15. Shamshirband, S. An appraisal and design of a multiagent system based cooperative wireless intrusion detection computational intelligence technique [Text] / S. Shamshirband, N. B. Anuar, M. L. Kiah, A. Patel, // Engineering Applications of Artificial Intelligence. – 2013. – Vol. 26, Issue 9. – p. 2105–2127. doi: 10.1016/j.engappai.2013.04.010
16. Мірошник, М. А. Розробка методів оцінки ефективності захисту інформації в розподілених комп'ютерних системах [Текст] / М. А. Мірошник // Інформаційно-керуючі системи на залізничному транспорті: науково-технічний журнал. – 2015. – № 4 (113). – С. 39–43.
17. Keunsoo, L. DDoS attack detection method using cluster analysis [Text] / L. Keunsoo, J. Kim, K. Hoon Kwon, Y. Han, S. Kim // Expert Systems with Applications. – 2008. – Vol. 4, Issue 3. – p. 1659–1665. doi: 10.1016/j.eswa.2007.01.040
18. Dilek, S. Applications of artificial intelligence techniques to combating cyber crimes: A review [Text] / S. Dilek, H. Çakır, M. Aydın // International Journal of Artificial Intelligence & Applications. – 2015. – Vol. 6, Issue 1. – P. 21–39. doi: 10.5121/ijaia.2015.6102
19. Patel, A. M. An intrusion detection and prevention system in cloud computing: A systematic review [Text] / A. Patel, M. Taghavi, K. Bakhtiyari, J. Celestino Junior // Journal of Network and Computer Applications. – 2013. – Vol. 36, Issue 1. – P. 25–41. doi: 10.1016/j.jnca.2012.08.007
20. Barman, D. K. Design of Intrusion Detection System Based On Artificial Neural Network and Application of Rough Set [Text] / D. K. Barman, G. Khataniar // International Journal of Computer Science and Communication Networks. – 2012. – Vol. 2, Issue 4. – P. 548–552.
21. Raiyn, J. A survey of Cyber Attack Detection Strategies [Text] / J. Raiyn // International Journal of Security and Its Applications. – 2014. – Vol. 8, Issue 1 –P. 247–256. doi: 10.14257/ijsia.2014.8.1.23
22. Kotenko, I. Integrated repository of security information for network security evaluation [Text] / I. Kotenko, A. Fedorchenko, A. Chechulin // Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA). – 2015. – Vol. 6, Issue 2. – P. 41–57.

Проаналізовано фактори невизначеності у процесі прийняття стратегічних рішень і проведено порівняльний аналіз традиційних статистичних моделей і методів прогнозування. Сформульовано основні завдання прогностичного забезпечення та обґрунтовано необхідність розробки моделі прогностичного забезпечення підтримки прийняття стратегічних рішень для потреб організації. Запропоновано чотирирівневу модель системи із принципами її методичного насичення, а також інструменти її налаштування

Ключові слова: прогностичне забезпечення, підтримка прийняття управлінських рішень, прогнозування, комплексування прогнозних оцінок

Проанализированы факторы неопределённости в процессе принятия стратегических решений и проведён сравнительный анализ традиционных статистических моделей и методов прогнозирования. Сформулированы основные задачи прогностического обеспечения и обоснована необходимость разработки модели прогностического обеспечения поддержки принятия стратегических решений для нужд организации. Предложена четырёхуровневая модель системы с принципами её методического насыщения, а также инструменты её настройки

Ключевые слова: прогностическое обеспечение, поддержка принятия управленческих решений, прогнозирование, комплексирование прогнозных оценок

UDC 658.5:004.94

DOI: 10.15587/1729-4061.2016.66306

FORMATION OF PROGNOSTIC SOFTWARE SUPPORT FOR STRATEGIC DECISION-MAKING IN AN ORGANIZATION

Yu. Romanenkov
PhD, Associate Professor*
E-mail: KhAI.management@ukr.net

V. Vartanian
Doctor of Technical Sciences, Professor*
E-mail: vartanyan_vm@ukr.net

*Department of management
M. E. Zhukovsky National Aerospace University «Kharkiv Aviation Institute»
Chkalova str., 17, Kharkiv, Ukraine, 61070

1. Introduction

The advanced development of modern information technologies and communications systems facilitates a continuous increase of various types of data for monitoring organizational and technical as well as socioeconomic systems that become accumulated in specialized databases, including time series. To various extents, these data reflect the dynamics of multifactor and hard-to-formalize processes, reproducing all the nuances characteristic of such reasons, factors, and relationships. Data accumulated in the form of time series are characterized by an objective uncertainty on the basis of the methods and means of monitoring as well as the subjectivity of an observer.

An intention to use the accumulated information for solving complex organizational and technical facility management tasks leads to the need for its purification and transformation in order to obtain prognostic estimates about exponents that are essential for managerial decision-making.

An object's position in the competitive technical and economic environment can be determined by formalizing the functional conditions for a complex organizational and technical object (for example, a large organization), in particular, by processing quantitative indicators of its external and internal environment. A group of these indicators forms a phase space in which the trajectory determines the efficiency of the object in its own life cycle.

Prognostic estimates on the coordinate values of a particular phased technical and economic environment are essential for a stable effective strategic management of complex organizational and technical facilities.

Examples of such complex objects are modern airlines, about thirty in Ukraine alone. To evaluate the cash flows of the airlines, suffice it to say that the cost of one hour on board the Yak-42 is about 1,000 euros. The annual revenue from operating just a single aircraft, subject to the declared number of hours, can be as much as 840,000 euros [1].

Therefore, the measure of risk at a wrong planning is significant, which entails tougher requirements for prognostic software in support systems for strategic decision-making used in this domain.

The urgency of the problem of scientific prediction is confirmed by the fact that the 2013 Laureates of the Nobel Memorial Prize in Economic Sciences were US economists Eugene Fama, Lars Peter Hansen, and Robert Shiller. As defined in an official statement of the Royal Swedish Academy of Sciences, the prize was awarded "for their empirical analysis of asset prices," i. e. for activities in prognostic estimations.

2. Analysis of previous studies and statement of the problem

A large number of studies have been published on the theory and practice of prognoses development. A prediction helps identify the areas and opportunities as a basis for setting forth the objectives of economic and technological development as well as for determining the directions and the most important issues as the object of development and decision-making [2].

The diversity of the types of time series is very large [3]. For example, non-stationary time series are quite common. In industries, trade and economy, prediction problems are often formulated as stationary time series with the help of a difference operator [4, 5]. The type of classical models for predicting time series includes regressive [6] and autoregressive [7] models.

Contribution to the development of the modern forecasting system is also made through studies by Ukrainian scientists specializing in different subject areas, for example, as in [8, 9].

