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Preliminary Statement

DIRECT AND INDIRECT APPROACH IN FORECASTING CROATIA'S TOTAL ENERGY CONSUMPTION

In forecasting aggregated time series different approaches can be used. The aim of this paper is to analyze and forecast aggregated time series of the total energy consumption in Croatia up to 2014, using Box-Jenkins methodology and applying two different approaches: direct and indirect. Forecast values were calculated indirectly by aggregating the forecast values which are determinate (with the different representative forecasting models) for all variables components in an aggregated time series. The components of total energy consumption in Croatia are: consumption of coal, fuel wood, liquid fuel, natural gas, hydro power and electricity. Direct approach in forecasting means that forecast values are determined directly applying appropriate forecasting model on aggregated time series. In forecasting Croatia's total energy consumption, ARIMA (1,1,1) model was selected as representative. The same model is chosen for dominant variable component: liquid fuel. The differences in forecast values of total energy consumption calculated directly or indirectly, are the consequence of applying different (representative) forecasting models for the different time series components of total energy consumption. From the statistical point of view, direct approach is preferred, but in a compliance with the expectation of continuing recession period in Croatia in the next two years, forecast values of total energy consumption calculated by indirect approach are more realistic then the same calculated using direct approach.

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1. Introduction

Current economic situation and the global economic crisis started in 2008 imposes spatially need of tracking and correctly predicting changes in macroeconomic variables. The variables of interest usually are: gross domestic product, unemployment rate, industrial production, energy production, energy consumption etc. There is growing interest in, so called macroeconomic forecasting. Some different forecasting methods and models can be used. In forecasting, parsimony principle is important: simple models are usually preferable to complex models. The chosen forecast methods should produce a forecast that is accurate, timely and understood by management or government. So, we can use some different forecast approaches, methods and models which have varying degrees of complexity and different requirements for input data like judgmental (qualitative) forecast methods (the Delphi method, Scenario writing, Combining forecasts and so on). Qualitative methods and intuitive approach are preferable in condition of risk and uncertainty, when the historical data set don't exist. These methods can be very useful in the combination with quantitative (statistical) methods, as it can be seen in conclusion of this research in the end of the paper.

When we apply quantitative forecasting techniques, we can use two types of data: cross sectional data and time series. Cross-sectional data are observations collected at a single point in time. Time series are the data set collected over the successive increments of time. In forecasting total energy consumption, the historical data are available, so it can be various forecasting technique used. The major criterion in selecting forecasting technique is the identification and understanding of historical patterns in the data, and the smallest forecast errors. In forecasting stationary series can be used the following forecasting techniques can be used: naive methods, simple averages, moving averages, weighted moving averages, simple exponential smoothing and autoregressive moving average (ARMA) models (Box-Jenkins methods). In forecasting variable with a trend, we use moving averages, Holt's linear exponential smoothing, simple regression, exponential models, autoregressive integrated moving average (ARIMA) models (Box-Jenkins methods). When we have to make forecast for the seasonal series, we can use Census X-12, Winter's exponential smoothing, multiple regression and (ARIMA) models (Box-Jenkins methods). The most useful techniques that we use in forecasting cyclical series are econometric models, multiple regression, leading indicators and (ARIMA) models (Box-Jenkins methods).

One of the main difficulties in developing accurate forecasts of total energy consumption is the unexpected and significant shift in key economic factors like prices on the energy market, inflation and broad policy changes by country government, so combination of qualitative and quantitative forecasting approaches in doing final forecast is very important. The forecasts generated by the forecasting model should be modified using the forecaster's judgment.

Importance of the impact of the total energy consumption, as a variable in the field of sustainable development, on economic development and its significant role in the formation of national macroeconomic policies in Croatia was recognized with increasing scarcity of energy and especially in recession period.

There are six components of the total energy consumption: coal, fuel wood, liquid fuel, natural gas, hydro power and electricity. All of those components are very important variables in the field of sustainable development, so it is considered to forecast them in an effort to produce information which helps managers in making best decisions. Aggregated time series of total energy consumption (as a linear combination of six variables components) can be forecasted using direct or indirect approach.

In our research the Box-Jenkins approach is applying with the aim to develop an appropriate ARIMA model with the purpose to analyze and forecast the total energy consumption in Croatia. Two different approaches are applied: direct and indirect. Direct method of forecasting means that forecast values of aggregated time series total energy consumption are determined by directly applying the appropriate forecasting model on aggregated time series. Forecast values can be calculated indirectly by aggregating the forecast values determinate for all variables components in an aggregated time series (with the different, representative forecasting models).

In statistical terminology, the time series of total energy consumption is called aggregated time series. Aggregated time series has two or more time series of variable components. In this case, there are six time series components of Croatia's total energy consumption. In this paper different analytical forecast values of aggregated time series and their variables components are presented. There are different forecasting methods and in accordance with this, there are different forecasts dependent (among other things) on analytical criterion in method selection which is not only exact but experimental as well. In our research, the basic characteristics of time series of total energy consumption are quantified and the short-term forecasts of them are made. The evaluation of models and the selection of the representative forecasting model are made on the basis of forecasting errors and in accordance with the theoretical grounds of applying each of the forecasting models. In accordance with this, the hypotheses in this paper are given as follows:

H1: Applying different (appropriate and representative) forecasting model on total energy consumption in direct approach, we produce forecasts which are not the same or the similar to those calculated using indirect method. Forecasting models are based on different methodological ground. The selected representative forecasting model of the dominant component in total energy consumption is the same as the model of the total energy consumption (aggregated series).

