UDC 004.89:519.22](043.3)
DOI: 10.15587/2706-5448.2023.286516

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THE IMPROVEMENT OF THE INTELLIGENT DECISION SUPPORT SYSTEM FOR FORECASTING NON-LINEAR NON-STATIONARY PROCESSES

The paper is focused on solving the modern scientific and applied problem related to development and practical use in Decision Support Systems (DSS) of information technologies directed towards forecasting of non-linear non-stationary processes (NNP) that take place in economy and finances as well as in many other areas of activities. Thus, object of study are non-linear non-stationary processes taking place in economy and financial sphere.

The basic problem of the study is development of new mathematical models and methods of analysis and forecasting non-linear non-stationary processes in economy and finances, improvement of information decision support technologies that would help to enhance quality of forecast estimates and respective decisions in conditions of uncertainties and risk. The methods given in the paper are used for automating the process of intellectual data analysis that describe the processes under study and automatizing model constructing procedures.

As a result of the study performed the information technology was developed to be used in DSS based upon system analysis principles, taking into consideration possible data uncertainties, regression and intellectual data analysis. The technology provides for constructing adequate models of the process under study and computing high quality forecast estimates. The particular feature of the approach proposed is that it provides for high quality of experimental results due to taking into consideration special features of non-linear non-stationary processes that take place in various spheres of activities and their evolution is influenced by many specific factors.

The use of the technology proposed in decision support systems of enterprises, state governmental organs, and local self-government will create basis for effective solving the tasks of governing development of non-linear non-stationary processes that take place in many spheres of activities. The approaches proposed in the paper can be used in practice as separately as well as parts of existing information systems at enterprises and organizations.

Keywords: *forecasting, non-linear non-stationary processes, decision support system, data uncertainty, system analysis principles.engineering.*

Received date: 07.07.2023
Accepted date: 29.08.2023
Published date: 30.08.2023

How to cite
Bidiuk, P., Prosyankina-Zharova, T., Diakon, V., Diakon, D. (2023). The improvement of the intelligent decision support system for forecasting non-linear non-stationary processes. Technology Audit and Production Reserves, 4 (2 (72)), 37–46. doi: https://doi.org/10.15587/2706-5448.2023.286516

1. Introduction

The growing uncertainty of external environment increases the requirements for the quality, reasonability and efficiency of managerial decision-making [1–3]. Most often, the weakly structured problems of research, changes in the behaviour and structure of socio-economic systems under the influence of predictable and non-predictable external factors, the most complete use of available potential and ensuring support for making optimal managerial decisions regarding development of systems under study need to be solved today [4–7].

Although socio-economic systems, like other complex systems, are functioning according to certain laws, they have a significant number of elements and connections between them, hidden laws of functioning in data, non-linear variable and parametric constraints, which are difficult, and sometimes impossible to determine and describe formally using separate mathematical models or models of economic dynamics [8–13]. The complexity of solving such problems is primarily related to the choice of optimal and suboptimal tools and methods [2, 5, 6, 14].

That is, the urgent issue today is development of methods and models that would create methodological basis for carrying out research relevant to development of socio-economic systems in conditions of uncertainty [15–18], building forecasts and recommendations for decision-making [19–21], forming an effective mechanism for managing their functioning [22–25], and determining the prospects for their short- and long-term development [26–30].

Implementation of specific methods and models in decision making support systems will provide a decision-maker with modern means of information analysis, generating of

ISSN 2664-9969

decision options (alternatives), modeling of problem situations and scenarios, assessments of risks and uncertainties, selection and construction of the best solution [31–35]. However, these questions are related to the complex intellectual tasks, burdened by both uncertainty and the need to involve significant amounts of structured and unstructured data, and knowledge from various relevant subject areas [36–40].

Most of the processes available for analysis in economics and finance as well as in many other areas of practical studies, exhibit nonstationary behavior and contain nonlinearities with respect to variables and/or parameters [7, 10, 11, 17, 23]. Such processes received the definition of nonlinear and nonstationary ones (NNP). These characteristics require special attention and efforts for constructing adequate models and estimating the model-based forecasts [1, 2, 6, 22]. A substantial help in solving these problems can provide appropriately designed and implemented decision support system (DSS), and Intelligent DSS (IDSS) [15, 16, 25, 35], based upon known system approach to analysis principles [22]. The principles that have been used in practice to construct computer based control, diagnostic and other decision support systems are basically as follows: hierarchical functional system structure; application of necessary set of preliminary data processing methods; optimization and model adaptation procedures where necessary; identification and taking into consideration possible data uncertainties of statistical, structural and parametric types; application of appropriate statistical criteria set to guaranty high quality of data, constructing adequate models and generating high quality forecasts, and possibly control actions; providing for a set of appropriate (competing) decision generating procedures necessary for computing decision alternatives and selecting the best one of them for further practical implementation.

Next, let's consider IDSS constructing procedure and important tasks to be solved using this procedure, for example, identification and fighting possible uncertainties met in modeling and forecasting based on statistical data. And application of the DSS to solving practical problems of NNP modeling and short-term forecasting. As an example, the heteroscedastic processes were selected the ones widely spread in financial analysis.

The aim of the research is to improve the IDSS characteristics through development and implementation of models and methods that take into account the peculiarities of processing non-linear non-stationary economic and financial processes, and possible similar processes of other origin. In particular, preparation of input data, identification of uncertainties and determining of means for their disclosure, selection of optimal mathematical models for short-term forecasting of future evolution of the processes under study.

