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INTELLECTUAL TECHNOLOGIES AND DECISION SUPPORT SYSTEMS FOR THE CONTROL OF THE ECONOMIC AND FINANCIAL PROCESSES

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ABSTRACT

A computer based decision support system is proposed the basic tasks of which are adaptive model constructing and forecasting of various types of processes that are developing in socio-economic systems under the influence of fundamental structural changes. The complexity and urgency of the solvable problem is the need to provide acceptable quality forecasts of financial and economic indicators for short data samples, when the usage of retrospective data is impossible or significantly limited.

The DSS development is based on the system analysis principles, i.e. the possibility for taking into consideration of some stochastic and information uncertainties, forming alternatives for models and forecasts, and tracking of the computing procedures correctness during all stages of data processing. A modular architecture is implemented that provides a possibility for the further enhancement and modification of the system functional possibilities with new forecasting and parameter estimation techniques. In addition, the proposed system, thanks to the modular architecture, can be improved by using the software of different vendors without any additional structural changes. A high quality of the final result is achieved thanks to appropriate tracking of the computing procedures at all stages of data processing during computational experiments: preliminary data processing, model constructing, and forecasts estimation. The tracking is performed with appropriate sets of statistical quality parameters. Example is given for estimation of financial risk in insurance sphere and the electricity consumption in terms of energy saving. The examples solved show that the system developed has good perspectives for the practical use. It is supposed that the system will be universal and find its applications as an extra tool for support of decision making when developing the strategies for companies and enterprises of various types.

Keywords: *Mathematical Model, System Analysis Principles, Adaptive Forecasting, Decision Support System, Risk Estimation*

1. INTRODUCTION

Increasing the efficiency of operational and strategic management of the development of socio-economic systems, especially in the context of structural reforms, requires a specialized analytical apparatus to make managerial decisions in the context of defined measures [1]. As a special feature of the subject area of this problem is the complexity of its formalization, the presence of uncertainties associated with the incompleteness of data, cyclicality and seasonality of the investigated processes, the presence of a significant number of closely interrelated, not only quantitative, but also qualitative indicators that describe them. The impossibility of forming sufficiently long time series of these indicators remains the problematic issue. That is, the decision-making problem occurs in conditions of uncertainty and multicriteria. Solution to this problem is related to the need for in-depth detection and processing of uncertainties of various types, while taking into account that the object of the study is an element of a complex stratified system. In addition, in conditions of abrupt changes in the vector of development of the national economy, there is a need for an adequate assessment of the situation that has developed both currently and in retrospect, the recognition of situations and processing of expert conclusions. This requires the availability of specialized software for pre-processing large volumes of input data from statistical indicators, observation and survey results, information from Internet sources, etc., that will be used to build forecast models, script development, strategic and operational planning.

Many works [2, 3, 4], of both domestic and foreign scientists, are devoted to the mentioned issues. However, most of them consider either the application of decision support systems to solve individual tasks of enterprise management or forecast the development of macroeconomic, economic or financial processes in general. Works [5-8] describe the use of specialized statistical or econometric software tools [9], consider the possibilities to use such powerful analytical tools as SAS [10], SPSS [11], etc. Such “dot” application gives acceptable results in a stable economy given the availability of best practices of planning and forecasting, full information provision of the decision maker. In conditions of active structural reforms, social transformations, decision-making is complicated not only by increasing requirements to their optimality, but also by the need for the correct recognition of the situation, the preservation of a set of factors that affect the final result. Therefore, the development of a methodology for the application of the relevant information technologies in the decision-making process through the study of social, financial and economic processes of different nature in their interaction and with the use of limited amounts of information is relevant.

2. ANALYSIS OF LITERARY DATA AND PROBLEM STATEMENT

The need for sound management decisions in a rapidly changing socio-political and socio-economic situation has raised interest in applying intelligent technologies and decision support systems to analytical activities in the field of economic and financial management [12]. Some researchers consider these issues in the context of management of enterprises [13], regions [14], national economics [15]. As noted [16], the task of decision-making management for the development of socio-economic systems is complex and weak-formalized, requiring a comprehensive solution. Therefore, it must be solved based on both the nature of the processes occurring in it, and the multifactorial dependencies that arise in the process of its development [16]. It is noted in [16, 17] that since any socioeconomic system is complex, multilevel, dynamic, has a significant number of elements and is developing, then to solve decision-making tasks under the influence of many internal and external factors related causative links, the intellectual instrument is the necessary tool. That is, to solve the task of research and forecasting the development of economic and financial processes, it is expedient to use not only methods of system analysis, mathematical modeling, but also intellectual analysis, which involves the processing of significant data arrays, including the processing of Internet resources.

Some researchers [18, 19] prefer to use methods of collective decision-making, which in their view allow optimizing decision-making process and minimizing the impact of the human factor. In particular, the authors of work [18] focused mainly on general presentation of such technique, with little attention being paid to the study of the conditions of uncertainty and risk. As a result, the issue of applying econometric modeling and presenting the results of forecasting remained unworked. In decision-making process, in this case, forecasting modeling is used, during which a decision maker is offered a set of mathematical models describing individual economic and financial processes. In the process of constructing mathematical models, it is proposed to use automation tools [20] such as SAS, STATISTICA, SPSS, etc. This allows us to obtain forecasts of acceptable quality for certain financial and economic indicators [20]. However, suggested approach does not take into account the patterns of development of the studied system, its interaction with the external environment and risks, which are the consequence of such interaction [20].

In [21-23] discusses the development of a computer system for decision support, note that economic and financial processes are directly related to human activity, are cyclic, often fractal, have a seasonal nature, and a sample of data describing them, have a significant number of omissions. Therefore, when applying this approach, there is a problem of working out time series of economic and financial indicators, which have omissions and inaccuracies of data [22]. The solution to this problem is presented in works [23, 24]. A significant drawback of work [23] is that the investigated processes are considered solely in terms of long-term dynamics of time series, not changes of general macroeconomic trends in the country or in the relevant financial market. Therefore, this technique is difficult to adapt to the conditions of structural reforms. The difficulty lies in the fact that when a sharp change in macroeconomic or foreign economic course is possible, it is impossible to unambiguously use and fully utilize previous trends. This causes difficulties in the development of alternatives, fulfilment of tasks of assessing the situation and choosing models and procedures for their solution, assessing the quality of the solution and finding the best solutions [23]. Work [24] describes an approach that eliminates the drawbacks of the approach suggested in [23]. And use of the method proposed in [25] allows to significantly expanding the potential capabilities of software tools used to solve decision-making problems. However, the use of data mining methods has not been taken into account, which would improve the quality of pre-processing of input data. Works [25, 26] have developed views on the use of intelligent technologies and decision support systems in the management of economic and financial processes. Despite the suggested approaches, the methods of solving the problem are given only conceptually. The author provides only a general scheme for the use of intelligent data analysis, and is limited to general representation of the mathematical apparatus and the scheme of decision support system.

