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MODELING ENERGY MARKETS USING NEURAL NETWORKS AND SPECTRAL ANALYSIS

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Overview

Energy commodity markets have become crucial for the economic growth policies and investment strategies in the last decade. Crude oil prices have experienced unprecedented volatility due not only to structural features but also to geopolitical issues, to the recent discovery of shale gas and to the increased use of gas turbines. Moreover, the deregulation of electricity markets requires an efficient tool to describe the price features whilst standard econometric procedures cannot provide an accurate description of the actual price dynamics.
In the present work we illustrate the application of filter banks and neural networks to predict prices of specific energy commodities, which play a crucial role in the international economic and financial context. The proposed approach is assessed by the numerical results obtained for US crude oil, natural gas and electricity daily prices.

Methods

Filter banks represent a signal processing tool limiting the spectral distribution of time series to be predicted in every subchannel. They are adopted in association with neural networks to predict the subsequences regardless of the specific filter bank implementation. Filter banks process a broadband scalar signal by decomposing it in a number of directly adjacent frequency bands (i.e., the *subbands*) and by performing a given operation in each subband (see figure). The decomposition is performed in the analysis filter bank (AFB) and each subband is associated a scalar sequence. A processing unit (PU) performs the specific operation, i.e. the prediction in our case, usually working in parallel in each subband (or *channel*) of the filter bank. Then, the processed scalar signals are used as inputs to the synthesis filter bank (SFB), which performs a filter operation in order to reconstruct the whole predicted signal.

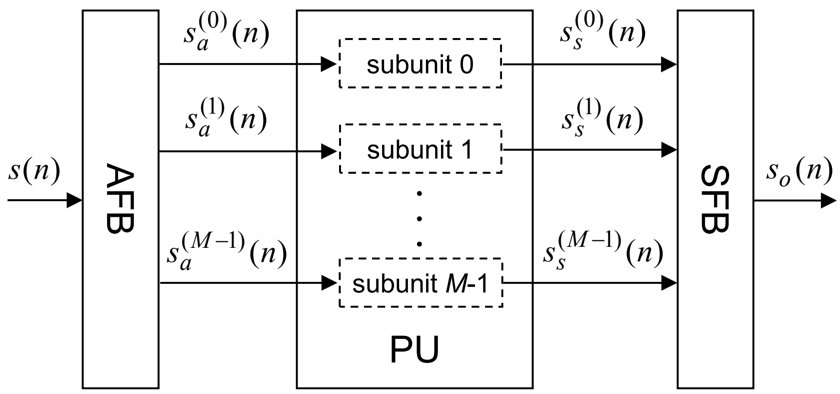

Figure. A typical filter bank structure useful for prediction.

Filter banks may operate in two way: generating *maximally decimated* subsequences, each subsampled (sample reduction) by a factor *M* that is equal to the number of channels; maintaining the number of samples of each sequence but translating (modulation) in the *baseband* its spectrum. We propose this solution since we do not obtain a reduction of computational cost, but the sequences are highly interpolated and thus, with respect to the normalized spectrum, they contain only low-frequency components that should be predicted more easily.

Given the complexity of the daily price series, the prediction model in each subchannel must be a nonlinear function inferred by a regularized learning paradigm and estimated through a given set of observed samples. This task can be solved by a data driven technique in the framework of computational intelligence for time series forecasting. We consider well-known neural network models for prediction: the Radial Basis Function (RBF) neural network and the Adaptive Neuro Fuzzy Inference System (ANFIS), whose rules are generated by applying a suited clustering method. A comparison is also performed with respect to a linear model whose parameters are estimated by a least-squares (LSE) technique. These models can be re-trained at every sample, in such a way that the prediction can follow the intrinsic non stationarity or seasonality that are typical in energy commodity prices.

Results

The proposed approach is evaluated considering daily price series for crude oil, natural gas and electricity. Data refer to the 2001-2010 period in the US markets; the results are similar to those obtained for the European data set. The US energy commodities and the related indexes considered in the following are: Henry Hub natural gas (HH, in $/MMBtu); crude oil (WTI, in $/barrel), and electricity (PJM, in $/MWh). We have approximately 250 prices per year; all the predictors are trained on 500 samples (about two years) and tested on the successive 250 samples (about one year). Three different time slots are considered in the last decade: 2001-2002 (training) and 2003 (test); 2004-2005 (training) and 2006 (test); 2008-2009 (training) and 2010 (test). The performance is measured by the Normalized Mean Squared Error (NMSE) defined as the ratio between the mean squared prediction error and the variance of the sequence to be predicted.

The subband prediction using maximally decimated filter banks allows an average NMSE reduction of about 5% with respect to the classic broadband approach for almost all the sequences under investigation and all the adopted prediction models: linear, RBF and ANFIS. Furthermore, the NMSEs obtained by using baseband filter banks reveals a further dramatic reduction of about 60% with respect to the maximally decimated version. It is important to notice that neural network models can fail using the latter type of filter banks, because of the reduced cardinality of training sets obtained by decimated sequences.

Conclusions

The proposed approach is based on filter banks for obtaining baseband demodulated subsequences with a smooth behavior that can make prediction easier. This is suited to describe high frequency data and in particular financial time series, which show high volatility and non-linear dynamics, especially in compound with neural models for subchannel prediction. The results obtained for major energy commodities prove the validity of the proposed approach.

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