In [10], it is noted that the diversity of manifestations of socioeconomic systems further generates a variety of methods of their prediction. In [11], it is stated that there are over a hundred forecasting methods, which raises the problem for experts to choose those methods that would provide adequate predictions for studying processes or systems.

The contemporary amount of monitoring data and the high standards for forecasting tasks entail a consistently high accuracy of predictions and, consequently, development of effective methods of setting predictive models and methods of their integration.

The best-known application software packages that implement the methods of forecasting are BMDP, CART, CSS, Deductor, Forecast Expert, MVSP, Predictor, SAS, S-plus, SPSS, STADIA, STATISTICA, STATGRAPHICS, SYSTAT, ClassMaster, MESOSAUR, OLYMPUS: StartExpert, EUREST, and Statistician-Consultant.

Predictive support includes decision-making as one of the functions of information support for the administrative cycle process. For example, in [12, 13], the authors analyse the main models of the management cycle, and all of the models, in one form or another, involve the function of predictive support.

Predictive support is one of the key elements of decision support systems (DSSs). The results serve as an information basis for management action by leaders of different ranks, and, therefore, need to be precise, reliable, and stable [14].

At the present stage of development of information technologies, an essential direction in providing analysis and prediction of time series is data mining [15, 16].

Mathematical tools for data mining include neural networks and fuzzy models as well as methods of artificial intelligence, and they are designed to operate large data arrays. However, the class of real problems of the predictive management in the decision-making process involves situations in which a statistical data sample is small. Besides, as practice shows, only small fragments of the problem of time series analysis can be effectively addressed in the automatic mode [17].

Under the existing circumstances, it seems possible to distinguish between two ways of providing the full range of methods and means of prognostication in solving management problems: either by expanding the methodological data mining toolkit (this is actually happening, albeit slowly) or by synthesizing specialized forecast information systems, taking into account available resources of data mining.

The second way involves establishment of a predictive support model and construction of a "path" for prognostic research, which entails development or selection of methods to set up low-level models as well as synthesis of an adaptive predictive model of integrated top-level prognostic estimates [18]. To date, there is a gap between the successful implementation of a particular forecasting method and the development of a complex prediction system [19] to satisfy the long-term needs for organizing prognostic support.

Specialized forecast centres, which are equipped with modern methodological bases and access to databases of branch monitoring, are still periodically forced to solve the problem of choosing an effective forecast model and consolidating forecasts [20].

3. The purpose and objectives of the study

The purpose of this study is to improve the quality of predictive systems support in strategic decision-making in organizations through the development of methods, models and tools of statistical information processing.

To achieve this purpose, the following objectives should be reached:

– to analyse the factors of uncertainty in the strategic decision-making within the organization activities,

– to carry out a comparative analysis of the current models and forecasting techniques (traditional),

– to develop a predictive model of providing strategic decision-making support.

4. Development of a four-level model of a predictive support in strategic decision-making

4. 1. Analysis of uncertainties in the process of strategic decision-making within the organization activities

To analyse adequately the object of the study, it is necessary to consider the factors that add different kinds of uncertainty to the strategic decision-making process within the organization activities.

Fig. 1 shows the sources and types of uncertainty in the decision-making process that lead to risks and, therefore, possible financial losses in the organization. Among all their diversity, there can be distinguished a group that characterizes data uncertainty.

4. 2. A comparative analysis of contemporary models and methods of prediction

A comparative analysis of the forecasting methods and predictive models of multicomponent processes [21] is shown in Table 1, which illustrates the strengths and weaknesses of the currently used forecasting methods.

The comparative analysis can result in the following conclusions:

1. Among the predictive methods, there is no universal method that would be characterized by exceptional accuracy. To improve the accuracy of forecasting, it is advisable to use combined (sometimes called "hybrid") predictive models that integrate advantages of the classical methods and level off their individual shortcomings.

2. From the large variety of methods of analysing and forecasting, it is necessary to identify about ten methods that can be called basic. Among them, the most practical and commonly used are regression models and methods as well as models and methods of exponential smoothing [21].

3. Prediction of complex multi-component processes requires not only selection of a specific forecasting method but also a parametric setting of the predictive model.

4. To implement an effective predictive activity on a regular basis, it is necessary to develop a predictive support-providing model for strategic decision-making to comply with the needs of an organization; it also requires configuration tools as well as monitoring and timely updating of the model.

4. 3. A four-level model of prognostic support for strategic decision-making

Let us formulate the main tasks in developing prognostic software of support systems for strategic decision-making:

(1) collection, verification and accumulation of statistical information on the key coordinates of the phase space for the object of strategic management;

(2) formation of a group of the main methods of low-level forecasting, suitable for working with time series while taking into account their specific features (including stationarity, omissions, and noise pollution);

(3) development of an adequate model of multi-adaptive predictive estimates from different sources;

(4) provision of an interactive mode of parameter settings for both predictive models of the low level and model aggregations, which allows an informed intrusion by a system operator.

