Wavelet Approach to Electricity Spot-Price Forecasting in a Deregulated Electricity Market

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Summary
The purpose of deregulation is to give consumers free choices of their electricity supply. Electricity generators, transmission, and distribution companies are driven by the market to maximize their profits. The accuracy of electricity spot price forecasting is crucial to any of the above participating companies, since it provides them with spot price signal in the future that is used to optimize the operational planning. In this article, we propose a wavelet multiscale decomposition based autoregressive approach for the prediction of one-hour ahead and one-day ahead electricity spot price based on historical electricity price and predicted electricity load data. This approach is based on a multiple resolution decomposition of the signal using the redundant Haar à trous wavelet transform whose advantage is taking into account the asymmetric nature of the time-varying data. We assess results produced by this multiscale auto-regressive (MAR) method, with single resolution autoregressive (AR), and multilayer perceptron (MLP) model. Numerical results are based on the New South Wales (Australia) electricity load and price data that is provided by the National Electricity Market Management Company (NEMMCO).
Keywords:
Wavelet transform, electricity price forecast, time-series, multi-layer perceptron.

1. Introduction

Modern societies have become very much depend on power energy to function and operate. Hence, power systems are being pushed to their limits to meet their customers' demands, and spend a lot of money in their operation scheduling. Furthermore, power systems need to operate at even higher efficiency in a deregulated electricity market in which the participating companies such as electricity generators and retailers have to compete in order to maximize profits to their stakeholders and minimize risk due to price spikes. Thus, accurate spot price forecasting plays a key role in ensuring adequate electricity generation to meet the customer's demands in the future. For many years, the electricity industry has been operating as monopoly under a budget and pricing structure, directly or indirectly set by the government in most countries. During pre-deregulation era, generators, retailers, and consumers participating in the electricity supply industry plan their business strategies assuming the price of electricity was constant in terms of tariffs, whereas the price of the electricity varies every half-hour or an hour in a deregulated electricity market. Over a decade or so, many countries have begun major electricity industry deregulation and restructuring. The purpose of deregulation is not only to implement a new structure where a central management body operates a wholesale market for trading electricity between generators and retailers, but to maximize returns to their stakeholders as well. Subsequently, it gives consumers free choices of their electricity supply. Fig. 1 shows that the generators compete by providing generation bids and their associated prices to the central management body. The retailers also compete by providing the consuming bids. The central body then matches the supply with the demand, and selects the generators required to produce electricity power at different times for the whole day. In turns, the retailers pay for the electricity they use from the electricity pool and distribute it to the consumers.

In the deregulated market, all electricity supply industry market participants being generators, retailers or consumers could have a big advantage in terms of making profits by using an electricity spot price forecast. Thus, the participant with accurate and best forecast of the future prices would be in the most confident position to negotiate contracts of greatest benefits to their stakeholders. The aim of spot price forecast is to predict future electricity price based on historical spot price and predicted load data [5], [6].

Traditionally forecasting methods are mostly based on statistical linear regression such as Autoregressive (AR), and Autoregressive-Integrated Moving Average (ARIMA), and General Autoregressive Conditional Heteroscedasticity (GARCH) models [8], [13[, [23], have been used for spot price forecasting [9], [12], [16]. Time-series models [18], [29] have also been used for price forecast. In recent years, modern methods based on artificial intelligence have shown promising results. The Feed-forward Artificial Neural Network (ANN) or Multi-Layer Perceptron (MLP) based methods have received great attention for price forecast. The ANNs as supervised models have been used to deal with the nonlinearity and non-stationary in electricity pool price prediction by producing good and

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satisfactory results [19], [22], [27]. The ANNs are well suited to modeling the complex, nonlinear relations involved in price forecasting. These complex relationships are modeled through a process of learning from examples so called "training". This training consists of learning from examples of past price and load behaviors. During the process, ANNs develop internal relationships among these factors, and then use these relationships to synthesize the price forecast. Good reviews on spot price solver can be found in [7].

