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Time Series Modelling of Powerline Communication Impulsive Noise: Queuing Theory Approach

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ABSTRACT: The rate at which powerline communication (PLC) impulsive noise arrives and lasts in the channel determines the severity of signal degradation, with impulsive noise bursts capable of causing complete signal loss. Consequently, the PLC impulsive noise requires an appropriate description to enhance the reliability and effective utilisation of the PLC channel. This paper employs the queuing theory approach to analyse and model the PLC impulsive noise inter-arrival and service time distribution, where the impulsive noise is categorised into single-impulse noise events and burst-impulse noise events. The Erlang-k distribution is proposed for modelling both the inter-arrival and service time distributions for the PLC impulsive noise with the process viewed as an infinite queue with a single server. The impulse noise events are assumed to traverse k stages before entering the PLC network and also pass through k stages before leaving the PLC network, with each of the stages following an exponential distribution. The proposed models are then validated through measurements from different indoor environments and compared to the exponential distribution model, commonly employed in modelling inter-arrival and duration of PLC impulsive noise. The $E_k/E_k/1$ queue model is determined to adequately model the burst-impulse noise events. In regards to the single-impulse noise events, the exponential distribution is observed to provide a suitable fit for the inter-arrival time distribution. The occurrence of PLC impulsive noise events is also found to achieve a state of equilibrium for all the measurement data under study.

1. INTRODUCTION

PLC impulsive noise has been the subject of sustained research through the years, yet still, a standard unified model that describes its characteristics has not been established. This is due to the adverse effect of this erratic noise on the transmitted signal that may even lead to burst errors resulting in a complete signal loss. As a result, significant efforts are still in progress to fully explain PLC impulsive noise characteristics so as to design mitigation strategies that will improve the electrical network's reliability and efficiency. Despite the harsh channel characteristics exhibited by the PLC network, PLC technology has been able to attain high data rates with speeds up to 2 Gbps [1]. Additionally, the PLC network provides a cost-effective yet ubiquitous infrastructure as compared to other data transmission technologies such as optical fibre and Ethernet. Moreover, with the increasing demand for communication in recent years, PLC provides an attractive solution to bridge this gap. Therefore, to realise the benefits of PLC technology in data transmission, its reliability and efficiency must be addressed.

A significant contribution to the use of this cost-effective and vast infrastructure is the development of statistical models that fully describe the impulsive noise characteristics of the PLC network. Due to the intricate nature of the electrical network, most of the PLC noise models proposed are stochastic, where measurements are first performed, and then statistical models are developed to fit the data. Accordingly, extensive measurements have been carried out [2–8] and still need to be carried out in order to develop models that perform well and are consistent for different measurement data. The PLC impulsive noise model can be broadly categorized into frequency domain models, which capture the average noise spectrum, and time domain models, which capture the impulse amplitude, inter-arrival time, and duration, depending on the measurement method employed. The majority of the proposed models are based on the time domain, which can be further classified as those that focus on the amplitude distribution of the PLC impulsive noise and those that model the temporal correlation of the impulsive noise. Among the predominantly used models for describing the amplitude distribution are those based on Gaussian mixtures, such as the Bernoulli-Gaussian and the Middleton Class A models [9–12], with recent models in [13–18], applying machine learning to develop models that adapt to measurement. The Bernoulli-Gaussian model is limited to the impulsive and impulse-free states where the probability of either of the states occurring follows a Bernoulli distribution. The Middleton Class A model improves the Bernoulli-Gaussian model by assuming a finite number of states that occur according to the Poisson distribution. However, it was determined that the Middleton Class A model does not accurately describe PLC impulsive noise because it was designed for man-made impulse interference [3]. As for the model in [13], the amplitude of the PLC noise is assumed to be a superposition of various Gaussian mixture components, and the mixture weights are directly

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derived from the data through unsupervised learning while the generative adversarial networks are employed in [14]. The occurrence of bursts in PLC impulsive noise implies that there is a correlation between the past and future PLC events. As such, various PLC impulsive noise models have been developed to describe the temporal correlation. In [8], the multi-fractal analysis is investigated where the PLC impulsive noise is found to exhibit long-range dependence and multi-fractal scaling behaviour with varying strengths, based on the measurement location. The stochastic nature of the time-varying PLC noise process is also studied in [19, 20] and is observed to exhibit volatility clustering and seasonal behaviour.

The Markov chain model has been widely utilised in analysing the PLC impulsive noise temporal correlation. In [21], the exponential distribution is employed in modelling the impulse noise inter-arrival time and service time, where the Markov chain with two states is employed. From the impulsive noise measurements conducted in the PLC communication networks, it has been established that the durations and inter-arrival time of the impulses result from a superposition of a number of exponential distributions [2]. As such, further analysis is performed in [2, 5], where a partitioned Markov chain approach is employed to model the impulsive noise duration and inter-arrival time distribution. In this case, the impulse noise is divided into two groups, impulse-free and impulsive states, each group comprising transition states that are exponentially distributed. To find the elements of the transition matrices, curve fitting techniques are employed. The complementary probability distributions of the impulsive and impulse-free times are then determined as the sum of weighted exponentials. The Hidden Markov model was utilised to describe PLC impulsive noise in [22]. However, since the state transition could not be observed directly, a different set of stochastic processes was used to determine the impulse noise inter-arrival time and duration in the PLC network. To represent the burst events present in the PLC noise, a Markov Middleton model was employed in [10, 22]. In the models discussed, the transitional probabilities for the various states are not observable, and the limiting distributions were not taken into consideration. As such, the connection between the Markov chain and the PLC statistical properties is investigated in [6]. The methods discussed in [5, 10, 21–23] also do not take into account the type of noise whether single-impulse or burst-impulse. Further, the duration and inter-arrival time distribution for the various impulsive noise events are modelled in [6], where the log-normal, Gamma, and Weibull distributions are proposed for the duration, and exponential distribution is proposed for the inter-arrival times.

In this work, an alternative method based on the queueing theory approach is proposed for modelling the inter-arrival and service time distributions of impulsive noise in the PLC network. The queueing theory approach fully describes the PLC impulsive noise time series characteristics including the interconnection between the PLC noise characteristics and the Markov chain. The Erlang-k distribution is employed in this work in modelling both the service and inter-arrival time characteristics for single-impulse (SI) and burst-impulse (BI) noise events. The appropriate number of stages corresponding to the number of exponentials is determined from the mean and variance of the measured data. As such, the model adapts to the measurement data under study such that depending on the degree of variation of the time domain characteristic, a corresponding number of exponentials that best suit the data is defined. The queuing theory model proposed also enables the evaluation of the steady-state distribution of the impulse noise events through the utilisation of the traffic intensity of the PLC queueing system. The next sections are organised as follows. A detailed overview of the previous research on the PLC noise and a brief introduction of the PLC queueing system is given in Section 2. The procedure and equipment used for data acquisition are discussed in Section 3, while Section 4 describes in detail the proposed queue models for the impulsive noise. The results for the proposed models are validated through measurements discussed in Section 5 while Section 6 concludes the study.