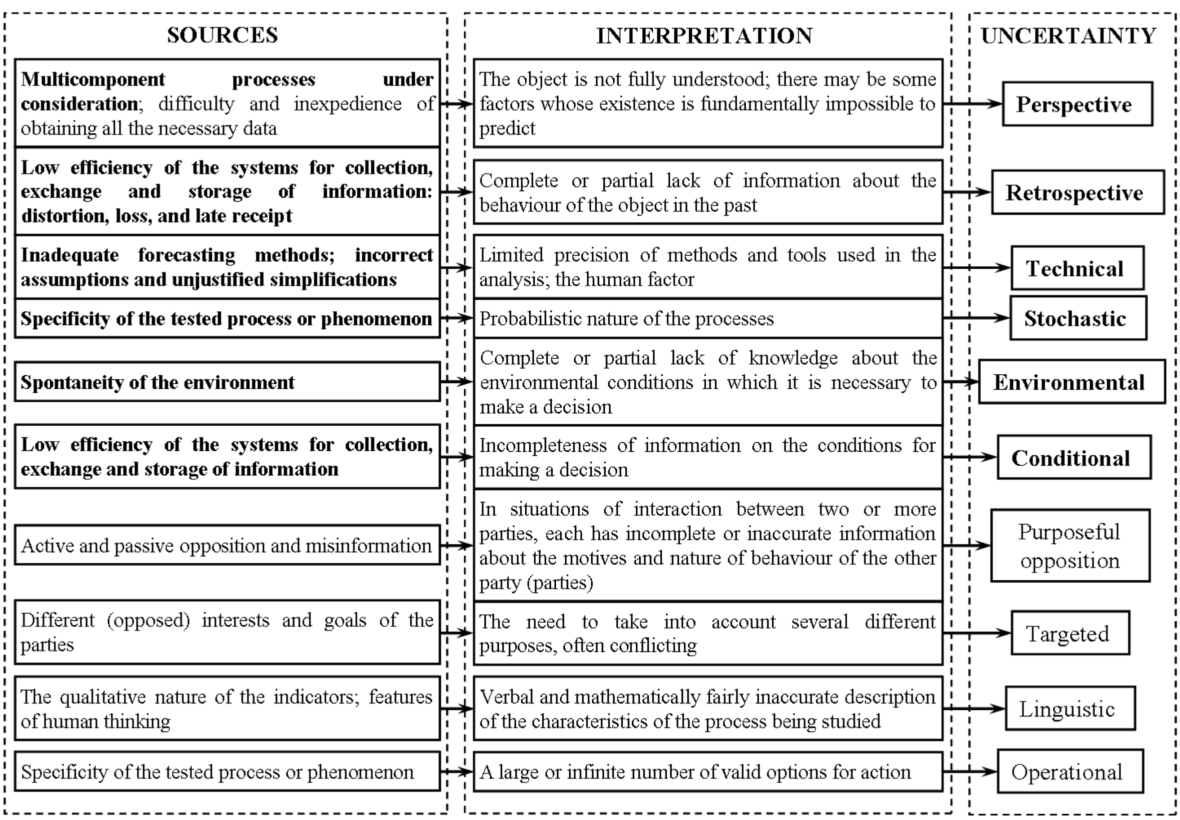

Fig. 1. Sources and types of uncertainty in decision-making

Table 1

A comparative analysis of the forecasting methods and predictive models

Models and methods	Types of models	Characteristics of models	Advantages	Disadvantages
1	2	3	4	5
Regression models and methods	A linear regression model. A multiple regression model	Determines the relationship between the initial process and one or many external factors (covariates)	Easy, quickly available prognostic results and interim results for analysis, as well as a possibility to identify the factors that have the greatest impact on the process	Limited use in forecasting (to calculate the future value of the process, it is necessary to know the future value factors) and an impossibility of modelling nonlinear processes
	A non-linear regression model	It is used when the relationship between the initial process and external factors can be described by a known function	It is possible to model non-linear processes, and intermediate results are available for analysis	It is difficult to determine the type of functional dependence and the dependence of the coefficients
Autoregressive models and methods	An autoregression model	The model is built on the assumption that the process value is linearly dependent on a number of previous values of the same process	Popularity, simplicity, and transparency of the modelling	The complexity and resource capacity of the model identification, low adaptability, and usability only for simulation of linear stationary processes
	An autoregressive-moving-average model	A linear multiple regression model that combines a filter in the form of a moving average (MA) and an avtoregression (AR) of the filtered process values	It is most commonly used in practice and characterized by fewer parameters in comparison with the AR and the MA	A complex model structure; an impossibility of nonlinear modelling
	A model of an autoregressive integrated moving average (a Box-Jenkins model)	It is a derivative of the model of an autoregressive moving average whose input in not the values of a time series but their d-th order difference that can be represented by a stationary process	Many modifications of the model, a possibility to model both stationary and non-stationary processes, as well as the ability of the algorithm to adjust the internal parameters in order to choose the most appropriate model prediction	It requires a relatively large amount of data. There is no easy way to adjust the model parameters when new data are used, so the model should be periodically rebuilt or substituted for by another model. It takes much time and substantial resources to build the model
Models and methods of exponential smoothing	The Brown model	A one-parameter model of a simple exponential smoothing, which is used for levelling off data series and for short-term forecasting	Easy; provides adaptive prediction	The model does not take into account the trend and seasonal changes
	The Holt model	A two-parameter model, or a model of double exponential smoothing; it is obtained by inclusion of the growth factor or the trend	It provides adaptive prediction	It does not take into account seasonality
	The Winters model	An extended Holt model obtained by inclusion of an equation describing seasonal components	It provides adaptive prediction and takes into account seasonality	Sensitivity to changes in trends in the forecast range
	The Holt-Winters model	A model of linear growth with a multiplicative seasonality, which is an integration of the Holt and Winters models	It considers the multiplicative trend and seasonality	Sensitivity to changes in trends in the forecast range
	A Theil-Wage model	A model of linear growth with additive seasonality; it is a complicated Holt model and an additive analogue of the Holt-Winters model to take into account an additive linear trend and seasonality	It shows good results, with a well-defined seasonal cycle and preservation process trends in the forecast period	The method provides a forecast for a step forward, but not for the period ahead; the trend in the Theil-Wage model is typically simplified, which, in the case of a small sample, can lead to a loss of accuracy

Continuation of Table 1

1	2	3	4	5
Structural models	Models and methods on the basis of classification and regression trees	A structural model, which simulates using a tree structure, threshold constants, and subsets	A possibility to model processes that are influenced by factors of various types as well as by the speed and simplicity of the learning process	Uniqueness of the algorithm for constructing the tree
	Neural network models and methods	The structural model is based on artificial neural networks, which allows modelling of a nonlinear dependence of the future value of a time series by its actual values and the values of external factors; the most popular among structural models	Prediction can be made in any number of steps; it is possible to provide instructions, to model a nonlinear dependence, to apply clustering to problem-solving, and to adapt	Non-determination, lack of transparency; a complexity of the choice of architecture, high requirements for data pre-processing, strict requirements for the training set, a complexity of the choice of the learning algorithm, a resource-intensive process of training, and a necessity for the user programming skills
	Models and methods based on Markov chains	It sets a relationship between the future value of the process and its current value on the basis of defining the multiple states of the process and selecting the state into which the transition probability is at the maximum. It is assumed that the future state of the process depends only on its current state regardless of the previous ones	Easy modelling, analysis, and design consistency	It is impossible to model long-memory processes; the applicability of the models is narrow

Based on the above analysis, a predictive activity of an organization can be devised in accordance with the model shown in Fig. 2.

The first level contains low-level models such as those of statistical forecasting. An organization actually forms a portfolio of predictive models and methods for solving real problems of prediction. It is obvious that the combination and the number of low-level models largely depend on the mathematical training of analysis specialists as well as their experience and preference in specific models. For example, in the case of a limited sample, satisfactory results are provided by the Brown model, and a number of studies (for example, [22–24]) have been published on its parameter setting.

Tremendous opportunities of a low-level model are provided by the currently popular interactive method Caterpillar-SSA [25–30], though it requires sampling of a considerable length to perform effective decomposition of the time series.

