ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ, СИСТЕМНИЙ АНАЛІЗ ТА КЕРУВАННЯ

UDC 004.942

P.I. Bidyuk[1], O.M. Trofymchuk[2], I.V. Karayuz[1]

[1]National Technical University of Ukraine “KPI”, Kyiv, Ukraine
[2]Institute of Telecommunications and Global Information Sphere at NAS of Ukraine, Kyiv, Ukraine

SHORT-TERM FORECASTING OF MACROECONOMIC PROCESSES WITH REGRESSION AND PROBABILISTIC MODELS

Background. Today there is a problem of constructing high quality mathematical models for short-term forecasting of macroeconomic processes. The most often approach used for solving the problem is based on regression models though there are also developed competitive probabilistic models that exhibit high forecasting quality in conditions of uncertainties of various kind and nature.
Objective. To perform analysis of current economic situation in Ukraine using statistical data; to construct regression models suitable for short-term forecasting of macroeconomic processes selected; to provide a generalized methodology for constructing probabilistic models in the form of Bayesian networks and to construct appropriate network models for macroeconomic processes; to perform necessary computational experiments aiming to model parameter estimation and compare quality of generated forecasts.
Methods. To solve the problems stated two basic approaches to construct mathematical models are hired: regression analysis and Bayesian networks constructing using statistical data and expert estimates. A generalized multistep methodology is developed for Bayesian belief networks constructing that uses statistical data and other possible prior information.
Results. The models resulted from regression analysis of actual data provide a possibility for generating short-term forecasts of GDP though not always of high quality. Another model was constructed in the form of a Bayesian network. The model turned out to be better than the multiple regression, it provides quite good estimates for probabilities of GDP growth direction.
Conclusions. It was shown that application of regression models for describing macroeconomic processes of economy in transition not always finalizes with positive results. This can be explained by numerous out-of-market events (factors) that influence development of the economy. The short-term forecasting results obtained in this case are not always of high quality though quite acceptable. On the other hand probabilistic models such as Bayesian networks provide a possibility for obtaining well substantiated probabilistic estimates for the direction of GDP growth in Ukraine. A substantial advantage of the simple heuristic method used for constructing BN is in its transparency and small number of computing operations.
Keywords: macroeconomic processes; forecasting; regression analysis; Bayesian networks.

Introduction

Modeling and forecasting dynamics of macroeconomic processes is very important task due to the fact that its results are directly used for further development planning. Practically most of the modern decision support systems hire the modeling approach for generating forecasts and decision alternatives. The forecasting results generated sequentially for successive time periods are necessary for developing dynamic plans in conditions of uncertainty. Say gross domestic product (GDP) is an integrated macroeconomic process that together with level of inflation characterizes to quite acceptable extent current state of macroeconomics. There exists a substantial interest to modeling and forecasting GDP with hiring various model types [1–3]. In [1] the issues are analyzed of pooling models for a given set of individual N units observed over T periods of time. It is shown that the forecasting results received by the authors exhibit high quality and outperform ordinary least squares based forecasts. The generalized factor model with infinite dynamics and non-orthogonal idiosyncratic components is considered in [2]. The authors constructed the coincident index for European Union. The dynamic factor model for forecasting the euro area GDP from monthly indicators is developed in [3]. It was found here that surveys and financial data contain important information for the GDP forecasts beyond the monthly real activity measures.

As an indicator of inflation process it is used very often well-known consumer price index [4]. To determine correct current estimate of macroeconomic state and to evaluate short-term forecast estimates for economic process of interest it is necessary to construct mathematical models using historical statistical data. At the same time the use of well substantiated mathematical models and forecasts that are based on them does not exclude the possibility of the quality expert estimates usage. These estimates could be useful in model constructing so that to determine initial conditions or prior probabilities, to form restrictions on key variables of interest, to select appropriate modeling techniques, to estimate elements of model structure, hidden variables etc [5, 6].

The forecasting models for financial and economic processes could be constructed at different complexity levels. A wide class of such models may include the following types: multiple regression, autoregression with moving average (ARMA) and extended autoregression (ARX), autoregression with integrated moving average (ARIMA), nonlinear polynomial regressions as well as numerous modifications and combinations of the structures mentioned. Also highly popular today are the models constructed with the use of artificial intelligence techniques such as neural networks, fuzzy logic, neuro-fuzzy models, genetic and immune algorithms, decision trees, a wide class of Bayesian type models (Bayesian regression and Bayesian networks, multidimensional conditional probability distributions), and the models built with application of support vector machine methodology [6, 7].

This study considers application of regression models and Bayesian networks to short term forecasting of macroeconomic processes using Ukrainian data.

Problem statement

The main tasks of the study are as follows: to construct regression type mathematical models for description of inflation rate and growth rate of GDP in Ukraine; to present a generalized methodology for constructing Bayesian networks, and to construct a model in the form of dynamic Bayesian network reflecting existing causal relationships between selected key variables and aiming to generate short term probabilistic forecasts. Finally a comparison of forecasts estimates should be performed computed with different types of models.

