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Performance Evaluation of Various Training Algorithms for ANN Equalization in Visible Light Communications with an Organic LED

Zahra Nazari Chaleshtori[1], Paul A. Haigh[2], Petr Chvojka[1], Stanislav Zvanovec[1], Zabih Ghassemlooy[3]

[1]Department of Electromagnetic Field, Czech Technical University in Prague, Prague, Czech Republic, 16627
[2]School of Engineering, Newcastle University, Newcastle upon Tyne, NE1 7RU, UK
[3]Optical Communications Research Group, Faculty of Engineering and Environment, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK
{nazarzah; petr.chvojka; xzvanove}@fel.cvut.cz, paul.haigh@newcastle.ac.uk, z.ghassemlooy@northumbria.ac.uk

Abstract—This paper evaluates the effect of training algorithms in an artificial neural network (ANN) equalizer for a feedforward multi-layer perceptron configuration in visible light communication systems using a low bandwidth organic light source. We test the scaled conjugate-gradient, conjugate-gradient backpropagation and Levenberg-Marquardt back propagation (LM) algorithms with 5, 10, 20, 30, and 40 neurons. We show that, LM offers superior bit error rate performance in comparison to other training algorithms based on the mean square error. The training methods can be selected based on the trade-off between complexity and performance.

Keywords-Artificial neural network equalizer; Equalization; Organic LEDs; Visible light communications

I. INTRODUCTION

Recently, visible light communications (VLC) have attracted significant attention as a complementary access network to the radio frequency (RF) based wireless systems in order to meet the growing demand for mobile data. In VLC systems, which utilizes the visible wavelength band (i.e., 370–780 nm) for transmission of data, both inorganic white light emitting diodes (LEDs) and organic LEDs (OLEDs) can be used [1, 2]. OLEDs offer several advantages over the conventional LEDs, such as large and arbitrarily shaped photoactive areas, mechanical flexibility, and ultra-low-cost wet processing methods but at the cost of much reduced modulation bandwidth B_{mod} (i.e., a few hundred kHz) [1-3]. As such, there is a growing interest in OLED-based VLC (OVLC) in certain applications such as display technologies, infrastructure-to-device (I2D) and device-to-device (D2D) communications, smart televisions, etc. [4].

In smart devices with OLED displays [5] pixels can be individually intensity modulated for data transmission, which can be received using the built-in camera of another smartphone (i.e., D2D communications) [6, 7]. A great deal of attention on the implementation of OLEDs in high-resolution displays and applications in low-cost future solid-state lighting are good reasons to extend the use of OVLC technology [8].

The optoelectronics devices (i.e., in this case OLED), with a typical luminous efficiency of 40-60 lm/W (120 lm/W in inorganic LEDs [9]) the low B_{mod} due to slow charge transport characteristics, depending upon the manufacturing process, materials and the physical dimensions [10], leads to a bandwidth bottleneck in optical transmission systems (i.e., much reduced data throughput) [1]. To overcome the bandwidth bottleneck in OVLC, a number of techniques have been investigated including equalization, signalling schemes and the optimum driver circuits [11].

A review of OVLC systems is provided in [12] which shows that using different organic devices, modulation schemes and digital signal processing techniques the achievable data rate R_b can be increased significantly from 550 kb/s [9] to > 50 Mb/s [13]. For instance, the first notable R_b of 10 Mb/s was achieved by adopting a polymer LED (PLED) with a B_{mod} of 270 kHz using on-off keying (OOK) in combination with a least mean square (LMS) equalizer [14]. The same R_b was achieved using orthogonal frequency-division multiplexing (OFDM) in [15]. Next, through low-temperature thermal annealing and crystallisation of the polymer, a slight marginal improvement in B_{mod} (i.e., 350 kHz) was reported, which was used in OVLC in combination with an artificial neural network (ANN) to achieve a R_b of 20 Mb/s [16]. In [4], using wavelength-division multiplexing (WDM) (i.e., red/orange, blue and green devices) and an ANN equalizer an aggregated link capacity of ~55 Mb/s was reported. Recently, a 51.6 Mb/s VLC link employing a monochromic OLED modulated by an offset-quadrature amplitude modulation (QAM)-based OFDM signal with bit- and power-loading and a joint linear minimum mean-square-error (LMMSE) based decision feedback equalizer (DFE) was reported [13], which is the highest single-wavelength transmission speed reported in OVLC so far.

