Fuzzy Tendency based Time Series Model for Forecasting Server Traffic

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Abstract - *For modeling of change of terminal server load, the approach including representation of time series of server parameters in the form of fuzzy time series is used. Further in the article the analysis of fuzzy time series is considered. The model of fuzzy tendencies is offered for terminal server traffic modeling. This model reflects change of the volume of terminal server traffic expressed linguistically, and it is used for its forecasting. The results of the forecast permit to determine linguistically expressed fuzzy tendencies on the basis of the offered model.*

Keywords— Fuzzy Time Series, Fuzzy Tendency, Fuzzy Neural Network, Forecasting, Terminal Server.

1 Introduction

During the last decade development of computing networks (CN) of different levels (from local area networks to global area networks) has resulted in the fact that the quality of production processes depends on the quality of network services more and more. Correspondence of scales of trade processes to the computer network can be achieved due to constant analysis of quality of CN functioning (including the application layer) and forecasting its development. Such analysis of existent network often rests upon results of time series (TS) analysis of server parameters.

Time series of server parameters have a number of peculiarities: non-stationarity, non-homogeneity, the complex form of dynamics, which limit the applicability of classical statistic methods of TS analysis such as regression and spectral analysis, exponential smoothing. In this connection, at present promising technologies of time series analysis are intelligent methods which permit to use expert knowledge and have no rigid requirements to initial data.

Modeling of experts' knowledge in the form of linguistic terms (evaluations) formalized as fuzzy sets became a prerequisite to TS modeling in the form of fuzzy time series.

Since 1993 a number of works have been dedicated to forecasting of fuzzy TS [1 - 4] constructed on the basis of numerical TS. In these investigations let us note the following problems which can be solved: increase of accuracy of numerical forecast owing to specification of the quantity and form of membership functions, decrease of computing owing to decrease of the number of fuzzy rules, increase of the level of automation when solving forecast problems. The indicated problems can be solved owing to application of methods of intelligent data analysis such as a fuzzy cluster analysis, genetic algorithms and neural networks.

The study [5] proposes the fuzzy neural network with initial weights generated by genetic algorithm (GFNN) for the sake of learning fuzzy IF–THEN rules. The result from GFNN is further integrated with an ANN artificial neural networks (ANN) forecast using the time series data from another ANN. Model evaluation results for a convenience store (CVS) company indicate that the proposed system can perform more accurately than the conventional statistical method and a single ANN.

In the work [6] the method of forecasting of TS inflation on the basis of fuzzy systems and a neural network is offered. To determine the fuzzy relation of the first-order fuzzy time series model, the neural network with SCL clustering technique was used to derive the rules directly from the database. The method may be of real usefulness in practical applications, where usually the expert can not explain linguistically, what control actions the process takes or there is no knowledge of the process.

To forecast fuzzy time series, in study [7] a backpropagation neural network is applied because of its nonlinear structures. Authors propose a hybrid model consisting of a neural network approach to forecast the known patterns as well as a simple method to forecast the unknown patterns.

Then the authors published the work [8] in which they proposed bivariate models in order to improve forecasting. The stock index and its corresponding index futures were taken as the inputs to forecast the stock index for the next day.

In this work there is offered a new hybrid forecasting model of TS in the form of a time series of fuzzy tendencies representing context-dependent interval linguistic evaluations of the traffic of the terminal server of a complex network. For the time series of FT, the model of forecasting of the first order is defined in terms of fuzzy tendencies to make more reasonable decisions on planning of network structure change.

In the part 2 the model and base operations of FT processing are defined.

In the part 3 a fuzzy neural network for generation of fuzzy rules of forecasting fuzzy tendencies is offered. The developed mathematical simulation model of the terminal server as an element of a computing network on the basis of time series of fuzzy tendencies presented in part 4 permits to forecast the traffic of the terminal server both in terms of fuzzy tendencies and in terms of the initial TS.