Current macroeconomic situation in Ukraine

Using the economic production methodology GDP could be computed as a sum of gross value added (GVA) for all kinds of economic activities plus net tax [8]. The model should take into consideration the growth rates for economy branches, consumer price index (CPI), production price index (PPI), GVA structure changes etc. The actual statistical data show that actual income of population has decreased in 2014 by 8.4 %; population's savings decreased by 26.5 %; CPI increased by 24.9 %; PPI for industrial production increased by 17.1 % [9] (figures taken from alternative sources may differ to some extent).

The dynamics of goods and services structure for separate economic activities is changing as shown in Fig. 1 [9].

The GVA structure is influenced by the following factors: changes of law (for example, the rate of rent for natural gas mining for joint ventures is 70 % from the cost of final product [6] what negatively influences attractiveness of such activities in 2015); the local war (LW) in the south-east of Ukraine (Crimea, Lugansk and Donetsk areas) has highly negatively influenced the volume of industrial production for these areas and Ukraine as a whole due to existing links between enterprises. The temporary occupation of Autono-

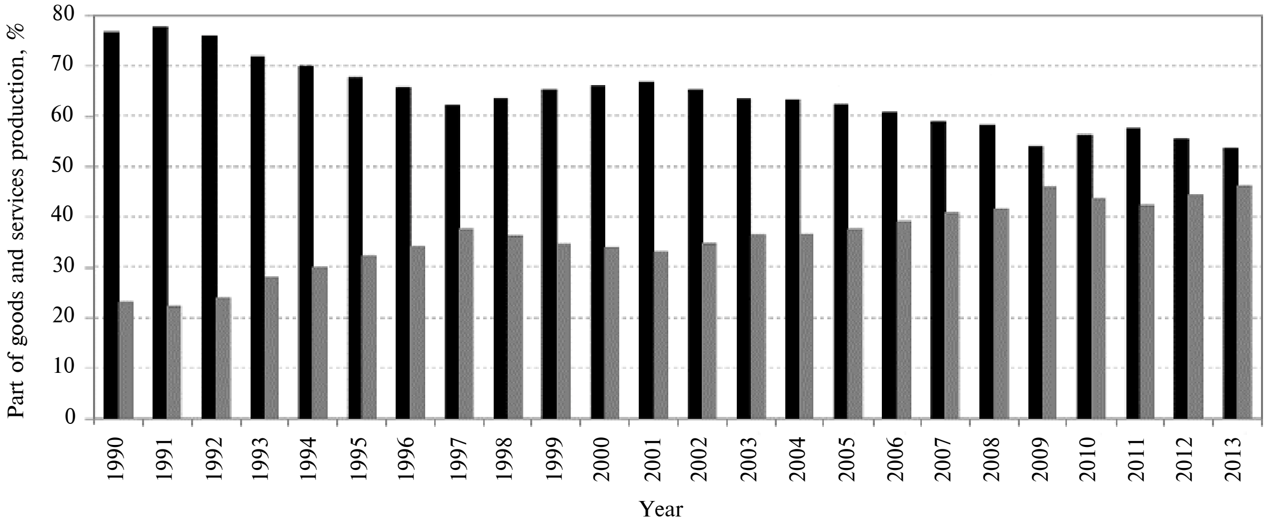


Fig. 1. Dynamics of the structure of goods and services production: ■ – sectors that produce goods; ■ – sectors that provide services [source: own study]

mous Crimean Republic and Sebastopol area resulted in substantial production volume reduction for many industries.

Figs. 2 and 3 show the rates of growth for GDP with respect to the same period of previous year. Each factor is informative for modeling and to reach quality forecasting it is necessary to take into consideration all the time series mentioned.

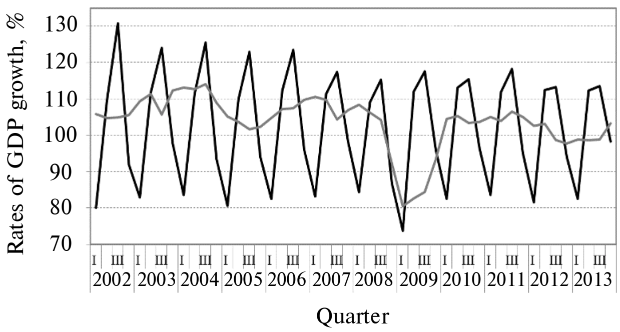


Fig. 2. Rates of GDP growth with quarterly data: — – to the previous period; — – to the corresponding period of the previous year [source: own study]

