

Enhanced Performance of Narrowband Power Line Communications using Recursive Least Squares Filter

B. Rajkumarsingh, D. Seegoolam,
*Department of Electrical & Electronic Engineering
University of Mauritius
Reduit, Mauritius
b.rajkumarsingh@uom.ac.mu.*

Abstract— Noises presented in a power line communication channel tend to distort the message signals, leading towards the reception of erroneous data at the receiver end. Mitigation of noise existent in power line has always been of prime interest and helped to improve the BER performance of a communication system as it accounts for efficient data transmission. In this work, adaptive filters based on the Recursive Least Squares (RLS) algorithm and Least Mean Square (LMS) algorithms have been implemented in Simulink to investigate the effectiveness of an Adaptive Noise Canceller for the mitigation of Gaussian and Impulsive Noises present in a narrowband power line channel model. The performance of the RLS algorithm against that of the LMS algorithm was compared in adaptive filtering for the same channel conditions. The error performances of BPSK and FSK schemes for the channel model in a generic digital communication system were also compared in Simulink. Furthermore, the use of convolutional codes and interleaving for the correction of random bit errors and for condensing the negative effect of burst errors respectively were investigated during the transmission of data signals over the generic communication system designed in Simulink. From the findings of the study, it has been concluded that the RLS algorithm proves to be more effective than the LMS algorithm. For a BER of 10^{-5} , a coding gain of less than 10 dB is achievable for both Binary Phase Shift Keying and Binary Frequency Shift Keying. With the addition of convolutional coding and convolutional interleaving, the error performance of the channel is further improved, rendering the power line channel more reliable for data communication.

Index Terms— Adaptive Noise Canceller; Recursive Least Squares Filter; Convolutional Codes; Power Line Communications.

I. INTRODUCTION

The main issues of the power line channel involve signal attenuation, principally due to the fluctuating impedance of the conductors with frequency, the poor channel characteristics in terms of noise robustness and the effect of multipath. Noise in the power line is mainly produced by the various electrical-connected appliances. From the findings of Lim et al. [1], it becomes apparent that the crucial sources of noise of in-house power line are due to electrical loads from corroded wiring links, vacuum cleaners, light dimmers and hair dryers. Additionally, PLC systems are highly prone to electromagnetic interference, which further deteriorates the quality of transmission [2].

Background noise and impulsive noise form the two major blocks of power line noise. The various types of noise under

each of the two categories contribute to the attenuation of message signals transmitted over the channel. Moreover, these noises tend to distort the message signals, and therefore leading towards the reception of erroneous data at the receiver end. From the analysis in [3], it is disclosed that for SNR of 0 dB, the BER can attain a value of 4 when transmitting data over a channel with the appropriate modelling of the various forms of noise present.

While noise mitigation helps to decrease channel losses [4, 5, 6], other parameters which come into consideration for the betterment of the performance of a communication system include modulation schemes, transmission filters, error-correcting codes and encryption algorithms. Variations of each need to be experimented in order to achieve desirable performance levels for a specific PLC channel noise profile.

Amongst the primal research areas pertaining to power line communication development, noise analysis has been figured as an expanding field of study, as it aims to contribute to the improvement of data transmission quality. Analysis of noise present in power line necessitates the designing of a suitable coupling circuit, which firstly filters out the harmful 230 VAC component from the channel and simultaneously allows higher frequency signals to pass through, to be then recorded. Such a methodology is laid out by Gassara et al. in [7]. A Butterworth band-pass filter (1 MHz – 30 MHz) is designed and implemented in [8] for broadband power line communication. The coupling circuit also serves to test the input impedance, attenuation characteristics and noise characteristics of the power line channel. Alternatively, M. P. Sibanda et al. describe a transformerless coupling circuitry for narrowband PLC which avoids unnecessary attenuation in [9].

From recorded noise profiles, an approximate channel model may be devised, whereby each noise type is subjected to varying modelling techniques [10]. A detailed description is provided in [11] for the proper modelling of impulsive noise. Noise analysis for PLC has rapidly transited from Narrowband PLC to Broadband PLC, owing to the fruitful development and implementation of the former. The high frequency noise spectrum in Broadband PLC has been the focus of adequate research and analysis for frequency ranges between 10 kHz and 100 MHz as laid out in [12] and [13]. Modelling techniques for Broadband PLC; however, the focus is mainly on background and appliance noise instead of impulsive noise [14].

Mitigation of noise existent in power line has also always

been of prime interest. Research has demonstrated that noise mitigation eventually helps to improve the BER performance of a communication system and account for efficient data transmission [15]. Findings from [3] and [16] suggested that the Least Mean Square (LMS) and the Recursive Least Squares (RLS) adaptive filters are proven to remarkably decrease bit error rate by mitigating impulsive noises [17, 18].

This study aims at improving the performance of a narrowband PLC channel through the use of noise mitigation techniques and error correcting codes. For this purpose, a previously modelled power line channel [19] for the electrical topology in the Microprocessors and Instrumentation Laboratory at the University of Mauritius was analysed and improved in terms of its error performance. The prominence of error correcting codes and noise mitigation procedures over the power line channel was to be investigated correspondingly.

The prime objectives are as follows: The first is to implement an adaptive filter based on the RLS algorithm over an existing PLC channel model and to assess its performance compared to the LMS algorithm in previous work. The second is to assess the performance of the narrowband PLC before and after adaptive filtering of the noise present therein. The third is to identify a proper modulation technique to suit the bandwidth requirements, channel capacity and to account for a low bit error rate over the narrowband PLC channel model. The fourth is to incorporate an appropriate error correction technique for the PLC channel model in order to decrease the risks of erroneous data reception. Finally, to assess the function of interleaving alongside an error correcting scheme for improved BER.

The paper structure is as follows: Section 2 highlights the fundamentals of adaptive filtering using the Recursive Least Squares (RLS) Algorithm. In Section 3, details on the methodological approach in the realisation of the project are provided. Section 4 provides a descriptive analysis of the improved error performance of the channel model with noise mitigation using the RLS algorithm, convolutional codes and interleaving. Finally, section 5 highlights the main findings of the study.