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2 Models and base operations of fuzzy tendencies processing

In the work [8] the evaluation of TS is analyzed which is expressed in linguistic terms, the concepts fuzzy time series (FTS) and fuzzy tendency (FT) are introduces for that. The fuzzy tendency of a fuzzy time series is the fuzzy label which expresses the dynamics (systematic motion) of a fuzzy time series. The concept "tendency", being modeled by the fuzzy set, can be described by the set of constructed empiric rules. To find the fuzzy tendencies, it is offered to use Fuzzy Neurons Network (FNN). The analysis of the FT permits to forecast the behavior of the time series on the basis of process dynamics by means of prediction of tendencies of development of the object being studied. With it forecasting of numerical values of TS is not foreseen, and it can be considered as a shortcoming of the offered methods.

The base operations of fuzzy tendencies processing are algorithmic operations of fuzzy tendencies processing, namely the operation of forming the time series of fuzzy tendencies by the initial time series and the inverse operation of generation of the series – a representative of the fuzzy tendency.

Definition 1. A fuzzy time series $\widetilde{Y}$ is the ordered sequence of observations of some phenomenon the character of which changes in the course of time if values which some quantity takes on at the instant of time are expressed by the fuzzy label:

$$\widetilde{y}_t^i = \{(\widetilde{y}^i, U_y, \mu_i(y_t)), t\},$$

where $\widetilde{y}^i$ is the i-th element of the term-set of the linguistic variable $(\widetilde{Y}, T_y, U_y, G_y, M_y)$.

Thus, a FTS is the vector time series of values of all fuzzy variables:

$$\widetilde{Y} = \{\widetilde{y}_t\},$$

where $\widetilde{y}_t = \{\widetilde{y}_t^1, ..., \widetilde{y}_t^n\}$, n is the number of terms.

Definition 2. Fuzzy tendency. Let $\widetilde{y}_\Delta = \{\widetilde{y}_1, ..., \widetilde{y}_m\}$ be the fuzzy time series of the linguistic variable $(\widetilde{Y}, T_y, U_y, G_y, M_y)$, $\widetilde{Y}_\Delta = \{\widetilde{y}_\Delta\}$ is the set of fuzzy time series of the same length. Then the fuzzy tendency τ, determined on the $\widetilde{Y}_\Delta$, is the aggregate of ordered pairs:

$$\tau = \{\widetilde{y}_\Delta, \mu_\tau(\widetilde{y}_\Delta)\},$$

where $\mu_\tau(\widetilde{y}_\Delta)$ is the degree of membership of $\widetilde{y}_\Delta$ to FT.

Determining the fuzzy tendency on all intervals [t-m+1, t] of the time series and positioning the beginning and the end of the interval to the time scale, we receive the time series of the fuzzy tendency.

Definition 3. The time series of a fuzzy tendency (TSFT). Let $\{\widetilde{y}_{\Delta t}\}$ be the set of fuzzy time series which length is equal to m, where $\widetilde{y}_{\Delta t} = \{\widetilde{y}_{t-m+1}, ..., \widetilde{y}_t\}$, $\widetilde{y}_t \in \widetilde{Y}$ t. Then the time series of a fuzzy tendency is the ordered in time fuzzy set:

$$\tau_t = \{t, \mu_\tau(\widetilde{y}_{\Delta t})\}.$$

For the linguistic variable FT, the time series of fuzzy tendencies is determined as the vector TS of values of all kinds of fuzzy tendencies:

$$\tau_t = \{t, \tau_t^1, ..., \tau_t^p\}.$$

Let us assume that there is dependence between fuzzy tendencies observed at different instants of time. Using the scheme of the differed equation (1) let us represent the model of the time on the basis of FT for one variable:

$$\tau_t = f(\tau_{t-1}, ...\tau_{t-l}), \tag{1}$$

where l is the time interval. For construction of the model of TS on the basis of FT, it is necessary to solve the following problems:

-to determine the procedure of fuzzyfication and defuzzyfication of the TS;

-to determine the procedure of description and identification of the FT;

-to determine the procedure of receiving the crisp time series from values of FT;

-to identify the functional dependence.

