Preface

The concern of this book is the use of emergent computing and self-organization modelling within various applications of complex systems. We focus our attention both on the innovative concepts and implementations in order to model self-organizations, but also on the relevant applicative domains in which they can be used efficiently.

First part deals with general modelling and methodology as conceptual approaches for complex systems description. An introductive chapter by Michel Cotsaftis entitled "A Passage to Complex Systems", treats the notion of "Complex Systems" in opposition to that of a "Complicated System". This can be, he claims, comprehended immediately from the latin roots as "Complex" comes from "cum plexus" (tied up with) whereas "complicated" originates from "cum pliare" (piled up with). The paper is a wide and rich dissertation with elements of history (of the technical developement of mankind) with its recents steps : mechanist, quantum and relativistic points of view. Then, the need for a "passage" is illustrated by the discussion, with tools borrowed from functional analysis, of a typical parametric differential system. The last and conclusive parts give tracks for the study of Complex Systems, in particular one can hope to pass to quantitative study and control of complex systems even if one has to consent a "larger intelligence delegation" to them (as announced in the introduction) by using and developing tools already present in dissipative Physics and in Mathematical functional analysis and fixed point theorems, for instance. This "passage" is followed by a wide bibliography of more than 90 entries. The (non hasty) reader is invited to read this deep and far reaching account before browsing through the book.

The chapter, "Holistic Metrics, a Trial on Interpreting Complex Systems" by J. M. Feliz-Teixeira et al., proposes a simple and original method for estimating or characterize the behaviour of complex systems, in particular when these are being studied throughout simulation. The originality of the chapter lies in the fact that the time/observable space is replaced by the corresponding variable/observable space (as one does for Wavelet Transforms and in Quantum Mechanics). Next chapter, “Different Goals in Multiscale Simulations and How to Reach Them” by P. Tranouez et al., summarizes the works of the authors on multiscale programs, mainly simulations. They present methods for handling the different scales, with maintaining a summary, using an environmental marker introducing a history in the data and finally using knowledge on the behaviour of the different scales to handle them at the same time. “Invariant Manifolds in Complex Systems” by J.-M. Ginoux et al. shows how to locate, in a general dynamical system (on a 2,3 dimensional variety) remarkable subsets which are flow-invariant. Part I ends with a chapter by Z. Odibat et al. entitled “Application of Homotopy Perturbation Method for Ecosystems Modelling” (HPM). HPM is one of the new methods belonging ranking as one of the perturbation methods. The attention of the reader is focused on the generation of the decomposition steps to build a solver using the HPM method. Concrete solvers for prey-predator systems involving 2 or 3 populations are computed and a special attention is paid on implementation aspects.

Second part deals with swarm intelligence and neuronal learning. We focus our attention here on how implement self-organization processes linked to applicative problems. Both swarm intelligence and neuronal learning give some ways to drive the whole system, respecting its complex structure. F. Ghezail et al. use one of the most efficient swarm intelligence processes, ant colonies method, to solve a multi-objective optimization problem. J. Franzolini et al. present a very promising new approach based on swarm intelligence, immune network systems. They give detailed explanation on the biological metaphor and accurate simulation results. The last chapter of this part, by D.A. El-Kebbe et al., deals with the modelling of complex clustering tasks involved in cellular manufacturing, using neural networks. On the basis of Kohonen’s self-organizing maps, they introduce Fuzzy Adaptive Resonance Theory (ART) networks to claim on their efficiency to obtain consistent clustering results.

Third part entitled “Socio-Environmental Complex Modelling and Territorial Intelligence”, deals with the complexity of systems where space is fundamentally the center of the interaction network. This space interacts on the one hand, with human themselves or their pre-defined or emergent organizations and on the other hand within natural processes, based on living entities inside ecosystems or also on physical features (like in the complex multi-scale phenomena leading to cliff collapse hazards described by Anne Duperret et al.). In the first case, we focus on geographical information systems (GIS) where humans are now able to notify, with an accuracy of location, the material based on their own organization. Even if these GIS contitute an impressive database in static way at a fixed time, they are still not able to restitute the complexity of the human organization dynamics and we propose in this book some research developments to lead their evolution toward their inherent complexity. H. Kadri-Dahmani et al. study the emergent properties from the GIS updating propagation process over an interactive network; R. Ghnemat et al. focus on the necessity of mixing GIS with active processes called agents which are able to generate emergent organization from basic simple rules like in Schelling's segregation model; D. Provitolo proposes a methodology deeply inspired from the complexity concepts, for modelling risk and catastrophe systems within dynamical systems; G. Prevost et al. propose an effective methodology, based on adaptative processes, to mix the two majors classes of simulation: differential approach and individual-based approach. Through the unavoidable expression of the complexity expressed in these different contributions, we can feel how the Complexity Science renovates the modelling approaches, respecting and highlighting the fundamental and classical methods by the "cum-plexus" combination of them to express the whole system complexity, more than by the addition of a long list of complicated scattered sub-systems.