H2: If the structure of Croatia's total energy consumption remains unchanged in forecasting period up to 2014, it is convenient to use the direct approach. The forecast errors in direct approach are smaller than the same which are calculated using the indirect approach.

H3: By reducing the relative share of liquid fuels (as the dominant component) in Croatia's total energy consumption, the predictive values of the total energy consumption calculated using the indirect forecasting method are less than those obtained by the direct method.

2. Total energy consumption in the concept of sustainable development in Croatia

Problems of energy development are increasingly present in the time in which we live. Issues related to energy policy and their impacts on economic activity are taking an increasingly important place in international debates. Accordingly, we try to find as many answers as we can to support that this development is moving in the positive direction. Knowing that it is very difficult to achieve a balance between a healthy society and the quality of the economy in the world burdened by poverty and lack of care for the environment leads to thinking about new concepts of social development. In accordance with this direction, economic growth must go in a direction that will not be as detrimental for environment and which will be in service of optimal social development. Although, the concept of sustainable development in relation to the sustainable forestry was for the first time used by von Carlovitz in 1713th. The concept becomes a relevant issue during the 1970s. In those years, appeared very clear consequences of pathological processes caused by (un)consciousness of unlimited capacity of ecosystems. These reasons create a strong need for fundamental change in the view of the economic development of mankind. In order to clearly determine and define the concept of sustainable development, it first requires a holistic approach to the important determinant of it. If we seriously consider the concept of sustainable development at all levels of its possible implementation, this will require drastic changes in almost all areas of life, not change of consumer habits, but there must be a complete change in consciousness in the fields of economy, society and ecology. In the public there are different views of the concept of sustainable development; therefore it is very difficult to determine its unique definition. Consequently there is a wide range of definitions of sustainable development. A large number of such definitions are based on the Brundtland report (1987)[1] that says that the sustainability is "meet the needs of present generations without compromising the ability of future generations to meet their own needs''. In the context of such an understanding, Goddland i Leddec (1984) comprehend the concept of sustainable development as a model of social and structural-economic transformation that displays economic and social benefits of now living people, without compromising the benefits of future generations. On the other hand, Ress (1988), Robbinson, Tinker (1995), see sustainability in the context of merging economic, social and ecological systems of which emphasize the importance of limited ecological capacity. Despite the differences in perception of the concept of sustainable development in general we can say that it is a process towards achieving a balance between economic, social and environmental requirements to ensure ''meet the needs of present generations without compromising the ability of future generations to meet their own needs''. In 1972 Croatia has already adopted the *Resolution on Environmental Protection*. After the World conference in 1992 in Rio de Janeiro, where the Declaration was adopted, Croatia elect for sustainable development. But only a few years ago, precisely in 2000 the topic of sustainable development becomes a current issue of public and economic interest. In February 2009, pursuant to article 44 paragraph 4 of the Environmental Protection Act (*Official Gazette*, No. 110/07) the Strategy for Sustainable Development of the Republic of Croatia has been adopted in the Croatian Parliament. The document specified the long-term Croatian economic and social development and environmental protection to ensure sustainable development.

In order to raise awareness of sustainable development, in this paper the variable of interest is the total energy consumption in Croatia and its components. In the past few decades, after the oil crisis in 70s and 80s the role of energy, as a very important component of sustainable development, in economic growth is becoming increasingly significant and a very common scientific topic of many authors. It is very clear that the role of energy with all its components (coal, fuel wood, liquid fuel, natural gas, hydro power and electricity) have gained much more research attention. After the Croatian Parliament adopted the Strategy of Energy Development (2009), Croatia has a strategic document that relates to energy development. In accordance with this, the Strategy is not only important in terms of energy but also in terms of political and socially important documents because the energy situation in one country ''spills over'' to other very importance areas.

[1] Gro Harlem Brundtland in Report of the World Commission on Environment and Development.

Also, because of the increasing scarcity of non-renewable energy sources, its impact is growing and simultaneously the requirements for its consumption are increasing. Renewable energy sources are increasingly being offered as one of the most important solutions in the fight against climate change and energy crisis, and yet they are often characterized like auxiliary sources of energy, which can only function as a substitute for conventional energy sources (Šimleša 2010). Nowadays, renewable sources do not have the appropriate share of the Croatian energy sector, although they have great importance and availability (especially solar energy, wind and biomass). Consequently a growing need has been detected of developing a suitable forecasting model that would be able to predict energy consumption trends in the country.

3. Box – Jenkins (ARIMA) methodology and dataset

ARIMA (Autoregressive Integrated Moving Average) models are a class of linear models that are able of representing stationary and nonstationary time series. The Box-Jenkins methodology is an iterative approach of identifying, fitting and checking ARIMA models with time series data (Hanke and Wichern, 2009). The chosen model can be used for forecasting. Forecasts follow directly from the form of the fitted model. In this paper the dataset of total energy consumption and their components in Croatia is used. The yearly data cover the period from 1992 to 2008 and are taken from the Croatian Bureau of Statistics (http://www.dzs.hr). Those are the latest available data.

