

# Neural Network – based Digital Receiver for Radio Communications

G. LIODAKIS, D. ARVANITIS, and I.O. VARDIAMBASIS

Microwave Communications & Electromagnetic Applications Laboratory,  
Department of Electronics,  
Technological Educational Institute (T.E.I.) of Crete - Chania Branch,  
Romanou 3, Chalepa, 73133 Chania, Crete,  
GREECE

*Abstract:* - This paper proposes a novel digital receiver, based on a multilayer perceptron neural network architecture, which works in a radio communications environment. Training is carried out by the variable learning rate back-propagation algorithm with momentum in a supervised manner and a batch training mode. We present computer simulation results comparing the performance of this receiver against the classical correlation receiver, for various modulation methods. The results show that the neural network – based receiver achieves better performance in terms of bit error rate for various  $E_b/N_0$  values, especially in the case of a Rayleigh multipath channel.

*Key-Words:* - Neural networks, digital receiver, correlation receiver, radio channel, signal detection, back-propagation learning algorithm, wireless communications.

## 1 Introduction

In a digital communication system, the transmitter generates a spectrally efficient signal in space, designating the system's performance. On the other end, the challenge for a digital receiver is to obtain reliable estimate of the transmitted symbols, taking into account the impairments introduced from the communication channel. This estimate is the result of a signal detection process performed by the digital receiver, in order to map the received signal onto a prescribed set of symbols (1s and 0s) at its output. A corresponding detection process arises in a multiuser Code Division Multiple Access (CDMA) communication system, where interference from other users is present. In both cases, the digital receiver is dealt with a binary hypothesis testing problem, the solution of which is optimized in some statistical sense.

The statistical communication theory often assumes that the channel is described by a stationary model and the signal is corrupted by noise of known statistics; actually, an additive white Gaussian noise (AWGN) model is assumed for the communication channel. However in mobile communications, nonstationarity of the received signals arises due to variations in environmental conditions, i.e. multipath propagation in a rural-hilly terrain or an urban area. So it may be feasible to view the received signal in

such a mobile system as quasi-stationary in the very short term and possibly stationary in long-term averages. Furthermore, in radio systems it is usually a reasonable assumption that the continuum (as opposed to impulsive) noise may be approximately stationary for milliseconds to seconds [1]-[2].

Classical digital communication receivers' design is centered around the correlation receiver (CR) [3]. The CR is composed by a matched filter and a detector. The matched filter correlates the received modulated noisy waveform in order to minimize the effect of the AWGN, while its sampled output is fed to the detector which makes the decision about what was sent. It can be shown that the CR is the optimum receiver for maximizing the signal-to-noise (SNR) ratio (i.e. providing the lowest possible bit error rate (BER)) for an AWGN communication channel. However, it should be mentioned that the CR's design approach is based on the mathematical model of the received signal (i.e. how it accounts for the communication channel's behavior) and ends up by testing the digital receiver's performance (i.e. its BER) with real data.

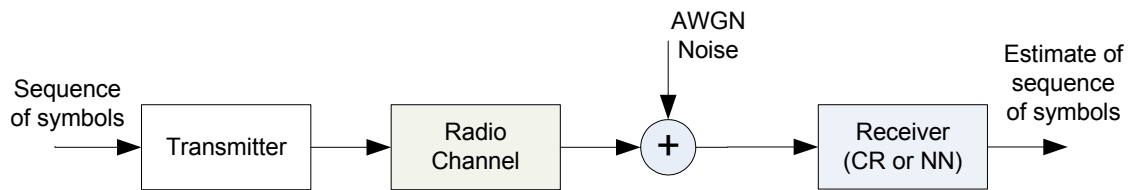
In this paper an alternate architecture of a digital receiver for radio communications over an AWGN channel is proposed. This receiver is based on an artificial neural network (NN) architecture, in order to exploit neural networks' generalization capability,

i.e. their actual response is statistically close to the desired response (the sequence of the transmitted 1s and 0s). The aforementioned generalization capability results from training the NN-based receiver and its degree of success is dependent upon two factors:

- the extent to which the training data set is adequate and representative of the wireless environment (in which the NN receiver operates),
- the degree to which the computational complexity of the NN receiver architecture matches the underlying dynamics' complexity of the communications environment.

