Extraction of Impulsive Noise from Measurements in a 400 kV Electricity Substation

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Abstract: - This work forms part of a larger project to investigate the vulnerability of wireless local area network (WLAN) and wireless personal area network (WPAN) technologies to impulsive noise in electricity substations. An algorithm has been developed to extract impulsive noise from measurements of the microwave noise environment in a substation. The algorithm, based on wavelet packet transformation, is described and its utility to extract impulsive noise time series demonstrated.

Key-Words: - Impulsive noise, de-noising, wavelet packet, electricity substation

1. Introduction
Impulsive noise has the potential to degrade the performance and reliability of wireless communications systems [1]. Such noise is especially prevalent in high-voltage electricity substations, and has discouraged electricity utility companies from deploying wireless technologies for operational purposes.

This paper reports the characterisation of impulsive noise from a 400/275/132 kV substation with special attention to noise energy in those microwave frequency bands not previously reported but relevant to new, short-range, technologies (e.g. IEEE 802.11a/b/g, Bluetooth, ZigBee).

The impulsive noise process in substations that is most likely to extend into the microwave frequency band is due to partial discharge (PD). This is the result of partial breakdown in a dielectric resulting in an impulsive (and random) component of current. Such current impulses may, like any accelerating charge, radiate electromagnetic energy. If the rise-time of the current pulses is sufficiently short the frequency spectrum will extend into the gigahertz region [2]. A model of PD noise specific to electricity substations is needed for the assessment of risk associated with the operational deployment of wireless communication technologies for monitoring and control in the electricity supply industry (ESI).

2. Extraction of Impulsive Noise
Whilst impulsive noise is strong close to its source it decays rapidly with distance. To characterise it properly, therefore, may require its extraction from a mixture of other unwanted signal and noise processes including coherent interference (e.g. broadcast and other radio communications and radar signals). This makes practical site-characterisation difficult since PD sources may be significant distances from buildings where sensitive measurement equipment can be protected against environmental extremes of temperature, humidity, ingress of water etc. An effective method of extracting PD from a background of higher-power noise and interference processes is therefore desirable.

Several methods of extracting PD from other noise processes have been investigated [3] and the wavelet transformation has been identified as being particularly useful [4]. Wavelet packet transformation (WPT) represents a generalisation of the wavelet transform [5].

An application of WPT for online PD detection in 11 kV cables has been reported [6]. The parent...
wavelet used was symlet-6 (Fig. 1) with 8-level decomposition. This method was shown to have a recovery probability of 60% for 1 ns impulses buried in white noise with a standard deviation 1.25 times greater than the peak pulse voltage. Whilst the work suggests that the performance of the WPT depends on wavelet selection as well as on SNR (the optimum wavelet being related to the duration of the impulses of interest) PD noise originating from cables has been successfully recovered from a noisy background (comprising both random and coherent processes) without any priori knowledge of the PD characteristics.

WPT has been used in conjunction with neural networks to separate corona from PD in a gas-insulated substation [7]. In this application 5-level wavelet packet decomposition (WPD) using the symlet-8 wavelet was used. Energy, kurtosis and skewness values were computed for each node in the WPD tree. Using large between-class, and small within-class, scatter criteria, feature data were selected from these values. With the feature data as inputs, a three-layer feed-forward neural network with a back-propagation learning rule was used to classify PD, corona and mixed signal (PD plus corona) events. The method successfully removed corona from a mixed signal data set.

3 Measurement Campaign

A PD noise measurement campaign over the frequency range 0.1 – 6.0 GHz has been undertaken at Strathaven 400/275/132 kV air-insulated electricity substation in central Scotland, Fig. 2. The substation is owned and operated by Scottish Power Ltd., a UK electricity utility. A detection system was deployed in the control room of the substation.