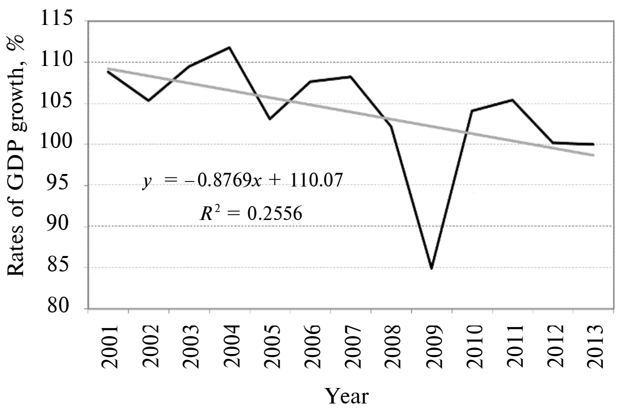


Fig. 3. Rates of GDP growth with annual data [source: own study]

Regression models

Theoretical model for inflation. An equilibrium equation for the volume of money in circulation and level of prices has a form [4]:

$$p(k+1)-\left(1+\frac{1}{\beta}\right)p(k)=-(m_a-\alpha)/\beta-\varepsilon(k)/\beta\,,$$

where $p(k)$ is a log of current level of prices; m_a is a mean volume of money in circulation; α, β are the model parameters; $\varepsilon(k)$ are random disturbances (usually $\varepsilon(k)$ is considered as a linear combination of random external disturbances, model structure and parameters estimation errors, as well as measurement noise). The solution to the difference equation given above is as follows:

$$p(k)=m_a-\alpha+\frac{1}{\beta}\sum_{i=0}^{\infty}\left(\frac{\beta}{1+\beta}\right)^{i+1}\varepsilon(k+i)+A\left(1+\frac{1}{\beta}\right)^{k}.$$

The arbitrary constant A is determined from initial conditions:

$$A=p_0-m_a+\alpha-\frac{1}{\beta}\sum_{i=0}^{\infty}\left(\frac{\beta}{1+\beta}\right)^{i+1}\varepsilon(i)\,.$$

Here the term $\frac{1}{\beta}\sum_{i=0}^{\infty}\left(\frac{\beta}{1+\beta}\right)^{i+1}\varepsilon(k+1)$ characterizes influence of future random disturbances on the level of prices. As far as $|\beta/(1+\beta)|<1$, influence of the random variable will be noticeable at initial part of the solution trajectory only. The model solution found could be useful for the long term forecasting of CPI. Short term forecasts are usually generated via regression models considered below.

Regression model for inflation. Several regression models were constructed for the consumer price index that is considered as a measure for inflation. The results of AR(1) constructing are given below:

$$\begin{aligned}\mathrm{CPI}(k)&=a_0+a_1\,\mathrm{CPI}(k-1)+\varepsilon(k)\\&=43.294+0.57\,\mathrm{CPI}(k-1)+e(k),\end{aligned}$$

where $e(k)$ are the model residuals that satisfy the following restrictions: $E[e(k)]=0$ and

$$E[e(k)\,e(k-l)]=\begin{cases}\sigma_e^2, & l=0,\\ 0, & l\ge 1.\end{cases}$$

Another model characterizes influence of GDP on the CPI:

$$\begin{aligned}\mathrm{CPI}(k)&=45.53+0.55\,\mathrm{CPI}(k-1)\\&-(1.37E-03)\,\mathrm{GDP}(k)+e(k).\end{aligned}$$

Table 1 contains the statistics that characterize various models constructed for CPI dynamics.

All the models presented in table 1 exhibit high quality though the best models are AR(1) that also include money aggregate M3 and GDP as independent variables (MAPE is less than 1 %).

Regression model for GDP. Consider the possibility for constructing model in the form of extended autoregression (ARX):

$$y(k)=a_0+\sum_{i=1}^{p}a_i y(k-i)+\sum_{j=1}^{q}b_j x(k-j)+\varepsilon(k)\,,$$

***Table* 1.** Results of modeling and short term forecasting of CPI

Model type	Model adequacy statistics			Forecasts quality statistics			
	R^2	$\sum e^2(k)$	DW	SSE	MAE	$MAPE$	$Theil$
AR(1)	0.415	141.99	1.931	1.360	1.020	1.008	0.006
AR(3)	0.317	135.14	1.992	1.360	1.020	1.011	0.006
AR(7)	0.346	127.24	1.811	1.360	1.012	1.002	0.006
AR(12)	0.435	97.80	1.941	1.337	1.020	1.013	0.006
ARMA(1,1)	0.416	141.78	1.996	1.362	1.016	1.005	0.006
AR(1) + M3	0.419	141.00	1.919	1.340	1.004	0.994	0.006
AR(1) + *gdp*	0.419	141.05	1.916	1.335	1.004	0.993	0.006

where: p is autoregression order; q is a number of regressors; $y(k)$ is the main dependent variable at discrete moment of time k; $x(k)$ is independent variable; a_i is i-th autoregression part parameter; b_j is j-th parameter of multiple regression part of the model; $\varepsilon(k)$ is random process that is formed by nonmeasurable stochastic external disturbances, measurement errors (noise), parameter computing errors, and model structure inadequacy. Such models provide a possibility for constructing forecasting functions that enable computing of forecasts for a necessary number of steps using conditional mathematical expectation operator.