Generalization of the results of the performed research allows us to conclude that the vast majority of existing solutions focuses on approaches involving the use of analytical platforms of various developers, systems of computer mathematics, individual modules in their own development of enterprises, packages of applications for investment analysis, enterprise management systems, etc. Such approaches are optimal for the solution of certain "point" objectives [27], but their use has not been worked out for integrated use associated with strategic planning, forecasting the development of the economic or financial system under conditions of uncertainty and risk associated with structural reforms, socio-political transformations, etc. Since it is necessary to take into account the possible variants of the situation development to work out short samples of a large number of heterogeneous indicators, expert opinions and possible solutions. Therefore, it is necessary to take into consideration that in order to make sound decisions in the management of financial and economic processes under these conditions, it is necessary to provide both a comprehensive study of the subject area of the task and an overview of the options for the development of events as well as their outcomes for the future. This problem can be solved by developing a procedure for synthesizing an optimal solution based on the use of data mining, forecasting modeling, economic and financial analysis, and decision support systems.

3. STATEMENT OF THE PROBLEM

The purpose of the work is to research and develop information technology of intellectual decision support aimed at increasing the efficiency of management of economic and financial processes in the context of reforms and changes in the economic course. The article deals with the solution based on the application of intellectual data analysis and adaptive modeling of economic and financial processes under conditions of uncertainty and risk. The suggested decision support system provides an opportunity to provide acceptable quality forecasts of financial and economic indicators for short data samples, when the use of retrospective data is impossible or significantly limited.

To achieve this goal, the following tasks must be solved:

- to consider options for solving the problem, based on existing methods;
- to develop a methodology for applying data mining, based on the use of adaptive approach and decision support methods;
- within the framework of the method of application of the intellectual data analysis to work out methods of preliminary data processing, provision and analysis of their quality at all stages of use;
- to develop a scheme of decision support system that uses methods of data mining;
- check the efficiency of the proposed system on the example of specific tasks of the subject domain.

The use of the suggested methodology will reduce the influence of human factor and improve the quality of decision-making in the economy and finance, when the decision maker faces the risk of incorrect assessment of the current situation.

4. MATERIALS AND METHODS

Decision-making in economics and finance is usually complicated by multicriteria, the presence of uncertainties and risks, high requirements for the quality of forecasting modeling, the lack of a universal methodology for the application of

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information technology in accordance with the level of national economy and user needs.

To move the results of practical DSS application to the users of different levels such systems should satisfy some general requirements. We define DSS formally as follows [28]:

$$DSS = \{DKB, PDP, ST, PMSE, MPE, RGP, SE, DQ, MQ, REQ, AQ\},$$

where *DKB* is data and knowledge base; *PDP* is a set of appropriate procedures for preliminary data processing; *ST* is a set of statistical tests for determining possible effects contained in data, for example, integration or heteroscedasticity; *PMSE* are procedures for estimation of selected model structure; *MPE* are computational procedures for estimation of model parameters; *RGP* are procedures for generating risk estimates; SE are procedures for generating estimates of synergetic effects; the *DQ, MQ, REQ, AQ* are the sets of statistical quality criteria for estimating quality of data, models, risk estimates, and decision alternatives, respectively.

The systems should satisfy the following general requirements that result from the system analysis principles: 1) – contain highly developed knowledge and data bases with model structures, quality criteria for each type of data processing, best model selection rules, and appropriate computational procedures; 2) – to provide for high (acceptable) quality of the final result; 3) – the hierarchical structure of the system should correspond to the hierarchic process of decision making by a decision making person (DMP); 4) – the system interface should be developed using the human factors principles: user friendly, convenient and simple for use, and adaptive to the users of different levels (for example, engineering and managerial staff of various levels); 5) – the system should incorporate an ability for continuous learning during its functioning, i.e. accumulate necessary knowledge for solving the problems of selected class; 6) – appropriate use of modern artificial intelligence data processing and modeling techniques, helping to gradually transform DSS into intelligent system; 7) – organizational aspects of the system and hired techniques for computing should provide appropriate rate of computing that corresponds to *DMP* requirements regarding the rate of alternatives generating and reaching the final (stated) goal; 8) – precision of computational operations should satisfy preliminary established requirements by a user and developer; 9) – intermediate and final results of computations should be controlled with respective sets of statistical quality criteria, what would allow for enhancing significantly quality and reliability of the final result: decision alternatives; 10) – the DSS should generate all necessary for a user representations of formats and types for intermediate and final results; 11) – the system should contain the means for data and knowledge exchanging with other data processing systems via local and/or global computer nets; 12) – DSS should be easily expandable with new computational functions regarding data processing, results representation and control with appropriate statistical criteria, model constructing and alternatives generating; such approach will make the system functionality complete and flexible.

The suggested scheme for the introduction of intelligent technologies in DSS is the form presented in Fig. 1.

