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FORECASTING CHAOTIC PROCESSES IN HYDROECOLOGICAL SYSTEMS ON THE BASIS OF ATTRACTORS CONCEPTION AND NEURAL NETWORKS APPROACH: APPLICATION

It is proposed a new approach to non-linear modeling and forecasting chaotic processes in hydroecological systems, which is based on the conception of compact geometrical attractor and neural networks (artificial intellect) algorithms. As an illustrative example of using the method, the dynamics of the nitrates concentrations in the Small Carpathians river's watersheds in the Earthen Slovakia during 1969-1996 years is predicted.

Keywords: *hydroecological systems, chaotic processes, forecasting, attractor conception, neural networks algorithm*

Introduction

To date, the obvious is the fact that the overwhelming number of so -called geophysical, environmental, etc. systems, or, more formally, the systems studied earth sciences are very complex, and this feature is manifested at different spatial and temporal scale levels [1-14]. In this regard, the study of their fundamental properties is still far from satisfactory. As an example of problems whose solution lies in the problems considered in the article, it should be noted the analysis and prediction of the influence of anthropogenic impact on the atmosphere of the industrial city , the development of adequate schemes modeling the properties of the fields of concentration of the air basin industrial city [10]. Naturally, the task list for studying the dynamics of complex systems is not limited to the above examples. It is not difficult to understand that examples of such systems are the atmosphere, turbulent flows in a variety of environments, physical and chemical systems, biological populations, and finally, the society as a communication system and its subsystems: economic, political and other social systems [1-10].

Most important, the fundamental issue in the description of the dynamics of the system is its ability to forecast its future evolution, i.e. predictability of behavior. Recently, the theory of dynamical systems is intensively developed, and, in particular, speech is about the application of methods of the theory to the analysis of complex systems that provide description of their evolutionary dynamics by means solving system of differential equations. If the studied system is more complicated then the greater the equations is necessary for its adequate description. Meanwhile, examples of the systems described by a small amount of equations, are known nevertheless, theses systems exhibit a complicated behavior. Probably the best-known examples of such systems are the Lorenz system, the Sinai billiard, etc. They are described, for example, three equations (i.e., in consideration included three independent variables), but the dynamics of their behavior over time shows elements of chaos (so-called "deterministic chaos"). In particular, Lorentz was able to identify the cause of the chaotic behavior of the system associated with a difference in the initial conditions. Even microscopic deviation between the two systems at the beginning of the process of evolution leads to an exponential accumulation of errors and, accordingly, their stochastic divergence (as a result, the inability to accurately predict changes in meteorology forecast for a sufficiently long period of time). During the analysis of the observed dynamics of some characteristic parameters of the systems over time it is difficult to say to what class belongs to the system and what will be its evolution in the future. In recent years for the analysis of time series of fundamental dynamic parameters there are with varying degrees of success developed and

implemented a variety of methods, in particular, the nonlinear spectral and trend analysis, the study of Markov chains, wavelet and multifractal analysis, the formalism of the matrix memory and the method of evolution propagators etc. Most of the cited approaches are defined as the methods of a chaos theory. In the theory of dynamical systems methods have been developed that allow for the recording of time series of one of the parameters to recover some dynamic characteristics of the system. In recent years a considerable number of works, including an analysis from the perspective of the theory of dynamical systems and chaos, fractal sets, is devoted to time series analysis of geophysical characteristics, environmental, etc. systems [1-10]. In a series of papers [10-18] the authors have attempted to apply some of these methods in a variety of environmental and hydrodynamic problems. In particular, it is about analyzing and forecasting the anthropogenic impact on the atmosphere of the industrial city. An important result concerning temporal changes in the concentrations of nitrogen dioxide, sulfur dioxide, dust, etc. in the atmosphere of a number of industrial cities, is that the system (atmosphere) exhibits a manifestation of low-dimensional chaos. In connection with this, there is an extremely important task on development of new, more effective approaches to the nonlinear modeling and prediction of chaotic processes in geophysical and environmental systems. In this work we present an advanced approach to analysis and forecasting nonlinear dynamics of chaotic systems, based on conceptions of a chaos methods and neural networks modeling. Here we present a new approach to non-linear modeling and forecasting chaotic processes in hydroecological systems, which is based on the conception of compact geometrical attractor and neural networks (artificial intellect) algorithms. As an illustrative example of using the method, the dynamics of the nitrates concentrations in the Small Carpathians river's watersheds in the Earthen Slovakia during 1969-1996 years is predicted.

