modeling* (progressive training directly from the measurements)
- able to follow the *plant evolution*

The essence of this approach could be synthesized by the following sentence: **"not *control rules* but autonomous *structures able to generate optimized-control rules*".**
The main processes we are looking for application of the evolutionary control in the context of combustion plants are:

- Gas Turbines (High pressure, co-generation)
- Conventional combustion chamber (liquid, low pressure)
- Waste incinerator (urban refuses, energy/heat)
- Industrial burners (heat production)
- Engine control (vehicles, pollutant reduction, energy saving)

The basic idea consists in the reversal of the concept of the expert systems (ES). In the construction of the ES, the knowledge of the operators is verbally transferred to the ES builder. In our proposal, the process knowledge is not verbally transferred, but it is developed directly by the system through the measurements observation. The driving process is the dynamic building of a model on the basis of 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 real implementation of this idea consists in the realization of a system which receives measurements from the plant and activates an elaborate process based on the two following main steps (see the scheme of fig. 1 for a resume of the main components).

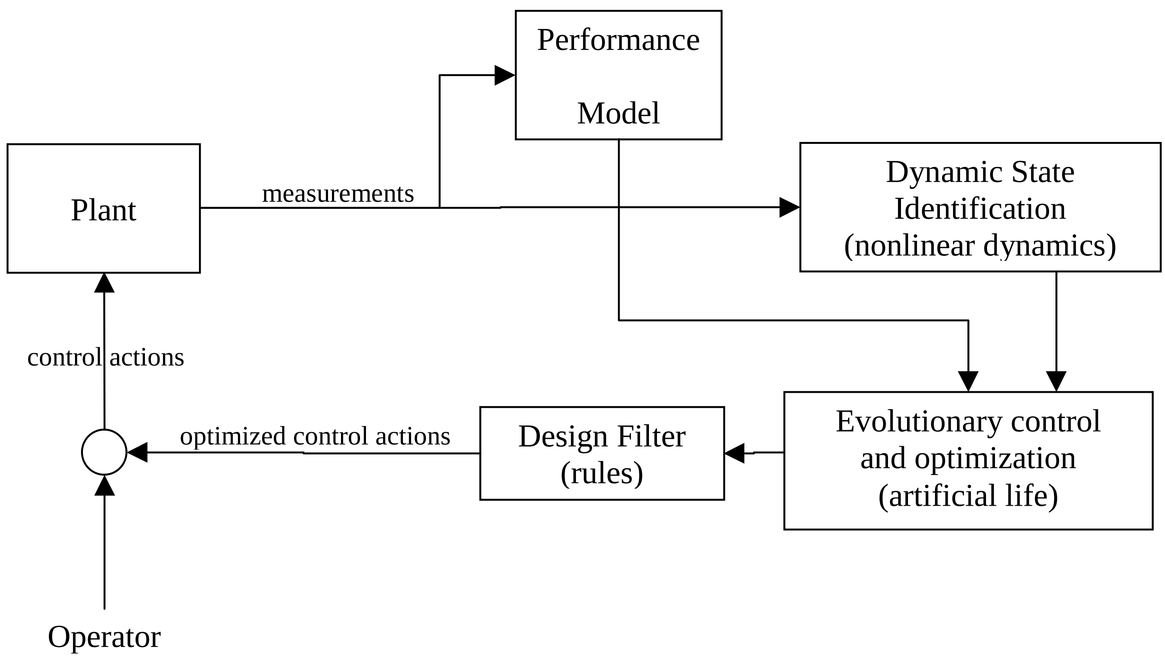


Fig.1 : A scheme of the evolutionary control approach

3 THE DYNAMIC STATE IDENTIFICATION

The plant is monitored with *process measurements* (values of process variables averaged on the time interval which defines the period of the plant monitoring) and *dynamic measurements* (sensors with dynamic response following the process dynamic fluctuation). The dynamic measurements are elaborated on the time interval and the chaos invariants are computed. These discriminants describe the *plant state*. The plant state is identified by the dynamic behavior that is determined by the dynamical system and the parameters values at which the plant is operating.

3.1 The Nonlinear Dynamic Moments

In (Annunziato 1996) is outlined a new methodology for the classification problems based on the attractor morphology using few discriminant parameters. This methodology has been successfully applied to the identification of the multiphase flow regime in oil production plants, to the characterization of combustion chambers for gas turbines, to the characterization of combustibles pollutants in conventional chambers (Annunziato 1999) , and finally to the identification of working state of waste incinerators (Annunziato 2000) . The basic idea is to compute a series of "moments of inertia" for the attractor, extending in order and dimensions. We build a series of shape descriptors, named *dynamic moments*. The technique consists in 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 enough well separated. Obviously for two and three dimensions we have easily visualizable geometric interpretation, while for n dimensions we lose visual representation and can reduce the calculation to an analytic procedure. 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 and T is the time lag which we vary from 0 to a high value that makes 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:

$$d_{1,i} = \frac{\sqrt{2}}{2}\left(x_i - y_i\right), \qquad [3.1]$$

$$d_{2,i} = \frac{\sqrt{2}}{2}\left(x_i + y_i\right), \qquad [3.2]$$

$$d_{3,i} = \sqrt{x_i^2 + y_i^2}\ . \qquad [3.3]$$

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

$$M_{m,j}(T) = \frac{\sum_{i=1}^{N} d_{m,i}{}^{j}}{N}, \qquad [3.4]$$

where N is the number of samples and m=1,2,3 the distance considered. 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 nonlinear 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. In three dimensions we introduce a third component z_i=s(it+2T) and three new symmetry references represented by three perpendicular planes along the directions of the attractor whose descriptions (naming *directrix* the bisector on the space whose attractor unfold around) and equations are:

