Inductive Computer Advisor for Current Forecasting of Ukraine Macroeconomy

Ivakhnenko A.G., Ivakhnenko G.A., Andrienko N.M.
Glushkov Institute of Cybernetics of NAS of Ukraina
Ukraina 252034 Kyiv Volodymirska 51/53, kv.14
email: gai@runbox.com, http://www.inf.kiev.ua/GMDH-home

Abstract. Basic set of variables, which characterize macroeconomy of Ukraine is chosen according to recommendations of economists. Using inductive Combinatorial GMDH algorithm, optimal most accurate non-physical models for four output variables forecast are received. Not only optimal models are found, but also necessary input factors given for normative forecasting are pointed out. High accuracy of short-term forecasting shows possibility of long-term stepwise forecasting of system under investigation.

Introduction

Forecasting of processes in macroeconomy has normative character, i.e. corresponds to rule "*if-then*", and because of that it may be used for computer advisor construction, for use in decision making for current regulation of macroeconomy [1,2,3]. Normative forecastings are received by GMDH polynomial networks [4,5,6] in result of observations of system for several years proceeding. It is enough to have in disposition averaged for quarters values of variables. Data sample should present time interval for which there were no essential changes in laws acting in the system. For example, for investigation of Ukraine macroeconomy the data for 1992-1995 are used.

Variants of normative forecastings received are defined by a priori information given to computer. Solution of following questions is especially important:

1) which full set of variables is available for computer for synthesis and sorting of forecasting models by external criterion. Experience of economists investigating the system should be used. But sorting of variables sets variants can be helpful too. That set is better for which forecasting error variance criterion minimum RR_{min} is smaller [7];
2) which variables are included into input factors subset, and which into subset of output optimized variables. Input factors of normative forecast are chosen usually among manipulated variables of macroeconomics control system. Input factors are used as arguments of forecasting non-physical models [6]. Manipulated control variables are used as arguments of a physical models of object. Models and purposes of forecasting and control are different. Therefore the sets of input factors and manipulated variables can be different too;
3) which constrains are given on maximum values of input factors and output variables.

The purpose of this paper is to present, on example of the Ukraine, the general method of normative forecasting of processes in macroeconomy for observation and control aims. There is shown one variant of full sets of input factors and output variables sets only. No doubt it should be interesting too, some other variants which use other set of factors and output variables.

1. Initial material characteristic and choice of variables set.

Let us denote input factors of normative forecast by x_i ($1<i<M$), output variables by y_j ($1<j<L$) and external disturbances by z_s ($1<s<K$).

In [1,2] we find that macroeconomics systems are characterized by values of following basic variables:
y_1 - Real internal whole product (IWP in billions of karbovanets of 1991};
y_2 - Consumer prices inflation (CPI);
y_3 - Budget deficit (in % of IWP);
y_4 -Unemployment (thousands of people);
x_1 - Monetary base increase (in % of IWP);
x_2 - Number of privatized plants;
x_3 - Consumer price index;
x_4 - Monetary circulation rate;
z_1 - Gryvna course for non-trade operations (to USA dollar).

Averaged for quarters values of variables for 13 quarters of 1992-1995 are presented in table 1:

Year and quarter	Y_1	Y_2	Y_3	Y_4	X_1	X_2	X_3	X_4	Z_1
1992									
Q_1	86.4	3.0	24.1	13.2	13.2	5	75.4	65.1	0.0016
Q_2	107.6	8.1	35.6	11.1	11.1	10	18.1	100	0.002
Q_3	97.5	9.3	60.7	18.5	18.5	20	19.2	123.3	0.0029
Q_4	96.4	17.7	70.5	45.2	45.2	30	28.5	81	0.0079
1993									
Q_1	84.7	1.1	79.5	32.4	32.4	430	39.7	54.3	0.0189
Q_2	78.9	13.2	73.3	35.9	35.9	830	39.4	38.2	0.0313
Q_3	72.3	6.2	78.7	27.7	27.7	1685	44.5	38.9	0.0835
Q_4	56.4	6.1	83.9	12.2	12.2	3585	66.4	20.6	0.2667
1994									
Q_1	38.8	6.4	98.6	11.8	11.8	5442	12.4	26.8	0.3559
Q_2	42.4	8.9	92.8	12.9	12.9	8402	5.0	33.3	0.4347
Q_3	46.9	19.8	88.9	22.6	22.6	10214	4.0	45.7	0.4665
Q_4	44.5	8.1	82.2	7.3	7.3	11552	39.5	25.4	1.1024
1995									
Q_1	36.2	8.0	86.6	3.7	3.7	12802	16.8	22.8	1.4278

