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Power Line Communication: Extreme Noise Events Modelling and Characterization over Low-Voltage Networks

Steven O. Awino* and Bakhe Nleya

Department of Electronic and Computer Engineering, Durban University of Technology, Durban, South Africa

ABSTRACT: This paper examines the use of extreme value theory (EVT) in modelling and forecasting extreme noise events in Power Line Communication (PLC) networks. PLC noise is characterised by random, high-amplitude noise spikes that significantly degrade PLC performance. As such, EVT, which is a branch of statistics that is concerned with modelling and analysing extreme deviations of random processes, is particularly useful for modelling PLC noise impulsive noise events, which are random since it focuses on the tail behaviour of the noise distribution. In this proposed EVT analysis, the probability of extreme noise events is estimated from the high-amplitude spikes. The heavy-tailed characteristics of PLC noise are estimated by the shape parameter (ξ) to model impulsive noise distributions, and the Block Maxima (BM) approach is employed to handle the worst-case PLC noise events lasting over long periods, consequently estimating the maximum expected noise over time. Lastly, the peaks over threshold (POT) method is proposed to handle the threshold exceedance probability, which can be used for threshold selection for PLC noise suppression.

1. INTRODUCTION

Power Line Communication (PLC) is a technology that uses the available electrical wiring network that was not originally designed for data transfer for data transmission. This renders PLC systems to be extremely sensitive to noise, particularly impulsive noise, which comprises brief, high-amplitude disruptions besides narrowband interferences from inside the power line network and radio broadcast stations operating within the same frequency band. This renders the power line network a complex and harsh channel elevating the level of uncertainty for data transmission.

In order to address this problem of impulsive noise present in the power line network, PLC noise was characterized and modelled as a mixture of background (Gaussian) and impulsive noise in [1–3]. In addition, it was assumed that the impulses in PLC noise were Poisson distributed. Nevertheless, this assumption could not capture the substantial tails seen in the PLC noise, nor did it fit well with burst impulsive noise. In [4–7], PLC noise was characterized by Markov models which is a memoryless state-dependent stochastic process in which the temporal dependence in PLC noise was captured via transition probabilities between states. This assumed conditional independence beyond a fixed order and failed to capture long-range dependence of extreme noise impulses. In addition, the continuous amplitude variation of noise PLC impulses were obscured thus reducing the fidelity in modelling the amplitude extremes. The Bernoulli-Gaussian model was employed in [8] to model PLC noise. This model combined Gaussian background nose with Bernoulli driven impulses. Even though this model is simple since it is based on the binary presence or absence concept allowing a simplistic impulse arrival model, it failed to capture correlation present in noise impulses as well as their variability. In [9] and [10], an Alpha-stable (α-stable) distribution is employed to solve the problem of heavy-tail characterisctics present in PLC noise. The heavy-tailed PLC noise is modelled using a symmetric α-stable distribution. However, this type of distribution lacks a closed form distribution function which in turn complicates parameter estimation. In addition, α-stable distribution has the tendency to overestimate performance in moderate noise which results in less accurate PLC noise model. In [11] and [12], time series models were applied to model and characterize the impulsive noise present in an indoor power line network. While these time series models excelled at capturing seasonality, autocorrelation, and trends, they fail to accurately capture the extreme heavy-tailed nature of PLC noise. In the recent work in [13], Queuing theory was used to solve the problem of noise in power line network within the indoor environment. This model focused on modelling the arrival and service time of noise in a PLC network. It characterized the distribution of queue lengths, associated waiting times and system congestion based on assumptions about arrival rates, service rates, and queue disciplines. However, this approach only modelled the burst arrivals, and not the noise amplitudes and failed to provide information on the statistical behavior of extreme noise events that are associated with high-amplitude impulses. These traditional noise models, frequently fail to capture the erratic variations present in impulsive PLC noise. Due to such extreme events in PLC noise, extreme value theory (EVT), a statistical framework for analyzing and predicting extreme events, can be used to improve the robustness of PLC systems. Combining EVT with PLC noise analysis builds a solid statistical base for understanding and reducing the effects of sudden noise, leading to more dependable and efficient communication systems.

* Corresponding author: Steven O. Awino (stevena@dut.ac.za).

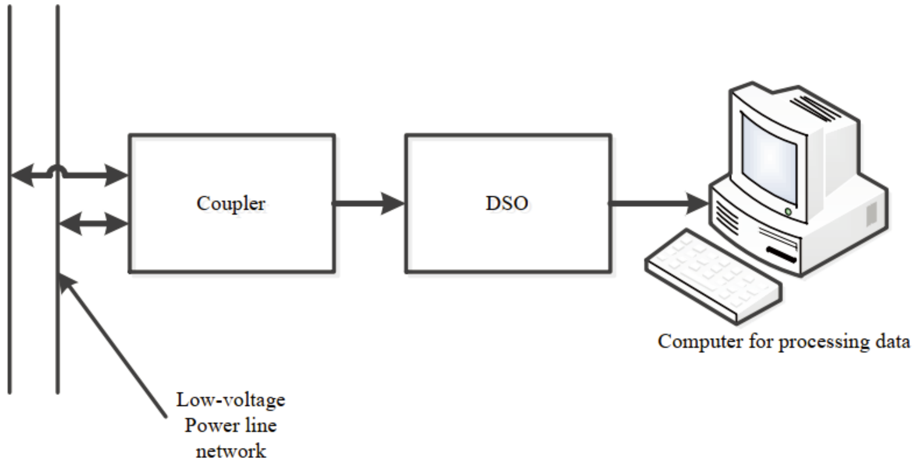

FIGURE 1. Experimental configuration.

EVT is a probabilistic technique that models the asymptotic behaviour of extreme (maximum or minimum) values within a sequence of independent identically distributed (i.i.d) random variables (r.v.'s). The statistical characteristics of extreme values that include the maxima, minima, intermediate order statistics and threshold exceedances are governed by the kurtosis of the underlying probability distribution. Conversely, the kurtosis of the underlying distribution's functional parameters can be estimated using statistical methods that exploit extreme and intermediate order statistics or exceedances above high thresholds. By concentrating on the tails, one can leverage parametric models specifically designed to capture the behavior of the distribution in these regions [14]. EVT establishes the probabilistic and statistical theory of a different sample statistic: unsurprisingly, of extremes.

