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Biosocial Culture Inspired Hierarchical Algorithm for MISO Block Oriented Nonlinear System Identification: Application to Ozone Modelling

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Abstract: A new solution to nonlinear systems identification of MISO Hammerstein and/or Wiener models is developed using tools from Evolutionary Computation based optimization. A hybrid genetic and swarming intelligence based Hierarchical Cultural Algorithm is used to adapt the structure of the bad less suited model and to estimate the parameters of its dynamics and nonlinearities representation. Performances of such solution, illustrated through a real life application show how this class of tools can be very helpful to solve complex nonlinear problems such as the ozone phenomenon identification.

1. INTRODUCTION

There has been concern of System Evolutionary Identification in several previous investigations. In 1992, Genetic Algorithms (GA) have been successfully applied to off and on-line parameters parametric and non-parametric identification approaches by Kristinson and Dumont [1], to nonlinear model structure selection for NARMAX models using mono objective by Fonseca et al in 1993 [2], to multi objective optimization strategy by Rodriguez-Vasquez et al in 1997 [3] and to rational nonlinear structure and parameters identification by Billings and Mao in 1998 [4]. Also, in 1998 Genetic Programming (GP), a generic class for GAs, where genes and subsequently, genetic operations are generalized to any abstracted class objects others than alphanumerical types [5], were applied by Gray et al to nonlinear system structure and parameters identification, and this by considering differential and integral equations as well as Simulink elementary blocks as genes [6]. Nevertheless, their robustness is not without draw back: their unclear distinction between genotypic and phenotypic properties which make difficult real life reproduction operations transposition and their high implementation and computation complexities, especially when dealing with high number of real parameters. Fortunately, a few years ago, an emerging class of evolutionary computation methods, namely Particle Swarm Optimizers (PSO), has been shown to be efficient to continuous optimization problems, and has been successfully applied in 2005 to the combined Hammerstein-Wiener nonlinear model parameters identification Naitali and Giri [7]. These methods involve social behaviour and cognitive knowledge of individuals namely particles within a swarm. Such a class of optimization tools was introduced in 1995 by Kennedy and Eberhart [8] as an alternative to GAs and where both computation and implementation complexities are strongly reduced.

Here, the identification problem for systems that can be represented by a series of elementary nonlinear blocks such as Wiener and Hammerstein plants is considered. More specifically, a hybrid Evolutionary Identification Algorithm inspired from both biologic adaptation and social learning Meta heuristics is designed to simultaneously select the model type, to adapt its structure and to find consistent parameters estimates; and this in the cultural evolution computing model framework. In this approach, artificial microbiologic operations are resorted to select the model and to adapt its structure, while an artificial intelligence learning metaphor is used for behavioural parameters estimation. For lecture convenience, the content of this paper is organized as follows. In Section II, the considered system identification problem is defined. Section III, is devoted to the introduction to culture (or cultural) algorithms computing model, while section IV is dedicated to the proposed biosocial culture based optimization algorithm for block oriented Nonlinear Systems Identification and which constitutes the aim of the paper theoretical contributions; which algorithm is validated in section V through an ecological real life application and which is in occurrence, the ozone identification of the Basse Normandie region (France). Finally, some concluding remarks end the paper.

2. THE CONSIDERED IDENTIFICATION PROBLEM AND THE PROPOSED APPROACH

2.1. The Considered Plant

As depicted in figure 1.a, we are considering nonlinear systems that can be modeled by a series of Hammerstein and/or Wiener nonlinear plants given in figure 1.b and 1.c, and which are considered here as elementary nonlinear subsystems namely blocks.