Receiving a FTS from a crisp TS is based on the operation of fuzzyfication, i.e. transition from quantitative values to linguistic evaluations. The procedure of fuzzyfication is widely enough described in literature. Let us denote the process of finding the value of membership function of elements Uy to the terminal set T_y by the functional Fuzzy:

$$\widetilde{Y} = Fuzzy[Y].$$

The functional supposes solving the problems of linguistic terms description and rules of use, choosing the corresponding membership functions. When determining the linguistic terms the following methods can be used: subjective description of the universe U_y on the basis of expert knowledge about the system and descriptive terminology accepted in the field being investigated; uniform partition of the universe (into 3-7 intervals, as a rule); clusterisation of values of the time series for determination of the most significant intervals on the universe.

Defuzzyfication is the problem inverse to fuzzyfication, i.e. receiving the crisp TS from a fuzzy one, is given by the functional deFuzzy:

$$Y' = deFuzzy[\widetilde{Y}].$$

The problem of determination of the FT is fundamental in the construction of the system of data analysis, decision of which will permit to start disclosing the connections between parameters of the object being investigated. This problem consists of the following sub-problems:

-determination of linguistic variables of the FT;

-construction of the time series of the FT.

Let us denote solving the problem by the functional Tend:

$$\tau = Tend[\widetilde{Y}_\Delta]$$

For determination of the linguistic variable expressing the fuzzy tendency, it is necessary to single out the typical behavior of the fuzzy time series, that is to make up the terminal set. The analysis of the initial series for evaluation of the dynamics can be done by the following methods:

-using the evaluations of the dynamics (increase, decrease, stability);

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-subjective description on the basis of expert knowledge about the systematic behavior of system parameters;

-clusterisation of values of the fuzzy time series for determination of the most significant tendencies on the universe.

For construction of TSFT, it is necessary not only to single them out (to denote linguistic terms), but to give a description and be able to find the tendency on the FTS. Thus, the functional Tend includes the tool of FT description, the algorithm of finding the correspondence of fuzzy time series to the chosen description, that is the algorithm of fuzzy evaluation.

For the analysis and construction of crisp TS by the fuzzy model, the operation of receiving the FTS from tendency evaluation is necessary. Let us denote solving of this problem by the functional *deTend*, which is inverse to the functional Tend:

$$\widetilde{Y}`_{\Delta} = deTend[\tau],\ \widetilde{Y}`_{\Delta} \in \widetilde{Y}_{\Delta},$$

where $\widetilde{Y}`_{\Delta} = \{\widetilde{y}`_{\Delta}\}$ is the set of typical (characteristic) fuzzy time series for FT which have the maximum value of membership function $\mu_{\tau}(\widetilde{y}`_{\Delta}) = \max(\mu_{\tau}[\widetilde{Y}_{\Delta}])$.

Using the functional of defuzzyfication *deFuzzy*, receiving the fuzzy time series from tendencies *deTend* solves the problem of crisp TS forecasting.

Let us denote the aggregate of components and equations:

$$\widetilde{y}_t^i = Fuzzy[y_t],\ y_t = deFuzzy[\widetilde{y}_t^1,...\widetilde{y}_t^n], i = 1..n,$$

$$\tau_t^j = Tend[\widetilde{y}_{t-m_j+1},...,\widetilde{y}_t],$$

$$\widetilde{y}_t^i = deTend[\tau_t,...,\tau_{t+m-1}], m = \max(m_j),\ j = 1..p,$$

$$\tau_t = f(\tau_{t-1},...\tau_{t-l}),$$

where n is the number of terms of FTS, p is the number of terms of FT, m_j is the interval of definition of FT, l is the time log, by the *model of fuzzy tendencies* (MFT) with characterizing parameters (n, p, m, l). In more detailed form these parameters can be denoted as (n, $\{p_k\}$, $\{m_k\}$, l), where p_k is the number of kinds of tendencies which have the interval of definition m_k.