2. PREVIOUS WORK

PLC noise in indoor networks can be broadly categorised as background noise, narrowband interference, and impulsive noise. Background noise emanates from a combination of several low-power noise sources and thereby characterised by a comparatively low power spectral density (PSD) that fluctuates with frequency. It occurs for long periods of time, from minutes to even hours. Narrowband interference, on the other hand, is present across virtually the entire frequency spectrum and is caused by broadcast transmitters in the short and medium wave frequency bands. This noise is characterised by sinusoidal signals with modulated amplitudes [5, 7, 24]. PLC impulsive noise is further classified as either periodic or asynchronous. Periodic impulsive noise with a repetition rate between 50 KHz and 200 KHz is primarily produced by switching power supplies, whereas impulses with a repetition rate of 50 Hz or 100 Hz are produced by power supplies that operate synchronously with the mains cycle. Thus, the PSD of this type of impulsive noise decreases with frequency and occurs for a short duration [5]. The asynchronous impulsive noise is characterised by a high PSD that can reach 50 dB above the background noise and also occurs sporadically and in bursts. Switching transients in the PLC network are the primary source of this troublesome noise [3, 5, 7].

Different models have been proposed for the various noise categories. Nakagami and Rayleigh distributions have been proposed in [25], for modelling of the background noise. Extensive noise measurements were carried out on narrowband interference in low-voltage indoor networks in [26, 27] with a 3D Markov chain model proposed in [28]. As for the periodic impulsive noise, [29] describes the noise as a cyclostationary Gaussian process given by the combination of simple and typical noise waveforms, whereas in [30], the cyclostationary behaviour of the periodic impulsive noise is observed to exhibit self-similarity. The spectral density of background noise increases rapidly at low frequencies below 1 MHz, contrary to the attenuation of the transmitted signal, which decreases as frequency increases. As a result, to limit the effect of background noise, a trade-off between path loss and background noise in the transmission frequency band must be identified. In PLC, this trade-off is determined to be at a frequency range of 1 MHz–20 MHz [7]. Transmission schemes such as spread spectrum techniques, discrete modulation tone, and orthogonal frequency division multiplexing can help cope with the disturbance caused by narrowband interference [7, 31]. As for the periodic impulsive noise, modelling of the service and inter-arrival time is straightforward due to its deterministic nature [2]. On the contrary, the asynchronous impulsive noise is the most difficult to describe due to the random nature of the time domain characteristics. The type of impulsive noise determines the extent of distortion of the signal transmitted. Thus, impulsive noise in the electrical network is commonly classified as either a single-impulse or burst-impulse noise event depending on the duration, frequency content and shape of the impulse. However, no restriction is placed on the shape of the pulse [2, 7, 23]. The SI noise events are often similar in shape to a damped sinusoid, while a BI noise event takes the form of superimposed damped sinusoids [2, 6]. Extensive research has been conducted on the amplitude distribution of the asynchronous impulsive noise in the previous works [13, 17], hence, the primary focus of this study is to model the impulsive noise events service and inter-arrival time distribution.

Impulsive noise levels vary based on the electrical devices plugged into the PLC network. As a result, each indoor environment will display distinct PLC impulsive noise behaviour. The impulsive noise sources on the PLC channel are numerous and can thus be deemed infinite due to the numerous electrical devices that have been built and are still under development. The demand for electrical power is endless as there are electrical devices that require power to operate, and must therefore be fully plugged in for extended periods. Furthermore, while some of the PLC network's electrical devices are unplugged, others are connected. As a result, the PLC impulsive noise can be viewed as an infinite queue. The time series analysis of the occurrence and duration of the impulsive noise events can be fully described as a queueing system. The main parameters of a queueing system are the inter-arrival and service time distributions, the number of servers, system capacity, the size of sources that generate impulsive noise, and queue discipline. These characteristics can be represented by the Kendall notation as $X/Y/Z/D/E/F$. If the queue discipline is first-in-first-out, and the system capacity and size of the sources are infinite, as the case with PLC, the last three terms are omitted as they are automatically implied. Consequently, a PLC queueing system can be represented as an $X/Y/Z$ queue, denoting the inter-arrival time, service time, and the number of servers, respectively.

Significant research with regard to the PLC impulsive noise service and inter-arrival time explores the implementation of the exponential distribution due to the random behaviour exhibited by this noise [2, 6, 21, 32–34]. Preliminary results on the implementation of the queueing approach of PLC impulsive noise are discussed in [32] and also employ the exponential distribution, where the BI noise events are observed to occur as the overlap of SI noise events. The $M/M/1$ queue for the inter-arrival times and the $M/M/1$ and $M/E_k/1$ queue models for the service time distribution were examined. The analysis of steady-state characteristics is investigated in [34], where further research on the PLC queueing system is studied. The PLC impulsive noise events are observed to achieve a steady-state, and the $M/M/1$ queue parameters at steady state were determined. However, it has also been observed to be insufficient in approximating the service and inter-arrival time characteristics of impulsive noise of different PLC measurement data [2]. Therefore, this work proposes an Erlang-k model, which offers greater modelling flexibility for the data under consideration, while taking advantage of the exponential distribution properties. Accordingly, the standard deviation for an Erlang-k model ranges between 0 and $1/ku$, such that when the value of k is 1, it reduces to the exponential distribution, and when k is ∞, it becomes a degenerate distribution. As a result, data with a high variation will have a lower number of stages (exponential distributions) than data with a less variation, and as $k \to 1$ represents a high fluctuation and as $k \to \infty$, the change in the service time or inter-arrival time is constant. The PLC impulsive noise measurements in this work are carried out at the receiver using a digital storage oscilloscope, hence, the number of servers in this work is limited to one.

3. MEASUREMENT SETUP

Presently, stochastic models are employed in modelling the PLC impulsive noise characteristics which employ the top-down approach. As a result, extensive measurement campaigns need to be performed to develop statistical models that provide an accurate description of the actual behaviour of the PLC impulsive noise. This work, like other stochastic models, employs a top-down method in which the parameters for the proposed models are obtained from measurement data for various low-voltage indoor locations. Fig. 1 shows the setup used to perform PLC noise measurements in the 1–30 MHz frequency band.

