WAVELETS BASED ANALYSIS OF NON-UNIFORMLY SAMPLED DATA FOR POWER LOAD FORECASTING

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ABSTRACT

In this paper, the compactly supported orthonormal symmetrical wavelets is used to estimate non-uniformly sampled and non-gaussian noise corrupted load consumption signals for the purpose of load forecasting in a typical electrical utility network. Power load forecasting is an important function of utility management and present methods invariably rely heavily on past historical load curves which are collected from the grid via various monitors placed at several nodes. Wavelet technology is proposed in this paper to recover irregularly sampled data, for denoising, compression and subsequent extraction of evolutionary trends in the signal in various time windows. Simple algorithms are outlined for each stage in a modular load signal analysis scheme.

***Keywords*:-** Wavelets, Multi resolution analysis, Load forecasting, Power system analysis

1. INTRODUCTION

Wavelet transforms is a relatively new mathematical tool that has been the target of rich exploitation in many fields including such varied areas like seismic studies, image compression, signal processing processes and mechanical vibrations. The flexible time-scale representations of wavelet transforms has positioned it in many applications that traditionally used modified forms of Fourier Transforms (FT) like Short Time FT (STFT) and the Gabor Transforms. Its rich temporal content and frequency isolation features has contributed to the successful results obtained by the application of wavelet transforms in the area of power systems analysis.

The power utility industry is currently undergoing many profound changes due to the deregulation of the utility industry. Consumption pattern recognition and prediction are becoming very important functions to a utility company as it is needed to support management decisions from output and maintenance scheduling to investment planning.

In a highly integrated and interconnected utility network or power grid, many monitors are placed at each node to monitor power system variables. Such signals are very vulnerable to high tension hum and electromagnetic noise. The correlation of these signals from various parts of a system would contain copious amount of noise. The nature of these signals is also unique in that they might contain a very wide range of frequencies and harmonics. These range from the extremely long wavelengths like trends from a weekly cyclical pattern of power usage to very high frequency transients caused by random events like lightning strikes, switching and other phenomena. Such higher-order harmonic contents are non-stationary and non-gaussian. Data collected are also prone to malfunctions of monitoring devices. This results in data-dropouts and non-uniformly sampled data sets. Recovery of such irregularly sampled data is thus a challenge. [1]

As large amounts of historical load patterns are needed in a typical load forecasting algorithm, even low sampling rates of 1 sample per minute generates a huge amount of data. Denoising and compression is thus desired.

To facilitate accurate load-flow analysis, a robust signal recovery, noise filtering, compression and trend analysis algorithm must be utilized to enable eventual automation of the analysis of large volumes of data generated by the monitoring and recording of load-flow consumption readings by any particular system.

Currently, several forecasting schemes utilize Artificial Intelligence (AI) methods like ANN and GA to perform load forecasting tasks. The common problem with such a method is that an AI scheme is only as intelligent as the program that trains it. This in turns depends heavily on the reliability of the training data collected. If such training data is in the first place corrupted by noise, it would mean that pre-processing of such data would be necessary. All these add to the implementation cost and set-up time. These includes the development and testing of the network topology, the collection of training data, pre-processing of such data, actual training and reconfiguration (if necessary) and subsequent re-training. Such a system when finally implemented is not portable as different utility networks have unique consumer patterns, holidays and weather conditions. [2]

A modular approach to the system design of such an analysis scheme is taken and schematically outlined in fig.1. This paper seeks to demonstrate the versatility and prowess of the symlet wavelet in application of the scheme.

2. WAVELET TRANSFORMS

The theory of wavelets is an involved one. There is no space here for such a discourse, thus the reader is directed to references [3,4,5]. For notational consistency, the discrete wavelet transform is outlined briefly:-

