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METHODS REGARDING THE EMERGING TECHNOLOGICAL PHENOMENA OF MODERN SECURITY IN NONLINEAR DYNAMIC SYSTEMS. APPLICATION STUDIES AND IDENTIFICATIONS METHODS

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ABSTRACT

The method of emergence of a technological mathematical system is the process by which complex behaviors are formed starting from extremely simple rules. This process is dynamic, with entities presenting emergence over a longer period of time (for example, the successive stages of evolution of multicellular structures from simple organisms to a human brain capable of consciousness. At the same time, emergence can occur between entities of sizes that differ by many orders of magnitude (for example, the interaction between a large number of neurons resulting in the human brain capable of rational thought, although the neurons themselves do not exhibit this ability.

KEYWORDS: cellular neural networks (CNN), electrochemical impedance (EIS), emergence, interaction, macrolanguage, microlanguage

1. Introduction

According to the dictionary, the phenomenon of emergence consists in the exit of a body, a substance, a radiation from the environment in which it is found. According to David Chalmers (2006): "*Emergence is a complex phenomenon, the interesting function of a high level is produced as a result of the simple combination between the mechanisms of a low level in simple ways*", "*emergence is a psychological property*". "*Emergence is the phenomenon when a system is created according to safe principles, but interesting properties appear that were not thought of before by the creator*".

According to Ronald "*the emergence tests are based on the surprise effect in a similar way to the tests for determining intelligence*". If we use a macro-language to describe the global behavior of a system, made in accordance with a microlanguage, the behavior observed in macrolanguage is not obvious to an observer, who experiences a surprise anyway, it can be concluded that the global behavior is an emergent one. Standish develops Ronald's idea by observing that the surprise effect in the previous test disappears after the first observation of an emergent behavior. Then he proposes the following definition of emergent: "*An emergent phenomenon is one that is simply described by the atomic concept available in macrolanguage, but cannot be described in microlanguage*". According to their regularity and homogeneity, cellular computational

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systems are the best suited for the development of a systematic theory and methods for "*making an emergent*".

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Standish develops Ronald's idea by observing that the surprise effect in the previous test disappears after the first one observation of emergent behavior. Then he proposes the following definition of emergent: *"An emergent phenomenon is one simply described by the atomic concept available in the macrolanguage, but cannot be described in the microlanguage"*. According to their ***regularity and homogeneity, cellular computing systems*** are the best composed for development a systematic theory and methods for *"realizing an emergent"*.

An emerging phenomenon is a phenomenon that cannot be described by microlanguage. Anyway, since the space chosen for generation is huge, it is of practical interest to develop methods for locating the parameters in this space, regions where the merger phenomenon is likely to occur. In fact, it is difficult to answer this question since the surprise effect is associated with emergence and does not allow us to specify in advance what we are actually looking for in the desired emergent behavior. The remaining question is: *under what conditions is an emerging system*? Emergent computing is a revolutionary process.

Complex systems are characterized by openness, interactivity, non-linearity and show a high degree of ordering, many states or level variables. There are multiple loops, negative and positive, they are non-linear. The behavior is often curious in contradiction with the seemingly counter-intuitive, showing a relative resistance to change. They present various pressure points through which the balance of the systems can be changed by resisting some actions from the outside, because they alter the internal balance of the system.

From the studies carried out it was found that a complex system is not a whole made up of parts but a whole made up of other wholes, where the components of the system interact locally: no component interacts directly with all the others but only with the neighboring ones.

The global behavior is independent of the internal structure of the components, being a global behavior of a well-defined system. Stability is a vital property of a system. The price of change is inertia, resistance to change. We cannot have stability without resistance to change, it is actually the same thing viewed from opposite angles. Changing a system involves subjecting it to strong pressures for a long time.

The emerging phenomena are *related* to *meta-equilibrium*: at the level of detail, the system is completely unbalanced; however from the global perspective, the system is stable and orderly. The system must be locally unbalanced to produce its order global.