This approach to complex process analysis will make it possible to improve substantially the quality of managerial decisions made in conditions of uncertainty, non-stationarity and risk.

The purposes of the study are related to solving the following tasks:

– refinement of IDSS constructing procedure directed towards possible uncertainties identification and determining the means for fighting the uncertainties;
– constructing mathematical models for the process selected and their conditional variance;
– analysis of the results achieved, and determining the possibilities for future studies and further improvement of IDSS functional characteristics.

2. Materials and Methods

2.1. Some data uncertainties met in modeling and forecasting. The hierarchical IDSS structure is characteristic for the most modern computer-based control systems, and it has flexible architecture/functionality capable to take into consideration possible changes of data structure and its content generate modeling alternatives, variety of necessary forecasts as well as control actions. The task of preliminary data processing provides mostly for correct preparing of data to subsequent modeling. The usually applied data processing functions at this stage are data normalizing, filtering noise, filling in missing observations, appropriate processing of outliers etc. These functions are mostly directed towards minimizing influence of possible data uncertainties that are considered as factors negatively influencing the computational procedures in data processing system and decreasing quality of intermediate and final results. Practically all types of mathematical modeling usually need to cope with various types of uncertainties related to observations: in the form of short samples, missing observations, noisy measurements, and outliers. Also, there are uncertainties of structure of a process under study and its model, parameter estimate uncertainties, and uncertainties relevant to the quality of models and forecasts as a whole [22, 30, 38, 39]. To avoid or to take into consideration the uncertainties and improve this way quality of intermediate and final result (forecasts of processes development and managerial decisions based on them) it is necessary to construct appropriate computer based intellectual decision support systems for solving correctly multiple specific problems [23, 25, 27, 31].

Minimizing negative influence of possible data uncertainties generally results in higher model adequacy and quality improvement of final decision. Possible parametric uncertainties of the models constructed are minimized by correct preliminary processing of data and correct selection of parameter estimation procedures. For solving this task there is a set of parameter estimation methods for the cases of various data distributions and linear/nonlinear model structures [6–10, 12, 13].

An important role in constructing IDSS plays correctly selected (or developed) the set of statistical criteria providing for a high quality of computational results at each stage of data processing, model constructing, forecast estimation, and generating decision alternatives. Quality of data can be tested with its variance that formally characterizes informational content. To perform this function, it is also useful to analyze time derivatives of data using appropriate polynomial model. Adequacy of models constructed and estimated forecasts are evaluated with their own sets of criteria. Analysis of decision alternatives can be performed with application of appropriate simulation procedures that show quality of the final results of decision making.

On the data analyzing stage two types of non-stationarity are usually met: availability of data trend (integrated processes), and heteroscedasticity – when the process variance is time-varying. The data analysis methodologies are available for both cases, and the model structures can be selected (or constructed by a researcher) successfully to reach necessary model adequacy. In the case of heteroscedasticity it is necessary to construct model of volatility describing time evolution of variance that is useful for estimating, for example, different risks.

Analysis of nonlinearity shows that the two basic types of nonlinearities met in practice are nonlinearities with respect to variables, and nonlinearities with respect to parameters. An important point here is in correct selection of model parameter estimation technique. The first type of nonlinearity allows application of linear and nonlinear least squares (LS) versions, though the second type of non-linearity requires application of maximum likelihood (ML) method, nonlinear LS, and Monte Carlo for Markov Chains (MCMC). It should be stressed that incorrect selection of the parameter estimation method usually results in biased parameter estimates and poor adequacy of resulting model based on data collected.

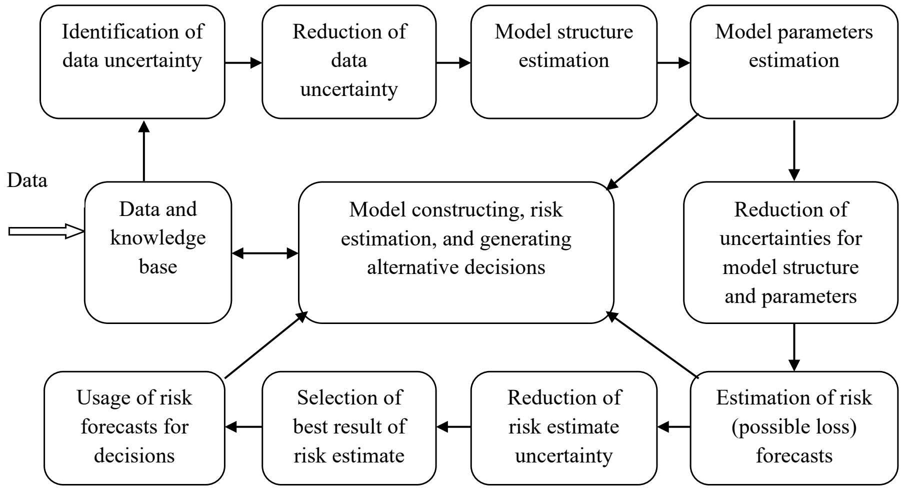

Fig. 1. The computational procedures applied for identification of possible uncertainties, and taking them into consideration

2.2. IDSS constructing and fighting uncertainties. Among multiple known types of DSS already used to solve various practical problems are intellectual DSS that have many useful functions. Consider definition for the IDSS given below [22, 25, 27].