In this article, we explore how the use of linear regression fed with wavelet-transformed data can aid in capturing useful information on various time scales. We also show that multi-resolution based autoregressive approaches outperform the traditional single resolution approach, and even the well-known nonlinear based neural network method (Multi-Layer Perceptron) to modeling and forecasting.

Wavelet transforms provide a useful decomposition of the time series in terms of both time and frequency. They have been used effectively for image compression, noise removal, object detection and large-scale structure analysis, among other applications [25], [26].

We use the Haar à trous wavelet transform throughout this article. The original signal data can be expressed as an additive combination of the wavelet coefficients at different resolution levels. We introduce the non-decimated Haar wavelet transform in [31], and this method was also used in [24]. This choice of wavelet transform was motivated by the fact that the wavelet coefficients are computed only from data obtained previously in time, and the choice of a non-decimated wavelet transform avoids aliasing problems.

The wavelet transform has been proposed for time series analysis in many papers, includes filtering and forecasting in recent years. For financial time series prediction [1], [24], [26], wavelet based on a neural network [2], [31], pool price prediction by Neuro-Fuzzy combination [15], Web traffic forecast [3], [4], Kalman filtering [10, and an AR (autoregressive) model [24]. See also [11] which relate the wavelet transform to a multi-scale autoregressive type of transform. Wavelet networks are supervised neural networks with wavelet functions replacing the widely used sigmoid transfer functions [30].

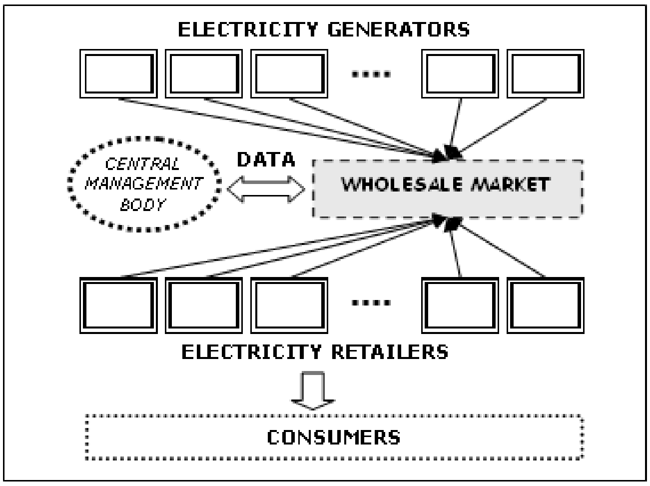

Fig. 1. A deregulated electricity market structure.

2. FORECASTING USING WAVELET DECOMPOSITION

Our task is to consider the approximation of a time series at coarser and coarser resolution, summarized in a multi-resolution decomposition. The individual time series resulting from the decomposition, taken together, can provide a detailed picture of the underlying processes.

2.1 The Haar à trous Wavelet Transform

The à trous wavelet can be described simply as follows. First, perform successive convolutions with the discrete low-pass filter h:

$$C_{i+1}(k) = \sum_{l=-\infty}^{+\infty} h(l) C_i\left(k + 2^i \times l\right) \qquad (1)$$

where the finest scale is the original series: $C_0(t) = X(t)$ (see e.g. [28]). The increase in distances between the samples points (i.e. $2^i l$) explains why the name à trous (with holes) has been applied to this method. The low-pass filter, h, is B_3 spline, defined as $\left(\frac{1}{16}, \frac{1}{4}, \frac{3}{4}, \frac{1}{4}, \frac{1}{16}\right)$. This is of compact support (necessary for a wavelet transform), and is point-symmetric. The latter does not allow for the fact that time is a fundamentally asymmetric. Now, from the sequence of smoothing of the signal, we take the difference between successive smoothed versions to obtain the wavelet coefficients w_i:

$$w_i(k) = C_{i-1}(k) - C_i(k) \qquad (2)$$

The latter provide the detail signal, or wavelet coefficients, which we hope in practice, will capture small features of interpretational value in the data. It is easy to show that we have the following expansion of the original data:

$$X(t)=C_p(t)+\sum_{i=1}^{p} w_i(t) \tag{3}$$

However, the à trous wavelet transform with a wavelet function related to B_3 spline function, as described above, is not appropriate for a directed (time-varying) data stream. To cater for the requirement that future data values cannot be used in the calculation of the wavelet transform, we use the Haar à trous wavelet transform, introduced in [31], and more details in [6].

