AN ADVANCED CONTROL METHODOLOGY: THE EXPERIENCE AT AN ITALIAN MSWI PLANT

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ABSTRACT

The extensive use of energy presents a severe challenge to the environment and makes indispensable to focus the research on the maximization of the energy efficiency and minimization of environmental impact (in particular the reduction of NOx and CO emissions). The proposed idea describes a novel approach, based on *artificial life (ALIFE) environments*, for on-line adaptive optimisation of complex processes for energy production/consumption by means of a *model of performance* of the process itself. Such approach is based on Evolutionary Control methodology that by emulating the mechanism of the biological evolution composes the capability of elaborate models with the continuous learning. In order to work with MSWI plant it was necessary to improve the stability of the optimiser to obtain a good compromise between stability and reactivity. So a specific MSWI *performance function*, based on fuzzy set theory, has been properly defined in order to characterize quantitatively the current status of the process. Then proper fuzzy sets and the composition criteria have been qualified over experimental data coming from the AGEA plant.

INTRODUCTION

The main problems with respect to the control of thermal processes and especially in the case of municipal solid waste incinerators [1][4] are the continuously changing fuel composition, the increasing complexity of a complete installation with the interacting sections of incineration, steam cycle and flue gas cleaning. These reasons, together with strong non-linearity in the process have the result that classical control strategies are no longer effective. In the present proposal the responses of the intelligent sensors and the conventional measurements are used into an innovative control approach based on an evolutionary methodology for medium-long term optimisation. The evolutionary model is based on the genetic evolution of autonomous agents, which observe the consequences on the plant performances of the control actions carried out from the operators or from the physical model. This continuous learning allows adaptation to time cycles (daily, weekly, seasonal) and aging or modifications of the plant.

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, inspired by mathematical and physical models of intelligence (Artificial Intelligence) and more recently of life itself (Artificial Life), are providing new tools and ideas for the solution of complex problems requiring evolving structures. In problems ranging from traffic regulation to energy process control and optimisation the not-adaptive approaches are not effective to solve the problem over the time. The not-controlled variables, the process ageing, the unforeseeable effects caused by human errors, 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. To reach the goal of evolving structures, a continuous learning of the system from the environment is necessary but not sufficient, and the ability of the system to change its internal structure is needed. In short, we need information structures able to *evolve* in parallel to the process we are modelling.

1. THE EVOLUTIONARY CONTROL

In this paper a new approach, *evolutionary control*, for the optimisation and control of complex processes based on evolutionary computation techniques and extensions of them is proposed. Our goal is to test the approach we are about to describe on a non-stationary system, whose defining scenario concerns:

1. *Hardness to build effective models.* Because of the high complexity of such phenomena, it is very difficult to model them. Moreover in real systems to build a data driven model we have to take into account that the amount of data available are often much less than the required and that not all variables are known in advance. It follows that we have to deal with approximate models.
2. *Non-stationary environment.* These are systems in which environmental conditions change in time. In this situation real adaptive systems must be able to keep track of the changes and to dynamically adapt to the new conditions.

The basic features of the methodology we propose are:

- *no intensive pre-modelling* (progressive training directly from the measurements) ;
- following of the *process evolution*.

In our proposal, the process knowledge is obtained directly by the system through the observation of the measurements. The dynamic building of a model is based on the observation of the effects that the regulation settings (acted by the operators or any other existing control systems) have on the process performance. The basic concept consists in the implementation of an artificial environment that *lives* in parallel to 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 performance. In this way measurements are composed by both process variables and performance. The system continuously gets measurements from the process and provides the process back with the control actions.

The main blocks (fig.1) of the control architecture are the **ALIFE environment**, the **performance measurement** and the **performance estimation.** The first one is an artificial environment composed by individuals able to find the optimal solutions. The other two provide a value which represents a judgement of quality (called *performance*) of the current/next states of the process/plant. As it will be described in the next paragraph, on the basis of such information ALIFE manages the artificial environment and selects the best solution (that is the individual whom genotype represent the best set of regulations) for the current state in order to drive the process toward optimal conditions.