Table 1. Initial data sample

2.0. Difference forecasting optimal non-physical models for explicit patterns

By pattern is called the graph which shows delayed arguments proposed to computer selection choice (fig.1). The use of implicit patterns leads to accuracy increase, but connected with a system of linear equations solution for each point of normative forecasting. For explicit patterns forecasting accuracy is smaller, but forecasting models are

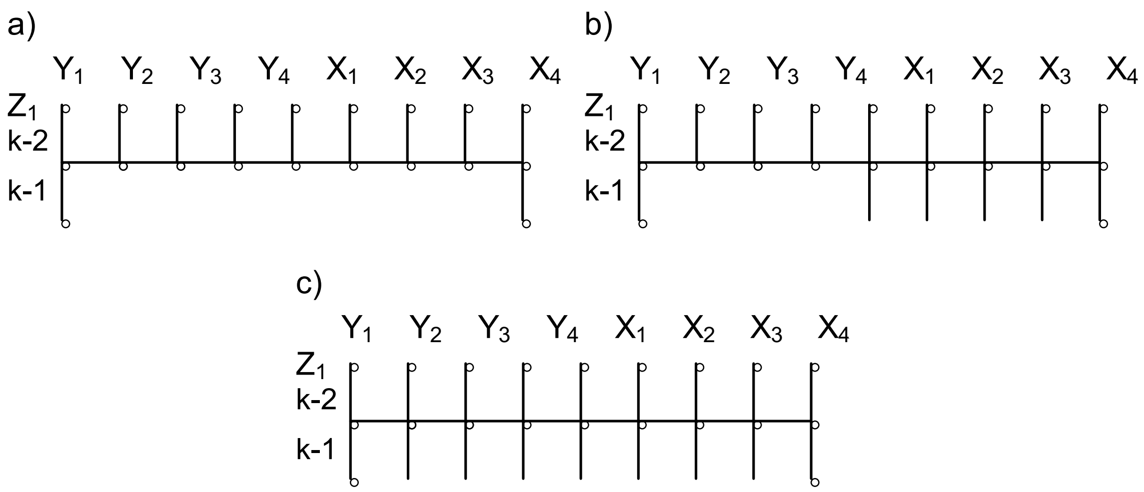

Fig. 1. Patterns:

a) explicit, for variable $Y_{1(k)}$ stepwise forecasting;
b) explicit, for normative $Y_{1(k)}$ forecasting;
c) implicit, for normative of $Y_{1(k)}$ $Y_{2(k)}$ $Y_{3(k)}$ and $Y_{4(k)}$ forecasting.

not linked and calculations are simpler. For first variable $Y_{1(k)}$ forecasting, using explicit pattern (b), fig.1. we can complete full regression equation in following form:

$$
\begin{aligned}
Y_{1(k)} = a_{00} &+ a_{11}\cdot Y_{1(k-1)} + a_{12}\cdot Y_{1(k-2)} + a_{21}\cdot Y_{2(k-1)} + a_{22}\cdot Y_{2(k-2)} + \\
&+ a_{31}\cdot Y_{3(k)} + a_{32}\cdot Y_{3(k-2)} + a_{41}\cdot Y_{4}(_{k-1)} + a_{42}\cdot Y_{4(k-2)} + \\
&+ a_{50}\cdot X_{1(k)} + a_{51}\cdot X_{1(k-1)} + a_{52}\cdot X_{1}(_{k-2)} + a_{60}\cdot X_{2(k)} + a_{61}\cdot X_{2(k-1)} + \\
&+ a_{62}\cdot X_{2(k-2)} + a_{70}\cdot X_{3(k)} + a_{71}\cdot X_{3}(_{k-1)} + a_{72}\cdot X_{3(k-2)} + \\
&+ a_{80}\cdot X_{4(k)} + a_{81}\cdot X_{4(k-1)} + a_{82}\cdot X_{4}(_{k-2)} + a_{90}\cdot Z_{1(k)} + a_{91}\cdot Z_{1(k-1)} + \\
&+ a_{92}\cdot Z_{1(k-2)}
\end{aligned}
\qquad (2)
$$

