A Hybrid Neuro-Fuzzy System and Neural Network Approach to Forecast the Electricity Spot Price in Brazil

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Background

- The aim is to present a Hybrid Neuro-Fuzzy/Neural Network model which incorporates inflow information to forecast the weekly spot prices in the Southeast subsystem of Brazil.

- The Southeast subsystem corresponds to the most densely populated and industrialized portion of Brazil.

- Part of the region is subject to occasional severe droughts that impact electricity generation.

Background

- **Power generation in Brazil is primarily hydroelectric, and hydro plants account for about 82% of the electricity generation in the country.**

- **Power plants are connected through long distances by a complex array of power lines, in what forms the so-called Brazilian interconnected system (SIN).**

- **SIN comprises about 97% of the total energy produced in the country.**

- **The concept of subsystem is intrinsically related to the concept of "equivalent reservoir".**

Background

- **Spot prices in Brazil are computed through an optimization process that attempts to minimize costs in equivalent reservoirs, one for each of 4 subsystems.**

- **Electricity spot prices are calculated through a sequence of complex optimization models that produce the marginal cost of operation.**

- **These models attempt to minimize the total cost of operations, computed as the sum of current and future costs.**

- **These costs are functions of (among other variables) the expected future inflows, the expected demand and the current reservoir levels.**

Background

- "ONS", the Brazilian Independent System Operator (ISO) employs a model based on Stochastic Dual Dynamic Programming to perform operations planning.

- This model groups hydroelectric power plants of basins with similar hydrological behavior into the so-called equivalent subsystems.

- Four equivalent subsystems (North, Northeast, Southeast/Central-West and South regions) are used.

- Hydrological scenarios are built into the system through a PAR(p) – Periodic Autoregressive Model.

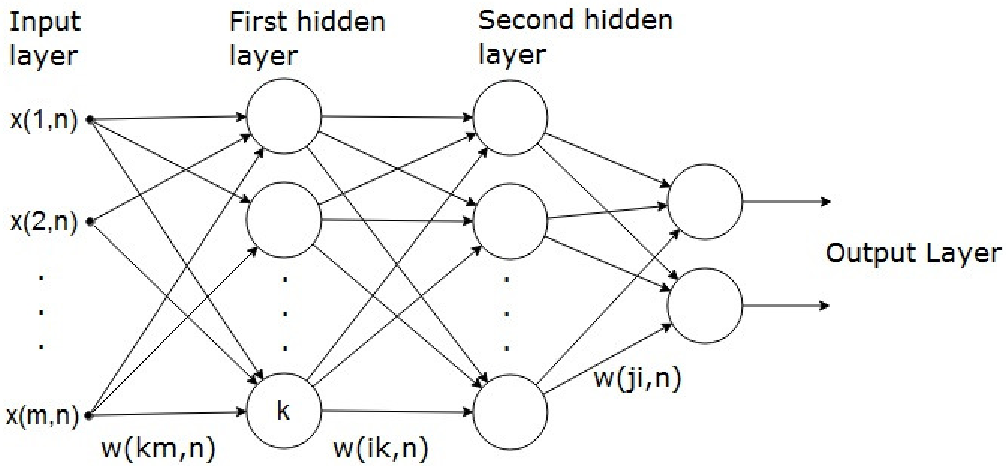
Background

- **Two quantities play an important role to determine spot prices:**
  - **“Stored energy” - maximum storage of the reservoir or basin;**
  - **“Natural inflow energy” – river inflows, expressed in energy units.**

- **Paranaíba and Grande river basins are the main basins in the Southeast subsystem, accounting for slightly over 60% of the subsystem’s reservoir’s capacity.**

