THE UNIVERSITY OF SYDNEY

ELECTRICITY LOAD FORECASTING BASED ON WAVELET PACKET TRANSFORM

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1. GOAL

Reliable operation of power systems requires accurate electricity load forecasting in a wide range of time leads. The major goals of this research are:

- *Multi-Resolution Analysis (MRA)* of electricity load data by applying Wavelet Packet Transform (WPT)
- To improve the accuracy of Very Short-Term Electricity Load Forecasting (5-minute ahead) by developing a new model based on the results of MRA of electricity load data and Model Tree

2. MOTIVATION

Very-Short Term Electricity Load Forecasting (VSTLF) assists trading, dynamic dispatching and spot market pricing. Reliable and accurate load forecasting has great implications on energy market operations. It has been estimated that reducing the Mean Absolute Percentage Error with 1% for a 10 GW generator saves US$1.6 million per year [*Hobbs and et al., 1999*].

Electricity load can be considered as a linear combination of various components of different frequencies. Predicting future electricity demands is challenging as the electricity load exhibits chaotic behavior and random fluctuations. We investigate if the prediction can be made more accurate and reliable by localizing and using the different frequency components in previous data in the time period just before the forecasting time.

3. OUR CONTRIBUTION

- We analyze electricity load data both in time and frequency domain simultaneously to localize different frequency components by applying WPT
- We introduce a new algorithm based on entropy criteria to select best basis from WPT decomposition
- We propose a new model that predicts each component of best basis by applying Model Tree (MTR), and then apply Inverse Wavelet Transform (IWT) to generate the final load prediction
- We evaluate the accuracy of the proposed model using 2 years of real data provided by Australian Electricity Market Operator (AEMO), and compare its performance with the state-of-the-art prediction models Multiple Linear Regression (MLR) and Back-Propagation Neural Network (BPNN), and also with the model currently used by industry forecasters (Industry Model).

4. APPROACH

WT is a mathematical tool recently introduced in signal processing. It provides both time and frequency domain representation of a signal simultaneously.

4.1 Wavelet Transform (WT): WT decomposes a signal into set of high and low frequency components. The Continuous Wavelet Transformation (CWT) of a signal X(t) and it reconstruction is given by

$$CWT_x^{\Psi}(s,\tau) = \int_{-\infty}^{\infty} x(t)\,\frac{1}{\sqrt{s}}\,\Psi^*\left(\frac{t-\tau}{s}\right) dt$$

$$X(t) = \frac{1}{C_\Psi^2}\int_s\int_\tau CWT_x^{\Psi}(s,\tau)\,\frac{1}{s^2}\,\Psi\left(\frac{t-\tau}{s}\right) d\tau\, ds$$

Where Ψ^* is the mother wavelet, s and τ are scale and translation parameters respectively.

The Discrete Wavelet Transform (DWT) of X(t) is given by

$$DWT(j,k) = \frac{1}{\sqrt{s_0^j}}\sum_n x(n)\,\Psi^*\left(\frac{n-k\tau_0 s_0^j}{s_0^j}\right)$$

where j and k represents scaling and translation parameters, and n is the discrete time index.

4.2 Wavelet Packet Transform (WPT): A generalization of WT that can provide better frequency resolution of a signal by decomposing both the approximation (low frequency component) and the details (high frequency component), see Fig.1.

For an L level decomposition, WPT provides more than $2^{2^{L-1}}$ bases to encode a signal