The non-decimated Haar algorithm is exactly the same as the à trous algorithm, except that the B_3 spline based low-pass filter h is replaced by the simpler filter $\left(\frac{1}{2},\frac{1}{2}\right)$. There, h is now non-symmetric, thus the Haar à trous algorithm. Consider the creation of the first wavelet resolution level.

We have created it by convolving the original signal with h:

$$C_{i+1}(k)=0.5\times\left(C_i(k)+C_i(k-2^i)\right),$$
$$w_{i+1}(k)=C_i(k)-C_{i+1}(k). \tag{4}$$

At any time point, k, we never use information after k in calculating the wavelet coefficient. The Haar à trous transform provides a convincing and computationally very straight-forward solution to troublesome time series boundary effects at the time point t. More experimental results with this redundant transform can be found in [31].

Fig. 2 shows the transform on a sample set of New South Wales (NSW) electricity spot price. The element wise sum of scales 1 through 6, plus the smooth trend, gives the original data set. Note the following: (*i*) all wavelet scales are of zero mean; and (*ii*) the smooth trend plot is very often much larger-valued (as it is the case here) compared to the max-min ranges of the wavelet coefficients.

Fig. 3 shows which pixels of the input signal are used to calculate the last wavelet coefficient in the different scales. A wavelet coefficient at a position t is calculated from the signal samples at positions less than or equal to t, but never larger.

2.2 Linear Multiscale Based Forecasting

We used the Haar à trous wavelet decomposition described above of the signal for forecasting. The forecasting problem considered is the determination of one hour-ahead electricity forecast. Instead of using the vector of past electricity price observations $X = (X_1,...,X_N)$ to forecast X_{N+1}, its wavelet transform is used. The pool price varies with the electricity load as shown in Fig. 4 during a typical day.

Renaud *et al.* [17], [20], [21] have found that the wavelet coefficients at each scale (j) that will be used for the forecast at time N+1 have the form $w_{j,N-2j(k-1)}$ and $c_{J,N-2J(k-1)}$ for positive value of k as shown in Fig. 5.

Assume a signal $X = (X_1,...,X_N)$ and assume we want to forecast X_{N+1}. We use the coefficients $w_{j,N-2\,j(k-1)}$ for $k=1,...,A_j$ where $j=1,...,J$ and $c_{J,N-2J(k-1)}$ for $k=1,...,A_{j+1}$. See Fig. 5 when J=4 and A_j=2 for $j=1,...,J+1$.

A one-step forward forecast of a linear autoregressive model or $AR(p)$ process is written:

$$\hat{X}_{N+1}=\sum_{k=1}^{p}\hat{\beta}_k X_{N-(k-1)} \tag{5}$$

where $\left(\hat{\beta}_k\right)$ are ordinary least squares estimators.

In order to use wavelet decomposition, we consider Multi-resolution AR forecasting (MAR) [20], [21]:

$$\hat{X}_{N+1}=\sum_{j=1}^{J}\sum_{k=1}^{A_j}\hat{a}_{j,k}\,w_{j,N-2^j(k-1)}+$$
$$\sum_{k=1}^{A_{J+1}}\hat{a}_{J+1,k}\,c_{J,N-2^J(k-1)} \tag{6}$$

where $w = (w_1,...,w_J,c_J)$ represents the Haar à trous wavelet transform of X, *i.e.* $X=\sum_{j=1}^{J}w_j+c_J$.