II. RECURSIVE LEAST SQUARES (RLS) ALGORITHM

A. Adaptive Filtering

One important procedure in the signal propagation process consists of filtering out the added noise signal from the original message signal. At this stage, filters are required. When it comes to digital signal processing, digital filters are preferred over analog filters since it becomes an easier task to reprogram them to attain the desired magnitude and phase responses. Furthermore, the adaptive characteristics of digital filters allow for the modification of the filter coefficients while they are in operation, hence offering the possibility of adaptive filtering [20]. An adaptive filter is a digital linear filter that has a transfer function $H(z)$ controlled by filter coefficients and a means to regulate those coefficients for every iteration according to an optimisation algorithm and input signal specifications so as to tally with the desired response. System Identification and Noise Cancellation [21] form a part of the fundamental applications of adaptive filters. Some of the adaptive noise cancellation algorithms include Recursive Least Squares (RLS), Least Mean Square (LMS), Normalised LMS and Variable Step-Size. Figure 1 demonstrates the working principle of an adaptive filter,

whereby the reference signal, $d(n)$ is subtracted from the filtered input signal, $y(n)$ to yield a close estimate of the required signal.

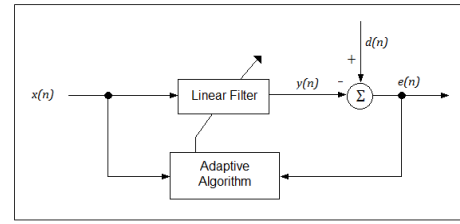


Figure 1: Typical block diagram of an Adaptive Filter

where, $x(n)$ is the input signal, $y(n)$ is the output signal of the linear filter, $d(n)$ is usually referred to as the desired response, $e(n)$ is the error signal denoting the difference between the desired response, $d(n)$ and the output signal $y(n)$.

B. Recursive Least Squares (RLS) Algorithm

The standard RLS algorithm performs the subsequent manoeuvres to update the coefficients of an adaptive filter for noise cancellation [22]:

1. The filter coefficients are initialised.
2. The output signal $y(n)$ of the adaptive filter is computed.
3. The error signal $e(n)$ is obtained using the equation:

$$e(n) = d(n) - y(n) \quad (1)$$

4. The filter coefficients are updated by using the following equation:

$$\bar{w}(n+1) = \bar{w}(n) + e(n) \cdot \hat{K}(n) \quad (2)$$

Where, $\bar{w}(n)$ is the filter coefficients vector and $\hat{K}(n)$ the gain factor. $\hat{K}(n)$ may be further described by the equation:

$$\hat{K}(n) = \frac{P(n) \cdot \bar{u}(n)}{\lambda + \bar{u}^T(n) \cdot P(n) \cdot \bar{u}(n)} \quad (3)$$

Where, $P(n)$ is the inverse correlation matrix of the input waveform and λ is the forgetting factor. $P(n)$ has an initial value $P(0)$:

$$P(0) = \begin{bmatrix} \delta^{-1} & 0 & 0 & \cdots & 0 \\ 0 & 0 & \delta^{-1} & \cdots & 0 \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \cdots & \delta^{-1} \end{bmatrix} \quad (4)$$

where, δ is the symbol for the regularisation factor.

To update the inverse correlation matrix, the RLS algorithm uses the formula:

$$P(n+1) = \lambda^{-1} P(n) - \lambda^{-1} \hat{K}(n) \cdot \bar{u}^T(n) \cdot P(n) \quad (5)$$

The flowchart of the standard RLS algorithm is given in [22].

III. METHODOLOGY

A. Outline of Functional Design

From the available data in [19, 23] and analysis therein, a set of procedures was devised to improve the error

performance of the modelled power line channel. These procedures include:

- i. Implementing an adaptive filter based on the RLS Algorithm in Simulink to demonstrate the mitigation of Gaussian Noise, Periodic Impulsive Noise and Aperiodic Impulsive Noise over the modelled narrowband power line channel.
- ii. Comparing the performance of the RLS algorithm against that of the LMS algorithm in adaptive filtering for the same channel conditions.
- iii. Comparing the error performances of BPSK and BFSK (two common modulation schemes for PLC applications) for the channel model in a generic digital communication system in Simulink.
- iv. Investigating the effect of higher FSK modulation orders on the BER measurements.
- v. Adding the convolutional codes for the correction of random bit errors during the transmission of data signals over the generic communication system designed in Simulink.
- vi. Adding the interleaving to condense the negative effect of burst errors in the power line channel, and hence improving the error performance of the communication system.

B. Adaptive Filtering Model in MATLAB® Simulink

The concept of an Adaptive Noise Canceller (ANC) is of a common practice in communication systems for the filtering of noise from message signals. For the purpose of this study, adaptive noise cancellation is extrapolated to PLC for the mitigation of Gaussian noise and Impulsive noises. In block diagram form, the design of an ANC for power line noise mitigation is illustrated in Figure 2. The procedure consists of feeding an adaptive filter based on the RLS algorithm with a reference input, which in this case would consist of Gaussian Noise, Periodic Impulsive Noise and Aperiodic impulsive noise. The filtered output of the adaptive filter is to be then subtracted from the input signal to finally obtain a close estimate of the desired signal, conditional of the effectiveness of the RLS algorithm.

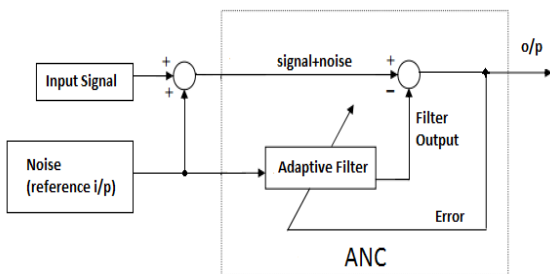


Figure 2: Ideology of noise mitigation with an ANC

The development of a model in Simulink proves to be a conceivable platform for the implementation of noise filtering based on an adaptive algorithm as described above. The setup is as shown in Figure 3.

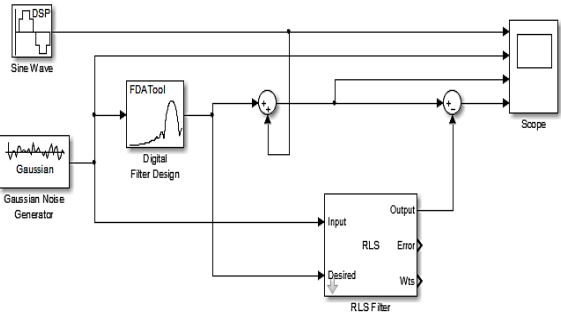


Figure 3: ANC model using an RLS filter

MATLAB® Simulink 8.1 (version R2013a) enables for the development of complex simulation and model based designs, with a graphical programming environment and powerful computational resources.

