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## A HYBRID FORECASTING APPROACH

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### Abstract

The objective of the paper is to establish the appropriateness of integrating in predictive simulation an econometric estimation of a given variable into a standard moving average process (a linear algorithm with constant positive weights of distributed lags). The empirical search relates to the Romanian input-output tables collapsed into ten sectors. The database concerning the final output during 1989-2009 years is herein analyzed.

**Keywords:** final output extrapolation, hybrid approach.

**JEL Classification:** C53, C67

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### Introduction

The last decades are characterized by an increasing research interest for modelling simulations based on joint use of several technical methods. An extended literature reveals the potential advantages and general principles of combining prognoses (Armstrong, 2001; Elliott, 2011; Simionescu, 2013), and also the possible procedures applicable in pursuing such a goal (Winkler and Clemen, 1992; Armstrong, 2001; Ravazzolo et al., 2007; Pilatowska, 2009; Koop and Korobilis, 2010; Bruno and Stevenson, 2012). The so-called consensus forecasting (Gregory et al., 2001; Schirm, 2003; Gregory and Yetman, 2004; Ager et al., 2007) relates to the same methodological mainstream.

Our intention is to empirically establish the appropriateness of integrating in predictive simulation an econometric estimation of a given variable (EE) into a standard moving average process (MA). By „standard” we mean a linear algorithm with constant positive weights of distributed lags, the sum of these weights being equal to unity. Conventionally, the moving average is called ‘simple’ when the corresponding weights are identical.

1. Two developments of the practical modelling post-sample simulations have inspired the present attempt.

On one hand, the moving average extrapolations tend quickly enough to stabilize the forecasted outcomes around a „frozen” level, or trend. Such a „robustness” frequently contrasts with the usual instability intrinsic to original statistical series.

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On the other hand, the econometric relationships (independently on chosen specification or adopted computational technique) often provide relatively volatile outcomes for the future. In this way, the dynamic pattern of the primary database would be reflected more faithfully, but the resulting fluctuations could exceed reliable limits. Such a risk remains significant even under the simplified procedure of using fixed estimators (ignoring, therefore, the intervals induced by their standard deviations).

Starting from these somehow symmetrical features of standard moving average and econometric estimations, we are trying to joint them into a hybrid algorithm. Since its unique goal relates the post-sample extrapolations, the colinearities which can consequently appear do not seem to have „unbearable” disturbing effects.

2. According to such an approach, the last term included into moving average is represented by the corresponding econometric estimation for  $t$ . An elementary formalization can be obtained using (as a general notation for any series  $z$ ) the symbols:

$z_t^*$  - the extrapolated value for  $t$  resulted from a moving average of  $m$  consecutive terms,

$ez_t$  - the econometric estimation for  $t$ ,

$w_k$  ( $i=1, \dots, m$ ) – the apriori established weights, in which  $m$  corresponds to the first term included into moving average and 1 to the last one; it is assumed that  $0 \leq w_k \leq 1$ , respectively  $\sum w_k = 1$ .

Our proposal, therefore, reduces to the relationship:

$$z_t^* = \sum w_k * z_{t-k+1}^* + w_1 * ez_t, \text{ in which } j=2, \dots, m \quad (1)$$

Normally, the first  $m$  post-sample extrapolated values involve mixed – statistical and estimated – data.

3. The empirical search relates to the Romanian input-output tables collapsed into ten sectors (the codes used hereafter are mentioned within parenthesis), namely: i) agriculture, forestry, hunting and fishing (1); ii) mining and quarrying (2); iii) production and distribution of electric and thermal power (3); iv) food, beverages and tobacco (4); v) textiles, leather, pulp and paper, and furniture (5); vi) machinery and equipment, transport means and other metal products (6); vii) other manufacturing industries (7); viii) constructions (8); ix) transports and post and telecommunications (9); and x) trade, business and public services (10). Such a classification was described by Dobrescu and Gafta (2012).