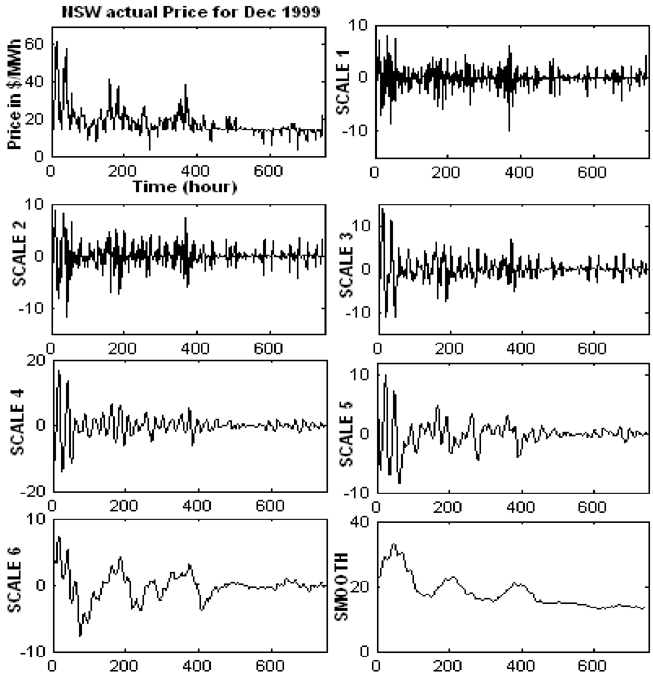

Fig. 2. A Haar à trous wavelet transform of a sample set, of 744-value, hourly electricity spot price.

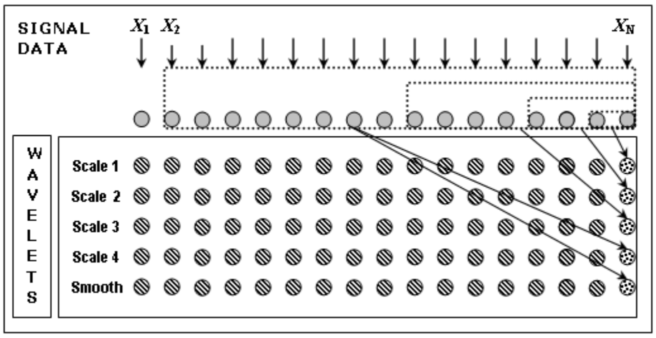

Fig. 3. Redundant Haar à trous wavelet transform - this shows which time steps of the signal data are used to compute the last wavelet coefficients at each different scale.

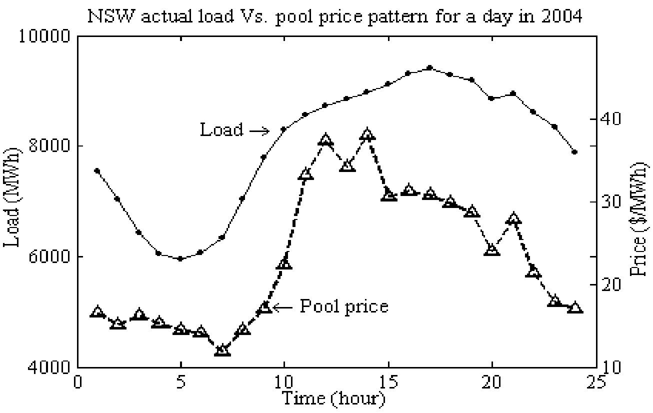

Fig. 4. Typical daily electricity load versus pool price pattern.

