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O.I Djumanov
Department of Information Technologies, Samarkand State University, Samarkand, 15, University blvd., 140104, Uzbekistan,, olimjondi@mail.ru

S.M Kholmonov
Department of Information Technologies, Samarkand State University, Samarkand, 15, University blvd., 140104, Uzbekistan,

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OPTIMIZATION OF FORECAST OF NON-STATIONARY OBJECTS BASED ON FUZZY MODEL ADAPTERS AT EXTERNAL INFORMATION INFLUENCE

O.I.Djumanov[1], S.M.Kholmonov[2]

Department of Information Technologies, Samarkand State University
Samarkand, 15, University blvd., 140104, Uzbekistan,
E-mail: [1]olimjondi@mail.ru

Absrtact. *The tasks of taking into account the sensitivity of fuzzy modeling based on the mechanisms for determining the range of elements of randomly chosen time series and the correction of the parameters of the functions of the accessories of linguistic variables, the use of the data property and the specific features of objects, the database and the knowledge base are solved. Computational schemes of dynamic identification based on polynomial models, nonlinear filters with fuzzy variable adapters are constructed. The effectiveness of generalized algorithms of fuzzy identification of randomly time series (RTS) is proved by comparison with the values of the characteristics of modal examples.*

Keywords*: non-stationary object, identification, information influence, regulation, correction, fuzzy logic, optimization, accuracy.*

Introduction

In the management systems of production and technological complexes, serious attention is paid to the problem of improving the quality of identification, data processing and forecasting of non-stationary objects associated with the need to build models that provide information impact of the environment, often having a non-linear character and given by power distribution. This requires the development and implementation of mechanisms for extracting statistical parameters, dynamic properties of information, specific characteristics of objects, accounting for the variation of random time series (RTS) of technological parameters, the nature of transient processes occurring in the structure of a non-stationary object. The key methods are the identification of RTS, the interpretation of the relationships "inputs and outputs", the obtaining of quantitative characteristics of transient processes in the form of entropy, the distribution function, the coefficients of the dynamic characteristics of a non-stationary object [1-3].

1. The tasks of optimizing the identification of non-stationary objects

To optimize the identification of non-stationary objects, the following tasks are solved [4]:

– consideration of the sensitivity of fuzzy modeling taking into account external information impact;

– Determining the range of changes in the analyzed parameters and variables included in the identification model;

– the construction of mechanisms for selecting and correcting the parameters of the functions of the accessories of linguistic variables in a wide range of variations in the factors of information impact;

– the construction of mechanisms for regulating variables based on the application of fuzzy logic, the use of the property and hidden regularities in the data, the specific characteristics of the object;

– formation of a database and knowledge base of fuzzy rules;

– implementation of computational schemes for dynamic identification based on the synthesis of polynomial models, nonlinear filters with fuzzy variable adapters;

– comparison of the results of identification algorithms with the values of the characteristics of the modal example for assessing their effectiveness.

For smoothing, a discrete Voltaire series $H_m[x(n)]$ is considered, given in the form of a polynomial filter of RTS [3].

$$y_m(n) = H_m[x(n)] = \\ = \sum_{n_1,\dots}\dots\sum_{,n_m\in R_r} h_m(n_1,\dots,n_m)\prod_{j=1}^{m} x(n-n_j), \quad (1)$$

where r – the dimension of reference region's elements R_r, $r \in R_r$; m – polynomial order; $n_j = [n_{j1},\dots,n_{jr}]$ – sequence of r-dimensional lattice.

To simplify the presentation of results, a polynomial filter is usually specified in an equivalent matrix form and the output of such an identifier of randomly time series is determined by solving the system of equations [5]

$$y(n) = h^T X, \quad (2)$$

where $X = \lfloor x_i^T \rfloor$ – The string of the constraint matrix, given in the form of the vector of input data, $i = 1,\dots,I$.

The interconnections "inputs and outputs" are interpreted in the form of a following vector [7]

$$y = hX, \quad (3)$$

where h – vector of filter coefficients.

The system of equations (3) is solved to determine the minimum mean-square error in the identification of RTS.

