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APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN POWERLINE COMMUNICATIONS IN TERMS OF NOISE DETECTION AND REDUCTION: A REVIEW

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Abstract:	The technology which utilizes the power line as a medium for transferring information known as powerline communication (PLC) has been in existence for over a hundred years. It is beneficial because it avoids new installation since it uses the present installation for electrical power to transmit data. However, transmission of data signals through a power line channel usually experience some challenges which include impulsive noise, frequency selectivity, high channel attenuation, low line impedance etc. The impulsive noise exhibits a power spectral density within the range of 10-15 dB higher than the background noise, which could cause a severe problem in a communication system. For better outcome of the PLC system, these noises must be detected and suppressed. This paper reviews various techniques used in detecting and mitigating the impulsive noise in PLC and suggests the application of machine learning algorithms for the detection and removal of impulsive noise in power line communication systems.

Applications of Artificial Intelligence in Powerline Communications in Terms of Noise Detection and Reduction: A Review

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ABSTRACT

The technology which utilizes the power line as a medium for transferring information known as powerline communication (PLC) has been in existence for over a hundred years. It is beneficial because it avoids new installation since it uses the present installation for electrical power to transmit data. However, transmission of data signals through a power line channel usually experience some challenges which include impulsive noise, frequency selectivity, high channel attenuation, low line impedance etc. The impulsive noise exhibits a power spectral density within the range of 10-15 dB higher than the background noise, which could cause a severe problem in a communication system. For better outcome of the PLC system, these noises must be detected and suppressed. This paper reviews various techniques used in detecting and mitigating the impulsive noise in PLC and suggests the application of machine learning algorithms for the detection and removal of impulsive noise in power line communication systems.

KEYWORDS

Additive white Gaussian Noise (AWGN); Artificial Intelligence (AI); Impulsive Noise; Machine Learning (ML) Techniques; Orthogonal Frequency Division Multiplexing (OFDM); Power line communication (PLC).

1. Introduction

Power Line Communication (PLC) is a scheme that is used to transfer data (information) through some existing electrical cables. Its main advantage is the avoidance of the installation of new cables as PLC can be designed using the existing electrical cables to transfer data, but on a different frequency to that of electric power. The process of transferring data over electrical lines was first introduced for the exchange of telecommand and telemetry which involved very low data rate (Hashmat 2012), and presently used for broadband services all over the world. PLC has been in use for over a hundred years. In 1838, remote-metered electricity supply to examine the level of batteries voltages at sites was suggested. In 1897, the testing of electricity meter for a power line signaling was implemented. However, from 1900 to 1970, many developments for reading electricity supply remotely have been introduced following the advancement in electronics (Wang, Xu, and Khanna 2011; Tonello and Pittolo 2015). PLC can be classified into two: The broadband (BB) and narrowband (NB) PLC. Table 1 illustrates the main difference between a narrowband PLC and a broadband PLC system (Tonello and Pittolo 2015).

Table 1. Comparison of Narrowband with Broadband PLC

PLC segment	Frequency	Data rates	Distance covered
Narrowband	3-500KHz	100s of kb/s	Longer range (Several kilometers)
Narrowband	18-250MHz	100s of Mb/s	Shorter range

The technology of PLC operates by having modulated data injected onto a medium (electrical cables) by a sender and the data demodulated by a receiver at the receiving end. This is done without extra wiring. A comparison of modulation scheme that can be used in PLC in terms of efficiency and complexity (cost) is given in Table 2 below.