2. Method.

The basic idea of the construction of our approach to prediction of chaotic properties of complex systems is in the use of the traditional concept of a compact geometric attractor in which evolves the measurement data, plus the implementation of neural network algorithms [15-18]. The meaning of the concept is in fact a study of the evolution of the attractor in the phase space of the system and, in a sense, modeling ("guessing") time-variable evolution.. From a mathematical point of view, it is a fact that in the phase space of the system an orbit continuously rolled on itself due to the action of dissipative forces and the nonlinear part of the dynamics, so it is possible to stay in the neighborhood of any point of the orbit $y(n)$ other points of the orbit $y^r(n)$, $r = 1, 2, \dots, N_B$, which come in the neighborhood $y(n)$ in a completely different times than n . Of course, then one could try to build different types of interpolation functions that take into account all the neighborhoods of the phase space and at the same time explain how the neighborhood evolve from $y(n)$ to a whole family of points about $y(n+1)$. Use of the information about the phase space in the simulation of the evolution of some geophysical (environmental, etc.) of the process in time can be regarded as a fundamental element in the simulation of random processes. In terms of the modern theory of neural systems, and neuro-informatics (e.g. [11]), the process of modeling the evolution of the system can be generalized to describe some evolutionary dynamic neuro-equations (miemo-dynamic equations). Imitating the further evolution of a complex system as the evolution of a neural network with the corresponding elements of the self-study, self-adaptation, etc., it becomes possible to significantly improve the prediction of evolutionary dynamics of a chaotic system. Considering the neural network (in this case, the appropriate term "geophysical" neural network) with a certain number of neurons, as usual, we can introduce the operators S_{ij} synaptic neuron to neuron u_i u_j , while the corresponding synaptic matrix is reduced to a numerical matrix strength of synaptic connections: $W = || w_{ij} ||$. The operator is described by the standard activation neuro-equation determining the evolution of a neural network in time:

$$s_i' = \text{sign}\left(\sum_{j=1}^N w_{ij}s_j - \theta_i\right), \quad (1)$$

where $1 < i < N$. Of course, there can be more complicated versions of the equations of evolution of a neural network. Here it is important for us another proven fact related to information behavior neuro-dynamical system. From the point of view of the theory of chaotic dynamical systems, the state of the neuron (the chaos-geometric interpretation of the forces of synaptic interactions, etc.) can be represented by currents in the phase space of the system and its topological structure is obviously determined by the number and position of attractors. To determine the asymptotic behavior of the system it becomes crucial information aspect of the problem, namely, the fact of being the initial state to the basin of attraction of a particular attractor. Modeling each geophysical attractor by a record in memory, the process of the evolution of neural network, transition from the initial state to the (following) the final state is a model for the reconstruction of the full record of distorted information, or an associative model of pattern recognition is implemented. The domain of attraction of attractors are separated by separatrices or certain surfaces in the phase space. Their structure, of course, is quite complex, but mimics the chaotic properties of the studied object. Then, as usual, the next step is a natural construction parameterized nonlinear function $\mathbf{F}(x, \mathbf{a})$, which transforms: $\mathbf{y}(n) \rightarrow \mathbf{y}(n+1) = \mathbf{F}(\mathbf{y}(n), \mathbf{a})$, and then to use the different (including neural network) criteria for determining the parameters \mathbf{a} (see below). The easiest way to implement this program is in considering the original local neighborhood, enter the model(s) of the process occurring in the neighborhood, at the neighborhood and by combining together these local models, designing on a global nonlinear model. The latter describes most of the structure of the attractor. Although, according to a classical theorem by Kolmogorov-Arnold-Moser, the dynamics evolves in a multidimensional space, the size and the structure of which is predetermined by the initial conditions, this, however, does not indicate a functional choice of model elements in full compliance with the source of random data. One of the most common forms of the local model is the model of the Schreiber type [3] (see also [10]).