All economic variables do not behave deterministically; there is indeed a wide variety of different influences acting on the observed variables. In this case we should use the appropriate analytical model that expresses the correlation of the time series with itself, lagged by one or more periods. In such model, values of the observed series with a shift in time take the role of independent variables. It is necessary to find an appropriate analytical expression (model) that can express the dependence of the current value of the phenomena of its lagged values (Šošić, 2006). Consequently, an economic phenomenon can be defined as a stochastic process $\left\{Y_t, t = 0, \pm 1, \pm 2, ...\right\}$.

The time series of energy consumption and some other economic variables often have nonstationarity problem that can be resolved through the appropriate procedures.[2] One of the reasons why the time series of these variables have the characteristics of nonstationarity may be attendance of the constant changes in

[2] Differentiation of time series of original value.

legal and technical principles and rules which certainly affect economic relations that have implications for changes in the time series of variables in this area. ARIMA (*p, d, q*) models are used to analyze processes with nonstationary components, or else, they are used to modelling the processes that contain a periodic variation in time. The mentioned models are often used to describe the dynamics of a large number of economic variables. Because of these reasons ARIMA (*p, d, q*) models are also suitable for the analysis of total energy consumption in Croatia. A RIMA (*p, d, q*) can be expressed as follows:

$$\varphi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t, \tag{1}$$

where $\phi(B)$ indicates an autoregressive polynomial of order p, and $\theta(B)$ represents the moving average polynomial of order q, assuming that zero points of these polynomials all lie outside the unit circle and the polynomials have no common zero point. d is the order of differencing (Bahovec and Erjavec, 2009). This is a positive number. In other words, d numerically represents how many times a time series is differentiated to eventually become stationary.

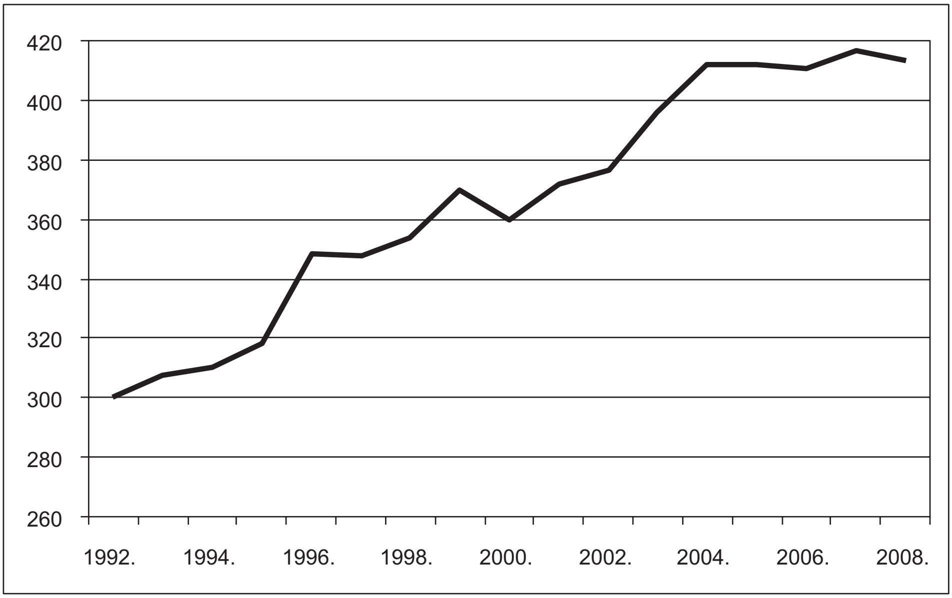
4. Empirical results

The empirical analysis consists of two parts. In the first part we have chosen representative forecasting model for total energy consumption and calculated forecasts up to 2014 (aggregated forecasting). In the second part we calculated forecasts of total energy consumption with the indirect method. Forecast values for all variables components are determined with the representative model. In the end, forecast values of variables components are summarised and compared with the same forecast values determined in the first part of the analyses. In selecting the appropriate forecasting approach we used qualitative (subjective, judgemental) criteria and forecasting errors as quantitative criteria.

The first part of model building process is model identification. It means the determination whether the series is stationary. The unit root tests, Dickey-Fuller and Augmented Dickey-Fuller tests are conducted. Those results are used to identify the order of integration for the variable total energy consumption (TEC) in Croatia. Then follow an ARIMA model selection using Box-Jenkins approach. The forecast values are calculated directly from the form of the fitted model (Hanke and Wichern, 2009).

Figure 1

TOTAL ENERGY CONSUMPTION (TEC) IN CROATIA
(EXPRESSED IN PETAJOULE)



Source: http://www.dzs.hr

The time series shown in figure 1 indicates the presence of an upward trend in total energy consumption in Croatia for the observed period. So the Croatia's total energy consumption (TEC) under the observed period has the characteristics of nonstationarity. The same conclusion is made by analyzing the correlogram, and is based on the results of Ljung-Box test.[3]

To eliminate the nonstationarity of the time series, the first differences were calculated. On the results of the unit root tests, Dickey-Fuller and Augmented Dickey-Fuller tests has been found that the series of first differences is stationary[4]. It is concluded that the time series of total energy consumption in Croatia is integrated order of 1; $I(1)$.