- plane A (perpendicular to plane xy and crossing directrix): x-y=0;
- plane B (perpendicular to directrix and crossing the origin): x+y+z=0;
- plane C (perpendicular to planes A and B): x+y-2z=0.

We computed the three distances from these planes and the distance from origin:

$$d_{A,i} = \frac{\sqrt{2}}{2}\left(x_i - y_i\right), \qquad [3.5]$$

$$d_{B,i} = \frac{\sqrt{3}}{3}\left(x_i + y_i + z_i\right), \qquad [3.6]$$

$$d_{C,i} = \frac{\sqrt{6}}{6}\left(x_i + y_i - 2z_i\right), \qquad [3.7]$$

$$d_{O,i} = \sqrt{x_i^2 + y_i^2 + z_i^2} \quad . \qquad [3.8]$$

We can introduce, with the same notations as in 2D, the dynamic moments of generic order j:

$$M_{h,j}(T) = \frac{\sum_{i=1}^{N} d_{h,i}{}^{j}}{N}, \qquad [3.9]$$

where h=A,B,C and O refers to the distance considered. In the same way as in 2D case, these moments can be mixed in various forms in order to extract specific morphological characteristics. A generalization in n-dimension derives from the observation of the distances from origin and from the directrix computed on 2D and 3D. Comparing them it is possible to note that we can generalize them to any number of dimensions, in this way:

$$d_{O,i} = \sqrt{\sum_{k=1}^{d} \left(s\left(i + (k-1)T\right)\right)^2}, \qquad [3.10]$$

$$d_{AX,i} = \frac{\sqrt{d}}{d} \sqrt{\sum_{k=1}^{d-1} \left[\left(s\left(i+(k-1)T\right) - s\left(i+kT\right)\right)^2 + \ldots + \left(s\left(i+(k-1)T\right) - s\left(i+(d-1)T\right)\right)^2\right]}, \qquad [3.11]$$

where d is the considered embedding dimension . As before, we can now define dynamic moments of generic order j:

$$M_{h,j}(T) = \frac{\sum_{i=1}^{N} d_{h,i}{}^{j}}{N}, \qquad [3.12]$$

where h=O or AX.
We consider these moments a strong instrument for chaotic analysis because they reveal the most specific and remote characteristic of the system dynamics.

3.2 Dynamic characterization of the Kuramoto-Sivashinsky model

In order to have a clean check the classification efficiency in combustion problems using the nonlinear dynamic moments, we have checked the possibility to use this methodology to characterize the Kuramoto-Shivashinsky model.

3.2.1 The Kuramoto-Sivasinsky Model

This model describes the propagation of unstable flame front in uniform combustible mixtures. We consider here spatio-temporal data obtained by numerical integration of the Kuramoto-Sivashinsky equation

$$u_t + \alpha u_x^2 + \beta u_{xx} + \gamma u_{xxxx} = 0 \qquad [3.13]$$

at values of α,β,γ which correspond to the regime of extensive spatio-temporal chaos. This well-known equation describes unstable regimes of flame front propagation (Sivashinsky 1977). For $\beta>0$ the uniform flame front u=0 is unstable with respect to long-wave periodic perturbations $\propto \sin kx$. The most unstable wavenumber is $k_0=\beta^{1/2}$. Nonlinearity leads to saturation of the instability and the onset of persistent non-stationary spatially non-uniform regime (cellular flame). The spatial and temporal scales of the fluctuations decrease with the increase of the control parameters. To generate simulated flame front position data, we employed the numerical integration scheme which used split-step pseudo-spectral method with 1024 mesh points, time step 0.1 and space step 0.1 (system size L=30.5). Figure 2 shows sample space-time plot u(x,t) for Eq.(3.13) for α=1.0 β=3.0 γ=1.0 starting from small-amplitude random initial conditions for $0< t <200$.

Fig 2: Simulated flames by the Kuramoto-Sivashinsky model

3.2.2 The Features Selection

Now we describe the two strategies we curried out (Annunziato 2000) in order to select the most significant among 27 different dynamic moments. Such moments differ for order, dimension and distance computation. Both strategies we are about to outline are supervised, in the sense that they use an a priori given parameter describing the chaotic regime and they basically differ on the cost function applied.

