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Data-driven Adaptive Filtering for Impulsive Noise Mitigation in Power Line Communication System in Industrial Application

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Abstract **Original Research Article**

Data-driven adaptive filters, in which a deep neural network is incorporated as a core architectural component, are applied to noise mitigation in industrial power line communication. Noise is modeled using an alpha-stable distribution, which is well suited to asynchronous impulses in industrial power line communication. The results indicate that data-driven adaptive filters can be effectively used for noise mitigation in industrial settings, ensuring stability and outperforming traditional least mean square filters and purely data-driven filters.

Keywords: Power Line Communication, Adaptive filtering, Data-driven signal processing, Noise Mitigation, Asynchronous impulse, Industrial communication systems.

I. Introduction

Power Line Communication (PLC) is one of the wired communication solutions for a number of applications, including home automation, smart grid, and vehicle communication (Casella et al., 2018). It is a well-established technology that enables data transmission through electrical lines and offers advantages that make it both a useful complement and a strong competitor to wireless solutions. PLC systems can exploit existing electric grid infrastructure to reduce deployment costs, provide a low-cost alternative to complement existing technologies in the pursuit of ubiquitous coverage, establish high-data-rate communication through obstacles that typically degrade wireless communications, and use technologies currently applied in other sectors.

Although PLC offers advantages over other communication schemes, it also has disadvantages resulting from several factors, such as the time-varying characteristics of power lines, which were originally designed to deliver electric power. One disadvantage of PLC systems is severe performance degradation caused by noise interference (Avril et al., 2007).

Several types of noise exist in PLC systems. Common noise types include colored background noise, narrowband noise, and impulsive noise (Lampe et al., 2016). Among these noise types, impulsive noise has the greatest negative impact on system quality. It severely degrades system performance; however, it is difficult to mitigate effectively and instantaneously because of its distinct properties, which other noise types do not exhibit.

Extensive research has been conducted to mitigate such severe impulsive noise. These approaches can be divided into adaptive filtering solutions and adaptive coding solutions (Bai et al., 2021). Adaptive filtering methods are implemented at the receiver and provide effective noise mitigation because their adaptation mechanisms actively adapt to time-varying systems. Adaptive coding methods are implemented at the transmitter.

In most cases, adaptive filtering solutions for impulsive noise mitigation rely solely on an explicit mathematical model of a certain type of noise. One of the most widely used algorithms is the Least Mean Square (LMS) algorithm (Cedarleaf et al., 2010). The LMS algorithm is widely used in several applications because of its effectiveness and low computational complexity (Xie, 2024) (Chiheb et al., 2024). However, it does not perform well for impulsive noise mitigation in the most severe situations (Ri et al., 2025). Instead of LMS, alternative solutions such as Normalized LMS and Recursive Least Square can be used for noise mitigation. These model-based algorithms perform well in impulsive noise mitigation, but they do not achieve a satisfactory level of performance.

In recent years, model-less or data-driven solutions for noise mitigation have gained popularity because of the availability of large datasets, a vast range of implementation tools, and their remarkable performance in areas that cannot be solved, or can only possibly be solved, by humans.

Data-driven adaptive filters using machine learning techniques may perform better in mitigating noise, including impulsive noise (Lin, 2025). However, they have high computational complexity, which renders them incapable of performing mitigation operations in real or near-real time.

A novel data-driven adaptive filtering architecture for noise mitigation was proposed in (Wang et al., 2025). In this research, a data-driven adaptive filter was proposed in which a deep neural network is embedded into the architecture of the adaptive filter. Its performance was validated under several non-Gaussian noise environments, including impulsive noise, and it demonstrated better mitigation capability than traditional model-based approaches. It opened a new avenue for noise mitigation because of its generalizability and lower computational complexity compared with other methods.

PLC technology is becoming increasingly popular and is being applied to a wider range of fields (Mawali, 2024). Most research has focused on consumer applications to date. Because PLC benefits from the ubiquitous electric power infrastructure, it also has the potential to be applied in industrial scenarios.

In industrial applications of power line communication, asynchronous impulsive noise mainly degrades the performance of communication systems, although other types of noise, including periodic impulsive noise and background noise, also exist (Tran et al., 2013).

Asynchronous impulsive noise in industrial power line communication has distinct properties, including non-Gaussian, explosive, and heavy-tailed characteristics.

Prior work modeled asynchronous impulsive noise as Middle Class A (Nassar et al., 2011). However, this model is not suitable for modeling heavy-tailed impulsive noise in industrial applications.

Based on the literature review, no solutions in which a deep neural network is embedded into the architecture have been proposed for the mitigation of impulsive noise in industrial PLC. In addition, impulsive noise was modeled as a Middle Class-A Mixture Model, which is not suited to industrial PLC. In industrial applications, heavy-tailed impulsive noise in PLC is better characterized by an alpha-stable model (J.P., 2009).

Clipping is needed to suppress noise, guarantee the convergence of adaptive filters, and prevent excessive noise power from overwhelming the system in real-world situations.