Neural networks

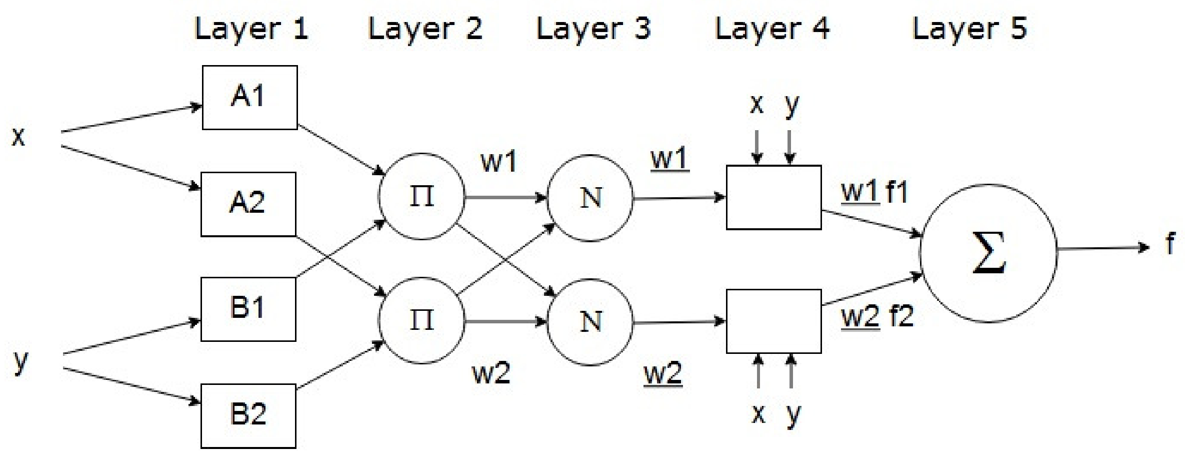
- ANNs have been extensively used in time series forecasting, due to their generalization and learning abilities.
- They can identify nonlinear characteristics of complex series.
- The architecture of a Mutilayer Perceptron (MLP) network is:



Neuro-Fuzzy systems

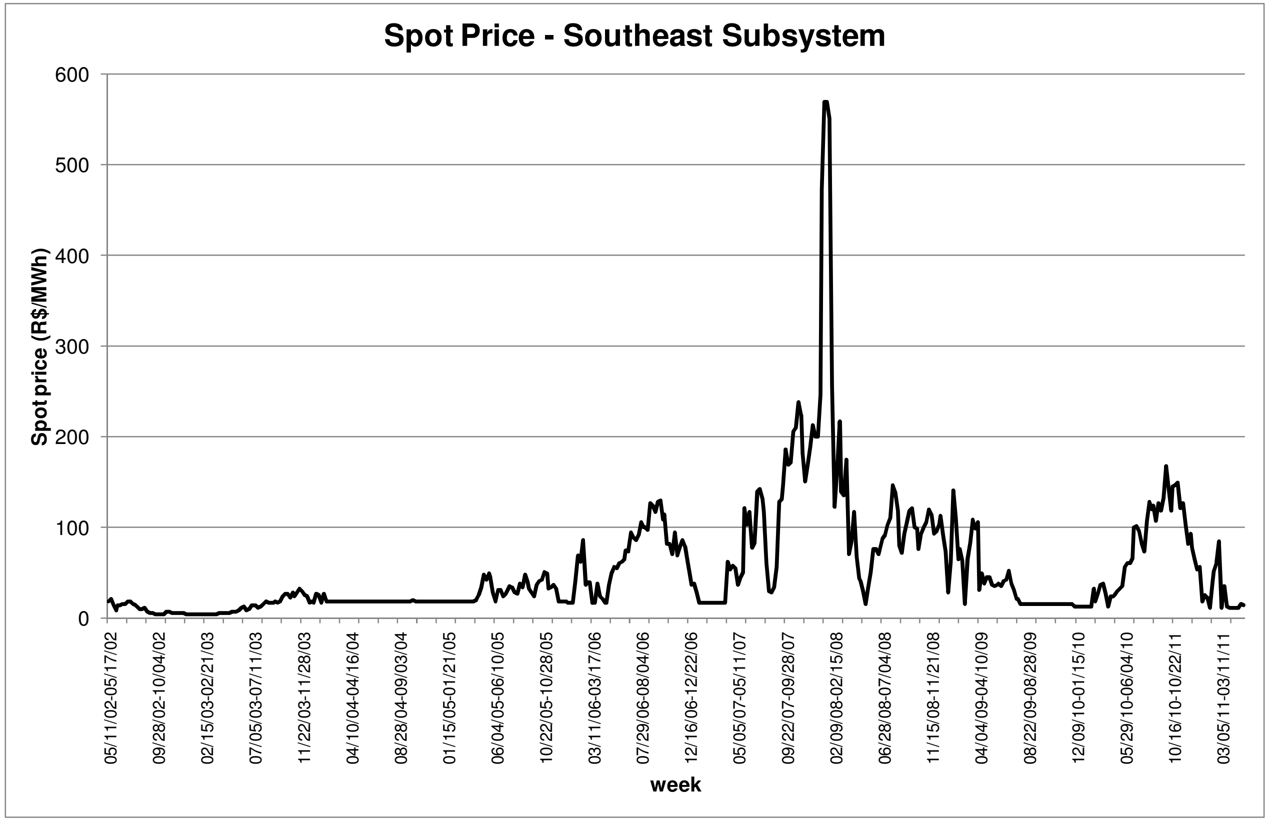
- **Neuro-fuzzy systems attempt to combine the advantages of both approaches: neural networks and fuzzy systems.**