In the literature, ANN equalization has been reported as an effective method to compensate for the limitation in R_b due to limited B_{mod} of OLEDs [17-19]. Note that, the working principle of an ANN is based on mapping the input-output sequence from the received data and a known dataset, and by checking the system's success using a test data [20]. Since the learning algorithm significantly affects the ANN performance, in this paper we investigate the effect of various learning algorithms and a number of neurons in the hidden layer and quantify the link performance in terms of the bit error rate (BER).

The rest of the paper is organized as follows. In Section II, ANN equalization is introduced. In Section III the results are discussed. Finally, conclusions are given in Section IV.

II. EQUALIZATION

Equalizers represent one of the most effective techniques to compensate multipath induced inter-symbol interference (ISI) in band-limited communication systems. Generally, equalizers can be classified into two categories; analog and digital with different complexity and performance [11]. Although an analog domain equalizer is simple, based on a high pass resistor-capacitor (RC) filter [21] can result in attenuation of low-frequency components, and hence, the baseline wander (BLW) phenomenon [1]. In [22], an OVLC using an OLED with B_{mod} of 150 kHz and an RC equalizer at a R_b of 2.15 Mb/s was reported.

On the other hand, digital equalizers such as LMS or recursive least squares (RLS)-based feedforward and DFE and ANN offer significant system performance improvement at the cost of increased complexity [1, 2]. The ANN takes loose inspiration from the human brain, which uses synapses and neurons to learn and compute. ANNs retain the neurons for computation and use tapped delay lines (in a transversal configuration) as the inputs. ANNs solve nonlinear problems via the neurons, which are divided into a parallel structure where the inputs to each neuron are scaled by an adaptive adjustable contribution of the synaptic weights of each input. Increasing the number of neurons boosts the ANN learning capacity while increasing complexity [23].

The structure of the model, the type of activation function, and the learning algorithm affect neural-network model implementation [20, 23]. The block diagram in Fig. 1 illustrates the fundamental model of a neuron, which forms the basis for designing a large family of NNs [24]. The neural model includes an externally applied bias b_k, which has the effect of increasing or lowering the contribution of each weighted input to the activation function. The output of the kth neuron is given by [24, 25]:

$$y_k = \varphi(v) \ , \tag{1}$$

where $v = u_k + b_k$ and u_k is the summed weighted contribution of the inputs defined as:

$$u_k = \sum_{j=1}^{n} w_{kj} x_j \ , \tag{2}$$

where $x_1, x_2, ..., x_n$ are the input signals, and $w_{k1}, w_{k2}, ..., w_{kn}$ are the weights of neuron k. Several activation functions are introduced in [24] including threshold function, piecewise linear function, and log-sigmoid function, however, any differentiable formulation may be used. In the following, a log-sigmoid function is considered for the hidden layer output and a linear function at the ANN output as is typical in the literature [3]. An example of the log-sigmoid function, employed in this work, is defined by [24]:

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \ , \tag{3}$$

where a is the slope parameter of the log-sigmoid function.

In general, there are four fundamentally different network architectures that can be used as an equalizer (*i*) feedforward single-layer; (*ii*) feedforward multilayer; (*iii*) feedback single-layer; and (*iv*) feedback multilayer networks. In a multi-layer configuration, the neurons are organized as follows; an input-layer consisting of an observation vector of incoming samples, a hidden layer where the processing occurs and an output layer. A recurrent (feedback) ANN is different to a feedforward NN in that has at least one feedback loop, see [24], which generally results in improvement in non-linear mapping at the cost of potential error propagation.
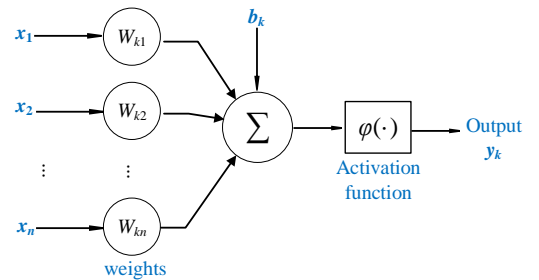

Fig. 1. The neural network model

For channel equalization, the multilayer perceptron (MLP), the functional link ANN (FLANN) and radial basis function (RBF) ANN are known as the popular choice of ANN [25, 26]. RBF and FLANN provide greater error performance, at the cost of increased computational complexity [25].