Stationarity was also noticed from the Sample Autocorrelation Function (SACF) and Sample Partial Autocorrelation Function (SPACF) for time series

[3] Results are available from the authors upon request.

[4] p-value is less than the significance level $\alpha = 0{,}05$. ADF test results are available from the authors upon request.

of the first differences of total energy consumption[5]. Both of the functions have a tendency to decrease. In the identification phase, the initial models were chosen: ARIMA(1,1,0) and ARIMA(1,1,1) with estimated parameters, as shown in tables 1 and 2.

Table 1

ARIMA(1,1,0) MODEL FOR THE CROATIA'S TOTAL ENERGY CONSUMPTION

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	452,4773	77,73031	5,821119	0
AR(1)	0,920802	0,063305	14,54558	0
R-squared	0,937936	Mean dependent var		370,2412
Adjusted R-squared	0,933503	S.D. dependent var		37,7843
S.E. of regression	9,743446	Akaike info criterion		7,507535
Sum squared resid	1329,086	Schwarz criterion		7,604109
Log likelihood	-58,06028	F-statistic		211,5739
Durbin-Watson stat	2,398034	Prob(F-statistic)		0

Source: Authors' calculations (in EViews 5.0)

ARIMA(1,1,0) with the backward shift operator can be expressed:

$$(1-0,92B)(1-B)Y_t = \varepsilon_t \tag{2}$$

p-value for the AR parameter is 0,0000 which means that the AR parameter is significant in the observed model at the level of significance 5%. It is known that the AR (p) process has the property of invertibility by definition; therefore it is not necessary to examine the conditions for satisfying this property. AR (p) process is stationary if it has MA (q) representation, or an AR(1)process is stationary if $|\phi| < 1$. In table 1 the AR parameter is $\phi = 0,92$ which is less than 1. This means that the ARIMA model satisfies the property of stationarity. ARIMA(1,1,1) with the backward shift operator can be expressed:

[5] Results are available from the authors upon request.

$$(1-0,935B)(1-B)Y_t = (1-0,940B)\varepsilon_t \tag{3}$$

Table 2

ARIMA(1,1,1) MODEL FOR THE CROATIA'S
TOTAL ENERGY CONSUMPTION

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	487,1824	46,27584	10,52779	0.0000
AR(1)	0,935301	0,025053	37,33249	0.0000
MA(1)	-0,940203	0,056029	-16,78054	0.0000
R-squared	0,959462	Mean dependent var		370,2412
Adjusted R-squared	0,953225	S.D. dependent var		37,7843
S.E. of regression	8,171812	Akaike info criterion		7,206619
Sum squared resid	868,1206	Schwarz criterion		7,351479
Log likelihood	-54,65295	F-statistic		153,842
Durbin-Watson stat	1,623505	Prob(F-statistic)		0

Source: Authors' calculations (in EViews 5.0)

The AR (1) and MA(1) parameters are significant in the observed model (at the 5% level of significance), since *p*-values for all parameters is equal to 0.0000. As AR and MA parameters are less than 1, this means that the ARIMA(1,1,1) model has the property of stationarity and invertibility. At the phase of model checking, the following criteria are used: adjusted R square ($\bar{R}^2$), residual sum of squares (RSS) and information criteria. Since the model is used for forecasting purposes, to select the most appropriate model, measures of predictive efficiency can also be used. Forecasting errors that are often compared are: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and Mean Absolute Error (MAE), as can be seen in table 3.

Table 3

COMPARISON OF CRITERIA FOR ARIMA(1,1,0)
AND ARIMA(1,1,1) MODELS

Criteria	ARIMA(1,1,0)	ARIMA(1,1,1)
$\bar{R}^2$	0,933503	0,953225
SR	1329,086	868,1206
AIC	7,507535	7,351479
RMSE	9,320695	9,598116
MAPE	2,242391	2,192870
MAE	8,164889	7,836630

Source: Authors' calculations (in EViews 5.0)

The measures of representativeness that were used in models evaluation and in selection the representative model are presented in table 3. Between those two models, ARIMA(1,1,0) and ARIMA(1,1,1), there are very small differences when we take into account the adjusted R square and Akaike information criterion ($\bar{R}^2$ is slightly larger and *AIC* is slightly smaller for ARIMA(1,1,1) than for ARIMA(1,1,0). If we compare the predictive efficiency of models, MAPE and MAE are smaller for ARIMA(1,1,1) model, while RMSE is slightly greater than the RMSE for the ARIMA(1,1,0) model[6].