The application targets the database for the final output ( $NY = \sum NY_i$ ,  $i=1, 2, \dots, 10$ ), during 1989-2009 years. We prompt that  $NY_i$  is the surplus of production ( $Q_i$ ) over the deliveries of the respective sector for intermediate consumption of the entire economy. Hence,  $NY_i = Q_i - \sum a_{ij} Q_j$ ,  $i=\text{fixed}$ ;  $a_{ij}$  are the well-known technical I-O coefficients. As newly created resources,  $NY$  is estimated in basic prices (as the production itself), and under restriction of the null foreign trade balance (due to this computational convention, algebraically  $NY_i$  can be positive or negative).

Our concrete analysis concerns the sectorial weights of the final output ( $w_{ny_i} = NY_i / NY$ ), according to National Commission for Prognosis (2013) and Dobrescu (2013, Annex 1). Evidently,  $\sum w_{ny_i} = 1$ .

4. Seven extrapolating procedures have been experimented.

4.1. Three of them are centered on standard moving average technique. This is applied in its simple (SMA) and Fisher (FMA) forms (see Fisher, 1937; Wit, 1998; Maddala, 2001; Jula and Jula, 2012). The Fisher distribution has been limited at 12 terms, taking into account that the assigned share - with the 13-th backward observation – becomes insignificant (lower than 1%). Consequently, the number of terms involved in the simple moving average was restrained again to 12.

In the case of the Fisher moving average, both possible variants are searched:

- as FMAc, in which the number of included terms is identic (12) for all ten series  $w_{ny_i}$ , and
- as FMAv, in which this number varies (between 2-12) for different sectors, based on the methodology described in Dobrescu (2013).

4.2. The specification adopted in this paper (system SySw) is also used for econometric estimations ( $w_{ny_i,e}$ ). As such, this specification refers to the first order differences  $d(w_{ny_i})$ , from which the preliminary  $p_{wny_i}$  are obtained ( $p_{wny_i}=d(w_{ny_i})+w_{ny_i}(-1)$ ). The multiplier  $\omega=1/\sum p_{wny_i}$  is then introduced, as a corrective parameter. Consequently, the searched values  $w_{ny_i,e}=\omega * p_{wny_i}$  observe the compulsory restriction  $\sum w_{ny_i,e}=1$ .

4.3. Three hybrid procedures additionally yield by incorporating the econometric estimations into the simple moving average (SMA-EE), the Fisher moving average with identic number of terms (FMAc-EE), and the Fisher moving average with variable number of terms (FMAcv-EE).

4.4. All these procedures are synthetically described in the Table 1.

**Table no. 1. Main characteristics of the computational procedures**

<b>Computational procedure</b>	<b>Number of included terms (m)</b>	<b>Weights of included terms (<math>w_k</math>)</b>	<b>Symbol of extrapolated series <math>i=1, \dots, 10</math></b>
Simple moving average (SMA)	Identic (12) for all series	Constant=1/m	$w_{ny_i,s}$
Fisher moving average with identic m (FMAc)	Identic (12) for all series	Fisher distribution	$w_{ny_i,cf}$
Fisher moving average with variable m (FMAv)	Variable (2-12) for different series	Fisher distribution	$w_{ny_i,vf}$
Econometric estimation (EE)			$w_{ny_i,e}$
Hybrid SMA-EE	Identic (12) for all series	Constant 1/m	$w_{ny_i,se}$
Hybrid FMAc-EE	Identic (12) for all series	Fisher distribution	$w_{ny_i,cfe}$
Hybrid FMAv-EE	Variable (2-12) for different series	Fisher distribution	$w_{ny_i,vfe}$

5. The post-sample extrapolations will be examined in relation with statistics for an entire computational cycle (equal to the number of sample observations, namely 21 in our

application). The comparison will concern main descriptive statistics, respectively mean, median, maximum, minimum, standard deviation, skewness, and kurtosis. Their values for the primary database are presented in Table 2.