Classes Overlapping

The first criterion is based on the principle of minimising the overlapping among the distribution of the data of different classes in the space of the selected discriminants. The idea is that *n* moments are good if they provide a good separability among the classes to be recognised. To perform this task we defined the following cost function on two classes:

$$f(m_1,...,m_n) = 1 - \frac{\sum_{1=1}^{k} C_1(i)C_2(i)}{\sum_{i=1}^{k} C_1^2(i)\sum_{i=1}^{k} C_2^2(i)}, \qquad [3.14]$$

where *n* is the number of moments to be selected, *k* is the number of cells in which the n-dimensional space has been partitioned, $C_j(i)$ is the density of class j in cell i.

Mutual Information

The second approach is based on the idea that if discriminants are independent from classification, then those discriminants will be not suitable for that classification. In this way as cost function we used the mutual information between classification and moments. To select the best moment we search for the maximum of the mutual information

$$I(m_i,c) = H(m_i)+H(c)–H(m_i,c), \qquad [3.15]$$

where $H(m_i)$ is the entropy of the distribution of the i-th moment, H(c) is the entropy of the classification distribution, and $H(m_i,c)$ is the joint entropy between the i-th moment and the classification. Note that if the distributions of the i-th moment and the classification are statistically independent, then the mutual information $I(m_i,c)$ turns into zero. Furthermore, to select the best pair of moments we use the following formula for the mutual information between a pair of moments and classification

$I(m_i,m_j,c) = H(m_i)+H(m_j)+H(c)–H(m_i,m_j,c)$ [3.16]

where $H(m_i)$ is the entropy of the distribution of the i-th moment, H(c) is the entropy of the classification distribution and $H(m_i,m_j,c)$ is the joint entropy among moment i, moment j and classification.

3.2.3 Results

We tested the approaches previously outlined on two known different chaotic regimes of the Kuramoto-Sivashinsky (3.13) equation generating 900 points for each of them. To stress the statistical instability of the moments and the overlapping between the classes we considered each point on a short time (1000 steps).
In the tables 1 and 2 we report the rankings given by the two approaches on one and two discriminants. From these results we conclude the similarity between the two approach.

Tab.1 : comparison of the best 5 single moments

Overlapping		Mutual Information	
10	0.9623	10	0.781512
1	0.962176	1	0.779873
4	0.947696	4	0.735537
13	0.927983	13	0.677474
16	0.919490	16	0.666863

Tab.2 : comparison of the best 5 couples of moments

Overlapping		Mutual Information	
10,20	0.977774	8,10	0.834606
1,8	0.977741	1,8	0.833297
1,20	0.977467	10,20	0.830875
8,10	0.977445	1,20	0.829037
1,23	0.977366	10,23	0.824313

Finally to validate the results we computed the classification rate using good and bad moments. To perform this task we used a simple multilayer perceptron with input the values of two moments. From this experimentations we got a rate of about 95% successful classification using the good ranked moments and a rate of about 60% for the bad ones. This result is remarkable because it tells us that with only two parameters we can identify the dynamical state of the flame.

3.3 Results on experimental data from a real scale waste incinerator

The proposed approach was 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.

3.3.1 The Waste Incinerator

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 produce the 37.5% of the annual requirements of the users. The plant, which is designed in the 1988 and it is been working since the end of 1993, can be considered a modern plant and 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.

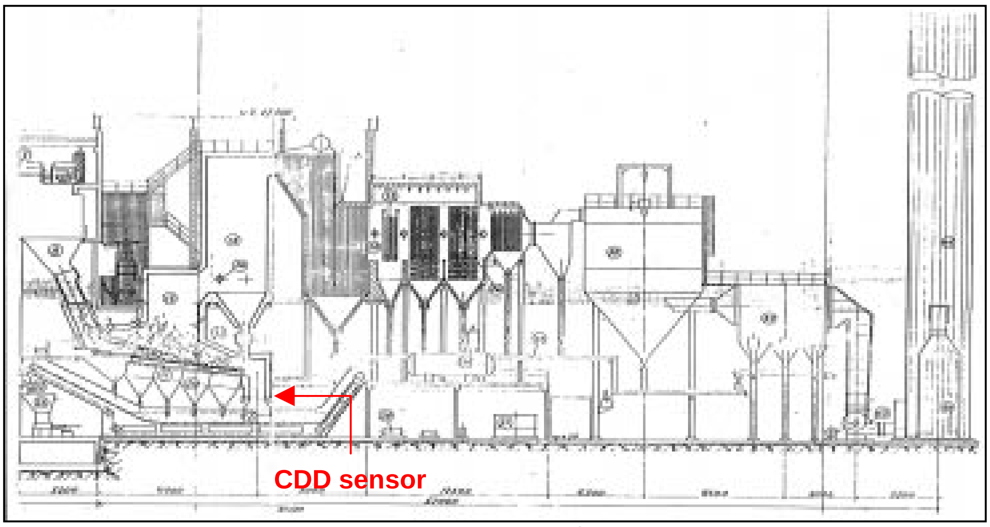


Fig. 3: Scheme of the plant

3.3.2 The Flame Dynamics Detection system

This instrumentation is composed by a PC with a fast image acquisition board and a CDD sensor 64x64 pixels of dimension, the software developed 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 (fig. 3). The sequences of images (about 30000 frames), of 255 levels of gray, are elaborated through a specific filter in order to clean the noise due overall to the presence of dust produced by the waste combustion, which cause often the darkening of the field of view by hiding the flame. The signal representing the light intensity fluctuation in the time for each pixel is used to calculate the dynamic moments (par. 3.1). 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/calculation is completed automatic and it doesn't need any action by the operator. Beside the previous and the present experience point out the robustness and the reliability of the FDD system, either from the point of view of the hardware either for the software, in critical and hard environments and then it shows optimal features for the industrial use.