The difference between the two above-mentioned blocks are summarised by following observations. The **performance measurement** block takes as input the principal variables measured from the process (that is outputs of the process/plant) and it computes the performance by the measurements using a mathematical formula, whom definition is arbitrary. In fact this definition is problem dependent and in general is discussed with process engineers. The goal is the mathematical formalisation of some practical and legal rules (for instance imposed constraints against the pollutant emissions), which are supposed to be respected in order to obtain a good or an optimal management. In the particular case of incinerators the performance value can be defined by a multi-objective fuzzy function that combine several membership functions related to different objectives. Since the computation is derived directly by the measurements this value monitors only the current and the past state of working.

On the contrary, the block called **performance estimation** provides an estimation of the performance by taking as inputs a hypothesis of regulations (that is inputs of the process/plant), which do not correspond to the present state but can be chosen as optimal in the next. In this case we have developed a model, which have the characteristics of a continuously updating the correlation between regulations and performance during the evolution of the plant.

Each time a new measurement is acquired, the correspondent performance value is calculated, the performance estimation model is updated (continuous learning) and a new individual, representing the new experimented/observed process condition, is inserted in the artificial environment. In this way the system is continuously updated, it follows the process not-monitored changes and drives the evolution towards better performances. Of course at 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 gives its suggestions when the performance model is trained.

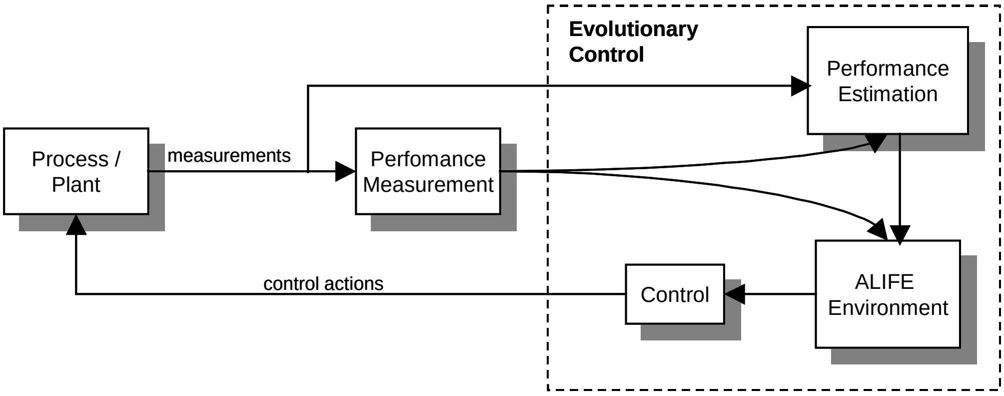


Figure 1 Evolutionary control approach scheme

1.1 The ALIFE environment

In this paragraph we will briefly describe the artificial life environment for the dynamic selection of the best control configurations. This environment derives from the *Artificial So*ciety approach illustrated in Annunziato et al.[3]. This approach has been tested for the optimisation of a static well-known problem, the Travelling Salesman Problem, in which it has reached the optimal value for the 30, 50 and 75 towns.[3].

The ALIFE context is a two-dimensional lattice (*life space*) divided in *nxn* cells. The life space is empty at the beginning of the evolution. In the metaphor of the artificial life, this lattice represents a flat physical space where the artificial individuals (or *autonomous agents*) can move around. During the single iteration (*life cycle*) all the living individuals move in the space. Every life cycle, the individual moves in the life space, can interact with other individuals, and can reproduce generating another individual. We suppose to carry out periodically a set of measurements (*measurement cycle)*, to calculate the current value of the process *performance* and to provide such an information to the control system. The performance is the target of the control we want to optimise and it is derived from measurements. At every cycle of measurement, a new individual is built on the base of the measured values, by means of codifying measures in the genotype (so that different measures correspond to different individuals), and inserted in the environment with a starting value of energy (*inlet energy*). A measurement cycle corresponds typically to several life cycles (10-1000).

Three blocks compose the data structure of the individual: the *genotype*, the *information* and the *status*. The first one includes a collection of behavioural parameters regarding dynamics, reproduction and interaction. These parameters don't change during the individual life. The *information* block includes a series of parameters related to the process to control: the regulation and measurement values; these variables 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 may change during the individual life, due to the current behaviour of the individual (which is in turn imposed by the fixed parameters codified in the genotype) in according to the movement models. The performance is continuously updated using an external problem-specific model (described in par.2). This is due to the possible changes in the unknown variables of the process not represented in the genotype.

