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INTELLIGENT INFORMATION TECHNOLOGY FOR INDUCTIVE MODELING OF COMPLEX PROCESSES ON THE BASIS OF RECURRENT-AND-PARALLEL COMPUTATIONS

The paper develops a novel intelligent information technology for inductive modeling of complex processes by experimental data, the high level of productivity of which is achieved by applying a new concept of combining the efficiency of recurrent and parallel computations. The implementation of such technology in modern intelligent information-and-analytical systems provides a significant increase in the efficiency and validity of making managerial decisions in the tasks of operational management of complex processes.

An example is done of using the developed technology for evaluation and forecast of the investment activity in Ukraine.
Keywords*: inductive modelling, intelligent technology, GMDH, COMBI, MULTI, vector autoregression, recurrent-and-parallel computations.*

Introduction

Inductive modeling [1] belongs to the most advanced and effective methods of computational intelligence and soft computing. A model here is derived from data representing the subject domain and it is further applied on new data. The model is usually constructed without taking into account any information about a particular new data-test one. An error is measured to estimate how well the new data fits into the model.

Group Method of Data Handling (GMDH) [2] is the main instrument of the theory of inductive modeling. It is an original and effective tool for solving a wide range of problems of artificial intelligence, including identification and prediction, pattern recognition and clustering, intelligent data analysis and patterns search.

Problem Statement

The processing time is an important criterion of the effectiveness for inductive-based software tools. Recurrent parameters estimation and parallel computing are one of the most effective means of achieving the high performance of such software products [3]. Since recurrent calculations provide a significant reduction in the number of operations and parallel computing – depending on the number of processors, the combination of these two powerful means allows one to get a synergistic effect in the form of previously unachievable increase in the productivity of GMDH algorithms.

High-performance algorithms and software tools on the basis of both recurrent and parallel computing were already developed and proved their efficiency [4–6].

The purpose of this work is to create an Intelligent information Technology for Inductive Modeling (ITIM) of complex processes on the basis of recurrent-and-parallel computations in order to increase the effectiveness of inductive modeling methods.

Basic Technology Requirements

To achieve this goal, it is necessary to develop a software tool that would provide the following:

1. Load data from text files with different extensions: .txt, .csv, .xlsx.
2. Build models for:
   - approximation;
   - extrapolation;
   - multistep-ahead prediction.
3. The following recurrent-and-parallel GMDH algorithms can be applied for modelling:
   - combinatorial COMBI;
   - multistage MULTI.
4. Use one of the basic (and the most frequently applied) GMDH regularity criterion *AR(s)* [1].
5. Give graphic and analytical representation of built models.
6. Save modelling results.

Modeling Tools for Information Technology

COMBI GMDH Algorithm [1]

An idea of the combinatorial algorithm consists in exhaustive search of all possible variants and finding the best model containing the most informative subset of input arguments (regressors). It has such main units:

- data conversion according to a basic class of models (linear in parameters);
- forming models of different complexity;
- calculation values of external quality criteria for all models being formed;
- selection of the best models.

For a linear object with m inputs, all possible models are compared in the process of exhaustive search. Total quantity of all generated models of the type

$$\hat{y}_v = X_v \hat{\theta}_v, \quad v = 1, \ldots, 2^m - 1 \qquad (1)$$

is 2^m-1. Decimal number v corresponds to binary number d_v in (1). Unit elements of d_v indicate inclusion regressors with corresponding numbers in the model, whereas zero elements signify exclusion.

MULTI GMDH Algorithm [7]

Since the volume of exhaustive search is an exponential function of the arguments number, it is obvious that the possibilities of combinatorial algorithm are limited. Therefore, it is necessary to use the methods of reduced searching in order to solve more complex problems.

The algorithm MULTI constructed for reducing the models search is, like the multilayer GMDH algorithms, selective, but has a finite number of stages (not more than m) and allows searching for the model in the same given functional basis which is used in exhaustive algorithms. The scheme of shortened search is characterized by applying the principle of non-final decisions which significantly increases the probability of obtaining the result of the exhaustive search.

