Complexity and Control of Combustion Processes in Industry

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Abstract

This paper reports some applications of artificial life environments to 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 developments carried out around mathematical and physical models of the 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* [17] have been developed on the base of the emulation of the human reasoning [16] and they have achieved large success in nonlinear modeling or control problems.

If the knowledge base of the expert is not-optimal, or the knowledge model is not accurate, or if the knowledge base or the neural network (in example the training data set) are not continuously updated following the process variations (*continuous learning*), the system is not 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, the continuos learning of the system from the environment is necessary but not sufficient, and an 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 [18] and developed in different directions [19]. 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 [23] or design problems [29].

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* [6]).

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 [1] and Von Foerster, 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 (i.e. Prigogine [2,3] and Kaufmann [4]) 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 [5], 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 open 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 [9,11,12,13], 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 which 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* [15]. The goal of these structures is the solution of a specific class of complex problems (design and engineering [37]) which require evolving structures. The basic idea is: instead of the *transfer the 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 assumes an importance very relevant in 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, [17]) 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 [31,32] (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. The recent developments in the field of nonlinear data analysis (dynamics invariants), make it more sensible and robust [30]). The complexity description opens the possibility of the development of a 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 [35].

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) [33, 34, 36]. 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).

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 which is determined by the dynamical system and the parameters values at which the plant is operating.

3.1 The Nonlinear Dynamic Moments

In 1996 Annunziato and Abarbanel [33] 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 [33], to the characterization of combustion chambers for gas turbines, to the characterization of combustibles pollutants in conventional chambers [36], and finally to the identification of working state of waste incinerators [34].

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.