For the analysis and construction of the crisp time series by the fuzzy model (the functional *deTend)* let us make the fuzzy time series which has the maximum value of membership function in the form of the rule $\widetilde{y}_{\Delta t} = (\tau_t) \circ R_2$ correspond to each kind of fuzzy tendency. For a example, the procedure *deTend* can be represented in the form of the system of rules:

if τ_t is jump, then y_{t-2} is low,
if τ_t is jump, then y_{t-1} is high,
if τ_t is jump, then y_t is low.

Let us represent the equation (1) also by the fuzzy relation:

$$\tau_t = (\tau_{t-1},...\tau_{t-l}) \circ R_3.$$

The MFT is realized by multilevel system of logical relations:

$$R_1 \Rightarrow R_3 \Rightarrow R_2,$$

where outputs in the form of fuzzy variables of one set of rules are applied to inputs of the next set of rules without defuzzyfication and fuzzyfication. Transformation into fuzzy and crisp values happens only in relations R_1 and R_2 correspondingly.

3 Fuzzy neural network

Let us use classical fuzzy neurons in which operations of addition and multiplication are replaced by triangular norms:

AND-neuron $\beta = T(S(\tau_1, w_1), S(\tau_2, w_2))$,

OR-neuron $\tau^0 = S(T(\beta_1, z_1), T(\beta_2, z_2))$.

It can be interpreted in the linguistic form correspondingly as:

if *($\tau 1$* or *w1*) and *(*τ_2 or w_2) then β,
if (β_1 *and* z_1) or *(*β_2 *and* z_2) then τ_0.

On the basis of such neurons it is possible to construct the network of logical inference by Mamdani for finding the fuzzy tendency τ by adding weight coefficients. In a formalized way such network can be expressed in the following form:

$$\tau^0 = \mathop{S}_{i=1}^{k}[T(\beta_i, z_i)],\ \beta_i = \mathop{T}_{j=1}^{m}[S(\tau_j, w_{j,i})],$$

where T is the operator of conjunction, S is the operator of disjunction, k is the number of rules, m is the number of inputs. Weight coefficients are interpreted in the following way: z_i is the degree of influence of i-th rule on the general result (0 – has no influence, 1 – has influence); $w_{j,i}$ are degrees of no influence of j-th input on i-th rule (0 – has influence, 1 – has no influence). The basic idea of FNN learning consists in the iterative procedure of weights optimization (z_i, $w_{j,i}$) and removal of insignificant connections (network reduction), as a result of which the necessary composition and number of rules are formed.

The order of search fuzzy dependences on the basis of FNN is the following:

-Initialization of the fuzzy neural network.

-Learning: optimization of network weights.

-Analysis of the network: network reduction.

At the initialization stage it is necessary to determine input variables: kinds of tendencies and the time log. It is necessary to generate an excessive number of "complete" rules, which include all inputs with arbitrary weights in the interval (0,1).

The stage of learning is the process of FNN weights change on the basis of the learning sample. Network learning is possible by the method of back error propagation. For this purpose let us determine the function of error $E = \frac{1}{2}(\tau^0 - \tau)^2$ which is to be minimized by the method of gradient lowering. For decrease of the squared error E, it is necessary to change weights (z_i, $w_{j,i}$) in the direction of antigradient of the function E:

$$w_{j,i}^{+1} = w_{i,j} - \eta \frac{\partial E}{\partial w_{j,i}},\ z_i^{+1} = z_i - \eta \frac{\partial E}{\partial z_i},$$

where η is the speed of learning with the limitation $w_{j,i}^{+1} \in [0,1]$, $z_i^{+1} \in [0,1]$. For calculation of the derivative error, it is necessary to choose the corresponding functions of t-norms and t-conorms. The indication of completion of learning is reaching the error level.