General scheme of the algorithm is as follows: first, all models with one argument are built, and several of the best ones are selected; in the second stage, different arguments are added to these models one at a time, and models with two arguments are chosen, which improve the criterion value, etc. while it worsens. Such an algorithm is multistage, in contrast to multilayer, where the number of layers can be infinite.

The main properties of the MULTI algorithm are the following:

- the algorithm is selective, with a finite number of searching stages, and the freedom of choice at each stage and the breakpoint are determined automatically;
- at each step, the complexity of particular models increases by only one argument;
- the algorithm allows one to obtain some known search schemes, such as full search and sequential search (inclusion method);
- if the true arguments are more correlated with the output y than the redundant ones, the algorithm provides the result of a full search, since the selec-

tive search procedure chooses the most probable ways of complicating the models. In more complex cases, the probability of achieving the full search result remains high enough. After obtaining the true model (or model of optimal complexity with noisy data), the algorithm is certainly stopped;

- the number of models being built is a power function of the number of arguments m instead of the exponential dependence 2^m at exhaustive search, that is, the algorithm is also operable when the number of arguments significantly exceeds 100. That is, the algorithm has the polynomial complexity.

Vector Autoregressive (VAR) Modelling [8]

VAR model generalizes the model of autoregression to multidimensional case. It is built by the stationary time series. It is the system of equations, in which every variable (component of multidimensional time series) is linear combination of all variables in the previous time points. The order of such model is determined by the order of the lags.

In the general case for l time series and k lags, the model will be the system of l equations and its matrix form will be of the form:

$$X(t) = \sum_{j=1}^{k} \theta_j X(t-j), \qquad (2)$$

where θ_j, $j = \overline{1,k}$ – matrices of model (2) parameters of the size $l \times l$.

The COMBI (or MULTI) GMDH algorithm may be used for VAR modelling by exhaustive search of all possible variants (or shortened search) and finding the best model for every time series containing the most informative subset of input arguments.

VAR Modelling with External Influences

Such a model takes into account external influences (additional variables) that are measured but not predicted. They can be predicted separately in order to build a general prediction. For l time series and k lags the model in matrix form will looks like:

$$X(t) = \sum_{i=1}^{k} \theta_j A_i X(t-i) + \sum_{j=1}^{k} B_j U(t-j), \qquad (3)$$

where A_i, B_j, $i, j = \overline{1,k}$ are matrices of model (3) parameters of the size $l \times l$.

Enhancing the Effectiveness of Inductive Modelling

Recurrent Estimation of Parameters

It is advisable to use algorithms recurrent in the number of parameters in structural identification problems for the parameters estimation of model structures being sequentially complicated.

Efficient recurrent modifications of classic Gauss and Gramm-Schmidt algorithms were offered in [5]. Short-form description of Gauss method is done below.

The modification, in a nutshell, is as follows. The matrix $H_S = X_S^T$ of the size $s \times s$ is reduced to superdiagonal form by computing only elements h_{is}^s, $i = \overline{2, s-1}$, h_{si}^s, $i = \overline{2, s}$, and $g_s = X_S^T y$ at every step s, $s = \overline{1, m}$ during the direct motion. The elements of the nested matrix H_{s-1} of size $(s-1)\times(s-1)$ (reduced to superdiagonal form on the previous step) remain changeless. So only "bordering elements" (bold fonts) are computed on step s:

$$\left[\begin{array}{ccccccc|c}
h_{11} & h_{12} & h_{13} & \dots\ h_{1s-1} & \mathbf{h_{1s}} & \dots & h_{1m} & g_1 \\
h_{21} & h_{22} & h_{23} & \dots\ h_{2s-1} & \mathbf{h_{2s}} & \dots & h_{2m} & g_2 \\
h_{31} & h_{32} & h_{33} & \dots\ h_{3s-1} & \mathbf{h_{3s}} & \dots & h_{3m} & g_3 \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
h_{s-1,1} & h_{s-1,2} & h_{s-1,3} & \dots\ h_{s-1,s-1} & \mathbf{h_{s-1,s}} & \dots & h_{s-1,m} & g_{s-1} \\
\mathbf{h_{s1}} & \mathbf{h_{s2}} & \mathbf{h_{s3}} & \dots\ \mathbf{h_{s,s-1}} & \mathbf{h_{ss}} & \dots & h_{sm} & \mathbf{g_s} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
h_{m1} & h_{m2} & h_{m3} & \dots\ h_{m,s-1} & h_{ms} & \dots & h_{mm} & g_m
\end{array}\right]$$