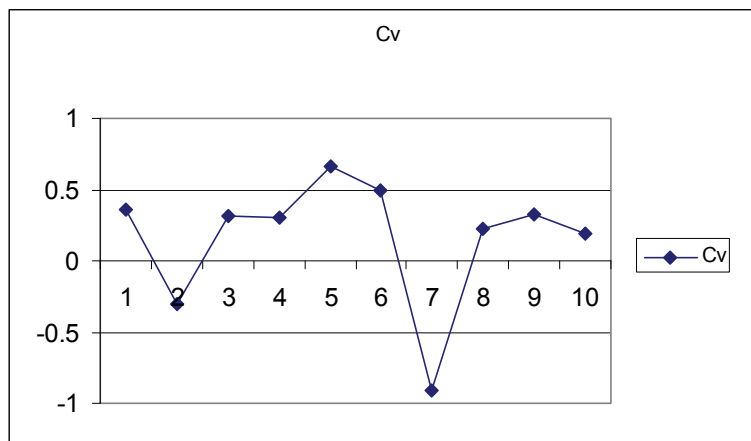
**Table no. 2. Descriptive statistics of primary wny<sub>i</sub> series**

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wWny1	0.121703	0.122762	0.192613	0.048262	0.044148	-0.237729	1.839381
wWny2	-0.033544	-0.029894	-0.021618	-0.058376	0.010061	-1.12155	3.224054
wWny3	0.02054	0.021493	0.032751	0.004601	0.006573	-0.750332	3.379687
wWny4	0.099896	0.101425	0.150968	0.053667	0.030505	0.100558	1.791457
wWny5	0.048312	0.035899	0.147187	0.017935	0.032136	1.844426	5.718006
wWny6	0.066253	0.056554	0.150087	0.02339	0.032671	1.251806	3.882668
wWny7	-0.032371	-0.031657	0.033051	-0.072506	0.029399	0.618976	2.449654
wWny8	0.132128	0.120787	0.203408	0.097833	0.02984	1.156884	3.174897
wWny9	0.100455	0.118364	0.127652	0.030189	0.033068	-1.049881	2.428623
wWny10	0.47663	0.521259	0.568862	0.313964	0.08939	-0.595452	1.87583

The robustness of extrapolated series and their degree of similarity to the primary database will be the main perspectives of our following analysis.

6.1. The first can be approximated by the coefficient of variation (Cv), computed as a ratio of the standard deviation to corresponding mean. This is plotted on Graph Cv (Figure 1) for the sample series wny<sub>i</sub>.

**Figure no. 1. Graph Cv**



Hence, in module, the coefficient of variation oscillates between 0.3-0.4 in four cases (wny1, wny3, wny4, wny9), exceeds 0.4 in other three (wny5, wny6, wny7), and is situated below 0.3 in the rest (wny2, wny8, wny10).

6.2. Regarding the similarity degree of extrapolated series to the primary database, the correlation coefficient (Galtung-Pearson and Spearman rank order) will be involved, as a simple and easily interpretable measure.

7. The rest of our work is structured as follows: the second section describes the post-sample extrapolations obtained by the standard moving average and econometric estimations, when these procedures are applied as separate methods. The third extends the analysis on the results of their combination. Some concluding remarks are exposed in the final part of the paper.

**Standard Moving Average and Econometric Estimation as Separate Procedures**

As we have already mentioned, the attention will be focused on the first cycle of extrapolations (21 successive post-sample levels). In this case, the same statistical properties as primary database will be taken into consideration.

1. Table 3 details the results obtained by using the standard moving average, in its three variants: SMA, FMAc, and FMAv.

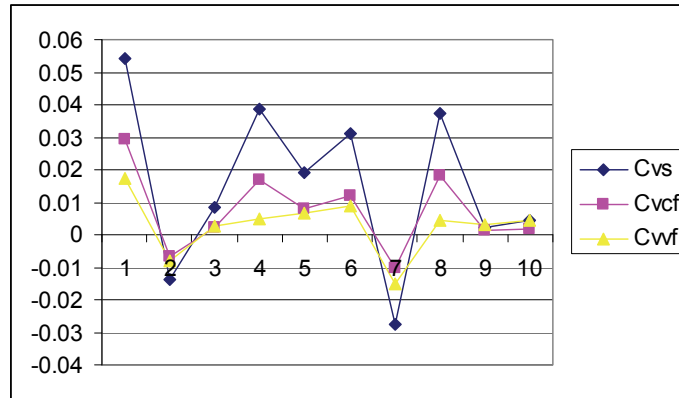
**Table no. 3. Descriptive statistics of wny(i) extrapolated by standard moving average**