Full equations of similar form were completed for output variables $Y_{2(k)}$, $Y_{3(k)}$ and $Y_{4(k)}$ too. Then, using Combinatorial GMDH algorithm [6], coefficients for these equations were found. Forecasts were calculated and their accuracy were evaluated.

3. An example of normative forecasting

For example, let us consider normative forecast of Ukraine macroeconomy on second quarter of 1995 using data presented in table 1. Variables having k index will be related to this quarter. Following values of coefficients were received for the model forecasting $Y_{1(k)}$:

a_{00}=-0.823	a_{11}= 0	a_{12}= 0	a_{20}= 0	a_{21}=-1.527	a_{22}=-1.539
a_{30}= 0	a_{31}= 0.549	a_{32}= 0	a_{40}= 0	a_{41}=-0.120	a_{42}= 0.798
a_{50}= 0	a_{51}= 0	a_{52}= 0.295	a_{60}= 1.226	a_{61}=-0.800	a_{62}= 0
a_{70}= 1.311	a_{71}= 0;	a_{72}=-0.581	a_{80}= 0.860	a_{81}= 0	a_{82}= 2.121
a_{90}= 0.734	a_{91}=-0.467	a_{92}= 2.364			

Models accuracy can be characterized by minimal value of RR criterion. For optimal non-physical forecasting model of $Y_{1(k)}$ was $RR_{min}=1.59e^{-14}$ (MSE=0.0). For forecast of variable $Y_{2(k)}$ $RR_{min}=7.55e^{-14}$ ($MSE=3.92e^{-15}$); for forecast of $Y_{3(k)}$ $RR_{min}=3.63e^{-5}$ ($MSE=6.77e^{-6}$); and for forecast of $Y_{4(k)}$ $RR_{min}=0.0026$ ($MSE=1.05e^{-4}$). Small minimal value of criterion shows high accuracy of variables forecasting [7].

Arguments which have zero coefficient are excluded from model. This means only that these arguments should be not used for accurate forecasting. Conclusions about reasonable use of them for control purposes are not true. For solution of questions about control the analysis of other, physical model (which us not considered here) is necessary.

Values of all variables for delayed moments $k-1$ and $k-2$ are known. Substituting them into equations for variables $Y_{1(k)}$, $Y_{2(k)}$, $Y_{3(k)}$ and $Y_{4(k)}$ for explicit patterns we receive four separated calculating equations:

$$Y_{1(k)} = a_0 + a_1.X_{1(K)} + a_2.X_{2(k)} + a_3.X_{3(k)} + a_4.X_{4(k)} + a_5.Z_{1(k)} \qquad (3)$$

$$Y_{2(k)} = b_0 + b_1.X_{1(k)} + b_2.X_{2(k)} + b_3.X_{3(k)} + b_4.X_{4(k)} + b_5.Z_{1(k)} \qquad (4)$$

$$Y_{3(k)} = c_0 + c_1.X_{1(k)} + c_2.X_{2(k)} + c_3.X_{3(k)} + c_4.X_{4(k)} + c_5.Z_{1(k)} \qquad (5)$$

$$Y_{4(k)} = d_0 + d_1.X_{1(k)} + d_2.X_{2(k)} + d_3.X_{3(k)} + d_4.X_{4(k)} + d_5.Z_{1(k)} \qquad (6)$$