Paralleling of Computations

The task of paralleling computations is an actual problem for combinatorial GMDH algorithms since the possibilities of recurrent parameters estimation (as the way for enhancing the modelling effectiveness) are limited. Thus, single-processor systems allow solving the problem of exhaustive search with 20 variables in 1 second while constructing $2^{20}-1=1048575$ models [9]. Parallelization allows increasing the number of constructed models in proportion to the number of computers for fixed time that is, for example, building $2^{26}-1=$

Table 1. **Approximate time of exhaustive search**

Arguments	Models	Time	
		1 proc.	100 proc.
20	1 048 575	1 s	0,01 s
21	2 097 151	2 s	0,02 s
...	...	...	...
40	1,1E+12	~ 12 days	~ 3 hours
...	...	...	...
50	1,1E+15	~ 34 days	~ 124 hours

=67108863 models for the same time on 2^6=64 processors.

Recurrent-and-Parallel Computations

The scheme of the combinatorial algorithm parallelization with the *standard binary generator* of structural vectors and the recurrent parameters estimation using the modified Gauss algorithm for solving linear equation systems was developed in [10]. In this scheme, the change of states of binary structural vector with elements 0 or 1 is organized on the basis of the binary counter.

The sequence of all possible model structure combinations for the task with m=3 arguments will be as follows (with corresponding binary structural vector):

$y_1 = a_1x_1$ {1, 0, 0}
$y_2 = a_2x_2$ {0, 1, 0}
$y_3 = a_1x_1 + a_2x_2$ {1, 1, 0}
$y_4 = a_3x_3$ {0, 0, 1}
$y_5 = a_1x_1 + a_3x_3$ {1, 0, 1}
$y_6 = a_2x_2 + a_3x_3$ {0, 1, 1}
$y_7 = a_1x_1 + a_2x_2 + a_3x_3$ {1, 1, 1}

Table 1 shows the approximate modeling time using this scheme. Already for more than 50 arguments, an exhaustive search (in acceptable modeling time) becomes impossible even for cluster system containing one hundred processors.

The scheme with *sequential binary counter* uses such sequence of binary numbers generation when all combinations with one unit in structural vector appears first of all, then with two units, and so on to complete model comprising all arguments.

Table 2. **Approximate time of restricted search**

Arguments	Complexity	Models	Time, hours	
			1 proc.	100 proc.
50	15	3,7E+12	984	~ 10
100	9	2,1E+12	558	~ 6

The sequence of all possible combinations of model structures for 3 arguments will be the following:

$y_1 = a_1x_1$ {1, 0, 0}
$y_2 = a_2x_2$ {0, 1, 0}
$y_3 = a_3x_3$ {0, 0, 1}
$y_4 = a_1x_1 + a_2x_2$ {1, 1, 0}
$y_5 = a_1x_1 + a_3x_3$ {1, 0, 1}
$y_6 = a_2x_2 + a_3x_3$ {0, 1, 1}
$y_7 = a_1x_1 + a_2x_2 + a_3x_3$ {1, 1, 1}

This scheme allows to partially solve the problem of exhaustive search when arguments number exceeds capability of the algorithm with a standard binary generator. In this case it is advisable to execute an exhaustive search not among all possible models but only for models of the restricted complexity.

Table 2 shows approximate modeling time of COMBI algorithm with successive complication of structures for models of complexity no more than 15 out of the total 50 arguments (i.e., to build all models for which 50-elements binary structural vectors contain from 1 to 15 units) [11].

The scheme of COMBI algorithm with successive complication of structures on the basis of recurrent-and-parallel computations is not effective when arguments amount exceeds 100. In this case it is advisable to use MULTI algorithm.

Construction of Intelligent Information Technology for Inductive Modeling of Complex Processes on the Basis of Recurrent-and-Parallel Computations

The functional diagram of the software tool, which implements the developed intelligent information technology, is presented in Fig. 1.

