Mitigation of Impulsive Noise in OFDM Channels Using ANN Technique

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Abstract--- **Orthogonal frequency division multiplexer (OFDM) is a recent modulation scheme used to transmit signals across power line communication (PLC) channel due to its robustness against some known PLC problems. However, this scheme is greatly affected by the impulsive noise (IN) and often causes corruption with the transmitted bits. Different impulsive noise error correcting methods have been introduced and used to remove impulsive noise in OFDM systems. However, these techniques suffer some limitations and require much signal to noise ratio (SNR) power to operate. In this paper, an approach of designing an effective impulsive-noise error-correcting technique was introduced using three-known artificial neural network techniques (Levenberg-Marquardt, Scaled conjugate gradient, and Bayesian regularization). Findings suggest that both Bayesian regularization and Levenberg-Marquardt ANN techniques can be used to effectively remove the impulsive noise present in an OFDM channel and using the least SNR power.**

Keywords— Artificial Neural Network, Bayesian Regularization, Bit error rate, Binary Phase Shift Keying, Levenberg-Marquardt, Machine learning, Scaled-conjugate, Clipping and Nulling, Power Line Communication.

1. INTRODUCTION

Orthogonal frequency division multiplexer (OFDM) is a developed modulation technique that is recently used in powerline communication (PLC) due to its robustness against some known PLC challenges such as frequency-selective fading, multipath and interference [1]. An OFDM system is a multicarrier communication technique that uses both inverse fast Fourier transform (IFFT) and fast Fourier transform (FFT) for modulation and demodulation respectively. Industrial application of OFDM includes field-programmable gate array (FGPA) that is commonly used for high performance computing, communication and broadcast [2].

Despite its merits, OFDM is still disturbed by some noise signals such as impulsive noise (IN) that spreads among its subcarriers during transmission. This impulsive noise imposes the risk of data corruption at the receiver end and increases when the energy present in the impulsive noise exceeds a certain threshold (background noise level) [3, 4]. Hence, the need for an impulsive-noise removal technique is essential in an OFDM system. The impulsive noise is categorized into three: periodic impulsive noise synchronous to the main frequency, asynchronous impulsive noise (AIN), and periodic impulsive noise asynchronous to the main frequency [5, 6]. The periodic impulsive noise synchronous with the mains is a cyclostationary noise that commonly exists in silicon-controlled rectifiers (SCR) power supply and operates at certain frequency (e.g. 50 Hz or 100 Hz in European countries) [7, 8]. AIN is a form of noise that occurs rapidly due to ON and OFF of electrical devices while periodic impulsive noise asynchronous to the main frequency is a type of noise similar to the synchronous impulsive noise but operates at a frequency [8].

Different error-correcting techniques have been proposed and used to remove impulsive noises from OFDM channel. However, most of these techniques suffer some limitations. For example, clipping and nulling (blanking) technique was used to remove impulsive noise [9]. However, this technique demands a good knowledge of the impulsive noise magnitudes and predicting a clipping threshold that only removes impulsive noise below the clipping threshold [10]. Similarly, iterative technique, an impulsive-noise correcting method that works with the difference between the impulsive noise (IN) and the received signal vector (r). Iterative technique requires a high number of iterations for performance improvement, time consuming, and does not eliminate the complete impulsive noises from the PLC channel [11]. Lastly, the use error correcting codes such as turbo, convolution coding and Reed-Solomon (RS) code and low parity check coding that exhibits a high performance in removing impulsive noise in PLC suffers different shortcomings [12]. For instance, convolution code performs poorly with BPSK modulator (a component in OFDM channel) while convolution codes are unsuitable for non-linear time invariant (NLTI) systems [13].

The contribution of this paper is to introduce an innovative use of artificial neural network (ANN) for the mitigation of impulsive noise from an OFDM channel. Second contribution is a work done using three different ANN optimization techniques (Levenberg-Marquardt, scaled conjugate, and Bayesian ANN) to determine a more fitting ANN method that can be considered for impulsive noise mitigation in OFDM systems.