In this paper, the following contributions are proposed:

1) Data-driven adaptive filters for mitigating impulsive noise modeled using an alpha-stable model in industrial PLC.

2) Clipping to suppress noise that exceeds the threshold specified by the operator.

3) Performance analysis of the proposed filter

through simulation.

This paper is organized as follows. Section 2 explains noise in industrial PLC in detail. A full explanation of data-driven adaptive filters is presented in Section 3. The system model is presented in Section 4, and the simulation results are presented and explained in Section 5. Section 6 concludes the paper.

II. Materials and Methods

A. Noise modeling in power line communication in industrial sector

Asynchronous impulsive noise is modeled with several empirical models. There are mainly two exact classifications of modeling: Middleton-class A and Alpha-stable distribution model.

Alpha-stable distribution model fits the heavy tailed data better than Middleton-class A. In industrial application, asynchronous impulsive noise has heavy-tailed characteristics (Tran et al., 2013). Therefore, an alpha-stable distribution model is used for noise modeling.

$$\phi(t) = e^{(j\omega t - \delta^{\alpha}|t|^{\alpha}[1+j\beta sgn(t)\omega(t,\alpha)])} \quad (1)$$

α is a characterization factor, also known as the characteristic exponent $(0 < \alpha < 2)$. When $\alpha = 1$, this is Gaussian distribution. δ is scale parameter, also known as coefficient of dispersion. $(\delta > 0)$ β is skew parameters used to determine the slope of the distribution. $(-1 \leq \beta \leq 1)$ μ is positional parameters.

B. Data-driven adaptive filter

The embedding architecture mentioned in (Wang et al., 2025) is considered the core model for designing the adaptive filter architecture. The training dataset comprises two datasets. The input dataset consists of data samples generated through simulations of model-based adaptive filters because the model approximately fits the samples. The output dataset consists of the corresponding derivatives of the probability density function of the input dataset, which are estimated using kernel density estimation with a Gaussian kernel.

A deep neural network is adopted to establish a nonlinear mapping from the input dataset to the output dataset. A multi-layer perceptron and a functional link neural network are used as candidates. The choice between these two deep neural network architectures depends on the specific circumstances in which the adaptive filters are used.

The core architecture is presented in Figure 1.

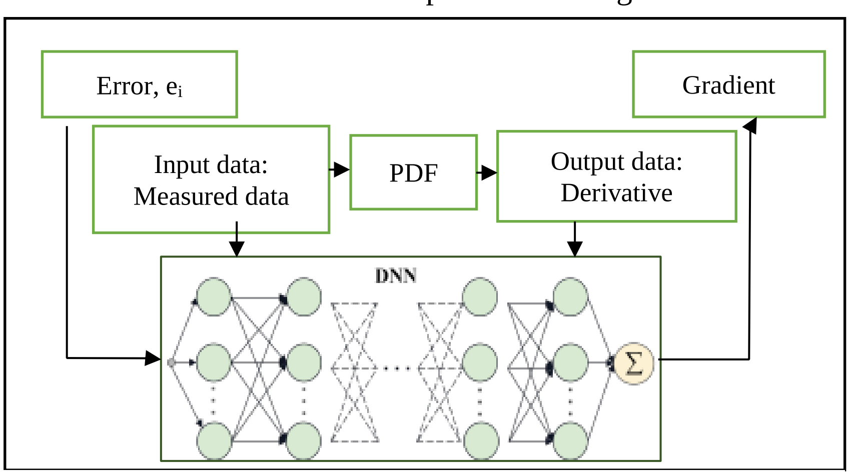

Fig 1. Core architecture of data-driven adaptive filter

C. Dataset

The output dataset can be obtained by utilizing the Kernel Density Estimation (KDE) method. KDE is one of the methods used to reconstruct the underlying power density function of the input data. The details of the KDE algorithm are presented in (Sugiyama, 2016).

D. System model

The main idea of all adaptive filters is to continually modify parameters according to the predetermined algorithm, using both input information and auxiliary information from the output of the entire system.

Adaptive filters use adaptive algorithms to minimize the values of the error signal. ("e(n)=d(n)-y(n)")

The cost function that is commonly used in filter design is the mean square error(MSE).

$$J = E[(d(n) - \hat{d}(n))^2\,] \qquad (2)$$

In Fig 2, d(n) is the desired signal and y(n) is the estimate of the desired signal output of the adaptive filter.

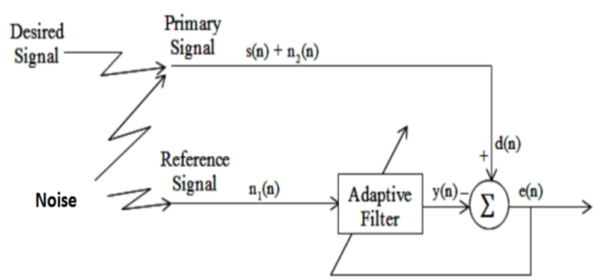

Fig 2. General architecture of adaptive filters

The objective of the adaptive filter is to make the estimate of the adaptive filter(y(n)) reach to the desired signal(d(n)) as closely as possible by adjusting filter coefficient adaptively.