In EVT, there are two main approaches that are widely used; the block maxima and Peak over threshold (POT) approaches. The block maxima approach is particularly useful for the estimation of the worst-case PLC noise levels over long period of time. This allows for the determination of the maximum noise amplitude that could occur within a given time frame which can consequently be used to set noise suppression thresholds for robust PLC receiver design, while peaks over threshold (POT) is critical for determining the likelihood of extreme impulsive noise events that surpass a threshold that affects data transmission in the power line network. This enables the estimate of the density of extreme noise spikes, which aids in error correction coding and recovery methods that can be used in adaptive noise suppression algorithms.

This paper is organized as follows. In Section 2, we provide the mathematical framework for EVT for PLC noise modelling in the frequency range of 1–30 MHz. The experimental procedure used for data collection and processing of measurements is provided in Section 3. In Section 4, the results and discussion are presented. Lastly, the paper ends with concluding remarks in Section 5.

2. MATHEMATICAL FRAMEWORK

There are various definitions of "extremes" that give rise to different, but complementary, limiting distributions. In this section, we formalise what is meant by "extreme" in the context of PLC impulsive noise analysis as well as introduce the terminology that will be prevalent throughout this work. The approach of sampling maxima from blocks is known as block maxima approach. The block maxima method is an appropriate statistical model for PLC impulsive noise where the most extreme data (noise-amplitudes) are present over fixed interval. Due to the periodocity observed in the measured noise data, we remove some dependence by dividing the blocks in such a way that dependence may exist within the block but not between blocks [14]. Since it is inefficient to analyse only the most extreme observation when making conclusions about the tail of a distribution, we may be able to gain significant information by considering more than just the maximum. In such instances, we may study the exceedances over a (high) threshold. This is the peaks over threshold (POT) approach. In this instance, the idea is that statistical inference is based on observations that exceed a high threshold ς. The derivation and formalisation of the block maxima and POT approaches for PLC noise problem are provided in the subsequent subsections.

2.1. Block Maxima Approach

The formal classical EVT primarily focuses on limiting results for the distribution F of the block maximum $M_n = \max(R_1, R_2, \ldots, R_n)$ of n random variables $R_1, R_2, \ldots, R_n$, when the R_i are assumed to be i.i.d [15]. If for some constants $a_n > 0$, b_n

$$P\left(\frac{M_n - b_n}{a_n} \leq r\right) = H_\xi(r), \tag{1}$$

as $n \rightarrow \infty$, then $H_\xi(r)$ is the generalized extreme value (GEV) distribution [14–17]:

$$H_\xi(r) = \begin{cases} \exp\left(-(1+\xi r)^{\frac{-1}{\xi}}\right), & amp;\ \xi \neq 0, 1+\xi r\ \ gt;0 \\ \exp\left(-e^{-r}\right) & amp;\ \xi = 0, r \in \mathbb{R} \end{cases} \tag{2}$$

where ξ is the shape parameter: For $\xi > 0$, the distribution is of Fréchet type (heavy-tailed); for $\xi = 0$, the distribution is of Gumbel type (light-tailed); and for $\xi < 0$ the distribution is of Weibull type (bounded-tailed).