ANNs require a training sequence to adjust the neuron weights in order to map the input-output sequence of the system under test. For early stopping, algorithms update the neuron weights until the error between the equalized data and the target data does not exceed an objective error. It is also possible to allow ANN to run its training algorithm for objective epochs or seconds [3]. There are a number of training algorithms (see Table 1) that could be used, which are also available in the Matlab™ [27, 28]. One of the most popular ones is Levenberg-Marquardt back-propagation (LM) [25]. The conventional form of the conjugate-gradient (CG) training algorithm requires a time-consuming line search but a modified version of it (i.e., conjugate-gradient (SCG)) introduced by Møller [29] avoids the use of a line search [24].

When comparing against other digital equalisation techniques, ANNs offer several advantages: (*i*) *generalization* - due to input-output mapping, as opposed to ISI estimation, complex decision boundaries are created and hence, even when an error or bit sequence not included in the training sequence can be estimated [25]; and (*ii*) *evidential response* - to reject ambiguous patterns in classification, where a NN can provide information of particular pattern selected as well as the confidence in the decision made [24]. ANNs have been palpable in communication systems as a result of their flexibility and

learning capability. There are a large number of algorithms, which could be used for determining the network parameters and for training NNs. It is noticeable that the training algorithm and the network topology affect the performance of the NN [28]. Therefore, in this paper, we investigate the effect of the various network types and number of neurons in the hidden layer on the learning performance of the NN using LMBP, SCG, and conjugate gradient backpropagation (CGP) algorithms for feedforward networks.

The training algorithms and their main features are summarized in Table I [27, 28].

TABLE I.   THE TRAINING ALGORITHMS [27, 28]

Algorithm	Feature - Method used to update weight and bias values
Levenberg–Marquardt LM	Levenberg-Marquardt optimization.
Conjugated gradient descent CGB	Conjugate gradient backpropagation with Powell-Beale restarts.
SCG	Scaled conjugate gradient method.
CGP	Gradient backpropagation with Polak-Ribiére updates.
Resilient backpropagation RP	Resilient backpropagation algorithm.
Quasi-Newton algorithm OSS	One-step secant method.
BFG	BFGS quasi-Newton method.

III. EQUALIZATION RESULTS

In this work, a feed-forward multi-layer NN equalizer for an OOK-OVLC link is investigated. The schematic system block diagram is shown in Fig. 2. At the transmitter (Tx), a pseudo binary data pattern with a length of 10^6 is used for intensity modulation of the OLED. Note, OLED is modelled as a low pass filter with B_{mod} of 100 kHz. The optical signal propagating along the channel of 0.15 m long is converted back into an electrical signal using an optical receiver which consists of the photodetector and a trans-amplifier, and processing was carried out in the Matlab domain. The matched filter used as the detection type and synchronization with the transmitted data is carried out before being passed through a low pass filter (LPF) then downsampling the signal is applied to ANN equalizer in order to overcome the bandwidth limitation of OLED. The output of ANN passed through the threshold detector for comparison with the transmitted signal as shown in Fig. 2. The inclusion of a low pass filter is to perform the combined functions of noise, and anti-alias filtering, whereas