3.3.3 Feature Selection

In this section we show the results obtained by applying the methodologies described in section 3.2.2 to the experimental data, coming from the waste incinerator just described, in order to select the dynamic moments which best describe the dynamical state of the real flame. Preliminary results have been curried out on a data set composed by 3872 points belonging to 3 different plant conditions and we applied on such data the generalization of the overlapping (3.14) formula and a slight modification of the mutual information (3.16) one. In the following tables the feature selection results are shown.

Tab.3 : comparison of the best 5 couples of moments for the real flame

Overlapping		Mutual Information	
1,3	0.840272	1,5	0.560384
1,5	0.840222	4,5	0.560238
3,4	0.840194	1,3	0.558246
4,5	0.840116	3,4	0.557660
1,7	0.839705	1,7	0.556860

Tab.4 : comparison of the best 5 three moments for the real flame

Overlapping		Mutual Information	
1,5,14	0.844403	1,5,14	0.704343
4,5,14	0.844344	4,5,14	0.704278
1,2,14	0.843944	1,3,14	0.701245
2,4,14	0.843867	1,7,14	0.701170
5,6,14	0.843832	1,8,14	0.701018

Finally we tested the results on a neural network with input the values of the best moments. From this experimentations we got a rate of about 75-80% successful classification. Further experimentations will be curried out in the near future with more data coming from new experimental campaigns.

4. OPTIMIZATION WITH ARTIFICIAL LIFE

In order to demonstrate the power of the alife-based optimization, in this section we describe our artificial life environment and compare its performance in terms with respect to other more classical optimization algorithms. The life context is an initially empty two-dimensional space. In the beginning, a few individuals are placed in the space and they begin to reproduce and develop a population. An individual is a point moving on the 2D lattice. All the parameters for the dynamics, reproduction, and death are recorded in a genetic map that is defined at the birth of an individual and remains unchanged throughout the individual life. The movement of an individual is composed of a deterministic component and a random component. The reciprocal importance of the two components is regulated by a parameter. High values for this parameter cause totally random movement; low values cause totally deterministic movement. Different models defining *characters* have been developed for the deterministic component. For example, a movement with a uniform probability of changing direction; or a higher probability associated to pre-fixed curvature; or finally, a movement with a curvature changing with the time. The reproduction is asexual and the sons have a genetic map similar to that one of the fathers, however some mutations in the genetic parameters can occur controlled by the mutation rate. Through this mechanism, the population evolves and different phenotypes can develop in the course of evolution. In the genome of each individual we incorporate a block of information that represents the parameters of the specific problem to optimize (configuration or solution). On the basis of this information a *fitness function* is computed which represents the quality related to the configuration recorded in the genome. The optimization problem consists in maximizing this function. In the reproduction, we apply the mutations only within this block of information. Upon the meeting of two individuals, a mechanism of competition is activated. The competition is based on the value of fitness of the two individuals: an individual that has a higher fitness survives. After a while, individuals that have higher fitness are able to survive and continue the evolution. In this way the best solution that corresponds to the individual with the highest fitness, increases continuously its presence in the population reaching the optimal values.

4.1 Benchmark: The Travelling Salesman Problem

In order to compare the optimization power of the *artificial societies*, we have tested the algorithm on several benchmark problems comparing the results with other approaches that are not problem-dependent. In this section we report the results obtained for the Travelling Salesman Problem. The Travelling Salesman Problem (TSP (Reinelt), (Moscato)) is one of the most famous and well-studied optimization problems. Its formulation is the following, "Given *n* towns find the minimal path such that each town, except the first, is visited exactly once". It is known to be a NP hard problem and researchers (Oliver 1987), (Whitley 1989), (Fogel 1993), (Lin 1993) use this problem as a benchmark for optimization algorithms. In order to test the capabilities of the artificial life optimization strategy, we customized the algorithm to solve TSP and compared the results with those obtained with the most successful algorithms based on the genetic approach. The numerical experiments have been carried out on two classical problems (Oliver 1987), (Eilon 1969): Oliver30 (30 towns) and Eil51 (50 towns). The path, or the ordered list of towns, is the part of the genome that defines the solution of the problem. The fitness corresponds to the inverse of the global path length. In the reproduction, a son has a very similar genome with respect to his father, but a mutation can occur in the list of the town: in particular, two towns can exchange their reciprocal position in the ordered list. In order to improve the performance of the artificial society we have included a modification in the algorithm that allowed the possibility to develop cycles of development of the biodiversity in the sense of different genomes and cycles of selection. This effect was achieved by including modification in the reproduction. In most cases, the son can survive after the birth only if his fitness is higher than the father's. But in some very few cases the son can also survive with a lower fitness. The effect of this assumption is that the population selects the best individuals by decreasing the probability of new births and consequently decreasing the number of living individuals (phase of *selection*). When an individual survives to the father with a low fitness, he is able to generate another specie of individuals: the probability of birth increases for this species and the number of individuals and their information explodes (phase of *development of the biodiversity*). Using this approach, the population exhibits continuous oscillations periodically renewing its content of information. The following table shows a comparison among the best results achieved by different strategies in terms of path length for the same cities locations. In the first column there are the results obtained by applying a simple greedy strategy, the second column is for the simple Genetic Algorithm (Holland 1975), the third column shows the outcome of the Dynamic Evolution approach (Annunziato 2000b). The fourth column exhibits the results of the Ant Colonies Systems (Colorni 1996), the fifth those of the Evolutionary Programming (Fogel 1993), and the last column reports the results using the Artificial Societies approach described in this section.