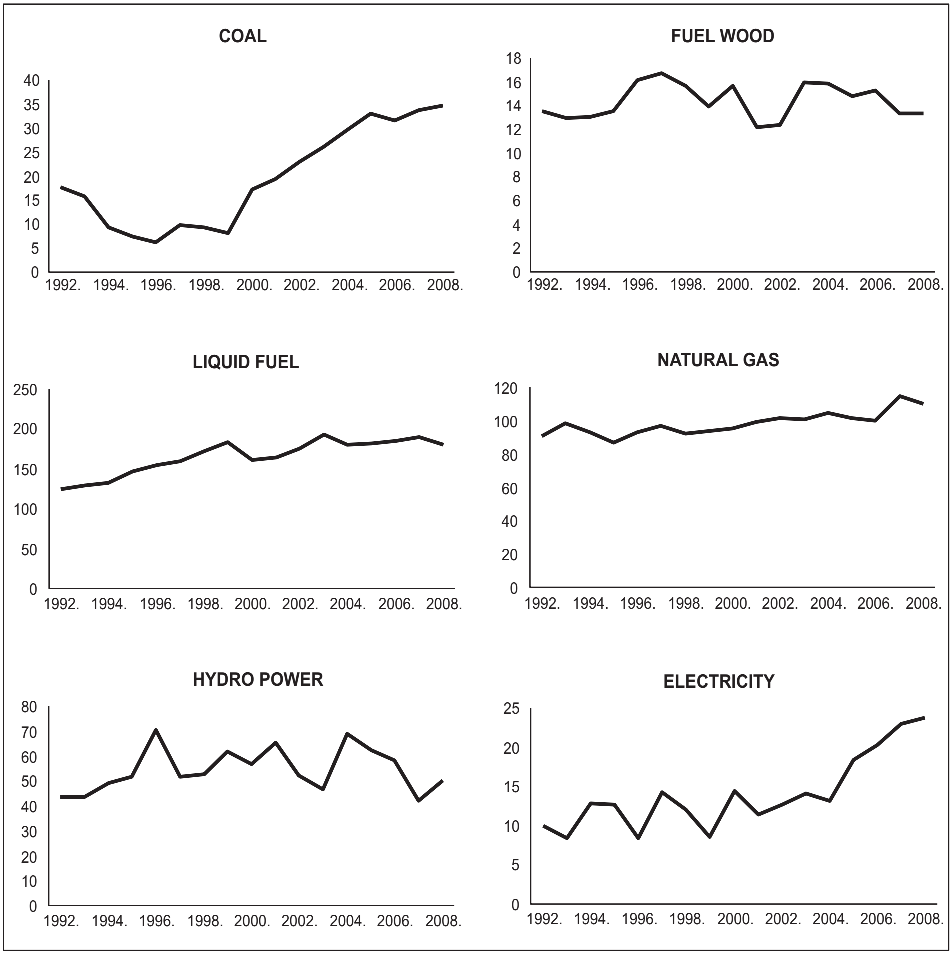
It can be seen that on the basis of criteria presented in table 3 it is difficult to draw conclusions on the selection of the final model. Although, looking at the values of selected criteria, more of them are in favour of the ARIMA(1,1,1) model. But differences are almost minimal. As the art of selecting the model depends on experience and the ability of analysts, we decided to employ both models in forecasting future values of total energy consumption. It was direct approach in forecasting aggregated time series of Croatia's total energy consumption. Further, indirect approach in determining forecast values is applied (as mentioned above).

The time series shown in Figure 2 represents the original values of variables components of the total energy consumption in Croatia for the period 1992 - 2008.

[6] In the selected models, there is no residual autocorrelation up to the fourteenth lag.

Figure 2

ENERGY CONSUMPTION IN CROATIA (EXPRESSED IN PETAJOULE)



Source: http://www.dzs.hr

Figures of original values of fuel wood, natural gas and hydro power indicate the possible stationarity of these time series. Therefore, in the case of this series it won't be necessary to make the first differences. On the other hand, the figures of the original value of coal, liquid fuels and electricity show just the opposite. On these figures the presence of an upward trend can be observed and in accordance with this we can conclude that these time series have the characteristics of nonstationarity and in their case it will be necessary to implement the operator of differentiation in order to obtain the desired stationarity as in the case of time series of fuel wood, natural gas and hydro power.

Using unit root tests[7], which represent a very useful tool for determining the order of integration of the observed time series, we confirmed the previous conclusions. It is concluded that the time series of fuel wood, natural gas and hydro power in Croatia is integrated order of 0; $I(0)$. On the other hand, to eliminate the nonstationarity of the time series of coal, liquid fuel and electricity, the first differences[8] were calculated. For time series of liquid fuel and electricity a series of first differences are calculated and it has been found to be [9]stationary. It is concluded that those time series are integrated order of 1, $I(1)$. For time series of coal a series of second differences is calculated and only then it has been found to be stationary[10]. In the phase of model identification, for each component of total energy consumption, models with estimated parameters were chosen as it can be seen as follows.

In table 4 the results of model estimation and model checking for the appropriate, representative forecasting model of coal are presented[11]. The ARIMA(1,2,2) model has property of stationarity and invertibility.

Table 4

ARIMA(1,2,2) MODEL FOR COAL:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	97,21246	1181,204	0,082299	0,9358
AR(1)	0,991445	0,128868	7,693504	0,0000
MA(1)	0,552453	0,326479	1,692156	0,1164
MA(2)	-0,442987	0,287142	-1,542742	0,1488
R-squared	0,896904	Mean dependent var		19,63875
Adjusted R-squared	0,871130	S.D. dependent var		10,64156
S.E. of regression	3,820153	Akaike info criterion		5,730776
Sum squared resid	175,1229	Schwarz criterion		5,923923

[7] ADF test results are available from the authors upon request

[8] Results are available from the authors upon request.