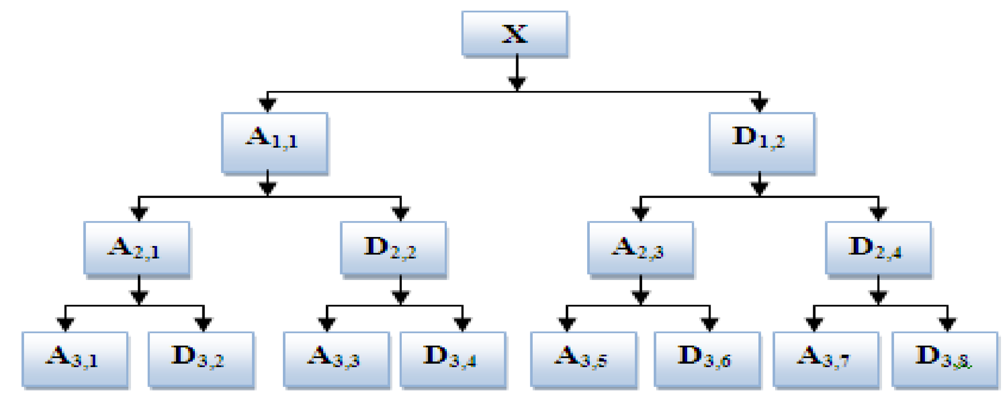

Fig.1: Wavelet Packet Decomposition Structure

4.3 Best Basis Selection

The best basis from the WPT decomposition has been selected using two entropy measures (n is the number of samples in the signal X(t)):

Shannon Entropy:

$$E(x) = -\sum x_i \log(x_i)^2$$

Stein's Unbiased Risk Estimate (SURE):

$$E(x) = n - \{i \text{ such that } |x_i| \le p = [2\log_e(n\log_2(n))]\} + \sum_i \min(x_i^2, p^2)$$

4.4 Proposed VSTLF Approach

Our approach consists of three steps, see Fig.2: Data Pre-processing by WPT, Feature Selection based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), and Forecasting by MTR.