The concept of dynamic systems is a mathematical formalization for any fixed rule that describes time dependent on the position of the point in its ambient space. Examples include mathematical models that describe the movement of a clock's pendulum, the fluctuation of water in a pipe, and the number of fish in a lake each spring. A dynamical system has a status determined by a collection of real numbers or, more generally, a group of points in a fixed space-suitable. Small changes in the establishment of a system correspond to small changes in numbers. The numbers are too the coordinates of *some geometric spaces – a variety*. The dynamic system evolution rule is a fixed rule that describes the following determinations that come from an *ordinary determination*. ***The rule is decisive:*** for a given time interval only one subsequent determination follows from an ordinary determination.

I find the modern phenomena of emergence applied in many situations. In digital systems: new functions emerge when identical simple parts correctly connected, logically named, match, being made for emergence in digital systems, where the phenomenon is revolutionary, the emergence of new functions being sometimes a matter of guessing or inspiration. ***In biology:*** New structures and functions emerge from the correct decoding of the ***DNA structure.*** Life itself is an emergent phenomenon. ***In electronics:*** The various information processing functions emerge from the correct interconnection of cells. ***In society:*** Competition and cooperation emerge in human society and other forms of existence.

As for example, in all the research we have obtained in recent years, there was the development of emerging electrochemical security systems based on ***Electrochemical Impedance Spectroscopy (EIS)***, which with the help of this method, we obtained information about the state of the components of some cells of combustion (e.g. membranes), where we were able to identify operational ***problems of a modern emergent security system.*** A very good example is the use of *the Electrochemical Impedance method (EIS)*, according to the research carried out and which I publicly supported during ***my studies (2020-2022)*** at the **"Nicolae Bălcescu" Land Forces Academy of Sibiu** and where it is still in the ***final experimental phase within the*** **Extreme Light Infrastructure – Nuclear Physics (ELI-NP)**, where it will later be used for the characterization of the electrical properties of the materials and for the study of the interfaces with the electrodes. Such measurements are useful in identifying the kinetic resistance of *the electrochemical system, the ohmic resistance, the electrolytic resistance, the contact resistance and the porous layer*, as well as the transport limitations of the reactant.

The components of some fuel cells that influence the impedance are the current collectors, the porous electrodes, the catalyst layer and the membrane. But *artificial neural networks* can also be used as a way to represent *nonlinear dynamic systems* presented in this article. The main characteristic of artificial neural networks used in system control is their ability to approximate functionals, where the training of a neural network uses the inputs and outputs of a nonlinear dynamic system, which can be seen as a problem of approximating a nonlinear functional.

2. Emerging Applied Study of Some Neural Methods regarding Dynamics System

From my point of view, ***dynamic nonlinear neural models*** are ***modern security models*** that are more sophisticated and implicitly closer to biological reality, which from a mathematical point of view are dynamic nonlinear systems and result from recurrent interconnection in neuron networks. ***Neuron models*** are in this case dynamic models in which time plays an important role. Such dynamic models can be obtained by supplementing static models with consideration of the time variable or based on careful analyzes of biological phenomena. The neural models used to build predictive filters for dynamic systems are:

– *feed-forward neural networks*: the multilevel perception, presented as an example, which is the weakest in terms of representation capacity; networks with radial basis functions, a type of feed-forward networks that use in representation linear combinations of nonlinear functions with certain characteristics;

– recurrent neural networks in which the dynamics of the modeled system is learned by adapting the internal dynamics a the network; this type of networks can best represent dynamic systems.

There is the possibility of modeling in continuous time (closer to biological reality) or in discrete time (much more suitable for numerical modeling on the

computer). In the first case, from a mathematical point of view, the model is ***a system of ordinary differential equations***. Examples of better known ***dynamic neural models:***

- the Hodgin-Huxley model and the simplified version (FitzHgh Nagumo), explain the propagation of nerve impulses through the axon;
- Hopfield's associative memory model;
- Walter Freeman's cortical model (explains the role of chaos in the neural processing of information);
- cellular automata (Wolfram, in his book "A new kind of science" suggesting the universality of such a model for explaining all phenomena including biological and social);
- non-linear neural cellular networks.