- **Sine Wave Generator:** Outputs an 80 kHz sine wave with sampling rate of 200 kHz.
- **Gaussian Noise Generator:** Generates AWGN sampled at a rate of 200 kHz. This block is replaced by the appropriate noise models for the mitigation of periodic and aperiodic impulsive noises.
- **Digital Filter Design:** Implements an FIR (order 40) bandpass filter of passband 75 kHz to 85 kHz for the initial filtering of unwanted signals prior to RLS filtering, hence setting more favourable initial conditions for the adaptive algorithm.
- **RLS Filter:** Performs adaptive filtering of the message signal based on the RLS algorithm.

Additional parameter configurations for the produced model are included in Table 1.

Table 1
Simulation parameters for Adaptive Filtering

Software	MATLAB® R2013a / Simulink 8.1
Signal Source	80 kHz Sine Wave Phase Offset: 0 rad. Output Complexity: Real
Noise Source (≤ 100 kHz)	Gaussian Periodic Impulsive Aperiodic Impulsive
Timing	Sample Time: 500 ns Samples per frame: 1
Linear Filtering	Filter Type: Direct-Form FIR Window: Bartlett-Hanning Order: 40 Response Type: Bandpass Attenuation at cut-off frequencies: 6 dB
Adaptive Filtering	Algorithm: RLS, Normalised LMS Filter Length: 32 Forgetting Factor: 1 Initial value of filter coefficients: 0 Initial Input Variance Estimate: 0.1
Transmitted signal power (1Ω ref.)	1 W

C. Generic Digital Communication System based on BPSK and BFSK in MATLAB® Simulink

Data bits are transmitted over the modelled channel with BPSK and BFSK modulation schemes. Convolutional Coding and Convolutional Interleaving are also incorporated in the system to improve the error performance before and after adaptive filtering based on the RLS algorithm. The major building blocks of the generic communication system as illustrated in Figure 4, comprise a message source in the

form of binary data bits, a convolutional encoder/decoder and a convolutional interleaver/deinterleaver. The interleaved bits are to be digitally modulated into an analog signal for transmission over the AWGN channel consisting of a superposition of Gaussian noise, Background noise and Impulsive noises. At the receiver, a reverse process ensues for the transmitted data bits to be demodulated, decoded and de-interleaved to be then detected at the sink. Figure 5 illustrates the complete model of the digital communication system set up in Simulink.

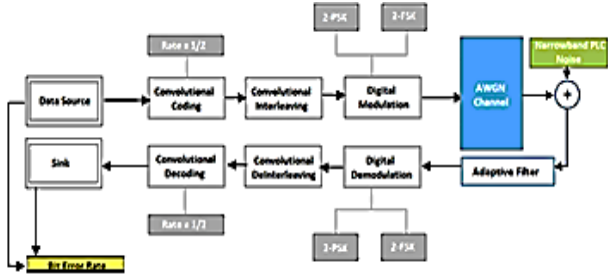


Figure 4: Block diagram of generic digital communication system

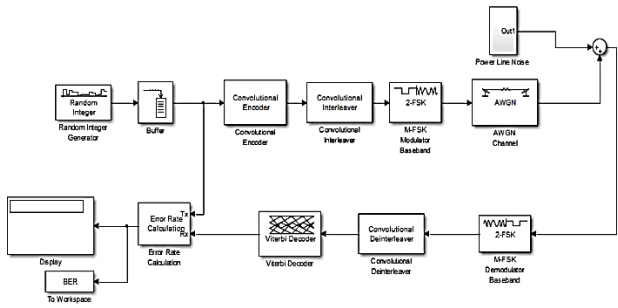


Figure 5: SIMULINK® Model

- **Random Integer Generator:** Generates data bits in the form of uniformly distributed integers of value 0 and 1.
- **Convolutional Encoder:** Convolutionally encodes the data bits at a rate of $1/2$.
- **Convolutional Interleaver:** Interleaves the encoded bits to reduce burst errors.
- **Baseband Modulator:** Performs BPSK or FSK modulation on the encoded data bits, depending on the chosen modulator block.
- **AWGN Channel:** Allows for the variation of the signal-to-noise ratio by specifying a value for E_b/N_0 .
- **Noise Block:** It contains the modelled power line noises, which are added to the AWGN channel. Both the AWGN block and the noise block serve as the channel of the communication system.
- **Demodulator Block:** Demodulates the recovered message signals from the channel.
- **Convolutional DeInterleaver:** Deinterleaves the recovered data to be fed to the Viterbi Decoder.
- **Viterbi Decoder:** Performs convolutional decoding using a hard decision and traceback depth of 48.
- **Error Rate Calculation:** Computes the BER to be able to plot BER v/s E_b/N_0 graphs
- **Adaptive Filtering (embedded in the Power Line Noise block) – Comparative Analysis of the RLS and LMS Algorithms for Power Line Noise Mitigation**

Adaptive filtering of power line noises based on the RLS algorithm is performed and compared to the results of the LMS algorithm.

From the comparison of the two sets of simulated data, the better performing adaptive filter between the two is able to be determined.

IV. RESULTS

A. Noise Mitigation

1) Mitigation of Gaussian Noise

Gaussian noise mitigation is performed with the RLS and the LMS algorithms and the outcomes of both are summarised in Figure 6 and 7 respectively.

