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# Optimization of Data Processing of Non-Stationary Processes Based on Setting the Parameters of Fuzzy Models

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**Annotation:** Scientific and methodological foundations, methods, models and algorithms for processing data of non-stationary objects based on the mechanisms for setting the parameters of fuzzy sets using genetic algorithms have been developed. The processes of transformation of input data into output data are modeled based on the use of the properties of fuzzy sets and functional connections of inputs and outputs. Methods of intellectual analysis and data processing are implemented for forecasting in automated process control systems.

**Keywords:** data processing, fuzzy sets, non-stationary object, genetic algorithm, optimization, technological process.

**Relevance of the topic.** Many real random processes occurring in control systems of production and technological complexes are characterized by great uncertainty and require adequate models for the identification, approximation, and prediction of non-stationary objects. Effective methods and algorithms for intellectual analysis and data processing can be built on the basis of the synthesis of neural networks (NN), fuzzy set models, fuzzy logic, neuro-fuzzy networks (NFN), genetic algorithms (GA) [1,2].

This work is devoted to the development of a technique for representing fuzzy sets, the synthesis of a genetic algorithm with time series forecasting models, methods for determining and adjusting boundaries, the number of intervals for partitioning the universe, and the degrees of membership of time-series elements [3].

**Representation of time series in a fuzzy environment.** Consider fuzzy time series represented as fuzzy sets of the first and second types [4,5].

The discrete fuzzy set of the first type FM, defined on the $U$ universe, is given in the form

$A = f_A(u_1)/u_1 + f_A(u_2)/u_2 + ... + f_A(u_n)/u_n$, (1)

Where $f_A(u)$ is the membership function (MF) of the fuzzy set FM;

$f_A(u): U \to [0,1]$, $f_A(u_r)$ is the degree of membership of the element of the time series $u_r \in A, r = \overline{1,n}$;

$Y(t)$, $(t = 0,1,2,...)$ is the universe defined on the set of real numbers;

$F(t)$ is a set of $f_i(t)$, $(i = 0,1,2,...)$ functions defined on the $Y(t)$ universe and representing a fuzzy time series on the $Y(t)$ universe.

Let $F(t) = F(t-1) \circ R(t,t-1)$, where $R(t,t-1)$ is a fuzzy relation; $\circ$-composition of max-min operations.

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Let us designate the dependence $F(t)$ as $F(t-1)$, where $F(t-1)$ and $F(t)$ are fuzzy sets.

If $F(t)$ depends on $F(t-1),\ F(t-2),\ \ldots,\ F(t-k)$, then the $F(t-k),\ldots,F(t-2),F(t-1)\rightarrow F(t)$ fuzzy logical dependence is a one-factor forecasting model based on fuzzy time series, where $k$ is the order of the forecasting model.

Dependence with $k=1$ will be written as

$$F(t-1)\rightarrow F(t). \qquad (2)$$

Let's represent the fuzzy data of the $i$-th and $(i+1)$-th periods as fuzzy sets $A_j$ and $A_k$ on the universe $U$.

The fuzzy logical dependence is represented as: $A_j \rightarrow A_k$, where $A_j$ is the current state, and $A_k$ is the next state of the fuzzy dependence [6,7].

Let $f_i(t)=T_i$, $i=1,2,\ldots$ be the real values of the time series for some factor.

The $U$ universe for factor value increments is defined as

$$U=[D_{\min}-D_1, D_{\max}+D_2],$$

Where $D_{\min}$ and $D_{\max}$ are the minimum and maximum increments of the factor values;

$$(\,D_{\min}=\min_t(\,f(t)-f(t-1)),\ D_{\max}=\max_t(\,f(t)-f(t-1))\,);$$

$D_1$ And $D_2$ are real numbers that ensure the breaking up of the universe $U$ into $n$ intervals $u_1,u_2,\ldots,u_n$ of equal length.

The linguistic terms of $A_r\,(r=\overline{1,n})$ are presented as

$$A_1=1/u_1+0{,}5/u_2+0/u_3+\ldots+0/u_{n-1}+0/u_n;$$
$$A_2=0{,}5/u_1+1/u_2+0{,}5/u_3+0/u_4+\ldots+0/u_n.$$
.........................................................................
$$A_n=0/u_1+0/u_2+\ldots+0/u_{n-2}+0{,}5/u_{n-1}+1/u_n.$$

If the value of the increment of the predicted factor belongs to the interval $u_1$, then the corresponding fuzzy value is

$$X_n=1/A_1+0{,}5/A_2.$$

If the value of the factor increment belongs to the interval $u_n$, then

$$X_r=0{,}5/A_{n-1}+1/A_n.$$

Let $X_k$ and $X_j$ be fuzzy increment values for the $i$-th and $(i+1)$-th periods of the time series.

