Method for Automatic Analysis of Compliance of Expenses Data and the Enterprise Income by Neural Network Model of Forecast

Tatiana Neskorodieva[1[0000-0003-2474-7697]], Eugene Fedorov[2[0000-0003-3841-7373]].

[1] Donetsk National University named Vasyl Stus, Vinnitsa, 600-richchia str., 21, 21021, Ukraine
t.neskorodieva@donnu.edu.ua
[2] Cherkasy State Technological University, Cherkasy, Shevchenko blvd., 460, 18006, Ukraine
fedorovee75@ukr.net

Abstract. The problem of automation of audit data analysis the prerequisite "Compliance of costs and incomes" based on the forecast is considered. A neural network model for forecast based on a gateway recurrent unit is proposed. For parametric identification of this model, adaptive cross entropy is proposed. This allows you to increase the forecast efficiency by reducing computational complexity and improving the forecast accuracy.

Software was developed using the Matlab package that implements the proposed method. The developed software is studied when solving the problem of forecasting indicators in the task of analyzing the data mapping “settlements with suppliers - settlements with customers”.

Keywords: automatic analysis, audit data, "settlements with suppliers - settlements with customers" mapping, forecast, neural network, gateway recurrent unit.

1 Introduction

In the process of international and national economies development and industry of IT in particular, it is possible to distinguish the following basic tendencies: digital transformations realization, digital economy forming, socioeconomic processes globalization of and of IT accompanying them [1, 2]. These processes result in the origin of global, multilevel hierarchical structures of heterogeneous, multivariable, multifunction connections, interactions and cooperation of managing subjects (objects of audit), the large volumes of information about them have been accumulated in the informative systems of account, management and audit. Thus, the intercommunications mentioned above, have a network structure at every level.

In relation to the enterprises of Ukraine, in the publications of Ukraine State Financial Inspection [3] it is marked that in the conditions of swift infrastructure development and deepening of informatization of economic processes efficiency of enterprises activity, establishments and organizations are all more depend on the information technologies (IT) used in management system. Now environment of information technologies (IT-environment) as a structural constituent of organization is the difficult system, that unites various informative, programmatic, technical, human and other types of resources for the achievement of aims of organization, enterprise.

According to the Law of Ukraine "On Amending the Law of Ukraine" On Accounting and Financial Reporting in Ukraine "regarding the improvement of certain provisions" dated October 05, 2017 No. 2164-VIII and the Law of Ukraine "On Auditing Financial Statements and Auditing" dated 21.12. 2017 No. 2258-VIII (Audit Law), enterprises of public interest and medium-sized enterprises must conduct an annual audit and publish financial statements together with an audit report (Table 1).

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Table 1. Enterprise Classification

Enterprise	**Micro-**	**Small**	**Medium**	**Large**
Book value of assets	up to 350 thousand euros	up to 4 million euros	up to 20 million euros	over 20 million euros
Net income from sales of products (goods, works, services)	up to 700 thousand euros	up to 8 million euros	up to 40 million euros	over 40 million euros
Average number of employees	up to 10	up to 50	up to 250	over 250

Companies of public interest:

- enterprises - issuers of securities whose securities are admitted to trading on stock exchanges;
- banks, insurers, non-state pension funds, other financial institutions (except for other financial institutions and non-state pension funds related to microenterprises and small enterprises);
- large enterprises;
- public joint stock companies.

These tendencies determine conceptions of modern audit development and corresponding to them information technologies of treatment of financial and economic information about activity of enterprise and decision support systems in an audit [4].

Consequently, nowadays the scientific and technical issue of the modern information technologies in financial and economic sphere of Ukraine is forming of the methodology of planning and creation of the decision support systems (DSS) at the audit of enterprises in the conditions of application of IT and with the use of information technologies on the basis of the automated analysis of the large volumes of data about financial and economic activity and states of enterprises with the multi-level hierarchical structure of heterogeneous, multivariable, multifunction connections, intercommunications and cooperation of objects of audit with the purpose of expansion of functional possibilities, increase of efficiency and universality of IT-audit.

Automated DSS audit means the automatic forming of recommendable decisions, based on the results of the automated analysis of data, that improves quality process of audit. Unlike the traditional approach, computer technologies of analysis of data in the system of audit accelerate and promote the process accuracy of audit, that extremely critical in the conditions of plenty of associate tasks on lower and middle levels, and also amounts of indexes and supervisions in every task.