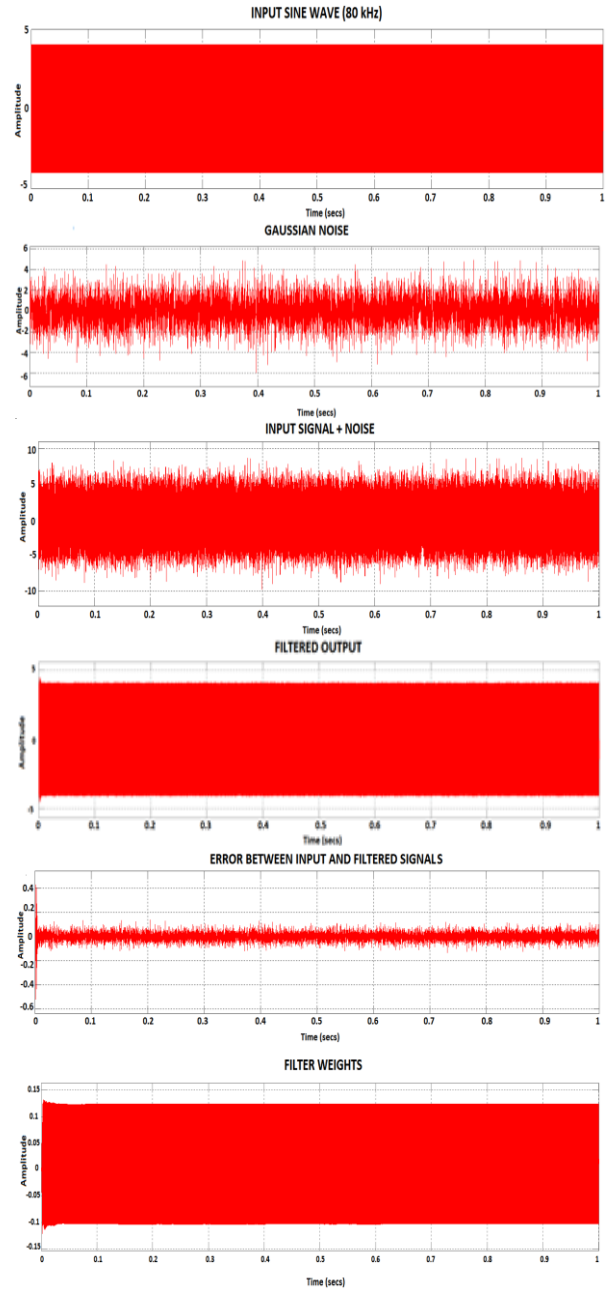


Figure 6: Mitigation of Gaussian Noise with the RLS algorithm

From Figure 6, it may be observed that the filtered output of the RLS model barely contains traces of Gaussian Noise, with an error of magnitude approximately 0.1 between the input sine wave and the output of the adaptive filter.

Similarly, the LMS algorithm also filters out the Gaussian Noise efficiently, accounting for an error of only 0.08 between the input and output signals. While the LMS algorithm is as powerful as its RLS equivalent, it may be

argued that the latter performs its operation faster than the former, as explained below. From Figure 7, it may be observed that the filtered output of the LMS filter settles just before the $t = 0.1s$ mark, while the output of RLS filter settles nearly instantaneously after being triggered.

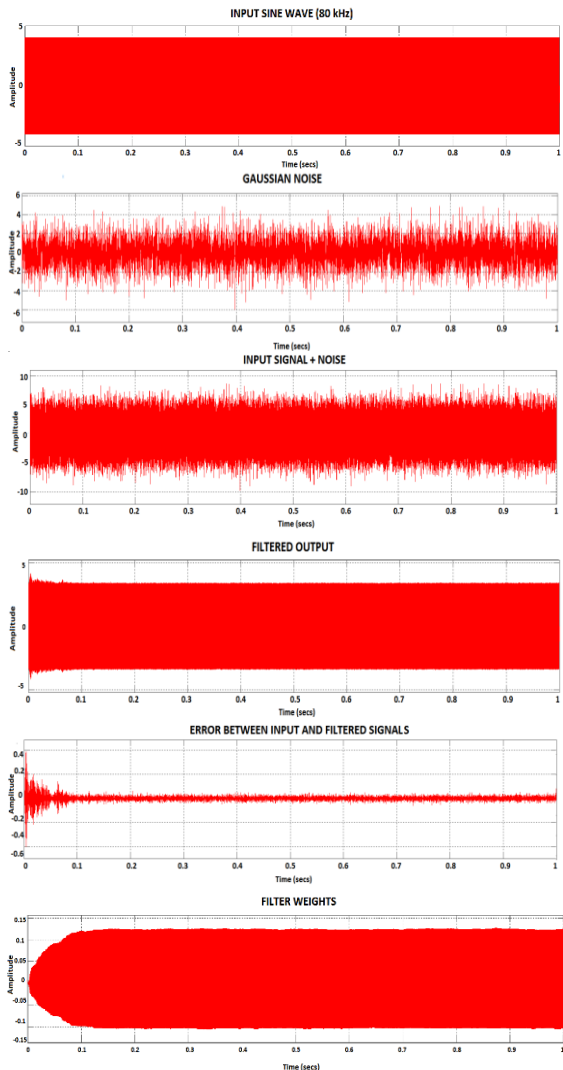


Figure 7: Mitigation of Gaussian Noise with the LMS algorithm

2) Mitigation of Periodic Impulsive Noise

Next, ANC is conducted on a highly impulsive noise profile as seen in Figure 8. The modelled noise profile simulates appalling channel conditions to test the RLS and LMS algorithms.

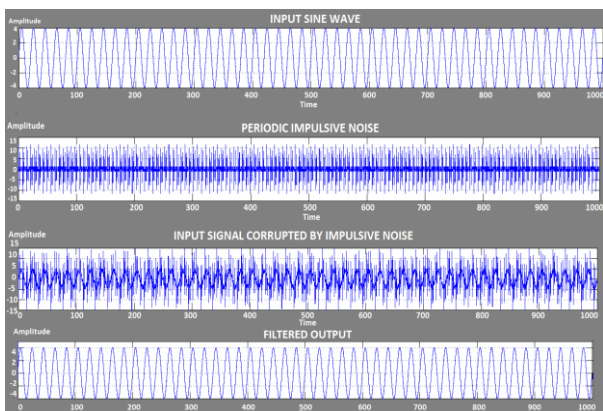


Figure 8: Mitigation of periodic impulsive noise with the RLS algorithm

From Figure 8, the simulation results demonstrate the high degree of effectiveness, even when it is used in a deplorable channel environment. Moreover, the RLS filter updates its filter coefficients rapidly to achieve a stable output. Again, the LMS algorithm proves to be as efficient as the RLS algorithm for the same channel conditions, but updates its coefficients gradually ($t = 0$ to $t = 80s$) until the point where all of the periodic impulsive noise has been mitigated. The simulation results for the LMS algorithm are illustrated in Figure 9.