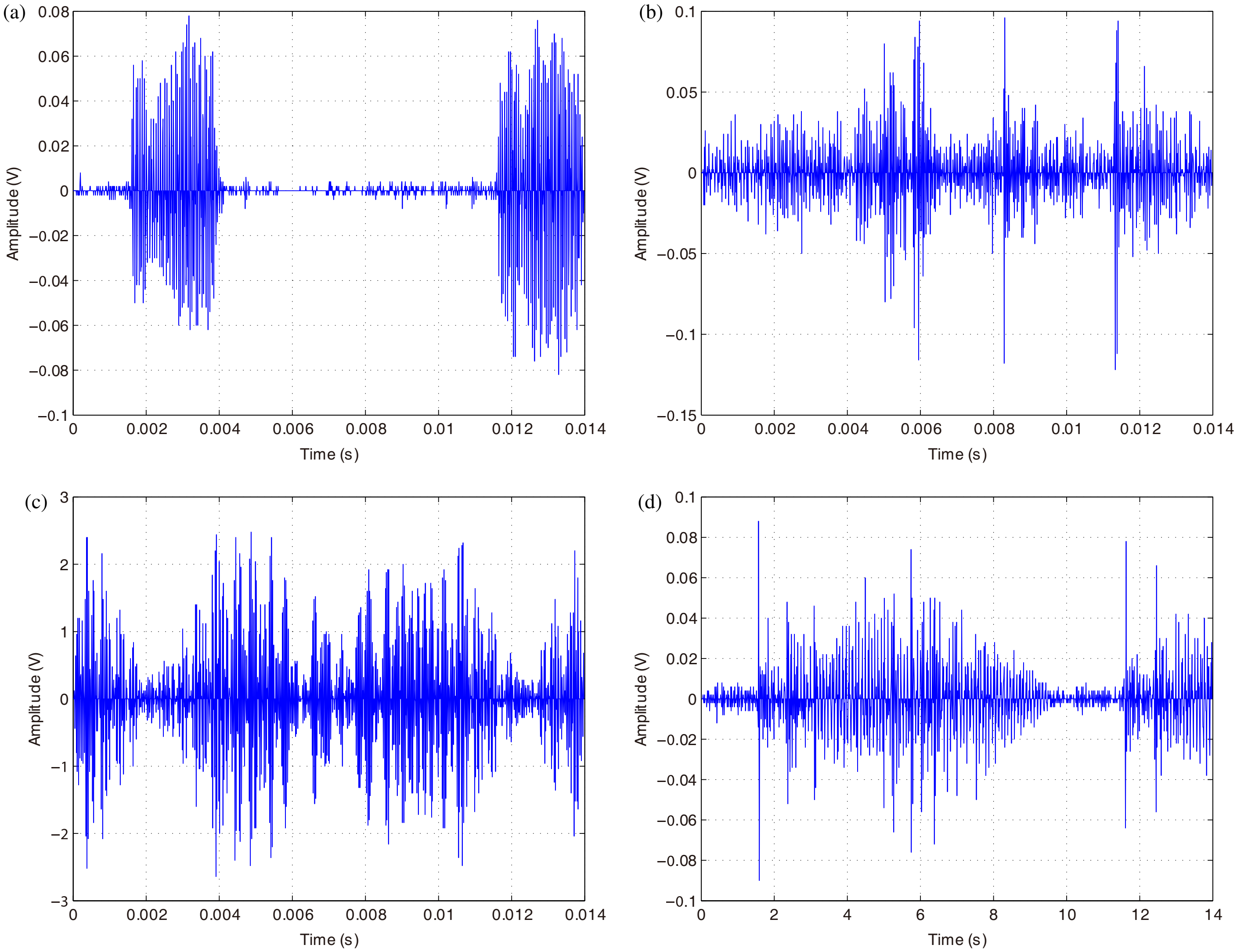

FIGURE 2. Power line noise measurements from: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

2.1.1. Parameter Estimation for GEV Distribution

GEV distribution can also be described as GEV $(\vartheta, \varsigma, \xi)$ [17], where ϑ is the threshold parameter, ς the scale parameter, and ξ bears its usual meaning as in (2). The log-likelihood for m block maxima $M_{n_i}, \ldots, M_{n_m}$ is [17],

$$\ell(\vartheta, \varsigma, \xi) = -m \ln \varsigma - \left(1 + \frac{1}{\xi}\right) \sum_{i=1}^{m} \ln \left(1 + \xi \frac{(M_{n_i} - \vartheta)}{\varsigma}\right) - \left(1 + \xi \frac{(M_{n_i} - \vartheta)}{\varsigma}\right)^{\frac{-1}{\xi}}, \quad (3)$$

subject to: $(1 + \xi \frac{(M_{n_i} - \vartheta)}{\varsigma}) > 0$, where the appropriate ϑ, ς, and ξ parametrizations are obtained through the maximum likelihood estimation (MLE).

2.1.2. Repeat Interval Estimation

The repeat interval, Λ, is the estimated average time (τ) between different impulsive noise events. It is developed from the GEV distribution and models the maxima of block data in the observed data given by [14–17],

$$\Lambda = \vartheta + \frac{\varsigma}{\xi}\left[\left(\frac{1}{\tau}\right)^{\xi} - 1\right] \quad (4)$$

where the other parameters bear their usual meaning.

2.2. Peaks Over Threshold (POT) Approach

In this approach, the focus is on noise-amplitudes that surpass a threshold, ϑ. This exceedance follows the genaralized Pareto distribution (GPD) defined by [14–17],

$$F(r) = 1 - \left(1 + \frac{\xi(r - \vartheta)}{\varsigma}\right)^{\frac{-1}{\xi}}, \quad r > \vartheta \quad (5)$$

where ϑ is the threshold that is set high enough to capture extreme noise events; ξ is the shape parameter similar to the GEV distribution; and ς is the scale parameter that determines the

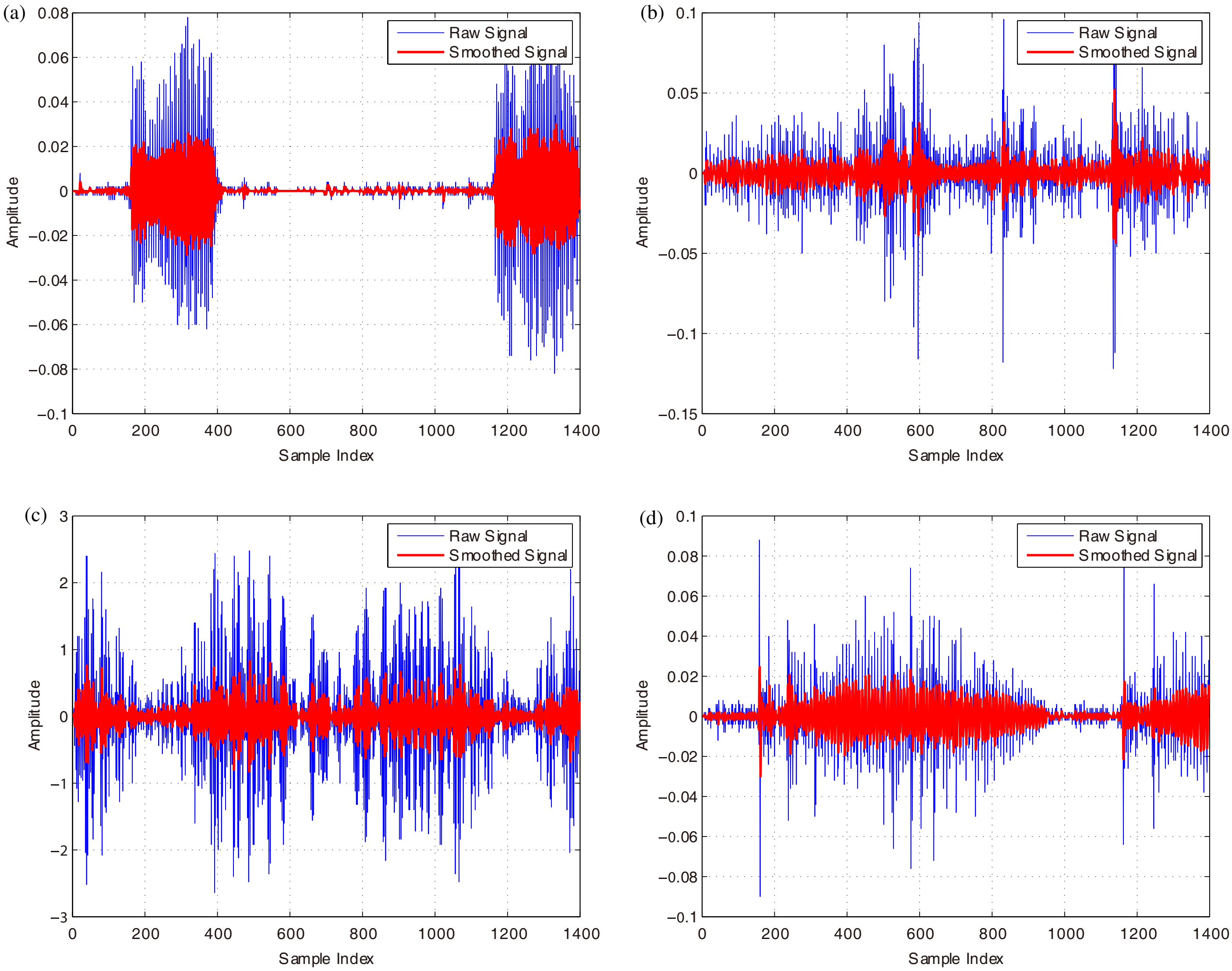

FIGURE 3. Raw vs smoothed impulsive noise from: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