For the $i$-th period, the fuzzy logical dependence will be written in the form of $X_k \rightarrow X_j$.

Similarly, for all known values of the time series, dependency groups are determined [6, 7].

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After that, dependencies $X_k \to X_j$, $X_k \to X_l$, $X_k \to X_s$ are combined into a group: $X_k \to X_j, X_l, X_s$.

The MF of the FM group is defined as

$$f_X(u_r) = \max_{r=\overline{1,n}}(f_{X_j}(u_r), f_{X_l}(u_r), f_{X_s}(u_r)).$$

The resulting FM of the time series for the $(i+1)$-th period is found as a union of FM included in the right side of the group of fuzzy dependencies of the $i$-th period [8, 9].

And the desired value of the predicted value is found as the sum of the real value of the time series of the factor $T_i$ for the $i$-th period and the defuzzified (clear) value of the increment of the factor $y_{i+1}$ [10]:

$$F_{i+1} = T_i + y_{i+1}. \quad (3)$$

A clear value of the factor increment for the $(i+1)$-th period is found using the center of gravity method for one-point sets:

$$y_{i+1} = \sum_{r=1}^{n} w_r \cdot z_r / \sum_{r=1}^{n} w_r, \quad (4)$$

Where $n$ is the number of $u_r$ $(r=\overline{1,n})$ intervals; $z_r$ - the middle point of the $r$-th interval; $w_r$ - the value of the membership degree for the $r$-th interval of the resulting FM, which describes a group of fuzzy dependencies.

**Representation of a fuzzy model of the second type.** Note that, in contrast to the model of the first type, the fuzzy set model of the second type takes into account various uncertainties that prevent an adequate representation of the time series [11].

The interval discrete fuzzy set of this model, defined on the $U$ universe, is written as

$$\tilde{A} = f_{\tilde{A}}(u_1)/u_1 + f_{\tilde{A}}(u_2)/u_2 + ... + f_{\tilde{A}}(u_n)/u_n, \quad (6)$$

Where $f_{\tilde{A}}(u) = \underline{\mu}_{\tilde{A}}(u),\ \overline{\mu}_{\tilde{A}}(u)$;

$\underline{\mu}_{\tilde{A}}(u),\ \overline{\mu}_{\tilde{A}}(u)$ -"lower" and "upper" boundaries of the MF;

*FOU* - the degree of belonging of the element to the "lower" and "upper" boundaries of the MF.

Linguistic terms $\tilde{A}_r$, $(r=\overline{1,n})$ are defined as

$$\tilde{A}_1 = 1/u_1 + V/u_2 + 0/u_3 + ... + 0/u_{n-1} + 0/u_n;$$
$$\tilde{A}_2 = V/u_1 + 1/u_2 + V/u_3 + 0/u_4 + ... + 0/u_n;$$
$$\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots$$
$$\tilde{A}_n = 0/u_1 + 0/u_2 + ... + 0/u_{n-2} + V/u_{n-1} + 1/u_n.$$

Where $V = \alpha_{lower}, \alpha_{upper}$;

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$\alpha_{lower}$ And $\alpha_{upper}$ are the values of the "lower" limit of the MF $\underline{\mu}_{\tilde{A}}(u)$ and the "upper" limit of the FP $\overline{\mu}_{\tilde{A}}(u)$ at the point $u_r\,(r=\overline{1,n})$.

Each linguistic term $\tilde{A}_r$ corresponds to $FOU_r$, the boundaries of which are determined using the MF $\underline{\mu}_{\tilde{A}}(u)$ and $\overline{\mu}_{\tilde{A}}(u)$. The forecasting model is built similarly to the model of the first type.

