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A Case Study of Post-Stabilization Inflation Dynamics via Neural-Nets Approach

Cvetko J. Andreeski, Georgi M. Dimirovski, and Goran Petreski

Abstract— **The recent emerging trend in financial systems engineering relies on exploiting soft-computing technologies, and on employing neural-nets techniques, in particular. Simultaneously, recently experienced observation studies on economy stabilization programs implemented worldwide have clearly demonstrated that, after the successful disinflation, the inflationary process can no longer be captured and explained using the traditional variables and models provided by economy theory. This paper proposes a combined stochastic and artificial neural-nets approach in expert support systems to the identification of inflation dynamics by means of Box-Jenkins ARIMA and Elman-ANN models. Both capturing the empirically established phenomenon in inflationary processes and its use in forecasting based decision and control policies became feasible. The approach is illustrated by the case-study on inflation dynamics in the pre- and post-stabilization period of the nineties in the Republic of Macedonia.**

Index Terms— **Financial time series, inflation dynamics, neural networks, regression modeling.**

I. INTRODUCTION

FOR a long period of time, the analysis and identification of time series has been successfully used to support the decision and control in a number of non-technical real-world applications, which in turn made them an indispensable system theoretic tool for recognition of evolution patterns and predictive representation models of forecasting and control in socio-economic systems (e.g., see [3]-[5], [10], [17]-[19], [22], [23], [25], [27]). In the classical setting, pattern recognition modeling has been concerned primarily with detecting feature patterns in arrays of measurements/observations that persist as the time evolves, traditional applications involve classification of input vectors into one of several classes (discrimination analysis) or approximate representation of dependences between cause and effect variables (regression analysis). These applications habitually use linear system models in identification. Yet successful capturing of the underlying systems dynamics in economic time series remained an ever open problem due to features of time-variation, non-linearity, non-stationarity, and uncertainty involved [10], [17], [23]. With regard to non-linearity phenomenon, more traditional techniques based on statistical and mathematical analysis provide solutions with considerable limitations [e.g. [5], [23], [18], [27]], which are further emphasized in problems such as the ones of inflation dynamics and alike [12]-[14]. In turn, this has given rise to search for alternative approaches based on the use of approximation and/or learning capacities of artificial neural networks (e.g, see [1], [2], [7], [8], [9], [11], [30], [31]).

Experiences from the implementation of economy stabilization programs worldwide gained during the last decade, suggested two distinct phases of the inflation dynamics ought to be considered [12]-[13], [24], [26]. The first phase featured rather quick falling of the inflation while starting from an initially very high level. The second one as a rule exhibited high persistence in inflation movement, the so-called "inertia" feature, after the inflation has been reduced to moderate or low level. Apparently, in all known economic stabilization programs, the dynamics of the inflationary processes during the implementation phase differs significantly from the ones in the post-stabilization period. In addition, observation studies have confirmed that, after the successful disinflation, the inflationary process generally cannot be explained using the variables offered by the standard macroeconomic theory such as the money supply, exchange rate depreciation, nominal wage growth etc. Hence the successful completion of disinflation is associated with a structural break within in the inflation motion, which implies that inflation dynamics in the post-stabilization period cannot be adequately explained using the empirical model, which is relevant for the stabilization period [24], [26]. This finding is most relevant in research studies as well as in practical monetary policies.

Recently, the special 2001 issue on neural networks in financial engineering [1] showed that use of ANN based computing structures and system models rapidly expanded into the field of economic time series analysis due to their capabilities to capture and emulate the underlying nonlinear system dynamics in the economic data sets. Generally, the way in which ANN computing structures are employed in the analysis and modeling of such time series is based on a common approach to use an autoregressive model with exogenous inputs [2], [7], [8], [11]. Cheng et al. in [11] have thoroughly explored the use of ANN in the problem of inflation forecasting via three classes of neural networks having different activation functions, and proved their tight root mean squared error (rms) bounds on the convergence rates of ANN estimators, which was pointed out in [2]. In

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the work [9] Bastos et al. explored an evolutionary design of ANN computing structures for wide range of applications while Doffner in his study [16] has focused on ANN structures especially designed for time series processing. Monograph [8] gives a comprehensive coverage neural-nets solutions to financial time series identification modeling. In our previous work [7], we have explored the potential of Elman ANN models for emulating the class of NARX (Nonlinear Auto-Regressive model with eXogenous variables) in representation models of economic time series with forecasting capacity, and elaborated a comparison investigation relative to the celebrated Box-Jenkins method. This paper reports on their use to capture the dynamics of the post-stabilization inflation motion.

The paper is organized as follows. In the next Section II, an analysis based statement of the problem and conceptualization of the solution is given. Thereafter an outline of the ANN computing structure employing the class of Elman networks is presented in Section III. Section IV presents the applications on system modeling of inflation dynamics by means of both Box-Jenkins ARIMA and Elman-ANN NARX model based methodologies in two subsections in conjunction with a relevant discussion of the case-study results. Conclusions and references are given thereafter.