Table 2. Modulation Schemes comparison

Modulation Schemes	Efficiency of the Bandwidth	Complexity (Cost)
BPSK	Average	Low
SFSK	Low	Average
FSK	Average	Low
OFDM	High	High

From Table 2 above, OFDM can be accepted as the most preferred since it has a high bandwidth efficiency (Al-Mawali, Al-Qahtani, and Z. M. Hussain 2010). In the PLC system today, OFDM is the major modulation technology due to its sturdiness against frequency-selective fading, multipath and other forms of interference (Al-Mawali, Al-Qahtani, and Hussain 2010). The OFDM modulation scheme has major use in FPGA (field-programmable gate array) and ASIC (application-specific integrated circuit). The OFDM is a multicarrier communication technique that is modulated using inverse fast Fourier transform (IFFT) and demodulated using fast Fourier transform (FFT). However, OFDM has a longer duration which allows an impulsive noise to spread among the OFDM subcarriers when transmitted simultaneously (Ghosh 1996). This is an advantage of OFDM that can easily become a disadvantage when the energy present in the impulsive noise surpasses a specific limit. Therefore, the impulsive noise must be mitigated by any effective method.

In recent days, power line communication is widely applied in smart grid. An example is its use in automatic meter reading through which home appliances that consume high power such as washing machine, electric stove, electric oven, refrigerator, freezer, iron, air conditioner, water heater and dishwasher can communicate with the smart meter. The smart meter collates the information with the help of PLC on maximum pricing hours from the utility, and the appliance can then switch ON or OFF according to the price variations (Brown 1999). This is beneficial to the consumer who would now be able to save on the electricity bill, and the utility by being able to manage peak demands better (Brown 1999). PLC is also implemented in smart energy generation (mainly in micro inverters used in solar energy), traffic light control, vehicle to grid communications, security of buildings, building automations and for load control in many EU nations (Brown 1999).

However, since Power line communication transmits data over cables whose original purpose is to supply power to electrical appliances, it is susceptible to impulsive noise that is produced by these appliances and background noise. These noises interfere with the signal transmitted over the line. The signal is also affected by high attenuation and frequency selecting fading etc. The Power Spectral Density of impulsive noise is between 10-15dB above the background noise, hence, impulsive noise poses a severe challenge for the transmitted data. For good result of the PLC system, impulsive noise in the modulated signal must be detected and suppressed.

This paper will present the use of artificial intelligence (machine learning) for detecting and suppressing the noise.

1.1 Classification of Noise in Broadband Plc

- **Background Noise**: these noises vary slowly with time and comprises of:
  A. Narrowband noise
  B. Colored background noise
- **Impulsive Noise**: this kind of noise vary rapidly with time and are categorized as:
  A. Asynchronous impulsive-noise
  B. Periodic impulsive-noise synchronous to main frequency
  C. Periodic impulsive-noise asynchronous to main frequency (Zimmermann and Dosert 2002)

This classification is further depicted in Figure 1 below which also shows how the noise affects transmitted signal. Each class is briefly described after the diagram.