[9] p-value is less than the significance level $\alpha = 0,05$. ADF test results are available from the authors upon request.

[10] Stationarity was also noticed from the Sample autocorrelation function (SACF) and Sample partial autocorrelation function (SPACF). Results are available from the authors upon request.

[11] Testing was conducted at the significance level $\alpha = 15\%$.

Log likelihood	-41,84621	F-statistic	34,79888
Durbin-Watson stat	2,080340	Prob(F-statistic)	0,000003
Inverted AR Roots	,99		
Inverted MA Roots	,44	-1,00	

Source: Authors' calculations (in EViews 5.0)

In table 5 the results of model estimation and model checking for the appropriate, representative forecasting model of fuel wood are presented. The chosen model is ARIMA(0,0,1).

Table 5

ARIMA (0,0,1) MODEL FOR FUEL WOOD

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14,36279	0,492263	29,17708	0,0000
MA(1)	0,514352	0,223726	2,299030	0,0363
R-squared	0,174349	Mean dependent var		14,37059
Adjusted R-squared	0,119306	S.D. dependent var		1,445409
S.E. of regression	1,356448	Akaike info criterion		3,557747
Sum squared resid	27,59928	Schwarz criterion		3,655772
Log likelihood	-28,24085	F-statistic		3,167484
Durbin-Watson stat	2,087294	Prob(F-statistic)		0,095381
Inverted MA Roots	-,51			

Source: Authors' calculations (in EViews 5.0)

Based on Table 5 it can be concluded that the selected model satisfies the property of invertibility. MA parameter is $\theta = 0{,}514$ wich is less than 1 and thus confirms the conclusion that the ARIMA model satisfies the property of invertibility. As the MA (*q*) process by its definition is always stationary, it is not necessary to examine this property.

In the identification phase, two ARIMA models for time series of liquid fuel are chosen. They are the same as the models selected as representative for the total energy consumption: ARIMA(1,1,0) and ARIMA(1,1,1). It was expected because liquid fuel was 44% of total energy consumption in 2008. The results of model estimation and model checking for both models are presented in table 6 and table 7, as follows.

Table 6

ARIMA(1,1,0) MODEL FOR LIQUID FUEL

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	180,2100	13,94573	12,92223	0,0000
AR(1)	0,782184	0,114095	6,855528	0,0000
R-squared	0,770485	Mean dependent var		167,7850
Adjusted R-squared	0,754091	S.D. dependent var		19,66320
S.E. of regression	9,750817	Akaike info criterion		7,509048
Sum squared resid	1331,098	Schwarz criterion		7,605621
Log likelihood	-58,07238	F-statistic		46,99827
Durbin-Watson stat	2,180288	Prob(F-statistic)		0,000008
Inverted AR Roots	,78			

Source: Authors' calculations (in EViews 5.0)

AR parameter is $\phi = 0{,}782$. It is less than 1. In accordance with this it can be concluded that ARIMA(1,1,0) satisfies the property of stationarity. Considering that the AR(p) process is always invertible by its definition this means that the ARIMA(1,1,0) model has property of both stationarity and invertibility.

Table 7

ARIMA(1,1,1) MODEL FOR LIQUID FUEL

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	185,9013	4,324740	42,98554	0,0000
AR(1)	0,794549	0,047605	16,69045	0,0000
MA(1)	-0,968076	0,058576	-16,52684	0,0000
R-squared	0,881957	Mean dependent var		167,7850
Adjusted R-squared	0,863797	S.D. dependent var		19,66320
S.E. of regression	7,256846	Akaike info criterion		6,969128
Sum squared resid	684,6035	Schwarz criterion		7,113989
Log likelihood	-52,75303	F-statistic		48,56476
Durbin-Watson stat	1,917723	Prob(F-statistic)		0,000001
Inverted AR Roots	,79			
Inverted MA Roots	,97			

Source: Authors' calculations (in EViews 5.0)

AR parameter is ϕ = 0,794 and MA parameter is θ = 0,968 and based on this, it can be conclude that ARIMA(1,1,1) model also satisfies both properties as well as the ARIMA(1,1,0). At the values of selected criteria in model checking, the ARIMA(1,1,1) model has better characteristics and smaller forecasting errors.

The same procedure of model identification, model estimation and model checking is conducted for the time series of natural gas. The chosen model is ARIMA (1,0,0). Results are presented in table 8.

Table 8

ARIMA (1,0,0) MODEL FOR NATURAL GAS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	101,6742	5,404736	18,81206	0,0000
AR(1)	0,702917	0,215184	3,266593	0,0056
R-squared	0,432524	Mean dependent var		98,76250
Adjusted R-squared	0,391990	S.D. dependent var		6,851004
S.E. of regression	5,342072	Akaike info criterion		6,305573
Sum squared resid	399,5283	Schwarz criterion		6,402147
Log likelihood	-48,44458	F-statistic		10,67063
Durbin-Watson stat	2,048979	Prob(F-statistic)		0,005624
Inverted AR Roots	,70			

Source: Authors' calculations (in EViews 5.0)

For time series of natural gas, selected ARIMA model also has the property of stationarity and invertibility, AR parameter is $\phi = 0{,}702$ which is less than 1.

For the time series of hydro power, the selected model is ARIMA (2,0,1). Model caracteristics are in table 9.

