Evolutionary Control and On-Line Optimization of a MSWC Energy Process

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ABSTRACT

The extensive use of energy generation processes 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 like NOx and CO emissions. The proposed idea describes an approach, based on an artificial life environment, for on-line optimization of complex processes for energy production. Such an approach is based on the evolutionary control methodology which, by emulating the mechanism of the biological evolution, composes the capability of sophisticated models with the continuous learning. In order to work with MSWC (Municipal Solid Waste Combustion) it was necessary to improve the stability of the optimizer to obtain a good compromise between stability and reactivity. In this way, a specific MSWI *performance function* has been properly defined in order to quantitatively characterize the current status of the process. The evolutionary control approach has been successfully tested on a MSWC simulator and subsequently installed on a real MWSC plant which produce electricity and heat for a small Italian town (Ferrara). The paper reports the first promising experimental tests on the real plant for optimization of energetic efficiency and pollutant emission reduction.

Keywords: Evolutionary control, on-line optimization, artificial life, waste incinerator, energetic efficiency, emission reduction.

1. OPTIMIZATION AND CONTROL OF COMPLEX PROCESS FOR ENERGY GENERATION

In problems regarding the control and optimization of complex energy process 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 cases require the change of the basic model or the objectives, or even the whole strategy of the process management. A continuous parametric adaptation is necessary but very often is 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 dealing with. The typical problem with respect to the control of thermal processes, and especially in the case of municipal solid waste incinerators [1,2], are the continuously changing fuel composition and the increasing complexity of a complete installation. These kind of process burns solid waste with a mixed and variable composition, produces water steam to generate electrical power and finally it is often connected with remote heating for public buildings. For these capability of energy recovery, they are considered in a similar value to the renewable energy source. These complex production networks, together with the strong non-linearities in the process itself, have the result that classical control strategies are no longer effective. Moreover, model based approaches are difficult because of the impossibility to model the process and in general to measure all the variables influencing the process.

2. THE EVOLUTIONARY CONTROL

In this paper an approach based on an evolutionary methodology for on-line optimization is presented [3]. The content here discussed concern the main results of the European Project NNE5-2001-000141: “Development of Evolutionary Control Technology for Sustainable Thermal Processes” (ECOTHERM) [4]. 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 by the optimization system itself. This continuous learning allows adaptation to time cycles (daily, weekly, seasonal) and to aging or modifications of the plant.

The use of an evolutionary approach is connected with non-stationary processes, missing information and hardness to build effective models. The basic features of the methodology we propose are:

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

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 optimize it. We suppose to always measure from the process its current regulations and a quality index called process *performance* in the following. In the more general approach the information about the optimal operation point produced by the evolutionary optimizer is supplied to a control system which should manage the regulations in order to reach the optimal point identified by the evolutionary optimizer [4]. This control system is not simple to obtain in case of MSWC process because of the difficulty to model the process [1]. On the other hand, the evolutionary approach gives some limited information about process modeling. For this reason our approach has to include some aspects of control directly in the optimization system. Later in the paper, we will discuss the limits of this choice concerning the experiments in a real process.

The architecture

The main blocks (fig.1) of the optimization architecture are the artificial life environment (ALIFE), the performance measurement and the performance estimation.

The first one is an artificial life environment composed by a population of *particles* (called i*ndividuals* in the following) which represent *solutions*. A solution is an operational state of the process that identifies a vector of set points for the regulations controller. As it will be described in the next paragraph, on the basis of such an information, *ALIFE* manages the artificial environment and selects the best solution for the current state in order to drive the process toward optimal conditions.

The other two modules provide a value which represents a judgment of quality (*performance*) associated to a specific solution. The difference between the two above-mentioned blocks are summarized by following observations.

The input of the performance *measurement* block are the variables measured from the process. It computes the performance using an arbitrary definition representing the goal of the process managers (high production, energetic efficiency, low emissions, stability, constraints related to laws or process critical situation....). Most of these variables are outputs of the process (production, emissions, temperatures, etc..) and the performance reflects practical and legal rules, which are supposed to be respected in order to obtain a good or an optimal management. In the case of incinerators, the performance value can be defined by a multi-objective fuzzy function that combines several membership functions related to different objectives. Since the computation is derived directly by the measurements this value monitors only the current state of the process.

At the contrary, the performance *estimation* block provides an estimation of the performance by taking as inputs a hypothesis of regulations. This hypothesis does not correspond to the present state but is only a *candidate* for the next control point to be applied in the process. In this case we have developed a simple structure which has the characteristics of continuously updating the relation between regulations and performance during the evolution of the plant.