variability over the set threshold. Threshold selection is done using the mean excess function [14–17],

$$e(\vartheta) = \mathbb{E}[R - \vartheta | R > \vartheta] \tag{6}$$

which under the GPD has the closed-form expression,

$$e(\vartheta) = \frac{\varsigma + \xi\vartheta}{1 - \xi}, \quad (\xi < 1) \tag{7}$$

where $\mathbb{E}[\cdot]$ is the expectation taken with respect to the probability distribution of R while all the other parameters bear their usual meaning. This linear relationship provides the criterion used for threshold selection where the empirical mean excess plot $\hat{e}(\vartheta)$ versus ϑ is examined, and the threshold is selected at the lowest point where approximate linearity begins. To maintain statistical reliability, this selection is validated using parameter stability plots for the GPD shape and scale parameters besides ensuring a sufficient number of exceedances above the threshold.

2.2.1. Parameter Estimation for GPD

To estimate the parameters for GPD, MLE approach is used due to its efficiency. For n exceedance $r_1, r_2, \ldots, r_n$, the likelihood function is given as [14–17],

$$L(\varsigma, \xi) = \prod_{i=1}^{n} f(r_i; \xi; \varsigma) \tag{8}$$

where,

$$f(r_i; \xi; \varsigma) = \frac{1}{\varsigma}\left(1 + \frac{\xi r_i}{\varsigma}\right)^{-\left(\frac{1}{\xi}+1\right)}$$

$\therefore$ the log-likelihood becomes,

$$\ell(\varsigma, \xi) = -n \ln \varsigma - \left(1 + \frac{1}{\xi}\right) \sum_{i=1}^{n} \ln\left(1 + \frac{\xi r_i}{\varsigma}\right) \tag{9}$$

subject to: $(1 + \frac{\xi r_i}{\varsigma}) > 0$, where all parameters bear their usual meanings.

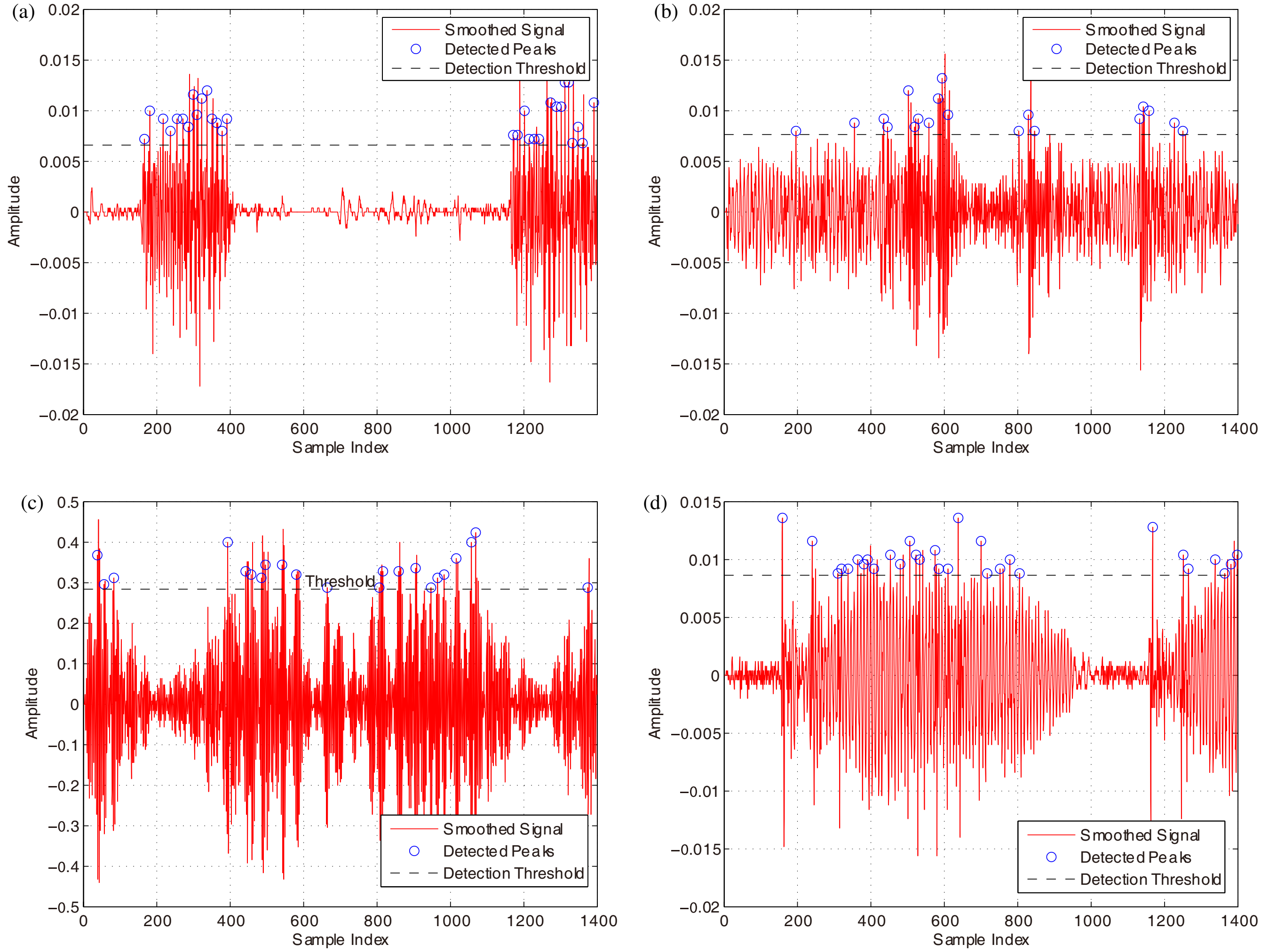

FIGURE 4. Detected peaks with detection thresholds from smoothed signals from: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