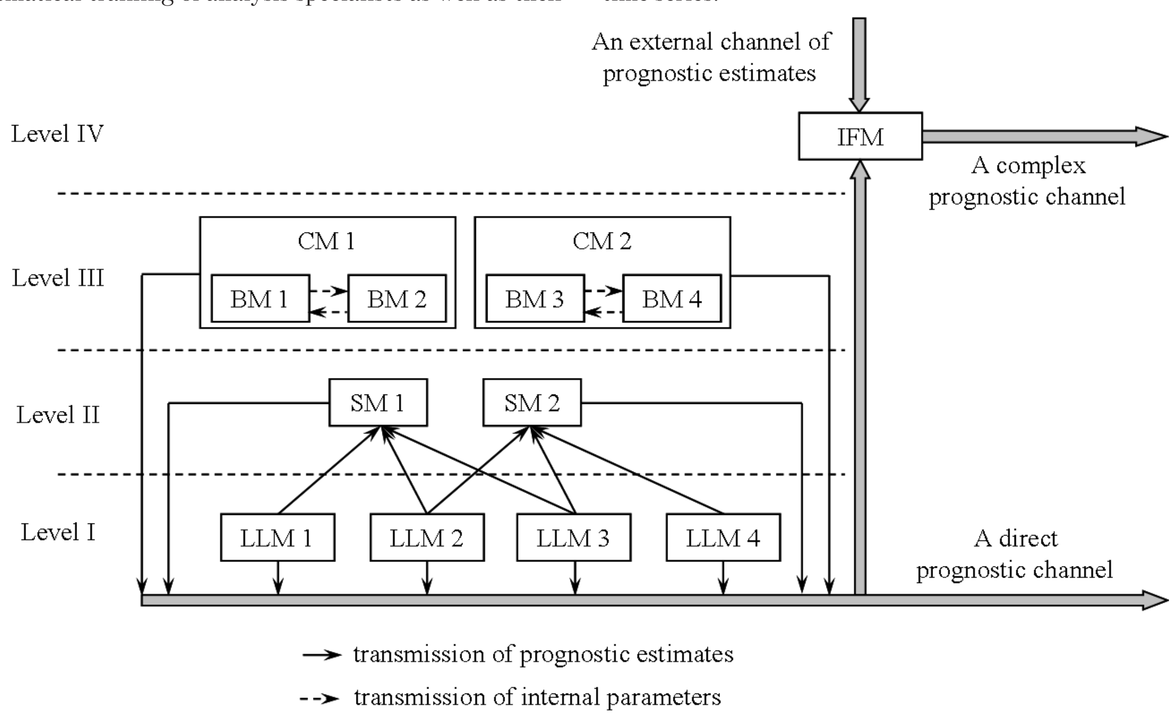

Fig. 2. A four-level model of predictive support for strategic decision-making: LLM is a low-level model, SM is a selective model, CM is a combined model, BM is a base model (in relation to the combined model), and IFM is an integrated forecasting model

The second level involves selective predictive models synthesized from low-level models on the basis of decision rules. Various approaches to synthesizing selective models are described, for example, in [31–33]. The general rule and the actual essence of a selective model imply selection of the best model by a selected criterion at each prediction step.

The third level includes hybrid or combined models that entail a parametric structure-sharing in order to compensate for the natural disadvantages of the basic models. The spectrum of the basic models to form combined model is very wide; examples of such models are given in [34–39], including those developed by the authors of [40]. Combined models can be considered as probably the most effective models in predictions made by using a single method, i. e. without constructing any prognostic technology.

The logical upper level of the suggested model contains integrated forecasting models, designed to synthesize consolidated forecasts by using two or more sources. It is noteworthy that the term "aggregation" with respect to forecasting estimates [41–43] in the studies is used alongside the term "integration" [44, 45].

The fourth level of the model is necessary because the professional IT environment entails external prospective assessments of relatively important organization settings. Such estimates should be used and coordinated (aggregated) with account for the results of the organization's own prognostic activities. In this case, the methodological basis of external predictive estimates usually remains hidden from the end user's expectations.

Some methodological tools included in the suggested model can refer to the group of data mining means. It is assumed that this part will increase as a result of the continued expansion of the methodological spectrum of data mining. Nevertheless, the organization's conscious tendency to diversify its prognostic support will continue.

Besides, an important feature of the suggested model is its openness, i. e. a principle possibility of expanding the methodological base. For example, if the organization's sectorial environment contains effective factor forecasting models (such as neural networks or fuzzy models), they can be involved at the low level.

It is assumed that, regardless of the prediction tools involved, the top-level models (integrated forecasting models) will be able to provide prognostic support of a satisfactory quality.

A practical embodiment of the suggested model can be implemented as a specialized prediction complex whose structural model can be represented as in [46] (Fig. 3). Alternative approaches are described, for example, in [47, 48].

The functions of the suggested model are implemented in the monitoring unit and in the functional unit of the prediction complex that consists of clusters of preliminary data analysis, forecasting, and aggregation. Efficiency of the prediction complex is provided by the methods and means unit as well as the models and methods synthesis unit.

5. The practical significance and testing of the research results

Let us consider how the low level can involve the use of the adaptive predictive Brown model [49]:

$$F_t = \alpha A_{t-1} + \alpha(1-\alpha)A_{t-2} + \ldots + \alpha(1-\alpha)^{n-1} A_{t-n} = \\ = \sum_{i=1}^{n} \alpha(1-\alpha)^{i-1} A_{t-i}, \quad (1)$$

where F_t is the prediction of the controlled parameter at the point in time t, A_{t-1}, A_{t-2}, ..., A_{t-n} are line values at respective points in time, n is the length of the sample, and α is the parameter (constant) of smoothing.

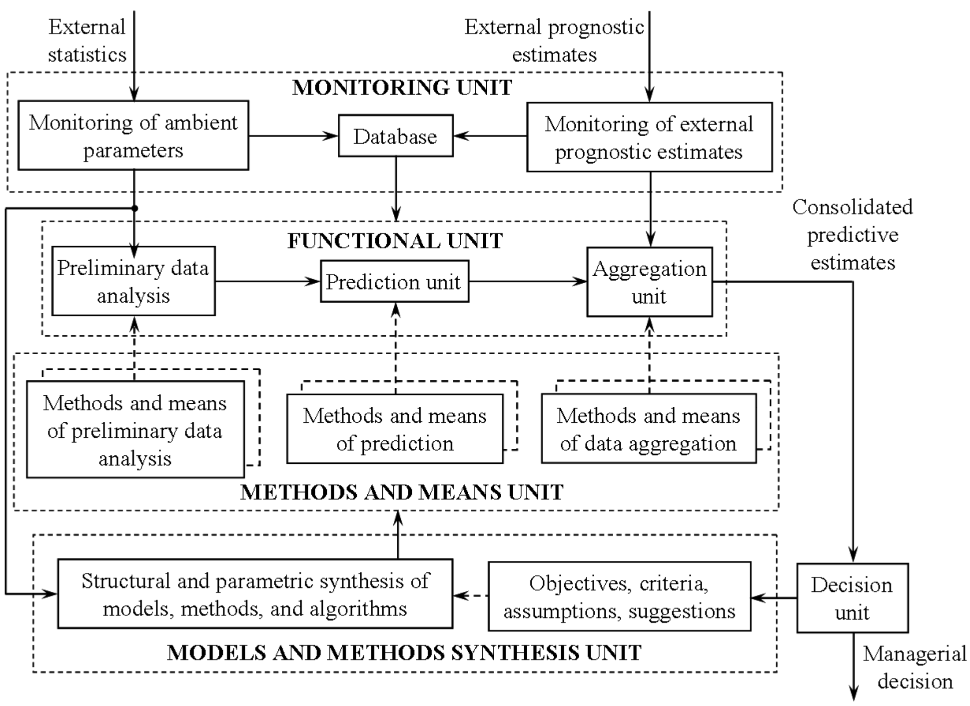

Fig. 3. The structural model of a prediction complex that implements the four-level model of predictive support for strategic decision-making