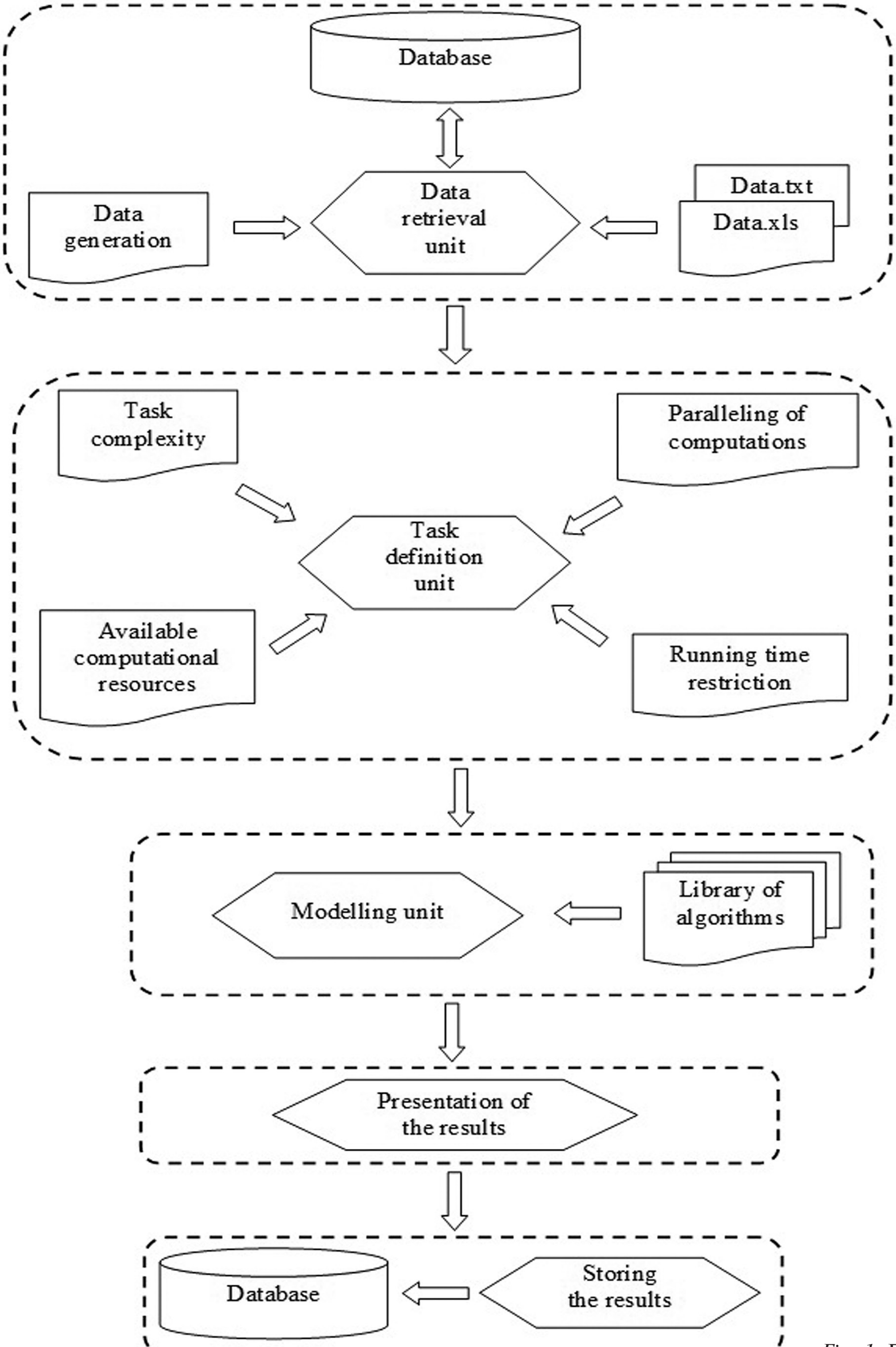

Fig. 1. Functional diagram of the software tool

A modular architecture was used to build the software tool. Within this architecture, 4 independent units were developed:
- data retrieval unit;
- task definition unit;
- modelling unit;
- results storage unit.