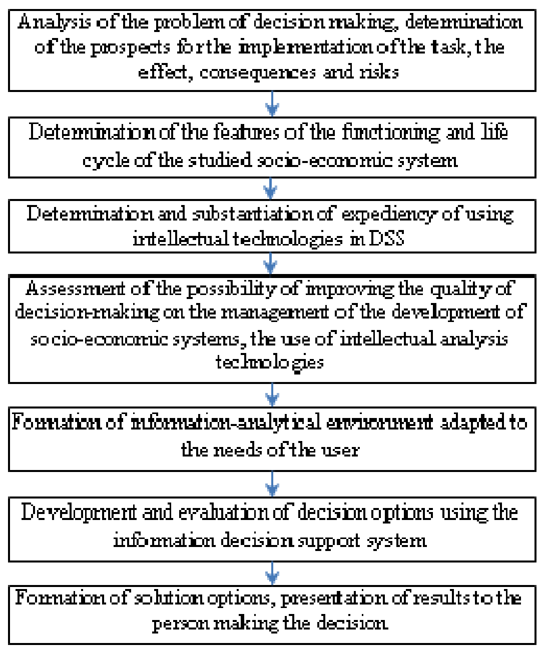

Figure 1: Scheme for the implementation of data mining in DSS

In this decision support system, the socioeconomic system studied is considered to be a complex hierarchical structure [29, 30]:

$$S_0 = S_1 \times S_2 \times \ldots \times S_i \times \ldots S_m, \quad (1)$$

where S_i is intellectual hierarchical level, m – the number of hierarchical levels.

$$S_i = \langle M_i, P_i, R_i, X_i, Y_i, f_i, \phi_i \rangle, \quad (2)$$

where M_i, P_i, R_i is the set of real objects, subjects and subsystems of intellectual hierarchical level; X_i, Y_i, is the set of internal and external parameters of the system of intellectual hierarchical level and the

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external environment; ϕ_i, f_i – functionals that determine the relations between the corresponding parameters on m levels represented by:

$$\phi_i : X_i \rightarrow Y_i;\ f_i : Y_i \rightarrow Y_{i-1}; \qquad (3)$$

Specifying the above, somewhat general model, it should be noted that the feature of economic and financial systems is that they actively interact with the external environment, are constantly under the influence of both management system and a number of uncontrolled factors.

Since for most requirements, their submission as a system of restrictions cannot be considered effective because of the incomplete input for such representation. Therefore, it is necessary to identify and solve the problem of managing the development of complex socio-economic systems as a task of multimodal and multi-criteria choice of effective solutions on a set of mathematical models of type, completing the approach presented in [30]:

$$M = \{M_0(Y, I, P), M_E(X), M_{OE}, M_S, \\ M_D(Q), M_{MO}, M_{ME}, M_U, A, M_H, M_{RS}, M_V\}, \qquad (4)$$

where M_0 (Y, I, P) – is an identifying system model; Y – endogenous variables; I – vector of controlled variables; P – vector of resources; M_E (X) – model of the environment; X – exogenous variables; M_{OE} –model of the interaction of the object and the environment; M_S – a model for creating a synergistic effect in the system; M_D (Q) – model of system behavior; Q – disturbing influences; M_{MO} – model for changing the state of the system; M_{ME} – model for changing the state of the environment; M_U – model of control system; A – the rule of selecting the process of changing the object; M_H – model of influence of decision maker and research results; M_{RS} –is a model of systemic risk, M_V – model of interaction with subsystems of other levels.

The set of different requirements for solutions leads to a multi-level multicriteria statement of decision-making problem [31]. In such setting, it should be borne in mind that alternatives of different levels are interlinked in a similar way, since socio-economic and financial systems are also hierarchical. Alternatives to the first level $S_i = \{a_1, a_2, \ldots, a_n\}$ are evaluated on the set of criteria $C = C_1 \cup D$. Alternatives to the second level on $S_{i+1} = \{b_{i1}, b_{i2}, \ldots, b_{ik}\}$. The subset of the criteria $C_1 = \{c_1, c_2, \ldots, c_p\}$, is used to evaluate only the first level alternatives and the set of criteria D for both the first and second levels. Each element of set A (subsystem of the first level) corresponds to the set of alternatives of the second level. Then it is necessary to rank alternatives of set A, taking into account the multicriterial estimates of the alternatives of set B.

In the general case, each solution is evaluated by one or more indicators within one or more models.

It is possible to state that in most cases of DSS development it is necessary to use the following mathematical methodologies and methods: – methods and methodologies for mathematical (statistical and probabilistic) modeling using statistical/experimental data; – risk estimating and forecasting techniques on the basis of the models constructed with possibilities for combining the forecasts computed with different selected techniques; – operations research optimization techniques and dynamic system optimization (optimal control) methods; – the methods for forecasting/foresight of generated decision implementation consequences; – the sets of selected/developed special statistical criteria to control the processes of computations performed at each stage of data processing, model constructing and alternatives generation aiming to reach high quality final result.

All the methods, methodologies and approaches aforementioned are described with necessary completeness in special literature. The task for a DSS developer is in appropriate selection of preliminary data processing techniques, model classes, modeling and optimization techniques, sets of necessary quality criteria as well as relevant methodologies for appropriate organization of the whole computational sequence.

As far as we work with collected stochastic data, application of modern statistical and artificial intelligence techniques provides a possibility for approximate estimation of an object/system model structure. To find the best model structure it is recommended to apply convenient adaptive estimation schemes that provide automatic search in a given range of model structure parameters (model order, time lags, and nonlinearities). Usually the search is performed in the class of regression type (stationary and nonstationary linear and nonlinear) models with the use of integrated statistical quality criterion of the following type [32]:

$$V_N(\theta, D_N) = e^{|1-R^2|} + e^{|2-DW|} + \alpha \ln(1 + \frac{SSE}{N}) + \\ + \beta\{\ln(1 + MSE) + \ln(MAPE)\},$$

where Θ – is a vector of model parameters; D_N – data in the form of time series (N is a sample size); R^2 – is determination coefficient; DW – is Durbin-Watson statistic; MSE – is mean square error; $MAPE$ – is mean absolute percentage error for

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estimating forecast quality; *α, β* – are adjustment coefficients selected by expert. Usually there are multiple possibilities for adaptive model structure estimation: (1) automatic analysis of partial autocorrelation function for determining autoregression order; (2) automatic estimation of exogeneous variable lag and detection of leading indicators; (3) automatic analysis of statistical properties for residual; (4) analysis of distribution type for statistical data and its use for selecting correct model parameter estimation method; (5) adaptive model parameter estimation with hiring extra collected data; (7) selection of optimal weighting coefficients for exponential smoothing, method for nearest neighbor search and some other techniques; (6) the use of adaptive approach to selection of model class: stationary/nonstationary, and linear/nonlinear. The use of a specific scheme of model adaptation depends on volume and quality of data, specific problem statement for modeling and forecasting, established requirements to forecast estimates etc.

To forecast economic and financial processes, many various methods have been worked out, using various mathematical models and approaches, namely:

1. Regression models of different types.
2. Models incorporating a trend component and taking into account balances (the difference between real and forecast values) included in the model as a moving average, provided that there is correlation between the balances and the target variable.
3. Various models of exponential smoothing class - Holt, Brown, Winters (with an additive or multiplicative seasonal component), taking into account a damp trend and other modifications.
4. Neural networks.
5. GLM models (Generalized Linear Model, GLM - the name of the generalized linear model);
6. Specialized probabilistic models;
7. Fuzzy methods.