Intellectual DSS is interactive computer-based system that provides the means for intellectual data and expert estimates analysis, and provides decision making person with support at all stages of making decision including the following tasks:

– analysis and identification of the problem under consideration as well as formulation of the main goal for decision making; creating understandable and refined problem statement;

– planning and generating the ways for reaching the main goal, i. e. planning necessary actions to be performed;

– alternatives generating for solving the problem under consideration using accessible knowledge, situational models, as well as information relevant to the known previously used alternative ways of solving the specific problem;

– selection of the best way (methods) for solving the problem stated;

– IDSS should also possess the feature of self-learning in the processes of solving similar problems; this valuable feature helps user to store potentially useful knowledge during current system sessions and use the knowledge repeatedly in the future problem-solving applications.

Thus, IDSS should possess ability of storing knew knowledge regarding the application area, to learn on the basis of analysis of the experience acquired, to adapt to changing environment and possible users as well as to current state of the problem being solved. The IDSS should also contain one or several methods for intellectual data analysis, for example, fuzzy logic, neural networks, neuro-fuzzy models and techniques, Bayesian data analysis techniques and methods for generating probabilistic inference, genetic and clonal algorithms etc.

The problems of data processing using the IDSS can be divided into the following several groups: preliminary data processing and analysis; identification and taking into consideration possible data uncertainties, constructing necessary models (model structure and parameter estimation), estimation of forecasts, application of the models and forecasts computed for decision making (Fig. 1).

The first set of tasks is related to preliminary data processing and includes the following procedures: imputation of missing observations; normalizing the observations; determining distributions of observations; digital and/or optimal filtering of data; computing and analysis of first and higher order differences; classification of types of the processes under consideration (stationary/nonstationary, linear/nonlinear, integrated or heteroscedastic) using multiple statistical criteria.

Performing all these tasks is necessary for deeper understanding of the process features under study and identification of possible uncertainties so that to take them into account during further steps of data processing and model building. Imputation of possibly missing observations is one of the operations directed towards minimization of influence of available uncertainties. All the procedures necessary for performing preliminary data processing are described in details in special literature on statistical data analysis.

It should be noted that correct application of optimal filtering algorithms requires knowledge of data distribution and their parameters (e. g., variance and covariance). For example, classic application of optimal Kalman filter supposes normal distribution of observations. Also, there is a difference between processing linear and nonlinear processes. Besides filtering, the Kalman data processing algorithms are applied for constructing dual control systems (optimal filtering + optimal control), estimation of non-measurable variables, short-term forecasting, combining measurements coming from multiple sources to refine estimates of state vector components, and statistical parameters estimation for stochastic external disturbances and measurement noise. As far as analysis of nonlinear nonstationary processes requires application of nonlinear filtering, here it is necessary to apply (for example) unscented Kalman or probabilistic Bayesian filter that suits well for the cases of analyzing NNP.

A special attention in the IDSS is paid to identification and taking into consideration (fighting) possible data uncertainties that are very often inherent to observations. To fulfill the task statistical and probabilistic techniques are applied, as well as intellectual data analysis methods such Bayesian data analysis, fuzzy and neuro-fuzzy models, appropriate simulation techniques etc. Table 1 below shows some possibilities for solving the problem of coping

ISSN 2664-9969

with data uncertainties. According to definition [17, 22], uncertainty is a factor of negative influence to the computational procedures of the IDSS that leads to decreasing quality of models, forecasts and finally quality of decisions. The structural uncertainties are related to estimating structure of mathematical models to be further used in the procedures of risk estimation. The methods used to decrease influence of possible uncertainties are given in the fourth column of Table 1. To fight uncertainties Bayesian data analysis (BDA) methods are often successfully applied, such as particle filters, static and dynamic Bayesian networks (BN), decision trees etc. The success of BDA application is explained by the fact that the very nature of these methods corresponds to the problem stating regarding uncertainty identification and correctly taking it into account. The conditional uncertainties widely used in Bayesian data analysis say that some event may happen or not dependently on other relevant (conditional) influences [26, 41]. And the model of BN is constructed in a way to give correct answer to such questions. Availability of alternative methods for formulating Bayesian inference also stresses that BN model is directed towards taking into consideration possible various causal dependences (alternatives).

Table 1 can be considered as an example of analyzing possible data uncertainties met in the modeling procedures and the methods of correctly coping with them. In practice such table can be extended according to the requirements of specific problem statement. All the tasks necessary for processing uncertainties are solved successfully with appropriately designed and implemented IDSS possessing special features for processing the types of uncertainties mentioned. Application of the IDSS described above provides a possibility for achieving high quality results of modeling and short-term forecasting for nonlinear nonstationary processes met in economics and finance.

2.3. Intellectual features of the IDSS. Current version of the IDSS exhibits some features of «intellectuality» thanks to the use of methods that belong to the class of artificial intelligence, and it also generates recommendations for a user by making use of menu that helps to select textual option of explanations. The help (explanations for a user) provided by IDSS is related to the following items: general possibilities of the system regarding data processing, model development and risk estimation, explanations regarding methods of missing data imputation, and possible types of mathematical models selection for a formal description of the NNP under study; explanations regarding method for model parameter estimation; possibilities for selection of various quality criteria to be used at each step of data processing; and explanations regarding type and methods of financial risk estimation etc. Another possibilities for getting help on behalf of the IDSS are in generating explanations regarding the use of statistical testing of the data available and interpreting the results of testing.

Such explanations provided by the system for a user usually make substantially shorter the time required for problem analysis, the user has a possibility for deeper understanding the tasks it has to perform, the results of data processing, model constructing and risk estimation are comprehended better by the user and help it to select best decision alternative. The results of intermediate and final computations acquire, as a rule, higher quality, and they are better adjusted for solving the problem stated.