Fourth part deals with emotion modelling within the cognitive processes as the result of complex processes. The general purpose here is to try to give some formal description to better understand the complex features involved in the essential emotion–cognition–action interaction. Decision making is one of the result of this interaction: K. Mahboub et al. study and propose a model to mix in a complex way the emotional aspects in some player choices. In a second paper, S. Baudic et al. propose a relevant approach leading to confront theory and clinical practice to better improve the knowledge of emotion and its interaction with memory (with practical illustration based on Alzheimer's disease) and with cognition (through the fear behaviour). Therapeutic applications can then be implemented from this methodology.

Fifth part deals with simulation and production systems. In that field, Complexity Science gives a new way to model the engineering process involved in some productions systems dealing with the management of a great number of components and dimensions in multi-representation and multi-scale description. The contribution of B. Kausch et al. deals with this complex process, applied to chemical engineering, using Petri nets modelling. The contribution of G. Giulioni claims that self-organization phenomena and complexity theory is a relevant way to model economic reality. This study proposes a model based on the economic result of a large number of firms based on the evolution of capital and the dynamics of productivity. The discussion from output results enlights the emergence of attractors on the aspects of limit cycles and possible transition to equilibrium. The contribution of A. Dumbuya et al. deals with the complexity of traffic interaction and the development of a driver model based on neural networks. The goal is to improve the behavioural intelligence and realism in driving simulation scenarios.

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Holistic Metrics, a Trial on Interpreting Complex Systems

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Summary. In this text is proposed a simple method for estimating or characterize the behaviour of complex systems, in particular when these are being studied throughout simulation. Usual ways of treating the complex output data obtained from the activity (real or simulated) of such a kind of systems, which in many cases people classify and analyse along the time domain, usually the most complex perspective, is herein substituted by the idea of representing such data in the frequency domain, somehow like what is commonly done in Fourier Analysis and in Quantum Mechanics. This is expected to give the analyst a more holistic perspective on the system's behaviour, as well as letting him/her choose almost freely the complex states in which such behaviour is to be projected. We hope this will lead to simpler processes in characterizing complex systems.

1 Introduction

There are presently very few notes on the kind of metrics that could be reliable and of practical relevance when applied to the interpretation of complex systems behaviour. These systems are often based on intricate structures where a high number of entities interact with each other. Metrics are there for appropriately characterizing the nodes or individual parts of such structures, or small groups of them, but when the intent is a measure for the complete structure either they fail or appear to be too simplistic. That is certainly a good reason for modelling those cases using a strategic point of view, removing the time variable from the process, as in doing so the complexity is reduced a priori.

But when a dynamic and detailed representation is essential, the interpretation of the results and the characterization of the system frequently fail. This issue seems sometimes also related to a certain tendency impregnated in the minds to look at the systems from a pre-established perspective. At this point, however, perhaps this may be considered a conflict between different scientific approaches: the classical western reductionism, of anglo-saxonic inspiration, which believes the best approach is to break the system into small parts and understand, model or control those parts separately and then join them together, therefore looking at the world in an individualist way; and a more holistic approach, a vision slowly spreading and largely inspired by oriental cultures, which considers that each part of the system must be seen together with the whole and not in isolation, and therefore locates the tone in how the interactions between such parts contribute to the whole behaviour. Hopp and Spearman [Hopp et al. 2001], for instance, comment about this saying that "too much emphasis on individual components can lead to a loss of perspective for the overall system".