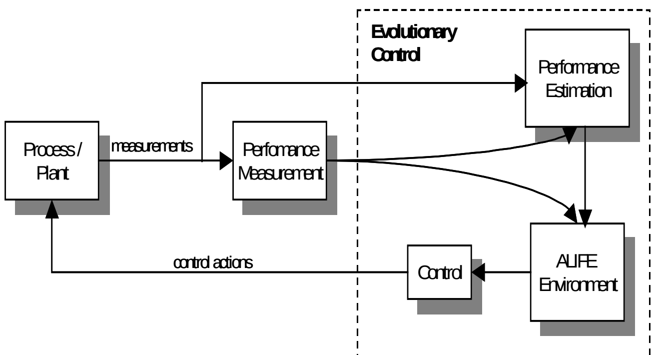


Figure 1. Evolutionary control approach scheme

Each time a new measurement is acquired, the corresponding performance measurement is calculated, the performance estimation model is updated and a new individual, representing the new observed process condition, is inserted in the artificial life environment. In this way the system is continuously updated.

The artificial life optimization approach

The main characteristics of evolutionary methods for problems optimization (genetic algorithms [5], ant systems [6], particle swarm optimization [7]) is a research strategy based on a population of evolving solutions generated directly in the n-dimensional parameter’s space. In this way, the *interaction* dynamics between the solutions is defined in this space. It consists in reproduction (crossover and mutation) and selection for genetic approaches and coordinated swarm movement in the case of swarm optimization.

In our approach we are exploring the possibility to use a supplemental two-dimensional *physical* space to manage solution’s interaction. The introduction of the physical space is inspired to the metaphor of the organisms carrying information (solutions) living and interacting in an environment (physical space). This is the typical situation for the artificial life simulation environments [8]. All the interaction dynamics are contextually located in the physical space. Reproduction produces child solutions located in physical cells adjacent to the parent solutions; the interaction between two solutions, regulating competition and selection, are activated when two solutions meet in the physical space.

Using this approach, a solution has a preferential high probability of interaction in the near local space. When the density of solutions in the physical space is high, the preferential local interaction pushes the population to form local groups producing a sort of local niches of evolution. Typically, the individuals located at the center of these jammed groups push up the evolution and individuals located at the boundary of these groups travel around producing a cross-fertilization between several niches. This mechanism is the idea we are trying to introduce in order to give the optimization population the possibility to continuously sustain a *biodiversity* of evolved solutions. This aspect is very important in continuous evolving systems where the fitness landscape can rapidly change in time and the system has to react (*adapt*) in short time finding a new effective range of optimal solutions to promote.

At this stage of research, it is difficult for us quantify these mechanisms and establish with accuracy, how much the physical space and evolution niches add to the ability of the system to adapt in the time. Deeper theoretical studies will be necessary in the future to better explore and quantify the effects physical space interaction dynamics.

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. [9]. This approach has been tested for the optimization of a static well-known problem, the Traveling Salesman Problem, in which it has reached the optimal value for the 30, 50 and 75 town. Recently has been compared with several other approaches (classical and evolutionary) for neural network training giving very promising results [10].

The ALIFE context is a two-dimensional lattice divided in *nxn* cells initially 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 can move around. During the single iteration (*life cycle*) all the living individuals move in the space, eventually interact with other individuals, and eventually reproduce generating another individual in haploid reproduction.

Every *m* life cycles (m = 10-1000) we apply an access to the process data acquisition to acquire new data (*measurement cycle*) and compute the current process performance. At every cycle of measurement, a new individual is built including in its structure measures, current regulations and current performance. Finally we insert this new individual in the environment with a starting value of energy.

Three blocks compose the data structure of the individual. The first one includes a collection of behavioral parameters regarding dynamics, reproduction and interaction. These parameters don't change during the individual’s life. The second 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's life too. The last block includes dynamics parameters (position, direction, curvature), age, energy and performance value. These parameters may change during the individual's life, due to the current behavior of the individual or to the process evolutions. The performance is continuously updated using an external problem-specific model (described in section 3). This is due to the possible changes in the unknown variables of the process not represented in the genotype.

Reproduction, Interaction and Selection. A haploid reproduction model has been implemented for the individual reproduction; self-reproduction can occur only if the individual has enough energy and owing to a positive probabilistic test. The genotype of the child individual corresponds to a probabilistic-random mutation of the parent's solution (regulation set points) in relation to a mutation average rate and mutation maximum amplitude.