Let $FOU_k$ and $FOU_j$ of factor increments for the $i$-th and $(i+1)$-th periods be defined, respectively. For the $i$-th period, the fuzzy logical dependence will be written as $FOU_k \to FOU_j$. If dependencies $FOU_k \to FOU_j$, $FOU_k \to FOU_l$, $FOU_k \to FOU_s$ are formed, then they are combined into a group: $FOU_k \to FOU_j$, $FOU_l$, $FOU_s$, and the "lower" and "upper" MF characterizing the group are defined as

$$f_{\tilde{A}}(u_r) = \max_{r=\overline{1,n}}(f_{\tilde{A}_j}(u_r),\, f_{\tilde{A}_l}(u_r),\, f_{\tilde{A}_s}(u_r)).$$

The desired value of the predicted value is found as the sum of the real value of the time series (factor) $T_i$ for the $i$-th period and the defuzzified (clear) value of the increment of the factor $y_{i+1}$ according to formula (3).

Now two "nested" fuzzy sets of the first type $L$ and $R$ are defined - inside the $FOU$ of the interval fuzzy set of the second type $\tilde{A}$. The sets $L$ and $R$ have the minimum and maximum possible centroids in $\tilde{A}$, respectively [12].

The resulting crisp value of the centric is defined as the average value from the centroids of the sets $L$ and $R$. In this case, the model is represented by the definition interval, as $[y_{left}, r_{right}]$, which is described using its left and right parts by the end points corresponding to the sets $L$ and $R$. Or with the help of its center and extent, like

$[c-s,\ c+s]$, где $c=(y_{left}+y_{right})/2$, $s=(y_{right}-y_{left})/2$.

The centroid of $C_{\tilde{A}}$ is defined through the centroids of all "nested", like

$$C_{\tilde{A}} = \int_{z_1\in Z_1}\!\!\dots\int_{z_n\in Z_n}\int_{w_1\in W_n}\!\!\dots\int_{w_n\in W_n} 1/(\sum_{r=1}^{n} w_r\cdot z_r/\sum_{r=1}^{n} w_r) = [y_{left}, y_{right}],\ (7)$$

Where $Z_r\,(r=\overline{1,n})$ is a model represents having a $c_r$ center and a $s_r\,(s_r \ge 0)$ length;

$W_r\,(r=\overline{1,n})$ Is a model with a center of $h_r$ and a length of $\Delta_r\,(\Delta_r \ge 0)$.

The calculation of the centroid $C_{\tilde{A}}$ is connected with the solution of the problem of minimization and maximization. To do this, by putting $z_r = c_r + s_r$ and $z_r = c_r - s_r$, respectively, in the function, two end points of the interval are found: $y_{left}$ and $y_{right}$

$$y(w_1,\dots,w_n) = \sum_{r=1}^{n} w_r\cdot z_r / \sum_{r=1}^{n} w_r,\ (8)$$

Provided

$w_r \in [h_r-\Delta_r, h_r+\Delta_r]$, $h_r \ge \Delta_r$, $r=\overline{1,n}$.

Let us differentiate the function $y(w_1,...,w_n)$ with respect to $w_k$, i.e.

$$\frac{\partial}{\partial w_k} y(w_1,...,w_n) = \frac{\partial}{\partial w_k}\left(\sum_{r=1}^{n} w_r \cdot z_r / \sum_{r=1}^{n} w_r\right) = (z_k - y(w_1,...,w_n)) / \sum_{r=1}^{n} w_r \,, \quad (9)$$

Since $\sum_{r=1}^{n} w_r > 0$, it follows from (9) that

$$\frac{\partial}{\partial w_k} y(w_1,...,w_n) \underset{\le}{\overset{\ge}{=}} 0, \text{ if } w_k \underset{\le}{\overset{\ge}{=}} y(w_1,...,w_n). \quad (10)$$

So, as from $y(w_1,...,w_n) = z_k$, it follows that

$$\sum_{r=1}^{n} w_r \cdot z_r / \sum_{r=1}^{n} w_r = z_k \,,$$

$$\text{Then } \sum_{r=1, r\ne k}^{n} w_r \cdot z_r / \sum_{r=1, r\ne k}^{n} w_r = z_k \,. \quad (11)$$

From (10) it can be seen that if $z_k > y(w_1,...,w_n)$, then $y(w_1,...,w_n)$ increases with increasing $w_k$; and if $z_k < y(w_1,...,w_n)$, then $y(w_1,...,w_n)$ decreases with a decrease in $w_k$.

To calculate the $C_{\tilde{A}}$ centroid, it is proposed to use the Karnik-Mendel algorithm [13, 14].