II. Analysis Based Problem Statement and Proposed Solution

In order to illustrate the main idea, we focused on the inflation motion in the Republic of Macedonia (R.M.) after the declaration of monetary independence. (Due to the escalation of civil wars in S.F.R. of Yugoslavia, the R.M. voted for independence on September 8, 1991, and on April 30, 1992 declared monetary independence as well as introduced its own currency.) Insofar neither economy theory nor any other science has provide a theoretical specification of the "true" model that has the capacity to explain the dynamics of inflation in the transition economies [12]-[14]. On the other hand, systems theory (see Figure 1) via the discipline of systems identification [9], [21] has provided a number of models and tools, and to a lesser extent so are provided by mathematical statistics [18], [19], [23]. Hence combining arguments from systems science and mathematical statistics seems to be rather appropriate and pragmatically most potential [8], [7], [15].

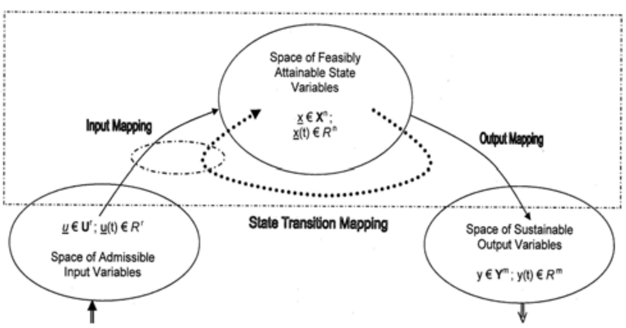

Fig. 1. General systems science view of real-world dynamical processes in engineering terms.

For the purpose of establishing a background that is commonly appreciated in economic science, we start from the traditional point of departure referring to a general regression model in several cause variables. These variables are those observed to represent sources of so-called inflationary pressure in both theoretical modelling [12]-[14] and empirical research in economics [24], [26]. Typical regression model is given in the form [10], [17]

$$\pi_t = \alpha_1 + \alpha_2\pi_{t-1} + \alpha_3 m_t + \alpha_4 w_t + \alpha_5 e_t + \alpha_6 v_t + \alpha_7 \pi^*_t + u_t, \quad (1)$$

where u_t is the term aimed at representing some essentially disturbance variables. In turn, we can regress the inflation rate π_t on several variables [6]: lagged inflation rate π_{t-1}, monetary aggregates m_t, nominal wages w_t, nominal exchange rate e_t, relative prices v_t, and foreign inflation π^*_t. Note the lagged inflation is accounted for in the regression in order to check for the presence of persistence or inertia in the inflation movements, which a common phenomenon in contemporary national economies, and in the transitional ones, in particular.

It is somewhat naturally for the monetary aggregates to appear in order to verify whether the hypothesis on inflation as a monetary phenomenon is relevant even in the short-term run. Similarly, the wages are included to catch the effect of the so-called "cost-push" inflation. Inclusion of the impacts of exchange rate and foreign prices has to be taken into the model whenever dealing with inflation in a small open national economy, volatile due to influences from abroad and also week in our case study. In this equation, the variable of relative prices represents a particular non-standard regressor. Their inclusion is justified, however, by the findings established in recent empirical studies [12]-[14] that are rather relevant for national economies in transition [24], [26] like in the R.M. For these showed that *variations in relative prices* appeared to be crucial sources of inflation in transition economies.

We have run the statistical regression for two periods in our country, 1992-95 and 1996-2000, in order to gain insight on inflation motion during the implementation of stabilization programme and after the stabilization. The first period covers years of sharp disinflation namely 1992-95, while the second one covers the post-stabilization period in the second half of the 1990s. The traditional statistics regression model was run using the gathered monthly data for years 1992-2000, and the results of the OLS based estimation are presented in Table I below.

It is readily inferred from the table, the results of the regression based estimations differ remarkably for the two periods: (i) for 1992-95 period, the inflationary process is well captured and explained by means of traditional variables offered by the macroeconomic theory; (ii) in contrast, regression processing of data 1996-2000, almost all of the variables are not statistically significant and therefore should be excluded from the regression equation. Apparently, the economic factors that have been proved to be the important driving forces behind the inflationary process during the disinflation period 1992-95 no more can capture and explain the underlying inflation dynamics in the post-stabilization period.

It may well be argued in favour of keep employing this approach by careful searching for other specifications of the econometric model, e.g, build a more higher-order model of inflation dynamics invloving additionally lagged values of the above variables. Still, whatsoever relevant specifications found again regression model failed to perform well. Question arose if any of those efforts can hardly yield satisfactory results? It is well known in econometrics the theoretical macroeconomic models also employ concepts such as the Phillips curve, potential output, output gap, etc. However, none of them can be used in the analysis of transition economies because most of the theoretical assumptions and concepts have been developed on the grounds of studying and applied to the industrialized market economies [17]-[19]. Simply, the underlying inflation dynamics of countries in economic transition is governed by peculiar nonlinear dynamical system(s) [24], [26]. The advantages of theoretical macroeconomic models approach can hardly be used in transitional economies.