Tab.5 : comparison of different techniques applied to TSP

Number of towns	Greedy	Simple G.A.	Adaptive Evol. Strategy	Ant Colonies	Evol. Progr.	Artificial Societies
30	473.32	425.94	**423.74**	**423.74**	**423.74**	**423.74**
50	505.77	443.98	428.98	427.96	**427.86**	**427.86**

As one can see, the results reached by the present approach are the best ones for both test cases considered. Obviously, we cannot generalize this conclusion to every optimization problem or for the specific TSP problem (we have considered only not problem-dependent algorithms), but it is sufficient to demonstrate that the optimization power of this approach is at least similar to the more classical genetic approaches. The important advantage of our approach is that it is not limited to the optimization but also includes to the ability to develop new configurations due the much more open structure. In fact, with respect to the genetic algorithms, the artificial society can have an oscillating population dynamics, the possibility to use the space localization to develop local societies (local evolution), and finally the possibility of self-organization.

4.2 Alife environment for control and progressive optimization

An artificial environment is evolved in parallel to the plant while acquiring information from the measurements. In this artificial environment we place the *live* individuals which represent the experimented/observed plant conditions. Furthermore, some other individuals are generated through a genetic reproduction mechanism. Each *individual* is defined by its genotype which includes the plant state description (derived by the measurements), the process performance (computed on the basis of the measurements), and the regulations state. An evolutionary mechanism selects continuously the plant conditions (individuals) which correspond to the best performance. This mechanism is based on the emulation of the natural selection. The interaction model is constituted by the competition on the basis of the individual fitness (plant performances). In this way the individual with the highest fitness can survive and reproduce. The reproduction is asexual and the sons have small mutations in the part of the genome that corresponds to the regulation state. Because the individual has a certain "expected lifetime", very old individuals can die according to a probabilistic model. This aging mechanism is very important to warrant the possibility to lose memory of very old solutions and follow the plant evolution. This mechanism takes into effect the aging of the optimization models due to the changes of non-monitored variables (e.g. combustibles in the waste incinerators or modifications introduced during the life of the plant). The selection mechanisms warrant the selection of the individuals (plant configuration) which have produced the highest fitness (best plant performances). In this sense the Alife environment is a good evaluator of the regulation actions of the operators mixing all the operators actions, judging the single control action in terms of positive or negative effects on plant performances and building the "optimal operator". The distinguishing feature of the proposed system is that the mechanism of the mutations introduces new regulation configurations never visited before. Therefore the environment has the possibility to generate and evaluate plant configurations completely new with respect to ones explored by the operators. For each time period, the process variables are processed in order to compute the performance of the plant (the fitness function) in the current measurement time frame using a fuzzy logic approach. The evaluation of the quality of a plant configuration is made through membership functions applied to the process measurements (pollutants, efficiency, and design constraints). The fusion of these functions is obtained through fuzzy operators and it represents the process performance (individual *fitness*). In order to evaluate the plant performance in configurations (individuals) already visited before we have developed a "performance map" model. This model is able to evaluate the differences in the process performances induced by a control action (a change in the regulation state) starting from a specific dynamic state (fig. 4).