One should agree with [33] that each model group is the most optimal for a certain class of tasks, and the universal method of forecasting modeling has not yet been developed. In particular, many publications on the practical implementation of short-term forecast modeling note that good results can be obtained using generalized linear models (GLM) and exponential disperse models (EDM).

The use of probabilistic-statistical models in the state space allows us to obtain good results too [34]. To do this, when using probabilistic-statistical models, the problem of the choice of model structure is first solved. The structure of the model is estimated approximately on the basis of the study of patterns of process flow, analysis of correlation functions, visual analysis of data. In this case, several most probable structures (candidates) are selected. Then the estimations of the parameters of the candidate models are calculated, the best ones are selected, using the corresponding statistical characteristics of the quality of the models.

Linear model in the state space for continuous time [35]:

$$\dot{x}(t) = \mathbf{A}(t)\mathbf{x}(t) + B(t)u(t) + w(t),$$
$$z(t) = H(t)\mathbf{x}(t) + V(t),$$

where *x(t)* – is the vector of variables of the state of dimension *n*, $\dot{x}(t)$ – the first derivative of the state vector with respect to time (the rate of change of the values of the state vector); *A(t)* – is the matrix of the dynamics of the object (subject) or the measurement process $[n \times n]$, which in the general case depends on the time; *B(t)* – is the matrix of measuring control coefficients $[n \times m]$, which may also depend on time; *u(t)* – is the vector of control signals of measurement $[m \times 1]$; *w(t)* is the vector of perturbation of the state of measurement $[n \times 1]$; *z(t)* – is the vector of measurements (experimental data of dimensionality $[r \times n]$; *H(t)* – is the matrix of dimension measures coefficients $[r \times n]$; *v(t)* – is the vector of errors (noise) of dimension *r*.

A model in the state space for discrete time [35]:

$$x(k+1) = Fx(k) + w(k),$$
$$\mathbf{z}(k) = A^T u(k) + H^T x(k) + v(k),$$

where *F*, *AT*, H^T – are matrices of dimension parameters $[n \times n]$, $[r \times p]$ and $[r \times n]$, respectively; *u(k)* – is the vector of regressors (exogenous variables) of dimension $[p \times 1]$,*w(k) v(k)* – state disturbance vectors and noise measurements in accordance with the following statistical characteristics [35]:

$$E\left[w(k)w^T(l)\right] = \begin{cases} Q, k = l \\ 0, k \neq l \end{cases}, \quad E\left[v(k)v^T(l)\right] = \begin{cases} R, k = l \\ 0, k \neq l \end{cases},$$

where $Q[n \times n]$, $R[r \times r]$, covariance matrices of disturbances and noises of measurements respectively. The sequences $\{w\ (k)\}$, $\{v\ (k)\}$ are uncorrelated for any time points:

$$E\left[w(k)v^T(l)\right] = 0, \forall k, l.$$

Taking into consideration the peculiarities of the investigated processes, it is expedient to use

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generalized linear models in the process of forecasting their development, in particular, Log-linear models, probit/logit models, Poisson regression, and others that represent a set of methods for constructing regression models and statistical data processing.

In the aforementioned models, the implementation of a random independent value *Y* with the expectancy μ with unknown parameters *β* is implied. The following linear model is called a generalized linear model:

$$y = g^{-1}(\sum_{i=1}^{n} \beta_i g_i(x)),$$

where *g(y)* is a communication function. It is usually assumed that the dependent variable has an exponential distribution.

The characteristic of a generalized linear model implies knowledge [36, 37]: distribution law of the dependent variable, the characteristics and parameters of the communication functions $g(\cdot)$; characteristic of the linear predictor $(X \cdot \beta)$. The communication function connects the linear predictor η with the value of the estimate μ of the value y. In the classical linear model, the expectancy and the linear predictor are identical, and the identity relation is plausible to the choice of η and μ arbitrarily, but from the set of real numbers. However, when dealing with the statistics and Poisson distributions, the mandatory requirement is $\mu > 0$.

Generalized linear models are an extension of the class of linear models, which is why the peculiarities of the components of this class of models were considered.

Model estimation is based on independent cross-classification data with multiplicative effect, and the communication function is expressed by logarithmic function:

$$\eta = \log(\mu), \text{ then } \mu = e^{\eta}.$$

The effect of additivity contributes to the multiplicity of η. Here the value of μ is necessarily positive.

Residuals are used to study the adequacy of the model, the choice of the function of communication, the analysis of variance and elements of the linear predictor. Generalized linear models require an expanded definition of residues with the aim of applying them to the analysis of distributions of different nature that can replace normal distribution. It is convenient when the remnants can be used for the same purpose as in the normal distribution law. Depending on the distribution form, there are three types of generalized residues: Pearson, Anscombe and deviance residuals.

This approach makes it possible to take into account the interaction between factors, the type of distribution of the dependent variable and the assumption concerning the nature of the distribution of the dependent variable. Generalized linear models differ from the general linear model, which is multiple regression in individual cases, with two different characteristics: the distribution of a dependent variable or variable of a reaction may be non-Gaussian and not necessarily continuous, for example, binomial; projected values of a dependent variable are obtained as a linear combination of predictors that are "bound" to a dependent variable through a communication function. In addition, as suggested by [37], it is expedient to apply the methodology of modeling and the creation of new mathematical models based on the use of structures of generalized linear models for the analysis and evaluation of the forecasts of the dynamics of the development of socio-economic processes. All stages of the implementation of this technique are accompanied by the use of appropriate sets of statistical criteria, which allows obtaining forecasts of good quality on various data samples.

To evaluate unknown parameters of the models worked out by [38] there are Bayesian approaches that are expedient to use in short samples which is very relevant for socio-economic processes, since they are often described by statistical indicators in 5-10 years. One of the problems in determining the structure of a model is to establish the existence of nonlinearities in the investigated process and the type of nonlinearities. To solve this problem, we use visual analysis of data and formal tests for the presence of nonlinearities. An important problem in the strategic management of socio-economic processes, and especially agricultural production, is the need to quickly identify the presence of segments with a linear or nonlinear trend, the presence of heteroscedasticity and significant impulse emissions (extreme values) that can significantly affect the quality of the model. For this, as a rule, tests are used for the presence of nonlinearity. The test is used when it is possible to gain several observation groups (implementations) for the same process.