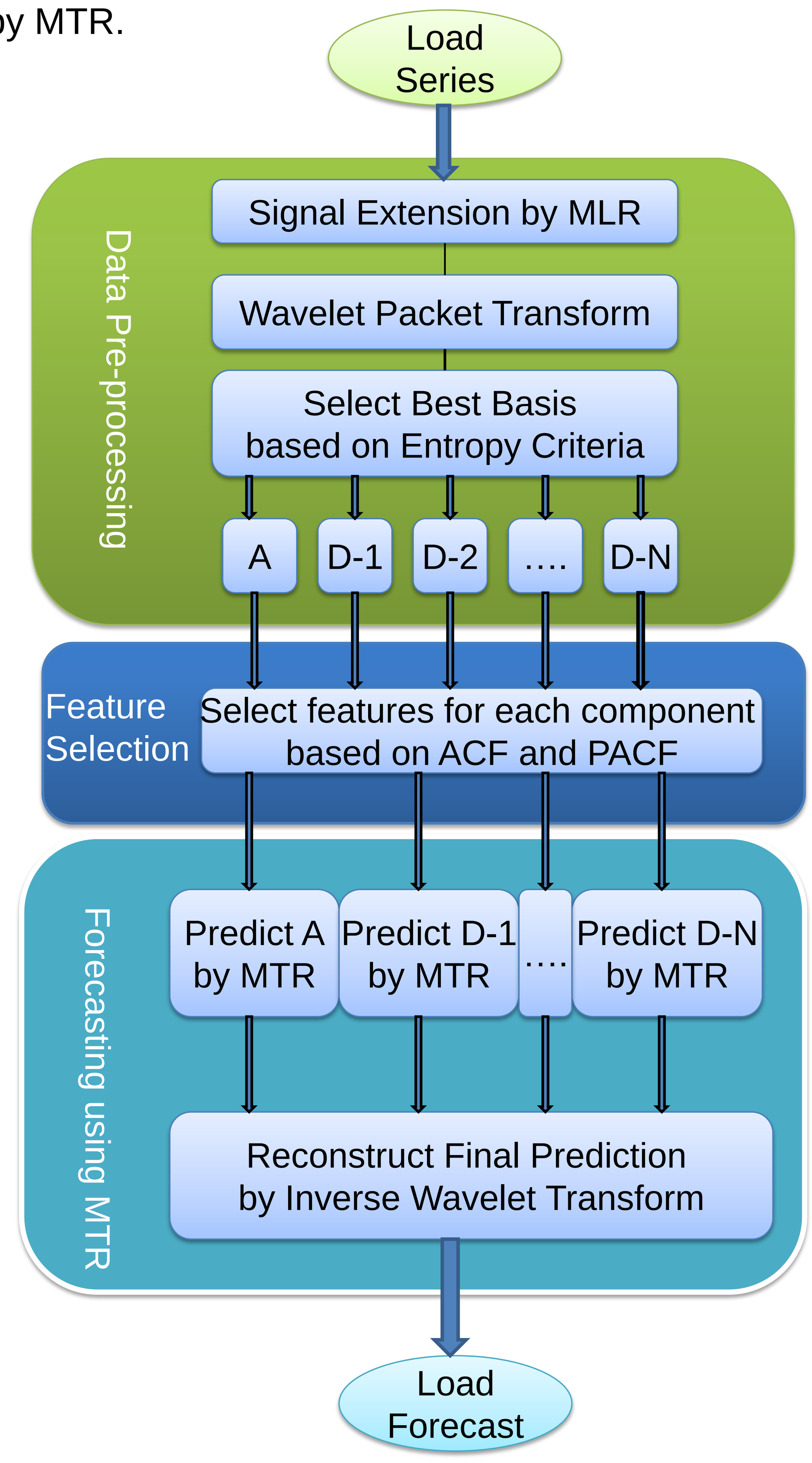

Fig. 2: Proposed VSTLF approach

4.5 Evaluation Metrics

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|L\_actual_i - L\_forecast_i\right|$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{L\_actual_i - L\_forecast_i}{L\_actual_i}\right| 100\,[\%]$$

5. RESULTS AND DISCUSSION

Fig. 3 shows the prediction accuracy of our method, BPNN, and MLR measured over 105,120 testing samples:

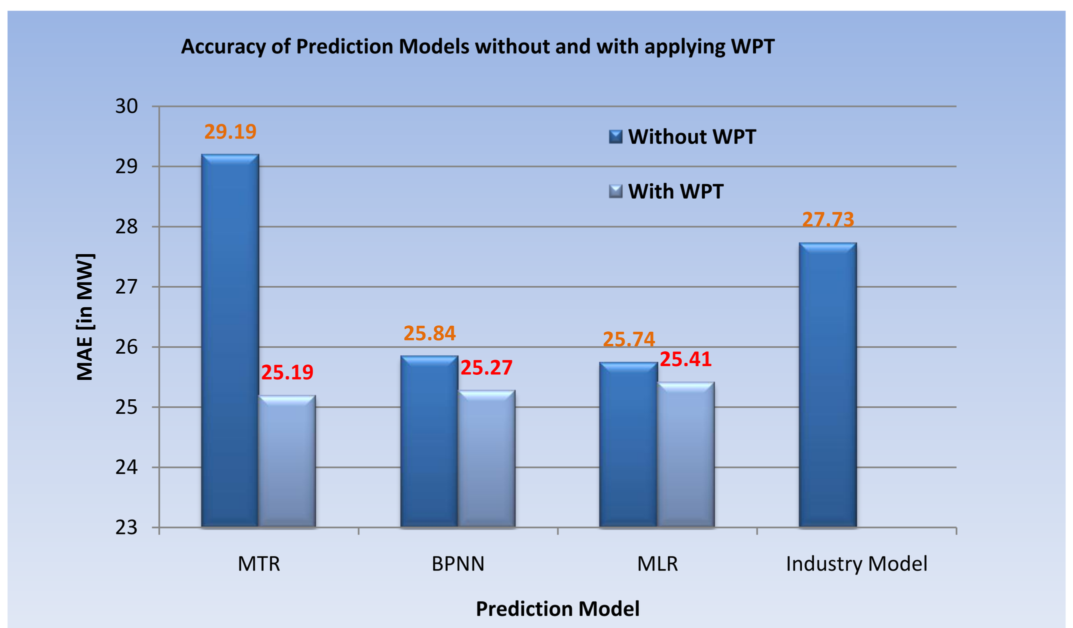

Fig.3: Performance of prediction models before and after applying WPT

Fig.4 shows a comparison of prediction accuracy with other methods:

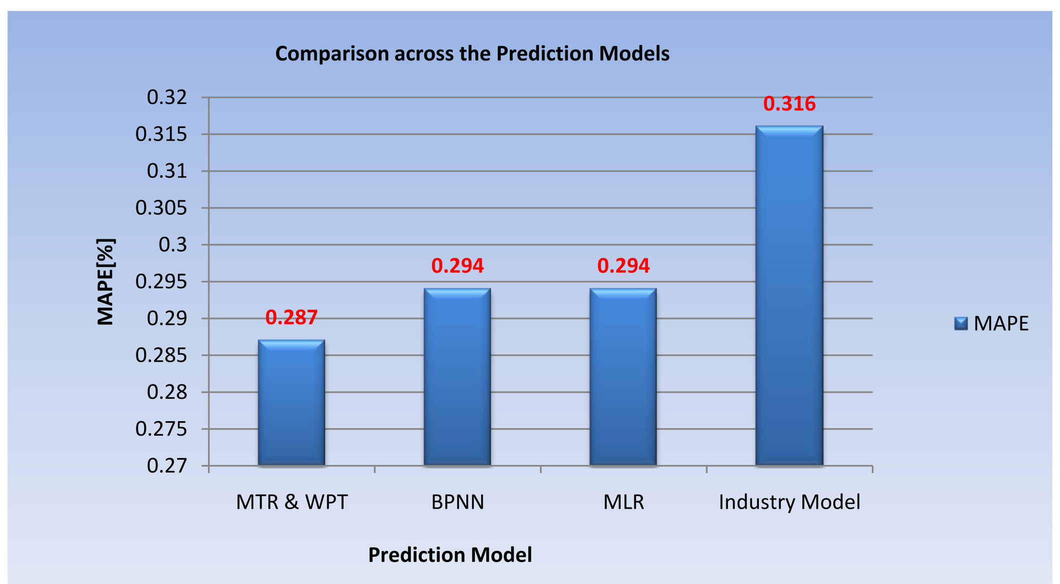

Fig.4: Comparison of our model with other prediction models

Fig.5 shows the hourly prediction errors of our model:

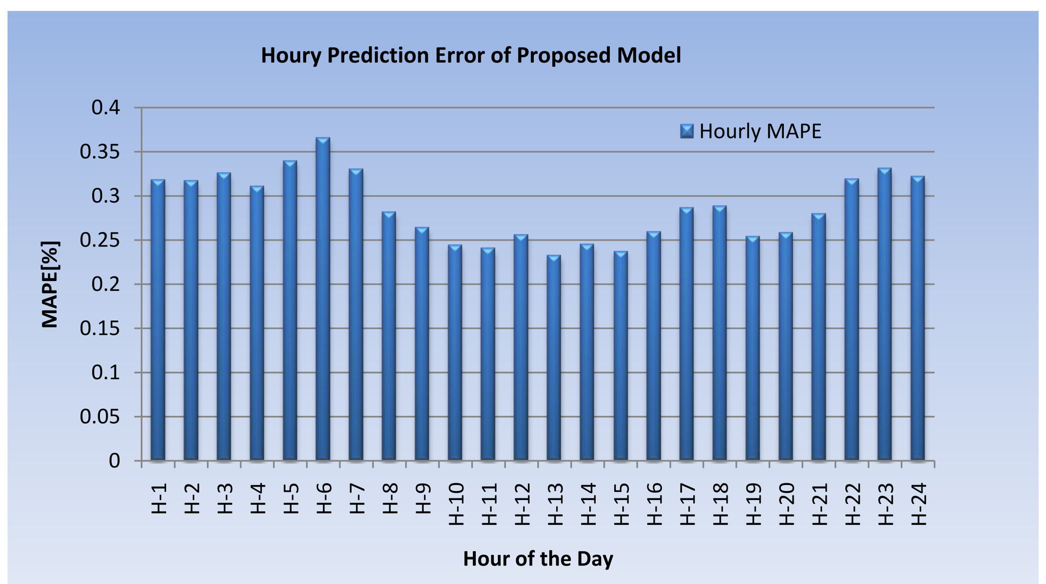

Fig.5: Hourly prediction error of our model

The main results can be summarized as follows:

- WPT helps to significantly improve the prediction accuracy of all models: MTR, BPNN and MLR.
- MTR shows the highest improvement in accuracy, which is about 14% after the application of WPT.
- Our method MTR when used with WPT outperformed all other prediction models in the literature and also the industry model.
- Our method achieves the highest accuracy during the business hours and the lowest accuracy at the start and end of the day.

6. CONCLUSIONS

- WPT shows strong potential to significantly increase the accuracy of VSTLF. The proposed WPT based model outperforms all the models in literature and the model currently used by industry.
- In future work we will investigate de-noising of electricity data using Non-Decimated Wavelet transform before building a prediction model.

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