Table 9

ARIMA (2,0,1) FOR HYDRO POWER

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	57,22242	0,290945	196,6781	0,0000
AR(1)	0,219516	0,286429	0,766390	0,4596
AR(2)	-0,539078	0,222270	-2,425329	0,0337

MA(1)	-0,941778	0,033846	-27,82504	0,0000
R-squared	0,551779	Mean dependent var		56,04000
Adjusted R-squared	0,429537	S.D. dependent var		8,320482
S.E. of regression	6,284380	Akaike info criterion		6,737190
Sum squared resid	434,4277	Schwarz criterion		6,926003
Log likelihood	-46,52892	F-statistic		4,513817
Durbin-Watson stat	2,253114	Prob(F-statistic)		0,026901
Inverted AR Roots	,11	,11		
Inverted MA Roots	,94			

Source: Authors' calculations (in EViews 5.0)

Model ARIMA(2,0,1) will satisfy the property of stationarity if the AR parameters are $\phi_1 + \phi_2 < 1$ and the property of invertibility if the MA parameter is $|\theta|$ < 1. In table 9 is 0,219 + 0,538 = 0,758 < 1 and 0,94 < 1 it brings us to the conclusion that this model satisfies the property of stationarity and invertibility.

The same procedure is conducted for the time series of electricity. The chosen model is ARIMA (1,1,0). Results are presented in table 10.

Table 10

ARIMA(1,1,0) MODEL FOR ELECTRICITY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18,64613	8,581697	2,172779	0,0475
AR(1)	0,837747	0,210549	3,978865	0,0014
R-squared	0,530695	Mean dependent var		14,24125
Adjusted R-squared	0,497174	S.D. dependent var		4,763769
S.E. of regression	3,378000	Akaike info criterion		5,388914
Sum squared resid	159,7524	Schwarz criterion		5,485487
Log likelihood	-41,11131	F-statistic		15,83137
Durbin-Watson stat	2,580774	Prob(F-statistic)		0,001372
Inverted AR Roots	,84			

Source: Authors' calculations (in EViews 5.0)

As AR parameters in model is less than 1, this means that the ARIMA(1,1,0) model has the property of stationarity and invertibility, because AR process by its definition is always invertible. In table 11 selected representative models for six components of total energy consumption are presented.

Table 11

FORECASTING MODELS

Energy consumption category	Models
Coal	ARIMA (1,2,2)
Fuel wood	ARIMA (0,0,1)
Liquid fuel	ARIMA (1,1,1)
Natural gas	ARIMA (1,0,0)
Hydro power	ARIMA (2,0,1)
Electricity	ARIMA (1,1,0)
Total energy consumption	ARIMA (1,1,1)

Source: Authors' calculations and conclusions

For six variables component of total energy consumption, different forecasting models are chosen as representative. If we summarise the forecast values (derived using selected appropriate models for all variables component) the forecast values for the total energy consumption can be calculated. The indirect approach produces different forecast values than if we use direct method (mentioned above). Forecast value derived using two different approaches are presented in table 12 and shown in figure 3.

Table 12

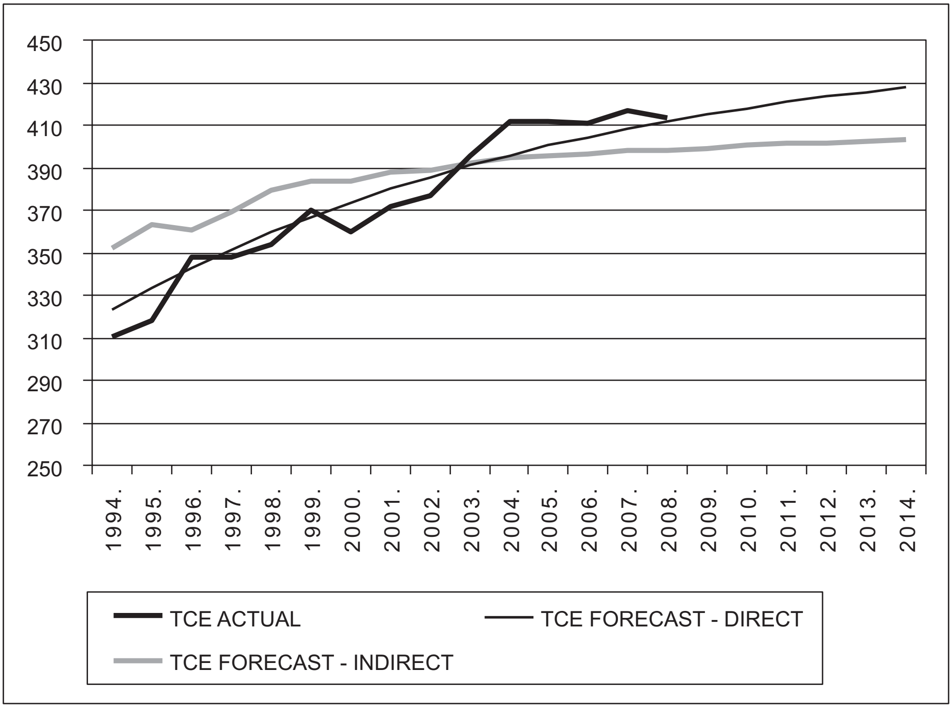
FORECAST VALUE (DIRECT AND INDIRECT APPROACH)
OF CROATIA'S TOTAL ENERGY CONSUMPTION