TABLE I
SOURCES OF INFLATION IN R. OF MACEDONIA, 1992-2000
DEPENDENT VARIABLE: RPI[a]

Regressor	(1)	(2)
CONST	0.9722	0.0339
	(1.377)[0.485][b]	(0.157)[0.830]
RPI(-1)	0.3100	0.0196
	(0.0676)[0.000]	(0.102)[0.848]
M2	-0.1440	0.0231
	(0.090)[0.120]	(0.032)[0.471]
W	0.3284	0.0578
	(0.113)[0.006]	(0.077)[0.459]
NEER	0.3541	
	(0.063)[0.000]	
USD		-0.0108
		(0.041)[0.795]
SKEW	0.0293	0.2142
	(0.358)[0.935]	(0.031)[0.000]
CPID		0.9684
		(0.650)[0.142]
Sample	1992-95	1996-2000
Observations	44	60
$\overline{R}^2$	0.7785	0.4412
S.E.	5.857	0.9411
F-test	31.221[0.000]	8.763[0.000]
LM-test[c]	15.355[0.223]	6.125[0.910]
RESET[d]	5.202[0.023]	0.457[0.499]
Jarque-Bera[e]	27.059[0.000]	265.727[0.000]
Heteroskedicity[f]	0.351[0.554]	0.128[0.721]

Remark on notes:
a) All variables except SKEW are given as growth rates.
b) The parentheses show the standard errors and the marginal level of significance (p-value).
c) LM-test for serial correlation in residuals.
d) Ramsey's functional form test.
e) Test for normal distribution of residuals.
f) Simple χ^2 heteroskedasticity test.

Hence alternative techniques, not based on the assumptions of macroeconomic theory, appeared to be an appealing option in modelling the inflationary process, and ought to be investigated. This was the incentive to investigate in parallel the applicability and potential usefulness of both methodologies Box-Jenkins ARIMA (Auto-Regressive Integrated Moving Average) and Elman-ANN, a model of class NARX (Nonlinear Auto-Regressive with eXogenous variables), in order to arrive at relavant representation models for economic time serise anlysis and for modelling and forecasting inflation dynamics in transitional economies (see [ ] for more details).

In depth presentations of methodologies based on ARIMA models can be found in any book dedicated to the analysis of time series. For instance, recent work [18] by Gujarati offers brief overview while more detailed presentations can be found in [22], [23], [25], [27]. The 1994 monograph by Box, Jenkins and Reinsel [10] gives a rater comprehensive and in depth coverage. On the other hand, the appealing alternative base on ANN computing sturctures is avilbale, and the next section gives an outline on Elman-ANN-NARX methodology as implemented in our research [6]. Fesible representation models of the underlying dynamics in economic time series were reported via their comparison analysis in [7].

For the the sake of argument in favour of the problem stated here, note albeit Elman-ANN-NARX methodology gives input-output models with superior accuracy due to nonlinear function approximation capacity, in particular when convergence rate rms bounds [2] are satisfied, Box-Jenkins-ARIMA maps better the underlying probabilistic nature. Hence the basic premise of our methodology [6], [15] for deriving relevant models of inflation dynamics in transitional economies is summarised in terms of an expert decision-support system identifying in parallel ARIMA and ANN NARX models, as seen in the sequel.

III. ON ELMAN NEURAL-NET MODELS FOR ECONOMIC TIME-SERIES PROCESSING

Most artificial neural networks have been initially derived for pattern recognition in static patterns; the temporal dimension has to be supplied additionally in an appropriate way. Some of them are worth mentioning [8], [20]: layer delay without feedback (time windows); layer delay with feedback; unit delay without feedback; unit delay with feedback (self-recurrent loops). In this research the class of recurrent network created by adding new elements in classic neural feed-forward networks, known as Elman networks (Figure 3), which can be trained during a certain sequence of time, have been studied.

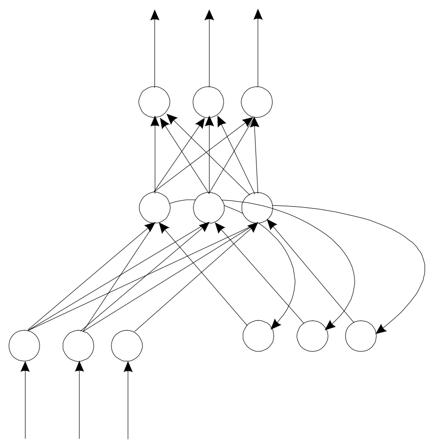

Fig. 2. Architecture of Elman artificial neural-networks.

It is common in processing of time series to use so-called (linear) state space models [10]. The assumption is that a time series can be described as a linear transformation of a time dependent state given through a state vector $\vec{s}$:

$$\vec{x}(t) = C\vec{s}(t) + \vec{\varepsilon}(t) , \qquad (2)$$

where C is some transformation matrix and $\vec{\varepsilon}(t)$ is a noise stochastic process. Usually a linear model of the following class

$$\vec{s}(t) = A\vec{s}(t-1) + B\vec{\eta}(t) , \qquad (3)$$

where A and B are appropriate matrices and $\vec{\eta}(t)$ is a noise process, just like $\vec{\varepsilon}(t)$ above, describes time dependent state vector. The model for the state vector evolution, in this version, is an ARMA[1,1] process basically. The basic assumption underlying this model is the so-called Markov assumption [10], [17], [19]: the next sequence element can be predicted by the state a system producing the time series is in, no matter how the state was reached. In other words, all the history of the series necessary for producing a sequence element can be expressed by one state vector.