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wWny1s	0.086574	0.085196	0.098373	0.080993	0.004702	1.146588	3.457578
wWny2s	-0.02936	-0.02952	-0.0283	-0.02978	0.000409	1.456776	4.248407
wWny3s	0.02282	0.022832	0.023235	0.022302	0.000197	-0.50632	4.187443
wWny4s	0.070534	0.069506	0.079142	0.068034	0.00274	1.945221	6.188191
wWny5s	0.031902	0.031833	0.033159	0.030889	0.000606	0.434681	2.654521
wWny6s	0.051871	0.052425	0.053354	0.047123	0.001604	-1.98515	6.008068
wWny7s	-0.05799	-0.05859	-0.05256	-0.05961	0.001602	2.22154	7.637913
wWny8s	0.149649	0.151527	0.157132	0.136057	0.005609	-1.0701	3.377466
wWny9s	0.121835	0.121807	0.122293	0.12119	0.000277	-0.30085	3.14117
wWny10s	0.552169	0.553096	0.55519	0.545123	0.002369	-1.44235	4.879516
wWny1cf	0.077871	0.076986	0.084856	0.076013	0.002281	2.020415	5.999458
wWny2cf	-0.03014	-0.03022	-0.02952	-0.03028	0.0002	2.071513	6.216038
wWny3cf	0.022856	0.02284	0.022956	0.02279	4.79E-05	0.974106	2.903264
wWny4cf	0.065883	0.065482	0.069628	0.065118	0.001109	2.407046	7.88214
wWny5cf	0.031446	0.03133	0.031999	0.031172	0.000258	1.088335	2.722804
wWny6cf	0.054589	0.054824	0.05504	0.052401	0.000647	-2.44756	8.019961
wWny7cf	-0.06065	-0.06088	-0.05851	-0.06108	0.000622	2.460944	8.25588
wWny8cf	0.160515	0.161707	0.162812	0.151816	0.002901	-1.94297	5.681035
wWny9cf	0.121426	0.121368	0.121748	0.121256	0.000141	1.142166	3.224672
wWny10cf	0.556203	0.556581	0.557072	0.552957	0.001024	-2.07766	6.394435
wWny1vf	0.066677	0.066351	0.071049	0.065802	0.001168	2.954083	10.96927
wWny2vf	-0.03044	-0.03052	-0.02955	-0.0306	0.000239	2.88314	10.54253
wWny3vf	0.022489	0.022491	0.022587	0.022274	5.75E-05	-2.28676	10.89892
wWny4vf	0.060307	0.060233	0.061389	0.059997	0.000297	2.674204	9.975144

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wWny5vf	0.031012	0.03094	0.031466	0.030797	0.000205	1.223308	3.245164
wWny6vf	0.056105	0.05626	0.056398	0.054259	0.000502	-2.89449	10.38707
wWny7vf	-0.05985	-0.06016	-0.0567	-0.06044	0.000893	2.584227	8.909055
wWny8vf	0.184009	0.183899	0.187372	0.183274	0.00081	3.583893	15.68
wWny9vf	0.119286	0.119372	0.119601	0.117852	0.000368	-3.12712	12.42025
wWny10vf	0.550408	0.551149	0.551747	0.541248	0.002387	-3.09758	11.80493