We suggest that the parameter setting, i. e. the choice of the smoothing parameter α, should be carried out according to the results of a retrospective analysis, namely by solving retrospective equations of the following type:

$$\Delta_{t-1}(\alpha)=0 \text{ or } \varepsilon_{t-1}(\alpha)=0, \quad (2)$$

where $\Delta_{t-1}(\alpha)$ and $\varepsilon_{t-1}(\alpha)$ are analytical dependences respective to the absolute and relative retrospective errors of prediction at the point in time $(t-1)$.

In this case, the choice of α is considered to be justified if it provides absolute precision of the retrodiction at the point in time $(t-1)$. Thus, the real roots of equation (2), pertaining to the multiplicity $K_{ext}=\{\alpha:\ 0\le\alpha\le2\}$, can be used as the smoothing parameter values for predictions realizable further in time.

Depending on the number of roots of equation (2) within the analysed interval, the parametric synthesis procedure may include appropriate steps of a comparative analysis of retrospective prognostic estimates [23] (Fig. 4).

To consolidate the prognostic estimates at the upper level, we suggest using a method of dynamic aggregation [41], the essence of which is as follows.

If the researcher has n prognostic estimates $\hat{F}_i[k]$ and $i=\overline{1,n}$ in relation to an exponent F at the point in time k on the basis of n sources, then the aggregated prediction is determined as the weighted sum of the obtained estimates:

$$\hat{F}_\Sigma[k]=\sum_{i=1}^{n} w_i\hat{F}_i[k], \quad (3)$$

where $\hat{F}_\Sigma[k]$ is the final prediction on the basis of aggregated prognostic estimates, w_i denotes weight ratios, and

$$\sum_{i=1}^{n} w_i=1.$$

We suggest determining the aggregated weight ratios on the basis of the prediction variance for a further point in time $\hat{e}[N+1]$. Let us consider a situation in which information about a prediction error is presented in the form of time series of absolute deviations for the whole period of instructional (retrospective) sampling:

$$\begin{aligned}
\{e_1\}_N&=\{e_1[k-N],\ e_1[k-N+1],\ \ldots,\ e_1[k-1]\},\\
\{e_2\}_N&=\{e_2[k-N],\ e_2[k-N+1],\ \ldots,\ e_2[k-1]\},\\
&\ldots,\\
\{e_n\}_N&=\{e_n[k-N],\ e_n[k-N+1],\ \ldots,\ e_n[k-1]\}.
\end{aligned} \quad (4)$$

On the basis of (4), it is possible to construct a time series of squared errors:

$$\begin{aligned}
\{e_1^2\}_N&=\{e_1^2[k-N],\ e_1^2[k-N+1],\ \ldots,\ e_1^2[k-1]\},\\
\{e_2^2\}_N&=\{e_2^2[k-N],\ e_2^2[k-N+1],\ \ldots,\ e_2^2[k-1]\},\\
&\ldots,\\
\{e_n^2\}_N&=\{e_n^2[k-N],\ e_n^2[k-N+1],\ \ldots,\ e_n^2[k-1]\}.
\end{aligned} \quad (5)$$

By analysing the series in (5), it is possible to obtain prognostic estimates of the variances $\hat{e}_1^2[k]$, $\hat{e}_2^2[k]$, …, and $\hat{e}_n^2[k]$ and to use them for determining the weight ratios w_i in the following way:

$$w_i=\frac{1/\hat{e}_i^2[k]}{\sum_{i=1}^{n}1/\hat{e}_i^2[k]}. \quad (6)$$

Integration of prognostic estimates by the described method allows taking into account while aggregating the accuracy tendencies of separate prediction sources. Fig. 5 shows a decomposition process of integrated forecasting.

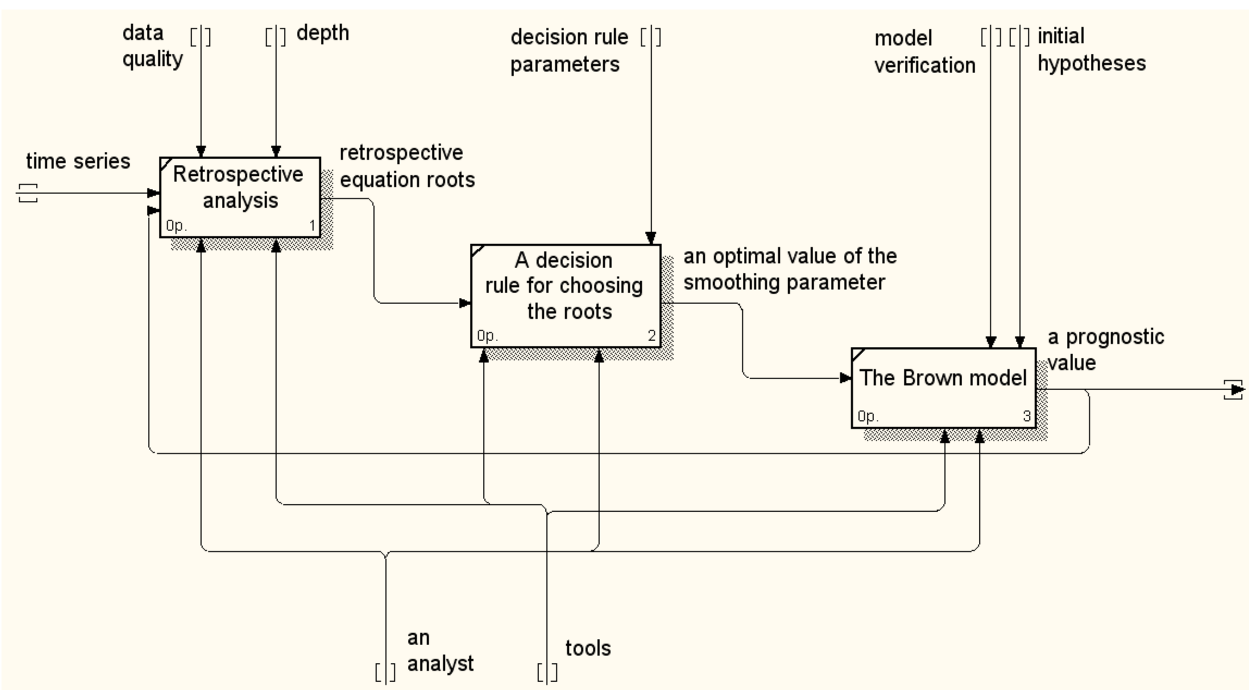

Fig. 4. Decomposition of the parametric configuration process for the Brown forecasting model based on a retrospective analysis