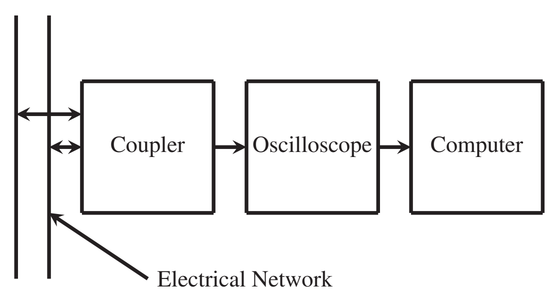

FIGURE 1. Measurement set-up.

In order to filter out low-voltage frequency signals and protect the oscilloscope from damage from the high-voltage mains supply, a high-pass filter coupler was used as an interface between the oscilloscope and electrical network. This is achieved by capacitors, a $1:1$ broadband transformer and Zener diodes present in the coupling circuitry. Galvanic isolation is provided by the transformer, while Zener diodes maintain the output voltage at 5 v to protect the equipment from power surges. The series capacitor on the other hand prevents the transformer from saturation and filters out the low-frequency signals. It has been established that the passive filter components present in couplers also generate a ringing effect that distorts the time do-

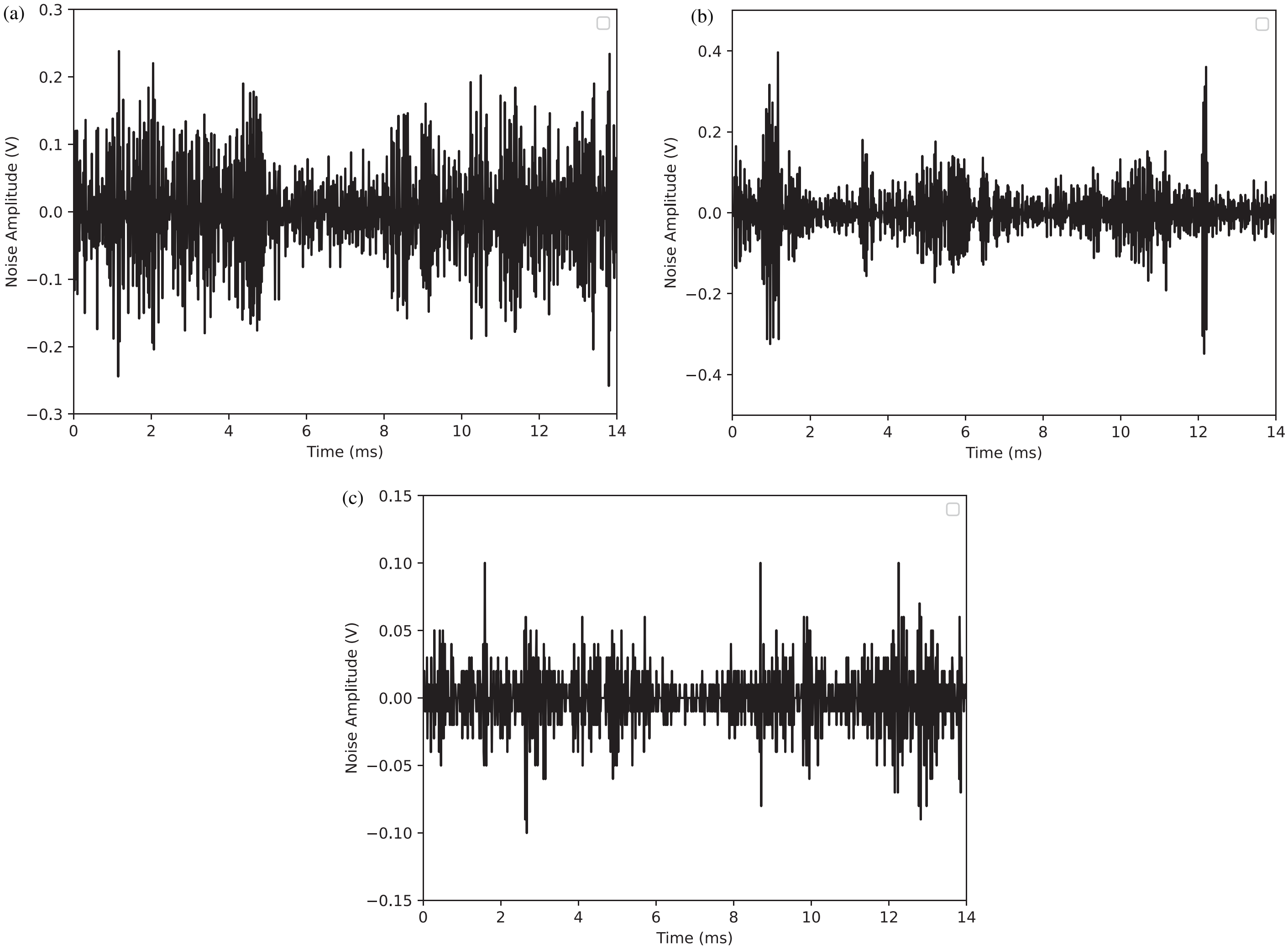

FIGURE 2. Sample PLC Noise Measurements. (a) Second-year Laboratory. (b) Postgraduate Office. (c) Computer Laboratory.

main characteristics of the impulse signal. This is due to the excitation of resonance points as the PLC noise traverses the coupling circuit [35]. In this work, the PLC noise is measured at the receiver, and thus the impact of the coupling circuit is not taken to consideration. For each of the measurements carried out, Rigol DS2202A was used to perform measurements, where the sampling rate was configured to 1 Giga samples/s, measuring 14 million samples with a window length of 14 ms. The computer is then used for analysis and storage of the measured data. The Second-year Laboratory (SYL), Post-graduate office (PGO), and Computer Laboratory (CL) at the University of KwaZulu-Natal are the locations for measurement in this study. Except for the various loading conditions, these locations serve as a representation of the actual PLC channels.

The loading conditions for the SYL include four air conditioners, thirty-six fluorescent lamps, and forty-two workstations each comprising the following: an electronic trainer board, a function generator, a simple 10 MHz oscilloscope, a DC power supply, a digital multimeter, and a board of passive components. The room dimension for the SYL is approximately 26 m by 13 m. The PGO is connected to the same electrical network as the other offices in the building with a dimension of approximately 10.8 m by 4.8 m. The PGO consists of two air conditioners, eight fluorescent lights, one heavy duty printer, and eight workstations — each consisting of either a desktop computer with its screen or a laptop computer and a phone charger. The CL, with a dimension of 16 m by 12 m, has the following loads connected to the PLC line: three air conditioners, twenty fluorescent lights, and sixty desktop computers with computer screens. The measurements were conducted as the students carried out their practicals.