If we talk about *Chaos Theory in mathematics and physics*, chaos theory describes the behavior of a certain ***nonlinear dynamic system***, which can manifest dynamics that are of great sensitivity to initiate conditions (popularly known as the butterfly effect). As a result of this sensitivity, which manifests itself as an exponential growth of disturbances in the initial conditions, the behavior of the chaotic system appears to be random. This happens even if these systems are deterministic, meaning that their modern future dynamics are fully defined by their initial conditions, with no random elements involved.

Another proven model would be the ***cellular neural networks (CNN) model***. The cell of this system is a continuous time and a system continuously determined dynamic with some unsaturated nonlinearity that is well constructed for implementation using analog circuits. Initially *the dynamic equilibrium* of the *cellular neural networks (CNN)* was more used for applications, and recently the dynamic non-equilibrium it is used for various interesting applications which is currently called *"wave computing"*.

In the following I will present an example of a nonlinear dynamic reaction-diffusion system. By reaction-diffusion it was proposed as a particular case of autonomous continuous time, as a discrete spatial model of the partial differential equation, which describes the physical process of reaction-diffusion. Below I have described an m-port cell described by nonlinear ODE which is a physical reaction model:

Example 1: The case of a Reaction Diffusion cell with von neighborhood.

$$\begin{aligned}
\dot{x}_1^1 &= f_1(x_1^1, x_1^2, \ldots, x_1^m, \mathbf{G}_1) + D_1\left(x_2^1 + x_3^1 + x_4^1 + x_5^1 - 4x_1^1\right), \\
&\cdots \\
\dot{x}_1^j &= f_1(x_1^1, x_1^2, \ldots, x_1^m, \mathbf{G}_j) + D_j\left(x_2^j + x_3^j + x_4^j + x_5^j - 4x_1^j\right), \\
&\cdots \\
\dot{x}_1^m &= f_1(x_1^1, x_1^2, \ldots, x_1^m, \mathbf{G}_m) + D_m\left(x_2^m + x_3^m + x_4^m + x_5^m - 4x_1^m\right)
\end{aligned} \tag{1}$$

Where $\boldsymbol{x_2^1}$ is the state variable of cell **k** (using the neighborhood index in Figure no. 1 with the central cell indexed as **k = 1**) in layer **j.** The gene is also distributed among layers as $\mathbf{G_1,\ldots.G_m}$ and in addition each layer is charcterized bythe scalar diffusion **coefficient $\mathbf{D_1}$** which corresponds pysically to the conductance of the resistors in the resistive grid in Figure no. 1.

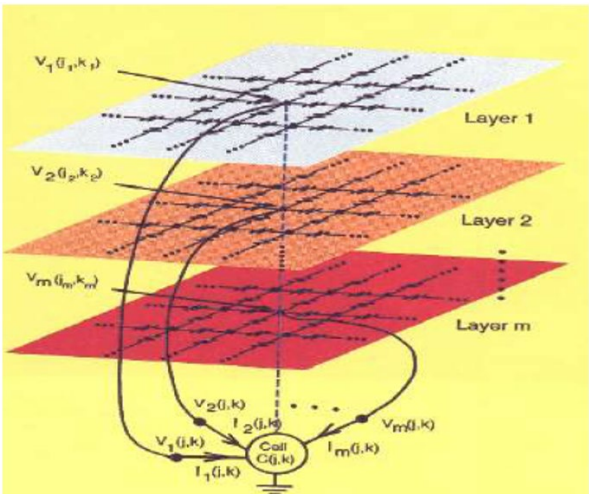

Figure no. 1: *The case of a reaction diffusion cell*

The reaction-diffusion model was created by simulating diffusion and reaction between two chemical substances **U** and **V**, where **U** diffuses faster than **V**.