The structure of this paper is arranged as follows, section 2 will present a summary of the used ANN techniques. In section 3, a report of the experiment setup and method is provided. Section 4 will present the results, and section 5 will include the conclusions.

II. ANN TECHNIQUES

Artificial neural network (ANN) technique is a machine learning technique that is commonly used to solve some worldly (both linear and non-linear) problems due to its fast computation time and accuracy. ANN incorporates the use of activation functions (e.g. tansig function) for computation task and the interconnection of several hidden layers and neurons to link the inputs and outputs (targets) of the network together [14]. ANN can be classified into feedforward and the feedback neural network (backpropagation). Examples of feedforward neural networks include multilayer perceptron (MLP), probabilistic neural network, Adaline and Madaline neural network while examples of backpropagation neural networks include Hopfield network, bi-directional and associative memory (BAM) neural network [15, 16]. Several ANN techniques have been used for different applications e.g. prediction of weather information, optimization of power in solar energy systems, classification of data samples, etc. [17]. This paper will focus on three-known ANN training techniques (Levenberg-Marquardt, scaled conjugate gradient, and Bayesian regularization ANN algorithms).

The Levenberg-Marquardt (LM) is a hybrid technique that combines the fast converging speed of Gauss-Newton algorithm and the stable capability of the steepest descent method for training process into a single algorithm [18]. The mathematical model of LM algorithm can be defined using equation (1) while the dual working operation of Levenberg-Marquardt algorithm is explained using equations (2) and (3),

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \tag{1}$$

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k \tag{2}$$

$$w_{k+1} = w_k - \alpha g_k \tag{3}$$

where μ is the combination coefficient, *I* is the identity matrix, J is the Jacobian matrix, $J^T J$ is the Hessian matrix, g is the gradient vector, e is the error vector, α is the learning constant (step size), w is the weight vector and k is the index of iteration [19]. When μ is very small (approaching zero), the Levenberg-Marquardt switches from equation (1) to equation (2) known as Gauss-Newton algorithm. Similarly, when μ is very large, the descent method represented by equation (2) is used [20, 21].

The Bayesian regularization is another ANN algorithm introduced lately and have been used by research scholars to solve real-world problems. The Bayesian regularization helps to reduce noise in the training data of ANN and ensures that smoother network-response. The Bayesian algorithm helps to accommodate large weight vector in ANN by fine-tuning the used objective function and with the addition of a penalty term that comprises of squares of all network weights [22, 23].

The scaled conjugate is an algorithm commonly used to train networks that have a large number of weights due to the rapid training speed that the algorithm exhibit [24, 25, 26, 27].

III. SIMULATION MODEL

To examine the feasibility of the proposed noise mitigation technique modelled using different ANN algorithm to identify the most suitable algorithm that can effectively remove the impulsive noise (IN) existing in the transmitted signal (T_x) in an OFDM channel, a case study was done with three different ANN techniques (Bayesian, Levenberg Marquardt, and Scaled cojugate gradient).

A complete OFDM system that comprises of Bernoulli binary generator for generating the transmitted bit signals of 0 and 1 (T_x), binary phase shift keying (BPSK) modulator, Inverse fast fourier transform (IFFT), FFT (fast fourier transform), BPSK demodulator, additive white Gaussian noise channel and randomly-corrupt impulsive-noise data of variance of 50% and probability of 50% were added to the OFDM model to achieve the objective of the experiment. The random impulsive noise datasets were produced using equations (4-6),

$$F_m(n_k) = \sum_{m=0}^{\infty} p_m \quad (n_k; 0, \sigma_m^2) \tag{4}$$

$$\text{where,} \quad P_m = \frac{A^m e^{-A}}{m!} \tag{5}$$

$$\text{and} \quad \sigma_m^2 = \sigma_i^2 \frac{m}{A} + \sigma_g^2 = \sigma_g^2 \left(\frac{m}{A\Gamma} + 1 \right) \tag{6}$$

$F_m(n_k)$ is the probability density distribution (PDF) of a noisy signal (n_k), $(n_k; \mu, \sigma_m^2)$ expresses the Gaussian PDF, μ is the mean, σ^2 is the variance with k -samples. σ_i^2 denotes the impulsive noise variance, σ_g^2 is the additive white Gaussian noise (AWGN). $\Gamma = \frac{\sigma_g^2}{\sigma_i^2}$ denotes the Gaussian-to-impulsive-noise power ratio. The parameter (A) is the density of impulses within a specific width and observation period.