Now, should the assumption that the states are dependent on the past sequence vector also holds, after neglecting the moving average term $B\,\vec{\eta}(t)$, one obtains

$$\vec{s}(t) = A\vec{s}(t-1) + D\vec{x}(t-1)\,. \tag{4}$$

Basically, this is a background equation to describe the type of recurrent neural networks known as Elman network, which is depicted in Figure 3. The important feature of this kind of neural networks is that they can identify dynamic systems with no need for more than one previous value of the input and output. Therefore these are capable of identifying dynamic systems of unknown order or with unknown time delay.

An Elman network is in fact a multi layer perceptron (MLP) neural-net computing structure possessing an additional input layer, called the state layer, which receives by feedback a copy of the activations from the hidden layer at the previous time instant. Should this network is employed for forecasting modeling, the activation vector of the hidden layer is equated with $\vec{s}$ and the only difference relative to Eq. (3) is the sigmoid activation function is applied to the input of each hidden unit. Hence

$$\vec{s}(t) = \sigma(A\vec{s}(t-1) + D\vec{x}(t-1))\,, \tag{5}$$

with $\sigma(.)$ being a standard in any MLP computing structure. Here $\sigma(.)$ refers to the application of the sigmoid (or logistic) function $1/(1+\exp(-a_i))$ to each element a_i of matrix A, which is associated with the activations in the precedent time instant. Thus the mapping becomes essentially a non-linear one according to the logistic regressor applied to the input data vectors.

The Elman network can be trained with any of the learning algorithms [28], [29] that are applicable to MLPs such as back-propagation (implemented in our application software) or conjugate-gradient, just to name a few. This network belongs to the so-called simple recurrent networks. Even though it contains feedback connection, it is not viewed as a dynamical system in which activations can spread indefinitely. Instead, activations for each layer are computed only once at each time step (each presentation of one sequence vector).

IV. Inflation Dynamics in Transition Economies: Case Study Results

Financial time series based on statistical observations as a rule exhibit hidden nonlinear evolution. Hence linear parametric time-series models are prone to fit data poorly (see below), yet still capture the statistical nature. The alternative approach is implementing nonlinear models via artificial neural networks. Two characteristic features [8], [20] that make them appealing for processing time series: the ability to approximate functions, and the direct relationship with classical models such as Box-Jenkins ones. Despite these advantages, there are delicate issues to be observed in identifying financial time series, which shall be seen in the sequel.

A. Modelling Inflation Dynamics by ARIMA methodology

The ARIMA methodology provides one alternative theoretic approach for modelling time series, since the specification of the empirical model does not emerge from the findings and concepts provided by economy theory. Instead, the time series is modelled by a combination of the autoregressive and the moving average terms, i.e., the current value of a variable is represented as a function of lagged values of that variable, and of past random shocks on the variable. In the problem of inflation dynamics, the appropriate variable to measure inflation is changes in the Consumer Price Index (CPI Inflation). For the case study of Macedonia in the post-stabilization period these are found in Table I, within Section II. We point out to have worked using monthly data, and the sample data set covers the period starting in January 1995 and ending with December 1999, i.e., till the beginning of year 2000.

In modelling the inflationary process, we did not make use of the entire available time series but rather the sample delimiting the end of 1999 on the grounds of economic argument. Namely, this is justified by the structural break in the inflation motion that occurred in April 2000. Of course, we are aware that the restricted sample appears to be a sort of handicap in modelling the series, since it reduces the reliability of the estimates as well as the power of some tests. (For instance, it is well known that unit root tests generally have little power in small samples; also the Q-test follows the χ^2 distribution only in large samples, i.e. with the number of observations exceeding 100.) Although we worked with small samples still the size exceeded the minimum of 50 observations, recommended in literature on ARIMA modelling [10], [17], [23], [27].

Given that the property of stationarity is a necessary precondition for successful modelling of time series, we first checked whether this assumption is satisfied. The results obtained from both the Dickey-Fuller (DF) and the Augmented Dickey-Fuller (ADF) tests are given in Table II below, and they confirm that the series can be regarded as being stationary. (A visual inspection of the curves suggested the presence of serial correlation with lags of six and twelve months, which justified the ex-ante inclusion of appropriate number of lags in the unit root test equation; the estimation revealed, however, that most of the lagged terms in the test equation were not statistically significant, hence we chose to employ the basic DF-test alongside with the ADF-test.) Therefore, we can perform the first stage of the ARIMA methodology – the model identification. At the same time, establishing that the original time series were stationary implied that the ARIMA model is actually reduced to an ARMA model [6], [7].