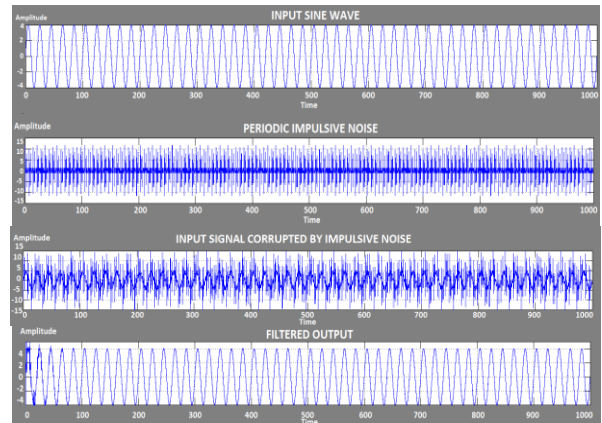


Figure 9: Mitigation of periodic impulsive noise with the LMS algorithm

3) Mitigation of Aperiodic Impulsive Noise

From Figures 10 and 11, it is observed that the mitigation of aperiodic impulsive noise using the RLS and LMS algorithms bear similar results to the mitigation of periodic impulsive noise, with the LMS filter being slower to converge than the RLS filter.

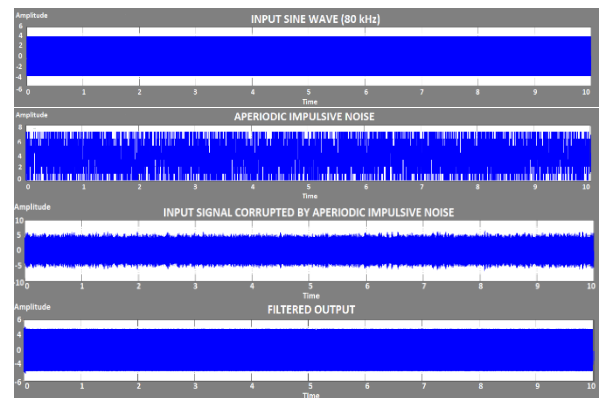


Figure 10: Mitigation of aperiodic impulsive noise with the RLS algorithm

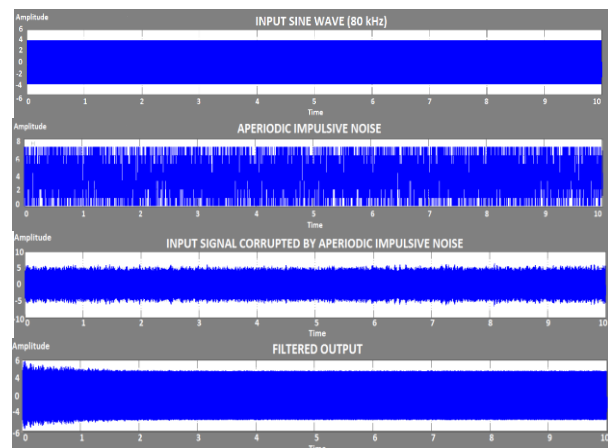


Figure 11: Mitigation of aperiodic impulsive noise with the LMS algorithm

To summarise the findings of this section, it may be stated that adaptive noise cancellation may be effectively employed for the mitigation of the noise present in a power line channel, for precisely Gaussian Noise, Periodic Impulsive Noise and Aperiodic Impulsive Noise. The RLS and LMS algorithms both tend to mitigate the specified noises by a substantial amount to improve channel conditions. However, it should be noted that the RLS filter is faster than the LMS filter in delivering a stable, filtered output. The simulation results do endorse of the properties of the RLS algorithm of having a faster convergence rate and robustness, rendering it more suitable for applications involving a dynamic environment.

B. Performance Evaluation of the Channel in a Digital Communication System

By combining an AWGN channel and the power line noises, the error performance of the overall channel in a model of a digital transmission system using BPSK and BFSK is analysed and discussed.

1) Error Performance of Channel without Adaptive Filtering

The error performance of BPSK modulation is firstly tested over the channel before adaptive filtering. The simulation results, as shown in Figure 12 indicate high error rates prior to the use of an ANC.

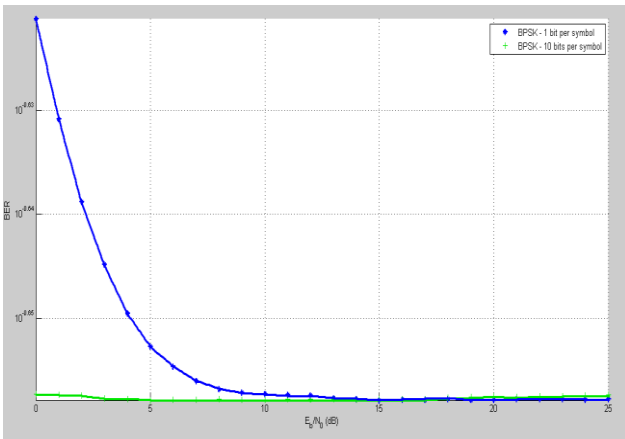


Figure 12: BPSK, before RLS filtering

A BER of 0.2392 is obtained for an SNR value of 0 dB when using a 1 bit per symbol. The BER gradually drops with an increase on SNR up to the 14 dB point, the BER curve settles at a value of 0.2198, signifying maximum error performance. Moreover, it has also been demonstrated that by increasing the number of bits to represent one symbol, the BER decreases for low SNR values. When using 10 bits to represent one symbol, the BER remains fairly constant at 0.2198.

For the case of BFSK modulation, as shown in Figure 13, it may be observed that at 1 bit per symbol, the BER is of 0.3879 for SNR 0 dB (more than for BPSK), but the error performance gradually improves for higher SNR values. At an SNR of 25 dB, a BER of 0.0834 is recorded (less than for BPSK) when using 1 bit per symbol, and a BER of 0.0738 is achieved for the same SNR when using 10 bits per symbol.

Increasing the number of bits per symbol enhances the error performance of the system for low SNR values as shown in Figure 14. Prior to noise mitigation, BFSK appears to be a more favourable modulation scheme than BPSK as it results

in a lower bit error rate.