The application of the mutation mechanism on the genotype can change radically the individual quality and it can change substantially the optimization strategy over time and situations. When the system is far from the optimum, high values for mutation amplitude are necessary to speed up the environment to recovery the performance. When the system is close to the optimal point, low values are necessary to locate the optimal maximum. For this reason we adopt adaptive value of the mutation amplitude with respect to the performance value. During a reproduction, we mutate the regulations, therefore we don't know the real performance of the child. For this reason we need the *performance estimation model* (section 3) to associate the estimated performance to the new individual.

When two individuals collide each other, a fight occurs. The winner is the individual characterized by a greater value of performance. The loser individual transfers a part of its 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. If an individual reduces its energy under a threshold it cannot reproduce anymore. If it reaches the null energy it is considered dead and removed by the environment.

Finally, at every measurement cycle the individual who has the best performance is selected and the corresponding solution is suggested as the optimal current solution for the process operation.

3. THE PERFORMANCE DEFINITION

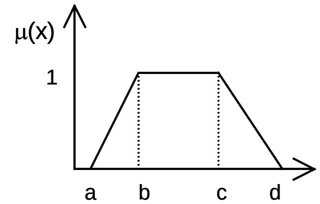
The definition of this index is obtained by means a problem specific multi-objective approach and it represents the global formalization of the goals we want to fulfill. The *measurement performance* module is aimed to provide the evolutionary controller with a global index of the performance, which is used to carry out the individual's selection. Such a value is defined out of the control context and it constitutes an immediate and powerful instrument to globally monitor the good operation of plant providing a global index in the range (0,1).

In order to properly compose the different variables and criteria the fuzzy sets methodology has been chosen because it allows the operator transparency, it provides a well established theoretical framework to solve this kind of problems and it is highly flexible because it can be transported to different plants with little effort.

Basic fuzzy sets

For any process variables, which influence the effectiveness of the incinerator management, it has been defined a fuzzy set and a membership function. As an 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*<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. The shape of the membership function (i.e. trapezoidal, sigmoidal, gaussian) changes according to the different objectives to be fulfilled and suggested by the process experts.

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 *penalty*. The difference between the two term lies in the composition of the previously defined fuzzy sets.

The membership function of the *optimality* type is defined as the weighted sum of the membership functions representing the *process production* we want maximize. Logically this operator represents a composition standing between AND/OR.

The *penalty* term concerns the approach of conditions close to the constraints violation or critical for the process maintenance or safety or critical for pollutant emissions. The resulting fuzzy set will be logically defined as the AND composition of the basic fuzzy sets.

The final fuzzy set describing the global fitness is the weighted difference 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 intended to describe a general evaluation of the performance giving each variable a different weight (importance). This fuzzy set is not meant to check the constraints, if one variable is out of range then it will not severely affect this evaluation.

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

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.

$$F_2 = X_1 \wedge X_2 \wedge \ldots X_N$$
$$\mu_{F2}(x_1,x_2..x_N) = \prod \mu_i(x_i),\ \mu_{F2}(x_1,x_2..x_N) = MIN(\mu_i(x_i));$$
$$\mu_{F2}(x_1,x_2..x_N) \in \Re,\ \mu_{F2}(x_1,x_2..x_N) \in [0,1] \quad (2)$$

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. 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.

$$F = F_1 \oplus F_2$$
$$\mu_F(x_1,x_2..x_N) = w\mu_{F1}(x_1,x_2..x_N) + w(\mu_{F2}(x_1,x_2..x_N) - 1)$$
$$\mu_F(x_1,x_2..x_N) \in \Re,\ \mu_F(x_1,x_2..x_N) \in [0,1];\ w \in \Re,\ w \in [0,1] \quad (3)$$

In the case of the application over real MSWI Italian plant (AGEA, Ferrara) 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
X1 : "steam flow rate *'good'* "
X2 : "O_2 *'good'* "
X3 : "temperature *'good'* "
X4 : "NOx *'low'* "
X5 : "CO *'low'* "
X6 : "flue gas rate *'low'*
X7 : "waste flow rate '*high*' "
X8 : "pressure drop furnace-chimney 'good' "

Table 1.Definition of fuzzy sets.