It should be noted although preliminary information on the possible model can be extracted from the simple visual inspection of the series (see figures below). As can be seen, the curves show clearly that the series exhibits regular peaks, which over time appear in the every twelfth month. Thus, this is reflecting the seasonal component in the movement of the inflation rate. Also, it is obvious that a series of upward movements are followed by a series of downward movements and, this suggests the presence of a strong autoregressive process. In addition, the fact that the peaks regularly change their signs from a positive to a negative one indicates that the autoregressive term has a negative sign. This obvious information, which is obtained by the visual inspection of the graph, does not preclude the use of most important analysis tool - sample autocorrelation (*Acf*) and partial autocorrelation (*Pacf*) functions along with the accompanying test-statistic (see Table II) [3]-[5], [10], [17], [21], [23].

TABLE II
UNIT ROOT TEST FOR INFLATION, 1995-99

Type of the Test	DF	ADF (6 lags)	ADF (12 lags)
Value of the Test Statistics	-6.1270	-3.5773	-3.5856
Critical values			
at 1% sign.	-3.5417	-3.5547	-3.5417
at 5% sign.	-2.9101	-2.9157	-2.9101
at 10% sign.	-2.5923	-2.5953	-2.5923

The *Acf* could not determine the precise form of the model (see Table III), but anyway, it offered a hint that the series can be modelled by a mixed stochastic process combining both AR and MA components. We are able to gain more information on the possible model, looking at the *Pacf*, where, again, only the autocorrelation coefficients on the lag six are statistically significant. Therefore, these functions confirm what was indicated by visual inspection .

Table III
'Acf' AND 'Pacf' INDICES OF INFLATION, 1995-99

<table>
<tr><th>ACF</th><th>PACF</th><th>Lag</th><th>AC</th><th>PACF</th><th>Q-Stat</th><th>P-value</th></tr>
<tr><td>. |** |</td><td>. |** |</td><td>1</td><td>0.200</td><td>0.200</td><td>2.5235</td><td>0.112</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>2</td><td>0.096</td><td>0.058</td><td>3.1091</td><td>0.211</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>3</td><td>-0.049</td><td>-0.082</td><td>3.2633</td><td>0.353</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.188</td><td>-0.179</td><td>5.6235</td><td>0.229</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>5</td><td>-0.227</td><td>-0.162</td><td>9.1173</td><td>0.104</td></tr>
<tr><td>****| . |</td><td>***| . |</td><td>6</td><td>-0.471</td><td>-0.421</td><td>24.406</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>7</td><td>-0.082</td><td>0.053</td><td>24.876</td><td>0.001</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>8</td><td>-0.063</td><td>-0.068</td><td>25.157</td><td>0.001</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>9</td><td>0.068</td><td>-0.011</td><td>25.493</td><td>0.002</td></tr>
<tr><td>. |*. |</td><td>.*| . |</td><td>10</td><td>0.100</td><td>-0.084</td><td>26.243</td><td>0.003</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.184</td><td>0.042</td><td>28.811</td><td>0.002</td></tr>
<tr><td>. |**** |</td><td>. |** |</td><td>12</td><td>0.469</td><td>0.323</td><td>45.838</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>13</td><td>0.104</td><td>0.019</td><td>46.686</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>14</td><td>-0.012</td><td>-0.094</td><td>46.697</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.065</td><td>0.039</td><td>47.049</td><td>0.000</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>16</td><td>-0.204</td><td>-0.092</td><td>50.560</td><td>0.000</td></tr>
<tr><td>**| . |</td><td>. | . |</td><td>17</td><td>-0.211</td><td>-0.006</td><td>54.425</td><td>0.000</td></tr>
<tr><td>***| . |</td><td>.*| . |</td><td>18</td><td>-0.373</td><td>-0.121</td><td>66.771</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>19</td><td>-0.056</td><td>-0.019</td><td>67.057</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>20</td><td>-0.073</td><td>-0.171</td><td>67.548</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>21</td><td>0.103</td><td>0.037</td><td>68.562</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>.*| . |</td><td>22</td><td>0.106</td><td>-0.106</td><td>69.658</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>.*| . |</td><td>23</td><td>0.129</td><td>-0.058</td><td>71.340</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>24</td><td>0.337</td><td>0.041</td><td>83.080</td><td>0.000</td></tr>
</table>

It is well known from the literature that usually the first phase of the Box-Jenkins methodology is not capable of yielding a definite, single model of the series, but it generally produces several competing preliminary models with similar performances. This was true in our case too. On the above grounds, the inflation dynamics in the post-stabilization period can be represented by any the three models:

$$\pi_t = \alpha + \phi\pi_{t-6} + \theta\varepsilon_{t-6} + \varepsilon_t , \tag{6}$$

$$\pi_t = \phi\pi_{t-6} + \theta\varepsilon_{t-12} + \varepsilon_t , \tag{7}$$

$$\pi_t = \theta\varepsilon_{t-12} + \varepsilon_t , \tag{8}$$

where, π_t is the inflation rate, α, ϕ and θ are the model parameters, and ε_t represents the disturbance term.