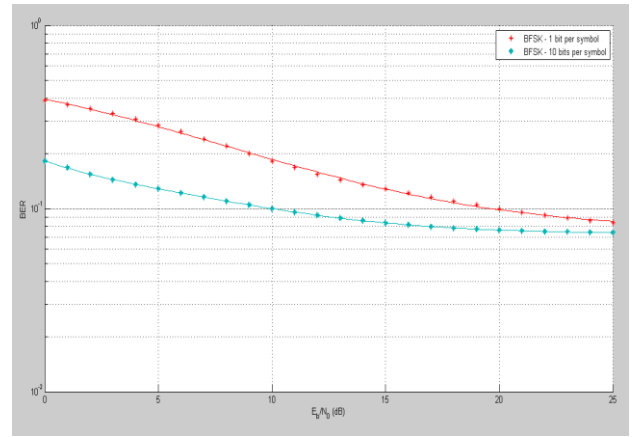


Figure 13: BFSK, before RLS filtering

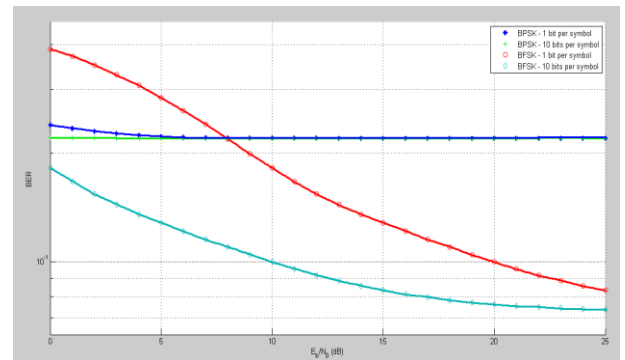


Figure 14: Comparison of error performances between BPSK and BFSK (before RLS filtering)

2) Error Performance of Channel with Adaptive Filtering

As shown in Figure 15 and 16, the BER plots before and after adaptive filtering show that the application of adaptive filtering for power line noise mitigation enables the complete reduction in transmission errors even for SNR values below 20 dB. With 1 bit/symbol, the BER drops from 0.2392 to 0.0821 for BPSK and from 0.3891 to 0.3496 for an SNR of 0 dB for BFSK. With 10 bits/symbol, the BER drops from 0.2201 to 4.1×10^{-5} for BPSK and from 0.1817 to 0.0347 for BFSK at SNR 0 dB.

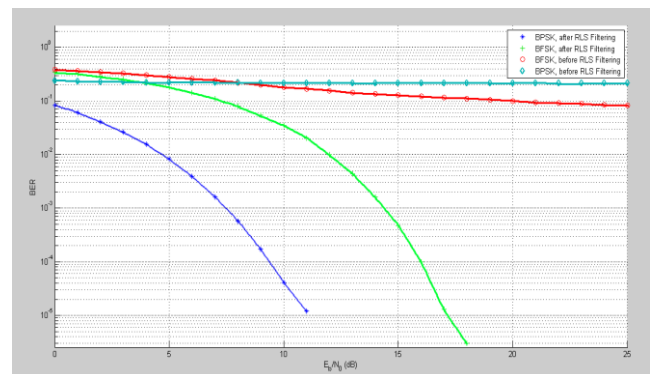


Figure 15: Comparison of error performances between BPSK and BFSK (after RLS filtering) with 1 bit/symbol

The truncated curves in Figure 15 and Figure 16 imply a BER of 0, which is the equivalent of error-free communication. The simulated graphs suggest that error-free transmission is realisable over the narrowband power line channel for SNR as low as 1 dB. After ANC, it is observed that BPSK outperforms BFSK considerably. With 1 bit per symbol, BPSK reaches a BER of 0 for an SNR of 12 dB, while for BFSK, a BER of 0 is recorded at an SNR value of 19. BPSK still remains the better performing scheme for higher number of bits per symbol.

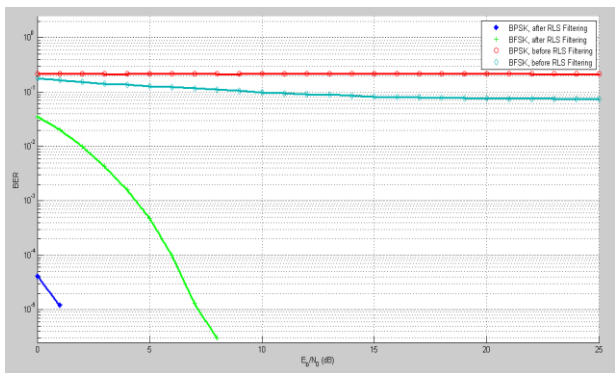


Figure 16: Comparison of error performances between BPSK and BFSK (after RLS filtering) with 10 bits/symbol

It can be deduced from Figure 17 that by increasing the order of a modulation scheme, degradation in error performance arises, suggesting that an increment in the data rate contributes to the likelihood of more errors occurring.

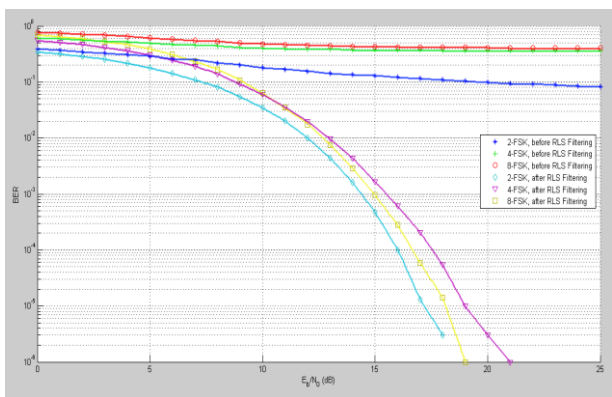


Figure 17: Increasing modulation order of FSK modulation

For SNR values below 10 dB at 1 bit/symbol, 8-FSK modulation produces the most errors before and even after adaptive filtering.

The same procedure as in the previous section is followed to evaluate the performance of the channel after adaptive filtering with the RLS algorithm. Table 2 and 3 below provide information on the simulation parameters for 1bit/symbol and 10 bits/symbols respectively.

It may be concluded that adaptive filtering actually does improve the error performance of a noisy narrowband PLC channel even in the absence of error correcting codes.