The definitions of the fuzzy sets 'optimal' (2) and 'constraints' (3) are therefore :

$$F_1 = X_1 \quad (4)$$
$$F_2 = X_2 \wedge X_3 \wedge X_4 \wedge X_5 \wedge X_6 \wedge X_7 \wedge X_8 \quad (5)$$

In order to validate the performance model a consistence campaign of tests at the AGEA plant was successfully carried out. The result shown good margins to increase the performance value. Most of the management problems were in the difficulty to maintain the process in a condition satisfying all the constraints. In some cases it generated the occurrence of a fast period of ageing of some process structures inducing high costs of maintenance and plant instability.

4. THE PERFORMANCE ESTIMATION

In the section 2 we anticipated the characteristics of this block developed to predict the value of performance related to a hypothetical set of regulations, representing the information block of new individuals, born in the ALIFE environment from the reproduction through the mutation mechanism.

The performance estimation is based on a *performance map*. This is a n-dimensional discretized matrix, where n is the number of control parameters (five for the MWSC process). At every measurement cycle, the performance of the current state of the plant calculated by the above-mentioned *performance measurement* module, is stored in the map, in the cell which the discretization of the parameter set refers to. The map discretization can be different in the several dimensions referring to the relative importance of each regulation parameter. The map 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 fairly simple. When the performance value of an empty cell is required by the new agents, a linear interpolation algorithm is utilized. This procedure leaves the map in a incoherent situation: some zones, typically at high performance, are frequently refreshed and characterized by high accuracy; other zones are rarely refreshed and large errors can arise in the performance estimation. For these reasons the performance map cannot be considered as a model of the process but only a way to organize the memory accumulation of the system.

By a general point of view, the performance map represents only a part of the system memory and a systematic scansion of the whole map to find the best location is not efficient because of the large estimation errors in not recently refreshed locations. The other fundamental component of the memory of the system is represented by the genotypes of the individuals which are currently living in the alife environment. Their dynamics determines the zones of the map that have to be explored and frequently refreshed to maximize the efficiency of the system information.

We have compared this simple approach with another more complex approach founded on a predictive model of the performance trough continuous training neural networks [11]. In general the predictive model of the performance is resulted useful when the frequency of external disturbances is low and their changes doesn't not affect very much the model efficiency. In the other more general cases, like in real plant cases, the disadvantage of to use a predictive model is a low ability to locally adapt to the new conditions and the result is a large temporal inertia to react to process unknown disturbances. For this reason, in the MSWI problem we decided to use exclusively a performance map.

5. SIMULATION RESULTS

In order to test the control/optimization architecture, a wide experimentation has been carried out on a mathematical simulator which reproduce the MSWC behavior developed by TNO (Netherlands) in the context of the Ecotherm EU Project. Basic description of the MSWC modeling are in [1]. The simulator is able to reproduce the MSWC dynamics and has been calibrated using the data coming from the real MSWI process where subsequently the system has been installed. The inertial time of the MSWC process ranges from 30 seconds to 20 minutes depending by the regulation we change.

In respect to the process experiments, the simulator experiment is more simple for several reasons. The first one is that we are able to easily understand the optimization results because we know all the system variables including fuel composition and water content in the fuel which are unknown disturbances in the real process. The second one is that the simulator does not take into account three-dimensional local stochastic effects in the combustion process which can affect very much the real system in term of a general unpredictable inertial behavior. The third one is that we suppose have no errors in the simulator sensor measurements. For all these reasons the goal of the simulator tests is the efficiency of the optimizer algorithm rather than a validation over the real MSWC process.

In the experiment discussed in the following, the control system regulates five variables: primary flow air, secondary flow air, air re-circulation valve, grid speed and waste flow. These are the main regulations of a grid based MSWC process. In these experiments we externally change the fuel composition and water content in the same way of the real process but we don't supply these information to the control system in order to reproduce all real process complexity and data missing.