2.2.2. Repeat Interval Estimation

Repeat interval, Γ, is the estimated average time (τ) between different impulsive noise events exceeding a set threshold. It is developed from GPD parameters and shows how frequent impulsive noise events are expected to occur. Mathematically, this repeat interval is defined as [14–17],

$$\Gamma = \vartheta + \frac{\varsigma}{\xi}\left[(\lambda\tau)^{\xi} - 1\right] \tag{10}$$

where λ defines the exceedance rate.

3. EXPERIMENTAL PROCEDURE

To establish the connection between the statistical features of EVT and empirical analysis of PLC noise, extensive empirical results were acquired from four different locations within the University. These venues which included a postgraduate office, an electronic lab, a computer lab, and an isolated apartment are considered typical scenarios for the deployment of PLC systems for communication. The postgraduate office contained fluorescent lights, desktop and laptop computers, two air conditioning units, an electrical kettle, and a shared heavy duty printer that served 100 postgraduate students. The electrical loading in the electronic lab was composed of fluorescent lights, air conditioners, and various test equipment that served 120 students as the electrical load, and the computer lab contained 60 computers, fluorescent lights, and an air conditioner while the isolated apartment had electrical loading that contained light dimmers, fluorescent lights, cathode ray tube television set, washing machine, two refrigerators, iron box, a vacuum cleaner, thermostat electric kettle, electric water heater, electric cooker, juice blenders, microwave oven, and security lights. All these electrical loads have been confirmed in [18–23] to contain thermostats, switched mode power supplies, and other switching devices that inject impulsive noise into the power line network.

Measurements were conducted during the operation hours when all the electrical loads in the venues were switched on using the configuration of Fig. 1 to capture real-world impulsive noise. This configuration is composed of a Rigol DS2202A digital storage oscilloscope (DSO) connected to the power line network via a differential mode PLC coupler based on the ETSI TS 102 578 standard [24] which enabled precise measurement

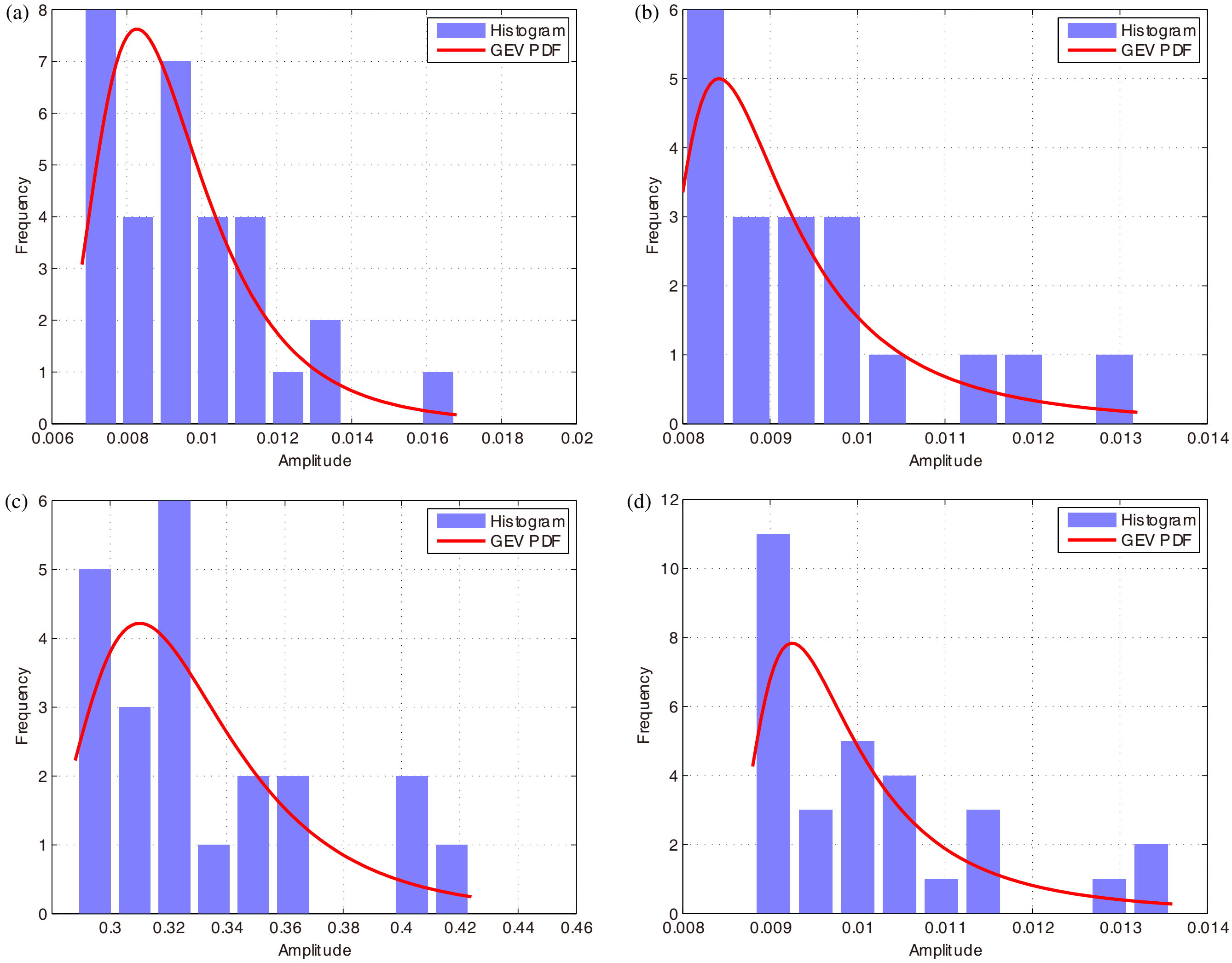

FIGURE 5. Histogram of Block Maxima with GEV PDF plots for: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

of impulsive PLC noise capturing the fastest impulses recorded accurately, providing highly reliable data for further noise modeling and system designing. The coupler isolated the power line network and protected the oscilloscope and personnel from high voltages.