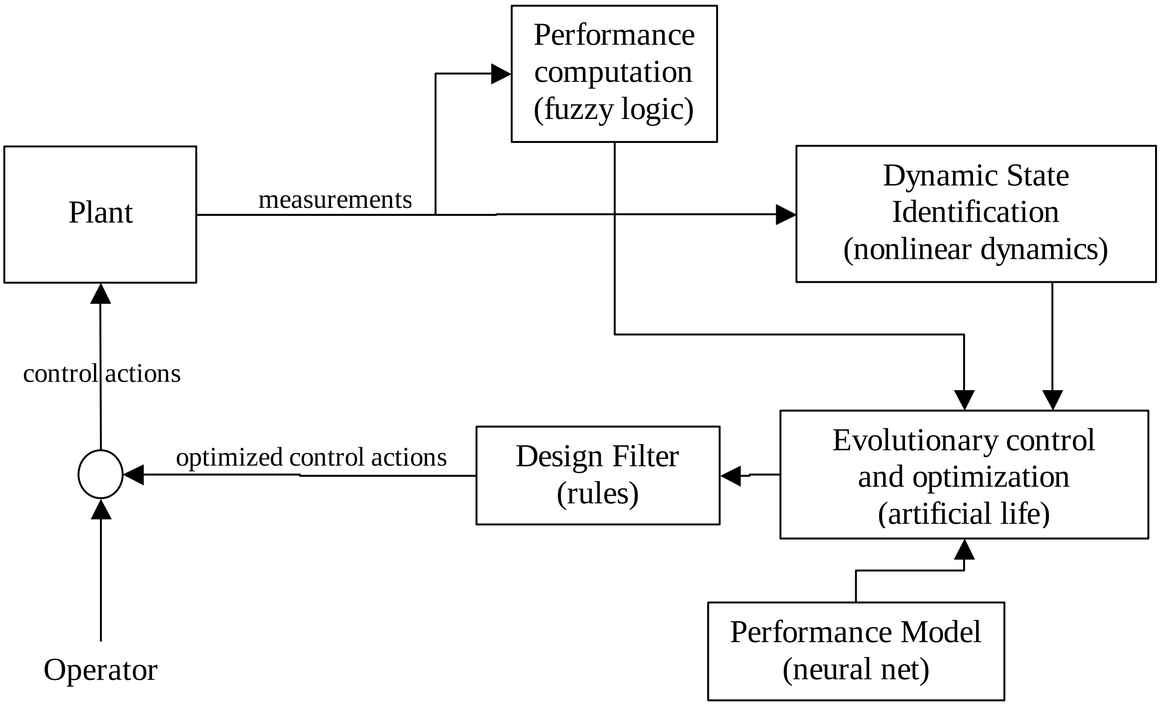


Fig.1 : A scheme of the evolutionary control approach

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 poin 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 metodology to characterize the 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

$$u_t ? u_x^2 ? ? u_{xx} ? u_{xxxx} ? 0 \tag{3.13}$$

at values of ? which correspond to the regime of extensive spatio-temporal chaos. This well-known equation describes unstable regimes of flame front propagation [38]. For ?>0 the uniform flame front u=0 is unstable with respect to long-wave periodic perturbations ? sin*kx*. The most unstable wavenumber is k_0=?$^{1/2}$. 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 parameter ?.

Fig 6: Simulated flames by the kuramoto-Sivashinsky model

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 6 shows sample space-time plot u(x,t) for Eq.(3.13) for ?=3.0 starting from small-amplitude random initial conditions for 0<*t*<200.

3.2.2 The Features Selection

Now we describe the two strategies we curried out [34] and compared 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 differ by 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:

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

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.

D. 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

$$H(m_i) = -\sum P(m_i)\log_2(P(m_i)) \qquad (3.16)$$

is the entropy of the distribution of the i-th moment, H(c) is the entropy of the classification distribution, and

$$H(m_i,c) = -\sum P(m_i , c)\log_2(P(m_i , c)) \qquad (3.17)$$

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, than 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,

$$I(m_i,m_j,c) = H(m_i)+H(m_j)+H(c)-H(m_i,m_j,c) \qquad (3.18)$$

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 The Results of the Classification

We tested the approaches previously outlined on two known different chaotic regimes the Kuramoto-Sivashinsky (1) 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 approache. In figure 5 we report as an example the distribution of the two “good” moments for the two different regimes studied here.

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.1 : comparison of the best 5 single 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

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

Finally to validate the results we computed the classification rate using good and bad moments. To perform this task we used a simple multilayer neural network with input the values of two selected moments. From this experimentations we got a rate of about 95% succesful 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 may be able to identify the dinamical state of the flame.

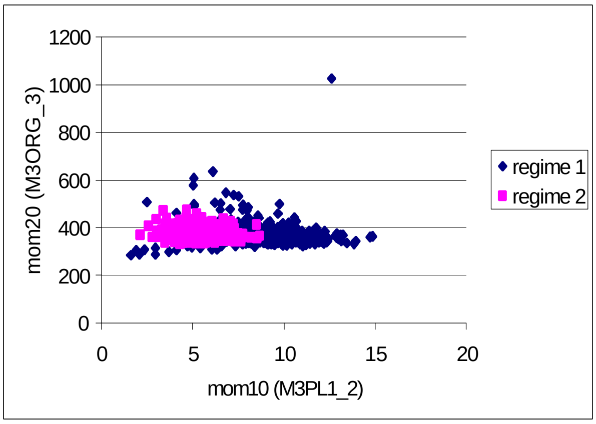


Figure 5. Distribution of the data in the moments space

3.3 Results on experimental data from a real scale waste incinerator

3.3.1 The Waste Incinerator

3.3.2 The Flame Dynamics Detection system

3.3.3 The Feature Selection

3.3.4 The correlation between dynamics and the system performance

4. Optimization with artificial life

In order to demonstrate the optimization power of the alife environments, in this section we describe an artificial life environment and compare its performances in terms of optimization qualities with respect to other more classical optimization algorithms.