The IDSS also «reminds» the user results of previous sessions (retrospective analysis) allowing it to use formerly accumulated information and compare faster former and generated results of current problem solving. All these possibilities make interaction of a user with the system easier, more interesting, and results achieved of higher level and more understandable. Finally, the system becomes capable of learning the processes of data analysis in specific problem statement and reproducing the knowledge for a user to get intermediate results of process analysis of higher level and better quality.

Table 1

Some general types of data uncertainties and methods for coping with them

No.	Some types of uncertainties	Reason of uncertainty existence	Methods of coping with uncertainty
1	Structural	– impossibility of discovering all causal dependences between variables of interest on the basis of available information; – approximate estimates of a model structure elements; – system under study is nonstationary what results in changes of its structural elements; – substantial random external influences resulting in changes of a system structure	– expert techniques; – statistical tests and hypothesis testing theory; – combined application of alternative model structure estimation techniques; – simulation of the system under study aiming to searching for the best model structure
2	Statistical	– availability of measurement errors; – availability of external stochastic disturbances; – multi-collinearity problem; – availability of extreme data values; – availability of missing data; – short samples	– digital filters; – optimal state estimation techniques; – the use of multiple distributions; – principal component analysis; – theory of extreme values; – data imputation techniques; – data propagation (multiplying)
3	Parametric	– incorrect selection of parameter estimation technique; – insufficient data sets	– the use of alternative parameter estimation techniques; – data generation and propagation techniques
4	Probabilistic	– complex mechanisms of causal dependences; – influence of a set of mutually dependent random events; – lack of necessary information	– static and dynamic Bayesian networks; – Markov models; – probabilistic (particle) filters; – Demster-Shafer theory
5	Amplitude uncertainty of observations	– availability of non-measurable variables; – measurement errors; – influence of external random processes	– Kalman filtering techniques; – fuzzy sets and data processing techniques; – alternative state estimation techniques

3. Results and Discussion

3.1. Results. The problem is in modeling and forecasting bank rate (y) and its variance. Here we are interested in dynamic models of LIBOR (London Interbank Offered Rate) bank rates for the currencies USD and EUR, mean monthly and 6-month values. LIBOR represents mean weighted rate for interbank credits. These credits are proposed for the banks that participate in the London interbank market and propose financial means in different currency and for different time terms: from one day to one year. LIBOR is one of the most frequently used index for short term percentage rates the world over. Actually, it is used as a basis for calculating of percentage contracts at the futures and option stock markets as well as instruments of determining the cost of the most instruments at out-of-stock lending markets. The LIBOR rate is established by the British Bankers' Association (BBA) starting from 1985 on a daily basis using the data provided by selected banks. To construct the model for each rate the time series of mean monthly values will be used within the period from 2000 and to 2006, and then the forecasts will be estimated for the first three months of 2007.

AR(1) model, that is necessary for estimating residuals, for the rate of LIBOR USD 1M, *usd*1*m* is like follows:

$$usd1m(k)=a_0+a_1\cdot usd1m(k-1)+\varepsilon(k), \quad (1)$$

where $\varepsilon(k)$ is residual process. And with estimated coefficients AR(1) and GARCH model for conditional variance we have the following result:

$$usd1m(k)=a_0+a_1\cdot usd1m(k-1)+\varepsilon(k), \quad (2)$$

$$\begin{aligned}\mathrm{var}_{k-1}[y(k)]&=h(k)=\\&=0.035+0.3964\cdot\varepsilon^2(k-1)+0.1221\cdot\varepsilon^2(k-2)+\\&+0.1276\cdot\varepsilon^2(k-3)+0.2238\cdot\varepsilon^2(k-4)-\\&-0.3969\cdot h(k-1)-0.4087\cdot h(k-2),\end{aligned} \quad (3)$$

where $h(k)$ is conditional variance for $y(k)$.

Assign the time series rate of mean monthly values the name of LIBOR USD 6M as *usd*6*m*. The required low order model (AR(1)) necessary for estimating residuals looks as follows:

$$usd6m(k)=a_0+a_1\cdot usd6m(k-1)+\varepsilon(k), \quad (4)$$

where $\varepsilon(k)$ represents residuals for this model. Corresponding GARCH model for *usd*1*m* (LIBOR USD 6M) conditional variance looks like follows:

$$y(k)=0.0315+0.9867\cdot y(k-1)+\varepsilon(k), \quad (5)$$

$$\begin{aligned}\mathrm{var}_{k-1}[y(k)]&=h(k)=\\&=0.0853+0.0267\cdot\varepsilon^2(k-1)+0.1481\cdot\varepsilon^2(k-2)-\\&-0.009\cdot\varepsilon^2(k-3)+0.1206\cdot\varepsilon^2(k-4)+\\&+0.0014\cdot\varepsilon^2(k-5)-0.0289\cdot\varepsilon^2(k-6)-\\&-0.0742\cdot\varepsilon^2(k-7)+0.1066\cdot\varepsilon^2(k-8)+\\&+0.0912\cdot\varepsilon^2(k-9)-0.4339\cdot h(k-1)-0.5707\cdot h(k-2).\end{aligned} \quad (6)$$