The estimated models along with the accompanying diagnosis tests are given in Table IV. As confirmed by the value of the tests, in all three models, the residuals behaved reasonably well, i.e., they are distributed normally and do not suffer from serial correlation. In addition, Figures 3 to 5 below present the graphical responses, which showed all three models to be almost equally successful in fitting the inflation dynamics. Since the competing models have similar performances, indeed it is very difficult to discriminate between them on the grounds of the goodness of fit and to select the most appropriate one. Anyway, provided the inflation can be assumed to have been generated by a stochastic process combining AR and MA components, one may favour the first and/or the second model. On the other hand, if model parsimony were the selection criterion, then one would select the third model.

TABLE IV
ARIMA MODEL OF INFLATION, 1995-99
DEPENDENT VARIABLE: CPI, MONTHLY GROWTH RATES

Regressor	(1)	(2)	(3)
CONST	0.2374		
	(0.122)[0.058][a]		
AR(6)	-0.9797	-0.2624	
	(0.039)[0.000]	(0.124)[0.038]	
MA(6)	0.9243		
	(0.033)[0.000]		
MA(12)		0.8794	0.8773
		(0.0258)[0.000]	(0.026)[0.000]
$\bar{R}^2$	0.5218	0.5052	0.4757
S.E.	1.039	1.057	1.088
AIC	2.963	2.981	3.023
SBC	3.068	3.051	3.058
LM-test[b]	0.389[0.961]	0.493[0.908]	0.876[0.576]
Q-test[c]	16.105[0.934]	16.423[0.925]	24.701[0.591]
Jarque-Bera[d]	0.577[0.749]	0.222[0.895]	0.981[0.612]

Remark on notes:
a) The parentheses show the standard errors and the marginal level of significance (p-value).
b) LM-test for serial correlation in residuals.
c) Joint test for significance of autocorrelation coefficients.
d) Test for normal distribution of residuals.

The issue of selection criterion, however, is not as simple as that. We believe that one should adopt the forecasting capability of the model as the selection criterion of primary importance whenever similar fits by several ARIMA based models are obtained, as in this case study. For the use of ARIMA methodology is intended primarily for short-run forecasting. For the purpose of selection among competing ARIMA models and of examining the performance in forecasting future inflation, we propose the following procedure: Estimate once more these models with an appropriate shorter sample data set, and then make use of these models to forecast inflation dynamics for the remaining segment of the dataset relevant for the immediately subsequent 'future'. This procedure has been demonstrated to yield most appropriate model discrimination solution always [6], [15].

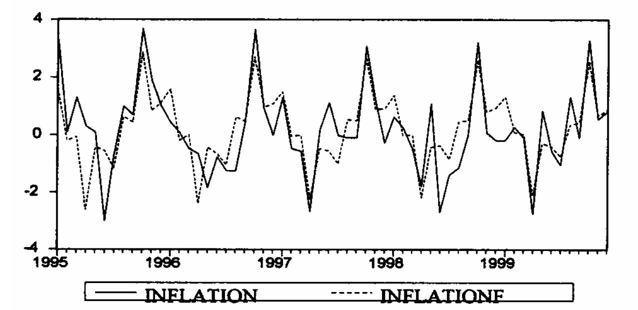

Fig. 3. Identified ARIMA model 1 (dotted curve).

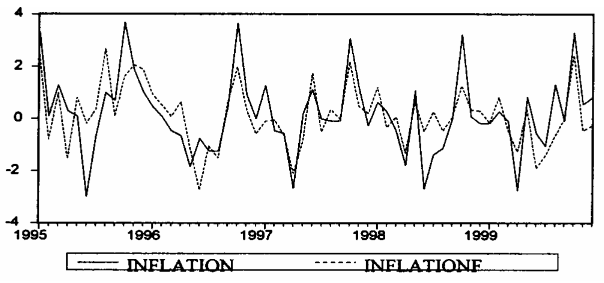

Fig. 4. Identified ARIMA model 2 (dotted curve).

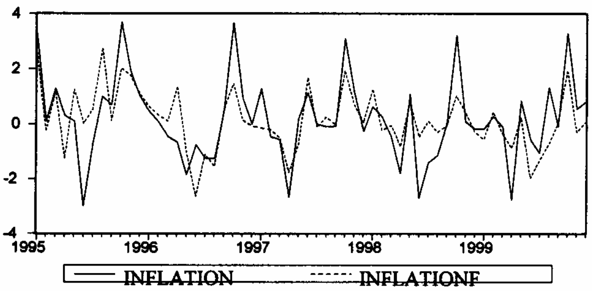

Fig. 5. Identified ARIMA model 3 (dotted curve).

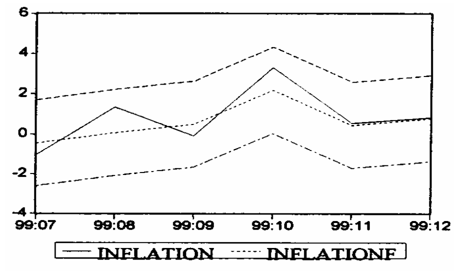

Fig. 6. Inflation forecasting by model 1.