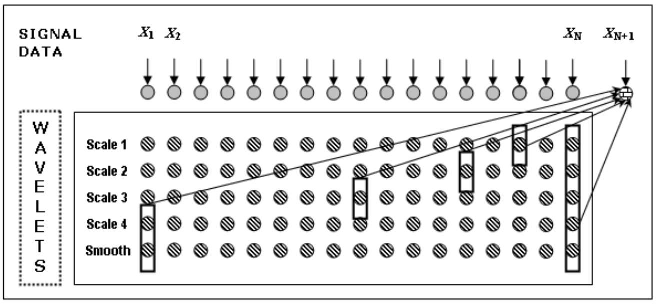

Fig. 5. Ten wavelet coefficients, MAR (2) with 4 wavelet scales plus the smoothed array, that are used for the forecast of the next value X_{N+1}.

Fig. 5 shows which wavelet coefficients are used for the forecasting using A_j=2 for all resolution levels j, and a wavelet transform with five scales (four wavelet scales plus the smoothed array). To estimate the $p=\Sigma A_j, j=1,\ldots,J+1$, unknown coefficient vector (β) whose variables are the ($a_{j,k}$) described above, we used the least squares method: minimizing the sum of squares of the differences between the forecast value in (6) and the actual value X_{N+1} over all the values of N in the training sample time, which lead to solve the normal equations: $Z\times\beta = X$ where Z is the matrix as $n \times p$ matrix composed of the n sample of the input variables $\{w_{j,N-2^j(k-1)}, c_{J,N-2^J(k-1)}\}$ and the observed (actual) $n\times 1$ vector X.

3. IMPLEMENTATION

In this article the MATLAB7.0 high level programming language has been used to implement the proposed forecasting methods, the single resolution autoregressive model (AR), multiscale wavelet based autoregressive model (MAR), and the multilayer perceptron neural network (MLP). The simulations have been run on a Microsoft Windows XP based platform (Intel Pentium processor 1400MHz, and 256 MB of RAM). The fast Levenberg-Marquardt back-propagation training algorithm was used to train the neural network due to relatively large training data sets.

The proposed spot price forecast system is composed of two forecasting modules as shown in Fig. 6. The first module is the load forecasting module [5], [6] and the second module is the spot price forecasting based on Haar à trous wavelet multi-resolution autoregressive method. It is summarized in 3 steps as follows:

Step1: Training and Testing Data Preparation
- Creating training and testing data sets for loads and prices.

Step2: Training
- Training daily data of loads and prices based on strictly historical data; produce one hour ahead prediction of load.

Step3: Generalization (Testing)
- Using historical data of load and price, and current predicted load, predict current price.

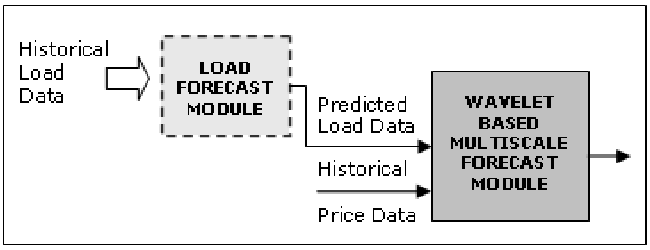

Fig. 6. wavelet-based multiscale autoregressive spot price forecast system.

4. NUMERICAL RESULTS

The above models were assessed on the New South Wales (Australia) real price data from electricity market data which is available publicly from the National Electricity Market Management Company (NEMMCO).

For comparison, the MAR model's results were compared with the ones produced by basic single autoregressive (AR) model [23], Levenberg-Marquardt back-propagation based multilayer perceptron (MLP)[14].

4.1 Input Data Preparation And Training

The input data consists of historical electricity price and load which was collected over 3 years (Jan 1 1999 to Dec 31, 2001): 26297 hourly actual load and price values, to train the above models; and data of one year (Jan 1 2002 to Dec 31 2002) is used for testing whereby the predicted load is used instead of actual load. In other words, it is a coupled model where load is being predicted [5], [6] and is being fed into the price forecaster during testing period as it is the case in real time when no current load (actual) is available. As examples for testing we chose days from different seasons, including 3 Jan 2002 (see Table I). The forecasting architectures used including MLP were defined from the training data; but data from test period was used – of necessity – to get the one-hour ahead forecast.