Sample measurement data from the SYL, PGO, and CL are depicted in Figs. 2(a), 2(b), and 2(c), respectively. The PLC noise data for the various locations is observed to exhibit distinct time domain characteristics; in comparison with CL, the amplitudes of PLC noise are higher in the PGO as well as SYL. This can be attributed to devices connected to the PLC network, such as electronic trainer boards and electric kettles, which are composed of silicon-controlled rectifiers and thermostats that generate high impulsive noise levels [3, 4, 36]. Moreover, for each sample measurement at each location, the impulsive noise occurrence varies. Therefore, developing a statistical model to describe this unpredictable behaviour is a daunting task.

4. PROPOSED QUEUEING MODELS FOR PLC

Let the PLC impulse noise events arrive at time instants t_m $(m = 0, 1, 2, \ldots)$ and that the service time for the m_{th} impulse noise event be s_m $(m = 1, 2, \ldots)$. Assuming that the inter-arrival and service times are independently and identically distributed (i.i.d) according to the Erlang-k distribution given by (1) and (2) respectively as [37, 38]:

$$a(m) = \frac{k\phi(k\phi m)^{k-1}\exp(-k\phi m)}{(k-1)!} \tag{1}$$

$$s(m) = \frac{k\psi(k\psi m)^{k-1}\exp(-k\psi m)}{(k-1)!} \tag{2}$$

whose means and variance for the inter-arrival times are defined by [37, 38]:

$$E[M] = \frac{1}{\phi} \tag{3}$$

$$Var[M] = \frac{1}{k\phi^2} \tag{4}$$

The service time means and variance are similarly defined as in (3) and (4), with the ϕ replaced by ψ. $\frac{1}{\phi}$ and $\frac{1}{\psi}$ thus denote the mean arrival time and mean service time of the impulse noise events, respectively. k is limited to be a positive integer ranging from $1 \leq k \leq \infty$ and represents the degree of variation of the data to the mean. From (1) and (2), it can be shown that when $k = 1$, the Erlang distribution is reduced to an exponential distribution given by [32, 37]:

$$a(m) = \phi\exp(-\phi m), \quad m \geq 0 \tag{5}$$

$$s(m) = \psi\exp(-\psi m), \quad m \geq 1 \tag{6}$$

for the inter-arrival and service time distribution respectively. As $k \to \infty$ the variance $\to$ zero, the Erlang-k distribution becomes deterministic. Accordingly, the Erlang-k distribution becomes more symmetrical and more closely centred around its mean as k increases. Since the Erlang distribution is composed of k i.i.d exponential distributions, each having a mean of $\frac{1}{k\phi}$ for inter-arrival times or $\frac{1}{k\psi}$ for service times, k can also be considered as the number of exponentials in the Erlang distribution [34, 37]. Due to its relationship with the exponential distribution, the Erlang model is more flexible in fitting the distribution to actual data than the exponential distribution and is thus beneficial in queueing analysis. Four queue models can therefore be derived from the Erlang-k distribution for modelling the PLC impulsive noise events, namely $M/M/1$, $M/E_k/1$, $E_j/M/1$, and $E_j/E_k/1$ queues due to their memoryless property and are considered in this work.

In order to ascertain that the proposed queue models are tractable, it is of paramount importance to determine if a steady state exists for the PLC impulsive-noise events under study. To achieve this, the traffic intensity is determined and defined by [34, 37, 38]:

$$\theta = \frac{\phi}{\psi} \tag{7}$$

If $\theta < 1$, then a steady state exists where the occurrence of an impulse noise event at a future time t_m as $t_m \to \infty$ is independent of the original state of the system. Consequently, the arrival or service process of the impulse noise events can return to any state with a probability of 1 with a mean return time $< \infty$. $\theta = 1$ indicates that the arrival and service process of the PLC impulsive noise events returns to any state with a probability of 1 both with a mean return time of ∞. Accordingly, the PLC system queue will increase over time, and the queue will grow indefinitely. For $\theta > 1$, the probability of the arrival and service process returning to the finite states is zero for the impulse-noise events, resulting in an infinite queue [34, 37, 38].

4.1. M/M/1 Queue

For the $M/M/1$ queue, the exponential distribution is employed in modelling the impulse noise events inter-arrival and service time distribution in the PLC network. Equations (5) and (6), respectively, define the density distribution (PDF) of the inter-arrival and service times. The birth-death process can then be used to model the steady-state probabilities of the $M/M/1$ queue as in [34]. As such, the rate at which the impulse noise events arrive and depart at the PLC network is equal as $t \to \infty$.

4.2. M/E_k/1 Queue

The arrival process of the PLC impulse noise events are assumed to follow an exponential distribution in the $M/E_k/1$ model, whereas the impulse noise events are considered to pass through k stages each with a rate $k\psi$ before departing the PLC network, and hence the service time follows the Erlang-k distribution. It follows that if there are m impulsive noise events in the system, and the impulsive noise currently at the receiver is in stage $j(j = 1, 2, \ldots, k)$ where k is the initial stage of service and $j = 1$ the final stage of service such that when stage 1 is completed, the impulse noise event leaves the electrical network, then state of the PLC system can be completely described by (m, j). Thus, for a system in state m, j, there are $m - 1$ impulse noise events in the queue, each requiring k stages, as well as an impulse noise event at the receiver having j additional stages yet to be completed. Therefore, the total count for the number of stages in the PLC system will be $(m - 1)k + j$. Accordingly, the state of the service process can be regarded as Markovian, and to derive the queue parameters, the knowledge of the number of impulse noise events and the current stage of service is sufficient. Consequently, (5) and (2), respectively, give the density functions of the inter-arrival time and service times.

4.3. E_j/M/1 Queue

The assumption in this model is that the impulsive noise event passes through k stages prior to entering the PLC network, with each stage having a mean of $\frac{1}{k\phi}$, while the

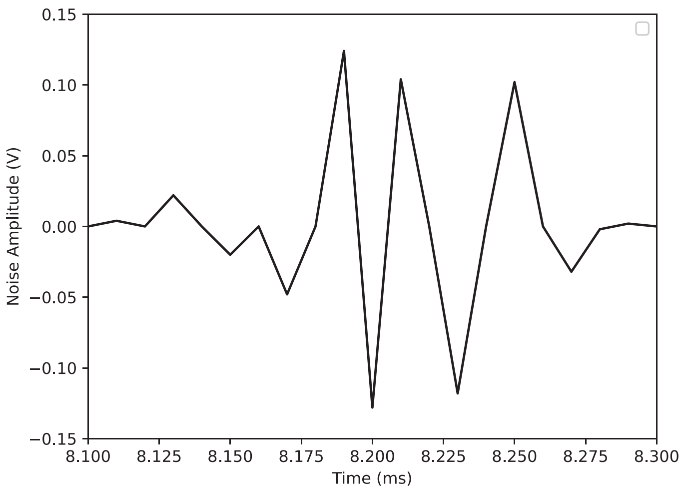

FIGURE 3. Sample single-impulse noise event.