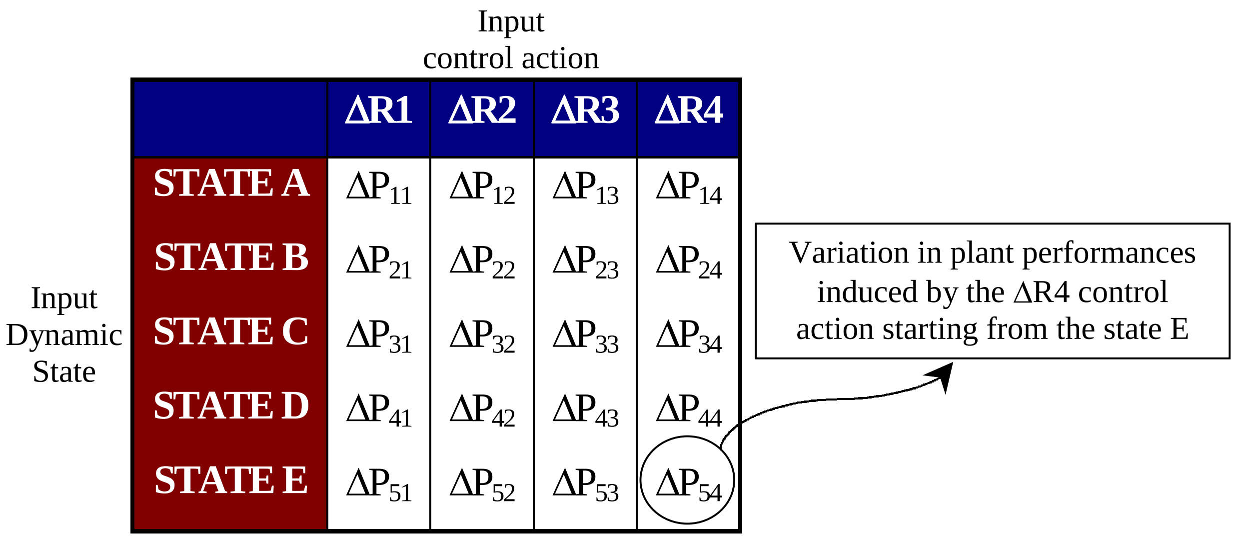


Fig. 4: The performance map to evaluate the increase/decrease performances of a control action.

The dynamic invariants, the regulations actions, and the performance evaluation continuously update such a map. This map gives the possibility to estimate the performance differences induced by regulation actions. In order to evaluate the performances in configurations (individuals) not visited yet, blanks entries of the performance map, a neural network estimator is provided. Compatibly with the statistical accuracy reached by the performance map, the best individual is taken at each time period as the system suggestion for the regulation actions. The suggestion is sent to filters (rule based) which take into account the compatibility of the suggested regulation actions with the design constraints or stability constraints. In the beginning, the system is not able to give suggestion but it only learns from the plant measurements. The artificial environment starts to become active and gives its suggestions when the performance map is more filled. After each cycle of measurements/suggestions the performance map is updated (continuous learning), and new individuals are inserted in the artificial environment. In this way the system follows the plant not-monitored changes and drives the evolution towards better performance.

5. A SIMULATOR TO STUDY THE CONTROL STRATEGIES

In parallel to the real processes experimentation, we have substituted it with a software simulator in order to study the best strategy for the control/optimization performed by the alife environment. The simulator is based on a mathematical model used for the flame front modeling: the Kuramoto-Sivashinsky model (Sivashinsky 1977) introduced in the section 3. The goal is to obtain a system to study the optimal features of the alife environment and point out the control strategies.

5.1 The control simulator

The model includes regulation parameters that influence the flame dynamics (the *dynamic state*).
For each configuration we compute a *process performance* on the basis of a model simulating the pollutants emissions and the energy efficiency. In addition to the regulation parameters we have included some disturbance parameters which represent the not controlled variables or the process aging.
In fig. 5 the scheme of the simulator has been reported.

5.1.1 Fitness definition

Fitness value is a kind of an estimation of the spatial location and shape of the synthetic flame. It is computed by studying the last line generated by the Kuramoto model and computing the weighted average of the derivative of this line. In this way it is possible to define a fitness value based on the discontinuity of the flames, because the horizontal line at the bottom represent the last temporal line generated by the model, and the horizontal direction is the spatial dimension of the front of the flames. In the simulator fitness is computed at each step and stored, but the influence of current fitness keeps memory of precedent fitness (system change in time, but it is deeply influenced by the previous history) and so the fit value is :

$$FIT = \delta * FIT + (1-\delta) * CURR\_FIT \qquad \text{with } 0<\delta<1 \qquad [5.1]$$

Where CURR_FIT is the current fitness value and Fit is the system fitness.