- **We use the ANFIS neural fuzzy inference system proposed by Jang.**



An Overview of the Data

- The spot series consists of 471 weekly observations (May 2002 to May 2011)



An Overview of the Data

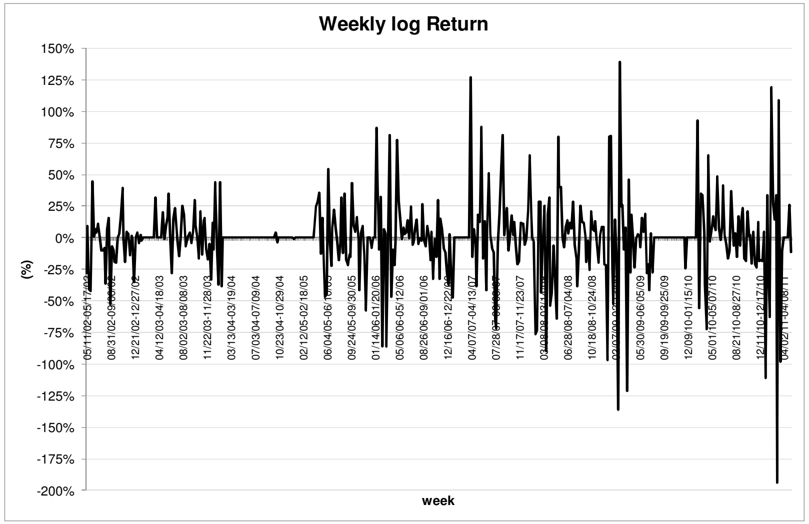
- From the previous figure two striking features emerge:
  - prices tend to stay at very low levels for long periods, but
  - they also exhibit high volatility.

- Both features are common in primarily based hydroelectric systems, such as the Brazilian.

- The high volatility of the series is also due to the non-storability of electricity and it is observed even in markets where prices are “actual” market prices, a consequence of bid and ask interactions, and not the result of optimization models, as in the Brazilian case.

An Overview of the Data

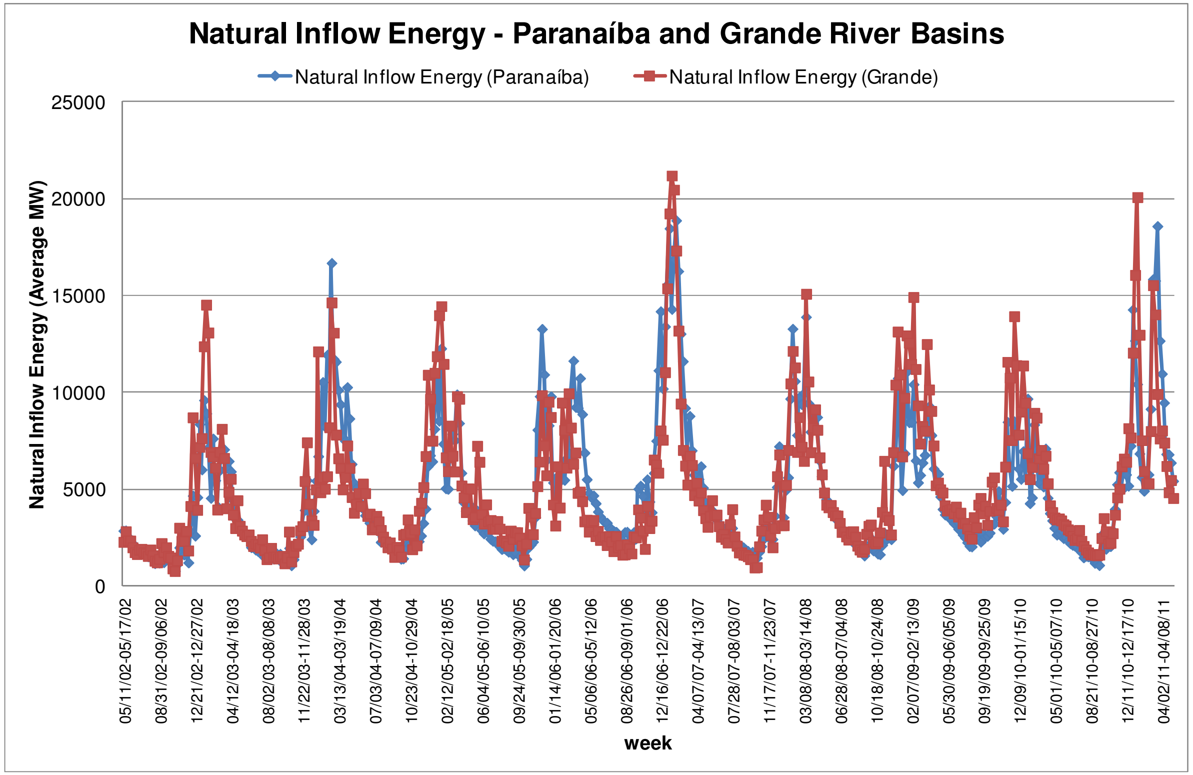
- Log-returns based on the weekly prices
- Extreme weekly returns (in excess of ±50%) are not uncommon in the sample