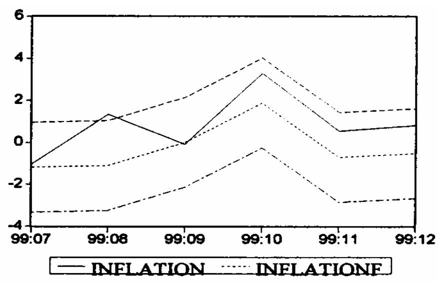

Fig. 7. Inflation forecasting by model 2.

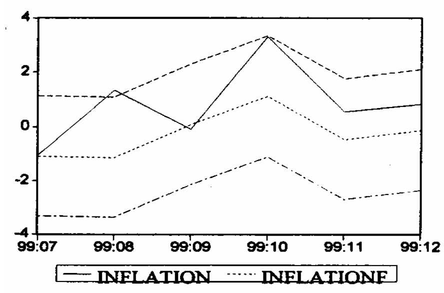

Fig. 8. Inflation forecasting by model 3.

We have applied this procedure when exploring the inflationary dynamics in the R.M. For this purpose, the shortened dataset January 1996 to June 1999 inclusive was taken as representing the past, and the remaining July-December 1999 dataset was considered in terms of the immediately subsequent future, which it was in fact. In turn, these models generated out-of-sample forecasts for the post-stabilization period that are shown in Figures 6 to 8.

Apparently, from the point of view of the forecasting performance on future inflation, the first model performs best, and this is not surprising given its system-theoretic structure described by Eq. (6) in contrast to Eqs. (7) and (8). For this model, the forecasted inflation curve moves relatively close to the actual inflation, and lies always within the ± two standard error confidence interval. On the other hand, both for the second and the third model, the forecasted inflation appears always smaller than the actual inflation, implying that these models systematically underestimate the inflation. In addition, for these models, the inflation evolution showed to break through the ± two standard errors confidence interval occasionally, which is a feature of concern about the acceptability of inflation forecasts. Therefore, on the grounds of better forecasting performance, the final choice ought to be the first model. Also it should be noted that this performance provided an additional confirming argument for the actual inflation being generated by a mixed AR plus MA stochastic process.

B. Modelling Inflation Dynamics by Elman-ANN Methodology

Although originally designed for technical systems, the use of ANNs was recently expanded in the filed of analysis of economic time series due to their advantages in the identification of non-linear systems. In this regard, it was shown that economic time series could be modelled successfully with the help of certain classes of neural networks, based on a non-linear autoregressive model, which could be upgraded with exogenous variables (For more recent applications of ANNs in the financial analysis, for instance, see [2], [8], [11]).

Various types of ANNs are used for modelling time series and they differ from each other on the basis of the mechanism employed in the estimation procedure (e.g., see [8], [16]). In our study, we applied Elman's class of recurrent neural networks created by inserting new elements into the classical ones, which are iteratively trained using the dataset from the original time series. These neural networks that are capable for identification of dynamic systems of an unknown order or unknown lag (e.g., see [7], [8], [16]). These networks are quite popular in modelling dynamic systems and belong to NARX models.

In this paper, we have used Elman's neural network for modelling the dynamics of inflation in the R.M. in the post-stabilization period 1995-99. Again, we work with monthly data and with the original time series with no differencing and/or any transformation. Only, we normalized the original values within the interval [0, 1] in order to make the series suitable for modelling with the ANN. Table V presents the results of Elman ANN based modelling via learning adaptation of the network through 160 training epochs.

TABLE V
PARAMETERS OF THE ANN BASED NARX MODEL

Epochs	160			
SSE	0.658			
$\overline{R}^2$	0.898			
Ljung-Box test:				
Lag	12	24	36	48
χ^2 - statistics	19.36	34.20	46.36	56.96

The number of training epochs is sufficiently large - 160, and it implies that the data set was analyzed 160 times before determining final network's weights. In addition, other parameters in the table confirm that the modelling of the inflationary process with the ANN can be well accepted. For instance, the value of $\overline{R}^2$ can be indeed regarded as relatively high, 0.898, meaning that the estimated model can explain approximately 90% of the variation within the time series, thus providing a satisfactory fit. Also, Ljung-Box statistic shows that the residuals represent a series that is not serially correlated and can be assumed to be white-noise processes.

The type of ANN that is used in the analysis can be identified as a non-linear AR(1)-type model of the NARX class. From the viewpoint of the fitting accuracy Elman-ANN-NARX models showed indeed much better fitting performance as their intrinsic property, which too is not surprising given their math-approximation capacity (via learned training). Hence it is well acceptable for modelling the inflationary process.