The life context is a two-dimensional space initially empty. At the beginning, few individuals are placed in the space and they begin to reproduce and develop a population. An individual is a point moving in the 2D lattice. All the parameters for the dynamics, reproduction and death are recorded in a genetic map which is defined at the birth of an individual and remain constant throughout the individual life.

The movement is the composition 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 a totally random movement; low values cause a totally deterministic movement. Different models defined *characters* have been developed for the deterministic component. For example, a movement with an uniform probability of changing direction; or a higher probability associated to pre-fixed curvature; or finally, a movement with a curvature evolving with the time.

The reproduction is asexual and the sons have a genetic map similar to that one of the fathers, but some mutations in the genetic parameters can occur depending by the mutation rate. Through this mechanism, the population evolves and different phenotypes can be developed in the same evolution.

In the genoma of each individual we incorporate a block of information that represents the parameters of the specific problem to optimize (configuration or solution). On the base of this information a *fitness function* is computed which represent the quality connected with the configuration recorded in the genoma. The optimization problem consists in the maximization of this function. In the reproduction, we apply the mutations only in 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 which has a higher fitness survives. After a while, individuals which 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 The Benchmark: 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 which are not problem-dependent. In this section we report the results obtained on the Travelling Salesman Problem.

The Travelling Salesman Problem (TSP [20,21]) 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 [23,25,26,27] 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 [23,24]: Oliver30 (30 towns) and Eil51 (50 towns).

The path, or the ordered list of towns, is the part of the genoma which defines the solution of the problem. The fitness corresponds to the inverse of the global path. In the reproduction, a son has a very similar genoma in respect to its father but a mutation can occurs in the list of the town: in particular, two towns can exchange their reciprocal position in the ordered list.

In order to improve the performances 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 genoma and cycles of selection. This effect was achieved by including modification in the reproduction. In most of the cases, the son can survive after the birth only if his fitness is higher than the father's. But in very few cases the son can also survive with a lower fitness.

The effect of this assumption is that the population select 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 have a continuous oscillation periodically renewing its content of information. In this figure an example of the population oscillation is reported.

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 of deep one, the second shows the simple Genetic Algorithm [18], the third columns show the outcome of the Adaptive Evolutionary approach [28]. The fourth column exhibits the results of the Ant Colonies Systems [22], the fifth those of the Evolutionary Programming [26] and the last column reports the results using the Artificial Societies approach described in this section.

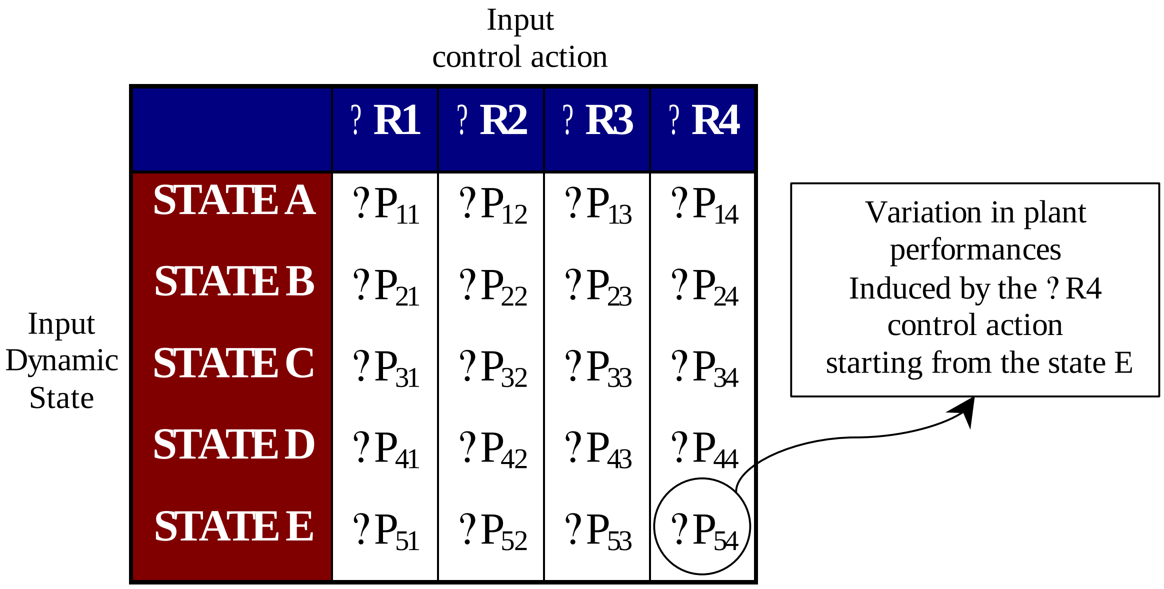
Number of towns	Greedy	Simple G.A.	Adaptive Evol. Strategy	Ant Colonies	Evol. Progr.	Artificial Societies
30	473.32	425.94	**423.74**	**423.74**	**423.74**	**423.74**
50	505.77	443.98	428.98	427.96	**427.86**	**427.86**