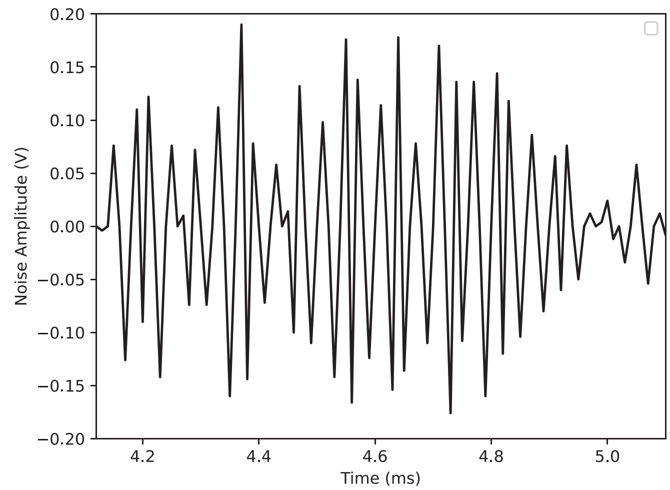

FIGURE 4. Sample burst-impulse noise event.

service time distribution follows a Poisson process. This model can be similarly described as a bivariate Markov process (m, j), with the first variable representing the number of impulse noise events in the PLC system and the second variable representing the number of completed stages as $\{(0,0); (1,1), (1,2), \ldots, (1,k); (2,1), (2,2), \ldots, (2,k); \ldots.\}$ [37]. In this case, m represents the number of PLC impulsive noise events, each with k completed stages, and j represents the number of completed stages corresponding to the arrival of the next impulse noise event. The inter-arrival time PDF is thus obtained from (1), whereas (6) gives the density distribution of the service time.

4.4. E_j/E_k1 Queue

The arrival and service process in this queue involves k stages, in which the PLC impulsive noise events traverse k stages before entering the PLC network and another k stages before leaving the PLC system. As a result, the arrival process is analogous to the $E_j/M/1$ queue model, while the service time is similar to the $M/E_k/1$ queue model. The inter-arrival and service time distributions are subsequently determined using (1) and (2) respectively.

5. RESULTS AND DISCUSSION

The impulsive noise measurement data in Section 3 was categorised into SI and BI noise events, since their effect on the transmitted signal varies, with BI noise events resulting in more severe effects. A single impulse noise event is made up of one or two noise impulses while for the PLC noise to be considered as a burst, it should comprise the occurrence of at least 3 single impulse noise events occurring consecutively [2, 32]. Figs. 3 and 4 show samples of a SI and BI noise event derived from the SYL noise measurement data in Fig. 2(a).

In order to determine the density distribution of the inter-arrival and service time, the parameters of the model first need to be determined. These parameters also provide guidance as to which density distribution is applicable to the data under consideration. Thus, the queue parameters, for the exponential and Erlang-k distributions, are summarised in Table 1. It is observed that for SI noise events, the number of i.i.d exponential distributions (k) in the Erlang-k model is one. As such, the exponential distribution is selected to model the impulsive noise inter-arrival times in all the data under consideration. This indicates that there is a high variation in the inter-arrival times and can be attributed to the burst impulse noise events that last for longer durations with varying service times. The service time distribution of the SI noise events can be modelled using both the exponential and Erlang-k distributions in all locations except for the CL, where only the exponential distribution is applicable. As for the burst impulse noise events service time and inter-arrival time distributions, both the Erlang-k and exponential distributions are applicable in the modelling of the data in the various locations. It is again observed from Table 1 that the mean service time in all the sample data under consideration is less than the mean inter-arrival time. Consequently, the PLC impulsive noise events can achieve a steady-state equilibrium.

The proposed models in Section 4 were then validated through the sample PLC impulsive noise measurement data in Section 3. It is observed from Fig. 5 that the SI noise events inter-arrival times are adequately modelled using the exponential distribution while for the BI events, the Erlang-k distribution provides a better fit. This can be attributed to the fact that the burst events last for longer durations that are also random and for a single-impulse event following a burst, will have a high variation. As regards to the SI noise events service time distribution, there is less variation, and thus, the Erlang distribution provides a better fit as shown in Figs. 6(a) and 6(b), though the number of exponential distributions needs for each data sample is different. However, the exponential distribution provides a suitable fit to the CL measurement data as shown in Fig. 6(c). The BI noise events have been found to comprise the largest percentage of the impulsive noise with up to 80% in the indoor PLC networks [6]. Although the BI noise events inter-arrival time varies, the degree of variation is not as significant as that of the SI noise events. Consequently,

TABLE 1. Queue model parameters.

	Single-impulse Events Inter-arrival time	Single-impulse Events Service time	Burst-impulse Events Inter-arrival time	Burst-impulse Events Service time
Second-year Laboratory				
Mean	0.3563	0.119	0.995	0.8538
Variance	0.3208	0.0088	0.3227	0.3236
K	1	2	3	2
Postgraduate Office				
Mean	0.4943	0.1376	1.0085	0.5893
Variance	0.3418	0.0054	0.4705	5.1984
K	1	4	2	2
Computer Laboratory				
Mean	1.0154	0.1471	0.6917	0.6005
Variance	1.7583	0.0157	0.0886	0.0488
K	1	1	5	7