The DSO was set to sample at 1 Giga-samples per second resulting in a 0.14 seconds window length (14 mains cycles). This sampling rate resulted in a window length with high temporal resolution that ensured accurate capturing of fast impulsive noise events. Fig. 2 shows the time series plots for each venue, showing the differences in amplitude, frequency of impulses, and burst patterns. From a visual inspection of these different noise waveforms, impulsive noise events, bursts, and background noise can be seen.

4. RESULTS AND DISCUSSION

In order to apply EVT distribution, the measured PLC noise (Raw signal) was first smoothed using a moving average,

$$\bar{x}_i = \frac{1}{\omega} \sum_{j=1-\omega+1}^{i} x_j \tag{11}$$

with a window size ω that replaced each data point x_i with an average of the ω most recent point. Smoothing the measured data ensures that the small random spikes from switching events and interferences are removed while the focus is maintained on the bursty noise of interest, thus enhancing the ability of the EVT to characterize the true extremes. The results of these extracted peaks are shown in Fig. 3, where it can be seen that small details and peaks in the noise are clearly maintained, confirming that the peak detection and extraction were done correctly. These detected and extracted peaks from different venues can be observed in Fig. 4, with a summary of the number of peaks extracted presented in Table 1. The number of detected peaks directly affects both the statistical accuracy and practical interpretation of rare events. This is because it determines the number of points used for GEV and GPD fitting, the stability of estimated parameters, and the bound of the confidence interval in the return level. From these results, the number of peaks can be considered optimal since they are neither "too few" nor "too many" and thus provide a balance, capturing real extremes in the measured data and not noise.

Once the peaks have been detected and extracted, the GEV and GPD distributions are fitted and parameters estimated.

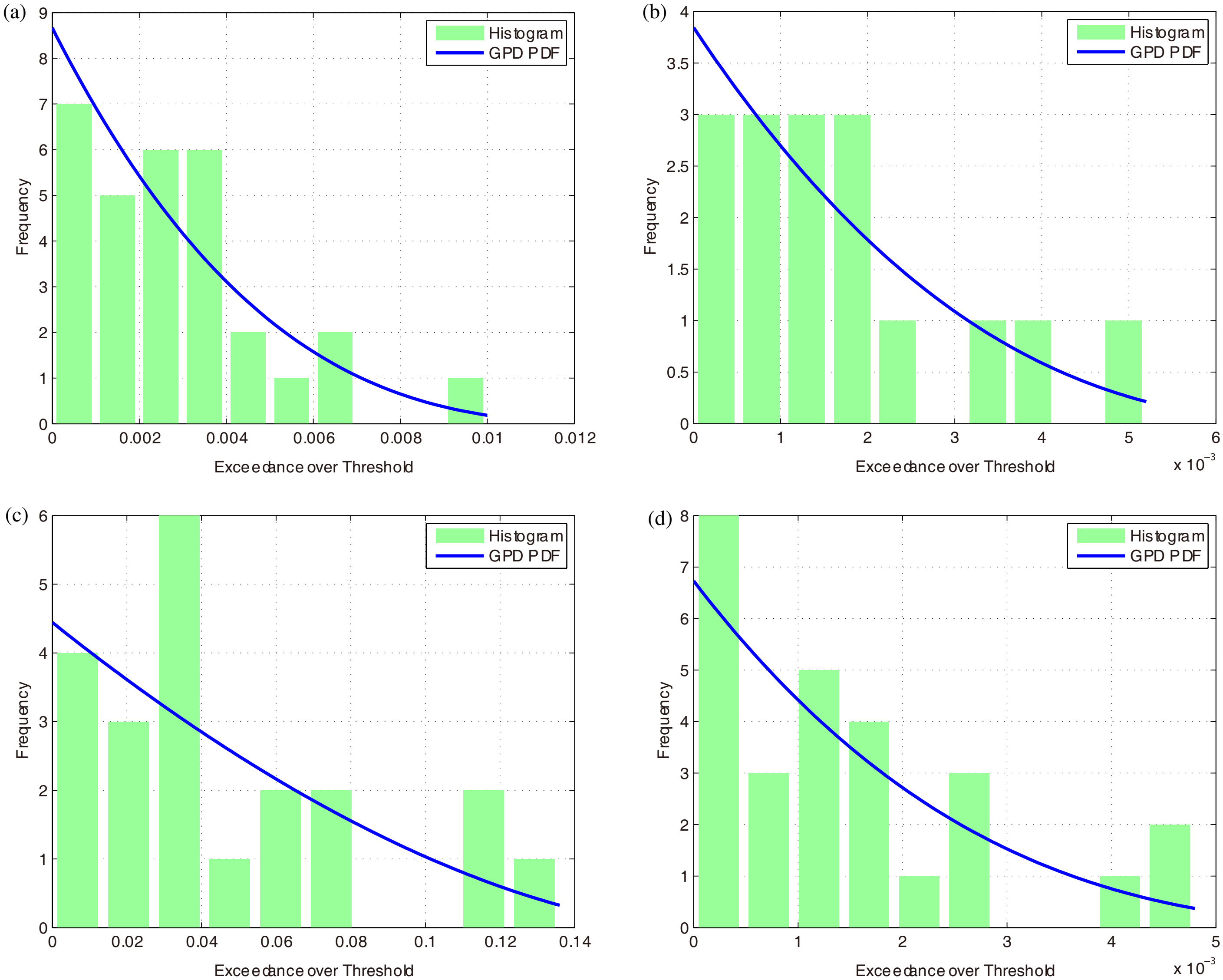

FIGURE 6. Histogram of GPD Exceedance with PDF plots for: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

TABLE 1. Parameter values for the EVT distribution.