According to the international standard of audit № 520 "Analytical procedures" [5], analytical procedures are the procedures, suggesting the analysis of financial indexes and tendencies with the subsequent study of rejections and relations that conflict with other corresponding information or deviate from the forecast sums.

In the standard mentioned, recommendations on application of analytical procedures during public accountant verification are also given. The analytical procedures consist of comparison of financial information of enterprise, for example with the following indexes:

- by analytical information for past periods;
- by the planned calculations of enterprise, such, as budgets, forecast, expectations of public accountant;
- to similar information on industry, such as, comparison of amount of sales, to the account receivable with middle indexes on industry or with data after other similar enterprises.

The basic condition of application of analytical procedures is the supposition, that there is certain intercommunication between data and it continues to be saved in default of proofs opposite.

In the last few years among analytical procedures of exposure of financial fraud the class of procedures, based on the methods of intellectual analysis of data, was formed. In practice different methods of extraction of data, namely: K-nearest neighbors, decision tree, fuzzy logic, logistic model, Bayesian belief networks, naive Bayes algorithm, Beneish M-Score, Benford's law, Altmann Z-Score, are being used for the improvement of accuracy of the fraud finding out [6 - 8].

One of the elements of analysis among the tasks of audit is a forecast of economic indicators. Methods of short-term forecast, such as regressive [9], structural [10, 11], logical [12 - 14] conduct forecast on the basis of indexes in current moment to time. Methods of long-term forecast, such as autoregressive [15, 16], exponential smoothing out [17] can conduct a forecasts on the basis of long temporal row. A compromise between the above-mentioned groups of methods is connectionist [18 - 21], that can use neural networks both for a short-term and for long-term forecasts. At the same time connectionist methods usually use parametric identification on the basis of local search, that reduces forecast accuracy.

The aim of study is to increase the efficiency of automatic data analysis in DSS audit based on the forecast method due to the model of the gateway recurrent unit and the method of its parametric identification.

For the achievement of the aim it is necessary to solve the following tasks:

- to offer the forecast neural network model due to the model of the gateway recurrent unit;
- to choose the criterion of estimation of efficiency of forecast neural network model;
- to offer a method for parametric identification of a neural network prediction model based on adaptive cross-entropy;
- to offer the method for automatic analysis of audit data;
- to conduct numeral researches.

2 Formal Problem Statement

In the DSS of audit, the verification of precondition “Compliance of expenses and income” of accounting provisions (standards) [22] at the average level is decomposed on the verification tasks of mapping of generalized values indicators: “settlements with suppliers - settlements with customers”, “accounts payable - debt".

The conversion of the data of settlements with suppliers into the data on the receipt of funds from customers in the accounting system can be represented as a functional structure of the data subsets transformation at the stages of operating activities (Fig. 1).

Denote:

$Q^1_{l_1}(t)$, $l_1 = \overline{1, L_1}$ are data sets of calculations by type of supplier l_1,

$Q^2_{l_2}(t)$, $l_2 = \overline{1, L_2}$ are data sets of stocks by type of raw material l_2,

$Q^3_{l_3}(t)$, $l_3 = \overline{1, L_3}$ are production datasets by type l_3,

$Q^4_{l_4}(t)$, $l_4 = \overline{1, L_4}$ are data sets of calculations by type of finished product l_4,

$t \in \left\{ t_{j_m}, T_m, j = \overline{1, J_m}, m = \overline{1, M}, T \right\}$.

The verification of sets mappings of the functional structure (Fig. 1) is preceded by an analysis of the values of quantitative indicators for the verification period with the purpose of exposure of values that deviate from the forecast. The forecast values are determined on the basis of conformities to law, that is formed from the tested data for other (as a rule, preceding) periods that is imported from the database of the system of account of enterprise in DSS of audit.

We will distinguish the first mapping «settlements with suppliers - settlements with customers». The values of the audit data at the verification stage of this mapping are formed on the basis of a set of quantitative indicators characterizing the transfer of funds to suppliers (raw materials and / or components) and the receipt of funds from customers for goods sold:

$$\left(V_u, \Delta_u\right),\ u \in U\ ,$$

$$\left(V_g, \Delta_g\right),\ g \in G\ ,$$

where:

V - quantitative indicator (in physical units),

Δ - monetary indicator (amounts transferred by suppliers / customers),

u - type of raw material,

U - set of types of raw material,

g - type of finished product,

G - set of types of finished products.