Statistics	Spot Price (R$/MWh)	Weekly Return (%)
Mean	54.33	-0.1%
Median	27.95	0.0%
Mode	18.59	0.0%
Standard Deviation	66.54	30.6%
Kurtosis	23.89	7.63
Skewness	3.92	-0.44
Minimum	4.0	-194.2%
Maximum	569.59	138.8%
Count	471	470

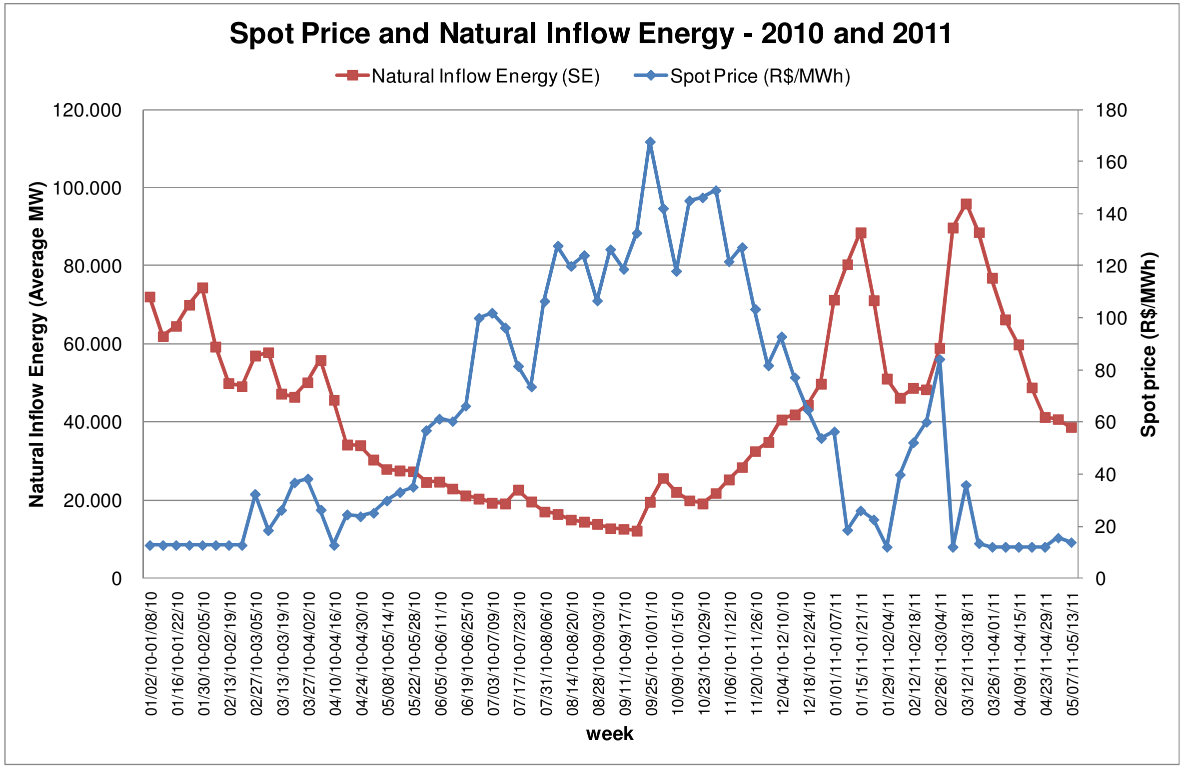
An Overview of the Data

- **Natural Inflow Energy in the Southeast Subsystem presents a distinct seasonal pattern.**