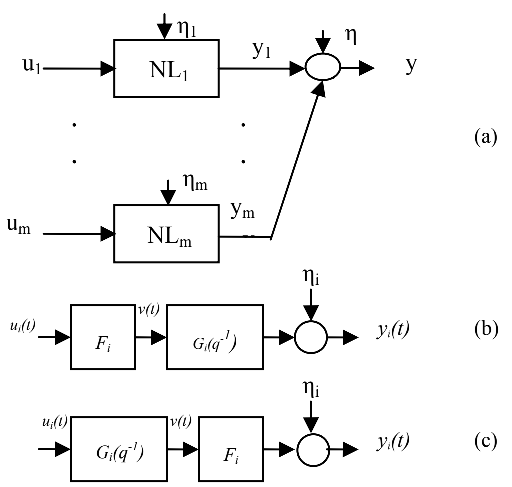

Figure 1 Miso nonlinear system Block sOriented Modelling: (a) the considered MISO Nonlinear plant and the retained elementary nonlinear block models (b) Hammerstein, and (c) Wiener.

$$y(t,\Theta) = \sum_{i=1}^{m} y_i(t,\theta_i) + \eta(t) \tag{1}$$

$$\Theta \overset{\Delta}{=} (\theta_i)_{i=1,..,m} \tag{2}$$

In such plant, by defining Θ as the concatenation of all blocks parameters (2), the Θ-parameterized system output y(t, Θ) can be defined as the noisy sum of all blocks output sequences, where each one is defined by equations (3) and (4), where H_i and W_i defined by (5-6) respectively denote the Hammerstein and Wiener nonlinear operators assumed to be real functions parameterized by a real vector θ_i concatenating the set of unknown block parameters to be identified.

$$y_i(t,\theta_i) = \mathsf{N}_i(\theta_i, u_i(t), \varphi_i(t-1)) + \eta_i(t) \tag{3}$$

$$\mathsf{N}_i \in \{\mathsf{H}_i, \mathsf{W}_i\} \in \mathsf{F}^2_{\Re \to \Re} \tag{4}$$

$$\mathsf{H}_i(\theta_i, u_i(t), \varphi_i(t-1)) = G_i(q^{-1}) \cdot F_i(u_i(t)) \tag{5}$$

$$\mathsf{W}_i(\theta_i, u_i(t), \varphi_i(t-1)) = F_i(G_i(q^{-1})u_i(t)) \tag{6}$$

$\{v_i(t)\}$ and $\{y_i(t)\}$ being internal immeasurable real sequences. The sequence $\eta_i(t)$ accounts for modeling errors and external zero-mean and bounded disturbances.

2.2. The Identification Problem Statement

be competitive in doing something, in addition to (i) sufficient skill and ability, a subject must not only (ii) be structurally adapted to the desired task, but also (iii) adapted to the environment where this task should be performed. Similarly, in addition to a sufficient knowledge, search agent's genotypic and phenotypic properties must be well adapted; and this by using socially motivated operators such as reproduction and learning. Morality, knowing that on one hand, genetic adaptation based algorithms are well suited to combinatorial optimization problems, and in the other hand that swarming intelligence based learning seems to be actually as one of most powerful evolutionary solution to continuous optimization problems, an hybridizing scheme based on a collaborative association, between Genetic adaptation and Particle Swarming intelligence computing models, seems to

Let G_i be the transfer function of the i[th] block dynamical part (7) where $A_i(q^{-1})$and $B_i(q^{-1})$ respectively designate the denominator and the numerator real polynomials in the backward shift operator $q^{-1}$of its dynamical part transfer function, expressed in the canonical form and where D_i, n_{Ai}, and n_{Bi} respectively denote the pure delay and degrees of $A_i(q^{-1})$ and $B_i(q^{-1})$ respectively; and **Let** $F_i(v)$ be the function approximating the nonlinear input or output static gains, and which is supposed to be d_i degree polynomial (8).