If a function *f(t)* resides in the Hilbert space V_o, where V_o is spanned by the orthogonal set of basis functions $\{\Phi(t-n)\}$, then f(t) can be expressed as:-

$$f(t) = \sum_n c_{o,n} \quad \Phi(t-n) \tag{1}$$

To form a Multi-resolution analysis (MRA), we have a series of nested subspaces $V_{j+1} \subset V_j$ where $V_{j+1}=V_j \oplus W_j$. $\boldsymbol{V_j}$ is spanned by the basis functions $\{\Phi(t/2^j - n)\}$ and $\boldsymbol{W_j}$ is spanned by the basis functions $\{\psi(t/2^j - n)\}$. In this case, ***f(t)*** can be decomposed to an arbitrary resolution level ***J*** as below:-

$$f(t) = \sum_n c_{j,n} \Phi\left(\frac{t}{2^j} - n\right) + \sum_{j=1}^{J} \sum_n d_{j,n} \Psi\left(\frac{t}{2^j} - n\right) \tag{2}$$

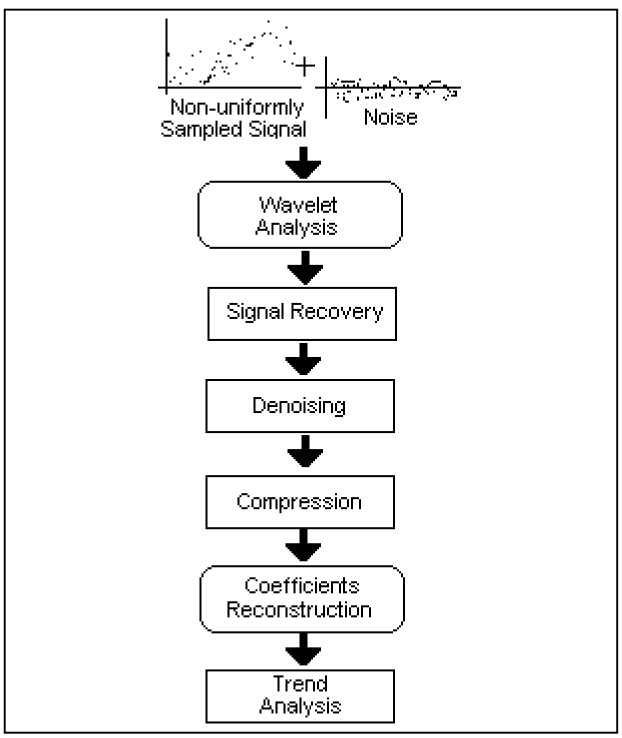

Fig 1: Block diagram of load analysis scheme.

3. APPLICATIONS

3.1 Recovery of Irregularly Sampled Data

Inspired by the work of *Ford* and *Etter* [6], we apply their Multiresolutional Basis Fitting Reconstruction (MBFR) algorithm to load consumption signals. A brief theoretical development is outlined below:-

If we want ***M*** uniformly distributed samples of a discrete signal but have only *P<M* samples of ***f*** on a *non--uniformly* sampled grid, the signal at hand can be written:

$$f_s = \left[f(t_o)\, f(t_1)\, f(t_2)........f(t_{P-1}) \right]^T \qquad \textit{where} \quad \{t_k \in \{0,....,M-1\}, k = 0,....., P-1\} \tag{3}$$

It is desired that load points missing due to monitoring failure be postulated based on the rest of the signal in a "consistent" way. Assuming the non-uniformly sampled signal is undersampled with respect to the Nyquist frequency of the complete, uniformly sampled signal and the interpolation must preserve the frequency content, we start by viewing the sampling grid given by the finest resolution level desired. A vector system of equations for any resolution level ***J*** ≥ 1 is obtained as below:-

$$f_s = G_J^S c_J + \sum_{j=1}^{J} H_j^s d_j \tag{4}$$

where ***G*** is the matrix of shifts of the scaling function samples at level ***J*** associated with time index $\boldsymbol{t_k}$ of each sample. **H** is the matrix of the shifts of the wavelet at each level ***j***. The wavelet coefficients for the signal at the highest resolution levels cannot be obtained as not all of the samples on the desired grid is available. The signal can however be approximated by its low-frequency components, temporarily ignoring the HF terms. We can thus estimate (4) without the second term and solve the system of equations in a least-squares sense for estimates of the low frequency scaling function coefficients. The support of the scaling function doubles for each successively coarser resolution thus ***J*** is the minimum resolution level for which the system is over-determined. The low frequency estimates of ***f*** is thus given as:-

$$\hat{f}_0 = G_J \hat{c}_J \tag{5}$$

where ***G*** is the matrix of shifts of the scaling function at level ***J*** at all *integral* shifts *[0….M-1]*. The error signal at each available signal is thus:-

$$\begin{aligned} e_0 &= f_s - \hat{f}_0 \Big|_{t=t_{k,k=0...P-1}} \\ &= f_s - G_J^s \hat{c}_J \\ &\approx H_J^s d_J \end{aligned} \tag{6}$$

$\boldsymbol{e_0}$ consists of the frequencies too fine to be represented by the scaling function and can be approximated by its next-finer frequency components represented by the lowest frequency band of the wavelet portion of the decomposition given by (2).