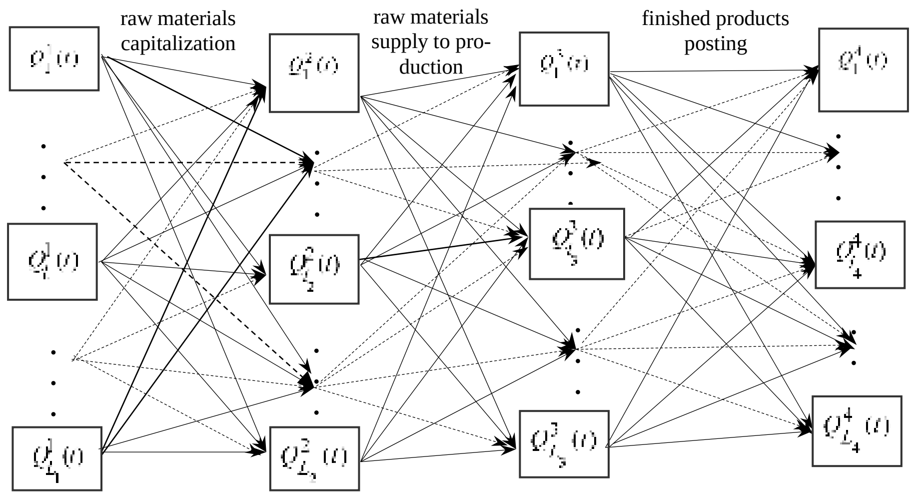

Fig. 1. Functional structure of the data subsets transformation at the stages on operating activities

At the analysis of this mapping (in direct and reverse direction) as elements of pairs of learning set can be chosen:

$$x = (V_u(t), V_u(t-1), \ldots V_u(t-M), u \in U_g)\ ,\ \ y = (V_g(t))\ ,\ \ g \in G\ ,$$

$$x = (\Delta_u(t), \Delta_u(t-1), \ldots \Delta_u(t-M), u \in U_g)\ ,\ \ y = (\Delta_g(t))\ ,\ \ g \in G\ ,$$

$$x = (V_g(t), V_g(t-1), \ldots V_g(t-M), g \in G_u)\ ,\ \ y = (V_u(t))\ ,\ \ u \in U\ ,$$

$$x = (\Delta_g(t), \Delta_g(t-1), \ldots, \Delta_g(t-M), g \in G_u),\ y = (\Delta_u(t)),\ u \in U,$$

where:

x is input signal,

M is time of delay or lead,

U_g - set of raw materials that are used in the manufacture of finished products of the type g,

G_u - finished products set , the production of which uses raw materials of the type u,

y – is output signal.

As the value of the lag M or lead can be selected the value of the indicator of the difference of the operating cycle (the average time between the operation of purchasing raw materials and the sale of finished products made from this raw material) and the production cycle. This indicator depends on the industry, type of production and range of products ($1 < M < 30$).

Direct analysis will reveal patterns of sales of finished products depending on the purchase of raw materials by type of finished product for the periods preceding the inspection period.

The reverse analysis will reveal patterns of raw material procurement for finished products sold, by type of raw material for the periods preceding the verification period.

Information for prior to the verification period is considered reliable. Therefore, the corresponding data can be selected as a training set.

A comparison of the predicted value for the model and the value of the control sample will allow us to identify the types of finished products and stocks and quantization periods for which there are significant deviations and which will be recommended by the decision maker for detailed study at the lower level.

So, for a forecast a learning set is given $S = \{(x_\mu, d_\mu)\}$, $\mu \in \overline{1, P}$.

Then, problem of increase of forecast accuracy on the model of the gateway recurrent unit (GRU) $g(x, W)$, here x - an input signal, W is a vector of parameters, appears as a problem of being for this model of such vector of parameters W^*, that satisfies to the criterion

$$F = \frac{1}{P} \sum_{\mu=1}^{P} (g(x_\mu, W^*) - d_\mu)^2 \rightarrow \min .$$

3 Literature Review

Regressive methods [9] conduct a forecast on the basis of regressive linear and nonlinear model. The advantages of these methods are simplicity of construction of model, design transparency. The disadvantages of these methods are high computational complexity of parametric identification, the absence of possibility of long-term forecast, that results in insufficient forecast accuracy.