Let *eur*1*m* represents the variable showing mean monthly values for the rate LIBOR EUR 1M. Corresponding model again includes two equations and looks like follows:

$$y(k)=0.0307+0.9898\cdot y(k-1)+\varepsilon(k), \quad (7)$$

$$\begin{aligned}\mathrm{var}_{k-1}[y(k)]&=h(k)=\\&=0.0114+0.4927\cdot\varepsilon^2(k-1)+0.0688\cdot h(k-1)+\\&+0.0898\cdot h(k-2)-0.0354\cdot h(k-3)-\\&-0.0104\cdot h(k-4)+0.0284\cdot h(k-5)-\\&-0.0878\cdot h(k-6)-0.0118\cdot h(k-7)-\\&-0.0630\cdot h(k-8)-0.0621\cdot h(k-9),\end{aligned} \quad (8)$$

where $\varepsilon(k)$ represents residuals for AR(1). Table 2 shows three-step forecasts for the process mathematical expectation and its variance as well as actual values.

Table 2

Three year forecasts of mathematical and conditional variance LIBOR rate

Month, year and parameters	2007:1		2007:2		2007:3	
	m	σ^2	m	σ^2	m	σ^2
Actual values	3.616	0.075	3.652	0.070	3.845	0.053
Variance forecast using GARCH model	3.634	0.034	3.627	0.011	3.621	0.014

The quality characteristics received for the forecasts are high: $MSE=0.12$; $MAE=0.08$; $MAPE=2.49$ %; $U=0.02$.

Here the mean absolute percentage error is only about, 2.49 %, what indicates to high quality forecasting model. Taking into consideration that PACF of the process under study, *eur*6*m*, actually indicates to the second order of autoregression, the AR(2) model should be built. Heteroscedasticity will be described by the GARCH equation:

$$\begin{aligned}y(k)&=0.0227+1.2481\cdot y(k-1)-\\&-0.2542\cdot y(k-2)+\varepsilon(k),\end{aligned} \quad (9)$$

$$\begin{aligned}\mathrm{var}_{k-1}[y(k)]&=h(k)=\\&=0.0017+0.4508\cdot\varepsilon^2(k-1)+0.1230\cdot\varepsilon^2(k-2)-\\&-0.2232\cdot h(k-1)-0.0727\cdot h(k-2)+\\&+0.1634\cdot h(k-3)-0.0023\cdot h(k-4)-\\&-0.0833\cdot h(k-5)+0.3712\cdot h(k-6),\end{aligned} \quad (10)$$

where $\varepsilon(k)$ are residuals of AP(2), constructed for $y(k)$.

Table 3 shows forecasts of mathematical expectation and conditional variance of the process, $y(k)$, using the models built as well as actual historical values of the parameters.

Table 3

Forecasts of mathematical expectation and conditional variance

Month, year and parameters	2007:1		2007:2		2007:3	
	m	σ^2	m	σ^2	m	σ^2
Actual historical values	3.890	0.037	3.944	0.030	3.997	0.023
Variance forecast using GARCH model	3.803	0.030	3.807	0.027	3.807	0.045

Statistics of the three-step forecasts quality are as follows: $MSE=0.11$; $MAE=0.08$; $MAPE=2.47$ %; $U=0.02$

Here the mean absolute percentage error is only about, 2.47 %, and Theil coefficient, $U=0.02$, what indicates to high quality forecasting model.

Thus, different process characterizing dynamics of percentage rates were analyzed. It was shown that these processes are heteroscedastic and contain are formally described well with GARCH models. The statistics received acquire high values for each process nonlinearities because their variance is time varying process. The modeling results show that the processes using the models constructed three-step forecasting of the rates and their variances was performed. The forecasts are suitable for market risk estimation and Monte Carlo simulations. The quality of forecasting was estimated with a set of statistical quality criteria, all of which demonstrated acceptable values given in Tables 4, 5.

The model's adequacy has also been proved by the results of comparing actual historical observations with forecasts.

As an example of an information technology for identifying uncertainties of various types and disclosing them in decision support tasks, the task, which is intended to manage the development of local socio-economic systems – united communities, is considered. The peculiarity of this task is that the processes that take place in such systems are mostly nonlinear and nonstationary, and in the course of the study, it is necessary to work out uncertainties of various types. The most problematic issues are working out data gaps and solving the problem of the «curse of dimensionality». After all, the time series of such socio-economic indicators contain gaps, are usually short, and the system under study is characterized by a significant number of indicators.

Table 4

Quality of forecasting variance for the process under study

Process analyzed		LIBOR USD 1M	LIBOR USD 6M	LIBOR EUR 1M	LIBOR EUR 6M
Model type		GARCH (2,4)	GARCH (2,9)	GARCH (9,1)	GARCH (6,2)
Forecast quality	*MSE*	0.21	0.21	0.12	0.11
	MAE	0.14	0.15	0.08	0.08
	MAPE	5.04 %	5.11 %	2.49 %	2.47 %
	U (Theil)	0.03	0.03	0.02	0.02

Table 5

Quality of short-term forecasting the processes themselves using low order models

Process analyzed		LIBOR USD 1M	LIBOR USD 6M	LIBOR EUR 1M	LIBOR EUR 6M
Model type		AP(1)	AP(1)	AP(1)	AP(2)
Fore-cast quality	*MSE*	0.16	0.21	0.28	0.25
	MAE	0.14	0.15	0.16	0.09
	MAPE	4.45 %	4.22 %	2.31 %	2.05 %
	U (Theil)	0.03	0.03	0.02	0.02

The proposed information technology is intended to be used in various IDSSs, as it is flexible enough to be customized for specific analytical tasks. Its scheme is shown in Fig. 2.