1.1.2 Reproduction, Interaction and Selection

A *haploid reproduction model* has been implemented; the self-reproduction can occur only if the individual has enough energy and owing to a positive probabilistic test. Actually in this reproduction model the genotype of the son corresponds to a probabilistic-random mutation of the father's one in relation to a *mutation average rate* and *mutation maximum intensity.*

The application of the mutation mechanism on the genotype can change radically the individual behaviour and can increase a lot the possibilities to optimise the search strategy over time and situations. When the system is far from the optimum, high values for these parameters are necessary to speed up the environment to recovery the performance. When the system is close to the optimal low values are necessary to locate the control at the optimal maximum. The performance value of the parent has been derived from the measurements, but during reproduction we change regulations through mutation mechanism. In this case we don't know the actual performance of the child we have built anymore and in order to solve this problem we use the *performance estimation model* (see par. 3).

When two individuals collide each other a fight occurs, the winner is the individual characterised by a greater value of performance. The loser transfers a part of its energy *(fighting energy*) to the winner, which becomes stronger and increases the probability to meet other individuals and to fight again pushing selection mechanisms of the best individuals in terms of performances.

At every life cycle, on the basis of the performance value, a list of individual is written out, the best is selected and it suggested to the control module.

2 THE PERFORMANCE DEFINITION

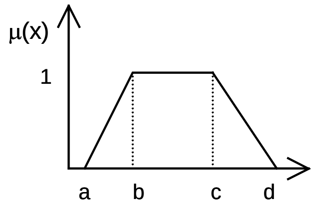
The definition of this index is obtained by means a problem specific multi-objective approach and it represents the global formalisation of the several goals we want to fulfil. The *measurement performance* module is aimed to provide the evolutionary controller with a global index of the performance, which is used to carry out the individual's selection. Such value is externally defined to the artificial life environment and also out of the context of the evolutionary control it constitutes a immediate and powerful instrument to globally monitor the good operation of plant.

In order to properly compose the different variables and criteria the fuzzy sets theory has been chosen because it allows the operator transparency, it provides a well established theoretical framework to solve this kind of problems (providing a global index in the lattice [0,1]) and it is highly flexible because it can be transported to different plants with little effort.

2.1 Basic fuzzy sets

For any process variables, which influence the effectiveness of the incinerator management, it has been defined a fuzzy set (membership function), for example we fix the characteristics of steam flow rate according the following natural phrase:

Fuzzy set : “Average steam flow rate *‘good’* ”



This fuzzy set is aimed to model the average steam flow rate (SFR) *‘goodness’*. SFR is considered good (= 1) if the steam average of the last *n* seconds, where *n* is to be properly set, is within the interval [*b*, *c*]. The number *n* can be considered as the integration time in order to avoid statistical fluctuations.
The constraint is that $a<\text{SFR}<d$, so values outside this range are considered not acceptable and therefore not belonging to the fuzzy set (= 0). The membership function of this fuzzy set will be trapezoidal shaped and will have as argument the real average SFR values.
Analogue fuzzy sets are defined for the other important parameters that contribute to the good operation of the plant. Obviously the shape of the membership function changes according to the different objectives to be fulfilled and suggested by the process experts.

2.2 Global fitness definition

The main idea driving the definition of the fitness criterion is that of having a flexible function capable to manage different criteria. In particular the fitness function will be the composition of two fuzzy sets describing two different requirements : *‘optimality’* and ‘*strictness’*. The difference between the two lies in the composition of the previously defined fuzzy sets.
The membership function of the first one will be defined as the weighted sum of the membership functions of basic fuzzy sets. Logically this operator represents a composition standing between AND/OR. This fuzzy set will fulfil the ‘optimality’ requirement because it allows to set the weights, the importance of each fuzzy set, according to the custom needs. In this way the optimiser will find the optimal solution for that particular setting of the weights giving the system scalability to different needs.
The second criterion will concern the strict constraints satisfaction defined in the basic fuzzy sets. The resulting fuzzy set will be logically defined as the AND composition of the basic fuzzy sets. It means that the resulting membership function will be the product or the minimum of the membership functions of the basic fuzzy sets.
The final fuzzy set describing the global fitness will be the weighted sum of the last two fuzzy sets. Weights will be defined by the developer according to the custom requirements depending on the relative importance of the two criteria.