1.1. The corresponding coefficients of variation are sketched on the Graph CvM (Figure 2).

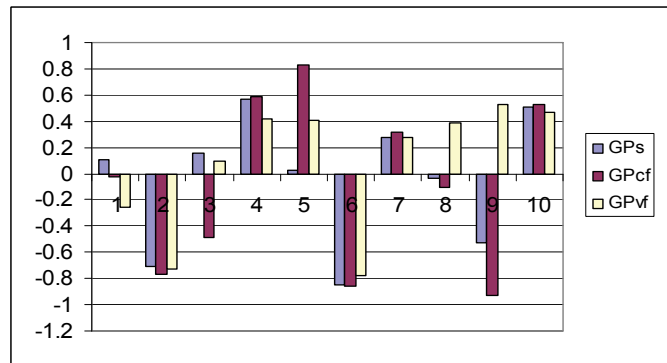
Figure no. 2. Graph CvM



As opposed to the recorded statistics, all the moving average schemes reduce considerably the coefficient of variation even during the first cycle of extrapolations.

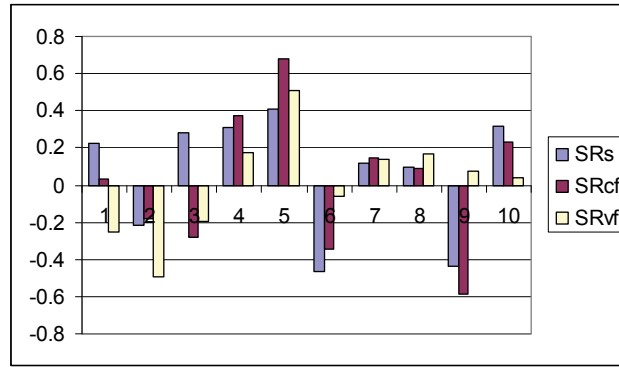
1.2. This is accompanied with a clear deviation of extrapolated series from the pattern of primary database, which is illustrated by the Galtung-Pearson correlation, presented in the Graph CorMGP (Figure 3).

Figure no. 3. Graph CorMGP



The Spearman rank order correlation consolidates this statement (Graph CorMSR in Figure 4).

Figure no. 4. Graph CorMSR



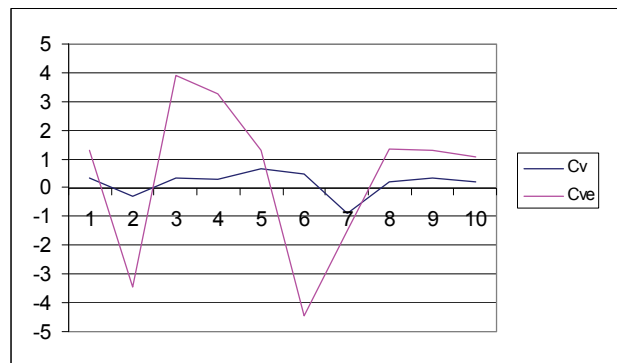
2. The econometric estimations generate significantly different results. The main properties of the post-sample extrapolated series (first cycle of 21 levels) are exposed in Table 4.

Table no. 4. Descriptive statistics of wny(i) extrapolated by econometric estimatios

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wWny1e	0.041777	0.035397	0.218204	-0.09451	0.055048	0.8717	7.612513
wWny2e	-0.01137	-0.02541	0.129315	-0.07238	0.039446	2.056324	8.922094
wWny3e	0.022718	0.02305	0.264512	-0.18389	0.088187	0.3982	5.443236
wWny4e	0.017308	0.005092	0.159261	-0.06876	0.056714	0.631828	3.028404
wWny5e	0.017894	0.015937	0.094583	-0.03551	0.023171	1.183999	7.889948
wWny6e	-0.08266	-0.09002	1.060575	-1.01673	0.367243	0.654368	7.237498
wWny7e	-0.09269	-0.09378	0.253871	-0.3867	0.139341	0.813978	4.886424
wWny8e	0.128886	0.143447	0.618906	-0.41372	0.17402	-0.44906	8.325712
wWny9e	0.085484	0.09415	0.399738	-0.25366	0.110305	-0.35161	8.221011
wWny10e	0.872656	0.89951	3.222083	-1.93719	0.927117	-0.56234	6.758118

2.1. The extrapolations derived from econometric relationships increase (in module) the coefficients of variation specific to primary database (Graph CvE in Figure 5).