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At the stage of analysis processing of FNN is carried out with the purpose of its simplification. The principle of removal of insignificant connections and neurons from the network forms the basis of reduction algorithms. One of simplest reduction methods is the method of projections which is realized in the following way. The synoptic weight is nulled if its value has fallen into the given range

$$w_{j,i} = \begin{cases} 1, w_{j,i} \geq (1-\varepsilon) \\ w_{j,i}, w_{j,i} < \varepsilon \end{cases}, \; z_i = \begin{cases} 0, z_i \leq \varepsilon \\ z_i, z_i > \varepsilon \end{cases},$$

where ε is some constant. On the basis of the chosen level of weights ε connections "input – AND-neuron", when $w_{j,i}=1$, and "AND-neuron – OR-neuron", when $z_i = 0$, are removed. Not used inputs and rules are also removed.

As a result the system of logical inference is got, which is the explaining function in the model of time series. Fuzzy rules are easily interpreted for an expert since they are expressed in terms inherent to the investigated field.

4 Server traffic modeling on the basis of the time series of fuzzy tendencies

For time series analysis on the basis of the offered model of a fuzzy time series, the software *FuzzyTendNet* is created.

Thus, for each time series a user assigns the set of linguistic terms with corresponding membership functions (trapezoid function form is used) and the set of fuzzy tendencies. The possibility of using several rules of identification and inverse rules for each tendency permits to describe various interval expert evaluations flexibly enough.

The equation of the model of a time series is the fuzzy neural network which has subnetworks for each output tendency. Each subnetwork is the system of logical deduction which consists of the set of rules. These rules can be formed manually and in the automatic mode with optimization on the basis of the algorithm of back error propagation. The method of projections is used for cancellation of the network. The following logical connectives (functions of triangular norms) are used: minimum and maximum — for rules of identification and inverse rules, product and probabilistic sum — for FNN.

For modeling of the traffic of the terminal server on the basis of the offered approach, seven parameters of the work of the terminal server were chosen, and time series were formed from them.

So, the server parameters of work were chosen (Table 1) and the statistics with 15 seconds interval during one day was collected.

Table 1. Description of variables

Parameter
X1 - Memory\ Pages exchange per second
X2 - Record accesses to disc per second
X3 - Read accesses from disc per second
X4 - % of processor load
X5 - Reading operations
X6 - Recording operations
Y - Traffic

For all parameters fuzzy variables of FTS describing the values "high" and "low" are determined. Fuzzy tendencies "load", "idle" are determined. Additional fuzzy tendencies "increase" and "decrease" are also determined for traffic. In Table 2 description of functionals of the MFT is presented.

Let us note the following:

-the functional deTend is described only for the dependent variable (traffic);

-FT determined on the unit interval, which have the semantic load analogous to variables of FTS, are used in the model.

Table 2. Description of tendencies of terminal-server model parameters change

Parameter	FTS	TSFT	
	$\tilde{y}$	τ	Tend
X1	low	idle	low(1) &low(2)
	high	load	high(1) & high(2)
X2	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
X3	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
X4	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
X5	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
X6	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
Y	low	idle	low(1) & low(2)
	high	load	high(1) & high(2)
		increase	low(1) & high(2)
		decrease	high(1) & low(2)

For comparison of models on the basis of fuzzy time series and fuzzy tendencies, a number of experiments were conducted.

The conclusion can be made that the model based on fuzzy tendencies describes the modeled process more successfully. On Fig. 1 the forecast for one step forward is presented for two models.