Fuzzy set F_1 : “Performance *optimal*”

This fuzzy set is aimed to describe a general evaluation of the performance giving each variable a different weight (importance). At first such weights are static, once defined they do not change in time, but in future they can be considered dynamic in the sense they change according to particular rules. This fuzzy set is not aimed to check the constraints, if one variable is out of range then it will not severely affect this evaluation.

$F_1 = X_1 \oplus X_2 \oplus \ldots . X_N$
$\mu_{F1}(x_1,x_2..x_N) = \sum w_i \mu_i (x_i)$; $\mu_{F1}(x_1,x_2..x_N) \in \Re$, $\mu_{F1}(x_1,x_2..x_N) \in [0,1]$; $w_i \in \Re$, $w_i \in [0,1]$, $\sum w_i = 1$

Fuzzy set F_2 : “Constraints *OK*”

This fuzzy set is aimed to strictly satisfy all constraints. If one variable is out of range then it will severely affect this evaluation.

$F_2 = X_1 \wedge X_2 \wedge \ldots . X_N$

$\mu_{F2}(x_1,x_2..x_N) = \prod \mu_i(x_i)$, $\mu_{F2}(x_1,x_2..x_N) = MIN(\mu_i(x_i))$;$\mu_{F2}(x_1,x_2..x_N) \in \Re$, $\mu_{F2}(x_1,x_2..x_N) \in [0,1]$

Fuzzy set F : "Fitness *good*"

This fuzzy set describes the global performance of the system as a compromise between the two criteria. It allows a different weight to each of them in such a way that it is possible to stress which of the two has to be considered more important. In this way, according to weight given to each criterion, the performance allows a different weight to all the variables and checks the constraints satisfaction of all variables. This definition allows a sensitivity recovery of the out of range variables. At first the weight is static, once defined it does not change in time, but in future it can be considered dynamic in the sense it changes according to particular rules.

$F = F_1 \oplus F_2$

$\mu_F(x_1,x_2..x_N) = w\mu_{F1}(x_1,x_2..x_N) + (1-w)\mu_{F2}(x_1,x_2..x_N)$

$\mu_F(x_1,x_2..x_N) \in \Re$, $\mu_F(x_1,x_2..x_N) \in [0,1]$; $w \in \Re$, $w \in [0,1]$

2.3 Experimental results

Particularly in the case of AGEA plant the variables considered and the correspondent basic fuzzy sets chosen together the plant engineers according to normative requirements and management 's rules are:

Fuzzy set	Membership function
X1 : "Average steam flow rate (SFR)*'good'* "	Gaussian (16.0,8.0):
X2 : "Average steam flow rate *'stable'* "	Gaussian (0,2)
X3 : "Average O_2 *'good'* "	Trapezium (6.0, 6.1, 8.0,15) constraints 6.0<T<15.0 ; optimal $O_2 \in [6.1,8.0]$
X4 : "Average temperature *'good'* "	Trapezium (950, 980, 1020, 1100): constraints 950<T<1100 ; optimal $T \in [980,1020]$
X5 : "Average NOx *'low'* "	Decreasing ramp (400 ppm/h)
X6 : "Average CO *'low'* "	Decreasing ramp (100 ppm/h)
X7 : "Average flue gas rate *'low'*	Trapezium (25k, 35k, 40k, 45k) constraints 25k<FGR<45k ; optimal $FGR \in [35k,40k]$
X8 : "Average waste flow rate *'high'* "	Increasing ramp

Table 1.Definition of fuzzy sets for AGEA plant.

The definitions of the fuzzy sets 'optimal' and 'constraints' are:

$F_1 = X_1 \oplus X_2 \oplus X_4 \oplus X_5 \oplus X_7 \oplus X_8$ $F_2 = X_3 \wedge X_4 \wedge X_5 \wedge X_6$

In order to validate the performance model a consistence campaign of tests at the AGEA plant was carried out. The figure 2 shows the performance analysis carried out on a one day real data set (~4320 points acquired every 20 seconds and sampled every 6 minutes for editing requirements), based on the given definition of fuzzy sets and criteria.