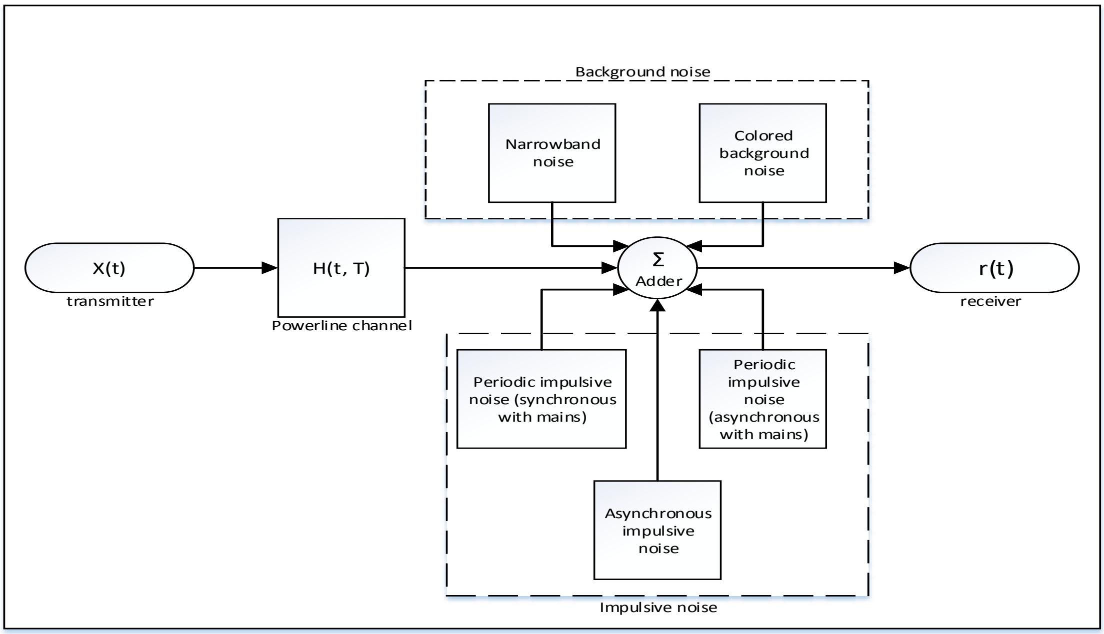

Figure 1. An Overview of Noise Affecting the Powerline Channel

- **Narrowband Noise:** its major constituent is amplitude modulated signals (sinusoidal). Over the frequency spectrum, the signals are fairly small while as for the amplitude, it fluctuates during daytime but higher at night-time, when the reflection-characteristics of the atmosphere is sturdier (Zimmermann and Dosert 2002). This kind of noise varies slowly with time.
- **Colored Background Noise:** this type of noise occurs with the addition of multiple sources of concentrated low power noises (Anju and Shyju 2015). With increasing frequencies, there is a decrease in its power density (Anju and Shyju 2015). The parameters of colored background noise fluctuate over time in terms of hours or minutes, in order words, it varies slowly with time.
- **Asynchronous Impulsive-Noise:** the switching transients in power network generate this kind of noise. It occurs between micro seconds to milliseconds. They are the major source of error in digital communication transmitted over powerline communication networks because

their power spectral density attains values over 50dB beyond the background noise (Zimmermann and Dosert 2002).

- **Periodic Impulsive-Noise that is Synchronous to Mains Frequency:** in this case, the swapping action of several electrical components such as the rectifier diodes generates this kind of noise. The noise occurs in short duration of micro seconds. It is often repeated at the rate of 50 to 200 KHz. With a drop in the frequency, the power spectral density decreases (Zimmermann and Dosert 2002).
- **Periodic Impulsive-Noise that is Asynchronous to Mains Frequency:** this form of noise occurs due to the switching of power supplies with a repetition rate between 50 and 250 KHz which results in the spectrum having discrete lines of frequency spacing based on its rate of repetition. Periodic impulsive noise that is asynchronous to the mains frequency occupies frequencies that is close to each other because of the higher repetition rate (Anju and Shyju 2015).

To improve the performance of the PLC system, the need for elimination of impulsive noises is deemed necessary. This paper suggests detecting and removing these noises using machine learning or artificial intelligence techniques. A brief knowledge of artificial knowledge is given next and then a review of previous related work is carried out in the later section.

1.2Artificial Intelligence

Artificial intelligence (AI) can be defined as the subdivision of computer science that focuses on creating computer programs and algorithms to solve problems that require extensive reasoning and knowledge in a close manner to the human approach (Witten and Frank 2005). In the early 1960s, the first conceptual design of AI was developed (Witten and Frank 2005). AI is subdivided into three branches based on its problem-solving approach (Ibrahim and Morcos 2002) but not limited to symbolic AI (Ibrahim and Morcos 2002), statistical AI and computational AI (also known as sub-symbolic AI) (Ibrahim and Morcos 2002; Farayola 2017)**.**

Machine learning (ML) can as well be defined as an aspect of artificial intelligence theory which evolved from the analysis of computational learning theory and pattern recognition (Witten and Frank 2005). Machine learning works by using input data to detect patterns, and modify program actions accordingly (Hasan 2013). In recent days, machine learning can be described as a vital division of information technology (IT). AI has shown accomplishment and powerful performance in monitoring, classification, prediction and optimization tasks (Samola and Vishwanathan 2008). Based on the learning techniques, machine learning techniques are classified into six learning techniques namely supervised learning, unsupervised learning, semi-supervised learning, transduction learning, and learning to learn technique (Stuart and Peter 2003).