Figure 2 displays the block diagram of a complete OFDM system modelled using ANN error-correcting schemes. The ANN training was conducted using Bayesian-regularization, Levenberg-Marquardt, and Scaled-conjugate gradient algorithm. These supervised ANN controllers learn using 10,000 samples of signals u and v, where u is the transmitted signal (T_x) mixed with impulsive noise and AWGN, and v -the impulsive noise are the input variables ***(u,v)*** (predictors) and signal t (output signal from the IFFT/AWGN block) is the target. For simplicity, the complex-variable data $u = u_1 + ju_2, v = v_1 + jv_2$, and $\vec{t} = \vec{t}_1 + j\vec{t}_2$ were split into real and imaginary components and both the real and imaginary parts of signals (u, v) were the ANN inputs (u_1, u_2, v_1, v_2) while the real and imaginary component of signal t (t_1, t_2) were used as targets. The ANN channel is then applied just before the BPSK demodulation in order to mitigate the impulsive noise from the trasmitted data.

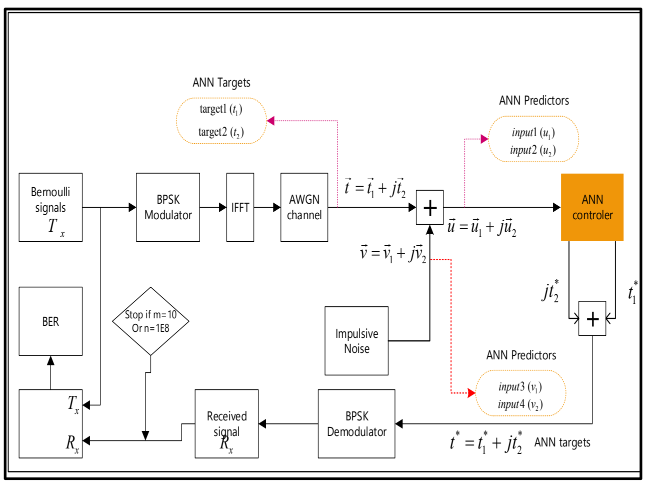

Fig. 2: Complete OFDM channel Using ANN Techniques

Figure 3 presents the amplitude level of the corrupted impulsive noise signal in the OFDM channel for 500 seconds.

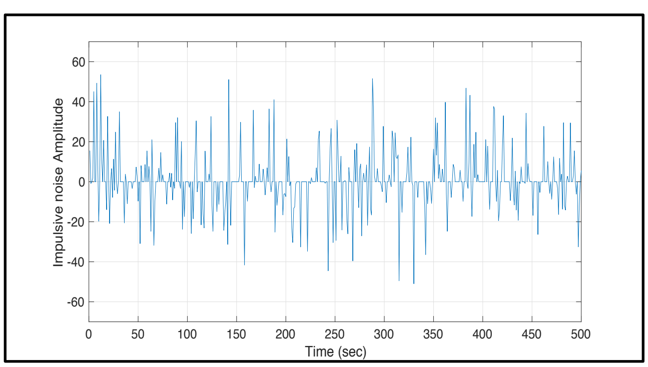

Fig. 3: Impulsive signal Magnitude

IV. EXPERIMENTAL RESULTS

Figures (4) – (7) and Tables (1) - (2) present the graphical results and tabulated results of the used ANN error correcting techniques done using MATLAB simulation approach respectively. From Table I, it can be seen that Bayesian regularization technique exhibited the best training performance with the lowest mean square error (MSE is 6.1834e-11) while scaled conjugate gradient exhibited the worst performance (MSE is 2.7545e-2). However, Bayesian regularization takes a longer time to train as the training for 1000 epochs was completed in 7 mins 20 seconds while Levenberg-Marquardt had the fastest training time (32 seconds).