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. Our interest is not only limited to the optimization power but it also includes the ability to develop new configurations due the much more open structure. In fact, with respect to genetic algorithms, the artificial society has an oscillating population, the possibility to use the space localization to develop local societies (local evolution) and finally the dimension of the self-organization.

4.2 The alife environment for control and progressive optimization

An artificial environment is created in parallel to the plant capturing 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 performances. 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 on the regulation state. Because the individual has an "expected life-time", 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 not monitored variables (i.e. 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, 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) never 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. 5).



	? R1	? R2	? R3	? R4
STATE A	$?P_{11}$	$?P_{12}$	$?P_{13}$	$?P_{14}$
STATE B	$?P_{21}$	$?P_{22}$	$?P_{23}$	$?P_{24}$
STATE C	$?P_{31}$	$?P_{32}$	$?P_{33}$	$?P_{34}$
STATE D	$?P_{41}$	$?P_{42}$	$?P_{43}$	$?P_{44}$
STATE E	$?P_{51}$	$?P_{52}$	$?P_{53}$	$?P_{54}$

Fig. 5: 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 a *performance map* built using a neural network (based on a Radial Basis Function approach). This map gives the possibility to estimate the performance differences induced by regulation actions. 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.

At 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 quite filled. After each cycle of measurements/suggestions the performance map is updated (continuos 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 the real process 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 [38] introduced in the section 3. The goal is to obtain a system to study the the optimization features of the alife environment and point out the control strategies.

5.1 The control simulator

The model, includes regulation parameters which 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. 7 the scheme of the simulator has been reported.