According to the correlation analysis performed the model should include CPI and PPI with lags 3 and 2, respectively:

$$\mathrm{GDP}(k) = 75.8 + 0.94\ \mathrm{GDP}(k-4)$$
$$-\ 0.21\ \mathrm{GDP\_4}(k-4) - 0.15\ \mathrm{CPI}(k-3)$$
$$-\ 0.31\ \mathrm{PPI}(k-2).$$

where GDP is relative GDP growth to the previous time period, %; GDP_4 is relative GDP growth to the same period of time period for previous year, %; CPI is CPI growth with respect to the previous time period, %; PPI is PPI growth with respect to the previous time period, %. Degree of adequacy for this model is characterised by the following statistics: $R^2 = 0.95$; $DW = 1.55$; $SSE = 429.1$. The parameters estimates correspond to the realities of GDP changes in time: when CPI and PPI are growing GDP growth rate is decreasing. The forecasts quality is characterized by the following statistics: MSE = 389.7; MAPE = 16.8%; U = 0.13 (Theil coefficient, $0 < Theil < 1$).

The statistical data in Table 2 were taken from the State Statistical Service of Ukraine (SSSU) as of March 20, 2015 [9]. As far as the mean absolute percentage error is about 17 % for the regression ARX model considered above it is necessary to try another approach to modeling GDP that would be ideologically different. Besides, this model cannot describe quantitatively and qualitatively an influence of the war in the south-east of Ukraine. Also one of important influence factors to development of GDP is support of the dollar/hryvna exchange rate practically at fixed level) from May 2012 till February 2014. Define this event as “Pseudo Stability”, PS).

***Table* 2.** Comparison of actual GDP (SSSU) and its forecast for 2014

Time period	GDP, %		Forecast error, %
	SSSU	Model	
QI 2014	76.4	83.2	8.91
QII 2014	108.4	111.1	2.52
QIII 2014	112.0	110.8	–1.03
QIV 2014	88.8	91.8	3.34
2014 year	93.2	100.2	7.55

General methodology for probabilistic network constructing

Bayesian network (BN) is a model in the form of directed acyclic graph (DAG) vertices of which are model variables, and its arcs show existing causal effects between the variables. Each variable of BN is characterized with complete finite set of mutually excluding states. Actual relations between the variables are established using expert estimates or by applying special statistical and probabilistic tests to statistical data (when available) characterizing the variables dynamics. The methodology for constructing BN is mostly the same as for other type models, say regression or neural networks models. As the model parameters for BN serve unconditional and conditional probabilities for specific values of variables, that are stored in respective probability tables. For parent variables these are unconditional probabilities and for daughter variables – conditional probability tables. Unconditional and conditional probabilities are determined by experts (in simpler cases), and by special computational algorithms when appropriate sets of statistical (or experimental) data are available. Thus CPT is assigned to each node of DAG that is used for computing probabilistic inference over the BN structure [7, 10].

The methodology of constructing a model in the form of BN can be represented with the following steps: 1) a thorough analysis of the process (object) under study aiming to detecting of its special functioning features and identification of parent and daughter variables; 2) search and analysis of existing process models and determining the possibility of their usage in respective decision support systems (DSS); 3) determining degree of relations between the process variables using special statistical tests and expert estimates; 4) reduction of the process state dimensionality whenever this is possible; 5) scaling and discretization of the data available when necessary; 6) determining semantic restrictions on the future model structure; 7) estimation of candidate models (directed acyclic graphs) structures using appropriate optimization procedures and score functions; 8) candidate models analysis and selection of the best one using model quality criteria (including values of score functions); 9) application of the model(s) constructed to solve the problem stated; 10) computing inference with the model(s) constructed regarding the variables selected, quality analysis of the final result. In our case the final result of the model application is computing of probability for accepting definite value by a variable with the conditions established by other model variables. According to alternative problem statement BN can be constructed for estimation of short term forecasts, operational or other type of financial risks etc.

To construct the forecasting model in the form of a Bayesian network introduce the following variables: Local War (LW) is a variable that takes value of "1" when there is a war on Ukrainian territory (say in southeast); Pseudo Stability (PS) takes a value of "1" if exchange rate for hryvna (Ukrainian currency) is fixed; Investment Climate (IC) takes value of "1" if the rate of investments growth in Ukraine is positive; CPI(–3) and PPI(–3) are equal "1" if their growth rate exceeds 15%; GDP is equal "1" if its growth rate is positive. Alternative values for the variables are usually zeroes.

The first BN was built by hiring expert estimates and with the use of model quality criterion called minimum description length (MDL), it is shown in Fig. 4.