Nonlinear modeling of chaotic processes is based on the concept of a compact geometric attractor, which evolve with measurements. Since the orbit is continually folded back on itself by the dissipative forces and the non-linear part of the dynamics, some orbit points $\mathbf{y}^r(k)$, $r = 1, 2, \dots, N_B$ can be found in the neighbourhood of any orbit point $\mathbf{y}(k)$, at that the points $\mathbf{y}^r(k)$ arrive in the neighbourhood of $\mathbf{y}(k)$ at quite different times than k . Then one could build the different types of interpolation functions that take into account all the neighborhoods of the phase space, and explain how these neighborhoods evolve from $\mathbf{y}(n)$ to a whole family of points about $\mathbf{y}(n+1)$. Use of the information about the phase space in modeling the evolution of the physical process in time can be regarded as a major innovation in the modeling of chaotic processes. This concept can be achieved by constructing a parameterized nonlinear function $\mathbf{F}(x, \mathbf{a})$, which transform $\mathbf{y}(n)$ to $\mathbf{y}(n+1) = \mathbf{F}(\mathbf{y}(n), \mathbf{a})$, and then using different criteria for determining the parameters \mathbf{a} . Further, since there is the notion of local neighborhoods, one could create a model of the process occurring in the neighborhood, at the neighborhood and by combining together these local models to construct a global nonlinear model that describes most of the structure of the attractor. Indeed, in some ways the most important deviation from the linear model is to realize that the dynamics evolve in a multidimensional space, the size and the structure of which is dictated by the data. However, the data do not provide "hints" as to which model to select the source to match the random data. And the most simple polynomial models, and a very complex integrated models can lead to the asymptotic time orbits of strange attractors, so for part of the simulation is connected with physics. Therefore, physics is "reduced" to fit the algorithmic data without any interpretation of the data. There is an opinion that there is no algorithmic solutions on how to choose a model for a mere data. As shown Schreiber [3], the most common form of the local model is very simple

$$s(n + \Delta n) = a_0^{(n)} + \sum_{j=1}^{d_A} a_j^{(n)} s(n - (j-1)\tau) \quad (2)$$

where Δn - the time period for which a forecast . The coefficients $a_j^{(k)}$, may be determined by a least-squares procedure, involving only points $s(k)$ within a small neighbourhood around the reference point. Thus, the coefficients will vary throughout phase space. The fit procedure amounts to solving $(d_A + 1)$ linear equations for the $(d_A + 1)$ unknowns. When fitting the parameters a , several problems are encountered that seem purely technical in the first place but are related to the nonlinear properties of the system. If the system is low-dimensional, the data that can be used for fitting will locally not span all the available dimensions but only a subspace, typically. Therefore, the linear system of equations to be solved for the fit will be ill conditioned. However, in the presence of noise the equations are not formally ill-conditioned but still the part of the solution that relates the noise directions to the future point is meaningless . Note that the method presented here is not only because, as noted above, the choice of fitting requires no knowledge of physics of the process itself. Other modeling techniques are described, for example, in [3,10].

Assume the functional form of the display is selected, wherein the polynomials used or other basic functions. Now, we define a characteristic which is a measure of the quality of the curve fit to the data and determines how accurately match $y(k + 1)$ with $F(y(k), a)$, calling it by a local deterministic error

$$\varepsilon_D(k) = \mathbf{y}(k + 1) - \mathbf{F}(\mathbf{y}(k), \mathbf{a}). \quad (3)$$

The cost function for this error is called $W(\varepsilon)$. If the mapping $F(y, a)$, constructed by us, is local, then one has for each adjacent to $y(k)$ point, $y^{(r)}(k)$ ($r = 1, 2, \dots, N_B$)

$$\varepsilon_D^{(r)}(k) = \mathbf{y}(r, k + 1) - \mathbf{F}(\mathbf{y}^{(r)}(k), \mathbf{a}), \quad (4)$$

where $y(r, k + 1)$ - a point in the phase space which evolves $y(r, k)$. To measure the quality of the curve fit to the data, the local cost function is given by

$$W(\varepsilon, k) = \frac{\sum_{r=1}^{N_B} |\varepsilon_D^{(r)}(k)|^2}{\sum_{r=1}^{N_B} [\mathbf{y}(k) - \langle \mathbf{y}(r, k) \rangle]^2} \quad (5)$$

and the parameters identified by minimizing $W(\varepsilon, k)$, will depend on a . Furthermore, formally the neural network algorithm is launched, in particular, in order to make training the neural network system equivalent to the reconstruction and interim forecast the state of the neural network (respectively, adjusting the values of the coefficients). The starting point is a formal knowledge of the time series of the main dynamic parameters of a chaotic system, and then to identify the state vector of the matrix of synaptic interactions $|| w_{ij} ||$ etc. Of course, the main difficulty here lies in the implementation of the process of learning neural network to simulate the complete process of change in the topological structure of the phase space of the system and use the output results of the neural network to adjust the coefficients of the function display. The complexity of the local task, but obviously much less than the complexity of predicting the original chaotic processes in geophysical or other dynamic systems .

