Neural Networks to Model Energy Commodity Price Dynamics

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Abstract

Energy commodity prices are a crucial variable in the economic context given their role in the consumption and production process, since energy commodities have recently become an asset class playing an increasing role in the risk management field. The pricing models and the techniques used to provide an estimation of price dynamics become more and more important. We propose in this paper a new methodology based on neural networks in order to build a forecast for specific standard price time series of energy commodities. In particular we analyze Crude oil, natural gas and electricity prices for the European and the US market. Using daily data over the period 2001-2010 we are able to provide very robust forecasts for a one year time horizon of the considered series. Furthermore, we perform a statistical assessment of the considered prediction models and we prove that some of them provide the first four unconditional moments of the predicted sequences almost equal to the moments estimated on the market data.

Keywords – energy commodity price, time series prediction, neurofuzzy networks, statistical assessment.

1. Overview

Several Energy commodity prices are a crucial variable in the economic context given their role in the consumption and production process. In particular, crude oil prices have shown unprecedented dynamics over the last decade having large effects on the entire commodity markets [1]. Energy commodities have recently become an asset class playing an increasing role in the risk management field. Financial managers and banks started to allocate part of their wealth in the commodity markets, this having an impact on the demands of the commodities and on the price dynamics. Spot markets for oil, gas and electricity are at hand and are largely used by various kind of participants also by financial institutions besides the traditional retailers or producers. A large set of energy derivatives have also been introduced in most European and US Exchanges providing an useful tool to hedge risk. In this context the pricing models and the techniques used to provide an estimation of price dynamics become more and more important.

In the present work we use standard price time series and a new methodology based on neural networks in order to build a forecast for specific energy commodity prices. The series we analyze are the Crude oil, natural gas and electricity prices for the European and the US market. The accurate prediction of future values of such sequences is crucial to the cost-effective management of available resources [2]-[5]. Using daily data over the period 2001-2010 we are able to provide very robust forecasts for a one year time horizon of the considered series. Three different approaches are used and a backtest is performed in order to identify the best performing method.

2. Methods

Several data driven modeling techniques have been taken into consideration: a linear model determined by the well-known least-squares approximation (LSE); a Radial Basis Function (RBF) neural network [6], [7] trained using the well-known Matlab® software package (version 6.1); an Adaptive Neurofuzzy Inference system (ANFIS) network, where the subtractive clustering (SUBCL) method is used for the rule extraction [8] and the rule parameters are obtained by means of a standard least-squares method coupled with the back-propagation optimization [9]; a Mixture of Gaussian (MoG) neural network, which is particularly suited for ill-posed and non-convex approximation and prediction tasks [10].

We use time series of daily prices of oil, gas and electricity for the period 2001-2010. Time series have been arranged in 3-years slots, since all the predictors have been trained on a 2-years time window and tested on the successive 1-year period. For any sample $S(n)$ to be predicted, a prediction model $f(\cdot)$ is fed by the previous D samples, where D is the prediction order; i.e.:

$$\hat{S}(n) = f\left[S(n-1) \quad S(n-2) \quad \cdots \quad S(n-D)\right], \tag{1}$$

where the hat symbol in $\hat{S}(n)$ stands for the predicted, estimated values.

The prediction model $f(\cdot)$ is estimated by means of a training procedure where the prices of the former two years are used. Suited routines are applied for this task on the basis of the chosen model. The prediction order D should be determined on the basis of information theory and this is a topic that will be further investigated in future research works. In this case, we have used a rule-of-thumb by which the previous five samples of the sequence, i.e. D=5, are used to predict the next one. The performances of the resulting predictors are measured by means of different measures of the prediction error; they are summarized in the following:

$$\text{MSE} = \sum\nolimits_n \left[\hat{S}(n) - S(n)\right]^2 , \tag{2}$$

$$\text{NMSE} = \frac{\sum\nolimits_n \left[\hat{S}(n) - S(n)\right]^2}{\sum\nolimits_n \left[S(n) - \overline{S}\right]^2} , \tag{3}$$

$$\text{SNR} = 10 \log_{10} \frac{\sum\nolimits_n \left[\hat{S}(n) - S(n)\right]^2}{\sum\nolimits_n \left[S(n) - \overline{S}\right]^2} , \tag{4}$$

$$\text{MAPE} = \frac{100}{N} \sum\nolimits_n \left| \frac{\hat{S}(n) - S(n)}{S(n)} \right| , \tag{5}$$

where N is total number of available samples and $\overline{S}$ is the average of actual samples $S(n)$ over this set.