An Overview of the Data

- **Spot prices and Natural Inflow Energy (ENA) exhibit an inverse relationship**



The Model

- Hybrid neural network/neuro-fuzzy model for the spot price
  - Comments on the choice of the ANN Model
  - Comments on the NFS set-up
  - The structure of the hybrid model

The Model

- **The proposed model is a combination of a backpropagation ANN and an ANFIS-type NFS.**

- **In our model, the ANN forecasts are added to the original inputs and fed to NFS to generate the spot price forecasts.**

- **Suppose the original ANN model contains n inputs. The final "hybrid" model will contain (n+1) inputs, the original ones plus an additional input, obtained by "fitting" the ANN to the dataset, generating one-step ahead forecasts and adding the one-step ahead forecasts as an additional input variable.**

The Model

- We created six different hybrid models.

- Each model specializes in a single forecasting horizon (one to 6 weeks ahead).

- Comments on the Choice of the ANN Model:
- The network structures for each model class include an intermediate layer with a sigmoidal activation function and an output layer with a linear activation function.

- ANNs with 6, 7, 8, 9, 10, 11 and 12 neurons in the intermediate layer were tested.

The Model

- <u>**Comments on the Choice of the ANN Model:**</u>
- **For each of these numbers of neurons, we tested networks with 1000 to 3000 epochs.**

- **The training period used for choosing the ANN models was 90% of the data set.**

- **One of the major issues regarding ANNs is the dependence on the initial weights.**

- **Due to this fact, the results produced by networks with the same structure may vary considerably.**

The Model

- <u>**Comments on the Choice of the ANN Model:**</u>
- **In search of a more robust procedure, we replicate the same network architecture several times and chose the particular network that led to the smallest one-step ahead MAPE in the training period.**

- **We tested 21, 25, 31, 51, 75, 101, 121, 131, 151 replications of the same structure of several different ANN models.**

- **We chose to use 75 replications of each architecture. In each, the ANN which produces the best result (lowest MAPE).**

The Model

- Comments on the NFS Set-up:
- As with the ANN model, several choices have to be made regarding the specification of the NFS implementation.

- The neuro-fuzzy system with n inputs most often outperformed the ANN with the same inputs.

- The hybrid model consists of two steps:
  - 1) Choose the “best” ANN with n inputs and record its one step ahead forecasts;
  - 2) Fit a NFS with the previous n inputs and an additional one, the one step ahead forecasts obtain in the previous step.

- The entire system requires a very modest amount of information – just the past prices and past natural inflow energy time series, which should be updated weekly.

The Model

- <u>**The structure of the Hybrid Model:**</u>
- **the hybrid forecasting approach is a two step procedure:**
- **in the first step, 75 replications of a MLP neural network with these inputs are adjusted and the best network is selected, using as a criterion the minimum MAPE during the training period**
- **The second step employs the previously mentioned inputs AND the forecasts generated by the best ANN obtained in the first step as inputs in an ANFIS neuro-fuzzy system**
- **the objective of this model is to generate forecasts up to six weeks in advance.**

The Model

- **<u>The structure of the Hybrid Model:</u>**

- **Let P(t) denote the price at week t, and suppose it denotes the current week.**

- **The forecast for P(t+1) uses as inputs the current and lagged values of the spot prices and the natural inflow energies at the subsystem and the basins, namely:**
  - **P(t), P(t-2),**
  - **ENA_SE(t) (inflow energy of the subsystem at the current week),**
  - **ENA_SE(t-1) (inflow energy of the subsystem one week ago),**
  - **ENA_GR(t-1) (inflow energy of the Grande river basin one week ago),**
  - **ENA_PA(t) (inflow energy of the Paranaíba river basin at the current week) .**