With the data retrieval unit, it is possible to create an initial data sample (obtained from an existing data file or generated before starting the modelling).

After the data sample is received, the task definition is performing taking into account (in automatic mode) task complexity, available computational resources, ways of computations paralleling, and running time restriction.

The modelling unit is associated with a library of sophisticated algorithms and is responsible for the proper transfer of initial data (as input parameters) to the chosen algorithm, as well as the further transfer of the modelling results to the storing unit.

The flow chart of the intelligent information technology is presented in Fig. 2.

Application of the Software Tool for Evaluation of the Investment Activity in Ukraine [12]

Data Description

The purpose of the task is to show how to use the developed information technology to build models for identification the state of a complex economic system and to perform a forecast of its indicators.

Names of indicators and a fragment of appropriate yearly data characterizing Ukraine's investment activity are given in Tables 3 and 4 (source: the Ministry of Economy).

Table 3. **Indicators of Ukraine's investment sector**

No	Indicators
1	The degree of depreciation of fixed assets, %
2	The share of direct foreign investment in the total volume of investments, %
3	The ratio of investments amount to the value of fixed assets, %
4	The ratio of investment amount in the fixed assets to GDP, %
5	The ratio of the volume of direct foreign investments to GDP, %

The data 1996-2018 were used for models building and testing their efficiency. And then forecasting the indicators for 2014-2020 with checking the accuracy at the period 2014-2018 were performed. The years were chosen to forecast because of rapid change of all indicators caused by the aggression of Russia in Ukraine. The impact was that e.g., direct foreign investment sharply dropped and depreciation of fixed assets became to decrease because of the loss of the assets in Crimea and Donbas.

In fact, the process here is highly non-stationary. Evidently, the autoregression fails here, so it was decided to use forecast only for one-year ahead with yearly adaptation of the model with accounting the new real data. This variant is named the "adaptive autoregression (aAR)".

When applying the adaptive model in the "step ahead" mode, each time (for each year) the actually measured values of the indicator are substituted in the model. This "step ahead" forecast can be further improved if the model is adjusted annually to new data. At the same time, the "adaptive forecast for a step ahead" will be made even more accurate,

Table 4. **Values of indicators of the Ukraine investment sector (1996-2018)**

No	1996	1997	...	2013	2014	2015	2016	2017	2018
1	40,00	38,00	...	77,30	83,50	60,10	58,10	55,10	59,28
2	7,89	9,39	...	20,98	4,65	13,56	17,47	14,24	12,27
3	1,49	1,43	...	2,38	1,48	1,83	2,08	2,42	2,34
4	15,40	13,28	...	19,80	15,34	15,46	17,36	18,44	17,96
5	1,21	1,25	...	3,11	4,46	4,84	2,18	3,15	3,29