3) Error Performance of RLS algorithm compared to the LMS algorithm

Adaptive filtering has been used to mitigate Gaussian and Impulsive Noises in the channel model. Subsequently, the performance of the channel depends only on narrowband

noise [23] and since both the RLS and LMS algorithms effectively mitigate the stated noises, the two algorithms are expected to result in identical error profiles, as seen in Figure 18. Simulations have been performed for 2-FSK modulation at 1 bit/symbol. The simulation parameters are given in Table 4.

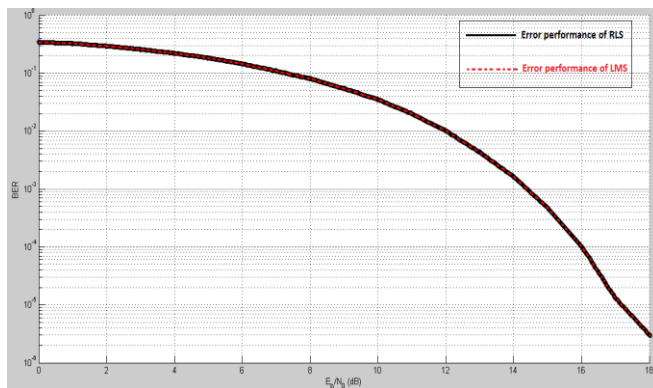


Figure 18: RLS algorithm v/s LMS algorithm

Table 2 Simulation Parameters

Modulation Scheme	BPSK
	BFSK Frequency Separation: 5 kHz Phase Continuity: Continuous Samples per symbol: 17
Data Rate	1 kbps
Bits/symbol	1
Timing	Sampling Rate: 10 kS/s Symbol Period: 0.1 ms
Transmitted signal power (1Ω ref.)	1 W
Buffer Size	
Adaptive Filtering	Output per channel: 1 RLS algorithm

Table 3 Simulation Parameters

Modulation Scheme	BPSK
	BFSK Frequency Separation: 5 kHz Phase Continuity: Continuous Samples per symbol: 17
Data Rate	1 kbps
Bits/symbol	10
Timing	Sampling Rate: 10 kS/s Symbol Period: 0.1 ms
Transmitted signal power (1Ω ref.)	1 W
Buffer Size	
Adaptive Filtering	Output per channel: 1 RLS algorithm

Table 4 Simulation parameters for the comparison of RLS and LMS algorithms

Modulation Scheme	BFSK Frequency Separation: 5 kHz Phase Continuity: Continuous Samples per symbol: 17
Data Rate	1 kbps
Bits/symbol	1
Timing	Sampling Rate: 10 kS/s Symbol Period: 0.1 ms
Transmitted signal power (1Ω ref.)	1 W

Buffer Size Adaptive Filtering	Output per channel: 1 RLS algorithm LMS algorithm
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C. Performance Evaluation of Convolutional Codes and Convolutional Interleaving

For improved BER without using appropriate adaptive filtering, error correction schemes can be employed. Simulations have been performed for BPSK and BFSK at 1 bit/symbol, with simulation parameters as indicated in Table 5 with the use of convolutional coding and convolutional interleaving before and after noise mitigation.

Table 5
Simulation Parameters

Modulation Scheme	BPSK BFSK	Frequency Separation: 5 kHz Phase Continuity: Continuous Samples per symbol: 17
Data Rate	1 kbps	
Bits/symbol	1	
Timing	Sampling Rate: 10 ks/s Symbol Period: 0.1 ms	
Transmitted signal power (1 Ω ref.)	1 W	
Buffer Size	Output per channel: 1	
Adaptive Filtering	(None)	
Error Correcting Codes	Convolutional Codes (2, 1, 3)	k = 1 n = 2 m = 3 Rate: 1/2
Interleaving	Convolutional Interleaving	

1) Error Performance of Channel without Adaptive Filtering (With Convolutional Codes and Interleaving)

As shown in Figure 19 and 20, the performance of BPSK is enhanced, leading to less error as opposed to BFSK. The addition of convolutional coding and convolutional interleaving decreases the BER from 0.0834 to 0.0623 for SNR 25 dB for BFSK. The BER for BPSK decreases from 0.2198 to 0.0549 for SNR 25 dB. It is again observed that without adaptive filtering of power line noise, a BER of 0 is not reached for SNR between 0 dB and 25 dB. Instead, the BER plots tend to settle to some constant value around the 15 dB mark.

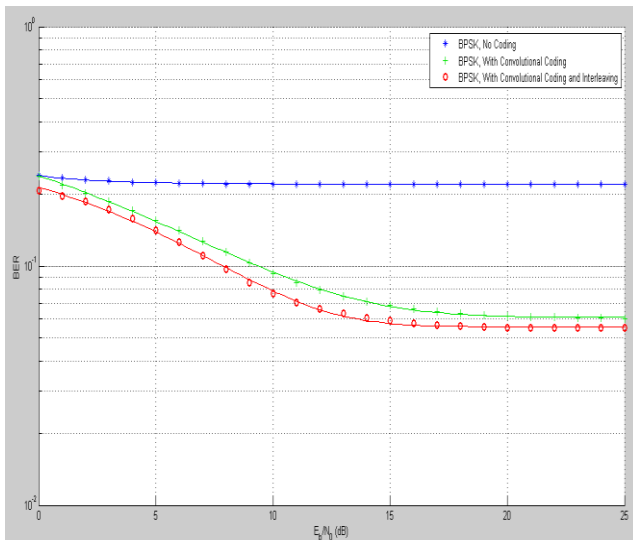


Figure 19: BPSK, before noise mitigation

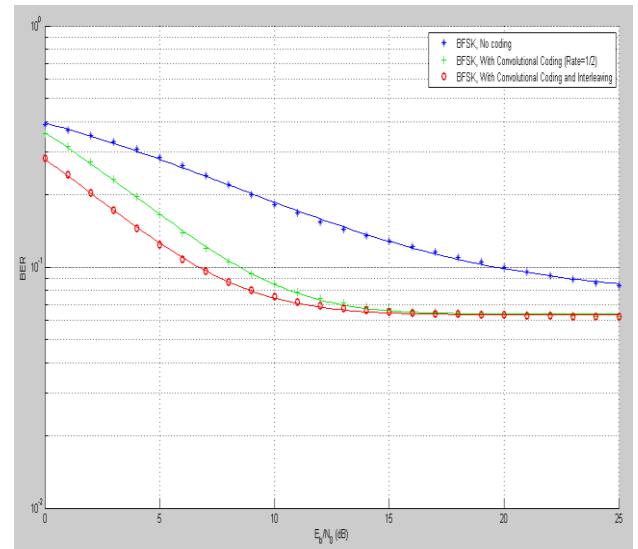


Figure 20: BFSK, before noise mitigation

2) Error Performance of Channel after Adaptive Filtering (With Convolutional Codes and Interleaving)