For equation (3) we receive:

$$a_0=-2.213;\quad a_1=0;\quad a_2=1.226;\quad a_3=1.311;\quad a_4=0.860;\quad a_5=0.734$$

computer algorithm teaches us that to receive accurate normative forecast of $Y_{1(k)}$ variable is necessary to point out the values of factors $X_{2(k)}$ $X_{3(k)}$ and $X_{4(k)}$. For equation (4) we receive:

$$b_0=0.337;\quad b_1=0.564;\quad b_2=0;\quad b_3=0;\quad b_4=1.542;\quad b_5=0$$

For normative forecasting of $Y_{2(k)}$ variable is necessary to point out factors $X_{1(k)}$ and $X_{4(k)}$. For equation (5) we receive:

$$c_0=-0.639;\quad c_1=0.088;\quad c_2=1.477;\quad c_3=0;\quad c_4=0;\quad c_5=0$$

For normative forecasting of $Y_{3(k)}$ variable, factors $X_{1(k)}$ and $X_{2(k)}$ should be pointed out. At last, for equation (6) we find:

$$d_o=0.003;\quad d_1=0;\quad d_2=0;\quad d_3=0.756;\quad d_4=0;\quad d_5=0$$

For the most accurate normative forecasting of $Y_{4(k)}$ variable should be pointed out only one factor $X_{3(k)}$.

4. Graphical visualization of variable $Y1_{(k)}$ normative forecasting

Let us show an example of output variable $Y_{1(k)}$ normative forecasting visualization using example considered above. Let give to variable $X_{4(k)}$ two values:

$$X_4(k) = 0.25 \quad \text{and} \quad X4(k) = 0.75$$

The variable $Y_{1(k)}$ change is shown by isolines on the plane of two input factors $X_{2(k)}$ and $X_{3(k)}$ (Fig.2a and Fig.2b). By comparison of figures 2a and 2b is possible, particularly, to conclude that increase of monetary circulation rate leads to increase of $Y_{1(k)}$; Most important is that using figures 2a and 2b is possible to establish quantitative connection between output variable and their input factors. Similar figures can be completed for each output variable.

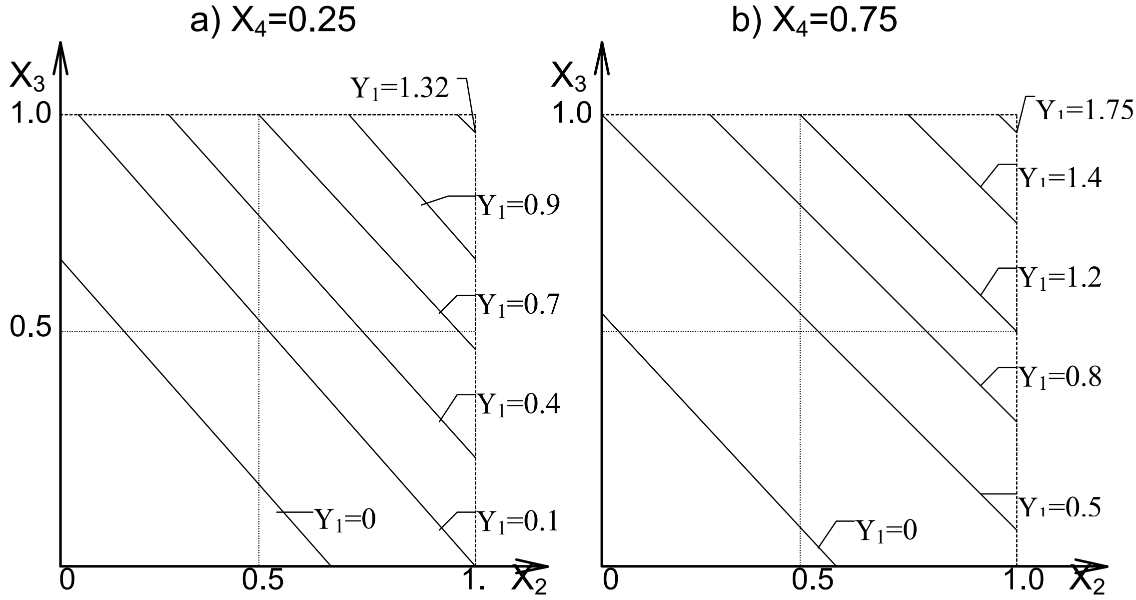

Fig.2. Graphical presentation of variable $Y_{1(k)}$ forecast.