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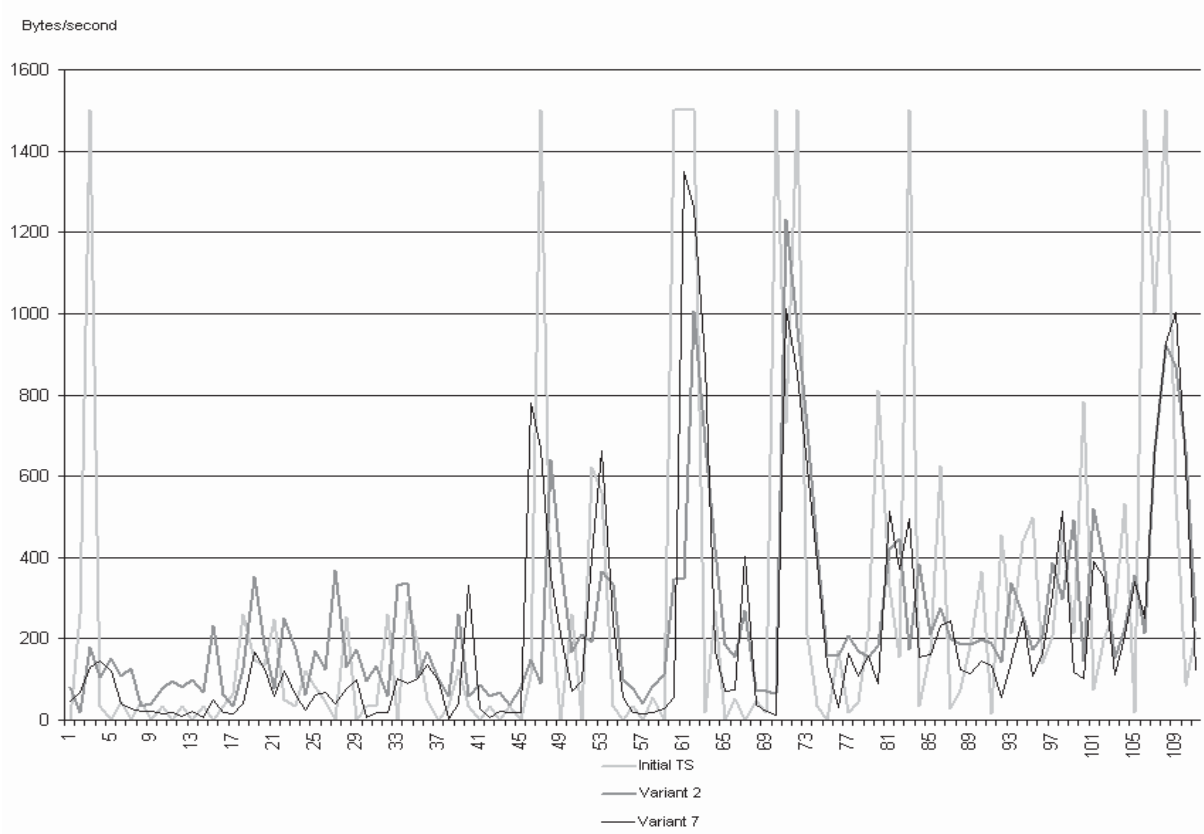