The evaluation of the quality of the output of fuzzy identification of randomly time series, taking into account external information impact, is specified by operators as

$$R_k^a = E_i \times E_j \times U_e^a, \quad (4)$$

$$i = \overline{1,n},\ j = \overline{1,n},\ e = \overline{1,n},\ k = \overline{1,n},$$

where E_i, E_j, U_e^a – fuzzy subsets to which the values of error discrepancies, error rate of change, external information influence variable $u^a \in U_e^a$.

Along with the external information impact, it is necessary to take into account the conditions of a priori failure, nonstationarity, uncertainty, and large inaccuracy in data processing, which justify the prospectivity of research into the application of neural networks (NN) and mechanisms for regulating the parameters of computer network components in order to optimize the forecast of RTS.

2.Optimization of the forecast of RTS based on NN

The problem of identifying randomly time series based on three-layer neural networks with a mechanism for regulating the parameters of the computational circuits of its components and learning algorithms is considered. A feature of the mechanism that regulates the parameters is the change in the weights of the neurons w_{ij} until the minimum value of the root-mean-square error of the output quantity [4,9].

The algorithm for adaptive learning of neural networks is based on procedures that regulate the learning speed, given by the increment of steps. At each step of the NN training algorithm, the current calculation of the weights is made, which are stored and the calculation of the new weights of the neurons is performed. The training of the NN is performed for a given number of iterations and the required network stability to errors.

The results of identifying RTS based on polynomial nonlinear filters and NN with a mechanism for regulating the parameters of the computational circuits of its components are obtained. It is established that the method of identifying randomly time series based on a polynomial nonlinear filter provides a mean square error of 0.69. At the same time, a hybrid model for the identification of randomly time series with a mechanism for regulating the parameters of the computing circuits of the components of neural networks makes it possible to achieve a mean square error of 0.42. The difference in the accuracy index of identification methods shows the achieved level of optimization of the forecast of RTS.

3. Optimization of the forecast of randomly time series based on fuzzy identification

When using fuzzy inference algorithms, the choice of the terms of input and output linguistic variables (LV), the type of accessories functions (AF), the definition of the boundaries of the MF, the common RTS values of the corresponding fuzzy sets.

For this purpose might be considered the P-shaped AF.

$$f(x;a,b,c)=\frac{1}{1+\left(\frac{x-c}{a}\right)^{2b}},$$

where a, b, c – parameters of AF; x – value of input LV.

For the output term of LV, the AF of the sigmoidal form are presented, in which the optimal value of the parameter a is determined.

It is determined that the mechanism of adjusting the value of the parameter a of the AF the output LV – y, based on fuzzy logic, helps to reduce the value of the root-mean-square error of identification, hence optimizes the forecast of RTS

Of great importance is the probabilistic analysis of the information impact of the environment on the quality of identification and forecast of RTS, because of which the element in the sequence passes from the state $x(t_0)$ at the time t_0 to another state $x(t)$ at the time t.

4. Probabilistic analysis of the information impact of the environment

In the often practical cases, the result of information impact is given by a following power distribution

$$p(x)=\frac{a}{x^{1+\alpha}}, \tag{5}$$

where α – distribution parameter; a – coefficient, the value of which is set within $0\le\alpha\le 2$.

When $\alpha=1$, it represents Zipf's law

$$p(x)=\frac{a}{x^2}. \tag{6}$$

Zipf's law, when $x\to 0$ increases infinitely, is limited from above by the value of a/r, where r is the coefficient reflecting the ability to detect turning points in transient processes.

This requires an amendment in the following form

$$p(x)=\frac{a}{r+x^2}. \tag{7}$$

We introduce the notation $r=\lambda^2$; $a=\lambda/r$.

To describe the state of the transition process, the following probability distribution function is given

$$F(t)=\frac{1}{2}+\frac{1}{\pi}arctg\frac{t-t_0}{\lambda}. \tag{8}$$

The differential $\frac{\partial F(t)}{\partial t}=f(t)$ is represented by a new expression that represents the Cauchy law

$$f(t)=\frac{\lambda}{\pi\left(\lambda^2+(t-t_0)^2\right)}, \tag{9}$$

Function (8) describes the dynamics of the transition of the process to a new state, which is used in modeling.

It is required to study the character of the behavior of the function (9). Wherefore, we consider the following differential equation

$$\frac{du}{dt}=k(1-u)^{\beta}, \tag{10}$$

where β – equation degree.