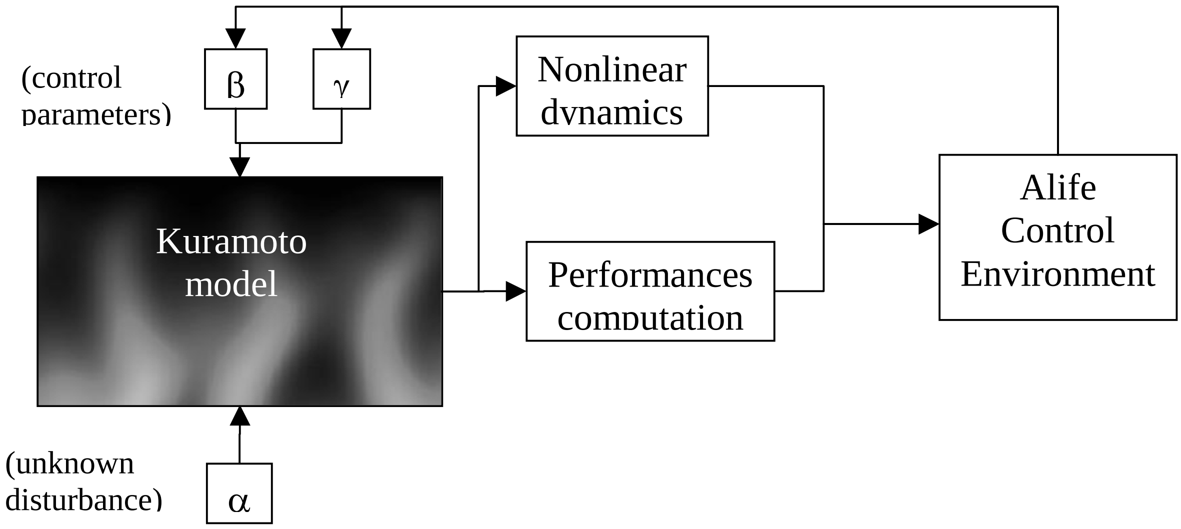


Fig 5: The scheme of the control simulator based on the Kuramoto-Sivashinsky model

5.1.2 Implementation details

The implementation of simulator is based on a visual window viewing a flame front generated continuously by a Kuramoto-Sivashinsky model based function. Due to the high complexity of the algorithm the window is not too big. But an history of the previous screen is stored in memory, in order to have a long statistic model to compute the dynamic invariants. To have a better computation we use several vertical lines of the screen, and the resulting invariants are the average of such lines of moments. At each step the program generates some horizontal lines (it is possible to define the vertical velocity of the system, in this way) and add them to the displayed window. The lines that go out from the screen are stored in memory. Fitness is evaluated at each step, computing the average of the gradient of the bottom line.

5.1.3 Parameters sensibility analysis

Here we can see some data from simulation with Kuramoto-Sivashinsky model. In figure 6 after some iteration parameter alpha is changed, and it is possible to see that the system (system status is identified by the fitness value) changes its status, going to a different range for fitness value an d it stabilizes itself.

Fig 6: Controlling the Kuramoto-Sivashinsky model thorough the alpha parameter

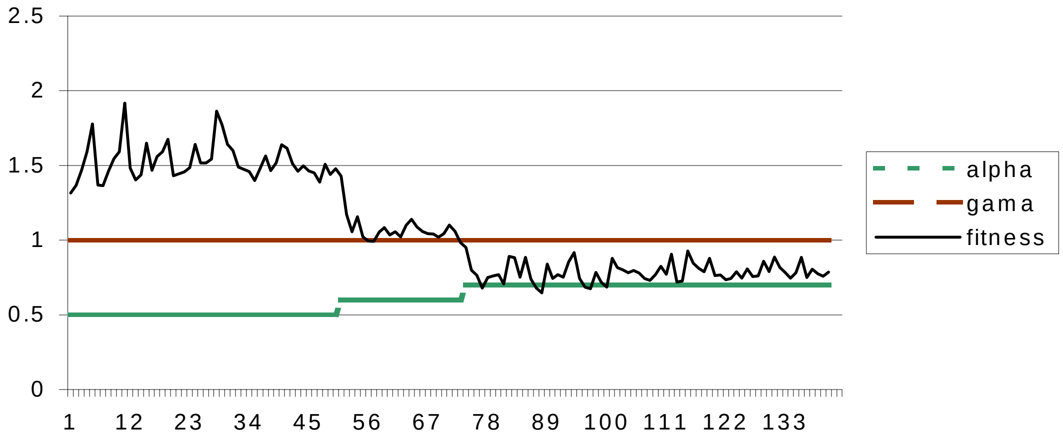
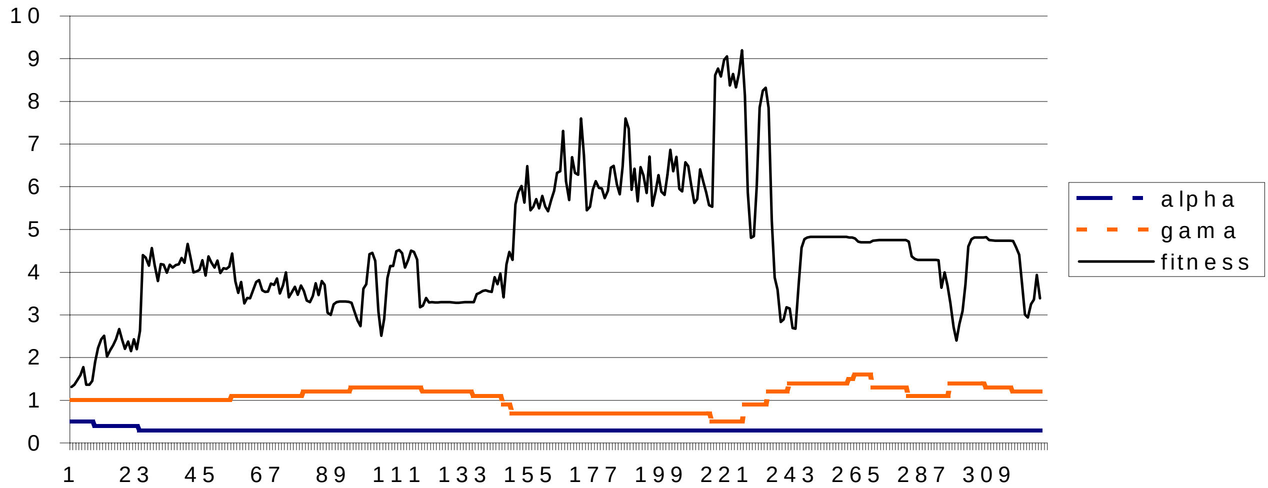