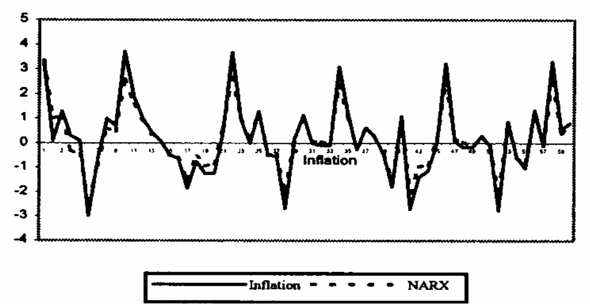

Fig. 9. Identified ANN-NARX model (dotted curve).

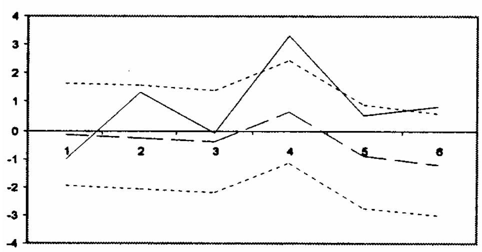

Fig. 10. Short-term forecasting of inflation by ANN-NARX model (full line).

Figure 9 above depicts the series generated by Elman-ANN model as well as the original time series dataset. It demonstrates too that the model generated by employing neural-nets technique was capable to match rather closely the dynamics of inflation during the sample period. As with other models before, again the performance of the ANN model in forecasting the future inflation has to be explored. Figure 10 shows the resulting out-of-sample forecasts of the inflation rate motion for the remaining six months of year 1999. Apparently, the forecasting ability of Elaman-ANN NARX model is weaker than that of Box-Jenkins ARIMA model. Firstly, this model provided only a tentative picture of the future inflation rate motion; secondly, the model systematically overestimated the future inflation; and thirdly, the inflation curve broke through the ± two standard error confidence interval. It should be noted, however, the poor performances of the ANN model with respect to forecasting capacity comes in part out of the rather short representing datasets of the inflation problem, because neural networks do require rather rich data sets for successful learned training.

The above presented investigation has clearly shows that ANN based models perform very well in describing the past but do not perform reliably well in forecasting the future of inflationary processes. This finding was expected as a matter of fact, since the literature shows that ANNs have not been proved yet to represent an appropriate tool for making economic forecasts, especially not in longer time horizons. For they have emanated from designs aimed at pattern classification and/or at for identification and control primarily by means of analyzing the history of the system's outputs and inputs. Therefore further improvements ought to be directed toward models that ensure white-noise residuals and simultaneously more accurate forecasts in short-run by exploring additional structuring, and recent studies [2], [11] seem rather in this regard.

V. CONCLUSION

The implementation of stabilization programs worldwide revealed that successful completion of disinflation is characterized by structural break in the inflation motion, hence intrinsic nonlinearity. Therfore the dynamics of the inflationary processes in the post-stabilization period considerably differs, and cannot be adequately represented and explained using the relevant empirical model for the implementation phase of stabilization. This finding has given incentives to alternative modelling techniques for economic time series of transitional economies.

The advantage of the ARIMA methodology lies in its approach to modelling time series not based on economy theory and econometrics, since the specification of the empirical model does not require knowledge of the "true" economy theory based model. Instead, the given time series is modelled by an AR-MA combination in which the current value of a variable is represented as a function of lagged values of that variable and the past random disturbance representing economic shocks (as established in [12]-[14], [24], [26] 9. A selection procedure based on forecsting capacity is proposed to choose among cometing identified models. Although these capture better the statistics of inflationary processes, the nonleariy of inflation dynamics in transtional economies reduces the usefulness of these parametric models.

The ANN models approach emerged as a potentially useful alternative in these economic time series modelling. The basic features that made ANNs apealing are twofold:

(a) these too represent system-theoretic and not economy-theoretic approach in economic time series analysis; and (b) have nonlinear function approximation capability as well as direct relation to more traditional ARIMA econometric models. Therefore they are esentially better in identification of economic time series that ARIMA models. Yet, their main drawbacks are their poorer forecasting capability due to vulnerablity to the short-sample problem, and thier complexity making more difficult proper understanding of appropriate usage in economic time series analysis.

Both approaches were applied to the case study of modelling the pre- and post-stabilization dynamics of inflation in the R.M. This investigation showed that when these two techniques are taken in paralel they guarantee satisfactory succesful identification of inflationary processes in transitional economies. Hence ARIMA and ANN methodologies should not be mistaken as substitutes or competitors to each other or to broader macro-econometric models (usually exploited by central banks), but rather as complementary tools in simulation based projections. Both methodologies, not emanating from economy theory, givr models with limited informational contents not explaining monetary policy affecting factors.

In turn, the following two concluding points are drawn: (a) despite producing excellent fits on datasets during the sample observation period, the ANN based model per-se has no capacity to generate reliable prediction forecasts of future inflation; and (b) in the forecasting problem, the stochastic nature of inflation dynamics prevails relative to its nonlinearity feature. These findings support strongly our thesis that expert decision support systems aimed at emulating inflation dynamics have to employ ARIMA and NARX models in parallel. It is believed, in addition, the alternative technique employing fuzzy-neural networks will overcome the weakness of neural-nets and exhibit equally good fitting and forecasting in modelling identification of inflation dynamics, which a topic of future research [15].

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