Venue	No. of Peaks	Excess Peaks	ξ	ς	ϑ
Apartment	31	30	0.121	0.002	0.008
Comp. Lab	19	16	0.366	0.001	0.008
Elect. Lab	22	21	0.128	0.026	0.288
Postgrad. office	30	27	0.367	0.001	0.009

Fig. 5 shows the GEV histogram that represents the empirical distribution of the block maxima extracted from the PLC noise signals from the different venues. Each noise peak defines the largest value present in a block or window. The red lines are GEV PDFs that represent the theoretical probability density functions fitted to the histograms using the GEV distribution. It can be observed that the GEV PDF curves follow the GEV histogram bars closely, indicating that the model is appropriate for describing the statistical behaviour of the noise block maxima. In addition, tail behaviours can be characterised as heavy-tailed (Fréchet) since the shape parameter, $\xi > 0$, is presented in Table 1. This shows the frequency of occurrence of rare but extremely high impulsive noise bursts in the indoor low-voltage network.

From Fig. 4 and Table 1, the excess peaks that are above the threshold parameter ϑ values can be observed. The difference in threshold exceedance values can be attributed to variations in the statistics of impulsive noise, which depend on factors such as wiring, electrical loading, network impedance, and background noise specific to each venue. Consequently, POT thresholding must be adapted to the specific environment. This means that a 95th percentile amplitude could be sufficient to capture impulsive noise events in some venues, while other venues may require a 99th percentile, automatically shifting the

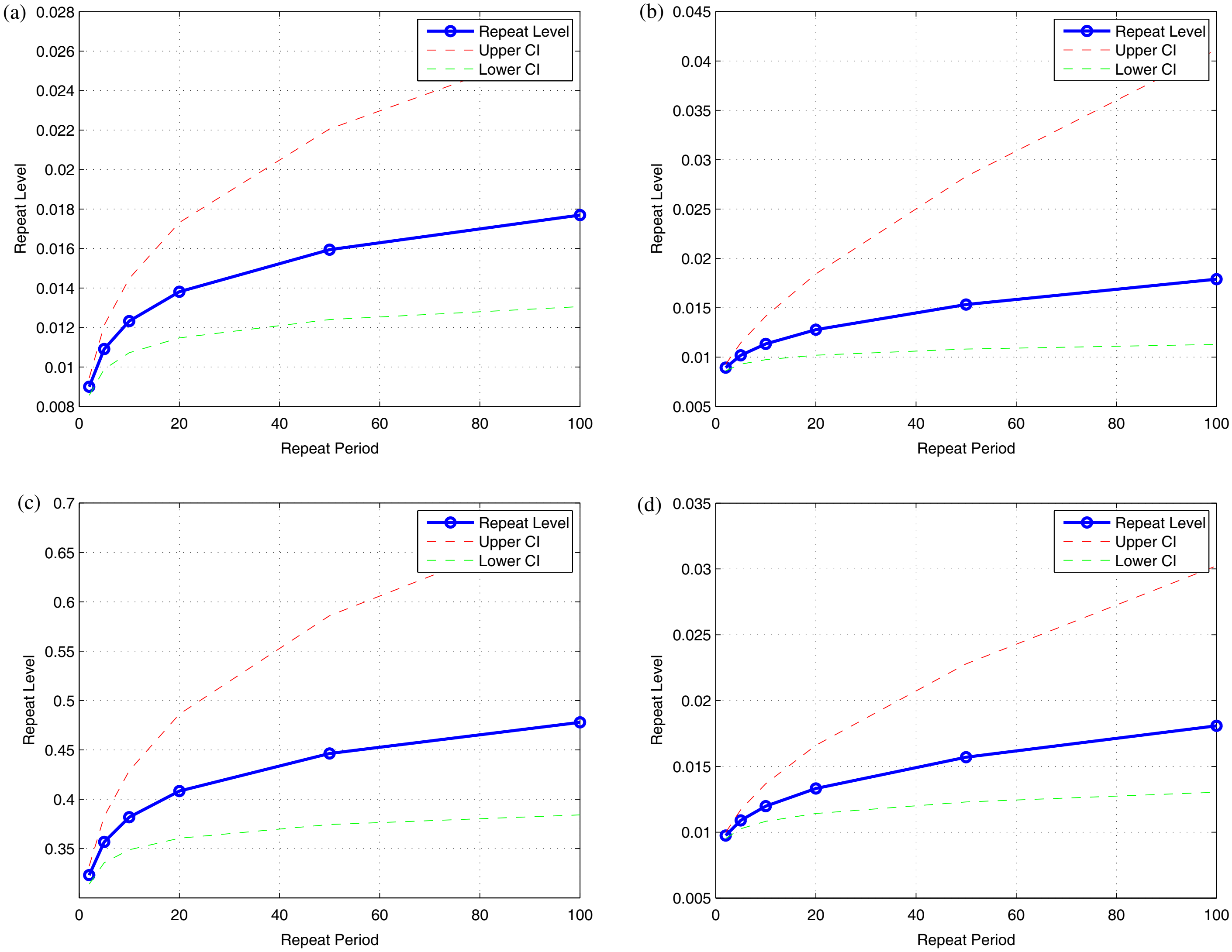

FIGURE 7. GEV repeat level plots with 95% confidence intervals for: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

POT threshold to either a lower or higher value. Fig. 6 displays the GPD histograms of the distribution of these exceedances in the noise signal. The green lines are the fitted GPD to these exceedances. From observation, the GPD PDF curves follow the GPD histogram bars closely, confirming that POT modelling is appropriate for the dataset. Unlike GEV, GPD focuses on extreme tail events only that represent the most significant disturbances. The tail behaviour can be characterised as heavy-tailed sice the shape parameter $\xi > 0$, as seen in Table 1. This confirms the occurrence of rare but extremely high impulsive noise bursts in the indoor low-voltage network.