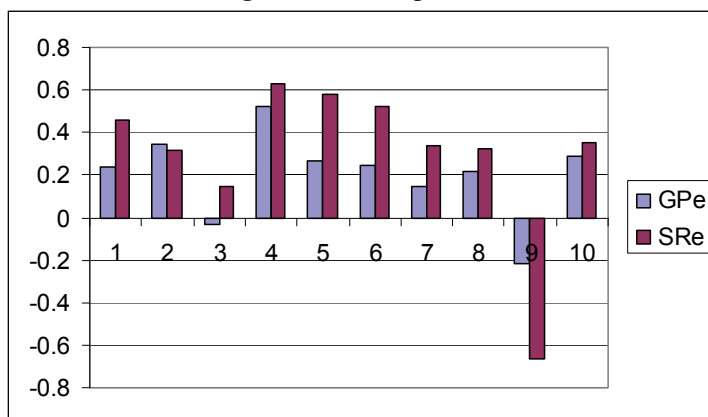
Figure no. 5. Graph CvE





2.2. In comparison with the standard moving average procedures however, both coefficients of correlation (Galtung-Pearson and Spearman rank order) indicate a greater similarity degree of extrapolations to the original statistical data (Graph CorE in Figure 6).

Figure no. 6. Graph CorE



3. Hence, as it was expected, the moving average algorithm (in all hereby illustrated versions) induces – due to its asymptotical properties – stable enough forecasts, fact clearly confirmed by the relatively low coefficients of variation. Then again, the degree of similarity to the original series (GP and SR correlations) is also weak.

To the contrary, the extrapolations based on econometric estimations distinguish themselves by a higher degree of similarity to the primary database, but under a more accentuated volatility.

**Combined Algorithms**

The series wny<sub>i</sub> have been extrapolated according to formula (1), again during an entire cycle of 21 post-sample terms.

1. Table 5 presents descriptive statistics of these series, using all the modalities of mixing the standard moving average with econometric estimations.

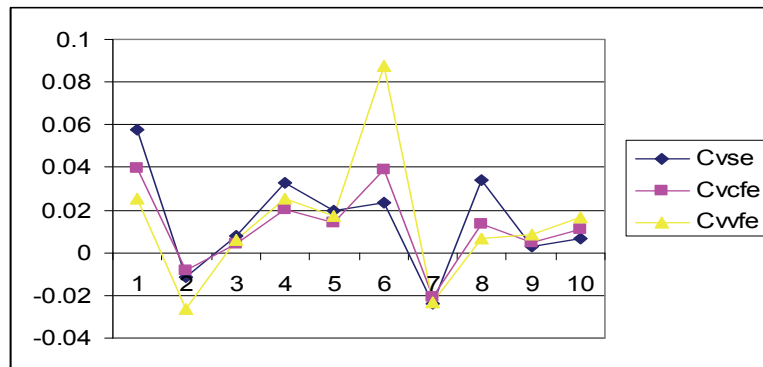
Table no. 5. Descriptive statistics of wny(i) extrapolated by hybrid approach

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wny1se	0.081711	0.079907	0.092222	0.077268	0.004696	1.324986	3.405632
wny2se	-0.0295	-0.02958	-0.02855	-0.02988	0.000333	1.360254	4.494128
wny3se	0.022779	0.022758	0.023208	0.02238	0.000185	0.27227	3.488382
wny4se	0.067808	0.066941	0.074131	0.065837	0.002235	1.788784	5.128758
wny5se	0.03178	0.03163	0.033163	0.030879	0.000632	0.841106	2.753884
wny6se	0.051135	0.051035	0.052776	0.047155	0.001206	-1.49599	6.784625
wny7se	-0.06007	-0.06053	-0.05572	-0.06144	0.001442	1.832027	5.688991