downsampling is used to reduce the number of sample points passed to the NN. Note, the procedure for training algorithms in multilayer perceptron NN is classified according to following steps (*i*) define the network structure - the network, activation functions is selected and the network parameters are initialized; (*ii*) define parameters associated with the training algorithm such as error goal, maximum number of epochs (iterations); and (*iii*) the training algorithm. The key system parameters adopted in this work are listed in Table II.
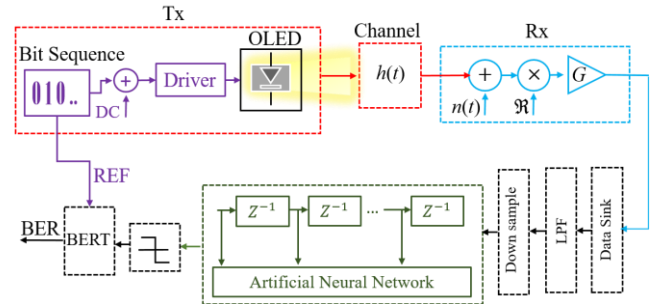

Fig. 2. The scheme of the OVLC with the post-detection ANN equalizer

Figs. 3(a)-(d) show the BER as a function of the energy/bit to noise ratio E_b/N_0 for training algorithms of LM, SCG, and CGP for MLP-ANN adopted in this work. Note, we have used a single hidden layer and a training length of 1000 bits for a range of number of neurons (i.e., 10, 20, 30, and 40). As in Fig. 3, for all cases, the LM algorithm offers the best BER performance compared to CGP and SCG. E.g., for 40 neurons and a BER of 10^{-4}, which is below the 7% forward error correction (FEC) limit of 3.8×10^{-3}, the E_b/N_0 penalties are much higher than 10 dB for SCG and CGP compared to the LM. Despite the storage requirement for LM and its long processing time compared to SCG and CGP it offers lower mean square errors (MSE), e.g., the MSE values are 7×10^{-15}, 3×10^{-5} and 5.3×10^{-6} for LM, SCG and CGP, respectively with enhanced performance as the number of neurons increases.

The effect of varying the number of neurons on the BER performance for LM algorithm is depicted in Fig. 4, which shows that 40 neurons in the hidden layer offer the best performance. E.g., at a BER of 10^{-3} the E_b/N_0 penalties are 12.5, 17.5, 18.5, and 19.5 dB for 30, 20, 10 and 5 neurons, respectively compared with 40 neurons. Note, that the BER performance of SCG and CGP also improved with increasing number of neurons.

TABLE II.   THE SYSTEM PARAMETERS

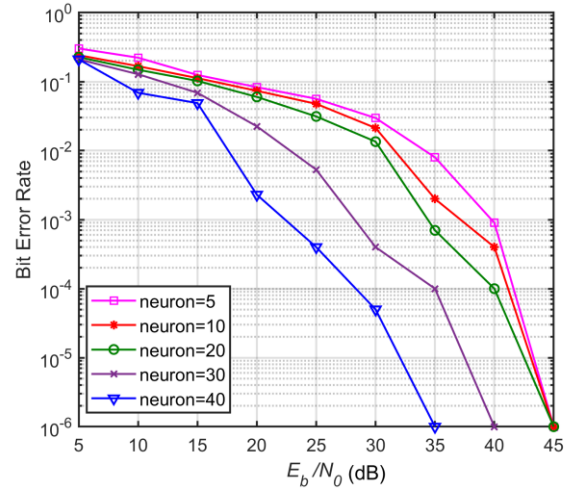| Parameter	Value
Link	
OLED bandwidth	100 kHz
Propagation length	0.15 m
Photodetector active area diameter	ϕ 1 mm
ANN Equalizer	
Network structure	MLP
Activation functions	log-sigmoid
Training algorithms	LM, SCG, CGP
Error goal	10^{-20}
Number of epochs	100
Training length	1000 bits
Number of neurons	5, 10, 20, 30, and 40