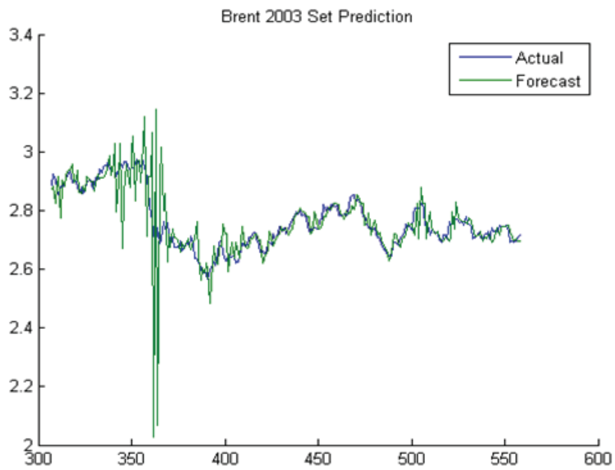
It is interesting to notice that the MSE is the energy of the prediction error, while in NMSE and SNR this energy is normalized to the energy (variance) of the actual sequence. Differently, using MAPE the accuracy is expressed as a percentage error in order to compare the error of fitted time series that differ in level. All such measures are suited to quantify how much the prediction has been corrupted by errors. In addition to this, it is also important to assess the robustness of the prediction model in a statistical sense. To this aim, the first four unconditional moments will be evaluated and considered for both actual and predicted sequences.

3. Results

The validity of the proposed approach has been verified by carrying out a complete set of tests using all the considered prediction models and all subsets of market data, partitioned in the 3-years periods from 2001 to 2010. We obtained a homogeneous behavior in such several tests, considering both the measures of prediction error, as in (2) to (5), and the statistical moments as well. In other words, for every sub-period and every price under analysis, a good performance is ensured by all the neural models and the ANFIS model is the one that is able to obtain the best results.

For the sake of illustration, we report in the following some results that are representative of the extensive experimental campaign we carried out in this regard. As we may see by the results obtained by RBF in the test of 2003 Brent, reported in Fig. 1, the prediction error is not always a comprehensive measure of prediction accuracy. For instance, even if we obtain a SNR of about 30 dB, the network fails on the third and fourth order moments; this is evident since some predicted samples in the test set are coarsely wrong. However, the accurate prediction of 2003 Brent is assured by the ANIFS network, as illustrated in Fig. 2, where all the statistical moments are now accurately fitted. Nevertheless, an example of good prediction of ANFIS networks is also shown in Fig. 3 in the case of 2003 WTI prices.

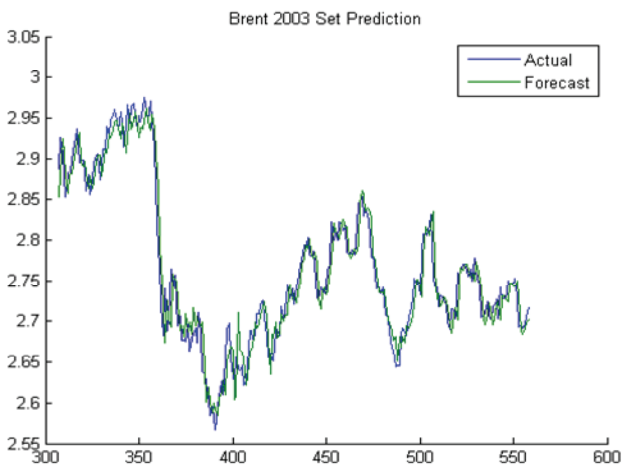
Given that energy prices represent a crucial variable for the choice of the adequate investment strategies, a successful model has to provide comparable statistical features on the simulated series. From this point of view, the results obtained by the proposed approach show that there exist suited prediction models by which the first four unconditional moments of the predicted sequences are almost equal to the moments estimated on the market data. Bearing in mind this consideration, we would like to remark that, among the different performance measures that can be adopted for the prediction error, the SNR is the only one allowing a calibration and an objective evaluation of the accuracy. In fact, we are able to fix a sound threshold that, if attained, assures a good performance especially for what concerning the statistical distribution. In this specific application, such a threshold can be determined in about 40 dB for any tests.