$$G_i(q^{-1}) = q^{-D_i} \frac{B_i(q^{-1})}{A_i(q^{-1})} = q^{-D_i} \frac{\sum_{k=1}^{nB_i} b_{i,k} q^{-k}}{1 + \sum_{k=1}^{nA_i} a_{i,k} q^{-k}} \tag{7}$$

$$F_i(v) = v(1 + \sum_{k=1}^{d_i-1} f_{i,k} v^k) \tag{8}$$

Then, **Under** the assumptions that for each block, (i)$\{v_i(t)\}$ and $\{y_i(t)\}$ are bounded; (ii) $\eta_i(t)$ zero-mean and bounded disturbances; (iii) $F_i(v)$ is continuous and not identically zero, bounded for any real v and satisfy the zero equilibrium condition ($F_i(0) = 0$); (iv) there is a known integer n_i that majors n_{Ai}, and n_{Bi} ; (v) $A_i(q^{-1})$ and $B_i(q^{-1})$ are co prime; (vi) all zeroes of $q^{nAi}A_i(q^{-1})$ are strictly inside the complex plan unit circle, and (vii) the input multivariable sequence $(\{u_i(t)\})_{i=1,..,m}$ is persistently exciting in the sense of the considered identification approach, The identification problem at hand can be stated as follows.

Given a consistent measurement data set containing the inputs $(\{u_i(t)\})_{i=1,..,m}$ and output $\{y(t)\}$ sequences,

Find for each elementary nonlinear block NL_i , the less complex plant structures (degrees), and parameters estimates θ_i corresponding to the coefficients of polynomials A_i, B_i and F_i that minimize the predicted output least mean square weighted error (8) in the time domain (LMSE).

$$\varepsilon(\Theta(d_{Max}, n_{Max}), \eta(t), t) = \frac{1}{N_s} \sum_{k=t+1}^{t+N} \lambda_k \| y(k) - \hat{y}(k) \|_2 \tag{9}$$

2.3. The Proposed Evolutionary Identification Approach

To solve this identification problem, here we propose a new evolutionary optimization algorithm for which the key idea was inspired from the following statement usually confirmed by observations made on living species such as bacterial, animal or human ones: **To**

be a good solution to the problem at hand. It is for these reasons that here we propose a new evolutionary Computing model based identification algorithm for MISO block oriented Nonlinear Systems; and this in a Biosocial Culture based evolution framework.

3. CULTURAL ALGORITHM: A BREIF OVERVIEW

3.1. Algorithm Structure and Components

A Cultural Algorithm (CuA) is a population based algorithm which has been introduced in the mid nineties by Robert G. Reynolds as a complement to evolutionary algorithms metaphor [9]. In such computing model, inspired from theoretical elements proposed in sociology and archaeology, culture is seen as an inheritance process, through which genotypic (structural) and phenotypic (traits) properties as well as behavioural (skill) methods are exchanged between collaborative societies (or nations) and transmitted through generations. This cultural process occurs in two evolutionary spaces. At one hand, the population space where individuals are evolved at the micro evolutionary level by using socially motivated operations such as reproduction and learning, and on the other hand, the belief space where socially accepted individuals are evolved at the macro evolutionary level, and this by using macro evolutionary operations based on current and archived best experiences exchanging and recombining.

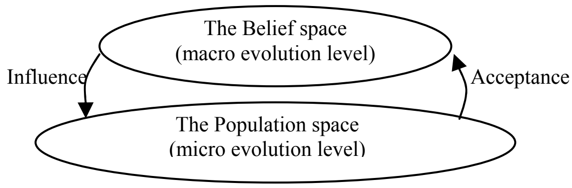

Figure 2 Cultural Algorithm evolutionary Meta model

These two spaces are linked together through two main relations: the Acceptance function which dictates some selection rules in the population space and the Influence one through which individuals in the population space are influenced by their neighbours accepted in the belief space. Which influence is conditioned by five knowledge sources stored in the belief space, namely the situational, normative, topological, historical and the domain ones and which will be briefly summarized here after. Topics related to system identification will be detailed in section 4.