Autoregressive methods [15, 16] conduct a forecast on the basis of autoregressive linear model. The advantages of these methods are simplicity of construction of model, design transparency. The disadvantages of these methods are high computational complexity of parametric identification, absence of ability of design of nonlinear processes, that results in insufficient forecast accuracy.

Methods of the exponential smoothing [17] conduct a forecast on the basis of linear model with one (single smoothing), two (double smoothing) or by three (triple smoothing) parameters. The advantages of these methods are simplicity of construction of model, design transparency, a result can be got quicker, than at the use of other models. The disadvantages of these methods are a subzero adaptivity, absence of ability of design of nonlinear processes, that results in insufficient forecast accuracy.

Structural methods [10, 11] conduct a forecast on the basis of Markov chain. The advantages of these methods are simplicity of construction of model, design transparency. The disadvantages of these methods are absence of possibility of long-term forecast, that results in insufficient forecast accuracy.

Logical methods [12 - 14] conduct a forecast on the basis of regressive tree. The advantages of these methods are design transparency, speed of process of construction of tree. The disadvantages of these methods are the problem of construction of optimal tree, the absence of possibility of long-term forecast, that results in insufficient forecast accuracy.

Connectionist methods [18 - 20] conduct a forecast on the basis of nonlinear model of neural network. The advantages of these methods are scalability, high adaptivity. The disadvantages of these methods are absence of design transparency; complexity of choice of model structure; hard requirements to training sample; problem of choice of method of parametric identification; that results in insufficient forecast accuracy high computational complexity of parametric identification.

The general feature of all the methods mentioned above is that they possess a high computational complexity and/or do not give high forecast accuracy.

Therefore an actual task is an increase of forecast efficiency by reducing computational complexity and improving forecast accuracy.

4 Forecast Model Based on a Gateway Recurrent Unit

Gateway recurrent block (GRU) [23, 24] has two gateways. Instead of a hidden neuron, a hidden block h is used, which is connected to the reset gateway r and update z. Gateways determine how much information to skip.

If the reset gateway is close to 1 and the update gateway is close to 0, then we get an Elman neural network (ENN), in which there is no control over the amount of information. If the reset gateway and update gateway are close to 0, then we get a multilayer perceptron (MLP), in which information from the hidden block (long-term) is ignored. If the update gateway is close to 1, then the input (short-term) information is ignored.

The forecast model based on the gateway recurrent unit is defined as follows:

$$y_i^{in}(n) = x_i \ ,$$

$$r_j(n) = f\left(b_j^r + \sum_{i=1}^{M} w_{ij}^{in-r} y_i^{in}(n) + \sum_{i=1}^{N^h} u_{ij}^{h-r} h_i(n-1) \right), \ j \in \overline{1, N^h} \ ,$$

$$z_j(n) = f\left(b_j^z + \sum_{i=1}^{M} w_{ij}^{in-z} y_i^{in}(n) + \sum_{i=1}^{N^h} u_{ij}^{h-z} h_i(n-1) \right), \ j \in \overline{1, N^h} \ ,$$

$$\tilde{h}_j(n) = g\left(b_j^{\tilde{h}} + \sum_{i=1}^{M} w_{ij}^{in-\tilde{h}} y_i^{in}(n) + \sum_{i=1}^{N^h} u_{ij}^{h-\tilde{h}} r_i(n) h_i(n-1) \right), \ j \in \overline{1, N^h} \ ,$$

$$h_j(n) = z_j(n) h_j(n-1) + (1 - z_j(n)) \tilde{h}_j(n) \ , \ j \in \overline{1, N^h} \ ,$$

$$h_j(n) = z_j(n) h_j(n-1) + (1 - z_j(n)) \tilde{h}_j(n) \ ,$$

were:

M – number of unit delays of the input layer,

N^h – hidden layer neurons number,

w_{ij}^{in-r} – weights between the input layer and the reset gateway,

w_{ij}^{in-z} – weights between the input layer and the update gateway,

$w_{ij}^{in-\tilde{h}}$ – weight between input and candidate layer,

u_{ij}^{h-r} – weights between the hidden layer and the reset gateway,

u_{ij}^{h-z} – weights between the hidden layer and the update gateway,

$u_{ij}^{h-\tilde{h}}$ – weight between hidden and candidate layer,

w_i^{h-out} – weight between the hidden and the output layer

5 Criterion Selection for Evaluating the Effectiveness of a Gateway Recurrent Unit

In paper for model training GRU the target function is selected, which means the choice of such values of the parameter vector $W = (w_{11}^{in-r}, ..., w_{MN^h}^{in-r}, u_{11}^{h-r}, ..., u_{N^h N^h}^{h-r}, w_{11}^{in-z}, ..., w_{MN^h}^{in-z}, u_{11}^{h-z}, ..., u_{N^h N^h}^{h-z},$

$w_{11}^{in-\tilde{h}},...,w_{MN^h}^{in-\tilde{h}},u_{11}^{h-\tilde{h}},...,u_{N^hN^h}^{h-\tilde{h}},w_1^{h-out},...,w_{N^h}^{h-out})$, which deliver a minimum of the standard error (the difference between the model output and the test output)

$$F=\frac{1}{P}\sum_{\mu=1}^{P}(y_\mu^{out}-d_\mu)^2\to\min_W,$$

were:

y_μ^{out} is μ-model output,

d_μ is μ-test output.

6 Method for Parametric Identification of a Model of a Gateway Recurrent Unit Based on Adaptive Cross Entropy

Cross entropy method (CE) [25] consists of two phases - the generation of a new population of potential solutions and the modification of the Gaussian distribution parameters.

In this paper, to control the convergence rate of CE and to ensure that the entire search space is investigated at the initial iterations and the search becomes directional at the final iterations, the iteration number is taken into account when generating potential solutions.

The proposed method consists of the following steps:

1. Initialization

1.1. Setting a parameter α that controls the rate of change of the Gaussian distribution parameters, and $0<\alpha<1$.

1.2. Setting a parameter β for generating a standard deviation vector, and $0<\beta<1$.

1.3. Setting the maximum number of iterations N, population size K, solution length M (corresponds to the length of the GRU model parameter vector), the maximum number of best solutions selected.

1.4. Random creating a vector of mathematical expectations

$\mu=(\mu_1,...,\mu_M)$, $\mu_j=x_j^{\min}+(x_j^{\max}-x_j^{\min})U(0,1)$,

were $U(0,1)$ – function that returns a uniformly distributed random number in a range $[0,1]$.

1.5. Create a standard deviation vector randomly

$\sigma=(\sigma_1,...,\sigma_M)$, $\sigma_j=\beta(x_j^{\max}-x_j^{\min})U(0,1)$

1.6. Determine the best solution (best GRU model parameter vector) $x^*=\mu$.

2. Iteration number $n=1$.

3. Create a current population of potential solutions P.

3.1. Solution number $k=1$, $P=\varnothing$.

3.2. Generate a new potential solution x_k.

$$x_{kj} = \mu_j + \sigma_j \left(\frac{N-n}{N} \right) N(0,1), \quad j \in \overline{1,M},$$

were $N(0,1)$ – function that returns a standard normally distributed random number.

3.3. If $k<K$, then $P = P \cup \{x_k\}$, $k=k+1$, go to step 3.2.

3.4. Sort P by target function, i.e.. $F(x_k) < F(x_{k+1})$.

3.5. $k^* = \arg\min_k F(x_k)$.

3.6. If $F(x_{k^*}) < F(x^*)$, then $x^* = x_{k^*}$

4. Modification of the Gaussian distribution parameters (based on the first B, i.e. best, new potential solutions from the population P).

4.1. $\mu_j = \alpha\mu_j + (1-\alpha)\tilde{\mu}_j$, $\tilde{\mu}_j = \frac{1}{B}\sum_{k=1}^{B} x_{kj}$, $j \in \overline{1,M}$.

4.2. $\sigma_j = \alpha\sigma_j + (1-\alpha)\tilde{\sigma}_j$, $\tilde{\sigma}_j = \frac{1}{B}\sum_{k=1}^{B} (x_{kj} - \tilde{\mu}_j)^2$, $j \in \overline{1,M}$.

5. If $n<N$, then $n=n+1$, go to step 3.

The result is x^*.

7 Experiments and Results

Numerical experiments were carried out using the package Matlab. The number of single delays (time lag) $M=10$, neurons number of hidden layer $N^h = 2M$.