Thus, the training data impose digital receiver's design and, if real data is used for training, the need for mathematical modeling is eliminated.

The communication system under simulation is presented in Section 2. In Section 3 we describe the architecture of the proposed NN digital receiver along with its training. Section 4 is devoted to the application of the NN receiver to the performance analysis of the communication system for various modulation schemes and communication channel models. Finally, in Section 5 we present some conclusions, along with a few directions for further research that are mostly related to adaptive NN communication receivers.



**Figure 1.** A digital radio communications system.

## 2 Communications System Simulation

The communication system's model, which is considered throughout this paper, is depicted in Fig. 1. The transmitter's input is assumed to be a sequence of  $m_s$  independent symbols extracted from the alphabet  $\{0, 1\}$ . Four different digital modulation methods (Amplitude Shift Keying (ASK), Frequency Shift Keying (FSK), Phase Shift Keying (PSK) and Quadrature Phase Shift Keying (QPSK)) are used, in order to study their performance (carrier signal's amplitude-frequency-phase change caused by the information symbols). The carrier frequency  $f_c = 900\text{MHz}$  is selected, as representative in a typical GSM-900 cellular system. Furthermore,  $m_s = 4$  or  $m_s = 8$  during simulation corresponding to  $m_b$  bits ( $m_b = m_s$  in case of ASK, FSK, and PSK modulation) or to  $m_d$  dibits ( $m_d = 2m_s$  in case of QPSK modulation).

In terms of the radio channel, line-of-sight (LOS) and non-line-of-sight (NLOS) communication scenarios are examined. In particular, the case of a multipath channel is characterized by a time-varying impulse response  $h(\tau, t)$ :

$$h(\tau, t) = \sum_{i=1}^{\infty} \beta_i(t) e^{j\theta_i(t)} \delta(\tau - \tau_i(t)),$$

where the random variables  $\beta_i(t)$  and  $\theta_i(t)$  are the time-varying amplitude and phase of the  $i$ -th path arriving with delay  $\tau_i(t)$ . For practical reasons, the path number ( $i$ ) is set to be finite and very small. In particular, the modeled radio channel consists either of one path [LOS and Rayleigh-1 simulation cases of Section 4] or of two paths [Rayleigh-2 and Rice simulation cases of Section 4, where: a) the Rice case incorporates a LOS path along with a NLOS path with Rayleigh statistics, b) the same average power  $P_{av}$  is used for Rayleigh statistics during simulation, c) a delay of  $0.003T_s$  ( $T_s$  being the symbol duration) between paths is used in the Rayleigh-2 case].

The radio channel output is corrupted by additive noise, assumed to be Gaussian with zero mean and variance  $\sigma_n^2$ . Thus, for the communication system under simulation, the variance for each path component of the modulated signal  $s(t)$  is:

$$\sigma_s^2 = \sum_{i=1}^N S_i^2 / N,$$

where  $N = N_b \cdot m_s$  is the number of instances (samples) of the modulated signal for  $m_s$  consecutive symbols and  $0.03T_s = 1/N_b$ . Then, for a specific value of  $E_b/N_o$ , the variance  $\sigma_n^2$  is found by the relation:

$$E_b/N_0 = \sigma_s^2 / \sigma_n^2.$$

Thus, in all simulation scenarios and for each path component, the signal  $s_n(t)$  at the input of the digital receiver can be formulated as

$$s_n(t) = \sigma_n N(0,1) + s(t),$$

where  $N(0,1)$  is a normal probability distribution.

### 3 Neural Network-based Receiver

The NN-based implementation of the proposed digital receiver is realized in the form of a multilayer perception (MLP) [4], which is trained by a modification of the classical backpropagation (BP) learning algorithm. The MLP generally consists of an input layer, one or more layers of hidden neurons

and an output layer of neurons. This kind of a structure is illustrated in Fig. 2, for the case of  $N$  inputs, one hidden layer with  $L$  neurons and  $M$  output neurons. Thus, the MLP's topology is specified by the notation  $N$ - $L$ - $M$ , where:

$N = N_b \cdot m_s$  (as mentioned in Section 2),

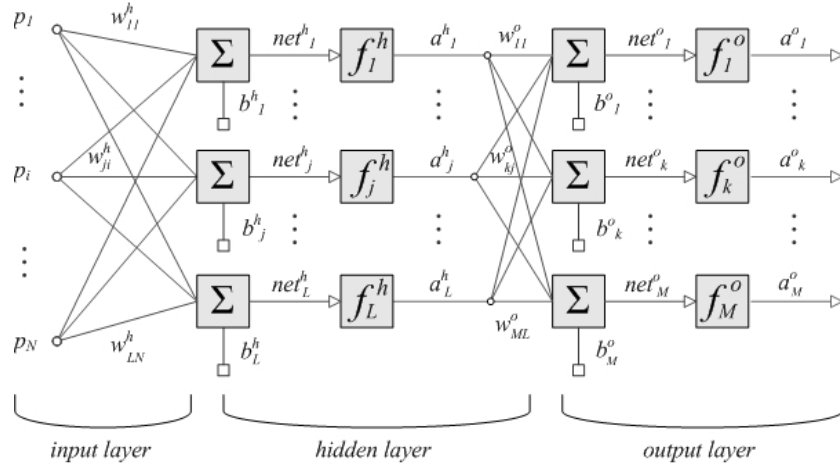
$L = 23$  or  $33$  (as in simulation results of section 4),

$M = m_s$ ,

in our NN-based communication receiver. Moreover the neuron model consists of a linear combiner followed by a nonlinear activation function, such as the sigmoid function:

$$f(\text{net}) = 1 / (1 + e^{-\text{net}}),$$

which is employed here for both the hidden and the output layer neurons.



**Figure 2.** NN receiver architecture.

The BP learning algorithm is a widely used technique for training multilayer neural networks in a supervised manner and is based on an error-correction learning rule. It consists of two passes through the different layers of the network: a forward pass (where an activity pattern is applied to the input layer, an actual response at the output layer of the network is produced and all the synaptic weights  $\bar{w}$  of Fig. 2 are fixed) and a backward pass (where all the synaptic weights  $\bar{w}$  of Fig. 2 are adjusted in accordance with the error-correction rule). The aforementioned weight adjustment may be made according to various approaches in order to minimize the error (i.e. the difference between the desired and the actual response). The adopted approach takes into account the presence of local minima on the error surface of the BP algorithm (as it can cause lock-up to non-optimal solutions), as well as the need for fast convergence of the BP

algorithm. Thus, the weight adjustment process employed in this paper follows the classical BP with gradient descent enhanced with a momentum and a variable learning rate [5]. Therefore, the new weight vector  $\bar{w}(t+1)$  for both hidden and output layers is defined as:

$$\bar{w}(t+1) = \bar{w}(t) - \text{lr}(t+1) \cdot \bar{g}(t+1) + \mu \cdot \bar{w}(t-1),$$

where  $\text{lr}$  denotes the learning rate parameter,  $\bar{g}$  the gradient of the error with respect to the weight vector and  $\mu$  the momentum constant. Furthermore:

$$\text{lr}(t+1) = \beta \cdot \text{lr}(t),$$

$$\beta = \begin{cases} 0.7; & \text{if (new error)} > 1.04 \cdot (\text{old error}) \\ 1.05; & \text{if (new error)} < 1.04 \cdot (\text{old error}) \end{cases}$$

In general, the learning rate parameter  $\text{lr}$  is used to determine how fast the BP learning algorithm converges to the optimum solution. The larger the learning rate, the bigger the step and the faster the convergence. However, if the learning rate is made

too large the algorithm will become unstable. On the other hand, if the learning rate is set to be too small, the algorithm will take a long time to converge. Thus, our approach is to utilize a larger learning rate when the error is far from being minimized and a smaller learning rate when the error is near from being minimized, in order to speed up the convergence time. Furthermore, the introduction of the momentum constant  $\mu$  allows the neural network to ignore small features in the error surface.