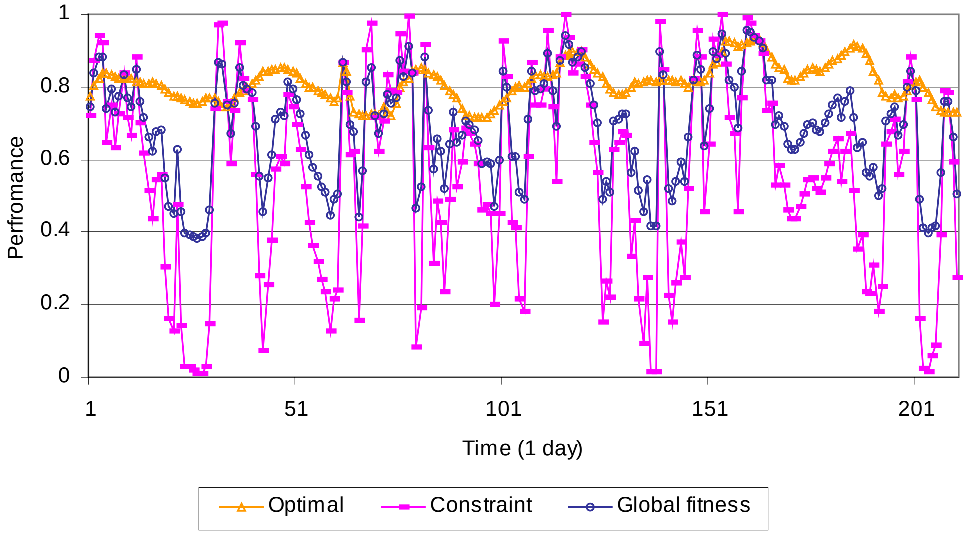


Figure 2 Example of global fitness index (circle), optimal (triangle) and constraints (dash)

The graph shows the trend of global performance index, the interpretation of such index can be made at different levels. At a superficial lecture it represents a powerful instrumentation for the operator to verify the global state of the plant, when the global fitness maintainS a constant course over 0.8, the operation of the plant can be considered satisfactory even thought not optimised. Otherwise by analysis of the "constraints" and "optimal" function it is respectively possible either to point out failures and overtaking of the admitted limits or requirements, either to obtain a track , which if it was followed, could suggest configuration at high performance.

3 THE PERFORMANCE ESTIMATION

In the paragraph 1 we anticipated the characteristics of this block developed to predict the value of performance related to hypothetical set of regulations, which represent the genotype of new individuals, born in the ALIFE environment from the reproduction of others through the mutation mechanism. In that sense we directed our major efforts to build an on-line learning model, based on evolutionary neural networks, which takes as input the values of the control parameters and returns an estimate of the corresponding value of the performance function. The scheme of the performance estimation module (fig. 3) is then constituted by three blocks: the *performance map*, the *evolutionary neural network (ENN)* and the *performance evaluator*.