A. Supervised Machine Learning Technique

Supervised machine learning technique is a learning technique that uses some distinguished datasets which consist of response values and input data to make predictions. Supervised learning machine builds a model from the given information, which predicts the response values when using a new dataset (Singh, Thakur, and Sharma 2016). Supervised learning is subdivided into two subcategories (Singh, Thakur, and Sharma 2016):

➢ **Supervised machine learning based on classification:** These techniques allow data to be separated into precise classes. Examples of supervised machine learning that uses classification techniques are the linear classifier such as Naïve Bayes classifier, support vector machine, k-means clustering, decision trees quadratic classifiers, discriminant analysis (Singh, Thakur, and Sharma 2016).

➢ **Supervised Machine Learning Based on Regression:** These are machine learning technique with unstable quantitative data. Common regression techniques include the linear and the non-linear regression, decision tree, ensembles and neural networks (Singh, Thakur, and Sharma 2016).

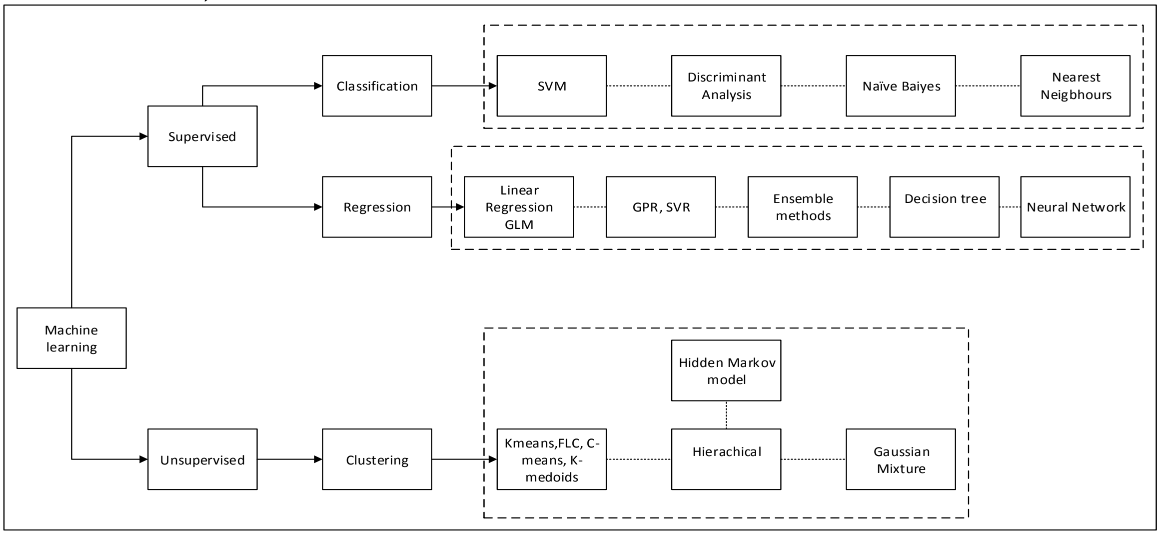

Figure 2. Machine Learning Algorithms

In supervised learning, training of the system model is done using samples, or test data sets. However, large training datasets often yield models with improved performance (Michie, Spiegelhalter, and Taylor 1994).

B. Unsupervised Machine Learning Technique

The technique can be used to predict new sets of inputs as the method only needs the input training samples. The major use of unsupervised learning is to find the hidden unknown structure and relationship between the training data which is known as clustering (Singh, Thakur, and Sharma 2016). A few examples of unsupervised machine learning techniques are Hebbian learning, expectation–maximization algorithm and blind signal separation (Michie, Spiegelhalter, and Taylor 1994).