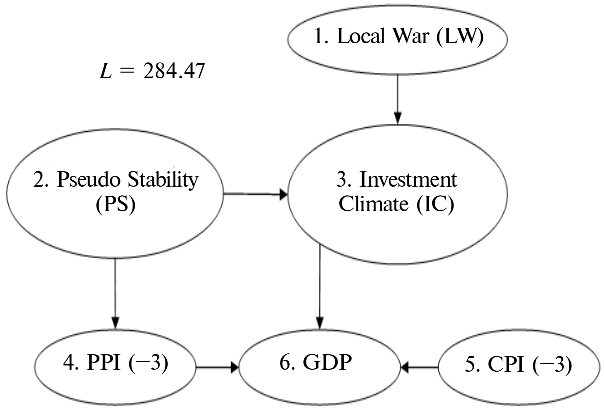


Fig. 4. Network for GDP of Ukraine built by expert [source: our own study]

The models given in Fig. 5 were constructed by heuristic algorithm [10] with the use of computed values for mutual information in the following way: a) without restrictions; b) with restriction that variable "6. GDP" can be only subordinated (child), and the variables "1. LW", "2. PS" can only be of parent type; c) with restrictions of type b) and without free vertices.

The network given in Fig. 5, *a* cannot be used in practice because GDP growth rate cannot influence growth rate of PPI that took place three quarters (9 months) before.

Expression for computing joint probability function for BN in Fig. 6:

$$P(\mathrm{PS}, \mathrm{LW}, \mathrm{PPI}(-3), \mathrm{IC}, \mathrm{GDP})$$
$$= \sum\{P(\mathrm{GDP} \mid \mathrm{PPI}(-3), \mathrm{IC})$$
$$\times \sum\{P(\mathrm{PPI}(-3) \mid \mathrm{PS}) \cdot P(\mathrm{PS})\}$$
$$\times \sum\{P(\mathrm{IC} \mid \mathrm{LW}) \cdot P(\mathrm{LW})\}\}.$$

Expression for computing the joint probability function for the BN in Fig. 7:

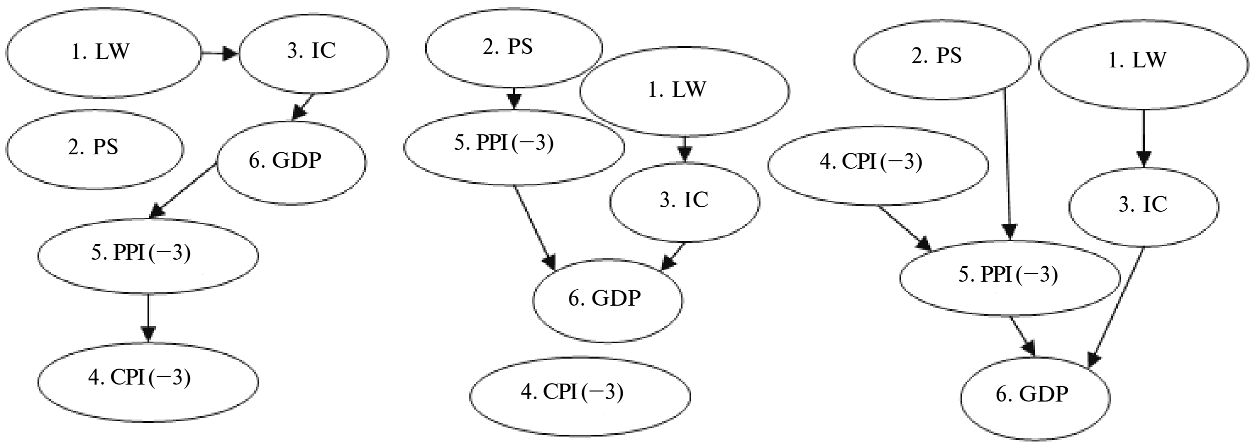
$$P(\mathrm{PS}, \mathrm{CPI}(-3), \mathrm{LW}, \mathrm{PPI}(-3), \mathrm{IC}, \mathrm{GDP})$$
$$= \sum\{P(\mathrm{GDP} \mid \mathrm{PPI}(-3), \mathrm{IC})$$
$$\times \sum\{P(\mathrm{PPI}(-3) \mid \mathrm{PS}, \mathrm{CPI}(-3)) \cdot P(\mathrm{PS}) \cdot P(\mathrm{CPI}(-3))\}$$
$$\times \sum\{P(\mathrm{IC} \mid \mathrm{LW}) \cdot P(\mathrm{LW})\}\}.$$

Expression for computing joint probability function for the BN in Fig. 8:

$$
\begin{aligned}
&P(\mathrm{PS},\mathrm{CPI}(-3),\mathrm{LW},\mathrm{PPI}(-3),\mathrm{IC},\mathrm{GDP})\\
&=\sum\{P(\mathrm{GDP}|\mathrm{PPI}(-3),\mathrm{IC},\mathrm{CPI}(-3))\\
&\times\sum\{P(\mathrm{IC}|\mathrm{LW},\mathrm{PS})\cdot P(\mathrm{LW})\cdot P(\mathrm{PS})\}\\
&\times\{P(\mathrm{PPI}(-3)|\mathrm{PS})\cdot P(\mathrm{PS})\}\cdot P(\mathrm{CPI}(-3))\}.
\end{aligned}
$$

Using the joint probability function and Bayes theorem we got the CPTs given in Table 3.