Fig 7: Controlling the Kuramoto-Sivashinsky model thorough the alpha and gamma parameters



In figure 7 we try to change the value for alpha, and, after the system stabilization on the new status, to put it back working on the gamma value.

5.2 Preliminary Results

Two experiments have been curried out:

- change the process regulations and verify that the artificial life environment is able to drive the process to the optimal conditions;
- introduce some disturbances and verify the system is able to find the new optimal conditions and drive the process to that conditions.

In figure 8 an example of preliminary results is shown in terms of ability of the system to recover disturbances. This example refers to the second mentioned experiment using a local linear interpolation. We insert continuous disturbances on the parameters and leave the control system manage the regulation parameters in order to maintain the flame propagation velocity at a fix value (1 m/sec). In order to understand the effect of the control we report the comparison between a controlled situation and a not-controlled situation. As you can note from the plot, when the system is under control the deviation respect the unity is much lower in respect to the not-controlled case. More detailed studies are necessary to evaluate the performances of the control methodology in terms of a) which are the times of intervention of the system, b) which disturbances can be recovered, c) which kind of new optimized configurations the system is able to generate. Finally test on real plants are necessary to validate the results of the project.

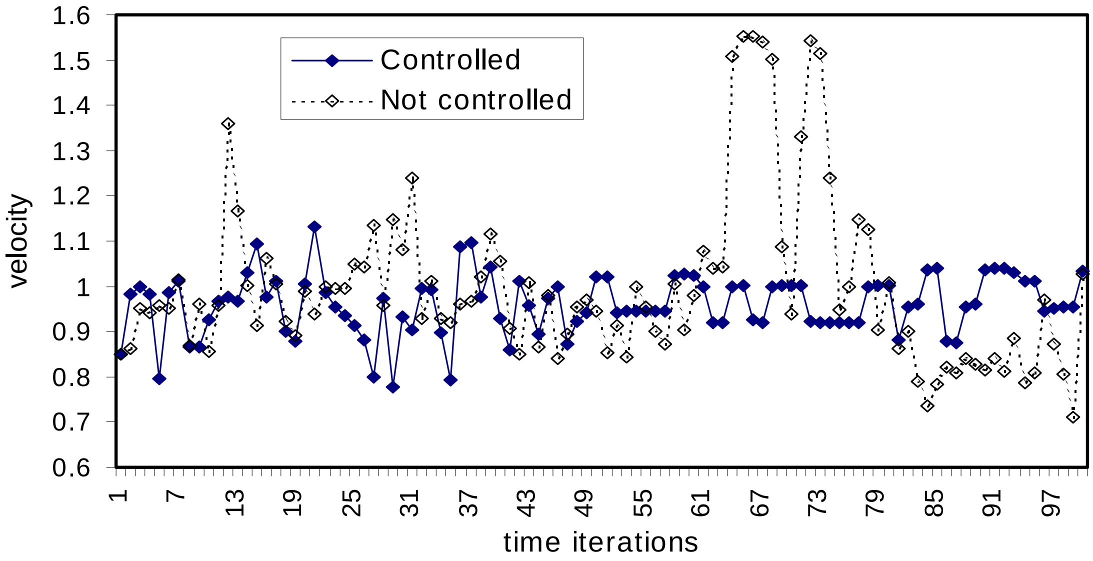


Fig. 8: Comparison between controlled and not-controlled conditions. The control is carried out in order to maintain at 1 m/sec the flame propagation velocity. The effect of the control reduces the deviations induced by artificial disturbances inserted in the system.

6 CONCLUSIONS

A new approach for the control and on-line optimization has been described in its main components. This approach is based on dynamic state identification of the system and evolutionary optimization on the process regulations. Good results have been obtained for dynamic analysis using the dynamic moments technique based on detection of attractor morphology. The results obtained for flame dynamics characterization are resulted better than the more classical nonlinear discriminants. The powerful of optimization have been shown by artificial life: in the standard Traveling Salesman Problem the obtained results are surely comparable (better in some cases in respect to other algorithms). A scheme of the overall implementation of the control strategy has been described. Finally a control simulator has been illustrated in order to study the control ability of the whole architecture. The Kuramoto-Sivashinsky model has been utilized to simulate the flame propagation front. Furthermore studies are necessary to evaluate the control performances and test the methodology in real plants.

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