Adaptation of model selecting criteria for nonlinear time series forecasting Research practise 2: Project presentation

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# Modeling methodology of time series for forecasting

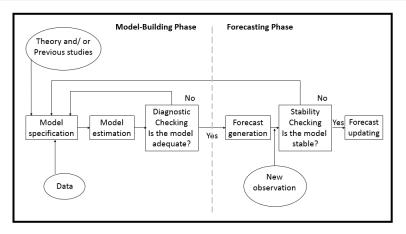


Figure: Conceptual framework of a forecasting system. Taken from [Abraham and Ledolter, 2009]

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A model of pth-order of time series is defined as [Li, 2003, Hwang et al., 1994]

$$X_t = f(F_{t-1}; \phi) + a_t \quad , \tag{1}$$

where

- f is a known linear or nonlinear function of past  $X_t$ 's.
- $\phi$  is a  $p \times 1$  vector of parameters.
- The noise process {a<sub>t</sub>} is assumed to be independent, with mean zero, variance σ<sup>2</sup><sub>a</sub>, and finite fourth order moment.
- Compared to the linear case, the nonlinear time series have been little explored and theory is not sufficient to uncover nonlinearities [Anders and Korn, 1999].
- One of the most critical issues is to select the appropriate forecasting nonlineal model [Qi and Zhang, 2001].

#### Model selection criteria

Model selection criterion	Definition
SSE	$\sum_{i=1}^{T} (y_i - \hat{y}_i)^2$
AIC	$\log\left(\frac{SSE}{T}\right) + \frac{2m}{T}$
AICC	$\log\left(\frac{SSE}{T}\right) + \frac{2m}{T-m-1}$
BIC	$\log\left(\frac{SSE}{T}\right) + \frac{m\log(T)}{T}$

Table: Model selection criteria, where m is the number of parameters and T the number of observations

#### Model selection criteria

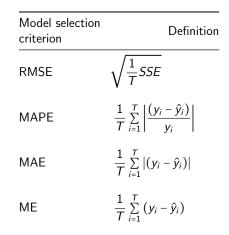


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#### Model selection criteria

Model selection criterion	Definition
DA	$\frac{1}{T}\sum_{i=1}^{T} a_i, \text{ where}$ $a_1 = \begin{cases} 1 & if(y_{i+1} - y_i)(\hat{y}_{i+1} - y_i) > 0\\ 0 & otherwise \end{cases}$
MDA	$\frac{\sum_{i=1}^{T-1} D_i}{T-1}$ , where $D_i = (A_i - F_i)^2$
Sign	$\frac{1}{T} \sum_{i=1}^{T} z_i, \text{ where}$ $z_1 = \begin{cases} 1 & if(y_{i+1})(\hat{y}_{i+1}) > 0\\ 0 & otherwise \end{cases}$

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### Weighted selection criterion

A weighted selection criteria using optimization was proposed by [Aladag et al., 2010]:

 $AWIC = w_1 RMSE + w_2 MAPE + w_3(1 - DA) + w_4 MDA + 0.1AIC + 0.1BIC$  (2)

- It is not shown a criteria for determining the weights of AIC and BIC.
- There are no guidelines to know which criteria to use, bearing in mind the inherent behavior of the time series.
- Heuristic methods have not been successful in the estimation of weights for the combined methods.
- This method does not consider the time series characteristics.



#### General Objective

Formulate a criterion for selecting models of nonlinear time series using multivariate analysis techniques and the inherent characteristics of the series.

## **Objectives** II

#### Specific Objectives

- Identify the different selection criteria formulated in the literature for non-linear time series.
- Determine the multivariate analysis techniques that allow the creation of synthetic indicators according to the characteristics of the data.
- Establish a methodological framework that considers the characteristics of the data and consider the advantages of the proposed selection criteria in literature to date.
- Validate the feasibility of the proposed methodology by experimental data.

## Selected models I

Nonlinear Autoregressive Model (NAR) [Aras and Kocakoç, 2016]:

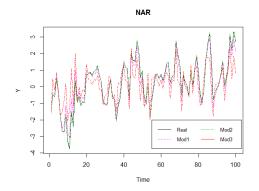


Figure: Variations of the model  $y_t = 0.7y_{t-1} - 0.017y_{t-1}^2 + \varepsilon_t$ 

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## Selected models II

Generalized Autoregressive Conditional Heteroskedastic (GARCH) [Ennio and Pablo, 2011]:

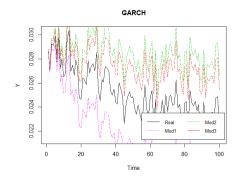


Figure: Variations of the model  $y_t = \sqrt{h_t \varepsilon_t}$  with  $h_t^2 = 0.00002281 + 0.0593y_{t-1}^2 + 0.901h_{t-1}^2$ 

## Selected models III

Autoregressive Model (AR):

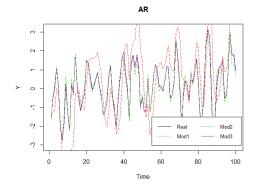


Figure: Variations of the model  $y_t = 0.67y_{t-1} - 0.41 * y_{t-2}\varepsilon_t$ 