Thus, the least possible probabilistic estimate for the negative direction of Ukrainian GDP growth in 2014 is 0.74 by condition that takes place local war. Respectively the most possible probabilistic estimate for the positive direction of Ukrainian GDP growth in 2014 is 0.26.



a) $L = 144.4$ *b*) $L = 185.07$ *c*) $L = 219.55$

Fig. 5. Networks for GDP of Ukraine built by heuristic algorithm: *a* – without restrictions; *b* – with restriction that variable “6. GDP” can be only subordinated (child), and the variables “1. LW”, “2. PS” can only be of parent type; *c* – with restrictions of type b) and without free vertices [source: our own study]

P **(PS)**	
PS = 0	**PS = 1**
0.85	0.15

P **(LW)**	
LW = 0	**LW = 1**
0.25	0.75

PS	***P*** **(PPI (−3)/PS**	
	PPI (−3) = 0	**PPI (−3) = 1**
0	0.49	0.51
1	1	0

LW	***P*** **(IC/LW)**	
	IC = 0	**IC = 1**
0	0.44	0.56
1	1	0

PPI (−3)	**IC**	***P*** **(GDP/PPI (−3), IC)**	
		GDP = 0	**GDP = 1**
0	**0**	0.67	0.33
0	**1**	0.07	0.93
1	**0**	0.91	0.09
1	**1**	0.70	0.30

Fig. 6. Conditional probability tables for the BN in Fig. 5, *b* [source: our own study]

P (PS)	
PS = 0	**PS = 1**
0.85	0.15

P (CPI (−3))	
CPI (−3) = 0	**CPI (−3) = 1**
0.875	0.125

P (LW)	
LW = 0	**LW = 1**
0.25	0.75

PS	**CPI (−3)**	*P* (PPI (−3)/PS, CPI(−3))	
		PPI (−3) = 0	**PPI (−3) = 1**
0	**0**	0.54	0.46
0	**1**	0.17	0.83
1	**0**	1	0
1	**1**	0.50	0.50

LW = 0	*P* (IC/LW)	
	IC = 0	**IC = 1**
0	0.44	0.56
1	1	0

PPI (−3)	**IC**	*P* (GDP/PPI (−3), IC)	
		GDP = 0	**GDP = 1**
0	**0**	0.67	0.33
0	**1**	0.07	0.93
1	**0**	0.91	0.09
1	**1**	0.70	0.30

Fig. 7. Conditional probability tables for the BN in Fig. 5, *c* [source: our own study]

P (PS)	
PS = 0	**PS = 1**
0.85	0.15

P (LW)	
LW = 0	**LW = 1**
0.25	0.75

PS	*P* (PPI (−3)/PS)	
	PPI (−3) = 0	**PPI (−3) = 1**
0	0.49	0.51
1	1	0

LW	**PS**	*P* (IC/LW, PS)	
		IC = 0	**IC = 1**
0	**0**	0.39	0.61
0	**1**	0.71	0.29
1	**0**	1	0
1	**1**	1	0

P (CPI (−3))	
CPI (−3) = 0	**CPI (−3) = 1**
0.875	0.125

PPI (−3)	**IC**	**CPI (−3)**	*P* (GDP/PPI (−3), IC), CPI (−3))	
			GDP = 0	**GDP = 1**
0	**0**	**0**	0.67	0.33
0	**0**	**1**	0.50	0.50
0	**1**	**0**	0.07	0.93
0	**1**	**1**	0	1
1	**0**	**0**	0.83	0.17
1	**0**	**1**	1	0
1	**1**	**0**	0.70	0.30
1	**1**	**1**	0.50	0.50

Fig. 8. BN with nodes as conditional probability tables for BN on Fig. 4 [source: our own study]

Table 3. Conditional probabilities for constructing BNs

LW	BN of Fig. 6, *b*		BN of Fig. 6, *c*		BN of Fig. 5	
	***P* (GDP/LW)**		***P* (GDP/LW)**		***P* (GDP/LW)**	
	GDP = 0	**GDP = 1**	**GDP = 0**	**GDP = 1**	**GDP = 0**	**GDP = 1**
0	0.534	0.466	0.535	0.465	0.510	0.490
1	0.833	0.167	0.833	0.167	0.737	0.263

Conclusions

The modern processes that appear in economy of transition are usually nonstationary, and very often nonlinear. They are developing in conditions of uncertainties of various types and nature. It was shown that application of regression models for describing the processes of economy in transition not always finalizes with positive results though in many cases the results exhibit acceptable quality. This can be explained by numerous out-of-market events (factors) that influence development of such "non-standard" economy. It is clear that substantial efforts are still required for explaining the realities happening today.