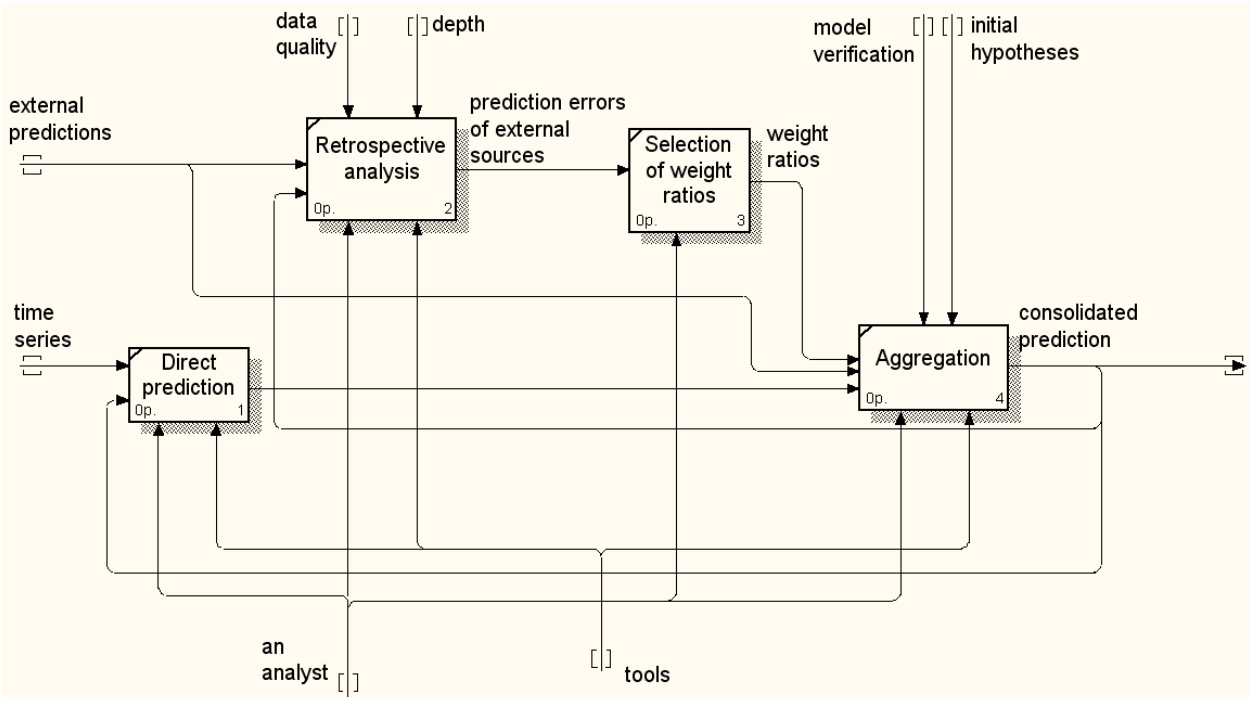

Fig. 5. A decomposition process of integrated forecastin

The suggested models and methods have been realised in the form of computer software, which has received copyright certificates [42, 43]. All the methods have been processed as algorithms and implemented in specialized software shells. A disadvantage of the suggested multi-level predictive model of strategic decision support is the difficulty in assessing the required number of models at each level. The authors intend to consider this issue in a subsequent study.

6. Conclusion

The study suggests a four-level model of a prognostic software system designed to solve the problems set forth for prognostic management of strategic decision-making support, including collection of statistical data, formation of a set of the main predictive methods, aggregation of prognostic estimates from different sources, and provision of an interactive mode of a parameter setting.

One of the models considered for the low level is the Brown prognostic model. A method of its parameter setting is suggested in the study on the basis of a retrospective analysis, which, unlike the existing ones, allows determining the tuning parameters of the model and ensures a maximum resistance of prognostic estimates to changes in the internal model parameters.

To create a means of prognostic data integration at the upper level, the study suggests a method of dynamic aggregation of prognostic estimates based on identifying prediction accuracy tendencies of alternative prediction sources, which, unlike the existing methods, ensures adaptability of the integration system and prognostic software support for strategic decision-making.

References

1. Ledenev, A. Infografika: gde zarabatyvajut samolety s ukrainskoj propiskoj [Electronic resource] / A. Ledenev. – Available at: http://forbes.net.ua/business/1411400-infografika-gde-zarabatyvayut-samolety-s-ukrainskoj-propiskoj
2. Frenkel’, A. A. Prognozirovanie proizvoditel’nosti truda: metody i modeli [Text]: monografija / A. A. Frenkel’. – Moscow: Jekonomika, 2007. – 221 p.
3. Kantorovich, G. G. Analiz vremennyh rjadov [Text] / G. G. Kantorovich // Jekonomicheskij zhurnal VShJe. – 2002. – Vol. 1-2.
4. Anderson, T. Statisticheskij analiz vremennyh rjadov [Text] / T. Anderson. – Moscow: Mir, 1976. – 757 p.
5. Kendjel, M. Vremennye rjady [Text] / M. Kendjel. – Moscow: Finansy i statistika, 1981. – 199 s.
6. Boks, Dzh. Analiz vremennyh rjadov. Prognoz i upravlenie [Text] / Dzh. Boks, G. Dzhenkins; V. F. Pisarenko (Ed.). – Moscow: Mir, 1974. – 406 p.
7. Nosko, V. P. Jekonometrika. Vvedenie v regressionnyj analiz vremennyh rjadov [Text] / V. P. Nosko. – Moscow: NFPK, 2002. – 273 p.
8. Bidjuk, P. I. Pobudova systemy adaptyvnogo prognozuvannja finansovo-ekonomichnyh procesiv ta i’i’ zastosuvannja [Text] / P. I. Bidjuk, A. V. Fedorov // Naukovi praci: Ser. Komp’juterni tehnologii’. – 2009. – Vol. 117, Issue 104. – P. 119–129.
9. Solovjova, M. I. Z istorii’ rozvytku koncepcii’ systemnogo planuvannja i prognozuvannja [Text] / M. I. Solovjova // Nauka j ekonomika. – 2009. – Vol. 2, Issue 4 (16). – P. 198–204.
10. Svetun’kov, S. G. Metody social’no-jekonomicheskogo prognozirovanija. Tom I [Text]: uchebnik / S. G. Svetun’kov, I. S. Svetun’kov. – SPb.: Izd-vo SPbGUJeF, 2009. – 147 p.