In the comparisons of model performance, the price forecast accuracy is determined in terms of two performance measures which are adopted here as follows:

Absolute Percentage Error (APE):

$$APE\,(\%) = \frac{|Actual\;(i) - Forecast\;(i)|}{Actual\;(i)} * 100$$

Mean Absolute Percentage Error (MAPE):

$$MAPE(\%) = \frac{1}{m}\sum_{i=1}^{m}\frac{|Actual(i) - Forecast(i)|}{Actual(i)} * 100$$

Root-Mean Squares Error:

$$RMS = \sqrt{m^{-1}\sum_{i=1}^{m}\left[Actual(i) - Forecast(i)\right]^2}$$

where m is the total number of hours predicted, *Actual*(i) is the actual spot price for the hour i, and *Forecast*(i) is the predicted spot price for the hour i.

4.2 One-Hour Ahead Spot Price Forecasting

The best linear AR model found, non-mutiresolution autoregressive AR (25), based on the Bayesian Information Criterion (BIC) [23]. An MAR(7), i.e. multiresolution AR(7) with 2 wavelet resolution scales, model provided better results, in terms of MAPE (%) and RMS performance measures described above, compared to AR and other non-linear approaches such as MLP (back-propagation, 3 layers, 3 input units: {1 input: price at same hour of previous day + 1 input: price at same hour of previous week + 1 input of predicted load at same hour [5], [6]}, 10 hidden units, 1 output unit), which gives best performance on the training data set during the learning process.

As shown in Table I, AR, MAR, and MLP models, as described above, have been used to forecast one-hour ahead electricity price.

- Fig. 7 shows simultaneous plots of the actual load versus respectively MAR, MLP, and AR based forecasted spot price for a day of January 3, 2002. It also shows a plot of the differences between actual and forecasted price, MAR, MLP, AR respectively.
- Table I and II describe testing results on a selected day based on 3 different models.

5. CONCLUSIONS

In this article a linear multi-resolution autoregressive (MAR) method has been proposed based on a wavelet transform to forecast one-hour ahead electricity spot price of the New South Wales (Australia) electricity market. This wavelet transform is the redundant Haar à trous wavelet transform which decomposes the signal data into multiple resolution scales and has the advantage of being shift-invariant. It is also easy to implement and is computationally efficient.

The simplest MAR method exhibits higher ability of generalization than the single AR method. Unlike AR, the MAR's forecasting method uses a small number of wavelet coefficients of the decomposition of the past values on each scale. MAR also outperformed the ordinary non-linear methods such as multilayer perceptron (MLP). The experiments show that MAR is the best forecaster. It also shows that MAR model is very well suited to give the competitive advantage of an electricity spot price forecast to generators, retailers and consumers. Hence, the participant with accurate and best forecast of the future prices would be in better position to negotiate contracts of greatest benefits to their stakeholders. Accuracy of the load forecaster model is absolutely crucial as it is fed into the spot price forecaster.

Table I

One-hour ahead hourly price forecasting results for a day of January 2002

Forecasted Day of January 3, 2002 (Summer spot price)			
Model	**Max APE (%)**	**MAPE (%)**	**RMS**
MAR(7)/Scale = 2	9.5785	2.7747	0.6326
AR(25)	23.1588	6.1952	1.7738
MLP (3-10-1)	27.5532	9.6908	2.2043

Table II

One-hour ahead hourly price forecasting results for a day of January, 3rd 2002

Hour	Actual Price in $/MW	Forecasted Spot Price by					
		MAR(7)/Scale=2		AR(25)		MLP 1	
		$/MW	APE %	$/MW	APE %	$/MW	APE %
00	22.90	22.23	2.93	17.60	23.2	20.16	12.0
01	20.02	19.88	0.72	16.68	16.7	17.42	13.0