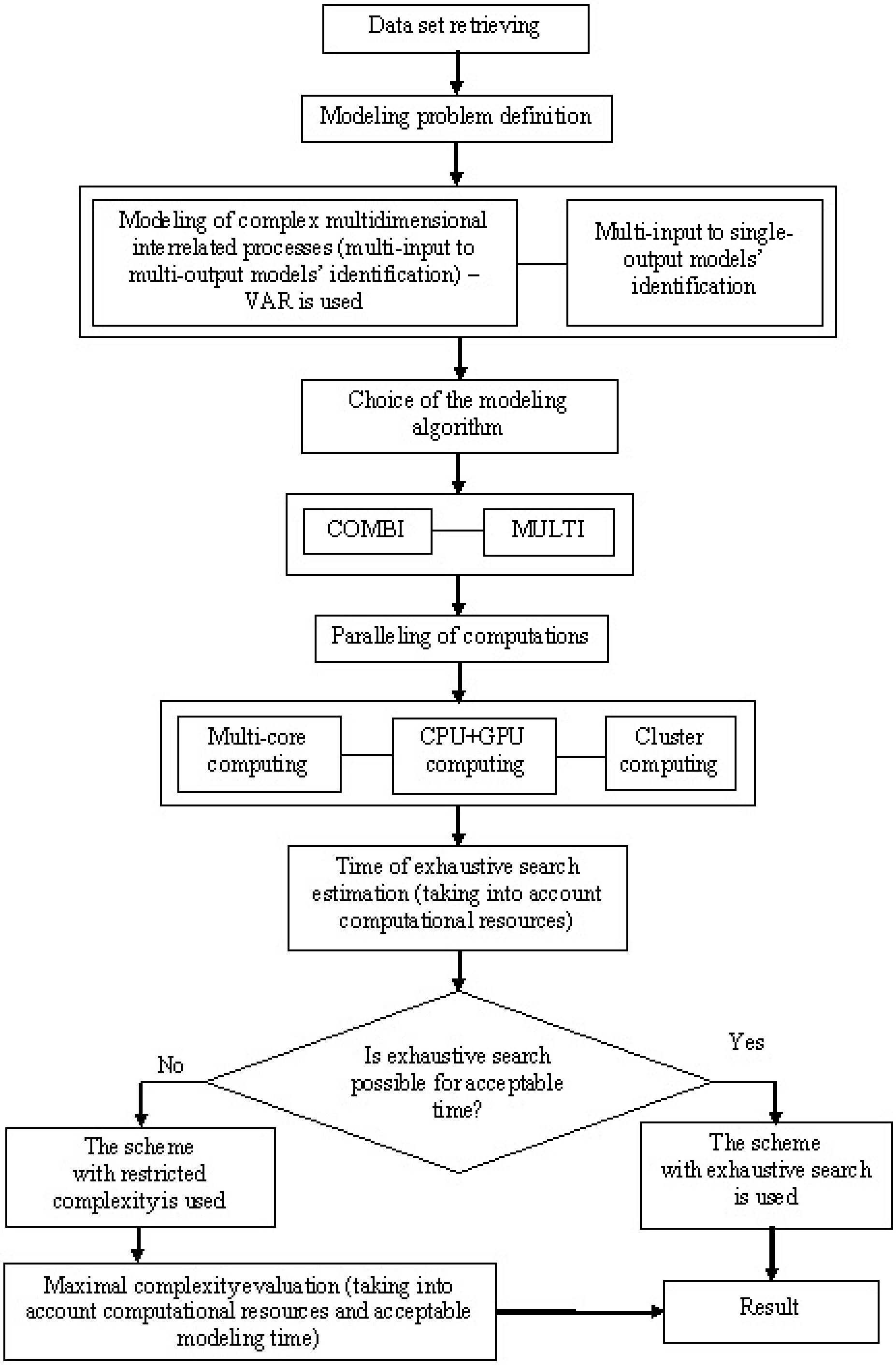

Fig. 2. Flow chart of the technology

as the model is adjusted annually. For example, for autoregression with one lag, the forecast model will look like:

$$x_{t+1} = p_{1t} x_{rt}, \tag{4}$$

where x_{rt} is the real value of the indicator for the previous period, p_{1t} is the adjusted parameter of the autoregressive model according to the sample data, including the interval t.

As the five indicators are substantially correlated, building vector autoregressive models for the system of dynamically interdependent indicators was used [13]. It is the system of five equations in which every variable (in this case indicator) is linear combination of all variables in the previous time points (two lags were used). COMBI GMDH algorithm was used for finding the best F models (10 in this case) for each of 5 indicators. Out of total 50 models, according to the value of the systemic integral criterion of vector models quality, 5 were selected and included in the resulting system model:

$$x_1(t) = 0{,}88679x_1(t-1) + 0{,}2277x_1(t-2) + 1$$ 3

$$+1{,}9092x_3(t-2) - 0{,}2736x_4(t-1) - 1{,}0244x_5(t-2),$$

$$x_2(t) = 0{,}1543x_2(t-1) + 0{,}5712x_2(t-2) +$$ 5

$$+1{,}791x_5(t-1),$$

$$x_3(t) = 0{,}8871x_3(t-1) + 0{,}2377x_3(t-2),$$

$$x_4(t) = 0{,}7651x_2(t-1) + 4{,}9441x_5(t-1),$$

$$x_5(t) = 0{,}0385x_1(t-2) - 0{,}0885x_2(t-1) -$$ 2

$$-0{,}0588x_2(t-2) + 0{,}5335x_3(t-2) +$$ 4

$$+0{,}10931x_4(t-1) - 0{,}04353x_4(t-2).$$

To enhance the accuracy of forecasting this highly non-stationary process, an adaptive approach was used. In this case adaptive procedure may be explained as follows. Starting with the first forecast, the optimal system model was built with a system forecast only for one year ahead. After that the real data for one year to the data sample was added with rebuilding the optimal system model and giving a forecast for the next year, etc.