The software implementation of this information technology is made in SAS Enterprise Guide [41] environment in SAS Base language. The application is flexible and can be easily reconfigured to meet the needs of the task as a whole or to implement individual stages of the analytical process. The structure of the application is shown in Fig. 3.

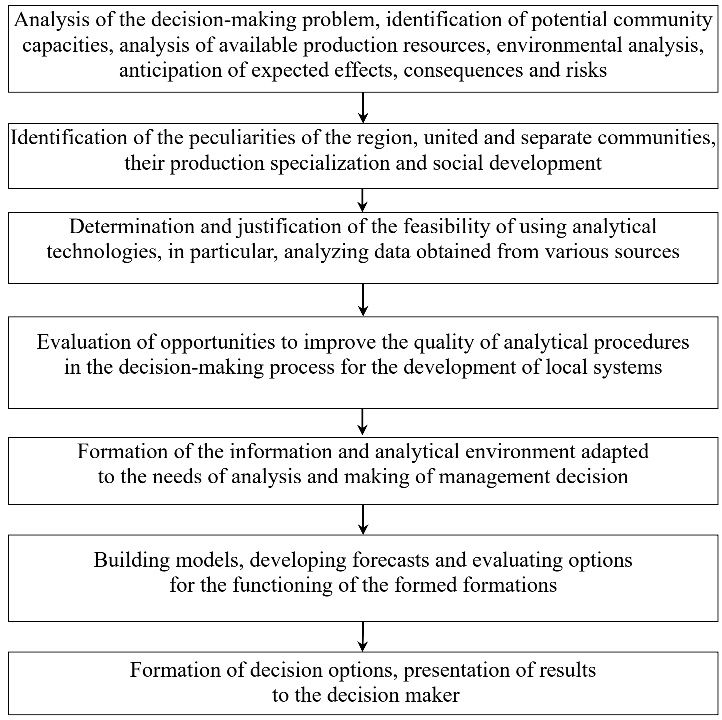

Fig. 2. Scheme of the developed information technology

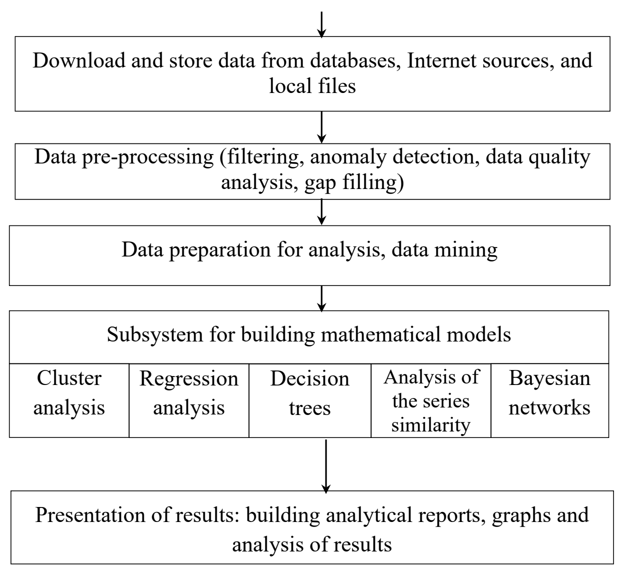

Fig. 3. Structure of the application developed on the basis of the proposed information technology

As shown in Fig. 3, the software implemented on the basis of the proposed information technology consists of several interconnected modules that form the basis of information support for the analytical process, which allows taking into account the specifics of the subject area, using various analytical tools, and expanding, if necessary, the set of mathematical models that can be used. Any necessary element can be added to the process chain by the user using the appropriate visual components of SAS environment in Enterprise Guide [41].

For the purpose of forecasting the capacity of communities, the statistical data on the socio-economic development of communities, indicators of financial sustainability of local budgets, results of comparative analysis of the effectiveness of budget programs and an expanded set of indicators used in the budget process are used. The study used data from more than 30 communities. Relationships between the data and hidden patterns were examined using data mining procedures. The data used in the analysis were preliminarily prepared for further use in building models using ETL procedures. Gaps in the data were filled in, interval variables were converted to categorical variables, and anomalous values were excluded from the analysis. The principal components method was used to eliminate multi-collinearity. To fill in the data gaps, the methods of finding the average between the first previous and the first subsequent values of the series, regression models (for small, up to 5 % of the number of gaps), and a significant (20 %) number of gaps were used. To assess the quality of the regression models used to fill in the gaps, MAPE indicator was used.

In addition, at the stage of data collection and preliminary processing, SWOT table was built to better understand the subject area and identify the most important factors for analysis.

The ultimate goal of using the proposed information technology was to forecast the revenue and expenditure side of the local budget of the united territorial communities.

For forecasting the indicator of «budget execution by expenses», the best model was a linear regression model with automatic selection of regressors using the Stepwise method (Fig. 4).

The estimation of the model coefficients for forecasting the indicator «budget execution by expenses, c. u.» is presented in Table 6.

The quality of the forecast can be analyzed using the data in Fig. 5.

The resulting mathematical model has the following predictive characteristics: $RMSE=224$, $MAPE=3.22$ %, $R^2=0.99$.

To predict the indicator «budget execution by revenues, c. u.», a linear regression model was built with the choice of regressors in the automatic mode using Stepwise method (Table 7).