Equations:

$$\frac{\partial u}{\partial t} = r_u \nabla^2 u - uv^2 + f(1-u)$$

$$\frac{\partial v}{\partial t} = r_v \nabla^2 v + uv^2 - (f+k)v$$

Chemical Reaction:

$$U + 2V \rightarrow 3V$$

$$V \rightarrow P$$

(Source: https://groups.csail.mit.edu/mac/projects/amorphous/GrayScott/)

This reaction is known as the Gray-Scott model. This system can form several types of patterns. Activator production is inhibited by the presence of inhibitors and increased by the presence of the activator. In contrast to this, the inhibitor is not self-increasing, which means that its production is not linked to the presence of other inhibitors, but to the presence of activators. Both substances are destroyed in a constant percentage and diffuse as described earlier. Mathematically it can be expressed as follows:

$$\frac{\partial A}{\partial t} = \frac{k_1 A^2}{H} - k_2 A + k_1 k_3 + D_A \frac{\partial}{\partial x}^2 A \qquad (2)$$

The equation above describes the changes in local activator concentrations where k1 regulates the production, k_2 is the activator destroyer, k_3 is the basic production without an activator present and Da is the diffusion of the activator.

$$\frac{\partial H}{\partial t} = k_4 A^2 - k_5 H + k_6 + D_H \frac{\partial^2}{\partial x} H \quad (3)$$

The equation above describes the changes in the local inhibitor concentration, where **k4** regulates the production, **k5** is the inhibitor destroyer, **k6** is the base production without an activator present and **Dh** is the diffusion of the inhibitor.

$$k_1 \approx k_2 \approx k_5 \;;\; k_6 \approx k_1 k_3 \;;\; D_A < D_H \;;\; k_4 << k_1 \quad (4)$$

It shows the relationship between the parametric to allow the global processes to enrich a stable determination after a while, otherwise the generated pattern would always change, following the scheme that again illustrates the global processes from a local point of view.

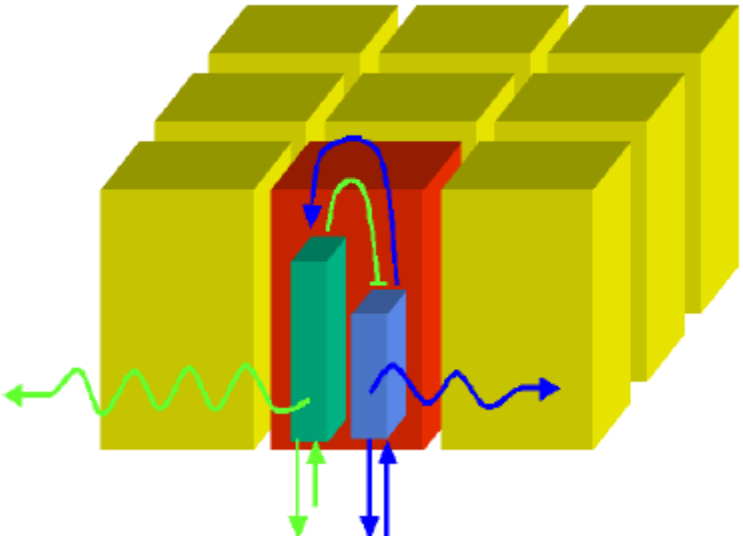

Figure no. 2: *Global process diagram*

The reaction and diffusion of some chemical species can produce a variety of patterns, reminiscent of those seen in nature. These partial differential equation models can be simulated with a variety of numerical techniques. One can also simulate a fundamental process, which is stoichiometrically conservative. The fact that all interactions are local makes it a good candidate for a parallel implementation. Diffusion can be modeled by an explicit conservative change process among neighbors where reactions are modeled locally for each section by a simulator processor.

The following figures, which represent a demonstration simulation of Gray-Scott, illustrate the types of patterns that can be obtained by varying the grid. In this simulation, each section of the reaction is represented by a simulator processor. The processors are asynchronous: each performs its own simulation steps at randomly chosen times. Each stimulation step is stoichiometrically conservative. In each of these figures **we have 4.000 reaction spaces**.