This variant is named the "adaptive vector autoregression (aVAR)".

The prediction results using these two variants were obtained for all 5 indicators and for the integral index. They are reflected in Fig. 3 –7 for indicators x_1 to x_5 of the Ukraine's investment sector.

The MAPE values for the 2014-2018 index forecasts are 13,63% for the adaptive AR and 14,80% for the adaptive VAR. Hence, both methods perform quite satisfactorily, but the 2nd more complex method showed no evident advantage as compared

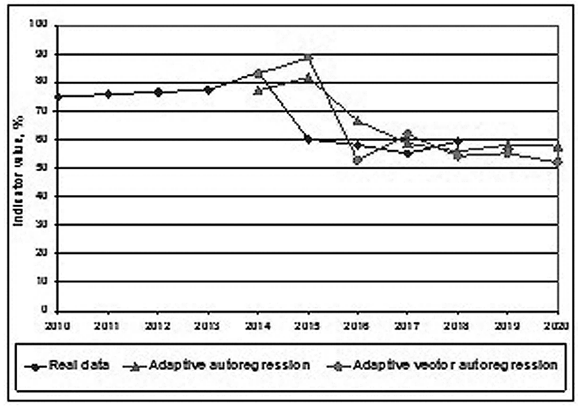

Fig. 3. Forecasts comparison for indicator x_1

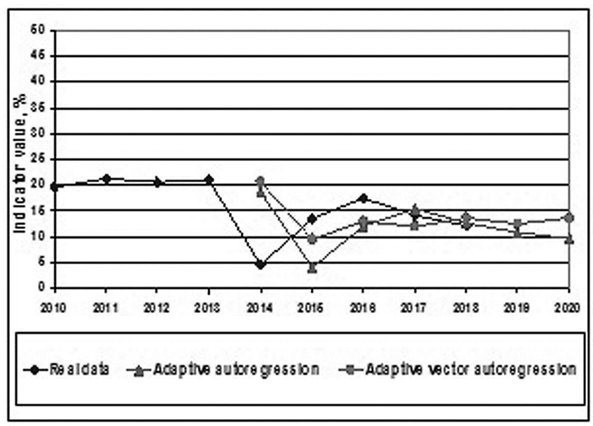

Fig. 4. Forecasts comparison for indicator x_2.

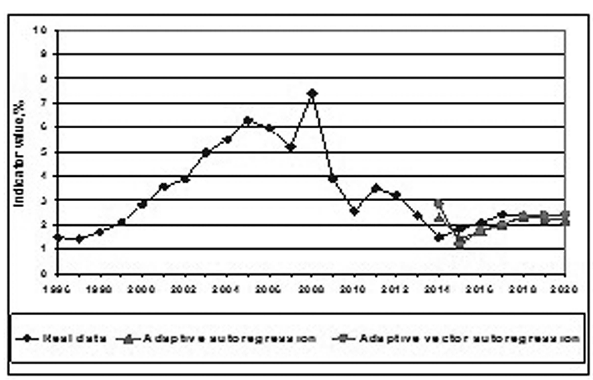

Fig. 5. Forecasts comparison for indicator x_3.

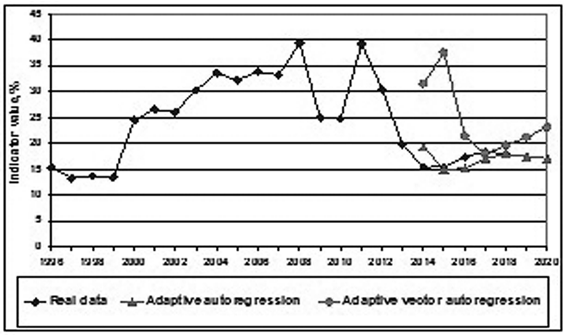

Fig. 6. Forecasts comparison for indicator x_4.