For data-driven adaptive filters, the cost function is implicitly the maximum likelihood function.

$$J = max\{p(e_i)\,\} \qquad (3)$$

III. Results and Discussion

A. Deep Neural Network architecture configuration

For simplicity, a simple multiple-layer perceptron is selected for the simulation process. It consists of eight fully connected layers organized progressively in a hierarchical structure. Such a structure is suitable for modeling the complexity of any type of asynchronous noise.

B. Simulation of asynchronous impulsive noise in industrial sector

The simulation parameters for asynchronous impulsive noise are selected to be the same as those specified in (Wang et al., 2025).

The following figure shows the simulated noise profile.

In Figure 3, asynchronous impulsive noise modeled by an alpha-stable distribution contains burst impulses with magnitudes exceeding 700. These impulses are similar to excessive impulse noise, which constitutes the main component of the overall impulsive noise occurring in industrial power line communication. Burst impulses with magnitudes greater than the threshold will be clipped by the clipping mechanism.

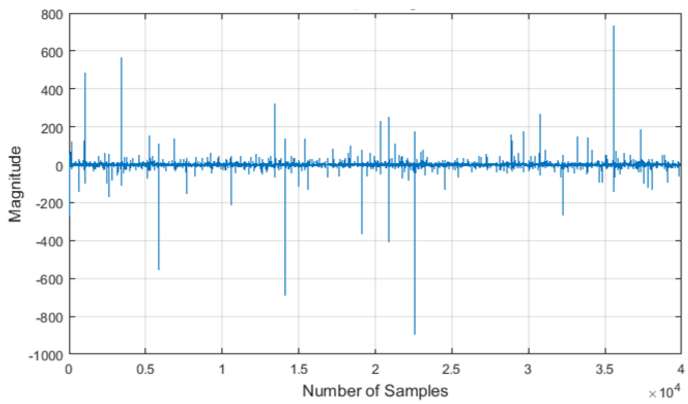

Fig 3. Simulation of asynchronous impulse

C. Derivative fitting results of asynchronous impulsive noise with deep neural network

The derivative fitting results using kernel density estimation, as explained in Section 3, are shown in Figure 4.

These results demonstrate excellent fitting accuracy for impulsive noise. Therefore, the output dataset for training neural networks can be computed effectively using kernel density estimation.

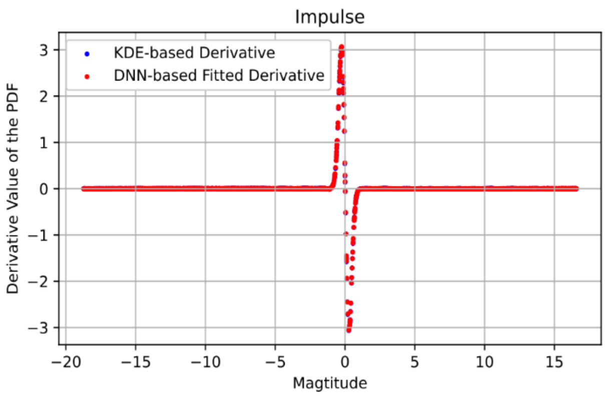

Fig 4. Derivative fitting results of impulsive noise with deep neural network

D. Performance of adaptive filters

The following figure 5 shows the performance of data-driven adaptive filters. As seen in figure 5, the first 6 graphs show the proposed data driven adaptive filter which have no clipping mechanism, the last 6 graphs show the proposed adaptive filter which have clipping mechanism. As the main parameter gamma varies in the range of [0-1], the proposed deep neural network- adaptive filter is displayed and compared with most common types of adaptive filter LMS and adaptive filter without having a clipping mechanism. As shown in figure, data-driven filter is guaranteed convergence in all cases. The data-driven filter shows the far lower steady-state error than the least mean square filter.

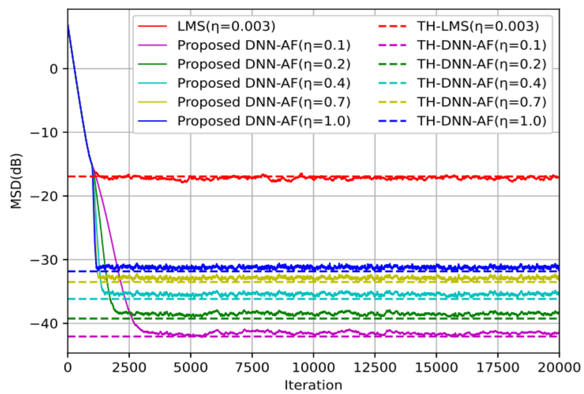

Fig 5. Asynchronous impulse noise modeled by alpha-stable distribution

IV. Recognition

Summary: In this paper, a data-driven adaptive filter is designed to enhance the communication reliability in industrial power line communication system. The study models asynchronous impulsive noise using an alpha-stable distribution that reflects the heavy-tailed characteristics of impulsive noise in the industrial sector. The proposed data-driven filtering solution demonstrates potential for future communication networks including smart-factory setting.

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