Fig. 4. BER as a function of E_b/N_0 for a range number of neurons (5, 10, 20, 30, 40) for LM training algorithm
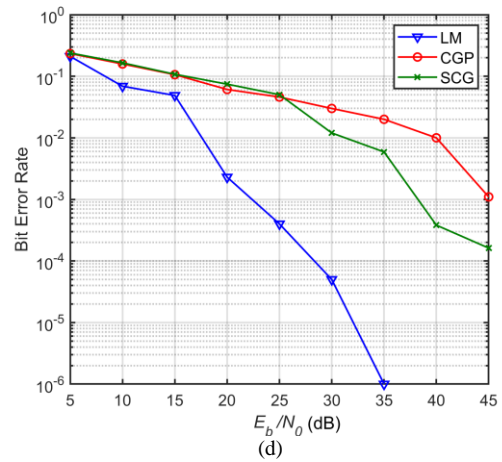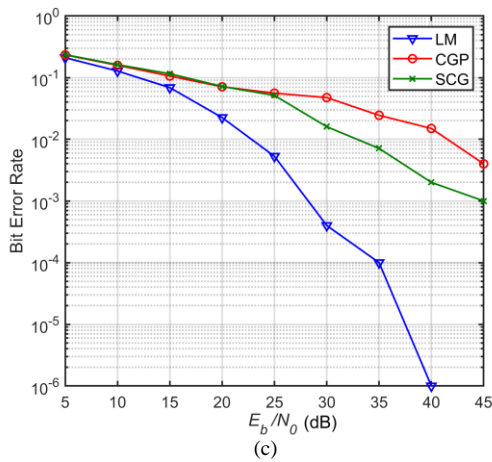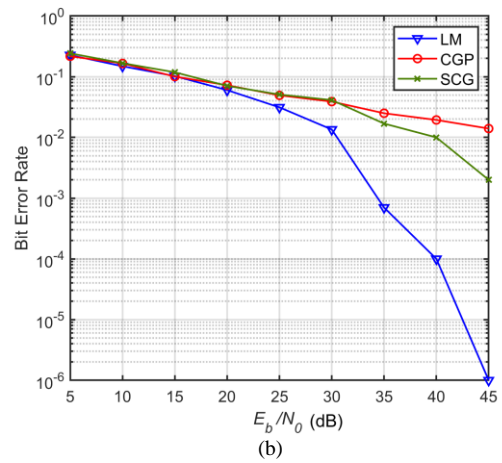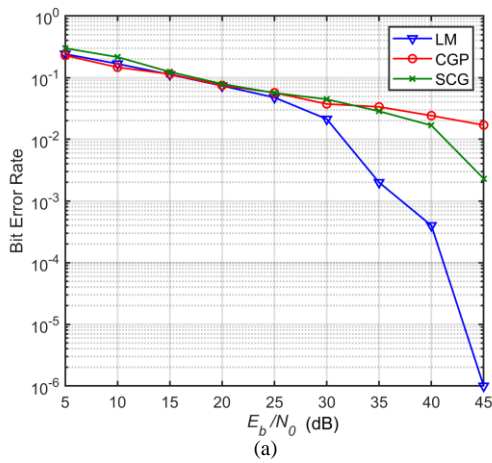

(a)

(b)

(c)

(d)

Fig. 3. BER performance against E_b/N_0 for LM, CGP and SCG training algorithms used in MLP-ANN equalizer with one hidden layer. The training length is 1000 bits, and the number of neurons used are (a) 10, (b) 20, (c) 30, and (d) 40.

IV. CONCLUSION AND FUTURE OUTLOOK

The widespread use of OLED-based devices in mobile devices, televisions and cameras with OLED pixels offers a tremendous benefit in modern technology that comes from OLED merits including very less stack thickness (100-500 nm), having large photoactive areas at a low cost, and low power consumption. It is a strong incentive to device-to-device communication growth. ANN equalizer has been popular to overcome OLED bandwidth restriction. In this paper, the effect of various learning algorithms, activation functions and numbers of neurons in the hidden layer were investigated. The structure of architectures and the training methods were selected based on the trade-off between complexity and performance. We investigated a range of training algorithms of LM, SCG and CGP as a part of the ANN equalization for OVLC systems, and showed that for a range of neurons the LM algorithm offered the best BER performance compared to CGP and SCG. In addition, LM algorithm offered the lowest mean square errors. In general, for networks with many neurons we showed that between the CG algorithms, SCG performed the best since it uses a low memory space and therefore performing faster than LM.

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