On the other side flexible probabilistic models such as Bayesian networks provide a possibility for obtaining well substantiated and quite good probabilistic estimates for the direction of GDP growth in Ukraine. A substantial advantage of the simple heuristic method used for constructing BN is in its complete transparency and a small number of operations. Disadvantage of the heuristic approach is that after every increment in a number of variables it is necessary to reconstruct the model graph (model structure). The minimum description length based algorithm operates according to the principle of entropy minimization (the higher is dependence between the variables the better is the case from the modeling point of view). Although such approach may result in some paradoxes regarding quality of the final model.

In the future it will be necessary to get down to the new modeling problem for the quantitative estimation of Ukrainian GDP growth rate. The regression model constructed in the paper should be modified with the results of structural analysis for GVA, and the interest rate of National Bank should also be taken into consideration. Another task to be solved is in combining forecast estimates generated by alternative techniques.

List of literature

1. *Hoogstrate A.J.*, *Palm F.C.*, *Pfann G.A.* Pooling in dynamic panel-data models: an application to forecasting GDP growth rates // J. Business & Economic Statistics. – 2000. – **18**. – № 3. – P. 274–283.
2. *The generalized* dynamic-factor model: identification and estimation / M. Forni, M. Hallin, M. Lippi, L. Reichlin // Review of Economics and Statistics. – 2000. – **82**. – № 4. – P. 540–554.
3. *Banbura M.*, *Runstler G.* A look into the factor model black box: publication lags and the role of hard and soft data in forecasting GDP // Int. J. Forecasting. – 2011. – **27**, № 2. – P. 333–346.
4. *Branson W.* Macroeconomic Theory and Policy. – New York: Harper & Row Publishers, 1989. – 656 p.
5. *DeLurgio S.A.* Forecasting Principles and Applications. – Boston: McGraw-Hill, 1998. – 802 p.
6. *Rutkowski L.* Metody i Techniki Sztucznej Inteligencji. – Warszawa: Wydawnictwo Naukowe PWN, 2005. – 520 p.
7. *Pole A.*, *West M.*, *Harrison J.* Applied Bayesian Forecasting and Time Series Analysis. – New York: Chapman & Hall/CRC, 1994. – 409 p.
8. *Макроекономіка* / За ред. В.Д. Базилевича. – К.: Знання, 2007. – 703 с.
9. Державна статистична служба України [Електронний ресурс]. – Режим доступу: http://www.ukrstat.gov.ua/
10. *Байєсівські* мережі в системах підтримки прийняття рішень / М.З. Згуровський, П.І. Бідюк, О.М. Терентьєв, Т.І. Просянкіна-Жарова. – К.: Едельвейс, 2015. – 300 с.

References

1. A.J. Hoogstrate *et al.*, "Pooling in dynamic panel-data models: an application to forecasting GDP growth rates", *J. Business & Economic Statistics*, vol. 18, no. 3, pp. 274–283, 2000.
2. M. Forni *et al.*, "The Generalized dynamic-factor model: identification and estimation", *Review of Economics and Statistics*, vol. 82, no. 4, pp. 540–554, 2000.
3. M. Banbura and G. Runstler, "A look into the factor model black box: publication lags and the role of hard and soft data in forecasting GDP", *Int. J. Forecasting*, vol. 27, no. 2, pp. 333–346, 2011.

4. W. Branson, *Macroeconomic Theory and Policy*. New York: Harper & Row Publishers, 1989, 656 p.
5. S.A DeLurgio, *Forecasting Principles and Applications*. Boston: McGraw-Hill, 1998, 802 p.
6. L. Rutkowski, *Metody i Techniki Sztucznej Inteligencji*. Warszawa: Wydawnictwo Naukowe PWN, 2005, 520 p.
7. A. Pole *et al.*, *Applied Bayesian Forecasting and Time Series Analysis*. New York: Chapman & Hall/CRC, 1994, 409 p.
8. *Macroeconomics*, V.D. Basilevych, Ed. Kyiv, Ukraine: Znannya, 2007, 703 p. (in Ukrainian).
9. The State Statistical Service of Ukraine [Online]. Avaliable: http://www.ukrstat.gov.ua/
10. M.Z. Zgurowsky *et al.*, *Bayesian Networks and Decision Trees*. Kyiv, Ukraine: Edelveis, 2015, 360 p.