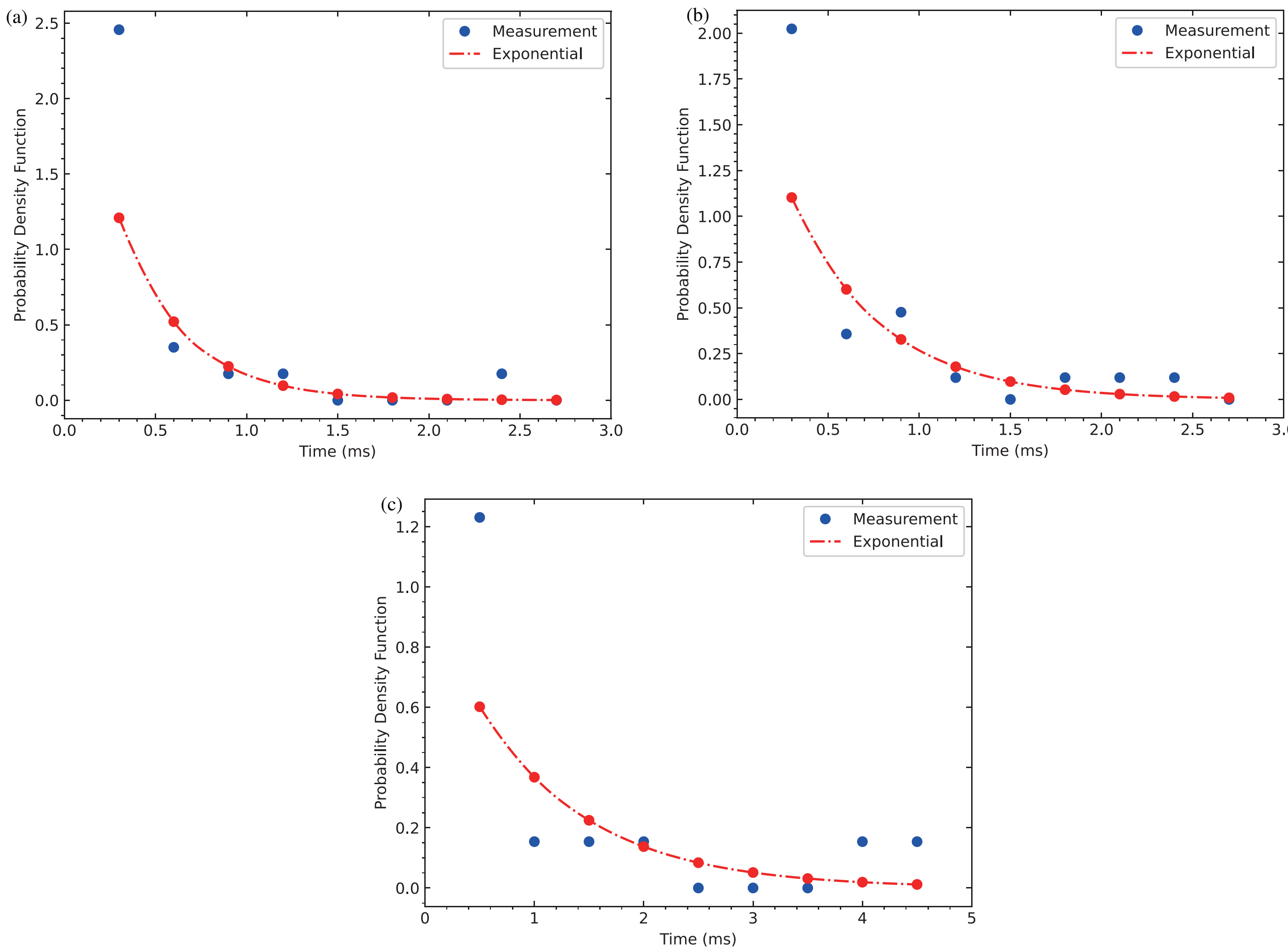

FIGURE 5. Single-impulse noise events inter-arrival time distribution. (a) Second-year Laboratory. (b) Postgraduate Office. (c) Computer Laboratory.

TABLE 2. Error analysis.

Single-impulse Events			
		Inter-arrival time	**Service time**
Second-year Laboratory			
RMSE	Erlang_k	x	0.7688
	Exponential	0.4248	1.0459
χ^2	Erlang_k	x	2.7272
	Exponential	1.074	5.7712
SL		15.5073	14.0671
Postgraduate office			
RMSE	Erlang_k	x	0.7185
	Exponential	0.3267	1.8717
χ^2	Erlang_k	x	1.2508
	Exponential	0.4833	10.1326
SL		15.5073	14.0671
Computer Laboratory			
RMSE	Erlang_k	x	x
	Exponential	0.2347	0.708
χ^2	Erlang_k	x	x
	Exponential	0.6363	2.8478
SL		15.5073	14.0671

Burst-impulse Events			
		Inter-arrival time	**Service time**
Second-year Laboratory			
RMSE	Erlang_k	0.226	0.1293
	Exponential	0.2679	0.1538
χ^2	Erlang_k	0.4412	0.568
	Exponential	0.5237	0.7245
SL		15.5073	14.0671
Postgraduate office			
RMSE	Erlang_k	0.2517	0.2322
	Exponential	0.291	0.2681
χ^2	Erlang_k	0.5713	0.6398
	Exponential	0.604	1.1544
SL		15.5073	14.0671
Computer Laboratory			
RMSE	Erlang_k	0.3625	0.4176
	Exponential	0.4431	0.6412
χ^2	Erlang_k	0.4301	1.4386
	Exponential	0.6875	4.8711
SL		15.5073	14.0671