1.2.1 Applications of Machine Learning

Machine learning is used in different field of study such as medicals, engineering, accounting, economics etc. (Dahhaghchi and Christie 1997). Other areas machine learning is constantly applied include oral language interpretation, genetics, weather forecast, medical diagnostics, stock market analysis, database marketing, spam filtering, bioinformatics, information retrieval, etc. (Kosko, 1992).

According to (Hasan and Shongwe 2016, 2017), some machine learning classifiers (Ensembles) algorithms used for detecting impulsive-noise include: Stacking, Bagging, Random forest, Boosting, K-Nearest Neighbour classifier, Naïve Bayes' classifier, Multilayer perceptron (MLP), and support vector machine (SVM).

A. Stacking: this ensemble technique is considered as one of the primitive machine learning methods (Hasan and Shongwe 2017). Stacking algorithm uses meta-classifier approach to combine numerous base classifiers that could belong to completely separate machine learning methods. Meta-classifier takes base classifiers as its input and output values (Wolpert 1992). This method has been used to achieve great performances, although it is an experimental method and does not give the assurance of perfection at all times (Wolpert 1992).

B. Bagging: bagging, also known as Bootstrap aggregation is a famous way used in obtaining multiple classifiers. In 1996, it was introduced by Breiman to adapt randomly trained classifiers outputs to improve the classification results (Mitchell 2010). Bagging regression learner (ensemble) is a multi-classifier technique that can be used to train classifiers in a random manner as bootstrap, restructuring the training set and constructing entities for its ensemble. In bagging ensemble, each training dataset is formed by arbitrarily drawing a certain number of instances with substitutes, where the number of samples exhibits an equal size with the original training samples. Many of the preliminary examples may occur in the subsequent training set while others may be discharged (Mitchell 2010; Moore 2004). However, in the ensemble, using dissimilar random instances of the training set can be used to produce a single classifier (Moore 2004).

C. Random Forest (RF): The random-forest method is realized by using random tree approach in order to build bagging models (bootstrap aggregation) (Tsypin and Röder 2007). In the random-tree technique, classification trees are developed on an arbitrary subcategory of descriptors. RF method is a very effective method in building vastly predictive classification models as it combines two learning methods, bagging and random space methods (Sutton 2012).

D. Boosting (Bos): boosting-ensemble was proposed by Freund and Schapire (Vemulapall, Luo, Pitrelli, and Zitouni 2010). The boosting algorithm encompasses a group of methods, with their aims being to generate series of classifiers. Boosting-ensembles are used to generate new classifiers that can simply predict cases when there is poor performance is experienced in the present ensemble (Moore 2004; Vemulapall, Luo, Pitrelli, and Zitouni 2010; Buhlmann 2010).

E. k-Nearest Neighbor Classifier (kNN): in this algorithm, classification is achieved by using a data-set with data points split into few separate groups (Tsypin and Röder 2007; Sutton 2012). Each classification case is characterized by p values xi, where, naïve = 1...... p, and is denoted by a point in p-dimensional space. In general, the positioning of kNN can be any metric measure. Neighbors-based methods are recognized as non-generalizing machine learning methods, since they simply “recall” all of their training data (Sutton 2012; Alsheikh, Lin, Niyato, and Tan 2014). In machine learning, the kNN algorithm is used for grouping and regression (Hasan, Twala, and Marwala 2014).

F. Naïve Bayes’ Classifier (NBC): this type of classifier utilizes a plain scheme for representing, studying and using probabilistic knowledge with clear semantics (Moore 2004). Fundamentally, given the class variable, NBC adopts that the presence or absence of a particular class feature is distinct to the presence or absence of any other feature. In machine learning, naïve Bayes classifiers operate by applying independent feature model, a Bayes’ theorem with firm (naïve) independence expectations, and with simple probabilistic classifiers

(Moore 2004). The fastness of the naïve Bayes' classifier and its resulting high accuracy makes it a popular technique (Mitchell 2010).