3.2. Knowledge Sources involved in cultural evolution

The situational knowledge, This knowledge source or at least a part of it is implicitly used in all evolutionary computation algorithms. As indicated by its name, it is used to relatively situate individuals in the fitness (or objective) landscape. Basically, for mono objective optimization problems, it is constituted by a set containing a small proportion of the fittest individuals in the population space, for e.g. 20%. When a multi objective optimization problem is considered, this set turns out to be a set including the non dominated individuals in the sense of Pareto Dominance. This source of knowledge is mainly used to select individuals in the belief space to whom influence roles should be assigned. For genetic and swarming intelligence evolutionary processes, these roles correspond to genitors and learning guides respectively.

The normative knowledge, This knowledge source is an intelligent version of boundary constraints used to delimit the search space in evolutionary computation based constrained optimization. But rather than being static, these boundaries are dynamically updated to delimit progressively promising zones within the search space. Among others, the search subspace delimited by these boundaries, namely the normative space, is used to spars individuals encoding unfeasible solution instead of uniformly randomizing them anywhere in the whole search space.

The topological knowledge, In its general form, this knowledge source corresponds to the set of parameters and relations characterizing individuals in both population and belief spaces. It is used to situate individuals in the search space, and thus to allow the selection of the nearest or similar best actor for the considered evolutionary operations such as guides for learning or partner for matting.

The historical knowledge, This source of knowledge is generally used to predict slowly time varying shifts in the objective landscape. It is usually extracted via statistical analysis of archived similar situations the algorithm was previously faced with. As one can suspect, such source may be very helpful when dealing with adaptive systems.

The Domain Knowledge, This knowledge is constituted by all domain oriented rules sets ensuring normal operating conditions of the system under optimization. Nevertheless, for robustness reasons, this knowledge is generally not used in the scope of constrained optimization.

4. BIOSOCIAL CULTURE BASED BLOCK-ORIENTED NONLINEAR SYSTEM IDENTIFICATION

In constrained optimization, the choice of the decision variable and subsequently the definition of the search space play a major role in the convergence properties of the computing model based search algorithm. This choice must be well adapted to the nature of the model used for the system representation especially in System Evolutionary Identification due to the damping nature of dynamical processes. Once this choice is made, and as it should be shown later, all design elements of the optimization algorithm implementation are subsequently developed.

4.1. Search Space and decision Variable Definitions

In block oriented nonlinear system identification, and with decreasing level of abstraction, a plant can be modelled by (i) a model type with unknown topology and unknown structure, (ii) a model type with unknown topology but known structure, or (iii) a model Type, with known topology and structure. In the present study, since block types and structures dimensions are also to be identified, the construction of an appropriate alphabet to describe elementary components of the system becomes necessary. Depending on the complexity of the considered model, several alphabets can be considered. For system identification, the most likely ones are the transfer function and polygonal functions for linear time invariant systems and static nonlinearities respectively. Here, for some duality reasons, we adopt the Hammerstein and the Wiener nonlinear plants (figures 1.b and 1.c), as elementary nonlinear blocks and which can be both represented by two natural numbers designating the polynomial degree d_i and the dynamic order n_i, and by the nonlinearity and dynamic polynomials coefficients. Nevertheless, this representation is not practice. It may lead to strongly irregular objective landscape and non compact search domain. To avoid this problem, here the search space is defined as the union set of subspaces that respectively contains the zeros, and the stable poles of the dynamics, and the roots of the static nonlinear function rather than the parameters of the canonical forms given in equations 7 and 8. Doing so, feasibility conditions such as stability and realization ones can be formulated as boundary constraints and subsequently be simply handled by standard boundary operators such as saturation or randomization commonly used in evolutionary optimization algorithms. In our point of view, this choice is the key idea which highly improves evolutionary Algorithms for automatic control problems. With this attention, polynomials $F_i(v)$, $A_i(q^{-1})$, and $B_i(q^{-1})$ previously introduced in equations (7) and (8) are rewritten in their roots forms as in (10), where $\sigma_k(X)$, $\rho_k(X)$ and $\gamma_k(X)$ denote the functions that retrieve the k^{th} real roots and imaginary and real parts of complex roots of the polynomial X respectively (X is any of F_i, A_i, and B_i) and where n_{XRR} and n_{XCR} respectively stand for their numbers; the symbol $(\bullet)$ is used to denote the considered polynomial variable.