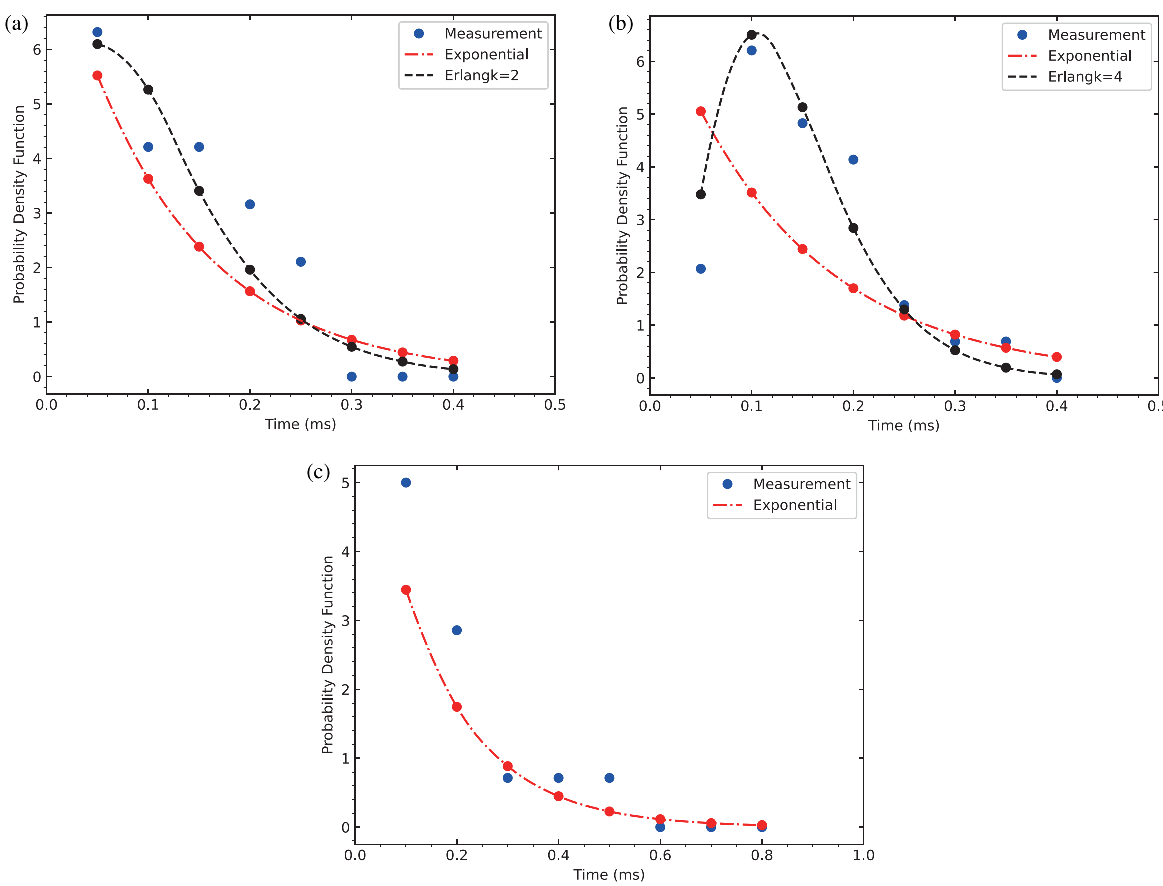

FIGURE 6. Single-impulse noise events service time distribution. (a) Second-year Laboratory. (b) Postgraduate Office. (c) Computer Laboratory.

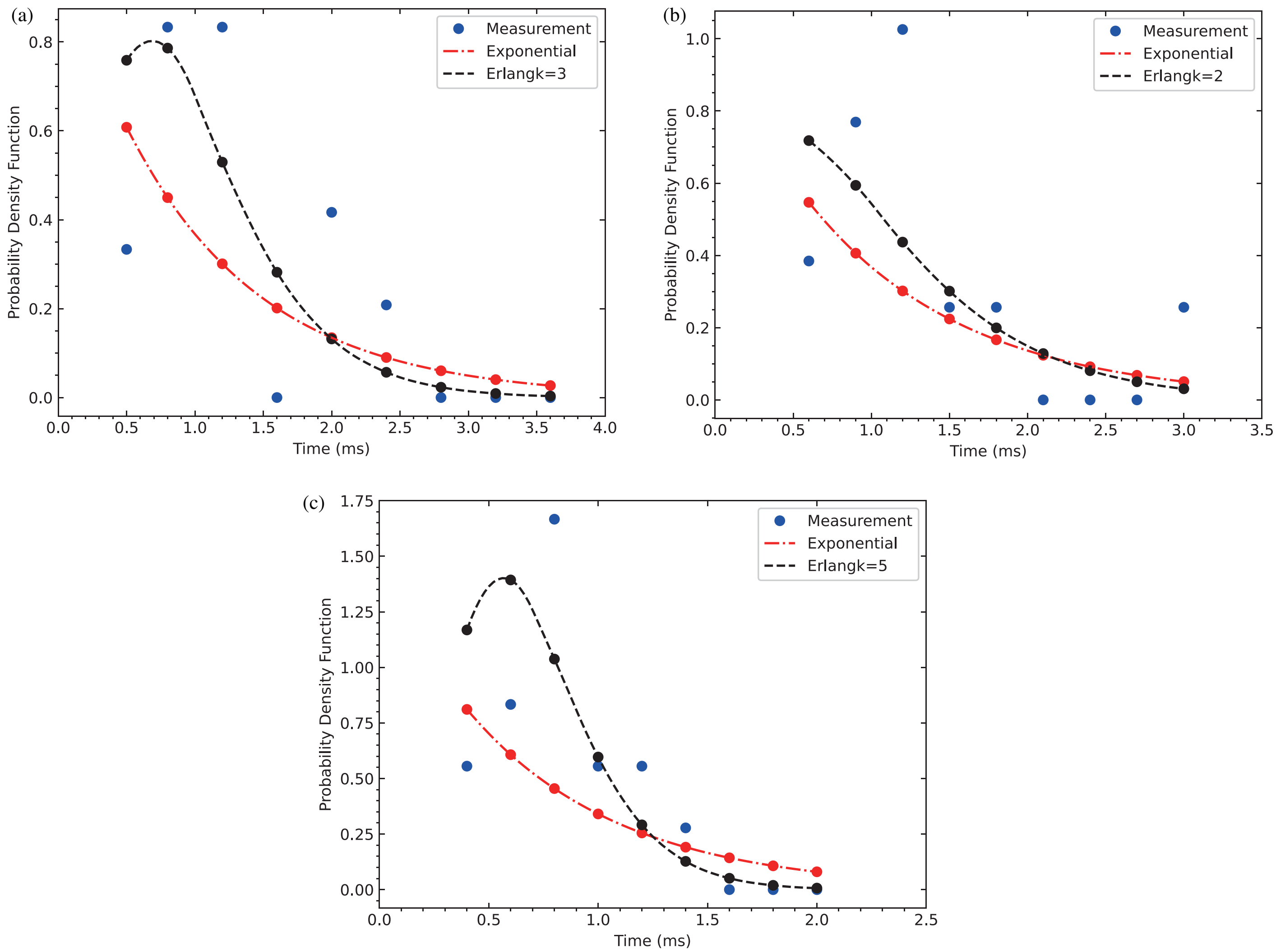

FIGURE 7. Burst-impulse noise events inter-arrival time distribution. (a) Second-year Laboratory. (b) Postgraduate Office. (c) Computer Laboratory.

in all the various locations, the Erlang-k distribution may be employed to model the inter-arrival times and is observed to adequately capture the measured data as compared to the exponential distribution with the value of k ranging from 2 to 5 as shown in Figs. 7. Moreover, the occurrence of the BI noise events are observed to have a higher variance in the SYL and PGO in Figs. 7(a) and 7(b), which have higher noise levels than the CL where $k = 5$ for the Erlang distribution as depicted in Fig. 7(c). Fig. 8 depicts the burst impulse noise event service time distribution in various indoor locations. The burst impulse noise events have a considerable variation for the SYL and PGO, with the Erlang-2 distribution observed to adequately fit to the measurement data. The exponential distribution is also observed to provide an adequate fit to the measurement data as depicted in Figs. 8(a) and 8(b). This is due to the high noise levels in these locations, which cause greater fluctuation. The Erlang-k distribution, on the other hand, provides a suitable fit where the measured distribution is found to approach a normal distribution in the CL where the noise levels are lower.