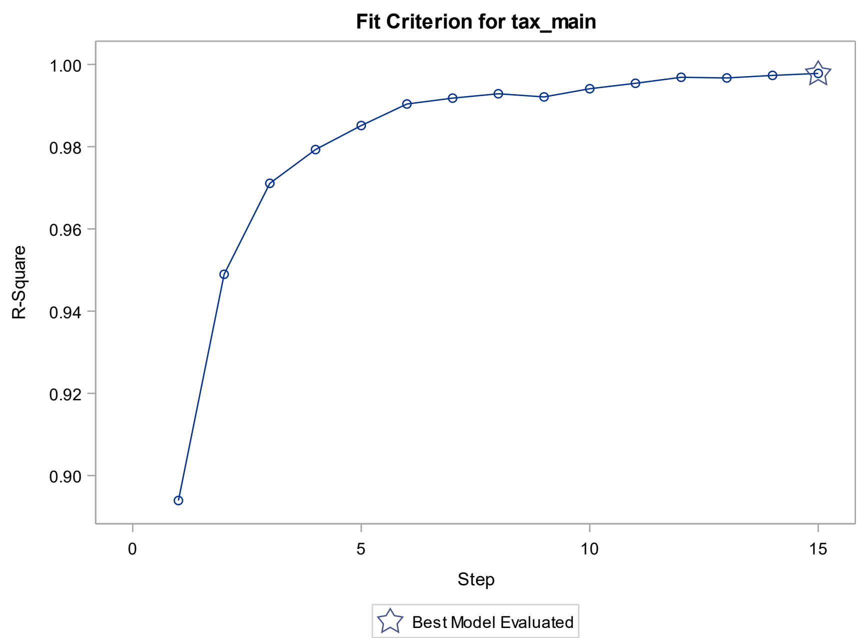

Fig. 4. Changes in R^2 statistic of the model depending on the choice and mixing of regressors in the model for predicting the indicator «budget execution by expenses» in the automatic Stepwise mode

Table 6

Estimation of model coefficients for forecasting the indicator «budget execution by expenses», c. u.

Variable	Parameter Estimate	Standard Error	Type II SS	F-Value	Pr>F
Intercept	254.10571	169.69266	197288	2.24	0.1537
Expenditures for:					
– national functions	0.99424	0.21527	1876760	21.33	0.0003
– housing and communal services	8.16851	0.49251	24201654	275.07	<0.0001
– health care	3.59989	0.35915	8839193	100.47	<0.0001
– financing of institutions	–0.39264	0.14507	644540	7.33	0.0156
– general secondary education	0.23663	0.09350	563553	6.41	0.0222
– public administration	1.61023	0.38901	1507459	17.13	0.0008
– public utilities	–4.21820	0.64945	3711586	42.19	<0.0001
– other institutions	1.18862	0.26600	1756854	19.97	0.0004
– culture and art	1.98848	0.51266	1323688	15.04	0.0013
– conducting elections	9.71807	2.49986	1329609	15.11	0.0013
– other expenses	0.85815	0.45286	315930	3.59	0.0763

 ISSN 2664-9969

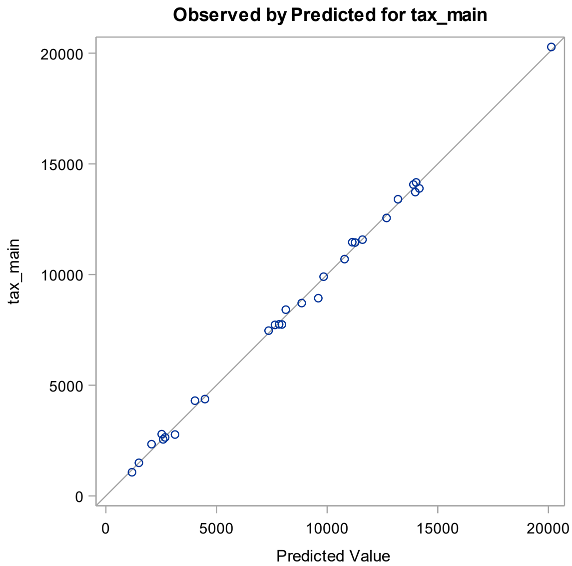

Fig. 5. Distribution of real and projected values of the indicator «budget execution by expenses», c. u.

Table 7

Estimation of model coefficients for forecasting the indicator «budget execution by revenues», c. u.

Variable	Parameter Estimate	Standard Error	Type II SS	F-Value	Pr>F
Intercept	590.70325	560.13206	2185481	1.11	0.3026
Tax revenues	0.92724	0.11791	121536845	61.85	<0.0001
Economic activity	1.82459	0.56346	20605728	10.49	0.0036
Subsidies from the state budget	–3.38282	0.77284	37649943	19.16	0.0002
Property tax	5.37428	0.84544	79408739	40.41	<0.0001

The quality of the forecast can be analyzed using the data in Fig. 6.

The resulting mathematical model has the following acceptable predictive characteristics: $RMSE=1074$, $MAPE=12.7$ %, $R^2=0.93$.