The measurement system, Fig. 3, comprises a low-band TEM horn, a high-band TEM horn, a disk-cone antenna, a dual-band (2.4/5.2 GHz) WLAN antenna, a four-channel digital storage oscilloscope (DSO) and an external hard disk drive (HDD). The antennas are connected directly to the DSO. The signals are simultaneously sampled at 20 GS/s. Each data record comprises 50 M samples corresponding to a 2.5 ms time-series. The records are saved to the HDD via a USB interface. It takes approximately 15 minutes for the system to complete one measurement/save cycle.
4 PD Extraction Algorithm

Wavelet packet transformation (justified by previous studies [6, 7]) is central to the extraction of PD from the Strathaven measurement records. The signal processing involves four steps: (i) decomposition, (ii) computation of best tree, (iii) wavelet-packet coefficient thresholding, and (iv) reconstruction. In (i) wavelet packet decomposition of the signal is computed up to level 12 using the symlet-6 wavelet. In (ii) the optimal wavelet packet tree with Stein's unbiased risk estimate (SURE) entropy function is computed. In (iii) hard thresholding is applied to the coefficients of each packet (except for the approximation). And in (iv) the required signal is reconstructed based on the original approximation coefficients at each level and the modified coefficients.

Symlet-6 belongs to a family of wavelets that have the largest number of vanishing moments for a minimum support. This means that in the presence of an impulse, at a certain scale and translation, the wavelet’s correlation with the impulse will be high, producing few, but large, wavelet coefficients.

Due to limited PC resources (CPU 2.33GHz, 1GB RAM) each time-series record of 50 M samples is divided into segments containing 200,020 samples (or fewer) prior to processing. A data segment with 200,020 samples could be decomposed into up to 14 levels. Since, at each decomposition level the data segment is down-sampled by a factor of two the minimum number of samples that can be decomposed to the lowest level is $4=2^2$. For a data segment with 200,020 samples, therefore, the maximum decomposition level is $17-3=14$ ($2^{17}=131072<200020<2^{18}=262144$). In this case the computation would take 28 hours, however, to extract a PD from a single 2.5 ms time series. Decomposition with 12 levels takes less than 3 hours to process each data segment.

Wavelet packet decomposition results a complete binary tree which offers the richest possible analysis. The tree may incorporate redundancy, however, and the cost of computation may be excessive. A smaller (optimal) tree can be computed with respect to some entropy criterion. The entropy measures signal energy spread over a particular basis. Lower entropy implies that fewer basis vectors are needed to represent the energy spread, and a more efficient decomposition. A SURE

![Graphs showing wavelet packet decomposition](image_url)
entropy function is employed for optimizing the decomposition tree in this study. This entropy function works well if a signal is normalized in such a way that the data fits the model \( x(t) = f(t) + e(t) \), where \( e(t) \) is a Gaussian white noise process with zero mean and unit variance. The SURE is defined by:

\[
T = \sqrt{2\ln(n) \log_2(n)}
\] (1)

where \( n \) is the number of signal samples.

Hard thresholding removes all those detail coefficients with a value lower than some threshold level. A signal is reconstructed with the original approximation coefficients at each level and the modified detail coefficients.

5 Result
Since each 50 M sample data sequence is too large for direct processing by a normal PC, processing is carried out in two stages. The data is first divided into five sub-segments. Each data sub-segment is then further divided into basis-data (not more than 200,020 samples per basis) before processing. The processed basis data are then recombined together in the same dimension as the segment-data.

An example of raw data obtained in the measurement campaign broken into five-segments is shown in Figs. 4(a) - (e). There is no obvious evidence of impulsive noise in this data.

The processed data corresponding to Figs. 4(a) - (e) is shown in Figs. 5(a) - (e). The presence of an impulsive process is now evident.

6 Conclusion
An algorithm for extracting impulsive processes from measurements of noise at microwave frequencies in an electricity substation has been reported. Examples of data in both raw and processed forms have been presented to demonstrate the algorithm’s effectiveness and utility.

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