5. External disturbance Z1(k) separate forecast [8]

Auxiliary forecast of external disturbances should be fulfilled separately by Combinatorial GMDH algorithm [6], as function of delayed arguments of variables pointed out in table 1. Full equation presented to computer in case of explicit pattern has following form:

$$\begin{aligned} Z_1(k) = {} & e_0 + e_1 \cdot Z_{1(k-1)} + e_2 \cdot Z_{1(k-2)} + e_3 \cdot Z_{1(k-3)} + e_4 \cdot Z_{1(k-4)} + \\ & + e_6 \cdot Y_{1(k-1)} + e_7\, Y_{1(k-2)} + e_8 \cdot Y_{1(k-3)} + e_9 \cdot Y_{1(k-4)} + \\ & + e_{11} \cdot Y_{2(k-1)} + e_{12} \cdot Y_{2(k-2)} + e_{13} \cdot Y_{2(k-3)} + e_{14} \cdot Y_{2(k-4)} + \\ & + e_{16} \cdot Y_{3(k-1)} + e_{17} \cdot Y_{3(k-2)} + e_{18} \cdot Y_{3(k-3)} + e_{19} \cdot Y_{3(k-4)} + \\ & + e_{21} \cdot Y_{4(k-1)} + e_{22} \cdot Y_{4(k-2)} + e_{23} \cdot Y_{4(k-3)} + e_{24} \cdot Y_{4(k-4)} + \qquad (7) \\ & + e_{26} \cdot X_{1(k-1)} + e_{27} \cdot X_{1(k-2)} + e_{28} \cdot X_{19(k-3)} + e_{29} \cdot X_{1(k-4)} + \\ & + e_{31} \cdot X_{2(k-1)} + e_{32} \cdot X_{2(k-2)} + e_{33} \cdot X_{2(k-3)} + e_{34} \cdot X_{2(k-4)} + \\ & + e_{36} \cdot X_{3(k-1)} + e_{37} \cdot X_{3(k-2)} + e_{38} \cdot X_{3(k-3)} + e_{39} \cdot X_{3(k-4)} + \\ & + e_{41} \cdot X_{4(k-1)} + e_{42} \cdot X_{49(k-2)} + e_{43} \cdot X_{4(k-3)} + e_{44} \cdot X_{4(k-4)} \end{aligned}$$

By first selection layer of Combinatorial GMDH algorithm (where simple linear models having form $y = a_o + a_1 x_i$ are sorted), from 36 pointed arguments were chosen following the

most effective:

$$Z_{1(k-1)}\ X_{2(k-2)}\ X_{2(k-3)}\ Z_{1(k-2)}\ Y_{1(k-2)},\ Y_{1(k-1)}\ Y_{3(k-2)}\ X_{2(k-4)}\ X_{2(k-1)}\ Y_{1(k-3)}$$
$$X_{1(k-1)}\ Y_{1(k-4)}\ X_{4(k-4)}\ X_{4(k-4)}\ X_{1(k-2)}\ Y_{3(k-1)}\ Y_{4(k-1)}\ X_{3(k-1)}\ Y_{2(k-1)}\ X_{4(k-2)}$$

For this set of most effective arguments the following forecasting non-physical model was received by Combinatorial GMDH algorithm:

$$Z_{1(k)} = 0.61 - 0.16 \cdot Y_{2(k-1)} - 0.06 \cdot X_{3(k-1)} - 0.34 \cdot X_{3(k-3)} - 0.46 \cdot X_{4(k-4)} + 2.19 \cdot Z_{1(k-4)}$$

Criterion of forecasting error variance is equal to RR_{min}=0.00028. Forecast for second quarter of 1995 is equal to $Z_{1(k)}$=1.07 This forecast was used above for output variables normative forecasting.

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