П.І. Бідюк, О.М. Трофимчук, І.В. Караюз

КОРОТКОСТРОКОВЕ ПРОГНОЗУВАННЯ МАКРОЕКОНОМІЧНИХ ПРОЦЕСІВ ЗА ДОПОМОГОЮ РЕГРЕСІЙНИХ І ЙМОВІРНІСНИХ МОДЕЛЕЙ

Проблематика. На сьогодні існує проблема побудови високоякісних математичних моделей для короткострокового прогнозування макроекономічних процесів. Найчастіше для розв’язання цієї задачі застосовують регресійні моделі, але разом із тим створюються альтернативні ймовірнісні моделі, які демонструють високу якість прогнозування в умовах наявності невизначеностей різної природи і типів.

Мета дослідження. Виконати аналіз поточної економічної ситуації в Україні з використанням статистичних даних; побудувати регресійні моделі для короткострокового прогнозування вибраних макроекономічних процесів; розробити узагальнену методику побудови ймовірнісних моделей у формі байєсівських мереж і побудувати мережеві моделі для прогнозування макроекономічних процесів; виконати обчислювальні експерименти з метою оцінювання структури і параметрів моделей та порівняти отримані результати прогнозування.

Методика реалізації. Для розв’язання поставлених задач використано регресійний аналіз і методику побудови ймовірнісних моделей у формі байєсівських мереж із застосуванням статистичних даних і експертних оцінок. Запропоновано узагальнену багатокрокову методику побудови байєсівських мереж на основі статистичних даних і апріорної інформації.

Результати дослідження. Побудовані регресійні моделі для індексу споживчих цін та валового внутрішнього продукту на основі фактичних даних в окремих випадках не забезпечують бажаної якості оцінок прогнозів. Для прогнозування напряму розвитку ВВП також побудовано моделі у формі байєсівських мереж. Такі моделі виявились кращими, ніж множинна регресія, вони забезпечують прийнятні оцінки ймовірностей для визначення напряму розвитку ВВП.

Висновки. Показано, що застосування регресійних моделей для опису макроекономічних процесів перехідної економіки не завжди забезпечує результати прогнозування необхідної якості. Це можна пояснити численними неринковими факторами, які впливають на розвиток економіки. Створені ймовірнісні моделі у формі байєсівських мереж дають можливість обчислити обґрунтовані високоякісні оцінки прогнозів напряму руху ВВП в Україні.

Ключові слова: макроекономічні процеси; прогнозування; регресійний аналіз; байєсівські мережі.

П.И. Бидюк, А.Н. Трофимчук, И.В. Караюз

КРАТКОСРОЧНОЕ ПРОГНОЗИРОВАНИЕ МАКРОЭКОНОМИЧЕСКИХ ПРОЦЕССОВ ПРИ ПОМОЩИ РЕГРЕССИОННЫХ И ВЕРОЯТНОСТНЫХ МОДЕЛЕЙ

Проблематика. Сегодня существует проблема построения высококачественных математических моделей для краткосрочного прогнозирования макроэкономических процессов. Чаще всего для решения этой задачи используют регрессионные модели, но вместе с тем разрабатываются альтернативные вероятностные модели, которые демонстрируют высокое качество прогнозирования в условиях наличия неопределенностей различной природы и типов.

Цель исследования. Выполнить анализ текущей экономической ситуации в Украине с использованием статистических данных; построить регрессионные модели для краткосрочного прогнозирования макроэкономических процессов; представить обобщенную методику построения вероятностных моделей в форме байесовских сетей и построить сетевые модели для прогнозирования макроэкономических процессов; выполнить вычислительные эксперименты с целью оценивания структуры и параметров моделей и сравнить полученные результаты прогнозирования.

Методика реализации. Для решения поставленных задач применены регрессионный анализ и методика построения моделей в форме байесовских сетей с использованием статистических данных и экспертных оценок. Предложена обобщенная многошаговая методика построения байесовских сетей на основе статистических данных и априорной информации.

Результаты исследования. Построенные регрессионные модели для индекса потребительских цен и валового внутреннего продукта на основе фактических данных в отдельных случаях не обеспечивают желаемое качество оценок прогнозов. Для прогнозирования направления развития ВВП также построены модели в форме байесовских сетей. Эти модели оказались лучшими, чем множественная регрессия, они обеспечивают приемлемые оценки вероятностей для определения направления развития ВВП.

Выводы. Показано, что применение регрессионных моделей для описания макроэкономических процессов переходной экономики не всегда обеспечивает результаты прогнозирования приемлемого качества. Это можно объяснить многочисленными нерыночными факторами, которые влияют на развитие экономики. Созданные вероятностные модели в форме байесовских сетей дают возможность получить обоснованные высококачественные оценки прогнозов направления движения ВВП в Украине.

Ключевые слова: макроэкономические процессы; прогнозирование; регрессионный анализ; байесовские сети.

Рекомендована Радою
Навчально-наукового комплексу
“Інститут прикладного системного
аналізу” НТУУ “КПІ”

Надійшла до редакції
12 жовтня 2015 року