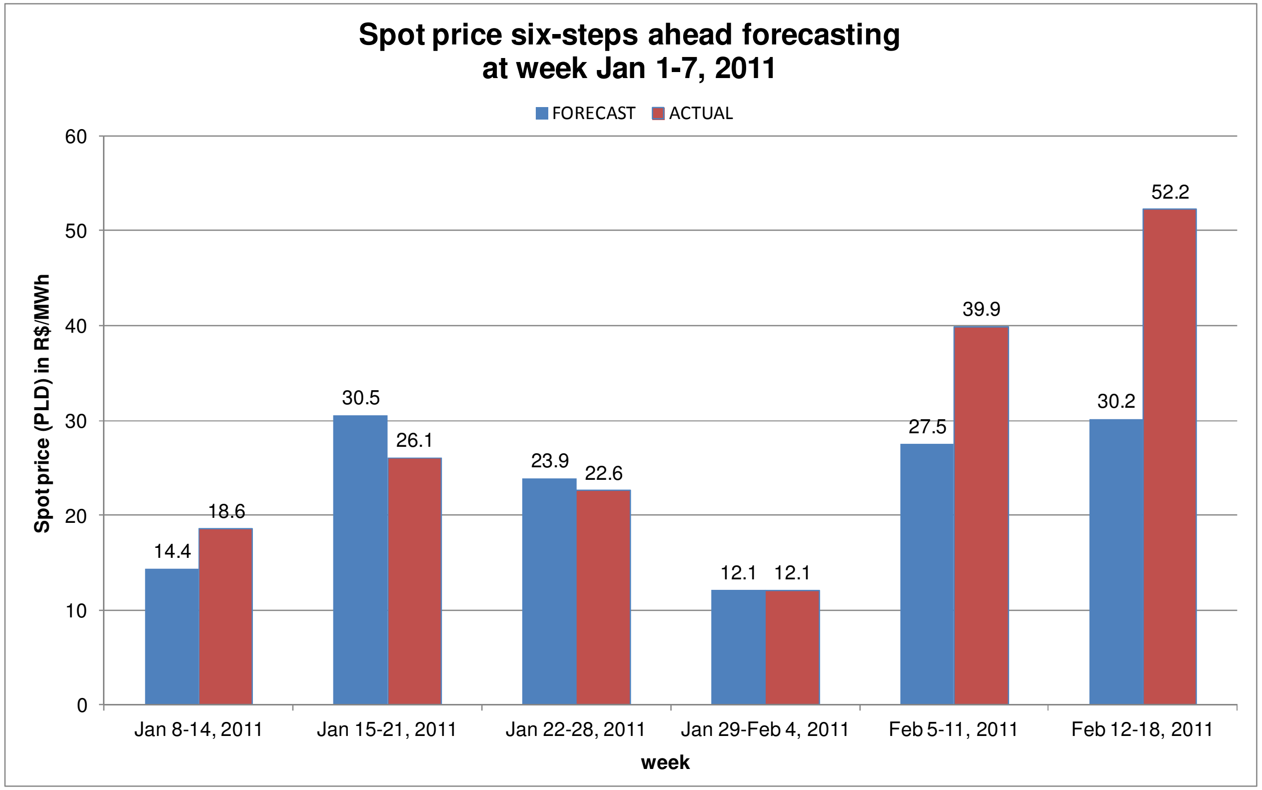
The Model

- **The structure of the Hybrid Model:**
- **It is necessary to forecast the input variables.**
- **The forecasts of all natural inflow energy series (ENA_SE, ENA_GR and ENA_PA) are obtained exogenously through univariate time series models, chosen to minimize the Bayesian Information Criterion (BIC).**

Natural inflow energy series	Model Structure	R^2 adjusted	MAPE	Durbin-Watson
Southeast	SARIMA(1,0,2)x(2,0,1) on ln of actual data	90.8%	12.1%	1.94
Paranaíba	SARIMA(1,0,0)x(1,0,0) on ln of actual data	87.7%	17.4%	1.99
Grande	SARIMA(1,0,2)x(2,0,1) on ln of actual data	85.6%	18.7%	1.92