G. Multilayer Perceptron (MLP): MLP is a feed-forward artificial neural network where a linear hyper-plane presents an instance space and can be represented using the simplest neural network known as perceptron (Hasan and Shongwe 2016; Wolpert 1992). In MLP, the layer is an arrangement of neurons comprising of hidden neurons. The hidden neurons are designed in a way that connection to the outside sources is disintegrated (Mitchell 2010). Each MLP contains an input layer with a minimum of a single hidden layer and a single output layer. MLP trains the network using a supervised learning technique called backpropagation (Hasan, Twala, and Marwala 2014).

H. Support Vector Machine: support vector machine is constructed on the perception of decision planes that describe decision boundaries. The splitting of a set of objects that have dissimilar class memberships is done by a decision plane. Inside the instances spaces, the highest margin that separates the linear hyper-plane is formed in the sample spaces that provides maximum separation between the two classes (Burges and Schölkopf 1997). The closest instances to the maximum margin that separates the linear hyper-plane from the support vectors are then properly classified (Breiman 2001; Kecman 2001). SVMs select the hyper-planes with the longest distance from the adjoining data points (margin) amid the possible hyper-planes. The linear hyper-plane is then created once the support vector data have been identified (Jalill, Kamarudin, and Mara 2010; Zhidkov 2008).

2. Prior Work on Impulse Noise Mitigation

In this section, earlier works on detecting and mitigating the upshot of impulsive noise in power line communication system performance is reviewed.

Some previous approaches employed parametric means in extenuating asynchronous impulsive-noise by evaluating the parameters of the specific noise model. Parametric methods include nulling and clipping methods, error correcting coding, pre-filtering technique, iterative decoders, and MMSE symbol-by-symbol detectors (Zhidkov 2008; Sargrad and Modestino 1990; Li, Mow, and Siu 2008; Nassar, Gulati, Sujeeth, Aghasadeghi, et al. 2011; Nassar, Gulati, DeYoung, Evans, et al. 2008, Haring and Vinck 2003; Nassar and Evans 2011; Haring 2002). The merit of parametric method is its avenue of improving the system performance by exploiting the information of the noise and its parameters. The demerit of parametric method is the need for extra training. Also, when the parameters or noise model mismatch the noise statistics, they tend to suffer performance degradation.

Recently, researchers are aiming to apply non-parametric methods. These methods exploit the sparse nature of an asynchronous impulsive noise in the time domain for denoising activity in PLC systems. For example, the application of compressed sensing (CS) which uses a few samples of a digitized signal to reconstruct the signal. The CS techniques as used in (Caire, Al-Naffouri, and Narayanan 2008) uses the tones which lack data or pilots (i.e. null tones) to estimate impulsive noise, while the amount of impulses in an OFDM emblem does not surpass a threshold. This threshold is uniquely related to the number of null tones and the size of the discrete Fourier transforms (DFT).

However, where multiple impulses corrupt an OFDM signal, the threshold is too resistive for common OFDM setting. A similar technique to compressed sensing used in combating impulsive noise is the adoption of the similarity between error correcting code (particularly Reed Solomon and Bose-Chaudhuri-Hocquengem codes) and DFT (i.e. Discrete Fourier Transform in OFDM). In (Wolf 1983), as far back as the 80's, this idea was implemented by Wolf by comparing the DFT to BCH codes, the comparison showed that in a DFT sequence, there is presence of superfluous information which can be used in the detection and correction of errors. A group of authors showed OFDM modulator to have similarity to a Reed-Solomon encoder and this similarity can serve as an instrument to detect and eliminate impulse noise (Abdelkefi, Duhamel, and Alberge 2005). Meanwhile (Mengi and Vinck 2009) used OFDM as a Reed-Solomon code. They observed all subcarriers, both those with redundancy symbols and those with the information symbols. Through this, their scheme achieved better impulsive error correction.