The method used to estimate the optimal weights of the proposed criterion for selecting time series models under the Principal Component Analysis (PCA) is as follows:



### Methodology model selection criterion using AHP

According to the frequency of use of each method in the literature was created a matrix of importance for the model selection criteria to obtain the weighted model with the Analytic Hierarchy Process (AHP):

SSE	RMSE	MAPE	MAE	ME	DA	MDA	Sign	AIC	
/ 1	7	5	3	7	5	9	10	2	SSE
1/7	1	1/3	1/5	1/2	5	9	7	1/9	RMSE
1/5	3	1	1/3	3	5	7	9	1/5	MAPE
1/3	5	3	1	2	2	3	3	1/3	MAE
1/7	2	1/3	1/2	1	1/2	3	5	1/10	ME
1/5	1/5	1/5	1/2	2	1	5	1/3	1/9	DA
1/9	1/9	1/7	1/3	1/3	1/5	1	1/2	1/10	MDA
1/10	1/7	1/9	1/3	1/5	3	2	1	1/7	Sign
1/2	9	5	3	10	9	10	7	1 /	AIC

Before applying the statistical methods to the obtained data, a correlation analysis was performed between the selection criteria.

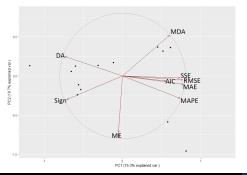
	SSE	RMSE	MAPE	MAE	ME	DA	MDA	Sign	AIC	BIC	AICC
SSE	1.00	0.942	0.46	0.939	-0.10	-0.104	0.69	-0.85	0.574	0.574	0.574
RMSE	0.94	1.000	0.59	0.999	-0.23	-0.076	0.68	-0.89	0.766	0.766	0.766
MAPE	0.46	0.585	1.00	0.576	-0.82	-0.432	0.62	-0.19	0.498	0.498	0.498
MAE	0.94	0.999	0.58	1.000	-0.23	-0.087	0.67	-0.89	0.766	0.766	0.766
ME	-0.10	-0.233	-0.82	-0.234	1.00	0.354	-0.26	-0.13	-0.220	-0.220	-0.220
DA	-0.10	-0.076	-0.43	-0.087	0.35	1.000	-0.49	-0.15	0.067	0.067	0.067
MDA	0.69	0.684	0.62	0.672	-0.26	-0.491	1.00	-0.49	0.506	0.506	0.506
Sign	-0.85	-0.889	-0.19	-0.891	-0.13	-0.145	-0.49	1.00	-0.685	-0.685	-0.685
AIC	0.57	0.766	0.50	0.766	-0.22	0.067	0.51	-0.69	1.000	1.000	1.000
BIC	0.57	0.766	0.50	0.766	-0.22	0.067	0.51	-0.69	1.000	1.000	1.000
AICC	0.57	0.766	0.50	0.766	-0.22	0.067	0.51	-0.69	1.000	1.000	1.000

#### Results II

For the nonlinear NAR model it was found that MDA and ME criteria are not significant, because they have a very low weight in the components. In addition, two groups of associations were identified:

Group 1: SSE, RMSE, MAPE, MAE and AIC

Group 2: DA and Sign.



	PC1	PC2	PC3	PC4
SSE	0.36842267	-0.02299887	-0.50664876	-0.20932938
RMSE	0.38428547	-0.04702933	-0.08712538	-0.05286600
MAPE	0.36838790	-0.27896182	-0.06205923	0.07378212
MAE	0.38894523	-0.10435533	-0.09531094	0.04451500
ME	-0.02518079	-0.70598204	-0.11918015	-0.45730021
DA	-0.36715807	0.24287362	-0.15669143	-0.63806274
MDA	0.30081839	0.50921407	-0.12944001	-0.40502644
Sign	-0.35676085	-0.29630947	-0.09606673	-0.10552733
AIC	0.27639149	-0.06366367	0.81119728	-0.39310435
	PC (	ב		

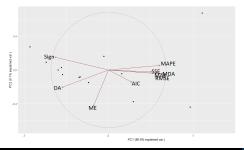
Figure: PCA rotations of NAR model

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#### Results III

For the AR model it was found that MDA criteria, opposite to the result obtained with the NAR model, is significant. But ME criterion also have a very low weight in the components. In addition, two groups of associations were identified:

Group 1: SSE, RMSE, MAPE, MAE, MDA and AIC Group 2: DA and Sign.



	PC1	PC2	PC 3	PC4
SSE	0.3266987	-0.04138381	-0.426870813	0.4240521
RMSE	0.3596530	-0.08178399	-0.169611387	0.1333069
MAPE	0.3885879	0.10113556	-0.028554145	0.0604021
MAE	0.3612480	-0.07924623	-0.161126110	0.1207773
ME	-0.1144983	-0.81184820	-0.293831555	0.1252542
DA	-0.3515510	-0.38948746	0.003745842	-0.1785826
MDA	0.3894182	-0.08620407	0.039724455	-0.4088894
Sign	-0.4044117	0.28835932	-0.205385011	0.5677995
AIC	0.1747105	-0.27149617	0.795062434	0.4969974

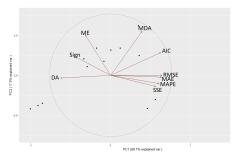
Figure: PCA rotations of AR model

#### Results IV

For the GARCH model it was found the same behavior as the NAR nonlinear model. And two groups of associations were identified:

Group 1: SSE, RMSE, MAPE, MAE and AIC

Group 2: DA and Sign.