Table 1: Parameters for the three ANN algorithms

	Bayesian Regularization	Levenburg Marquardt	Scaled Conjugate Gradint
Hidden neurons	10	10	10
Training MSE	6.1834e-11	5.6757e-10	2.7545e-2
Validation MSE	0	5.7723e-10	2.8855e-2
Testing MSE	6.9677e-11	6.9364e-10	2.6541e-2
Traing Regression	9.9999e-1	9.9999e-1	9.7451e-1
Validation Regression	0	9.9999e-1	9.7348e-1
Testing Regression	9.9999e-1	9.9999e-1	9.7519e-1
Epoch	1000	1000	124
Perfomance	6.18e-11	5.68e-10	0.0273
Time	7mins 20secs	32secs	33secs
Gradient	2.07e-6	1.27e-5	0.0135

Figure 4 displays the bit error rate (BER) graphical results of a comparison done with Bayesian regularization ANN impulsive-noise error-correcting technique and conventional (uncorrected) method using an OFDM system that has been corrupted with both both AWGN and impulsive noise. From the obtained graphical results, the high performance of the Bayesian regularization technique can be observed as it requires less than 10 dB power to achieve a BER of 10^{-4} whereas with an uncorrected OFDM channel requires a high SNR power.

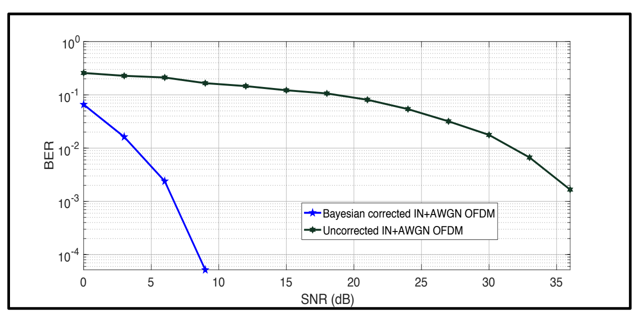

Fig 4: BER performanne of Bayesian Regularization algorithm

Figure 5 shows the BER results of the OFDM chanel (mixed with AWGN and IN) corrected using levenberg marquardt error correcting algorithm compared with the conventional uncorrected OFDM system. From the obtained results, the high impulsive-noise mitigating capability of the Levenberg-Marquardt can be seen as it requires less than 10 dB to achieve a BER of 10^{-4}, while the uncorrected corrupted OFDM channel consumes more SNR power.

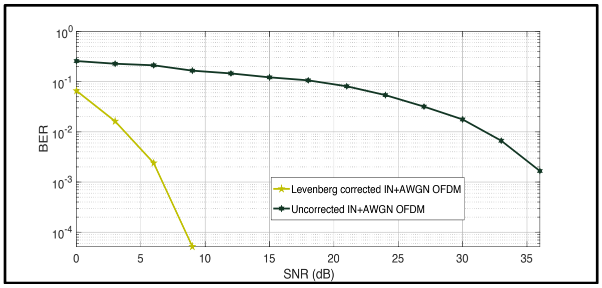

Fig 5: BER performance of Levenberg-Marquardt algorithm

Figure 6 presents the bit error rate (BER) performance of the OFDM channel (mixed with impulsive noise and AWGN) incorporated using scaled conjugate gradient ANN algorithm compared with the uncorrected OFDM system. From the obtained results, it can be seen that using scaled conjugate method requires approximately 10 dB SNR power to achieve a BER of 10^{-4}.