Works [39] describe the application of methodologies for averaging forecasts for several models. The results of acceptable quality allow the use of adaptive modeling [39, 40].

Generally we could define the following techniques to fight structural uncertainties: gradual

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refinement of model order (AR(p) or ARMA(p, q)) using adaptive approach to modeling and automatic search for the "best" structure using complex statistical quality criteria; adaptive estimation (improvement) of input delay time (lag) and data distribution type with its parameters; describing detected process nonlinearities with alternative analytical forms with subsequent estimation of model adequacy and forecast quality. An example of complex model and forecast criterion may look as follows [39, 40]:

$$J = \left|1 - R^2\right| + \alpha \ln[\sum_{k=1}^{N} e^2(k)] + \\ + 0.5\left|2 - DW\right| + -\beta \ln(MAPE) + U \rightarrow \min_{\hat{\theta}_l} ,$$

where R^2 – is determination coefficient; $\sum_{k=1}^{N} e^2 = \sum_{k=1}^{N}\left[y(k) - \hat{y}(k)\right]^2$ – is a sum of squared model errors; DW – is Durbin-Watson statistic; $MAPE$ – is mean absolute percentage error for one step-ahead forecasts; U – is Theil coefficient that measures forecasting quality of a model; α, β – are appropriately selected weighting coefficients; $\hat{\theta}_l$ – is parameter vector for the i - th candidate model. A criterion of this type is used for automatic selection of the best candidate model. The criterion also allows operation of DSS in the mode of model adaptation. Certainly, other forms of the complex criteria are possible. While constructing the criterion it is important not to overweigh separate members in the righth and side.

To a large extent, the problem of choosing the optimal method of forecasting modeling is associated with the availability and complexity of processing uncertainties of various types: situational, statistical, structural, probabilistic, etc. Although, most of the existing decision support information systems have the means to identify and predict the risks caused by such uncertainties, the focus is on the estimation of uncertainties only of certain types. Prospects for solving this problem include the introduction of intelligent technologies and facilities for processing large amounts of structured and unstructured data in decision support systems.

One of the main constraints on the active use of mathematical modeling and intelligent technologies in decision support systems in the economy and financial sphere is the problem of obtaining incoming information, well-formed and in amounts sufficient to construct mathematical models and intelligent data analysis. After all, to form a long time series of macroeconomic, economic and financial indicators is often not possible. Therefore, the decision maker has to face the problem of incompleteness and inadequacy of incoming information. This is especially true of periods of socio-political and structural transformation, economic and financial crises, and so on, although the set of indicators that can be processed can be quite significant.

However at the micro level this problem is primarily related to the lack of data accumulation practices for analyzing and forecasting the economic and financial performance of enterprises over a period of more than three to five years. Under such circumstances, it is not possible to form a training and validation sample at all.

Some researchers suggest using theta-method and its modifications. For this method, researchers focus on identifying short-term and long-term dynamics in the data under investigation. The main idea of this method is to identify significant patterns in the data through the decomposition of the output series with the exception of the seasonal component [40, 42].

Often, the processing of short data samples reduces to solving the problem of diminishing the dimensionality of models using such methods as the main components and their modifications, factor analysis, multidimensional scaling, etc., with subsequent use of different types of regression models, neural networks, etc. Considerable attention is also paid to the use of probabilistic models [40, 43]. Some authors [44] suggest using cognitive modeling and expert evaluation to select the most significant factors that best describe the structure and behavior of the studied system with their subsequent use to develop scenarios and forecasts for these scenarios.

Most economic and financial processes are nonlinear and non-stationary, therefore the task of estimating the quality of forecasting models is formulated as follows [43].

For non-stationary process $\{y(k)\} \sim N(\bar{y}, \sigma_y^2)$, where $E(y) \neq Const$,

$\sigma_y^2 \neq Const,\ k \in [0, T]$.

To evaluate the structure of the model:

$$y(k) = f_1(\psi, \varepsilon(k), h(k), u(k)),$$

$$h(k) = f_2(\theta, h(k-i), \sigma_y^2),\ \{u(k)\} \sim N(0,1),$$

Θ, ψ – unknown vectors of parameters by measurements $y(k)$, $k \in [0, T]$.

When solving decision-making tasks through analytical procedures [45], logical rules and rational expert evaluation, in many cases it is not possible to achieve the desired result in terms of the quality of estimates of forecasts, and therefore the problem of systematic use of alternative methods of forecasting to improve the quality of estimates. To solve this problem when solving decision-making tasks in relation to the management of the development of socio-economic systems, based on the methodology of system analysis, hierarchical analysis of modeling and forecasting processes, taking into account uncertainties of structural parametric and statistical nature, adapting the structure and model parameters to changes in processes is envisaged. Alternative methods for estimating model parameters are used to improve the estimation of forecasts, and the adequacy of models is estimated using a set of statistical quality criteria in accordance with the method presented in [43, 46].

Criteria for assessing the quality of models, are selected depending on the type of model of the study process and the selected methodology of forecasting modeling. Depending on this, both individual quality criteria and an integral criterion as well as comparative criteria are used. Taking into account that in solving problems of forecasting modeling of socio-economic processes, methods of forecasting are increasingly being used based on combinations of models of different types, to estimate the quality of such forecasts, use different variants of forecasting averaging and methods of optimization type.

The architecture of the suggested system is intended for solving decision-making problems under uncertainty, therefore the mandatory component is the control part with feedback (Fig. 2).

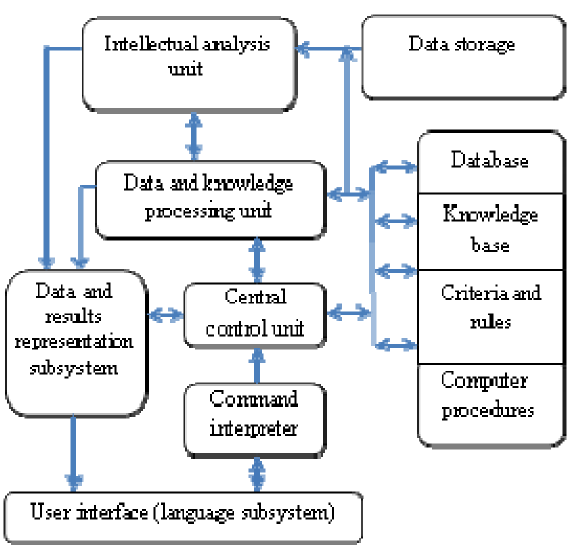

Figure 2: Architecture of decision support system

As can be seen from the diagram above, there is a possibility to improve the quality of forecasts by using an adaptive simulation scheme and a pre-data preparation block.