To determine the structure of the forecast model based on the gateway recurrent unit (GRU), a number of experiments were carried out, the results of which are presented in Fig. 2.

As the initial data for determining the values of the parameters of the forecast model over the neural network, calculation indicators with suppliers and customers of a machine-building enterprise were used with a two-year sampling depth with daily time intervals, the values of which are Indicators representing trade secrets, and they are scaled.

The criterion for choosing the structure of the neural network model was the minimum mean square error of the forecast. As can be seen from Fig. 1, with an increase in the number of hidden neurons, the error value decreases. For prediction, it is enough to use 10 time delays in the input layer and 20 hidden neurons, since with a further increase in the number of delays and hidden neurons, the error value changes insignificantly.

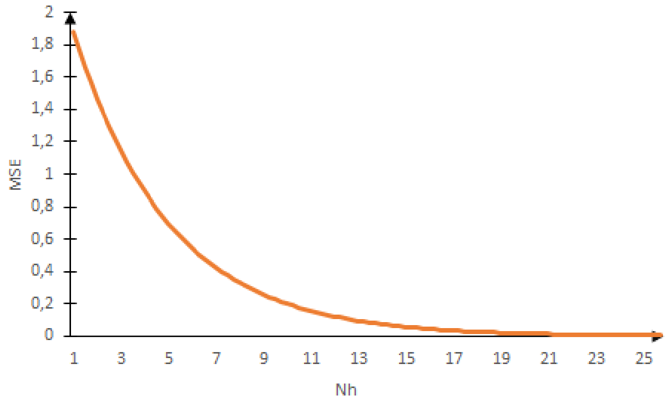

Fig. 2. The dependence of the mean square error of the forecast on the hidden neurons number

In this work, we studied neural networks for prediction by the criterion of the minimum mean square error (RMS) of the forecast. The following neural networks were used in the experiments (tabl.2): JNN (Jordan neural network), ENN (Elman neural network) also called SRN (Simple recurrent network), NARMA (nonlinear autoregressive-moving average), BRNN (bidirectional recurrent neural network), LSTM (long short-term memory), GRU (gated recurrent unit). According to tab. 2, LSTM and GRU have the greatest prediction accuracy, however, LSTM requires more computational complexity due to more connections between neurons.

Table 2. Comparative characteristics of neural networks for prediction

Network	NAR	JNN	ENN (SRN)	NARMA	BRNN	LSTM	GRU
Minimum MSE of forecast	0.2	0.14	0.17	0.16	0.13	0.08	0.08

This is due to the fact that the LSTM and GRU neural networks use control over the amount of information passed through.

According to the XYZ-analysis for classification of resources of enterprise depending on character of their consumption and forecast accuracy of changes in their necessity during a certain temporal cycle three categories are distinguished. Category of X-resources is characterized by the stable size of consumption, insignificant vibrations in their expense and high forecast accuracy. The coefficient value of variation is in an interval from 0 to 10 %. Category of Y- resources is characterized by the well-known tendencies of determination of requirement in them (for example, by seasonal fluctuations) and middle possibilities of their forecast. The coefficient value of variation is from 10 to 25 %. Category of Z - the consumption of resources is irregular, some tendencies are absent, forecast accuracy is not high. The coefficient value of variation is over 25 %.

This model was approved on the values of indexes of category of X. Comparing the values of coefficient of variation for the category of resources of X and an error of forecast on the network of GRU, that made 5%, it is possible to draw the conclusion, that this network befits for this category of resources.

8 Conclusions

The article considers the problem of increasing the efficiency of automatic data analysis in DSS of audit based on the forecast due to the gateway recurrent unit (GRU). Reached the further development of the method of parametric identification of the model GRU, which is based on adaptive cross entropy (ACE), which increases the accuracy of the forecast, because at the initial iterations the entire search space is investigated, and at the final iterations the search becomes directional. Software implementing the proposed method in the package Matlab, was developed and researched on the indicators of supply and payment of stocks of a machine-building enterprise with a two-year sampling depth with daily time intervals. The experiments confirmed the operability of the developed software and allow us to recommend it for use in practice in the automated analysis subsystem of the DSS of audit to verify the totality of the displays of the sets of calculation sets with suppliers and customers. The prospects for further research are to test the proposed methods on a wider set of test databases.

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