The number of wavelet coefficients at level $\boldsymbol{J}$ is approximately the same as the number of scaling function coefficients, thus (6) is also an overdetermined system which can be solved similarly for an estimate of the coefficients $\boldsymbol{d_J}$ We can then find the first refinement of the estimate at every point on the even grid as follows:-

$$\hat{f}_1 = G_J \hat{c}_J + H_J \hat{d}_J \tag{7}$$

where $\boldsymbol{H_J}$ is the matrix of shifts of the wavelet at level $\boldsymbol{J}$ at all integral shifts *[0…M-1]*.

From the given non-uniformly sampled data set, there will be sections of the irregularly spaced signal that are densely sampled such that we can solve locally for the difference signal at the resolution level *J-1*. The difference signal in those sections can thus be created:-

$$\begin{aligned} e_1 = & \quad f_s - G_J^s \hat{c}_J - H_J^s \hat{d}_J \\ \approx & \quad H_{J-1}^s d_{J-1} \end{aligned} \tag{8}$$

This is then solved in the least-squares fashion again for these sections. The process can then be repeated until the finest possible resolution level is reached.

3.2 Denoising and Compression

Wavelet denoising of noisy signals is straightforward. Various methods have been proposed differing usually in the way the threshold is selected and the measure of information and entropy. Wavelet based denoising can be simply expressed as a three step procedure:-

- Wavelet decomposition
- Thresholding of details coefficients based on some criterion
- Reconstruction of thresholded coefficients.

Compression schemes are very similar to denoising schemes except that soft thresholding or *averaging* is usually done as opposed to hard thresholding in denoising algorithms where certain values are set to absolute zero.[7]

Denoising and compression in this case is achieved inherently in the algorithm. From (8) we can see that we try to minimize $\boldsymbol{e_0}$ which represents the error in approximation. Assuming actual $\boldsymbol{f_s}$ contains noise which is non-gaussian and made up of very high frequency transients (typical of the signal at hand). These will not be recovered by the algorithm if the noise frequency is higher than what the scaling functions can isolate at level $\boldsymbol{J}$. Thus, by careful choice of the scaling function and the value of ***{min (J)}***, noise reduction can be achieved. It can be shown that noise frequencies that fall below the threshold and gets recovered should be taken as information bearing. [8] As there are no existing noise models in load consumption signals, these assumptions have to be specified.

It can also be shown that compression is realised and the compression ratio approaches $\boldsymbol{M/2^{min(J)}}$ as $\boldsymbol{M}$ becomes large where ***min(J)*** is the finest resolution level used in the algorithm.

We have chosen the use of a wavelets based MRA technique over more established methods like polynomial spline or Fourier methods as it affords a richer detailed content where sampling is denser whilst still allowing for global trends to be represented throughout the signal. The wavelet based MRA technique also allows for time-varying signals (and hence real-time analysis) while supporting the representation of trends at varying scales. This is a very important feature especially in the analysis of power consumption signals for forecasting as the capability of forecasting in varying time frames is desired.

The *Symlets* family of wavelets [9] are chosen because they are smooth and near-to symmetrical functions, making it very suitable for recovery of non-uniformly undersampled data. They possess the most vanishing moments for a given support width. This means that a zero coefficient is obtained for derivatives of the signal of the order upto the number of vanishing moments. This is intuitively appealing to compression as it derives the most zeros The Order 8 Symlets used here is compactly supported on a width of 15 and has a corresponding filter length of 16 with 8 vanishing moments and are the most symmetrical of popularly used wavelets. The Symlet8 is also orthogonal and biorthogonal. These features make it a good candidate as a denoising tool and trend evolution extraction apparatus for the expected signal features to be encountered in this scheme.