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
wny8se	0.153678	0.155625	0.160596	0.141733	0.005231	-1.12224	3.350382
wny9se	0.121364	0.121271	0.122091	0.120727	0.000374	0.529374	2.372306
wny10se	0.559312	0.560342	0.56348	0.550183	0.003654	-1.10711	3.429577
wny1cfe	0.072298	0.071751	0.078905	0.069105	0.002853	1.269766	3.62064
wny2cfe	-0.02976	-0.02977	-0.02932	-0.03009	0.000242	0.263427	1.935196
wny3cfe	0.022552	0.022514	0.022824	0.02247	9.46E-05	1.720783	4.82216
wny4cfe	0.06304	0.062821	0.066225	0.061629	0.001265	1.36309	4.02052
wny5cfe	0.030603	0.030459	0.031631	0.030156	0.000431	1.176981	3.182274
wny6cfe	0.05	0.05013	0.052794	0.046735	0.00194	-0.17225	1.720111
wny7cfe	-0.06372	-0.06382	-0.06033	-0.06544	0.001331	0.890469	3.242234
wny8cfe	0.163688	0.164482	0.165777	0.157872	0.002251	-1.74343	4.729785
wny9cfe	0.119847	0.119787	0.121031	0.119074	0.000562	0.50864	2.264772
wny10cfe	0.571452	0.571543	0.581087	0.558841	0.006256	-0.207	2.084231
wny1vfe	0.063152	0.063267	0.066443	0.06048	0.001615	0.27541	2.659005
wny2vfe	-0.02941	-0.02947	-0.02812	-0.03043	0.000769	0.19863	1.672227
wny3vfe	0.022362	0.022338	0.022623	0.02203	0.000131	-0.17589	3.601951
wny4vfe	0.057518	0.057606	0.059955	0.055011	0.001468	-0.06382	1.996524
wny5vfe	0.030149	0.030045	0.031316	0.029491	0.000525	0.868016	2.78688
wny6vfe	0.047101	0.046943	0.054799	0.040801	0.004129	0.113528	1.859818
wny7vfe	-0.06355	-0.0637	-0.05978	-0.06529	0.001472	1.231848	3.976151
wny8vfe	0.176081	0.175746	0.180304	0.175149	0.001209	2.444874	8.658742
wWny9vfe	0.117525	0.117416	0.119366	0.116083	0.000991	0.316732	2.03228
wWny10vfe	0.579072	0.580313	0.59239	0.557283	0.00975	-0.55106	2.48107

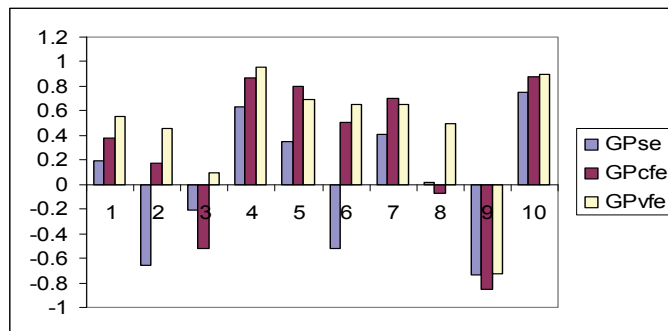
2. The coefficients of variation of extrapolated data are generally higher than the moving average algorithm, but in a relatively narrow band (Graph CvH in Figure 7).

Figure no. 7. Graph CvH

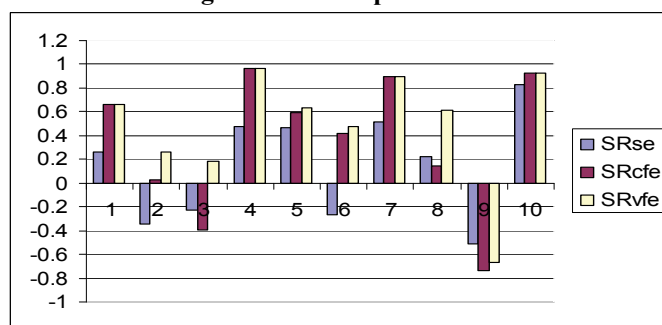


3. The correlations of extrapolations with the primary database are plotted on Graphs CorHGP and CorHSR in Figure 8 and Figure 9:

**Figure no. 8. Graph CorHGP**



**Figure no. 9. Graph CorHSR**



The combination of standard moving average with econometric estimations merges the above revealed symmetrical characteristics of their separate application.