The parameters are: **f = 0.04, k = 0.06, r_u = 0.01, r_v = 0.005**. The neighboring radius of action is **0.04**. Thus each simulator processor has about **20 neighbors**.

The patterns that can be seen are stable, where no significant change will occur, regarding the time of the process. Each pattern starts from the same random initial condition. The differences between the patterns are due in all cases to differences in the grid or differences in the initial condition.

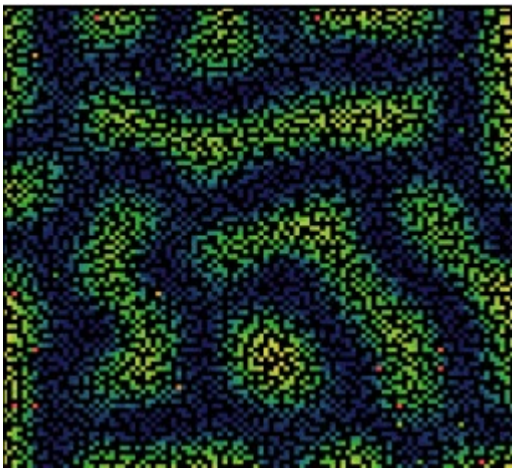

Figure no. 3: *Amorphous settlement (random, easy)*

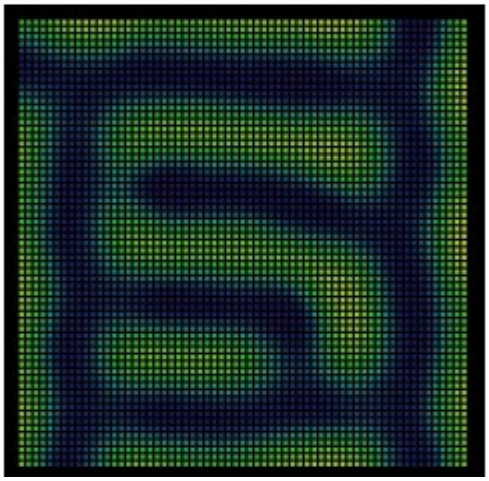

Figure no. 4: *Placement in the square*

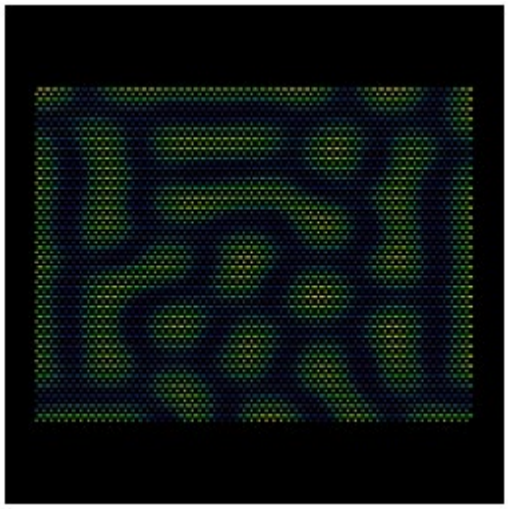

Figure no. 5: *A Placement in closed hexagonal package*

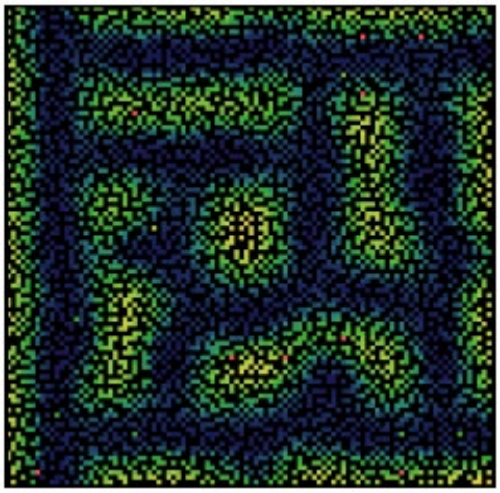

Figure no. 6: *Another amorphous settlement*

(Source: https://groups.csail.mit.edu/mac/projects/amorphous/GrayScott/)

Thus the details differ, where we can see that the general characters develop similarly, independently of the grid. Characteristics ofthey are of similar sizes and shapes. They are in a way aligned with the limit. If we reduce the range of neighbors to ***0.03***, thus reducing the average number of neighbors to ***11***, we find much more detailed corresponding features. We find modern emergent phenomena applied in many situations. At this moment, the amorphous settlements are characterized by less certain limits, so according to the characteristics that are smaller compared to the figure.