As it is expected, a combination of adaptive filtering and convolutional coding contributes in the minimisation of transmission data error over a digital communication system. For BPSK modulation, the BER plot is truncated at 11 dB, implying a BER of 0. With the insertion of convolutional codes of rate half, a BER of 0 is achieved for SNR 5 dB. The error performance is then further improved by applying convolutional interleaving, as seen in Figure 21. When relating the error performance of adaptive filtering to that of convolutional coding, the simulation results have shown that adaptive filtering becomes mandatory before introducing the error correction scheme. Such a statement is based around the fact that convolutional coding alone does not contribute in making the power line channel error free for low SNR values, irrespective of the use of BPSK or BFSK modulation schemes. A combination of adaptive filtering, channel coding and interleaving in the design of a PLC transceiver contributes to the minimisation of transmission errors to a notable degree – for a BER of 10⁻⁵ a coding gain of at least 8 dB may be attained for either BPSK or BFSK modulation. The simulation parameters are given in Table 6.

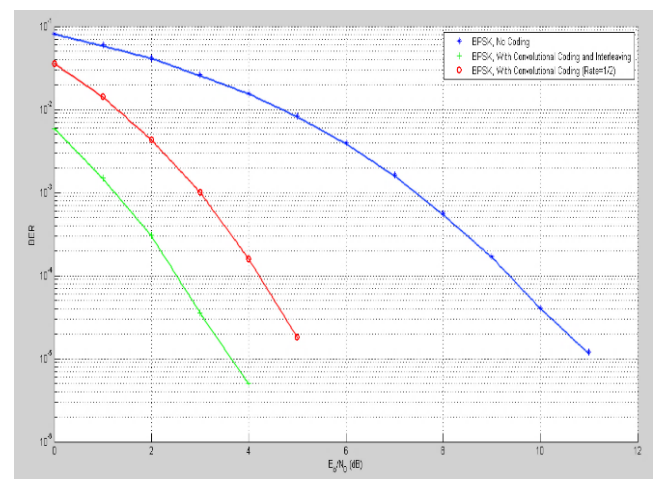


Figure 21: BPSK modulation

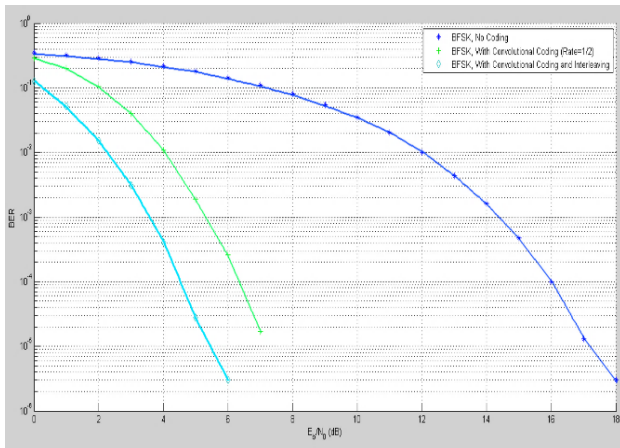


Figure 22: BFSK modulation

Table 6
Simulation Parameters

Modulation Scheme	BPSK	
	BFSK	Frequency Separation: 5 kHz Phase Continuity: Continuous Samples per symbol: 17
Data Rate	1 kbps	
Bits/symbol	1	
Timing	Sampling Rate: 10 kS/s Symbol Period: 0.1 ms	
Transmitted signal power (1Ω ref.)	1 W	
Buffer Size	Output per channel: 1	
Adaptive Filtering	RLS algorithm	
Error Correcting Codes	Convolutional Codes (2, 1, 3)	k = 1 n = 2 m=3 Rate: 1/2
Interleaving	Convolutional Interleaving	

V. CONCLUSION

Initially, RLS and LMS algorithms have been compared in terms of their error performances in a power line channel. It has been observed that while both algorithms are equally efficient in the mitigation of Gaussian and Impulsive noises in a narrowband power line channel, the RLS algorithm proves to be more effective than the LMS algorithm. The RLS filtering is found to converge fourteen times quicker than the LMS algorithm. Nevertheless, the RLS algorithm encompasses more complex mathematical operations and more computational resources than its LMS counterpart as it involves matrix inversion. After adaptive filtering, the remainder channel impairments consist of only narrowband noise in the PLC channel model.

Adaptive Noise Cancellation has also been proven as an efficient method of improving the BER performance of the PLC channel model. With the use of ANC, a drop of BER from 0.2198 to 0 at SNR 12 dB for BPSK is recorded and from 0.3879 to 0 for SNR 19 dB for BFSK. Hence, adaptive filtering helps to achieve error-free transmission for narrowband PLC. Without ANC, BFSK modulation results in less bit error compared to BPSK. At an SNR of 25 dB, the BER curves for BPSK and BFSK tend to settle at constant

values of BER of 0.2198 and 0.0834 respectively. After noise mitigation, BPSK proves to be a more reliable modulation scheme as opposed to BFSK even without the use of error correction – BPSK reached a BER of 0 for lower SNR values than BFSK, implying minimal to no error for bad channel conditions.

Moreover, it has been demonstrated that a growth in data rate leads to high bit error probability, as expected. By increasing the modulation order of the FSK scheme, a rise in the BER is recorded. It is concluded that 2-FSK is less prone to errors than 8-FSK for the PLC channel model.

Combined adaptive filtering, channel coding and interleaving in the design of a PLC transceiver contributes to the minimisation of transmission errors to a notable degree – for a BER of 10^{-5} a coding gain of at least 8 dB may be attained for either BPSK or BFSK modulation.

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