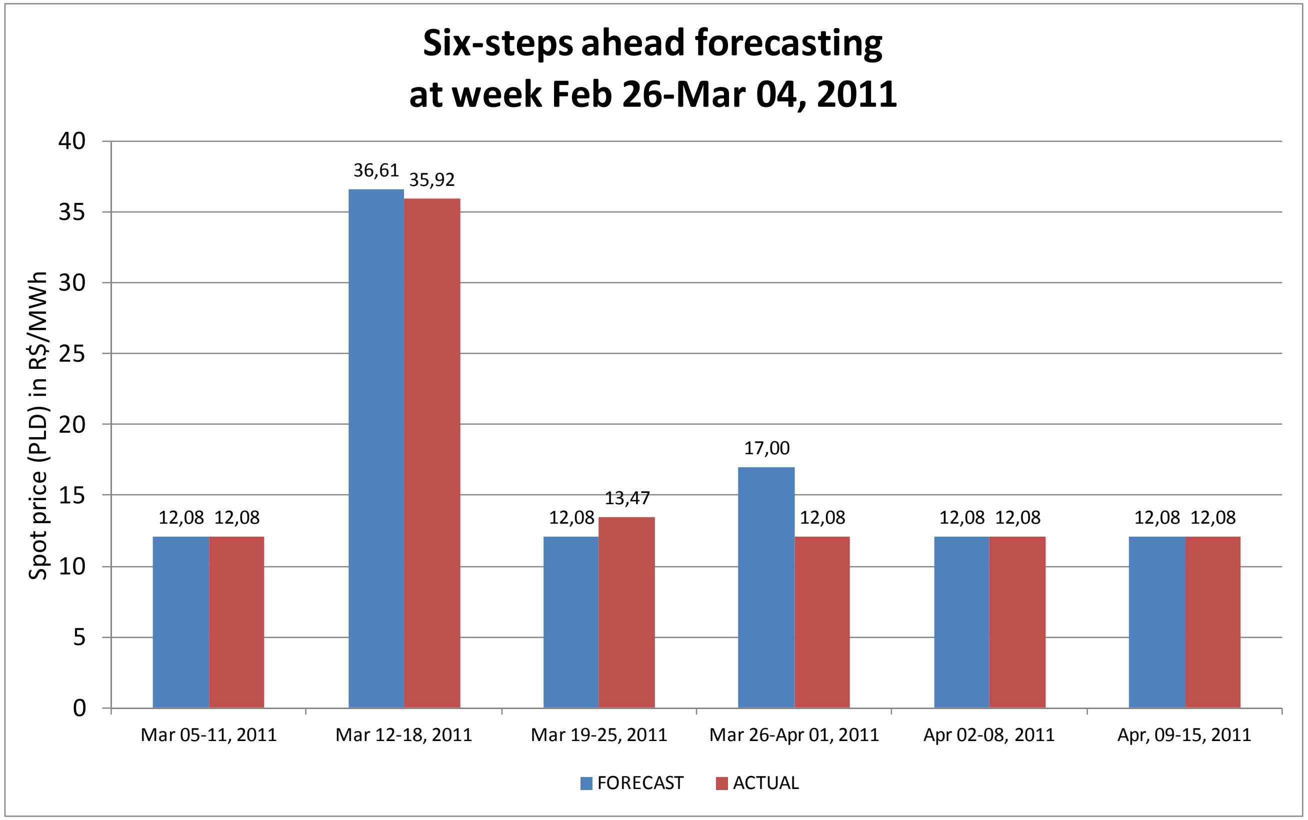
Empirical Results

- Southeast spot price six-step ahead forecasts at the week Jan 1–7, 2011



Empirical Results

- **Southeast spot price six-step ahead forecasts at the week Feb 26–Mar 04, 2011**