4. INITIAL TRIALS

We use a short sample of 60 minutes during a busy lunch hour at an urban area. The original signal (fig.2a) is sampled at a typical 1 minute interval. Figure 2b shows 20 irregularly spaced samples obtained and used in this study. This represents a very high dropout rate of 66.67%. We apply the recovery algorithm outlined above and fig. 2c shows the recovered signal superimposed on the available samples. It is visually discernible that the overall trend of the signal is preserved together with some detailed features where the sample is available. Figure 2d shows the denoised and compressed signal using the

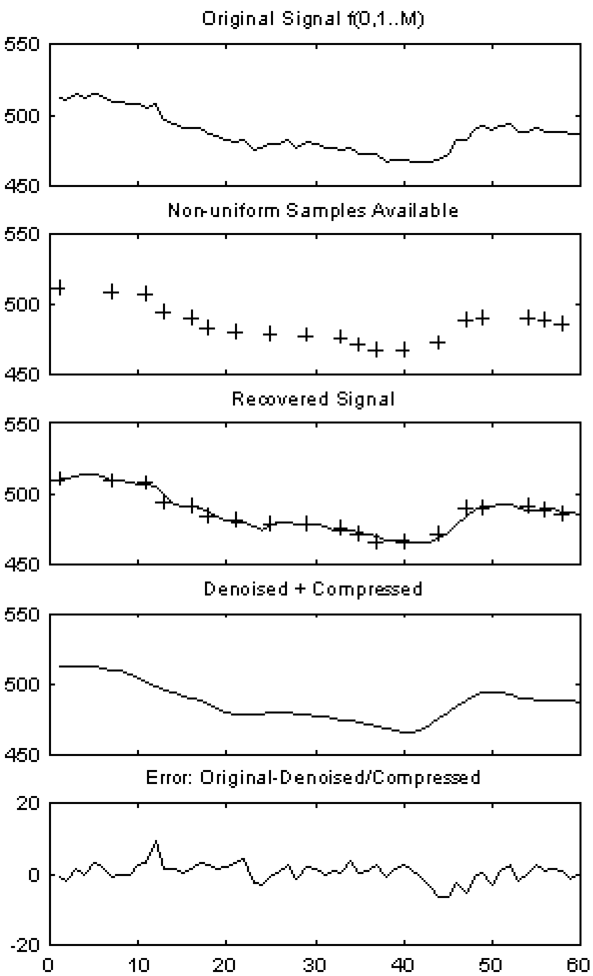

Fig 2a-e: Initial study using a 60-sample signal with a dropout of 67%.

symlet8 wavelet. The error signal, taken as the difference between original 60-sample signal and the final denoised/compressed signal is plotted in fig. 2e. We define a measure of error using the Nominal Mean Square Error as:

$$NMSE = \frac{\left\| s_0(n) - \tilde{s}_0(n) \right\|^2}{\left\| s_0(n) \right\|^2} \qquad (9)$$

The NMSE in this sample study is $\boldsymbol{5.536 \times 10^{-2}}$ or 5.5% which is good considering the dropout rate is 66.67%.

5. CONCLUSION

Wavelet applications in electrical load consumption forecasting signal analysis tool are presented. The scheme builds upon a published wavelet multi-resolutional basis fitting reconstruction algorithm to build in denoising and enhanced compression rates for the recovery and processing of electrical load consumption signal collected over the power network. Initial results have pointed to the immense potential for this scheme to be used in preprocessing of irregularly sampled signals to form an integral part of input data into a load forecasting system.

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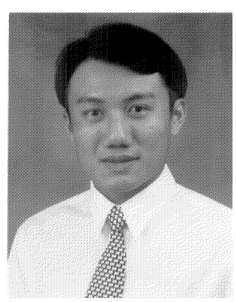
7. BIOGRAPHIES



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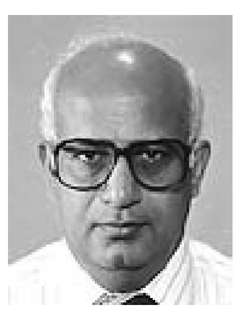

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