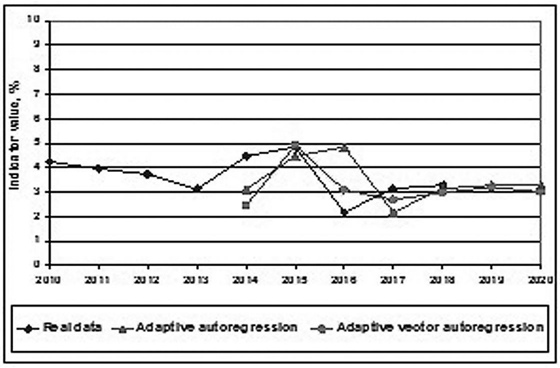

Fig. 7. Forecasts comparison for indicator x_5.

to the ordinary AR. This result may be reasonably explained by the non-stationarity of the processes.

Conclusion

Intelligent information technology is a technology that implements high-level information processing activities, such as data mining and decision-making ones.

The information technology constructed in this paper can be regarded as intelligent IT, because it is based on computer program development that applies advanced and effective methods of computational intelligence and soft computing. Also, it automatically estimates and judges the modelling complexity and available computational resources to be optimal at decision making in acceptable modeling time.

The developed novel intelligent information technology is based on the new concept of combining the efficiency of recurrent and parallel computations.

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ІНТЕЛЕКТУАЛЬНА ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ ДЛЯ ІНДУКТИВНОГО МОДЕЛЮВАННЯ СКЛАДНИХ ПРОЦЕСІВ НА ОСНОВІ РЕКУРЕНТНО-ПАРАЛЕЛЬНИХ ОБЧИСЛЕНЬ

Вступ. Індуктивне моделювання належить до найбільш сучасних та ефективних методів обчислювального інтелекту. Важливим критерієм ефективності програмних засобів для індуктивного моделювання є час виконання.

Рекурентне оцінювання параметрів і розпаралелювання обчислень є одними з найбільш ефективних засобів досягнення високої продуктивності таких програмних продуктів. Оскільки рекурентні обчислення забезпечують зменшення кількості операцій у декілька разів, а паралельні обчислення – в залежності від кількості процесорів, то поєднання цих двох потужних апаратів дозволяє отримати синергетичний ефект у вигляді раніше недосяжного збільшення продуктивності алгоритмів МГУА.

Мета цієї роботи – розробити інтелектуальну інформаційну технологію для індуктивного моделювання складних процесів на основі рекурентно-паралельних обчислень задля підвищення ефективності інформаційної підтримки оперативних управлінських рішень.

Методами дослідження є методи математичного моделювання та математичної статистики.

Результати. Розроблено інтелектуальну інформаційну технологію індуктивного моделювання складних процесів за даними спостережень, високий рівень продуктивності якої досягається застосуванням нової концепції поєднання ефективності рекурентних і паралельних обчислень. Застосування такої технології в сучасних інтелектуальних інформаційно-аналітичних системах забезпечує суттєве підвищення ефективності та обґрунтованості прийняття управлінських рішень у задачах оперативного управління складними процесами. Наведено приклад використання розробленої технології для оцінки та прогнозування інвестиційної діяльності в Україні.

Висновки. Інтелектуальною можна вважати технологію, яка реалізує дії з обробки інформації високого рівня, такі як аналіз даних і прийняття рішень. Інформаційна технологія, розроблена в цій роботі, є інтелектуальною, оскільки вона використовує сучасні та ефективні методи обчислювального інтелекту. Крім того, вона в автоматичному режимі враховує складність задачі та наявні обчислювальні ресурси для прийняття ефективних рішень за встановлений користувачем час. Розроблена інтелектуальна інформаційна технологія базується на новій концепції поєднання ефективності рекурентних і паралельних обчислень.

Ключові слова: *індуктивне моделювання, інтелектуальна технологія, МГУА, COMBI, MULTI, векторна авторегресія, рекурентно-паралельні обчислення.*