5. EXPERIMENT

The suggested method has been tested on several practical tasks. The work presents the results of the implementation of the methodology in the corresponding decision-making tasks, in particular, to increase the efficiency of energy consumption of the population and to forecast the costs of covering insurance cases.

The peculiarity of the implementation of the suggested method in decision support systems is the use of intellectual data analysis and forecasting modeling tools of SAS Enterprise Miner.

The quality of the obtained results of forecasting modeling proves the promise of the application of the proposed methodology for various economic and financial processes. Also, the suggested method has the advantages of automating the basic processes of data processing and forecasting modeling.

The block diagram of the implementation of information technology in the decision support system is presented in Fig. 3.

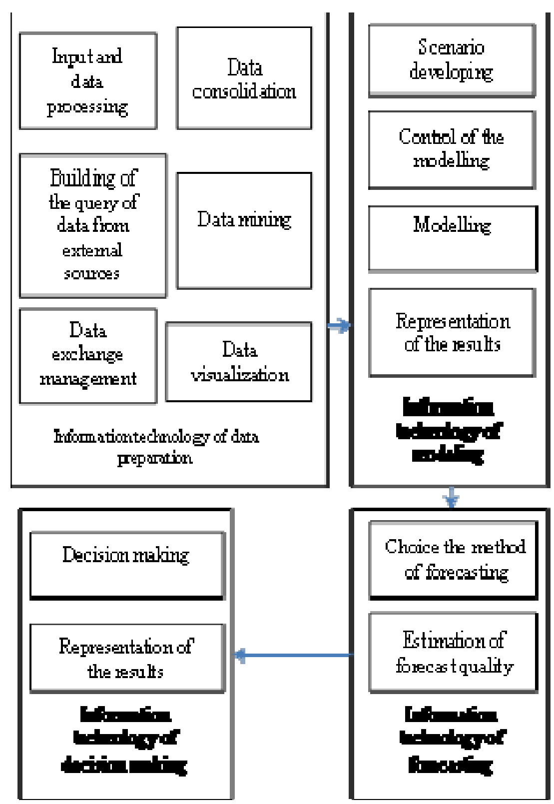

Figure 3: Scheme of the use of information technologies in the system of decision support system

However, the suggested system did not take into account the possibility of using expert assessments. Eliminating this disadvantage is the direction of further research. Further research should enable the use of methods of group decision-making and elements of expert systems.

Equally hard problem that needs to be solved in further research is the need to provide on-line processing of significant increasing amounts of information, in particular, statistical, accumulated both at the micro level and at the higher levels of economic and financial systems. In addition, much of this information is unstructured, contains inaccurate or incorrectly entered data.

In this regard, the development of decision support systems in economics and finance, in the long run, deserves special attention to the task of developing a methodology for using intelligent data analysis technologies, including for the processing of mass data of "mixed" (structured and unstructured) data in decision support system.

6. RESULTS

The components of the suggested system are software components that can be used as part of the decision support system or as separate modules. The block diagram of the system is shown in Fig. 4

Such a solution is due to the fact that not all users need absolutely all system modules, and the purchase of the system requires a lot of money. The system is designed for use both in financial institutions, as well as in analytical and situational centers.

With the help of the suggested decision support system, a study was made into the possibility of obtaining forecasts of acceptable quality of development of several socio-economic processes in the context of reforming the relevant systems.

The decision to reform the energy sector with a view to increasing its energy efficiency is considered on the example of the population's electricity consumption system. The information base of the study is data for 2015-2017 on the supply of electricity to consumers-individuals from more than twenty power units of one of the electricity suppliers in Ukraine.

Incoming data for constructing a long-term forecast used indicators of gross domestic product of Ukraine, the total population and the number of workers employed in industry. On the basis of these indicators, the calculated aggregate indicator reflects the state of general economic development and the population size - index (*I*), calculated according to the method presented in [45].

To construct a long-term forecast, the model as an auto-regression equation of the first order is used

$$Y(t) = 79{,}88 + 1{,}096 \cdot Y(t-1) - 3{,}864 \cdot I\ ,$$

where Y – electricity consumption, I – index of the state of development of the economy and population.

Statistical characteristics of the parameters of the model are presented in Table. 1

Table 1 : Statistical characteristics of the parameters of the model

Parameter	Evaluation	Built - in error	T – statistics	p-value
Y-intercept	79,88	13.242	6,03	0.0018
Y(t-1)	1.096	0.0241	45,59	<.0001
Index	-3.868	0.6405	-6,04	0.0018

As can be seen from the table, the value of p-value is much less than the critical alpha in 0.05, which indicates the adequacy of the selected model estimates. General statistical characteristics of the constructed model: $R^2 = 0{,}98$, MAPE=0,2%.

Taking into account possible scenarios, in the long run, forecasts are developed in several scenarios (Table 2). Table 2 shows the results of load forecasting (billion kW per hour) for 2018-2020 years.

Table 2 : Forecast of electricity consumption (billion kW per hour) for 2018-2020 year.

Year	Indicator values	Senario		
		Realistic	Pessimistic	Optimistic
2018	20,813	9,848	9,764	9,932
2019	20,835	10,082	9,997	10,166
2020	20,837	10,328	10,236	10,419

Note that in the long-term forecasts for the quarters or years it is necessary to take into account the possibility of crisis phenomena, resulting in a reduction in energy consumption and, accordingly, a reduction in electricity demand, which in turn worsens the performance of the electricity supply companies.

When used in models to predict the load temperature, it is necessary to realize that the most accurate is the weather forecast for the day ahead, and the forecast for two weeks ahead may not even be realized at all. More than this period, weather forecasts are better not to be used in models, or to switch to probabilistic models.

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With medium-term forecasting, on the lunar segments of data, a model of autoregression of the twelfth order and a Winters multiplicative seasonality were constructed for which the value of MAPE statistics is 2.64% and 2.6% respectively.