**Conclusions**

1. Our comparative analysis would be facilitated by involving more aggregated indicators for the coefficient of variation (ACv), the Galtung-Pearson correlation (AGP), and the Spearman rank order correlation (ASR). These are determined by summing the values (Cv, GP, and SR) of series wny(i), weighted with the mean values of the respective series. As before, the mentioned symbols will be completed with a distinguishing suffix for the involved computational method. The results are synthetised in Table 6.

**Table no. 6. Aggregated ACv, AGP, and ASR**

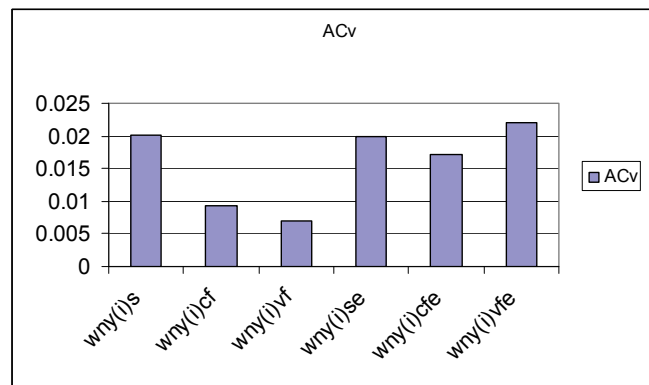
Series	ACv	AGP	ASR
wWny(i)	0.337791		
wWny(i)s	0.020116	0.22715	0.170255
wWny(i)cf	0.009232	0.170081	0.089989
wWny(i)vf	0.006926	0.374561	0.069369

Series	ACv	AGP	ASR
wWny(i)e	1.980591	0.244212	0.254792
wWny(i)se	0.019988	0.365539	0.463928
wWny(i)cfe	0.017226	0.459941	0.544496
wWny(i)vfe	0.022059	0.608575	0.646955

We prompt that the coefficients of correlation are calculated comparatively with the primary database (sample series wny(i)).

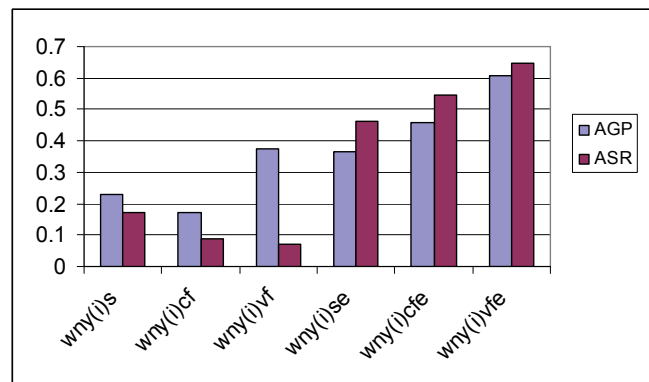
2. The aggregated ACv attests again the contrast between the relative stability of extrapolated data induced by the standard moving average algorithms (in all applied forms) and their high volatility in the case of econometric estimations. As a compromise, the hybrid methods are also characterized by low coefficients of variation, but these are slightly higher than MA procedures. Graph ACv in Figure 10 shows a comparison.

Figure no. 10. Graph ACv



3. The correlations between the forecasted series and the primary database are, however, categorically in favor of the hybrid methods (Graph ACor in Figure 11).

Figure no. 11. Graph ACor



4. Summarizing, a hybrid moving average/econometric estimation approach seems to be preferable comparatively with their separate application. Undoubtedly, several problems remain to be hereafter explored.

We have examined only three forms of moving average technique: simple, Fisher distribution with identical number of terms for all examined series, and Fisher distribution with variable number of terms. It would be of interest to search also another possible such variants, including new schemes of determining the weights of implied lags.

On the other hand, it is important to analytically and numerically study the possible asymptotical properties of the series resulted by using the hereby discussed hybrid moving average – econometric estimation forecasting approach.

Further research follows to explore these and other similar questions.

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