A significant number of authors defend this opinion, pointing out the importance of developing a more holistic point of view to interpret and study systems behaviour, in a way that analyses maintain enough fidelity to the system as a whole. As Tranouez et al. [Tranouez et al. 2003], who apply simulation to ecosystems, would say: a complex system is more than the simple collection of its elements. In management science, for instance, the "western" approach frequently generates difficulties at the interfaces between elements, typically of inventory or communication type. On the other hand, as just-in-time (JIT) systems give better emphasis to the relations and interactions and are continuously improving, the overall movements tend to be more harmonious. JIT already looks at systems in a certain holistic way. The same seems to be true in regard to other fields where simulation is applied, and mainly when the number of states to simulate is high.

2 Holistic measuring (a proposal)

But, what concerning metrics? How can one measure such a high number of states typically found in complex systems in order to effectively retrieve from them some sort of useful information?

As a metric is a characterization, we could think that maybe the modern Data Mining (DM) techniques could be extensively applied, for instance. These techniques use decision trees and other algorithms to discover hidden patterns in huge amounts of data, and are nowadays applied to almost any problem based on extensive data records, for instance, in e-Commerce for customer profile monitoring, in genetics research, in fraud detection, credit risk analysis, etc., and even for suspected "terrorist" detection (see Edelstein, [Edelstein 2001, Edelstein 2003]). However, they often imply the usage of high performance computers, sometimes with parallel processors, as well as huge computational resources to analyse GBytes or even TBytes of data. They are useful when any single record of data can be precious for the future result, and thus when all data must be analysed.

On the other hand, in many practical simulations a significant amount of data is not significant for the final conclusions, the simulation process is in itself a filter, and therefore such data may well be ignored in the outputs, even if it could have been essential to ensure the detailed simulation process to run. In the perspective of the author, maybe there is a way that could deserve some attention: the idea is to filter such data during the simulation execution and, at the same time, to turn the measures probabilistic by using an approach somehow inspired by the Fourier Analysis and the Quantum Mechanics. That is, to represent the overall system state (Ψ) in terms of certain base functions (Ψ_i), and then to measure the probabilities (α_i) associated with each of these functions. The interesting aspect of this is that each base state function (Ψ_i) could even be arbitrarily chosen by the analyst, and the probabilities (α_i) easily computed during the simulation process. Final results would then be summarised in some expression of the form:

$$\Psi = \alpha_1\Psi_1 + \alpha_2\Psi_2 + ... + \alpha_i\Psi_i + ... + \alpha_n\Psi_n \qquad (1)$$

which could be interpreted as: there is a probability of α_1 that the system will be found in the state Ψ_1, a probability of α_2 that the system will be found in the state Ψ_2, etc. This would be the final measure of the system, in a sort of characterization of expectations under certain conditions. This also corresponds to projecting the system behaviour into the generalised vectors base of state functions (Ψ_i). The amounts α_i simply correspond to the values of those projections.

In Fourier Analysis, for instance, the complex behaviour observed in the time axis (see the example of figure 1) is substituted by the decomposition of such a signal into *sine* and *cosine* mathematical functions, and that way transferred to the frequency domain.

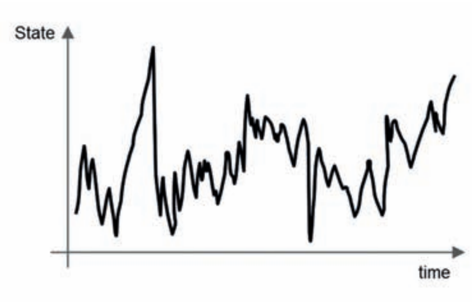

Fig. 1. Example of a general complex signal

The result is that the analyst is now much more able to visualize and to interpret the complexity of the previous signal, since it is as if this signal would be now expressed in terms of patterns (see example of figure 2). What firstly appeared as a confusing and almost randomly up-and-down behaviour may now be simply understood as the summation of some sinusoidal patterns with different amplitudes. Quantum Mechanics uses a similar formalism. We believe that the method proposed here will help generating such a clean view also when applied to the behaviour of complex systems.