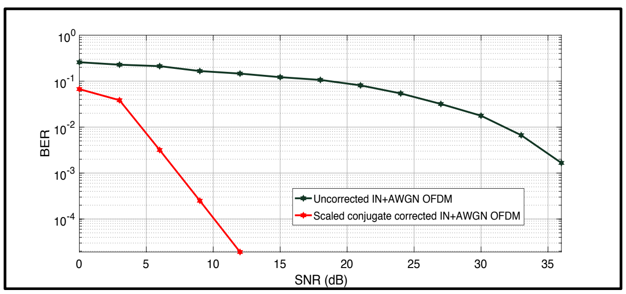

Fig 6: BER performance of scaled Conjugate Gradient

Figure 7 shows a comparison of the BER performances of the above-mentioned ANN algorithms (Levenberg, Bayesian, and scaled-conjugate) results and the conventional un-corrected OFDM results. From the obtained results, it can be seen that both Levenberg-Marquardt and Bayesian regularization requires the lowest SNR power for the mitigation of impulsive noise in a corrupt OFDM channel.

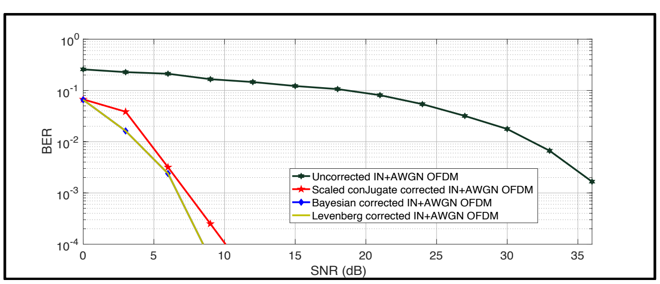

Fig. 7: Comparion of the BER performances of the Bayesian corrected OFDM, Levenberg-Maquardt corrected OFDM, scaled-conjugate corrected OFDM and the uncorrected OFDM

Table 2 displays the tabulated bit error rate (BER) results under different SNR (signal-to-noise ratio) power in decibels. T is the theorectical results for OFDM channel mixed with AWGN only. SC is the scaled conjugate error correcting algorithm, BR is the Bayesian regularization, LM is the Levenberg-Marquardt, and CO is the convential uncorrected results for OFDM channel that was corrupted with both impulsive noise and AWGN respectively.

Table 2: BER results for the theoretical, scaled-conjugate, Bayesian regularization, Levenberg-Marquart algorithm, and conventional uncorrected OFDM channel under different SNR power

SNR	T BER	SC BER	BR BER	LM BER	CO BER
0	0.0786	0.067110	0.06579	0.06579	0.2577
3	0.0228	0.038460	0.01623	0.01623	0.2278
6	0.0023	0.003177	0.00239	0.00239	0.2119
9	3.36e-5	2.500e-4	5.177e-5	5.177e-5	0.1658
12	9.00e-9	1.918e-5	-	-	0.1460
15	9.1e-16	-	-	-	0.1220
18	1.4e-29	-	-	-	0.1063
21	5.3e-57	-	-	-	0.08091
24	1e-111	-	-	-	0.0540
27	2e-220	-	-	-	0.03185
30	-	-	-	-	0.01768
33	-	-	-	-	0.006662
36	-	-	-	-	0.001662

From the obtained results (see Fig. 4-7 and Tables 1-2), it was observed that both Bayesian and Levenberg-Marquardt exhibited an effective impulsive noise error correcting capability while scaled conjugate algorithm displayed the lowest impulsive noise error-correcting performance.

V. CONCLUSIONS

This paper presents an innovative use of Levenberg-Marquardt and Bayesian regularization ANN machine learning techniques for the improved mitigation of impulsive noise in an Orthogonal Frequency Division Multiplexer (OFDM) channel. To validate the efficiency of the above-mentioned ANN techniques (Levenberg-Marquadt and Bayesian regularization), an OFDM channel that lacks an error-correcting scheme simulation results was compared with Levenberg-Marquardt results, Bayesian regularization results and with the results of another popular ANN technique (scaled conjugate) in order to validate the importance of impulsive noise error-correcting scheme and thus evaluate the effectiveness of the used error-correcting methods. Findings suggest that both Levenberg-Marquardt and Bayesian regularization exhibit better performance in removing the impulsive noise in the OFDM channel and required minimal signal-to-noise (SNR) power.

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