3. Application to hydroecological system and conclusions

In order to present an illustrative example of using the prediction model, we consider dynamics of the nitrates and sulphates concentrations in the Small Carpathians river's watersheds in the Earthen Slovakia during 1969-1996 years. In ref. [17] a chaotic behaviour in the nitrates and sulphates concentration time series in the watersheds of the Small Carpathians is

in details investigated. In this ref. it can be found all detailed information about problem. To reconstruct the corresponding attractor, the time delay and embedding dimension are calculated by the methods of autocorrelation function and average mutual information, and the latter is calculated by means of correlation dimension method and algorithm of false nearest neighbours. It is shown that low-dimensional chaos exists in the time series under investigation. In figure 1 we present the original data (solid lines) and 8-month forecasts (dashed lines) for the nitrates concentrations in the watershed Ondava (Stropkov; Slovakia) concerning the time 1969-1996 years (look details in [17] and refs. therein).

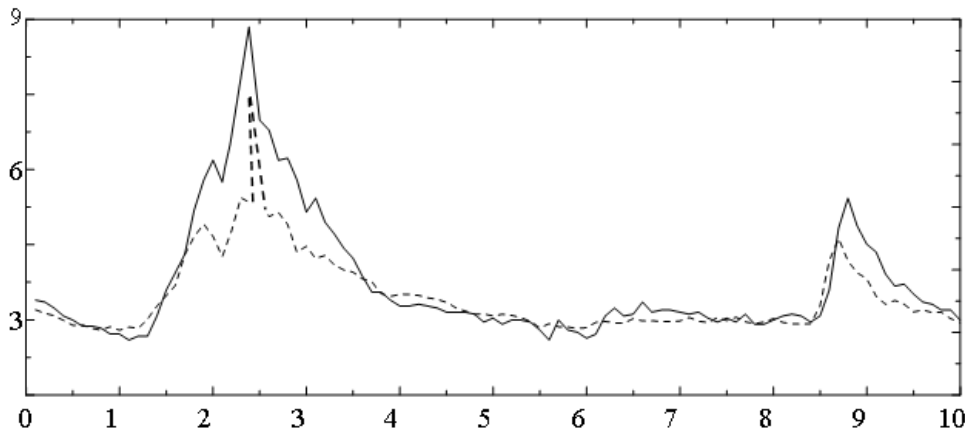


Figure 1 - Original data (solid lines) and 8-month forecasts (dashed lines) for the nitrates concentrations in the watershed Ondava (Stropkov; Slovakia) for thee period 1969-1996.
Axe X – the serial number of the term)

These results can be considered as the example of quite successful short-range forecast for the concentrations of watershed pollutants. The method provides the satisfactory results in the case, when the concentrations are sharply rising; at least, all the tendencies to the rising were revealed. In addition, we have used the simplest approach for the approximation of local model and more complicated methodology can provide hopefully the better forecasts. Using other elements of starting chaos theory method the proposed approach includes the application of the concept of a compact geometric attractor, and one of the neural network algorithms, or, in a more general definition of a model of artificial intelligence. The meaning of the latter is precisely the application of neural network to simulate the evolution of the attractor in phase space, and training most neural network to predict (or rather, correct) the necessary coefficients of the parametric form of functional display.

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Прогнозирование хаотических процессов в гидроэкологических системах на основе концепции аттрактора и нейросетевого подхода: Приложение
Хецелиус О.Ю.

Предложен принципиально новый подход к нелинейному моделированию и прогнозированию хаотических процессов в геофизических и экологических системах, который базируется на использовании концепции компактного геометрического аттрактора и нейросетевых (искусственный интеллект) алгоритмов. В качестве иллюстрации применения метода, приведены результаты прогноза флуктуаций концентраций нитратов в водных бассейнах в районе Малых Карпат (1969-1966).

Ключевые слова: гидроэкологические системы, хаотические процессы, прогноз, концепция аттрактора, нейросетевой алгоритм

Прогнозування хаотичних процесів в гідроекологічних системах на основі концепції аттрактора і нейромережевого підходу: Застосування
Хецеліус О.Ю.

Запропоновано новий підхід до нелінійного моделювання і прогнозування хаотичних процесів в фізичних та екологічних системах, який базується на концепції компактного геометричного аттрактора і нейромережевих (штучний інтелект) алгоритмах. Як ілюстрація застосування методу, наведені результати прогнозу динаміки флуктуацій концентрацій нітратів в водних басейнах в районі Малых Карпат (1969-1966).

Ключові слова: гідроекологічні системи, хаотичні процеси, прогноз, концепція аттрактора, нейромережевий алгоритм