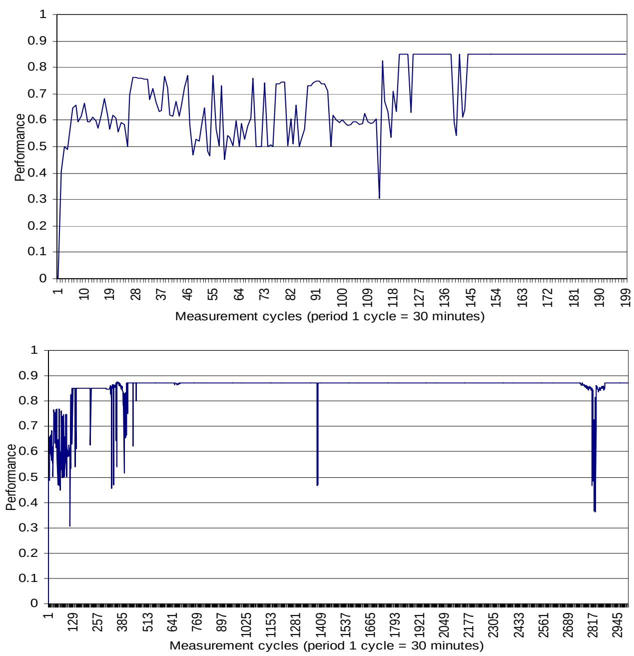


Figure 2. On-line optimization of the MSWC simulator (up: initial part, bottom: complete experiment)

In fig. 2 a typical simulator experiment of on-line optimization is reported. In the plot we show the global performance measured according to the definition reported in section 3. In this case we apply the regulation modification only every 30 minutes (optimization cycle) to avoid transitory effects and the experiment corresponds to about 60 days of the real process. This preliminary choice is only to allow a good data interpretation because the real process requires lower control times (1 minute).

In these experiments the performance map was initially set completely empty and no previous memory of the system has been considered. The initial part of the experiment shows clearly the ability of the alife optimizer to increase gradually the performance to the maximum value. It is to take into account that the value 1 of the performance is not always reachable but it depends on the calorific value of the fuel (fuel composition) that in the experiment is continuously changing. The second part of the experiment shows that the alife optimizer is able to improve the system after sharp disturbance changes but the recovery time is not sufficient to avoid large performance falls at low values (0.3). The low values peaks of the performance are due to the violation of some constraints and they can be dangerous for the process safety. These falls are induced by the fact that *alife*, through the reproduction mechanism, tries to explore zones never visited in the past, where the estimation error in the performance map is very high.

For these reason we have introduced some modifications in respect to the original *alife* model. The first modification was a limitation about reproduction. A child can born only if the corresponding cell in the performance map is already visited in the past or close to a visited cell. This limitation produce an exploration activity of the new solutions which is limited to the boundary of the already known zone. This position corresponds to longer time of exploration of the solution space but it is conservative in respect to the process safety. Furthermore a first *pre-learning* phase has been introduced before to leave the control to the artificial life environment.

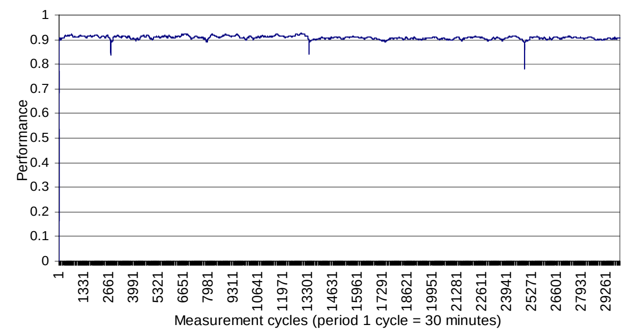


Figure 3. On-line optimization of the MSWC simulator after introduction of the boundary exploration

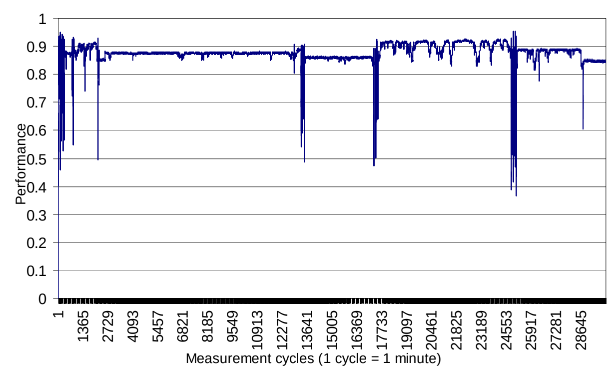


Figure 4. On-line optimization of the MSWC simulator over 1 minute integration time

In fig. 3 the results of these positions for the same experiment is shown. In this case the result is considerably improved avoiding the large performance falls and speeding up system recovery so we definitively apply these modifications.

Finally, we tried to apply the same optimization using very short optimization times in order to verify which is the ability of alife to manage and adapt in transient conditions due to the process inertia. This last experiment is much more realistic in respect to the real process operation. In this experiment we use 1 minute for optimization/control cycle. In this case the time duration of the complete experiment is about 20 process days. The results are still good in terms of response time of the alife system. Some performance falls (0.4) are still present but the time scale now is very short and the performance falls are recovered in few minutes.