For the case of short-term forecasting at hourly intervals, model learning took place from January 1, 2015 to September 31, 2017, and testing for the period from October 1 to December 31. Before the start of the modeling, graphical and statistical analysis of the data was sufficiently well executed for the presence of typical patterns and differences in behavior under different conditions. It was found that the least electricity consumption occurs in 4-5 hours, and most from 11 to 20 hours. Based on the recommendations of experts and international experience in constructing models as regressors, information on energy consumption on weekends and public holidays was used, and it was found that it is necessary to take into account its growth in the pre- and post-holiday days.

The overall structure of the resulting GLM ARIMAX model, taking into account holidays, can be represented as the equation:

$$Y=\beta_0+\beta_1\cdot Trend+\beta_2\cdot Y(t-1) + \beta_3\cdot WeekDay \cdot Hour + \beta_4\cdot \cdot Month + \beta_5\cdot T_0 \cdot Month + \beta_6 \cdot T_0^2 \cdot Month + \beta_7 \cdot T_0^3 \cdot Month + \beta_8 \cdot T_0 \cdot Hour + \beta_9 \cdot T_0^2\cdot Hour + \beta_{10} \cdot T_0^3\cdot Hour+ \beta_{11}\cdot T_1 \cdot Month + \beta_{12} \cdot T_1^2 \cdot Month + \beta_{13} \cdot T_1 \cdot Hour +\beta_{14} \cdot T_1^2\cdot Hour + \beta_{15} \cdot T_a \cdot Month+ \beta_{16} \cdot T_a^2\cdot Month + \beta_{17} \cdot T_a \cdot Hour + \beta_{18} \cdot T_a^2 \cdot Hour + \beta_{19} \cdot Holliday$$

The analysis of temperature and load data in the grid in the daily and monthly sections revealed the dependence in the form of the inverse phase, depending on the time of the year, that is, the value of the temperature indices must be taken into account in the model in the form of a third order polynomial in combination with specialized combined variables based on temperature and month, temperature and hours of day, temperature, and Sunday afternoon.

For short-term energy consumption forecasting, four models were constructed: in the form of a neural network, an exponential model with multiplicative seasonality, an GLIM model of the ARIMAX model, and a GLM model with holidays. Table 3 gives short-term forecasting quality estimates for several hours ahead.

Table 3: Comparison of results of modeling of hourly electricity consumption forecasting

Name of the model	ME	MAE	MARE
GLM model ARIMAX	-1414,69	29874,3	2.43
Exponential smoothing with multiplicative seasonality	-2786,98	30813,1	2.55
Neural network	-2443,8	39752,5	3.19
GLM model taking into account holidays	1364,21	29246,6	2.39

Apparently, model GLM taking into account holidays showed the best results, with error MARE 2.39%.

The calculated statistic values were obtained by the results of forecasting on the validation period from October 1 to December 31, 2017. Fig. 5 shows an example of the forecasts received for one of the 92 days validation interval.

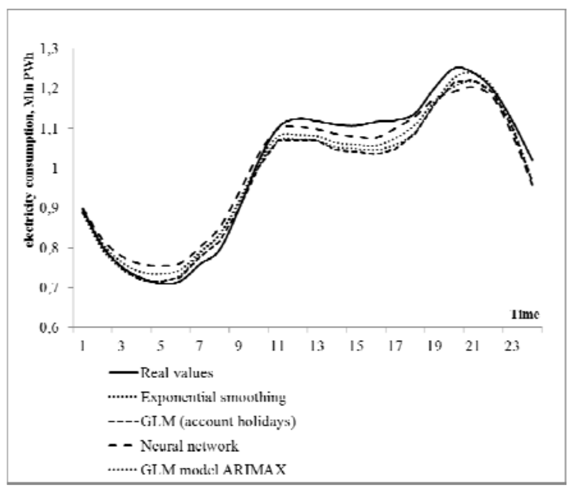

Figure 5 : Hourly Forecasting Results.

A more detailed analysis of the results showed that, in general, 93% of the previous value of load is taken into account in the following, with a trend in time data, and mixing in the regressor model describing the holidays increases the accuracy of forecast by MARE criterion by 0.04%.

Less accurate results were obtained with short-term forecasting on quarterly data, the error of autoregression of the fourth order reached the value of MARE statistics at 6.9%.

Model for forecasting the quarterly energy load is as follows:

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$$y(t) = 1861428237 + 0{,}03931 \cdot y(t-1) - \\ - 0{,}4818 \cdot y(t-2) + 0{,}0833 \cdot y(t-3) + \\ + 0{,}5842 \cdot y(t-4),$$

where $y(t)$ – quarterly energy consumption.

Statistical characteristics of the built model: Determination coefficient 0.98; mean square error 39.5 mlnMW; average absolute percentage error 6.9%.

Note that when constructing the above-mentioned long-term and medium-term forecasting models for several years, quarters and months ahead, the value of weather factors, in particular air temperature, is not used as input variable of analysis. For such forecasts, the use of intellectual data analysis for inclusion in a model of various economic factors, such as scenario assessments of future supplier development indicators, peculiarities of the prospects for the industrial production of the region, country, etc., demographic policy, etc., was appropriate. Another example of the use of intelligent technologies in making decisions is forecasting modeling for the formation of reserves of claims for insurance payments. Having performed a preliminary analysis of significant amounts of data on the occurrence of insurance events, during forecasting modeling, assumptions were considered that the normalized claims payments in different years of the occurrence of the insured event are independent and observation within one year of the onset of an insured event depend on [111], and observation over the years is independent. Consequently, the triangle of claim development can be represented as a special type of data, in which the years of occurrence of insurance cases are so-called "items". Applying an adaptive approach, a number of models were constructed, the best of which were generalized linear models and generalized estimation equations using Tweedie distribution.

The maximum likelihood function was used to estimate unknown model parameters. In order to obtain an estimation of unknown model parameters, iteratively weighted least squares algorithm (IWLS) was used. Using the model data, information from the bottom triangular matrix was used not only to find the amount of claims for each year of the occurrence of insurance cases, but also to determine the sum of general insurance claims in general. Table 4 presents the results of forecasting the amounts of insurance claims for one of the insurance companies. The correlation values between actual data and predicted for GLM and GEE models are 0.971 and 0.993, respectively.