	PC1	PC2	PC3	PC4
SSE	0.3423886	-0.165238288	-0.215855949	0.31464542
RMSE	0.3886483	-0.001139202	0.053896595	0.35381221
MAPE	0.3672652	-0.121318665	0.004204236	0.09831616
MAE	0.3859716	-0.027341777	0.055146954	0.29073122
ME	-0.1901388	0.591439835	0.035506793	0.58326632
DA	-0.3774784	-0.038918146	-0.465663113	0.43263077
MDA	0.2373385	0.649418871	-0.530652303	-0.38821312
Sign	-0.2631608	0.269311291	0.565158793	0.04038546
AIC	0.3789972	0.334125842	0.358250344	-0.04376153

Figure: PCA rotations of GARCH model

The obtained weighted selection criteria obtained with the three models were:

NAR

PC<sub>1</sub> = 0.4744SSE + 0.4765RMSE + 0.5084MAPE + 0.4897MAE + 0.2225AIC PC<sub>2</sub> = 0.5201DA + 0.4799Sign

AR

 $PC_{1} = 0.3997SSE + 0.4323RMSE + 0.4607MAPE + 0.4338MAE + 0.4587MDA$ + 0.2062AIC (4) $PC_{2} = 0.4584DA + 0.5416Sign$ 

GARCH

*PC*<sub>1</sub> = 0.4055*SSE* + 0.4498*RMSE* + 0.4511*MAPE* + 0.4544*MAE* + 0.4726*AIC PC*<sub>2</sub> = 0.5912*DA* + 0.4088*Sign* 

(5)

(3)

Based on the matrix established before, the AHP methodology was applied. With this measure is possible to set a weight for each selection criteria considered in this paper. The weighted selection criterion obtained is as follows:

 $C_{AHP} = 0.3098SSE + 0.0573RMSE + 0.1046MAPE + 0.1101MAE + 0.0483ME + 0.0339DA + 0.0162MDA + 0.0248Sign + 0.2950AIC$ 

(6)

	AHP				
	Group 1 Group 2				
	0	1	0.0838		
	0.4332	0.8263	0.3867		
	0.1690	1	0.2841		
	0.4518	0.8416	0.4012		
	0.6614	0.7976	0.4777		
	0.6232	0.7212	0.4237		
NAR	0.4447	0.8435	0.3959		
NAR	2.0119	0.2172	0.8666		
	2.1664	0.1224	0.9386		
	1.7677	0.4086	0.4800		
	1.2595	0.2882	0.6269		
	1.0868	0.4008	0.5701		
	1.8446	0.2533	0.7558		
	1.1722	0.3282	0.5979		

#### Table: Values obtained with the methodologies

	P	AHP	
	Group 1		
	0	1	0.0967
	0.1961	0.9672	0.3174
	0.3343	0.8503	0.3694
	0.3024	0.8880	0.3586
	0.5190	0.7761	0.4133
	0.3337	0.8812	0.3609
AR	0.5110	0.7847	0.4113
AN	1.5483	0.1447	0.5933
	0.6844	0.6400	0.4220
	0.5455	0.6746	0.4024
	0.9595	0.4147	0.4891
	1.6876	0.3287	0.7287
	2.3914	0.0155	0.9265
	0.8950	0.4712	0.4518

Table: Values obtained with the methodologies

	PC	AHP	
	Group 1		
	0.1895	0.7850	0.1543
	0.2913	0.8388	0.2660
	0	0.8925	0.0778
	0.1150	0.8925	0.1668
	0.9564	0.6775	0.5617
	0.0261	0.7850	0.0966
GARCH	0.1641	1	0.2082
GAILCH	0.3009	0.6775	0.2630
	0.5420	0.6775	0.3810
	0.7811	0.4088	0.4400
	0.8511	0.4088	0.4687
	2.9490	0	0.8930
	0.9731	0.6775	0.5839
	0.9920	0.6775	0.5884

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- It can be noted that the criteria belonging to the first group are related to measurement of the error between the actual and the estimated model and those belonging to the second group are related to the analysis of direction of the models.

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- When analyzing the associations made by groups after performing principal component analysis by type of model, you get that nonlinear models GARCH and NAR show the same configurations in the groups.
- It can be noted that the criteria belonging to the first group are related to measurement of the error between the actual and the estimated model and those belonging to the second group are related to the analysis of direction of the models.
- While the AHP technique is easy to use, the PCA technique yields better results in terms of the interpretation of results and group formation.

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## Thanks for your attention!!

Adaptation of model selecting criteria for nonlinear time series forecasting.

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