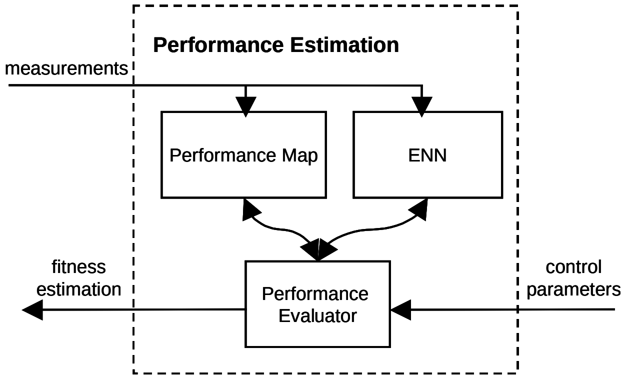


Figure 3. Performance model scheme

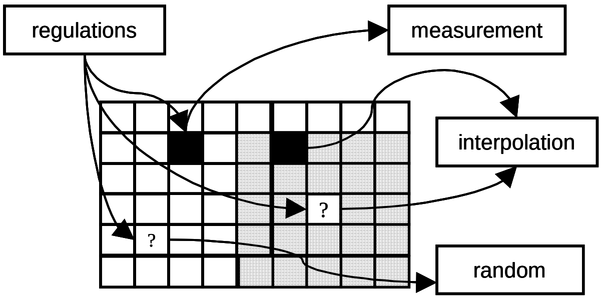


Figure 4. Performance evaluation

The performance map is an n-dimensional discretised matrix, where n is the number of control parameters. A every measurement cycle the related performance of the current state of the plant and calculated by the above-mentioned 'measurement performance' module is stored in the map, in the cell which the discretisation of the parameter set refers to. The map, then, has a twofold task: on one hand it is the long-term memory of the control system; on the other hand, it allows the continuous updating of the reference model and so it lets the control system itself to evolve in parallel with the process. So it roughly represents an *internal knowledge of the real system*. The process of updating of the performance map is rather simple.

The *evolutionary neural network* combines evolutionary computation and neural networks by optimising the weights of feed-forward neural networks when applied to variable prediction. The basic concept [5,6,7] consists in the realisation of an ALIFE environment running in parallel with the process and that synchronously communicates with it. We suppose to always measure from the process the data which continuously update a data set, representing the objective of our optimisation, since in this situation performance is defined as the capability of each neural network of *reconstructing the underlying dataset*.

In this context (Chaotic Population algorithm – CP[5,6,7]) each individual of the evolutionary environment represents a feed forward neural network, in competition with the others by means of their fitness, having as genotype the synaptic weights. The results obtained also in other areas of application[5,6,7], show the effectiveness of the ENN methodology in order to get predictive neural models capable to reach better accuracy than the gradient based methodologies (the Back Propagation algorithm - BP).

The *performance evaluator* is a module which each time verifies the strategy has to be used if the access to the map or to the on-line neural network, on the basis of the following consideration. It is noted that the (E)NNs have a high degree of accuracy inside of the training set, out of this range the probability of errors increases rapidly. For this reason we imagine to distinguish the map as whole in two regions, which change shape on the time: one constituted by cells related to the training set (type-1), which are recently (for example during the last week) visited and the other by the cells out of this range (type-2).

So, in order to predict the performance value of a type-1 cell, we use the ENN, for the type-2 cell we use the access to the map (fig.4), as it follows:

1. If the input refers to a filled cell, in which we have already inserted a **measure,** then we will consider that quantity as the estimation of the performance we are looking for; measures are related to performance according to a fuzzy definition of the performance index.
2. If the input refers to an empty cell, but close (in a fixed neighbourhood) to one or more filled cells we apply an **interpolation** mechanism.
3. Otherwise we put a random value.

3.1 Experimental results

In order to implement the above mentioned model different phases of tests were carried out. The main one was focussed on the tuning of the CP algorithm to provide the performance estimation of the AGEA's plant. So a deepened study of the correlation of the input/output (regulation/measurement) variables in order to select those which mostly characterise the plant behaviour. The figure 5 shows (~4320 points acquired every 20 seconds and sampled every 10 minutes for editing requirements) the results obtained to estimate the steam production by using different ENN's algorithms and traditional ones (BP).Such results point out the effective capability of the ENN to modelling any variable.

Analogue tests carried out to estimate the optimal performance (see par. 2.2) gave encouraging results, shown in the figure 6 for the training phase; in the table we report the values of the average errors both in the training and testing phase, with respect to those obtained by using either the average value or only the map.