3. Conclusions

In conclusion, emergent phenomena are properties of systems that appear from the collective interaction of their components, properties that cannot be predicted by analyzing only the structure or behavior of a small number of constituents subject to fundamental laws. Although emergent phenomena are ubiquitous in contemporary science and a significant part of today's research is focused on understanding them, their acceptance and incorporation into the fabric of thought seems to face invisible resistance. Reductionism, the possibility of deducing fundamental laws by simplification, does not imply the possibility of describing the initial complexity by reconstructing it starting from the fundamental laws thus discovered. And perhaps that interferes with our desire that the effort to understand has not been in vain. The simple fact that we can formulate these laws does not give us the right to reduce the complexity of the world to them, and it does not give us the right to establish a hierarchy of sciences. The fascination of these phenomena makes them an exceptional candidate for 21st century science, and including their exploration within fundamental knowledge can only broaden horizons, avoiding the temporal provincialism we have been guilty of in the past.

From my point of view, the modeling of biological phenomena from an emerging system (but also social or in general of the organized living world) can be done efficiently with the help of interconnected network models (continuous or discrete in time) in which the entities (modeled for example as static neurons) are locally interconnected with an elementary fraction of the entire population of n entities. The dynamic evolution of the model is exclusively determined by a series of parameters of the cells (entities), and the dynamics that best model the phenomena of the living world are the dynamics at the "edge of chaos", characterized by strange attractors but bearing the imprint of an apparent order. The object of current research in biological modeling is to narrow the search space in the parameter space so that dynamic behaviors correspond to biological realities. The establishment of such situations is equivalent to the discovery of mathematical (computer) models for biological phenomena that appear complex.

Following these studies, I tried to explain these phenomena from a microscopic point of view, considering it an emerging security phenomenon. His theory explains the gravitational field as the result of the exchange of information between various microscopic regions of space-time. Basically, when a mass appears in a volume of space-time, the informational content of the different regions changes giving rise to the gravitational field. Far from replacing, for the moment, the General Theory of Relativity, Verlinde's theory has so far passed the first experimental test by successfully explaining why, for distances much larger than the diameter of an average galaxy, the gravitational field is much stronger than the general theory of relativity predicts. Einstein's relativity. Practically, for the time being, considering gravity as an emergent phenomenon, Verlinde managed to correctly calculate the gravitational field at very large distances, which in Einstein's theory gives the wrong answer and requires the introduction of the so-called dark matter to explain the deviation of light at large distances from the observable mass of galaxies. Of course, further tests and refinements of the theory are needed, but this revolutionary shift in perspective, in which gravity is viewed as an emergent phenomenon, is perhaps, for now, the most promising way forward.

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emergent phenomena are ubiquitous in contemporary science and a significant part of today's research is focused on understanding them, their acceptance and incorporation into the fabric of thought seems to face invisible resistance. Reductionism, the possibility of deducing fundamental laws by simplification, does not imply the possibility of describing the initial complexity by reconstructing it starting from the fundamental laws thus discovered. And perhaps that interferes with our desire that the effort to understand has not been in vain. The simple fact that we can formulate these laws does not give us the right to reduce the complexity of the world to them, and it does not give us the right to establish a hierarchy of sciences. The fascination of these phenomena makes them an exceptional candidate for 21st century science, and including their exploration within fundamental knowledge can only broaden horizons, avoiding the temporal provincialism we have been guilty of in the past.

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