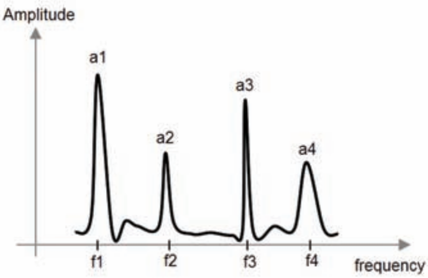

Fig. 2. Typical signal in the frequency domain

The present proposal may also be understood as an attempt to represent the system's behaviour in terms of a sort of generalised histogram, where the categories are the functions Ψ_i, which may correspond to the frequencies f_i in the previous figure, and the probabilities α_i are made to correspond to the amplitudes a_j in the same figure. In terms of this figure, the analyst would recognize a probability of a_1 that the system would be found in the state f_1, a probability of a_2 that the system would be found in the state f_2, etc.

3 An imaginary example

But, to help explain this, we can imagine a complex system like the Supply Chain shown in figure 3, for example. This is an example inspired by the company ZARA, the trendy Spanish clothes manufacturer of La Coruna. This company, from the INDITEX group, is worldwide known as a paradigm of success, despite its owner, and major manager, Mr Ortega, the second richest person in Spain, refusing several conventional practices claimed by most schools of management. ZARA refuses, for instance, the idea of advertisement. Forgive me if indirectly I am advertising it here. Returning to our subject, how can we apply our concept of holistic metrics to retrieve some useful information from such a complex case [1]? How can we specify the base functions

[1] In this figure is represented less than perhaps 10% of the real ZARA global Supply Chain structure.

(or base states) in which the system's behaviour will be projected? How will we calculate and represent the respective projections?

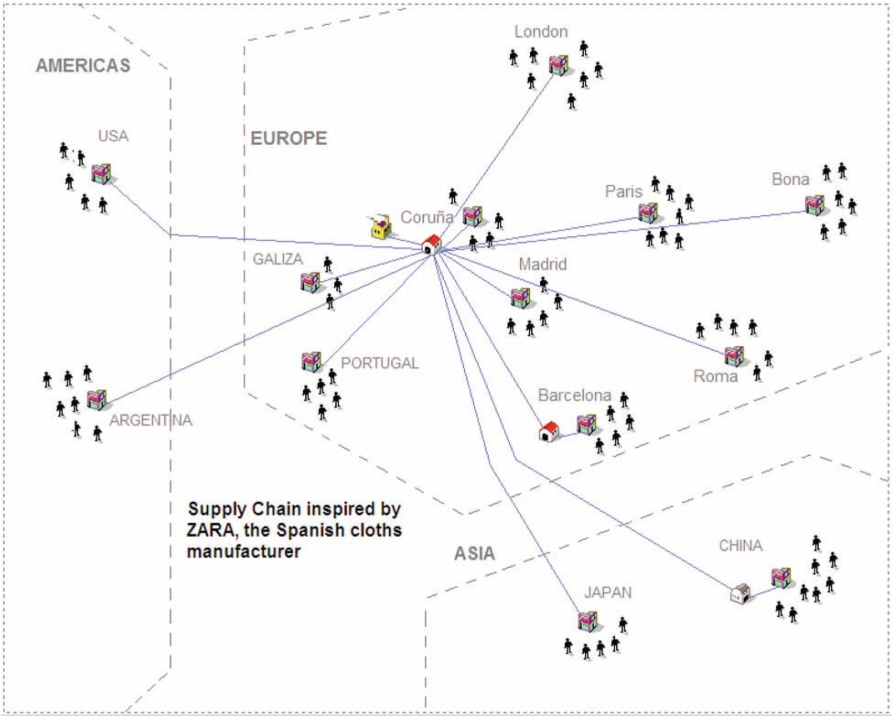

Fig. 3. Imaginary Supply Chain inspired by ZARA

First of all, we have to choose the Ψ_i functions into which the measures will be projected. We may choose them in terms of some specific *conditions* related to the information that must be obtained from the system. For example, if Mr Ortega is concerned about the levels of *stockouts*, *holdingcosts*, *servicelevel*, *turnover*, etc., which are typical measures of Supply Chain Management, he may for example define some sort of base functions by using conditions of the type:

Ψ_1 - *Stockouts* above 7%;
Ψ_2 - *Holdingcosts* above 5%;
Ψ_3 - *Servicelevel* under 75%;
Ψ_4 - *Turnover* under 2%.