In (Lin, Nassar, and Evans 2013), application of Sparse Bayesian Learning (SBL) technique was introduced to diminish the periodic impulsive-noise and asynchronous impulsive-noise present in OFDM PLC. At the receiving end of the transmitted signal, SBL techniques were used to estimate the volume of impulsive noise samples present through observation of the null and pilot subcarriers as well as all the subcarriers in order to alleviate asynchronous impulsive noise. The proposed algorithms were verified by simulating several statistical representations of asynchronous and periodic impulsive noise which serves as a medium for implementing non-parametric alleviation methods and can be applied to cases involving asynchronous impulsive-noise. The compressed sensing approach was modified by (Lampe 2011) to detect busty impulsive-noise by exploiting the block-sparsity of the noise. However, parameters that would normally adapt to the background noise level and the amount of noise bursts present in the OFDM system affected the functioning of the algorithm.

An effective and simple approach was proposed by (Gaofeng, Qiao, Zhao, et al. 2013) to mitigate the impulsive noise in the frequency domain through detection and sharing approach for OFDM demodulation. The FFT module detects the delayed subcarrier position as impulsive noise frequency. After which, the periodic impulsive-noise gets suppressed using an adaptive infinite-impulse-response (IIR) notch filter for compensation of the distorted signal. Although this method was found to have good performance, it is however more appropriate for the narrowband power line communication system (NB-PLC) compared to the broadband PLC system. The report of (Rahman and Majumder 2015) introduced alpha stable models for modelling the noise characteristics in indoor power lines. However, this approach faced a major setback through the absence of closed formulas for distribution functions and densities for some of the stable distributions.

The impulsive noise is considered as a sparse signal that can be recovered using compressed sensing approach. Compressed sensing technique involves the use of null subcarriers property. The use of smoothed l_o-norm minimization algorithm was investigated in (Juwono, Guo, Huang, Wong, et al. 2015) for detecting impulsive-noise in PLC using orthogonal frequency division multiplexer (OFDM). The L_1 magic tool combined with log-barrier algorithm compares the performance of the L_1 norm minimization with that of the smoothed l_o-norm minimization algorithm. The simulated results proved that the method proposed by (Juwono, Guo, Huang, Wong, et al. 2015) provides a good estimate and yields a lesser CPU processing time.

2.1 Impulse Noise Detection Using Machine Learning Techniques

Recently, attention is given to the use of machine learning to detect, estimate, and suppress impulsive noise present in an orthogonal frequency division multiplexing (OFDM) systems. For instance, the work of (Hasan and Shongwe 2016) concentrated on the use of machine learning techniques to predict and estimate impulsive-noise. Four machine learning (ML) algorithms (k nearest neighbor kNN, naïve Bayesian classifier NBC, support vector machines SVM, and multilayer perceptron MLP) were adopted for this purpose. These ML techniques were implemented using OFDM system corrupted by impulsive noise. Results show that these four machine learning techniques could predict the existence of impulsive noise successfully. However, the kNN technique had the highest prediction accuracy while SVM achieved the lowest result. Hence, the notion of using ML algorithms to predict and estimate impulsive noise in OFDM was achieved.

In (Hasan and Shongwe 2017), four powerful machine-learning multi-classifiers (ensemble) algorithms which comprises of Stacking (Stack), Bagging (Bag), Boosting (Bos), and Random Forest (RF) were trained using the Middleton Class-A noise model. In OFDM system, Middleton class-A is one of the most popular noise model used to simulate the behavior of the impulsive noise (Shongwe, Vinck, and Ferreira 2015). At the receiving end of the OFDM system, machine learning techniques were used to detect the occurrence of impulsive noise in the received signal. The results obtained from this technique further showed that ML techniques are more suitable in an OFDM system to predict impulse noise with higher accuracy. Table 3 presents the results obtained from comparing (Hasan and Shongwe 2016) and (Hasan and Shongwe 2017) in envisaging and estimating the presence of impulsive noise in OFDM systems.