$$X(\bullet) = (\bullet)^d \cdot \prod_{k=1}^{n_{Xrr}} \left(1-\gamma_k(X)(\bullet)\right) \prod_{l=1}^{n_{Xcr}} \left(1-2\sigma_k(X)(\bullet)+\rho_k^2(\bullet)^2\right) \qquad (10)$$

With respect to this representation, the searched parameters vector $\mathbf{\Theta}$ given in equation (2) corresponds to the concatenation of all nonzero real roots, and real and imaginary parts of nonzero complex roots of the polynomials F_i, A_i, and B_i' of all blocks constituting the system under identification; while zero roots, when they exist, are merged in a unique entry in $\mathbf{\Theta}$ and which corresponds to the product $(f_{i1}.b_{i1})$ of polynomials F_i and B_i first coefficients.

Subsequently, and as encoded in equations (11-17), a decision variable which fully describe the considered model (fig1) is composed by three fields: (i) the Karytype, a short binary string encoding all block types constituting the plants, (ii) the Genotype, a long binary string encoding the concatenation of the structural properties of all blocks, and finally (iii) the Skill, a real vector or Array corresponding to the behavioural parameters (static and dynamic).

$$\Theta = ((\mathsf{K}_i)_{i=1,..,m},(\mathsf{G}_i)_{i=1,..,m},(\mathsf{S}_i)_{i=1,..,m}) \in S \subset S' \qquad (11)$$

$$S' = \{0,1\}^m \times \mathrm{N}^{6m} \times \Re^{m(d_{Max}+2n_{Max})} \qquad (12)$$

$$\mathsf{G}_i = (n_{CPPi}, n_{RPi}, n_{CZPi}, n_{RZi}, n_{CRPi}, n_{RRi}) \in \mathrm{N}^6 \qquad (13)$$

$$\mathsf{S}_i = (R_i, P_i, Z_i, \tau_i) \in \Re^{d_i} \times \Re^{n_i} \times \Re^{n_i} \times \mathrm{N} \qquad (14)$$

$$R_i = \left(\left(\sigma_k(G_i), \rho_k(G_i)\right)_{k=1,..,n_{CRP\,i}}, \left(r_k(G_i)\right)_{k=1,..,n_{RR\,i}} \right) \qquad (15)$$

$$P_i = \left(\left(\sigma_k(A_i), \rho_k(A_i)\right)_{k=1,..,n_{CPPi}}, \left(r_k(A_i)\right)_{k=1,..,n_{RPi}} \right) \qquad (16)$$

$$Z_i = \left(\left(\sigma_k(B_i), \rho_k(B_i)\right)_{k=1,..,n_{CZP\,i}}, \left(r_k(B_i)\right)_{k=1,..,n_{RZ\,i}} \right) \qquad (17)$$

where $n_{CPPi}, n_{RPi}, n_{CZPi}, n_{RZi}, n_{CRPi}, n_{RRi}$ respectively designate complex poles pairs, real poles, complex zeros pairs, real zeros, complex roots pairs and real roots numbers, which lead to the following search space definition (18).

$$S = \left\{ \{0,1\} \times \{0,..d_{Max}-1\} \times \left\{0,..\left[\frac{d_{Max}-1}{2}\right]\right\} \times \left\{ \{0,..n_{Max}\} \times \left\{0,..\left[\frac{n_{Max}}{2}\right]\right\} \right\}^2 \times \Re^{(d_{Max}+2n_{Max})} \times N \right\}^m \qquad (18)$$