11. Tihonov, E. Je. Metody prognozirovanija v uslovijah rynka [Text]: ucheb. pos. / E. Je. Tihonov. – Nevinnomyssk, 2006. – 221 p.
12. Mironov, E. A. Upravlencheskij cikl kak tehnologija sotrudnichestva [Electronic resource] / E. A. Mironov. – Available at: http://www.coverdale.ru/pdf/article2.pdf
13. Pastovens'kyj, O. V. Osoblyvosti upravlins'kogo cyklu v umovah rozvytku gromads'ko-derzhavnogo upravlinnja zagal'noju seredn'oju osvitoju [Text] / O. V. Pastovens'kyj // Naukovi zapysky Ternopil's'kogo nacional'nogo pedagogichnogo universytetu im. Volodymyra Gnatjuka. Ser. Pedagogika. – 2012. – Vol. 2. – P. 128–133.
14. Afanas'eva, T. V. Modelirovanie nechetkih tendencij vremennyh rjadov [Text] / T. V. Afanas'eva. – Ul'janovsk: UlGTU, 2013. – 215 p.
15. Batyrshin, I. Z. Modeli i metody perceptivnogo data majninga vremennyh rjadov dlja sistem podderzhki prinjatija reshenij [Text] / I. Z. Batyrshin, L. B. Sheremetov // Nechetkie sistemy i mjagkie vychislenija. – 2007. – Vol. 2, Issue 1. – P. 152–161.
16. Kovalerchuk, B. Data Mining in Finance: Advances in Relational and Hybrid methods [Text] / B. Kovalerchuk, E. Vityaev. – Kluwer Academic Publishers, 2000. – 308 p.
17. Aleksandrov, F. I. Avtomatizacija vydelenija trendovyh i periodicheskih sostavljajushhih vremennogo rjada v ramkah metoda «Gusenica»-SSA [Electronic resource] / F. I. Aleksandrov, N. Je. Goljandina. – Available at: http://www.pdmi.ras.ru/~theo/autossa/files/Exponenta.Pro--paper--AutoSSA.pdf
18. Chen, K.-Y. Combining linear and nonlinear model in forecasting tourism demand [Text] / K.-Y. Chen // Expert Systems with Applications. – 2011. – Vol. 38, Issue 8. – P. 10368–10376. doi: 10.1016/j.eswa.2011.02.049
19. Matijaš, M. Load Forecasting using a Multivariate Meta-Learning System [Text] / M. Matijaš, J. A. K. Suykens, S. Krajcar // Expert Systems With Applications. – 2013. – Vol. 40, Issue 11. – P. 4427–4437. doi: 10.1016/j.eswa.2013.01.047
20. Jansen, W. J. Forecasting and nowcasting real GDP: Comparing statistical models and subjective forecasts [Text] / W. J. Jansen, X. Jin, J. M. de Winter // Original Research Article. International Journal of Forecasting. – 2016. – Vol. 32, Issue 2. – P. 411–436. doi: 10.1016/j.ijforecast.2015.05.008
21. Kashheeva, V. Ju. Informacionnaja tehnologija analiza mnogokomponentnyh processov po vremennym rjadam na osnove interval'nyh prognoznyh modelej [Text] / V. Ju. Kashheeva // Sistemi upravlinnja, navigacii ta zv'jazku. – 2013. – Vol. 3 (27). – P. 128–133.
22. Romanenkov, Yu. Analysis of the predictive properties of Brown's model in the extended domain of the internal parameter [Text] / Yu. Romanenkov // MOTROL. Commission of Motorization and Energetics in Agriculture. – 2015. – Vol. 17, Issue 8. – P. 27–34.
23. Romanenkov, Ju. A. Metod parametricheskogo sinteza modeli Brauna na osnove retrospektivnoj mnogokriterial'noj optimizacii [Text]: zb. nauk. pr. / Ju. A. Romanenkov, T. G. Zejniev // Galuzeve mashinobuduvannja, budivnictvo. – 2014. – Vol. 2(41). – P. 48–56.
24. Romanenkov, Ju. A. Parametricheskij analiz oblasti adekvatnosti adaptivnoj prognoznoj modeli Brauna [Text] / Ju. A. Romanenkov // Naukovi praci Pivdennogo filialu Nacional'nogo universitetu bioresursiv i prirodokoristuvannja Ukraini «Krims'kij agrotehnologichnij universitet». – 2014. – Vol. 162. – P. 228–236.
25. Goljandina, N. Je. Metod «Gusenica»-SSA: prognoz vremennyh rjadov [Text]: ucheb. pos. / N. Je. Goljandina. – SPb: Izd-vo SPbGU, 2004. – 52 p.
26. Vautard, R. Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series [Text] / R. Vautard, M. Ghil // Physica D: Nonlinear Phenomena. – 1989. – Vol. 35, Issue 3. – P. 395–424. doi: 10.1016/0167-2789(89)90077-8
27. Yiou, P. Spectral analysis of climate data [Text] / P. Yiou, E. Baert, M. F. Loutre // Surveys in Geophysics. – 1996. – Vol. 17, Issue 6. – P. 619–663. doi: 10.1007/bf01931784
28. Lisi, F. Combination of singular spectrum analysis and auto regressive model for short term load forecasting [Text] / F. Lisi, O. Nicolis, M. Sandri // Neural Process Lett. – 1995. – Vol. 2, Issue 4. – P. 6–10.
29. Hassani, H. Forecasting European industrial production with singular spectrum analysis [Text] / H. Hassani, S. Heravi, A. Zhigljavscky // International Journal of Forecasting. – 2009. – Vol. 25, Issue 1. – P. 103–118. doi: 10.1016/j.ijforecast.2008.09.007
30. Dai, W. Financial Time Series Forecasting Using A Compound Model Based on Wavelet Frame and Support Vector Regression [Text] / W. Dai, C.-J. Lu // 2008 Fourth International Conference on Natural Computation, 2008. – P. 328–332. doi: 10.1109/icnc.2008.455
31. Lukashin, Ju. P. Adaptivnye metody kratkosrochnogo prognozirovanija vremennyh rjadov [Text] / Ju. P. Lukashin. – Moscow: Finansy i statistika, 2003. – 416 p.
32. Berzlev, A. Ju. Adaptivnye kombinirovannye modeli prognozirovanija birzhevyh pokazatelej [Text] / A. Ju. Berzlev, M. M. Maljar, V. V. Nikolenko // Vestnik Cherkasskogo gos. tehnolog. un-ta. Serija: tehnicheskie nauki. – 2011. – Vol. 1. – P. 50–54.
33. Berzlev, A. Ju. Metody prognozirovanija dlja prinjatija jeffektivnyh reshenij v mnogourovnevyh modeljah [Text] / A. Ju. Berzlev, N. N. Maljar, V. V. Nikolenko // Nauch. vestnik Uzhgorod. un-ta. Serija matem. i informatika. – 2011. – Vol. 22. – P. 18–25.
34. Kurbatskii, V. G. On the Neural Network Approach for Forecasting of Nonstationary Time Series on The Basis of the Hilbert-Huang Transform [Text] / V. G. Kurbatskii, D. N. Sidorov, V. A. Spiryaev, N. V. Tomin // Automation and Remote Control. – 2011. – Vol. 72, Issue 7. – P. 1405–1414. doi: 10.1134/s0005117911070083
35. Zhang, W. Q. Time series forecasting method based on Huang transform and BP neural network [Text] / W. Q. Zhang, C. Xu // 2011 Seventh International Conference on Computational Intelligence and Security, 2011. – P. 497–502. doi: 10.1109/cis.2011.116
36. Lu, C.-J. ICA-Based Signal Reconstruction Scheme with Neural Network in Time Series Forecasting [Text] / C.-J. Lu, J.-Yu Wu, T.-S. Lee // 2009 First Asian Conference on Intelligent Information and Database Systems, 2009. – P. 318–323. doi: 10.1109/aciids.2009.28