	ACTUAL	FORECAST
MEAN	2,7645	2,7652
STD DV	0,0093	0,015
SKEWNESS	0,5547	-0,001
KURTOSIS	2,4811	11,5304

MSE	0,0076
NMSE	0,8145
SNR(dB)	30,0513
MAPE(%)	1,4493

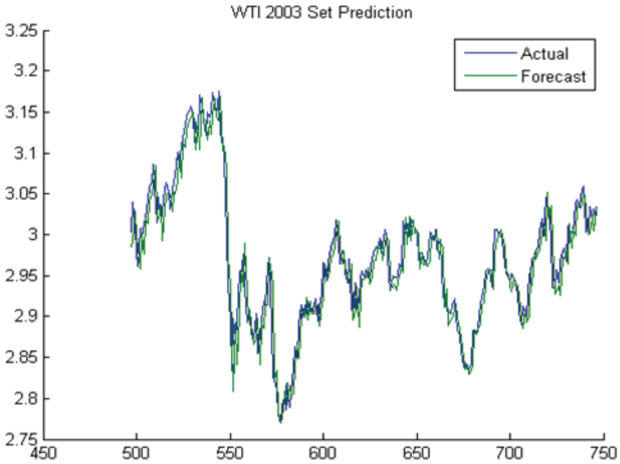
Figure 1 - Prediction of 2003 Brent using RBF.



	ACTUAL	FORECAST
MEAN	2,7645	2,7645
STD DV	0,0093	0,0088
SKEWNESS	0,5547	0,5064
KURTOSIS	2,4811	2,3676

MSE	0,0005
NMSE	0,057
SNR(dB)	41,604
MAPE(%)	0,6394

Figure 2 - Prediction of 2003 Brent using ANFIS.



	ACTUAL	FORECAST
MEAN	2,9718	2,9669
STD DV	0,0069	0,0067
SKEWNESS	0,2596	0,2538
KURTOSIS	3,1255	3,1028

MSE	0,0006
NMSE	0,0943
SNR(dB)	41,3292
MAPE(%)	0,6462

Figure 3 - Prediction of 2003 WTI using ANFIS.

4. Conclusions

The used approach provides a very efficient tool to generate energy price series within a one year time horizon, which will allow to accurately estimate possible relationships between the various commodities in order to set up risk management strategies.

Currently we are working on a more detailed analysis of the results obtained following the proposed approach, which will be divulgated by considering other classical statistical predictors as well. Nevertheless, we are investigating more advanced techniques to endogenously identify the optimal number of previous samples to be used for prediction, including the prediction order and hence the resulting complexity of neural models.

5. References

[1] H. Geman, *Commodities and Commodity Derivatives: Modelling and Pricing for Agriculturals, Metals and Energy*, The Wiley Finance Series, John Wiley, Chichester, U.K., 2005.

[2] A.N. Refenes, A. Zapranis, and G. Francis, “Stock Performance Modeling Using Neural Networks: A Comparative Study with Regression Models”, *Neural Networks*, Vol. 7, 1994, pp. 375-388.

[3] A.S. Weigend and N.A. Gershenfeld, *Time Series Prediction: Forecasting the Future and Understanding the Past*, Addison-Wesley, Reading, MA, 1994.

[4] C. Bishop, *Neural Networks for Pattern Recognition*, Oxford Univ. Press Inc., NY, 1995.

[5] F. Masulli and L. Studer, “Time series forecasting and neural networks,” in Invited tutorial in Proc. of IJCNN’99,Washington DC, 1999.

[6] S. Chen, C. Cowan, and P. Grant, “Orthogonal least squares learning algorithm for radial basis function networks”, *IEEE Transactions on Neural Networks*, Vol. 2, 1991, pp. 302-309.

[7] P. Wasserman, *Advanced Methods in Neural Computing*, Van Nostrand Reinhold, New York, NY, 1993.

[8] S.L. Chiu, “Fuzzy model identification based on cluster estimation”, *Journal of Intelligent Fuzzy Systems*, Vol. 2, 1994, pp. 267–278.

[9] J. S. Jang, C. T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice-Hall, Upper Saddle River, NJ, 1997.

[10] M. Panella, A. Rizzi, and G. Martinelli, “Refining accuracy of environmental data prediction by MoG neural networks”, *Neurocomputing*, Vol. 55, 2003, pp. 521-549.