6. REAL FIELD EXPERIMENTS

After the satisfying behavior over the MSWC simulator, we have installed the on-line optimization system in a real MSWC plant. This is a full scale medium size plant which supplies electricity and remote heating to the Ferrara town (Italy). It is managed by the AGEA/HERA company which is partner of the Ecotherm project. Because of the lack of automatic control due to the plant complexity, the regulation set points are ordinarily manually managed from the operators.
In fig. 5 a first preliminary experiment of the real plant on-line optimization is reported. The *alife* optimizer has been activated for about 6 hours after the first third of the experiment reported in the plot and deactivated in the last part.

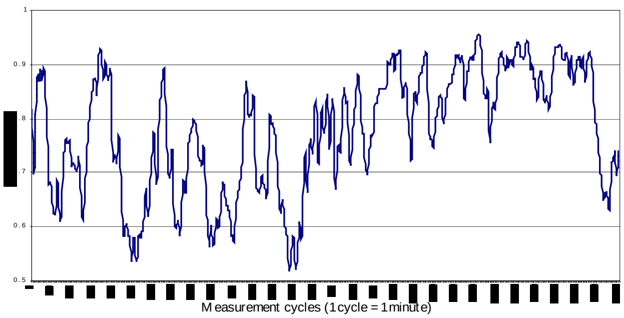


Fig 5: On-line optimization of the MSWC real plant

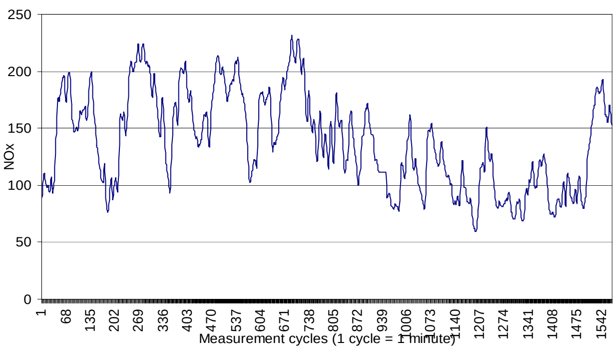


Fig 6: NOx emission on-line optimization

The results show the trend of about half day of experiments. This period is not still enough to give a complete judgment of the alife optimizer efficiency but some trend emerge quite clearly. The optimizer is able to take the control of the plant and also increase the performance of the process. This increase is related to the ability of alife to manage the regulation in order to better fulfill the process constraints. In the specific experiment of fig. 5 alife has increased the secondary air flow rate reducing the combustion chamber temperature. This had an effect in the reduction of NOx emission as resulted in the plot of fig. 6 corresponding to the same experiment. Furthermore, the management of the regulation carried out by alife seems quite more gradual in respect to the ordinary control strategy actuated manually by the operators.
On the base of these first experiments a significant limit seems to emerge when the performance value reach very low values due to sharp changes in external disturbances like suddenly changes in the waste calorific value. In these cases the alife optimizer is able to recovery the process but the recovery times (10-20 minutes) are not still compatible with plant requirements (1-5 minutes). This limit concerns the nature of the current alife structure which is an optimizer with some control ability but it cannot be considered as a stand alone controller. Future directions will focus this limit exploring faster response alife environments and/or integration with a controller module.

7. CONCLUSIONS

We have described an adaptive technique for on-line optimization 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 optimization of the process via a continuous learning and updating of its model.
Such methodology has been applied to improve the management of waste incinerators for energy generation. A multi-objective approach has been used to define a *performance index* for MSWC plant. The proposed approach is based over a fuzzy combination of several objectives of the optimization. A unique global index has been obtained to supply the evolutionary module. This definition takes into account the maximization of the process production (steam) with respect to the constraint in order to have a possibility to recover the process towards higher performances.
The method has been tested on a process simulator giving successful results in optimization and a good process control confirming the theoretical efficiency of the method.
Finally it has been installed on a real plant for field experimentation. Only preliminary tests have been carried out up to now and only qualitative conclusions are possible. On the base of the preliminary data, the system shows a good attitude in a continuous compensation of the external unknown disturbances gradually increasing performance and pushing the process in the full respect of the constraints. Future experimental tests are necessary to confirm these results in a large confident time period (i.e. months).
The limit of the method seems to be in the too slow time periods in the fast control that is necessary for process recovery after fall of performance due to external reasons. Future efforts are necessary to explore the possibility to increase the alife response time and/or integration with a control system.

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