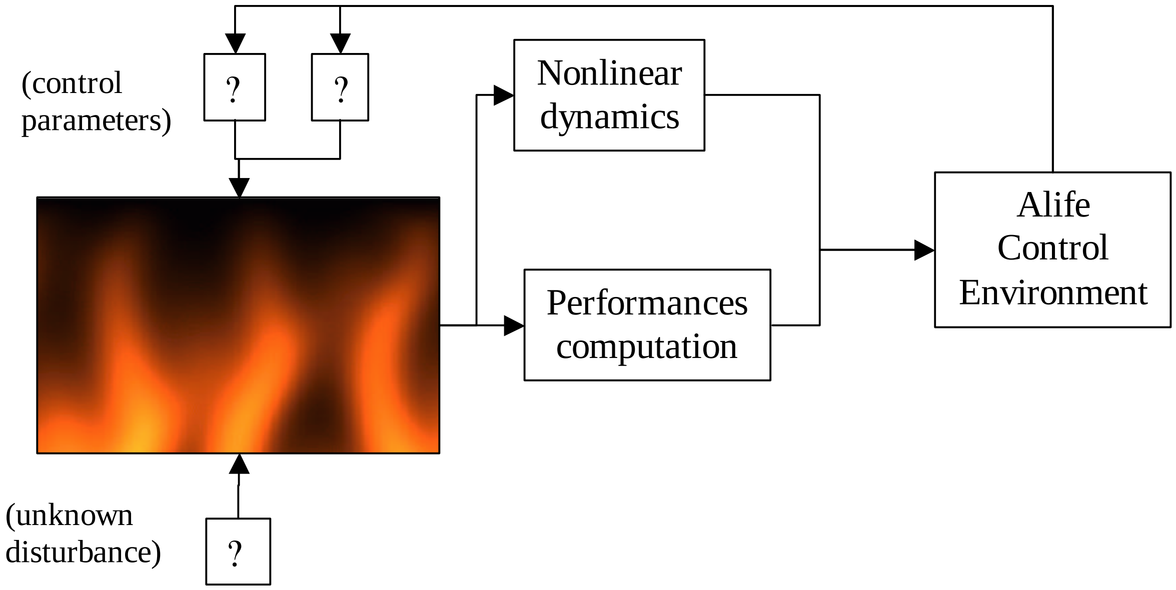


Fig 7: the scheme of the control simulator based on the Kuramoto-Sivashinsky model

-> fitness definition
-> implementation details
-> parameters sensibility analysis (fitness versus ? ??? ???)

5.2 Preliminary Results

Two experiments have been realized:

?? 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 fig. 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.

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 Traveller 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.

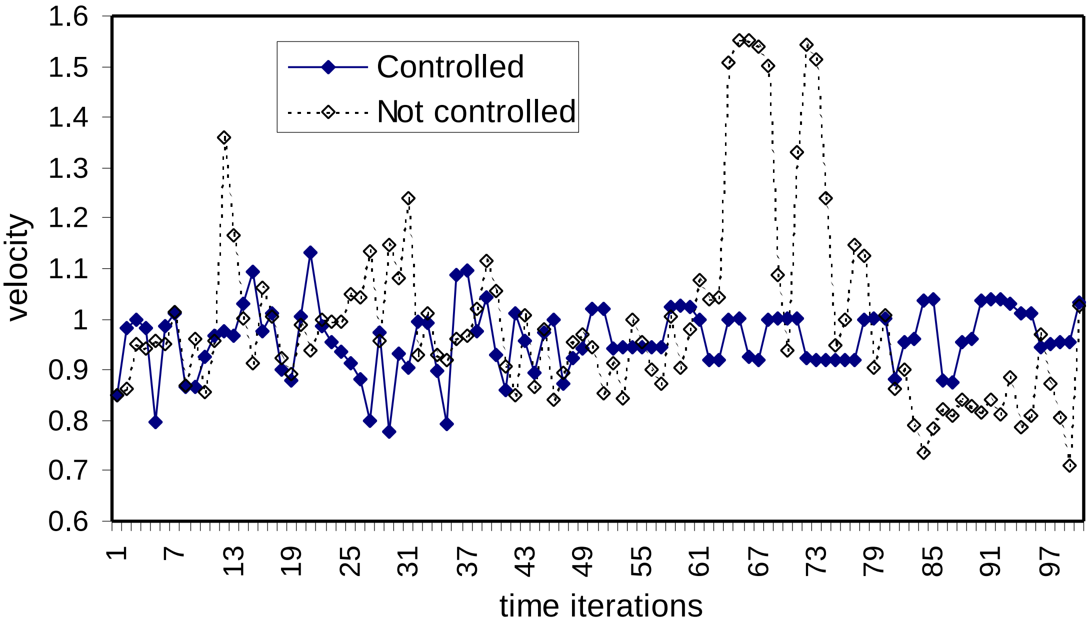


Fig. 8: Comparison between a controlled and a not-controlled conditions. The control is carried out in order to maintain at 1 m/sec the flame propagation velocity. The effect of the control reduce the deviations induced by artificial disturbances inserted on the system.

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