When $\beta=2$ the solution of equation (10) leads to the form of the function $f(t)$ (9).

To analyze the influence of information impact on the identification result, we use the measure of entropy estimated by the Gibbs-Shannon expression [8]

$$H_q^{(R)}(P)=\frac{1}{1-q}\ln\sum_{i=1}^{n}P_i^q. \tag{11}$$

The Gibbs-Shannon entropy increases with increasing parameter $\eta=1-q$, reaches its maximum at the maximum possible value $\eta_{\max}$.

When the entropy (11) depends on the parameter q ($0<q\le 1$), then when $q=1$ coincides with the Reine formula, which is given by the power distribution and the value of η is regarded as an order parameter.

The probability of finding an element of RTS in the state $x(t_0)$ at time t_0 is determined as following

$$P_0(t)=\frac{1}{1+\alpha}+\frac{\alpha}{1+\alpha}e^{-\beta t},$$

and to the state $x(t)$ at time t is defined as following

$$P_1(t)=\frac{\alpha}{1+\alpha}(1-e^{-\beta t}), \tag{12}$$

where $\alpha=\lambda/\mu$, $\beta=\lambda+\mu$, λ, μ - evaluation parameters.

It is of interest to analyze the change in entropy due to the information impact on the process of identifying RTS.

The quantitative entropy estimate of the Shannon information impact is given in the following form

$$R(t) = 1 - H(t)/H_{\max},$$

where $H_{\max}$ – maximum value of entropy.

Estimates of the information impact taking into account two possible states are given in the following form

$$R(t) = \left(\frac{1}{\ln 2}\right)\frac{[-q\ln(1+\alpha)]}{1-q} + \frac{\ln\left[(1+\alpha e^{-\beta t})^q + \alpha^q(1-e^{-\beta t})^q\right]}{1-q}. \quad (13)$$

Expression (13) was investigated depending on the parameter α in three characteristic regimes:

1) $x(t_0)$, $\alpha < 1$, $P_0 > P_1$;

2) $\alpha = 1$, equiprobable and $P_0 = P_1$;

3) $x(t)$, $\alpha > 1$, $P_0 < P_1$.

The expression (13), taking these modes into account, is written in the following form

$$R(t) = \frac{1}{(1-q)\ln 2}\ln\left[\left(\frac{(1+\alpha)+(\alpha'-\alpha)e^{-\beta'(t-t_0)}}{(1+\alpha')(1+\alpha)}\right)^q + \left(\frac{\alpha'(1+\alpha)+(\alpha-\alpha')e^{-\beta'(t-t_0)}}{(1+\alpha')(1+\alpha)}\right)^q\right]. \quad (14)$$

In Fig. 1 shows the dynamics of entropy, analyzed depending on the value of the parameter $\eta = 1-q$. The value of entropy is maximal for the largest value of the parameter η, which confirms the legitimacy of the accepted power distribution of information impact.

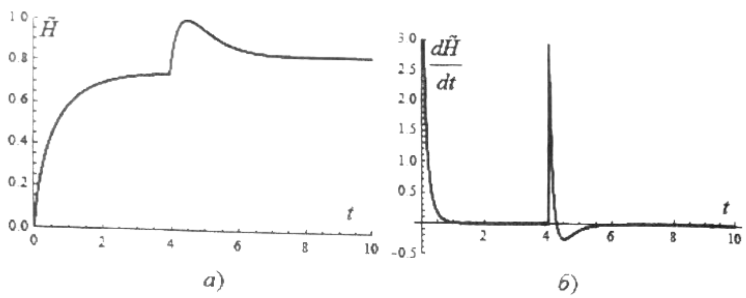

*Figure. 1. **Entropy estimation of information impact of the environment:***
a) graph of the function $R(t)$; b) graph of the derivative $dR(t)/dt$.

As can be seen from the graphs, as the critical value of the information impact approaches, the value of the uncertainty function also increases, which reflects disruptions to the trajectory and generation of another evolutionary branch.

Conclusion

The results of the studies justify the effectiveness of the developed methodology for optimizing the forecast of randomly time series based on hybrid models with mechanisms for regulating variables and taking into account the conditions of nonstationarity, a priori insufficiency, uncertainty, information impact.

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