4.2. Biosocial Culture Based System Identification

In the considered optimization problem, the task of finding both structural and behavioral properties by using a unique evolutionary operator based algorithm is not without posing some uncontainable problems, due at one hand to the numerical heterogeneity of structural and behavioral parameters, and at the other hand, to their strong interactions. Here, in order to separate evolution processes of heterogeneous properties, an interesting feature then is to divide optimization efforts and complexity on several evolutionary operators, by customizing each one for a particular optimization task; and this in a culture framework.

4.2.1. Evolutionary Operations For Biosocial Culture

Knowing that at one hand genetic adaptation based optimization approaches are well suited for combinatorial search problems and at the other hand that swarming intelligence is well adapted for continuous ones, here we use three evolutionary computing model: (i) a genetic programming algorithm which is used to adapt karitypic properties of the plant, (ii) a genetic algorithm to adapt its structure and finally (iii) a Particle swarm optimizer for behavioral parameters learning; and this according to diversity guided culture strategy depicted in figure 3.

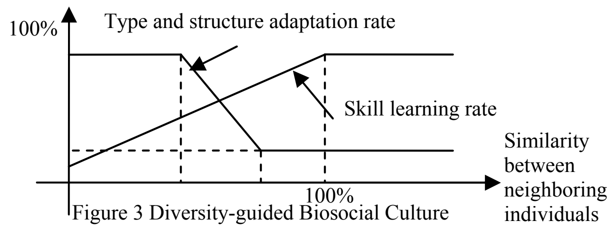

Figure 3 Diversity-guided Biosocial Culture

4.2.2. Decision Variable Encoding and Implementation

According to the considered evolutionary operators karitypic properties representing block types are encoded as logic states string in a single 8 bit word length. Block genotypic properties (numbers of real and complex roots of polynomials) are concatenated in a single 32 bit word length, which make possible to attempt degrees and orders up to 45, while real parameters are encoded as a real array of size m(2nMax+dMax+1) in an object class namely Particle.

TABLE I. Genotypic properties binary encoding

degree	order	delay	nRoots	nZeros	nPoles
$g_{31}..g_{28}$	$g_{27}..g_{22}$	$g_{21}..g_{16}$	$g_{15}..g_{12}$	$g_{11}..g_6$	$g_5..g_0$

Further more, to allow individuals learning from guides of different genotype, parameters or skill elements having the same sense must be located in the same entry, with this attention the roots of each polynomial are encoded in a formatted array (19) where all entries corresponding to non existing roots are filled with zero after each evolution (X is any of polynomials R_i, P_i and Z_i).

$$X \stackrel{\Delta}{=} \left[(\sigma_k, \omega_k)_{k=1,..,n_{crp}}, (0_k)_{k=1,..,n_M-2n_{crp}}, (\rho_k)_{k=1,..,n_{rr}}, (0_k)_{k=1,..,n_M-n_{rr}} \right] \qquad (19)$$

subsequently, block types and structural (block dimensions) and behavioral (static and dynamical) parameters of the hole system, can be reorganized in a global decision variable as defined in table II and where the ki's, si's and ri's respectively designate logic, integer and real numbers.

TABLE II. Kari type, Genotype and skill encoding

Blocks types (Karitype)	Structural properties (Genotype)	Behavioral properties (Skill)
$k_{m-1}\, k_{m-2}\, \ldots k_1$	$s_{32m-1}\, s_{32m-2}\, \ldots\, s_1\, s_0$	$r_{mx(2nMax+dMax)-1} \ldots r_1 r_0$
Logic String	*Binary encoded integers*	*Real Array*

Object classes developed for the implementation of this decision variable are given in table III.