Table 3. Comparison of different machine learning algorithms in impulsive noise prediction

Description	**Accuracy of the Prediction**	MAE	RMSE
Knn	99.80%	0.002	0.0329
NBC	97.71%	0.038	0.118
MLP	95.60%	0.041	0.041
SVM	76.05%	0.282	0.366
Bag	99.85%	0.002	0.022
Bos	99.51%	0.017	0.066
Stack	97.31%	0.028	0.028
RF	99.83%	0.002	0.030

In an OFDM PLC system, machine learning can be applied as illustrated in Figure 3 below, which was adapted from (Hasan and Shongwe 2017).

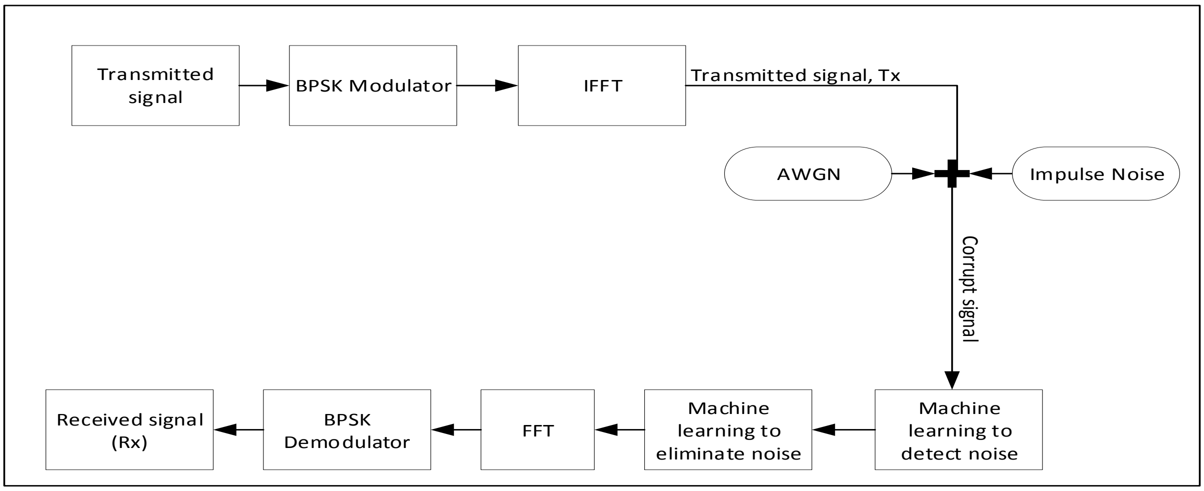

Figure 3. Application of machine learning in OFDM for noise detection and elimination

Most recently, (Himeur and Boukabou 2017) applied a machine learning approach specifically the adaptive neuro-fuzzy inference system (ANFIS) with chaotic interleave as an adaptive noise cancellation method for estimating and suppressing impulsive-noise in an OFDM system. The ANFIS adaptively suppresses the noise while the chaotic interleave ensures the data transmitted is secured and more robust against further impulsive bursts. This method proved easier to implement and had a faster convergence rate (Himeur and Boukabou 2017).

3. CONCLUSION

From the review done in this paper, it can be concluded that the machine learning approach gives faster and more accurate results than the older approaches for predicting or estimating impulsive noise, and eventually or suppressing it. The machine learning approaches are easier to implement and produce better noise estimation results in communication systems more efficiently. However, only a limited area of ML has been explored. More areas of ML algorithms such as, linear regression, logistic regression, decision tree, dimensionality reduction algorithms, concurrent neural fuzzy network (CNF), markov decision process etc., can be adapted for the purpose of detecting and eliminating the impulsive noise present in an OFDM system in order to improve powerline communication system.

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