Lastly, the GEV and GDP repeat interval plots with 95% confidence bounds are shown in Fig. 7 and Fig. 8, respectively. It can be seen that the GPD repeat interval plot has a similar layout to the GEV plot. The x-axis represents the repeat period, and the y-axis represents the repeat level. which shows the peak amplitude expected to be exceeded once every Λ observations and once every Γ observations. From Fig. 7, the blue solid lines represent the estimated repeat levels, while the red and green dashed lines are the confidence bounds around these estimates. It can be observed that as the repeat periods increase, the repeat levels increase as well. This means that rare peaks tend to be more severe. For example, a repeat level of 0.014 for $\Lambda = 20$ from Fig. 7(a) implies that a noise peak of approximately 0.014 units will occur once every 20 observed noise events. The width of the confidence bounds reflects uncertainty such that narrower confidence bounds at short repeat periods indicate higher certainty, while wider widths at longer repeat periods indicate higher uncertainty. On the other hand, the GPD plots shown on Fig. 8 are based on the exceedances over the threshold value and not on block maxima. The green solid lines are the predicted repeat levels, while the confidence bounds are shown in the red and green dashed lines. For a given repeat period, the peak amplitude that exceeds a specific threshold once every Γ exceedance is estimated. For example, a repeat level of 0.4 for $\Gamma = 20$ from Fig. 8(c) means that a noise burst > 0.4 is expected every 20 threshold-exceeding bursts.

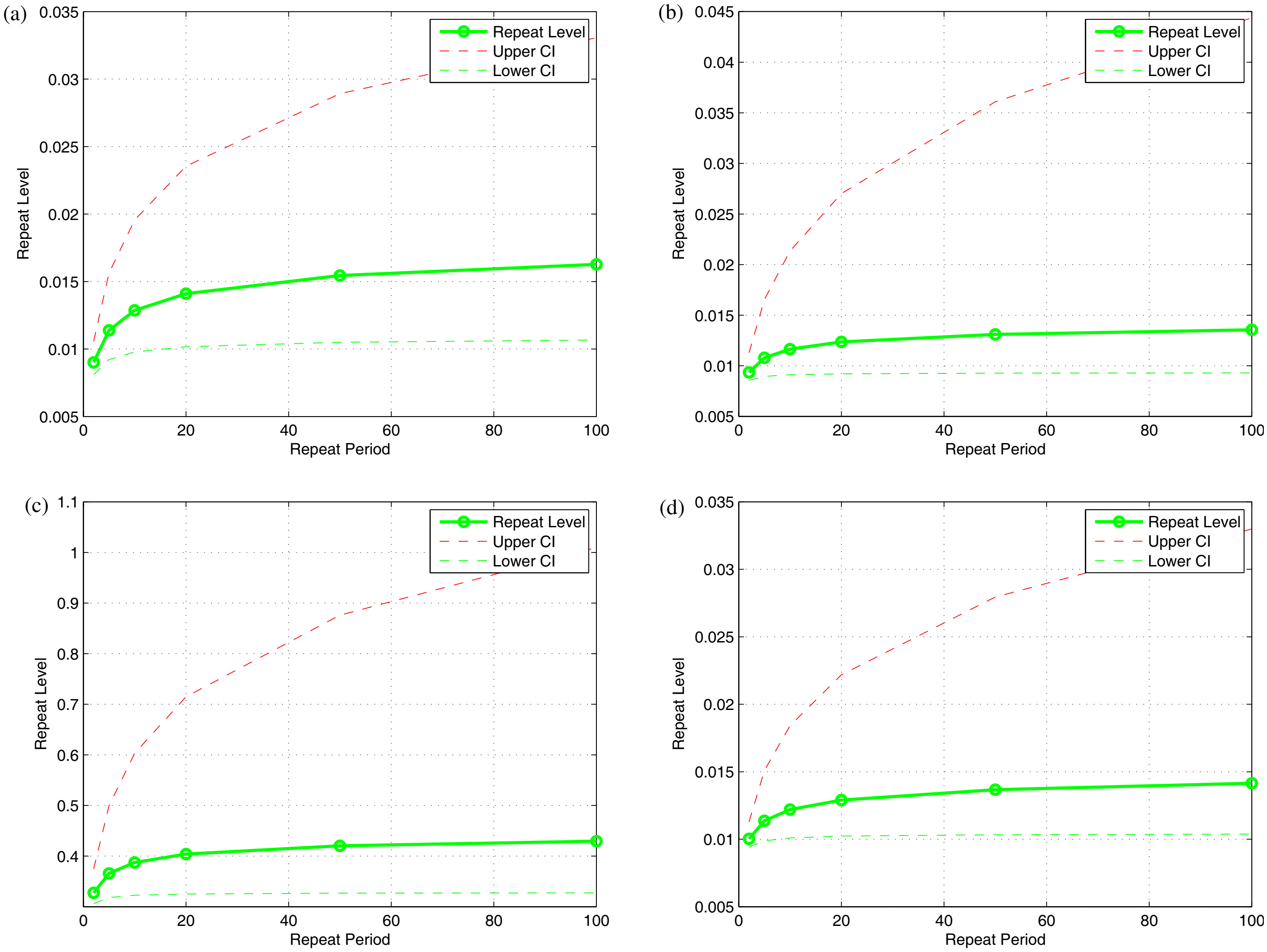

FIGURE 8. GPD repeat level plots with 95% confidence intervals for: (a) Apartment, (b) Computer Lab, (c) Electronic Lab and (d) Postgraduate office.

5. CONCLUSIONS

In this paper, the modelling and characterization of extreme noise events in PLC networks using the EVT approach have been done successfully. From the results, a well-fit GEV and GPD model justifies the use of block maxima and POT EVT approaches for estimating noise thresholds and repeat levels. As such, the frequency and severity of extreme impulsive noise bursts above a safe operating threshold can be estimated. Further, impulsive noise has been confirmed to possess heavy-tailed characteristics, implying more frequent and extreme noise bursts that occur in the network. This poses a risk factor for system stability and reliability in the PLC system. In addition, the shape parameter values are greater than zero, indicating that rare and severe impulsive bursts are plausible. Since the repeat levels of rarer noise peaks tend to be more severe in PLC networks, robust PLC receivers can be designed to tolerate such rare and extreme impulsive noise events besides informing mitigation approaches for improved noise immunity and selection of appropriate threshold levels for adaptive filters that can be used as protective mechanisms in low-voltage networks.

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