Table 4 : Results of projected modeling of insurance premiums reserves

The year of the insured event	Real data	Results of modelling	
		Generalized linear model Tweedie	Tweedie model using generalized estimation equations with correlation structure AR(1).
1989	34	63	63
1990	58	91	93
1991	91	146	156
1992	636	483	499
1993	1917	1346	1395
1994	3367	2605	2662
1995	6009	4847	4938
1996	10095	11896	11816
1997	20540	21864	21558
Total	42747	43341	43180

As can be seen from Table 4, especially in the first years, the projected required reserves for insurance claims are significantly underestimated or overestimated in some years, especially on the first. Tweedie model of generalized estimation equations with correlation structure AR (1) gives a better prognosis. This is due to the assumption, which was taken as a basis for the beginning, that the variables in the one year of the claim are dependent. This approach allows us to obtain adequate forecasts as for structural reforms caused by a sharp change in the political and economic course of the state in 1991-1992, galloping inflation, balancing the budget and introducing new monetary units in 1996.

Table 5 : MARE Results

Model	MAPE, %	Pearson Remains
GLM	31,8	19,87
GEE	32,0	10,73

Consequently, the quality of the models according to the MARE criterion is approximately the same. A reasonably high percentage is due to the fact that the proposed models make a rather poor-quality forecast for years when there is the greatest information uncertainty. As the economic situation in the country stabilizes, the error value is less than one percent. In general, the forecast error of the total required reserves is about 3 percent.

The use of intelligent data analysis has given a positive result in the preparation of data for analysis, the identification of the most significant variables and for the selection of models that are closed for large-scale transformations, and when the result of the analysis should not depend on the units of measurement of input data (for example, the currency used).

Subsequently, the methodology may be supplemented by scenario analysis, expert judgment and group decision-making methods.

7. DISCUSSION

The DSS proposed has the following advantages compared to similar systems previously used of other same systems used to analyze the state and development of the energetic and insurance companies.

First, the basic distinguished features of this approach are multimodel approach including the models of different classes such as liner regression, generalized linear models, extended autoregression with moving average, neural networks and exponential smoothing with multiplicative seasonality. The data used characterize various nonstatitonary processes such as energy consumption by population and financial losses in insurance. Second, the approach proposed to modeling and forecasting dynamics of economic and financial processes in conditions of uncertainty, limited and incomplete information, showed acceptable results regarding the models adequacy and quality of forecasts. The DSS provides intelligent decision support methods and the ability to generate alternative solutions to different social, economic and financial processes in the same conditions. Taking into consideration that usually accepted quality of forecasting, as determined by the mean absolute percentage error, is not more than 10%, the results of computational experiments carried out with the DSS proposed exhibit high quality. Short-, medium- and long-term forecasts computed showed quite acceptable quality of the forecasts estimates. It was determined that long-term forecast of energy consumption depends on economic indicators such as estimates of future company development, characteristics of industrial development of a region under study, demographic policy and others. To improve the quality of the forecasts it is necessary to take into consideration the appropriate time series of macroeconomic data. The results of short-term energy forecasting are characterized by high values of the mean absolute percentage errors in the range 2.39% – 3.19% for different models. In all cases of modeling these results show high quality. The results of modeling and forecasting financial processes are somewhat lower than for energy consumption. This can be explained by lower quality of data and low quality of forecast estimates at the first steps of forecasting process. Here mean absolute percentage error was approximately the same for both models constructed (GLM and GEE). The low quality forecasts could be improving at the beginning of the forecasting interval and changed to high quality at the last steps where error was less than one percent. The forecasts regarding necessary financial reserves showed error of about 3%, what can be considered as a high quality forecast. This example shows that the input data available plays very important role in solving the problems stated at the beginning.

Overall, studies have confirmed the effectiveness of the proposed models, methods and DSS to improve the quality of forecasts of the considered companies.

The some shortcomings of the software implementation of the decision support system, which was identified as a result of testing, has become quite of import datasets from FoxPro databases (and similar) to SAS Base. This applies only to similar situations. Now work is under way to optimize the developed software DSS which will eliminate this drawback.

This work continues the research of authors whose results were previously partially published in international publications [3, 4, 7, 21, 25].

8. CONCLUSIONS

This paper resolves the relevant task of DSS structure and software development in poorly structured and difficult formalization of the modeling and forecasting the development of modern processes in economy, finances, and technologies. These processes show high complexity of their behavior what is reflected in their nonstationary and nonlinearity of characteristics. The problems of their modeling and forecasting require development of systemic approach that can be implemented in the frames of specialized decision support systems.

The developed usage of new and modified quality criteria for data, models and forecast estimates are useful from the point of view of implementing adaptive features into modeling procedures and reaching high quality results at each stage data processing. Another positive moment of development of this specialized DSS is in a possibility of hiring mathematical models of different classes and models constructed with application of different ideologies. The described usage of improved model based on classic statistical approach to model constructing as well as the methods of intellectual data analysis what found its realization in Bayesian approach to GLM building and model parameters estimation allows improving the quality of solutions in the field of prognostic modelling of processes in economy, finances, and technologies. The numerical results achieved in the form of forecast estimates and statistics characterizing quality of the results reflect correctness of the approach used for development of the DSS. The possibility for incorporating adaptation into the modeling process and monitoring all the stages of computations with several sets of quality statistics allows achieve high quality results even in conditions of missing observations and relatively short samples. As the main parameter characterizing quality of forecasts was selected mean absolute percentage error that is easy for analyzing and comparing alternative results. Practically in all cases of modeling it showed high quality or acceptable results.

The proposed approach has made it possible to increase the understanding of the analyzed processes in computer DSS and to improve the quality of prognostic modelling for situations where there are only short data samples, when the usage of retrospective data is impossible or significantly limited.

In the future developments it will be possible and useful to further incorporate the features of intelligence into the DSS regarding its interface characteristics, automatized procedures for data structuring, model structure and parameter estimation, hiring alternative procedures for computing forecast estimates, and application of forecasts combining procedures. Preliminary studies show that promising high quality results of modeling and forecasting complex nonlinear nonstationary processes could be reached with combined application of optimal and digital filtering techniques, classic statistical and intellectual data analysis methods. More intensive use of the Bayesian approach to data and expert estimates processing as well as fuzzy sets techniques are planned.

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Figure 4: Structural scheme of information technology support decision-making