Figure 1:The graph of tested and forecasted TS

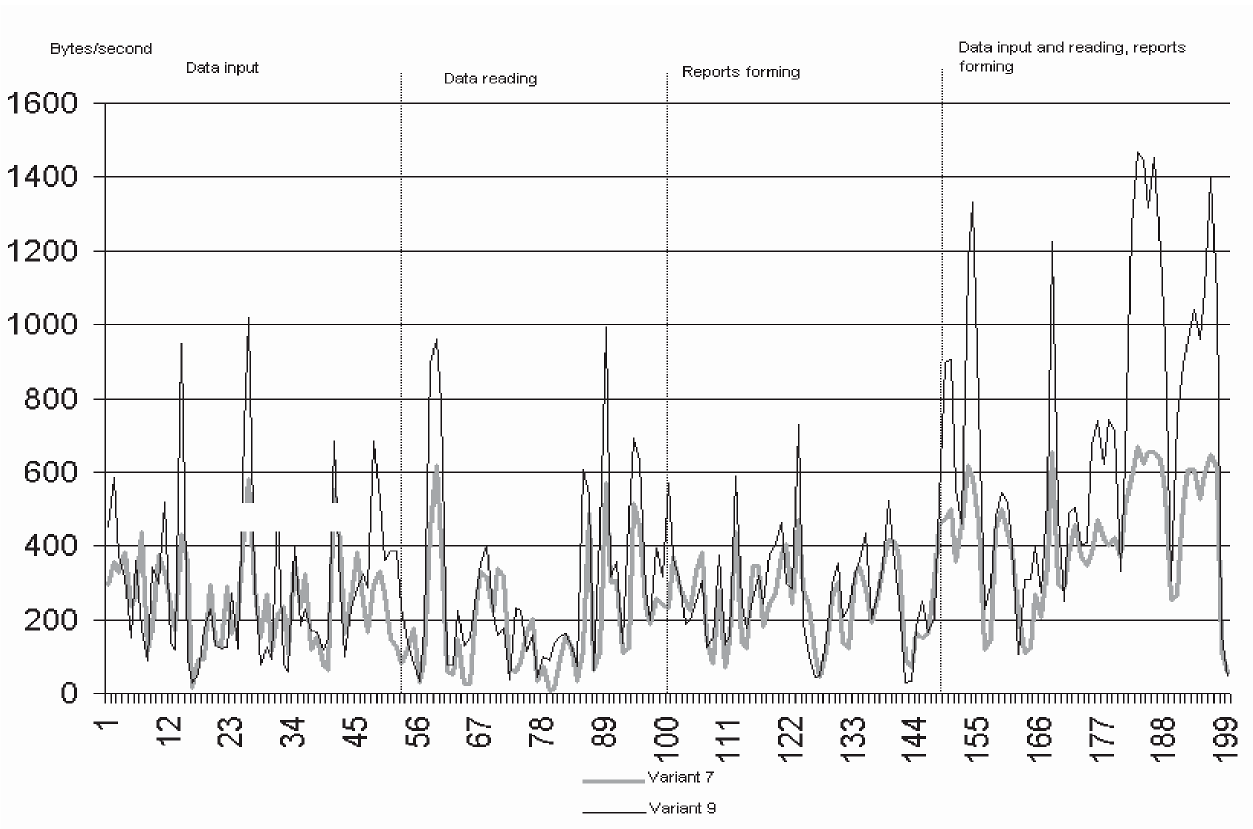

Figure 2:Load modeling

For server traffic volume modeling, the following modes of server work were described by the expert: data input, data reading, reports forming — with high values of corresponding groups of parameters. On Fig 2 results of modeling are presented.

By fuzzy tendencies low and high values of the traffic and its crisp values have been forecasted in different modes of work. The analysis of linguistic series of fuzzy tendencies showed increase of the traffic of the terminal server in the mode of data input and reports forming.

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Thus the conclusion can be made that increase of users performing the mentioned operations will be accompanied by increase of the traffic. When performing all operations on the server simultaneously, we can simultaneously observe both high and low traffic of the network, which can be explained by instability in this mode of work.

5 Conclusions

Thus, the time series of fuzzy tendencies is an effective indicator of development of a modeled process in a complex technical system described qualitatively by linguistic terms. Basic operations of fuzzy tendencies processing are algorithmic operations of fuzzy tendencies processing, namely the operation of forming the time series of fuzzy tendencies by initial time series and the inverse operation of generation of the series — a representative of the fuzzy tendency. The fuzzy neural network of the offered architecture is an effective generator of rules of fuzzy tendencies identification. The developed mathematical simulation model of the terminal-server as the element of the computing network on the basis of time series of fuzzy tendencies permits to forecast processor load, the outgoing and incoming traffic of the server.

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