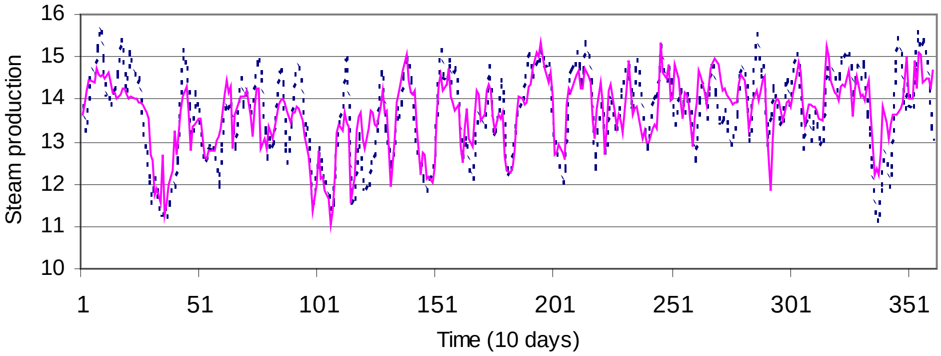
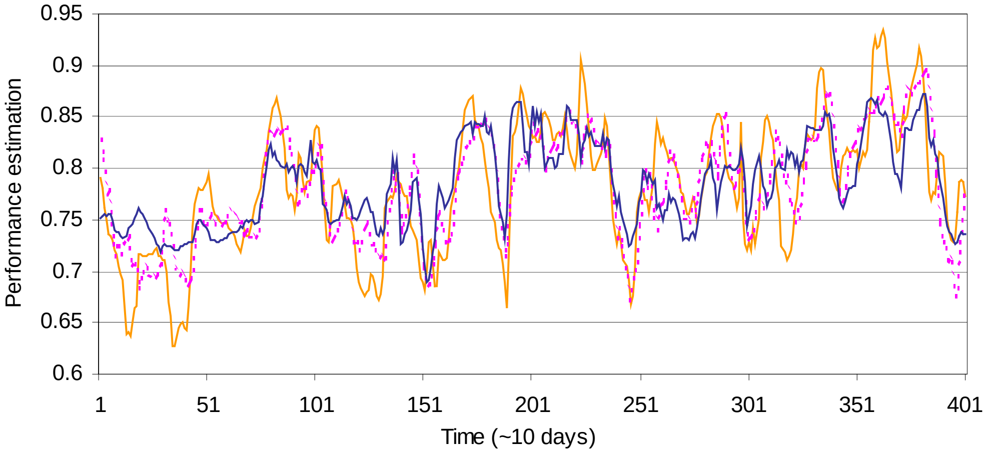


Figure 5. Comparison between estimation of steam production(-) and real value (--)



	Training	Testing
BP	0.031	0.042
CP	0.038	0.039
Average Value	0.055	0.050
Map	0.039	0.064

Figure 6. Estimation of optimal performance: Real (-) light, BP(--),CP (-) dark.

As future development we think to implement another type of algorithm for ENN characterised by a *on-line continuous learning*. We suppose to always measure from the process the data which continuously update a data set, representing the objective of our optimisation, since in this situation performance is defined as the capability of each neural network of reconstructing the underlying dataset. The update strategy is a first-in-first-out (FIFO) policy since we want to make our prediction on a travelling window whose length depends on the problem. In this situation every time the data set changes then a new network is dynamically found, therefore we have an evolutionary neural model capable to adapt and to follow in real-time the process evolution.

ACKNOWLEDGMENT

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CONCLUSIONS

We introduced a smart adaptive technique for control and optimisation of complex processes. We based our proposal on the development of an artificial environment evolving in parallel with the process. Exploiting its characteristics of evolution, biodiversity and adaptivity, we succeeded in achieving an on-line optimisation of the process via a continuous learning and updating of its model.

Such methodology has been applied to improve the management of incinerators. The critical point focussed on the present paper is the multi-objective approach used to define a *performance index* for MSWI plant. The proposed approach is based over a fuzzy combination of several objectives of the optimisation. A unique global index has been obtained to supply the evolutionary module. This definition takes into account the need with respect to the constraint but also the sensibility of the index when some constraint is out of the range in order to have a possibility to recover the process towards higher performances

The performance index has been calibrated over the specific process and experimented on real data coming from plant and it has demonstrated a powerful and immediate capability to represent the state of the plant in terms of effectiveness and fulfilment of the normative requirements.

From our observations this indicator plays a relevant role also out of the context of the evolutionary control. In fact it constitutes a powerful and immediate mean for the operator to observe the global operation of the plant. By the on-line observation of the graph of figure 2 it is possible immediately to realise the presence of some problems, to give an alarm, which can be better explained by the analysis of the other index (optimal and constraints).

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