Then, while the system is running, it must be *projected* into these set of functions, that is, the occurrences of each of these conditions must be counted up, whenever they are true. Thus, supposing n_j the accumulated number of occurrences of the condition Ψ_j, and N_j the total number of its samples, an estimation of α_j can simply be computed as:

$$\alpha_j = n_j/N_j \tag{2}$$

And the overall system state will therefore be expressed as:

$$\Psi = (n_1/N_1)\Psi_1 + (n_2/N_2)\Psi_2 + (n_3/N_3)\Psi_3 + (n_4/N_4)\Psi_4 \tag{3}$$

Notice that, in general, base functions are chosen to be orthogonal, or independent of each other, but in fact that is not a must for using this type of representation. One can also project a system into non orthogonal axis. As we said previously, such a measure may be seen as a characterization of expectations under certain conditions. The overall system state is, in reality, represented by the following weighted expression:

$$\begin{aligned} &\alpha_1 \times (Stockouts > 7) + \alpha_2 \times (Holdingcosts > 5) \\ &+\alpha_3 \times (Servicelevel < 75) + \alpha_4 \times (Turnover < 2) \end{aligned} \tag{4}$$

Now, if we build a histogram out of this data, we will characterize the system by means of a probabilistic graphical format, obtaining something of the type presented in the next figure (Fig.4), where the probabilities are the α_i.

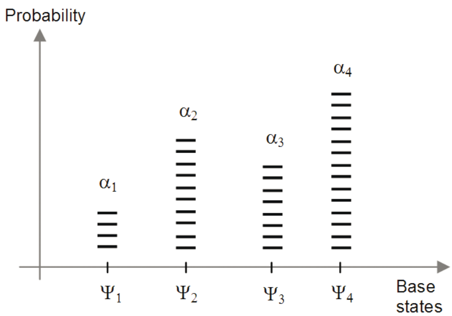

Fig. 4. Characterization of the system's behaviour

So, once the base states are well defined by the analyst, the characterization of the system is possible, no matters how complex the system is. We recall that in many practical cases the analyst is mainly focused in being sure that certain variables of the model do not cross some upper or lower limits, or, if they do, with which probability it happens. In order to evaluate the system in a wider range of modes of behaviour, several studies of this kind can be made with the system operating in different conditions. That will make possible to improve the knowledge about the system, or its characterization.

The former example was taken from a typical Supply Chain problem (see Feliz-Teixeira [Feliz-Teixeira 2006]), but this technique can be applied in general to other complex systems. For example, in a traffic system of a town, the complex states could be chosen to be the number of cars exceeding a certain value in a certain region, the travel time exceeding a certain value in another region, the number of public vehicles reaching a certain zone inferior to the minimum required, etc. As we recommend that these base functions (or complex base states) be well defined before simulation takes place, it implies that the simulation objectives must be well known prior to the start of the simulation process. Not always this is possible, of course, since simulation can be used to detect anomalous situations not predictable by means of other methods, for example.

This technique may, however, be also used as a method for analyse any sort of results, by being directly applied to the raw outputs of the complex system. In that case, the simulation will be a standard process and all the work is done by data manipulation. The results, in principle, will be the same, but that approach will in general be much more time consuming.

Finally, we would like to emphasise that we use the term "holistic metric" for distinguishing this kind of approach from those approaches which usually characterize systems by means of averages and standard deviations taken over a certain number of variables (usually a high number). These, as we know, frequently confuse the analyst's mind with the complexity of the results, instead of allowing a useful interpretation of the system's behaviour. Quantity of information is not all, and sometimes it can even generate confusion instead of clarity, if it is in excess. Besides, the method presented here goes on the trend of the "holistic" mind that seems to emerge in our days, as we defend.

4 Conclusions

Complex results generated by a complex system are very much dependent on how the analyst looks at the system and on how such results are analysed. We would say that any complex system can be minimally understood as long as the analyst knows what to search for, that is, if the objectives of the study are previously defined. This is because such objectives can in reality be used to establish the base functions (vectors) of an imaginary space where the complex behaviour will be projected, that way giving an automatic meaning to the results. This may also be seen as an attempt to measure the outputs of systems in the frequency domain (as in Fourier Analysis and in Quantum Mechanics), instead of in the time domain where signals usually are more difficult to interpret. Although no practical cases have yet been studied based on the idea presented in this article, we expect to use and test this approach in our next studies of simulation. We would also be pleased with receiving some feedback from anyone who decided to apply the same logic.

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