5.1. Error Analysis and Model Validation

Error analysis was then performed to determine how well the proposed models fit the data where the root mean square error (RMSE) and χ^2 statistic were employed to determine the goodness of fit of the proposed queue models. Equations (8) and (9) give the formulations for the RMSE and χ^2 statistic, respectively, where a 5% threshold of significance level (SL) was set for the χ^2 statistic.

$$RMSE = \sqrt{\frac{\sum_{q=1}^{Q}(x_a - x_p)^2}{Q}} \tag{8}$$

$$\chi^2 = \sum_{q=1}^{Q} \frac{(x_a - x_p)^2}{x_p} \tag{9}$$

where x_p and x_a are the proposed and measured model values, respectively, and Q is the total number of samples. Table 2 gives a summary of the proposed models' performance. The Erlang-k and exponential distributions proposed for mod-

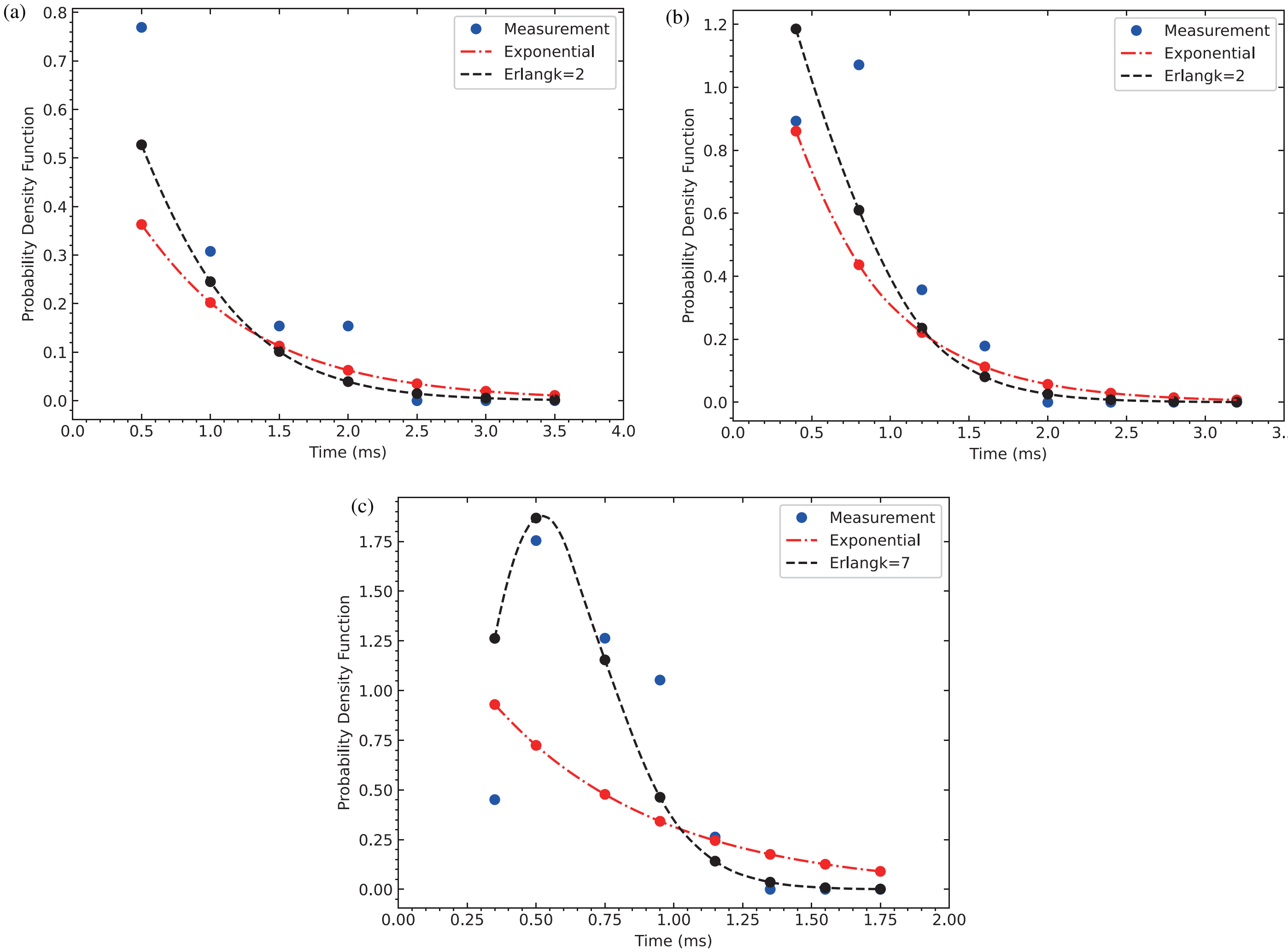

FIGURE 8. Burst-impulse noise events service time distribution. (a) Second-year Laboratory. (b) Postgraduate Office. (c) Computer Laboratory.

elling the various measurement data under consideration are determined to be statistically significant. The Erlang-k distribution is found to provide better accuracy as shown by the lower RMSE and χ^2 values than the exponential distribution. This is due to the flexibility of the Erlang-k model where the value of k varies depending on the measurement data under consideration. The results of the model parameters and performance analysis indicate that the SI noise events for the SYL, PGO, and CL can be effectively modelled using the $M/E_2/1$, $M/E_4/1$, and $M/M/1$ queue models, respectively. Accordingly, the exponential distribution adequately models SI noise events inter-arrival times. As regards to the BI noise events, the $E_3/E_2/1$, $E_2/E_2/1$, and $E_5/E_7/1$ queue models are determined to be the most effective models for the SYL, PGO, and CL, respectively. Therefore, the Erlang-k distribution is observed to adequately model the BI noise events service time and inter-arrival times.

6. CONCLUSION

The time series characteristics of the PLC impulsive noise events have been examined, and the queueing theory approach has been employed to model their characteristics in this work. Depending on the variability of the data under consideration, appropriate parameters have been derived and the applicable queue models employed to determine the service and inter-arrival time distributions. For all the SI noise events under consideration, only the exponential distribution is determined appropriate in modelling the inter-arrival times and provides a suitable fit, indicating a high variance. The Erlang-k distribution is observed to provide better accuracy than the exponential distribution in modelling the BI noise events time series characteristics. It is determined that the steady-state equilibrium of the impulse noise events inter-arrival and service time distribution exists. From the performance analysis, the proposed models are observed to provide a good correlation to the measure data with a high level of significance. The results obtained from this work can be employed to develop a simulation tool for the optimization of transmission schemes in the PLC system for improved performance and reliability.

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