TABLE III. Search Agents: Object Types and Related Operations

Object	Operations	Property	Class
System	Identification	Decision	Agent
Types	Genetic Programming based Adaptation	Kari type	Kari type
Structures	Genetic Algorithm based Adaptation	Genotype	Chromosome
Parameters	Swarming Intelligence Based Learning	Skill	Particle

Here, Genetic adaption is implemented by the well known Uniform binary mutation and the uniform crossover. The mutation operator associated with genetic programming adaption corresponds to a block type swapping from Hammerstein to Wiener and vice-versa. The Swarming intelligence based learning operator is the stochastic movement developed by psychological and social back motion forces applied to each particle exactly as the one used in standard particle swarm optimization.

4.2.3. The Considered Knowledge Sources

It is worth noting that all the five sources of knowledge introduced above can be used to solve the considered system identification problem. Here we use only the three main sources of knowledge and which are, with decreasing importance, the situational, the topological and the normative knowledge. For robustness ends the domain knowledge is not used; and since the plant is supposed to be stationary, the historical knowledge is also not considered.

The situational knowledge, In system identification, we are interested in finding an estimated model for which the predicted output match as well as possible the real (measured) one. This is generally achieved by minimizing the least mean weighted square error (9). In addition, since block structures are also to be adapted and the block type to be selected, optimization objectives turn to be a multiple one. In this situation, a commonly used concept for comparison between decision variables is the Pareto dominance. In practice, due to binary explosion problem, the e-dominance concept is used instead. Subsequently, the situational knowledge is implemented here as an archive or a collection containing the non dominated set.

The Normative Knowledge, The Normative knowledge is represented by a set of four real vectors indicating the lower and upper bounds of the considered search Space as well as the corresponding valued objectives.

The Topologic Knowledge, To distinguish solutions, many similarity or dissimilarity metrics are to be introduced according to the nature of the considered models and their complexity. Two solutions to the considered optimization problem, or simply individuals are said to be similar in certain view point if and only if the corresponding distance is less than a critical value. Here dissimilarity metrics are introduced in the mean of genetic adaptation and swarming intelligence based learning i.e. they constitutes a base criteria for selecting partner for matting and guide for learning. Subsequently, two classes of distances are to be considered for similarity evaluation, the Hamming (20-21), and the Euclidian (22) distances for structural (Kari types and genotypes), and behavioural (skill) properties and **where** $\mathsf{K}(x)$, $\mathsf{G}(x)$ and $\mathsf{S}(x)$ denote functions that retrieve Karitypic, genotypic and skill properties of an individual x.

$$d_{\mathsf{K}}\left(x_i, x_j\right) = d_H\left(\mathsf{K}(x_i), \mathsf{K}(x_j)\right) \tag{20}$$

$$d_{\mathsf{G}}\left(x_i, x_j\right) = d_H\left(\mathsf{G}(x_i), \mathsf{G}(x_j)\right) \tag{21}$$

$$d_{\mathsf{S}}(x, y) = d_E\left(\mathsf{S}(x_i), \mathsf{S}(x_j)\right) \tag{22}$$

Based on modelling approaches, the whole set of nonlinear models dedicated to represent nonlinear systems can be seen as a universe constituted by a collection of worlds where each one is corresponding to a given nonlinear system modeling approach. Among these worlds, here we are interesting in the one containing the set of block oriented nonlinear models based on Hammerstein and Wiener nonlinear plants.