37. Xiang, L. A hybrid support vector regression for time series forecasting [Text] / L. Xiang, Y. Zhu, G.-J. Tang // 2009 WRI World Congress on Software Engineering, 2009. – P. 161–165. doi: 10.1109/wcse.2009.130
38. Sallehuddin, R. Hybridization Model of Linear and Nonlinear Time Series Data for Forecasting [Text] / R. Sallehuddin, S. M. Shamsuddin, S. Z. M. Hashim // 2008 Second Asia International Conference on Modelling & Simulation (AMS), 2008. – P. 597–602. doi: 10.1109/ams.2008.142
39. Shhelkalin, V. N. "Caterpillar"-SSA and Box-Jenkins hybrid models and methods for time series forecasting [Text] / V. N. Shhelkalin // Eastern-European Journal of Enterprise Technologies. – 2014. – Vol. 5, Issue 4 (71). – P. 43–62. doi: 10.15587/1729-4061.2014.28172
40. Vartanjan, V. M. Evaluation of the frequency parameters of the model-Theil Veydzh in problems of short-term forecasting [Text] / V. M. Vartanjan, Ju. A. Romanenkov, V. Ju. Kashheeva // Eastern-European Journal of Enterprise Technologies. – 2011. – Vol. 1, Issue 5 (49). – P. 49–53. – Available at: http://journals.uran.ua/eejet/article/view/2362/2164
41. Romanenkov, Ju. A. Kompleksirovanie prognoznyh ocenok v sisteme monitoringa pokazatelej sostojanija biznes-processa [Text]: zb. nauk. pr. / Ju. A. Romanenkov, V. M. Vartanjan, D. S. Revenko // Sistemi upravlinnja, navigacii ta zv'jazku. – 2014. – Vol. 2 (30). – P. 79–86.
42. Bidjuk, P. I. Analiz kachestva ocenok prognozov s ispol'zovaniem metoda kompleksirovanija [Text] / P. I. Bidjuk, A. S. Gasanov, S. E. Vavilov // Sistemni doslidzhennja ta informacijni tehnologii. – 2013. – Vol. 4. – P. 7–16.
43. Sineglazov, V. M. Metod reshenija zadachi prognozirovanija na osnove kompleksirovanija ocenok [Text]: zb. nauk. pr. / V. M. Sineglazov, E. I. Chumachenko, V. S. Gorbatjuk // Induktivne modeljuvannja skladnih sistem. – 2012. – Vol. 4. – P. 214–223.
44. Vasil'ev, A. A. Ob'edinenie prognozov jekonomicheskih pokazatelej na osnove bives-ocenki s vesovoj funkciej H'jubera [Text] / A. A. Vasil'ev // Aktual'nye problemy gumanitarnyh i estestvennyh nauk. – 2015. – Vol 10-4. – Available at: http://cyberleninka.ru/article/n/obedinenie-prognozov-ekonomicheskih-pokazateley-na-osnove-bives-otsenki-s-vesovoy-funktsiey-hyubera (Last accessed: 23.03.2016).
45. Molev, M. D. Sintez prognoznoj informacii v praktike ocenki jekologo-jekonomicheskogo razvitija regiona [Text] / M. D. Molev, I. A. Zanina, N. I. Stuzhenko // Inzhenernyj vestnik Dona. – 2013. – Vol. 4. – Available at: http://www.ivdon.ru/magazine/archive/n4y2013/1993
46. Romanenkov, Ju. A. Sintez intellektual'nyh prognoznyh kompleksov v konturah upravlenija social'no-jekonomicheskimi sistemami [Text] / Ju. A. Romanenkov, V. M. Vartanjan; L. M. Savchuk (Ed.). – U kn.: Sistemi prijnjattja rishen' v ekonomici, tehnici ta organizacijnih sferah: vid teorii do praktiki. – Pavlograd : ART Sintez-T, 2014. – P. 372–379.
47. Demidova, L. A. Programmnyj kompleks prognozirovanija znachenij vremennyh rjadov s ispol'zovaniem gibridnyh tehnologij [Text]: mezhvuz. sb. / L. A. Demidova, T. S. Skvorcova // Matematicheskoe i programmnoe obespechenie vychislitel'nyh sistem. – Rjazanskij gosudarstvennyj radiotehnicheskij universitet, 2011. – P. 57–61.
48. Shhavelev, L. B. Sposoby analiticheskoj obrabotki dannyh dlja podderzhki prinjatija reshenij [Text] / L. B. Shhavelev // SUBD. – 1998. – Vol. 4-5. – P. 51–60.
49. Brown, R. G. Smoothing forecasting and prediction of discrete time series [Text] / R. G. Brown. – N. Y., 1963. – 480 p.
50. Komp'juterna programa «Korotkostrokove prognozuvannja makroekonomichnyh procesiv v umovah interval'noi' nevyznachenosti» [Text] / Revenko D. S., Vartanjan V. M., Romanenkov Ju. O., Art'omova A. V. – Svidoctvo pro rejestraciju avtors'kogo prava na tvir № 58201 vid 21.01.2015.
51. Komp'juterna programa «Dynamychne kompleksuvannja prognoznyh ocinok v systemi upravlinnja vyrobnycho-ekonomichnymy procesamy na pidpryjemstvi» [Text] / Romanenkov Ju. O., Vartanjan V. M., Revenko D. S. – Svidoctvo pro rejestraciju avtors'kogo prava na tvir № 58203 vid 21.01.2015.