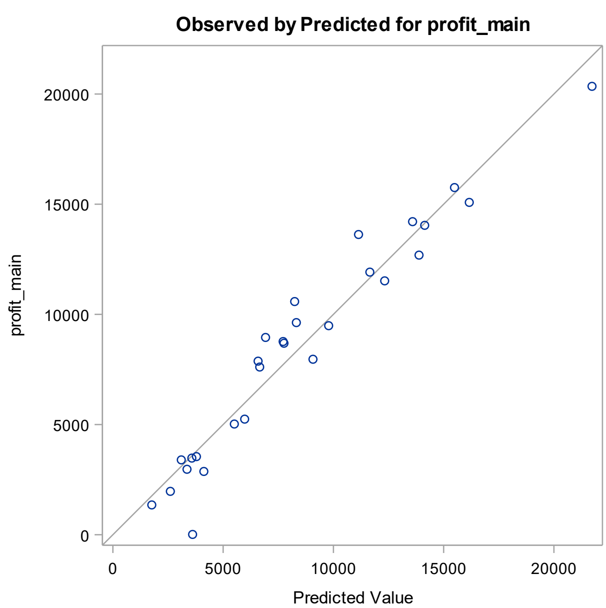

Fig. 6. Distribution of real and projected values of the indicator «budget execution by expenses», c. u.

3.2. Discussion. The results of modelling and forecasting achieved in this research are explained by complex application of system analysis principles for design and implementation of the system, correct use of preliminary data processing techniques, and application of several sets of statistical quality criteria: data quality, model adequacy, and quality of forecast estimates. The results achieved was distinguished from known by taking into consideration possible data uncertainties, their higher quality, applicability to support decisions for processes in economy and finances. But the applications of the developments are not limited by financial and economic processes; they are suitable for practical use in any applied area where non-linear non-stationary processes exist.

The practical applications have the models constructed, forecasts computed using the models, and proposed methodology of DSS constructing. The advantages of the proposed information technology are confirmed by the results presented in the examples of modelling and forecasting nonlinear nonstationary processes often met in economy, finances and many other areas was considered. The first example is created by heteroscedastic processes widely spread in financial analysis and other areas of study. Analysis of such processes is very useful practically because variance forecasts are necessary for risk estimation, diagnostics, and numerous other applications. The models were constructed for the processes themselves and their variance. The processes model structures were intentionally selected of low order because such models were necessary for estimating stochastic component of the process only. This component allows for further determining dynamics of the process conditional sample variance used for modelling.

The methodology of analysis NNP practically does not have special practical limitations. The IDSS designed and implemented according to the system analysis principles mentioned above will provide for high quality results in many practical applications of modelling, forecasting NNP, and respective decisions support. Some limitations have the optimization procedures used for model structure and parameter estimation, they should be adjusted to new (changing) requirements if area of study is changed. Also restrictions imposed on parameters and/or variables may also change. The example models constructed also have limits for practical applications to similar processes. They should be repeatedly constructed (adapted) when new (or modified) data is available, although the basic proposed methodology remains the same.

In future studies it will be necessary to expand the nomenclature of mathematical models: introduce combining of linear and nonlinear structural elements of models, actively use Bayesian data analysis methods, neural networks and neuro-fuzzy models etc. Refinement of existing and development of new model structures and parameter estimation computational procedures. In addition, the future studies will be concentrated on further improvement of the models quality as well as on automatizing the whole modelling and forecasting process. New predictive model structures will be developed for the processes under study enhancing model adequacy. The studies on application of the modelling methodology to financial risk estimation are carried out. Also the instrumental system functions will be refined from the point of view of further increasing the quality of their computational results and enhancement of intellectual features directed on improvement of man-machine dialog and quality of advices generated by the system for a user.

Existing military situation in Ukraine created negative impact on carrying out the research from the point of view of collecting necessary data, and cooperation between researchers.

4. Conclusions

In the research the development of new information technology for the predicting nonlinear nonstationary processes of different types in economy and finances using a multi-model approach, modern mathematical forecasting methods and decision-making methods based upon system analysis principles was carried out.

The features of the proposed method are:

– using the improved method of revealing uncertainties of different types using probabilistic and statistical methods in order to correctly solve the problems of predicting the future development of selected processes;

– using the improved methods of predicting nonlinear non-stationary processes based on the complex application of combined forecasts where each model type should be used for fulfilling specifically set problem;

– the regression modelling methodology provides the possibility for constructing models on the basis of possible independent variables (regressors), their optimal selection for building specific model with subsequent estimation of single- or multistep forecasts;

– improving the set of the methods of identification and taking into consideration possible uncertainties of different types based on the application of the intellectual data analysis methods that provides the possibility for constructing adequate models of the processes under study and estimation of high quality forecasts;

– proposed methodology of DSS constructing is based upon systemic approach, the set of the identification methods and taking into account possible uncertainties, application of the regression and intellectual data analysis methods that provides the possibility for constructing adequate models of the processes under study and estimation of high-quality forecasts.

Thus, the developed information technology is based on the principles of a multi-model approach, modern mathematical forecasting and decision-making methods, usage of which ensured high quality of intermediate and final results. It was confirmed by the computational experiments in both cases that high quality of models and short-term forecasts were achieved what is supported by appropriate quality statistics. It should be noted that predictive characteristics of most models constructed are as follows: $MAPE=3.0–12.0$ %, $R^2=0.93–0.99$.

The scientific results of the research are original information technology for solving the problems of forecasting nonlinear non-stationary processes in economy, finances and other areas based upon system analysis principles.

The practical value of the results achieved is in the following: the methodology and system for correct analysis of nonlinear non-stationary processes were proposed that was successfully tested experimentally. Especially important is that this information technology creates realistic perspectives for analyzing and forecasting different nonlinear non-stationary processes that take place in conditions of uncertainty relevant to many branches of modern economy.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship, or any other, that could affect the study and its results presented in this article.

Financing

The study was conducted without financial support.

Data availability

The study has no associated data.

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