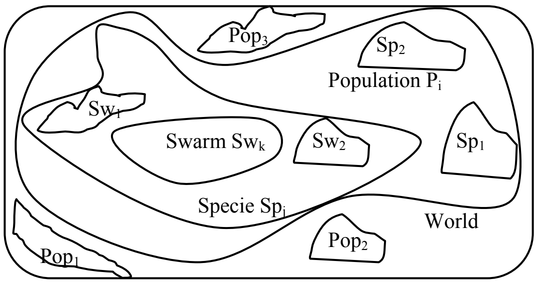

Figure 4 Ecological/Governmental Evolutionary computations Meta Model

Based on similarity metrics indicated by karitypic, genotypic and skill distances (20-22), and as depicted in figure 4, one can organize the world of Hammerstein and Wiener Block oriented nonlinear models as a set of populations where each one is composed by models or equivalently individuals having similar Karitypes, and where each population is divided into subsets of individuals having similar structures and forming species, themselves organized as swarms containing individuals with similar skills. Such hierarchical organization which finally constitutes the topological knowledge is implemented as a dynamic clustering multi-nary tree (figure 5).

4.2.4. Algorithm Structure, Components and Statement

Algorithm structure, To support the considered sources of knowledge, and especially the topological one, the proposed algorithm is implemented as a 4-level multi-nary tree.

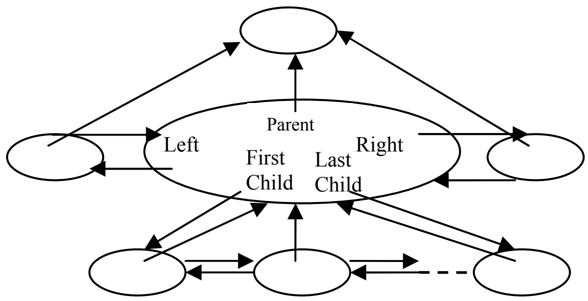

Figure 5 hierarchical cultural Algorithm

In such tree, each node is itself a cultural algorithm where population and belief spaces are dynamically managed according to karitypic, genotypic and skill clustering properties of all individuals. Collection object classes designed for the purpose of this study as well as their main operations and methods are given in table IV.

TABLE IV COLLECTIONS OBJECTS AND METHODS

Collection Objects	**Class**	**Operations**
nonlinear Models	Universe	selection
Block oriented nonlinear models	World	selection
Group of models, within a world, with similar karitype	Population	karitype Adaptation
Group of models, within a population, with similar structures	Specie	structures Adaptation
Group of models, within a Specie, with the same structure and similar skills	Swarm	Skill learning

1. Refer to the root algorithm;
2. switch (clustering level){

3. case WORLD: Update feasibility and objectives of each individual in the world, update knowledge sources, select an evolution Strategy and update its parameters; break;

4. case POP: if (genetic computation is retained by the selected strategy) execute a genetic programming operation step and update .. , if necessary; break;

5. case SPECIE: if genetic evolution is retained by the selected strategy) execute a genetic algorithm operation step and update, if necessary; break;

6. case SWARM: Swarming(n_S); break;
}
7. For each child algorithm, execute the sequences 2 to 7;

Figure 6 Hierarchical Cultural Algorithm Statements

Algorithm statement, In the initial state, all individual are grouped in the population space of the root algorithm, population spaces of child algorithms are then obtained by hierarchical clustering according respectively to block types, genotype and skill properties. Once clustering properties are evaluated, all individuals in the population and belief spaces are bio sociologically evolved. These operations are sequentially launched until the meeting of the considered optimization objective.

4. APPLICATION TO OZONE IDENTIFICATION

We seek a block oriented nonlinear modelling of the ozone process based only on inputs and output data measurements. The used data has been collected by AIRCOM at different measurement sites of the French city Caen. The input variables that showed the highest correlation with the output are [10]: NO2, NO, Temperature, Wind speed, Humidity, and Solar radiation. The used model is the one depicted in figure 1. Only swarming intelligence based learning culture has been activated. Karitypic and genotypic properties were manually selected after some try runs. The model is a Wiener with one poles pair, one real zero, 7 complex root pairs and 7 real roots, which corresponds to a second order dynamic and a 21 degree polynomial nonlinearity, and the all initial niching radius for clustering were set to 0.135. The model obtained with 3000 generation and only 64 agents turned out to be quite satisfactory, [11].

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