**Algorithm Karnik-Mendel.** Let $h_r \ge \Delta_r$ be so that $w_r \ge 0$ is for $r = \overline{1,n}$. The maximum (minimum) value that $w_k (k = \overline{1,n})$ can take is equal to $h_k + \Delta_k (h_k - \Delta_k)$.

The $y(w_1,...,w_n)$ function reaches its maximum value if:

- $w_k = h_k + \Delta_k$ For those $k$ values for which $z_k > y(w_1,...,w_n)$;
- $w_k = h_k - \Delta_k$ For those $k$ values for which $z_k < y(w_1,...,w_n)$.

The $y(w_1,...,w_n)$ function reaches its minimum value if:

- $w_k = h_k - \Delta_k$ For those $k$ values for which $z_k > y(w_1,...,w_n)$;
- $w_k = h_k + \Delta_k$ For those $k$ values for which $z_k < y(w_1,...,w_n)$.

The maximum of the $y(w_1,...,w_n)$ function is determined by the procedures of the following algorithm, which includes the following steps.

It is assumed that $z_r = c_r + s_r$, $(r = \overline{1,n})$ and all $z_r$ are in ascending order, i.e. $z_1 \le z_2 \le ... \le z_n$.

Step 1. Let $w_r = h_r$ be for $r = \overline{1,n}$. $y' = y(h_1,...,h_n)$ Is calculated by the formula (8).

Step 2. $k (1 \le k \le n-1)$ is determined such that $z_k \le y' \le z_{k+1}$.

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Step 3. Let $w_r = h_r - \Delta_r$ for $r \le k$ and $w_r = h_r + \Delta_r$ for $r \ge k+1$. $y'' = y(h_1 - \Delta_1, ..., h_k - \Delta_k, h_{k+1} + \Delta_{k+1}, ..., h_n + \Delta_n)$ is calculated by formula (8).

Step 4. If $y' = y''$, then the calculations are over, and $y''$ is the maximum of the $y(w_1, ..., w_n)$ function. If $y' \ne y''$, then carried out go to step 5.

Step 5. We assume $y' = y''$ and carry out the transition to step 2.

The algorithm requires no more than $n$ iterations, where one iteration consists of steps 2-5.

The minimum of the $y(w_1, ..., w_n)$ function is determined by similar procedures, where $z_r = c_r + s_r$, $(r = \overline{1, n})$.

And in step 3 to calculate the

$y'' = y(h_1 + \Delta_1, ..., h_k + \Delta_k, h_{k+1} - \Delta_{k+1}, ..., h_n - \Delta_n)$ is supposed to be $w_r = h_r + \Delta_r$ for $w_r = h_r - \Delta_r$ with $r \ge k+1$.

**Forecasting is based on setting the parameters of fuzzy models.** Fuzzy logical dependencies are formed in the form of the following groups 1 - 7: $FOU_1 \rightarrow FOU_2$, $FOU_2 \rightarrow FOU_5$, $FOU_6$., $FOU_3 \rightarrow FOU_2$, $FOU_3$, $FOU_4$, $FOU_7$., $FOU_4 \rightarrow FOU_3$, $FOU_5$., $FOU_5 \rightarrow FOU_1$, $FOU_3$, $FOU_5$., $FOU_6 \rightarrow FOU_5$., $FOU_7 \rightarrow FOU_4$.

In table. 1 shows the results of calculating the parameters of fuzzy models.

Table 1. Results of calculating the parameters of fuzzy models

| Parameters | "model 1" | "model 2" | "model 3" |
|---|---|---|---|
| $D_1$ | 816,486940898299 | 818,938883168293 | 818,914669508277 |
| $D_2$ | 662,918661869601 | 656,198590769605 | 656,765458625010 |
| $D_3 = n$ | 7 | 7 | 7 |
| $D_0 = \alpha$ | 0,5 | 0 | – |
| $\alpha_{upper} (\alpha_{lower})$ | – | – | 1 (0) |

**Conclusion.** Thus, the scientific and methodological foundations of intellectual analysis and data processing have been developed for predicting non-stationary objects based on NN, fuzzy sets, fuzzy logic, dynamic models for forecasting time series by defining and setting boundaries, the number of intervals for splitting sets, degrees of element membership. To optimize the identification of time series, a technique for choosing an objective function, optimizing and tuning genetic operators is proposed. It is proved that when synthesizing fuzzy set models and evolutionary calculations, an efficient search for optimal parameters is carried out and high accuracy of time series forecasting is achieved.

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