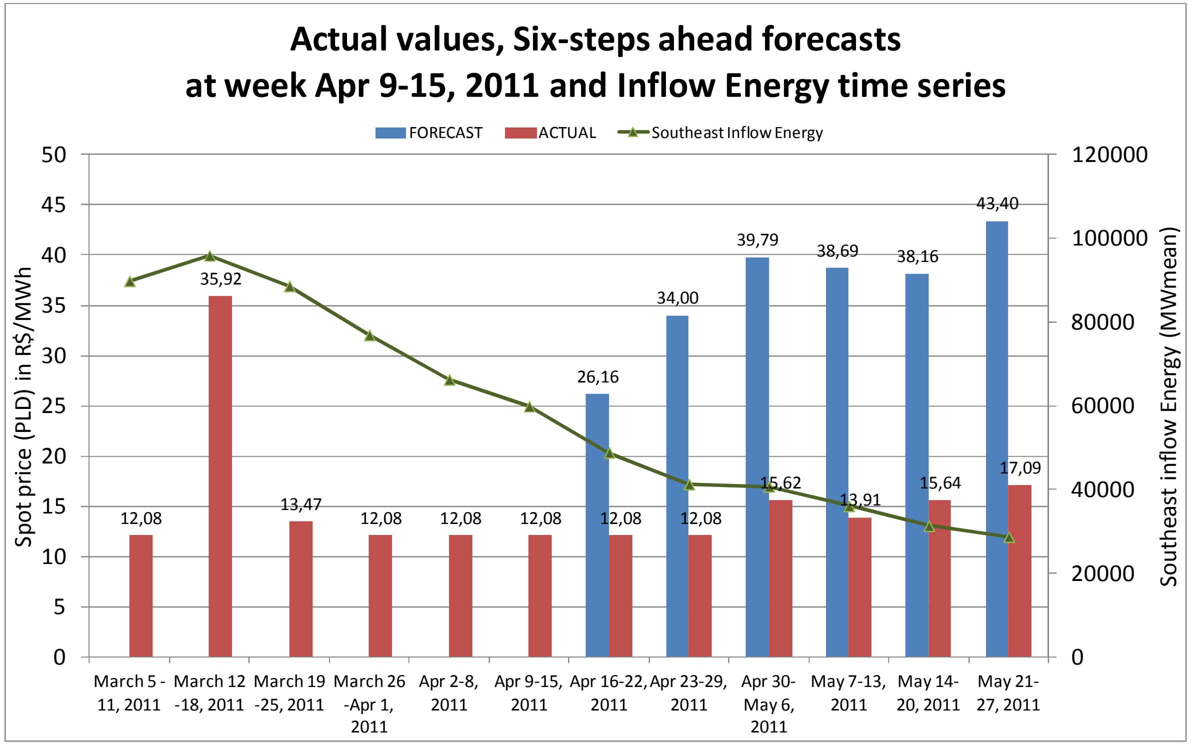
Empirical Results

❑ Error statistics of the six step ahead forecasts (%)

Forecasts starting at week:	1 step ahead	2 steps ahead	3 steps ahead	4 steps ahead	5 steps ahead	6 steps ahead	MAPE (week)
Jan 1-7, 2011	22.67	17.22	5.59	0.00	31.01	42.21	19.78
Jan 8-14, 2011	55.86	4.96	46.57	94.26	34.56	47.90	47.35
Jan 15-21, 2011	1.76	46.57	32.12	53.27	60.67	55.16	41.59
Jan 22-28, 2011	46.57	32.12	53.08	60.54	55.03	85.66	55.50
Jan 29-Feb 4, 2011	32.12	53.08	60.54	55.03	85.66	212.91	83.22
Feb 5-11, 2011	7.70	20.10	29.11	85.66	192.26	65.35	66.70
Feb 12-18, 2011	5.43	15.38	85.66	193.21	64.91	24.02	64.77
Feb 19-25, 2011	26.09	0.00	1.91	6.52	38.35	0.00	12.15
Feb 26-Mar 04, 2011	0.00	1.91	10.32	40.71	0.00	0.00	8.82
MAPE (forecast horizon)	22,02	21,26	36,10	65,47	62,49	59,25	

Empirical Results

- Forecasts produced in week April 9th-15th, 2011 and the following ones tend to be higher than the actual values, and sometimes the forecast errors are quite high, for no apparent reason
- a possible explanation for this fact is that the subsystem inflow energy has a decreasing trend on the weeks preceding April 9th-15th, 2011.



- This behavior, in a hydro based system, would lead to the dispatch of thermal plants to save water and increase reservoir levels resulting in an increase in the spot price.

Conclusions

- The input variables considered are thought of as important leading indicators of price movements in a primarily hydroelectric system such as Brazil's
- The forecasts produced were adequate most of the time. However, in some instances, short-term dispatch decisions affected prices in ways that could not be anticipated by the model

Conclusions

- The model can be improved further by incorporating other variables, specifically those related to thermal generation.
- In fact, a trial neuro-fuzzy model has been tested to forecast thermal generation, and the forecast can be used as a "threshold" – if above a certain amount, the forecast of the original model need to be corrected upwards to account for the dispatch of the thermal plants. These results are, however, at a very preliminary stage, so they were not reported here.