Year	Forecast value, Pj (direct approach)	Forecast value, Pj (indirect approach)
2009	*414,9946*	*399,26681*
2010	*417,9632*	*400,33074*
2011	420,6966	401,12104
2012	423,2136	401,81052
2013	425,5313	402,51481
2014	427,6653	403,21500

Source: Authors' calculations (in EViews 5.0)

Figure 3

ACTUAL AND FORECAST VALUE OF TIME SERIES VARIABLE TOTAL ENERGY CONSUMPTION IN CROATIA (IN PETAJOULES), DIRECT AND INDIRECT APPROACH



Source: Authors' calculations

5. Concluding remarks

In our research, two ARIMA models are selected as representative for forecasting total energy consumption: ARIMA (1,1,0) and ARIMA (1,1,1). The same models are chosen for time series liquid fuel, because the liquid fuel is dominant in total energy consumption (44% in year 2008). If we include in planning and forecasting Croatia's total energy consumption the judgmental approach, in conditions in which their economy will be in the next two or more years (high energy prices and insufficient orientation to renewable energy sources and prediction of the recession conditions in the next three years) the selected model is ARIMA(1,1,0).

In accordance with this, the ARIMA(1,1,0) will be more appropriate forecasting model than the model ARIMA(1,1,1) because it predicts a slightly lower level of total energy consumption in Croatia up to 2014, but ARIMA(1,1,1) model have "better" measures of representativeness, as could be seen in table 3.

It can be concluded that the forecast values calculated directly or indirectly are not the same values. Differences are consequence of applied different (representative) forecasting models for the different time series of variables components of total energy consumption. The pattern is determined with the model which is chosen as representative forecasting model of time series of dominant component (liquid fuel) and their relative part in total energy consumption. On the basis of results presented in the paper all of tree hypotheses defined above, can be accepted. Forecasting models are based on different methodological ground, so forecast values are not the same. The forecast will be similar only if the structure of total energy consumption remains unchanged all over the forecasting period, because the selected representative forecasting model of the dominant component in total energy consumption is the same as the model of the total energy consumption (aggregated series). By reducing the relative share of liquid fuels (as the dominant component, with 44% in 2008) in Croatia's total energy consumption, the predictive values of the total energy consumption calculated using the indirect forecasting method will be smaller than those obtained by the direct method.

In accordance with the characteristics of Croatia's economic situation and expectation, the indirect approach which forecasts lower total energy consumption is preferred. This conclusion is based primarily on subjective expectations and judgments. Preferring indirect approach is in a compliance with the conclusion of expectation of continuing recession period in Croatia up to 2014 (on intuition and judgement). If the structure of Croatia's total energy consumption remains unchanged in forecasting period up to 2014, it is convenient to use the direct approach. From the statistical and methodological point of view, direct approach is preferred, because forecast errors (MAD, MAPE, MSE and RMSE) in this approach are smaller than the same errors calculated using indirect method. Finally, successful forecast can be made as a combination of qualitative and quantitative criteria in selection of convenient forecasting and predicting methods and models.

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IZRAVNI I NEIZRAVNI PRISTUP U PREDVIĐANJU UKUPNE POTROŠNJE ENERGIJE U HRVATSKOJ

Sažetak

U prognoziranju agregiranih vremenskih serija koristimo se različitim pristupima. Cilj je ovoga rada analizirati i prognozirati agregiranu vremensku seriju ukupne potrošnje energije u Hrvatskoj do 2014. Box-Jenkins metodologijom primjenom dvaju pristupa: direktni i indirektni. Prognostičke vrijednosti izračunate su indirektno agregiranjem prognostičkih vrijednosti koje su utvrđene (različitim reprezentativnim prognostičkim modelima) za svaku varijablu komponentu agregirane vremenske serije. Komponente ukupne potrošnje energije u Hrvatskoj su: potrošnja ugljena, ogrjevnog drva, tekućih goriva, prirodnog plina, energije vode i električne energije. Direktni pristup u prognoziranju znači da se prognostičke vrijednosti određuju direktno primjenom prikladnog prognostičkog modela na agregiranu vremensku seriju. U prognoziranju hrvatske ukupne potrošnje energije ARIMA (1,1,1) model je odabran kao reprezentativan. Isti model izabran je i za prognoziranje dominantne varijable u ukupnoj potrošnji energije: tekuća goriva. Razlike u prognostičkim vrijednostima ukupne potrošnje energije izračunate direktno ili indirektno, posljedica su primjene različitih (reprezentativnih) prognostičkih modela za različite vremenske serije komponenti ukupne potrošnje energije. S metodološkog (statističkog) stanovišta, preferira se direktni pristup, ali u skladu s očekivanim nastavkom recesijskog razdoblja u Hrvatskoj u slijedeće dvije godine, prognostičke vrijednosti ukupne potrošnje energije izračunate indirektnim pristupom su realističnije nego one izračunate direktnim pristupom.

Ključne riječi: prognoziranje, agregirana vremenska serija, ukupna potrošnja energije, stacionarnost, Box-Jenkins pristup, ARIMA model, ADF test.