02	16.53	17.12	3.57	16.37	0.99	16.19	2.08
03	14.66	16.06	9.58	15.04	2.60	14.02	4.35
04	15.23	15.66	2.85	14.68	3.63	13.72	9.91
05	14.95	16.20	8.36	15.03	0.54	14.62	2.19
06	16.34	16.85	3.12	15.79	3.38	16.88	3.33
07	17.93	17.62	1.74	16.67	7.01	18.08	0.85
08	17.74	17.98	1.37	17.62	0.68	19.51	10.0
09	22.18	21.15	4.67	19.24	13.3	24.11	8.70
10	22.43	22.07	1.59	20.50	8.60	25.33	13.0
11	22.90	22.33	2.50	20.67	9.74	25.06	9.43
12	22.90	22.12	3.40	21.40	6.54	25.08	9.54
13	22.90	22.47	1.86	22.21	3.00	25.04	9.35
14	22.90	23.12	0.98	22.17	3.17	25.08	9.51
15	22.90	23.22	1.42	23.72	3.56	25.07	9.48
16	22.90	23.73	3.63	25.44	11.1	25.07	9.48
17	22.90	22.65	1.11	23.09	0.82	25.05	9.40
18	19.74	20.04	1.54	19.32	2.11	23.76	20.4
19	17.08	18.19	6.48	18.72	9.59	21.79	27.6
20	18.26	18.00	1.45	18.13	0.70	19.36	6.00
21	16.90	16.76	0.82	15.93	5.74	18.58	9.91
22	16.97	17.11	0.80	16.03	5.55	18.65	9.90
23	18.16	18.18	0.13	16.98	6.52	20.58	13.3
		Max APE (%)	9.58		23.2		27.6
		MAPE (%)	2.77		6.20		9.69
		RMS	0.63		1.77		2.20

[1] input neurons=3 (fed by original data), hidden neurons=10, output neurons=1. MLP's learning parameters of Levenberg-Marquardt training algorithm (mu=0.001, mu_dec=0.1, mu_inc=10, mu_max=10^{10}).

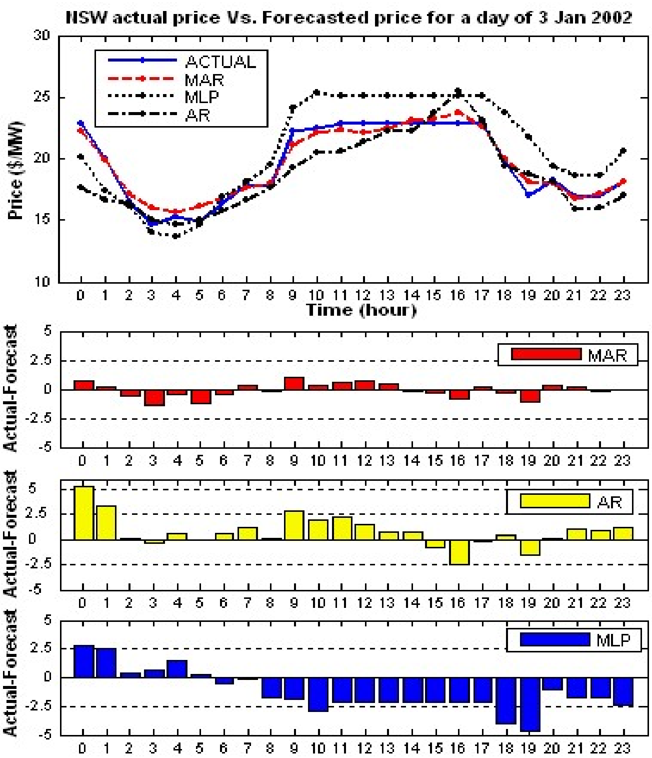

Fig. 7. Actual spot price for 3 Jan 2002. Below: actual minus MAR, MLP, AR respectively, based forecast.

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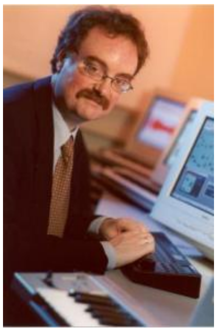

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