As for the error itself, we strive for the minimization of the mean square error (MSE). In particular, for each activity pattern  $P_\kappa$  during the training of the NN-based receiver, MSE is given by

$$\text{MSE}_{P_\kappa} = \frac{1}{2} \sum_{\kappa=1}^M (d_{P_\kappa} - a_{P_\kappa})^2,$$

where  $d_{P_\kappa}$  and  $a_{P_\kappa}$  are the desired and actual responses for the pattern  $P_\kappa$  under consideration. Therefore, if  $N_p$  is the total number of activity patterns, the overall MSE to be minimized is given by

$$\text{MSE} = \sum_{i=1}^{N_p} \text{MSE}_{P_i}.$$

The whole training process described in this section as well as the MLP architecture of Fig. 2, lead to the following set of equations for the hidden layer's neurons of the NN receiver:

$$a_j = f_j(\text{net}_j), \quad \text{net}_j = \sum_{i=1}^N w_{ij} p_i + b_j; \quad j = 1, 2, \dots, L,$$

where  $w_{ij}$  is the weight strength between the  $j$ -th hidden layer's neuron and the  $i$ -th input  $p_i$ , and  $b_j$  is the bias of the  $j$ -th hidden layer's neuron. In a similar way, the output  $a_\kappa$  of each neuron of the output layer, is given by the equations:

$$a_\kappa = f_\kappa(\text{net}_\kappa), \quad \text{net}_\kappa = \sum_{j=1}^L w_{j\kappa} a_j + b_\kappa; \quad \kappa = 1, \dots, M,$$

where  $w_{j\kappa}$  is the weight strength between the  $\kappa$ -th output and the  $j$ -th hidden layer's neuron, and  $b_\kappa$  is the bias of the  $\kappa$ -th output layer neuron. Thus, the decision of which symbol was transmitted (for a sequence of  $m_s = M$  symbols) is based upon the output  $a_\kappa$ . It should, also, be mentioned that the training of our NN-based receiver is carried out with initial weight values following a uniform

probability distribution of zero mean in range  $[-0.5, 0.5]$ , while the initial bias and learning rate values are set to 1 and 0.2, respectively.

## 4 Simulation Results

The training of a given neural network and the simulation determining its performance are computationally intensive and time-consuming.

**Table 1.** Training process details of the NN-receiver

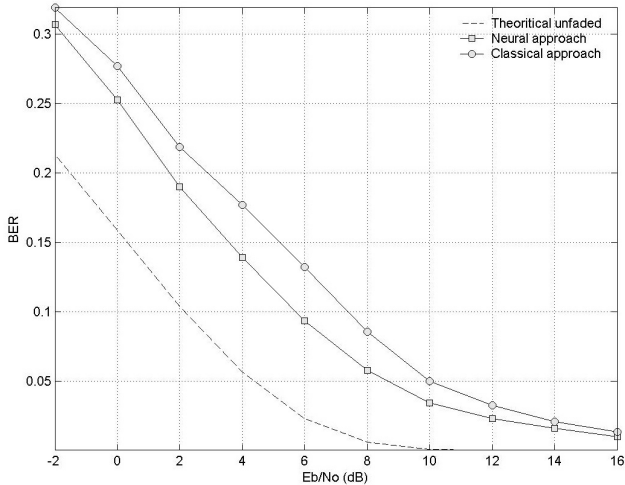
Parameter	Modulation Method			
	ASK	FSK	PSK	QPSK
NN-receiver topology	132-23-4	132-23-4	132-23-4	132-33-4
$m_s$	4,000	4,000	4,000	4,000
$m_v$	1,000	1,000	1,000	1,000
$E_b/N_o$ (dB) for training	0, 4, 8, 12, 16	0, 4, 8, 12, 16	0, 4, 8, 12, 16	0, 4, 8, 12, 16
Training patterns	25,000	25,000	25,000	25,000
Simulation time (sec)	85	71	76	163
$\text{MSE}_t$	0.0455	0.0401	0.0157	0.0375
$\text{MSE}_v$	0.0611	0.0474	0.0226	0.0537
Epochs' number	59	53	53	63

Therefore, in order to study the performance of the proposed NN receiver and to get a reliable BER calculation for each modulation method under examination, we consider the following:

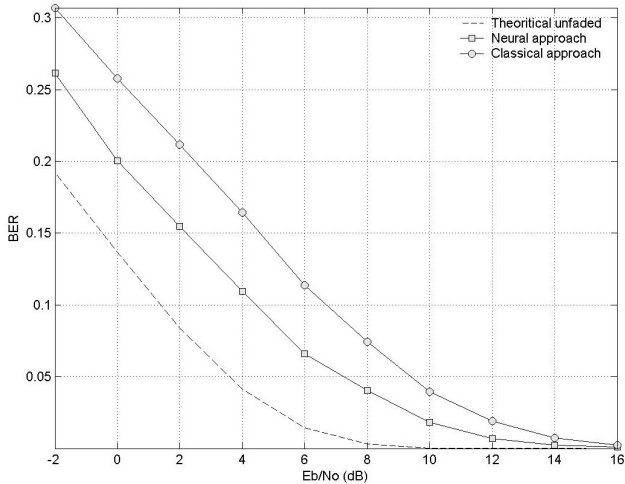
- Batch training mode: Due to the fact that our NN receiver's task is to minimize the MSE over the entire training set of  $N_p$  patterns, a single MSE is calculated and the network is updated once, according to that MSE after the completion of one epoch. Thus, batch mode is consequently faster requiring less weight updates, and also provides a more accurate measurement of the required weight changes. Actually, batch training mode refers only to the weight adjustments, as the errors must be back-propagated for every training pattern of a total of  $N_p = 5m_s$  (to account for five different values of  $E_b/N_o$  and the number  $m_s$  of modulated signals used for training).
- Concurrent training and validation: An additional smaller set of  $m_v$  patterns is used for validation

purposes and serves as an online measure indicating that the training of our receiver should stop. Thus, the training process stops when the MSE corresponding to the validation set ( $MSE_v$ ) begins to increase, in order to avoid overtraining.

- Testing of the NN and CR receivers is accomplished by averaging the BER values after four simulation runs. During each simulation run, a set of 400 testing patterns for various  $E_b/N_0$  values for each modulation method is used.



**Figure 3.** Performance comparison for ASK modulation (two-path Rayleigh simulation case).

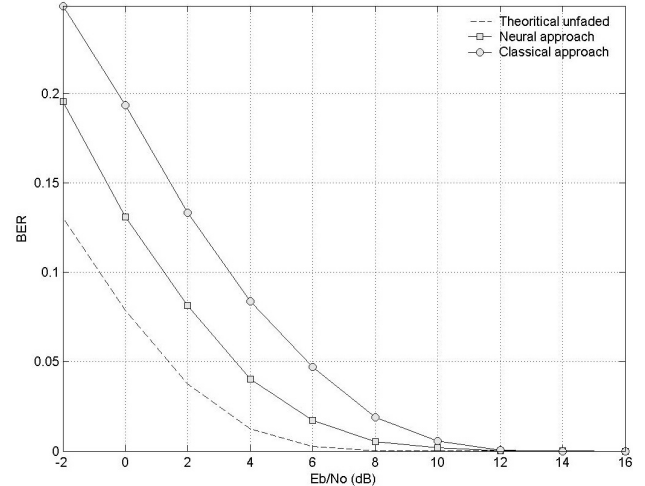


**Figure 4.** Performance comparison for FSK modulation (two-path Rayleigh simulation case).

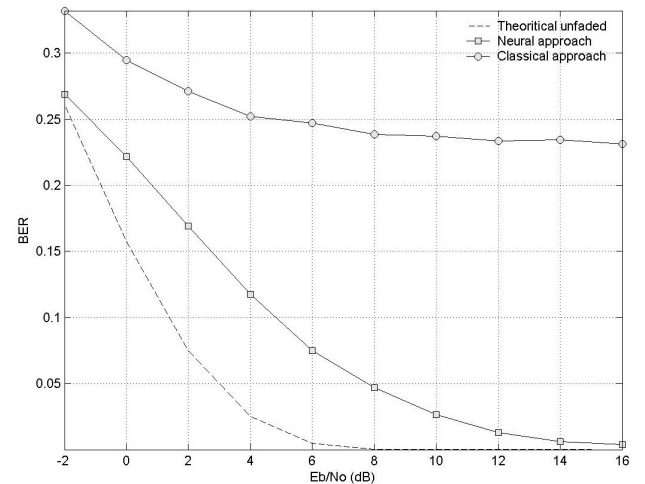
Several details about the training process are summarized in Table 1 for each modulation method in case of a two-path Rayleigh fading channel.

Actually, the proposed NN-receiver revealed a clear performance advantage over the classical CR-receiver in the Rayleigh-2 simulation case (as

shown in Figs. 3-6, where simulation results in case of fading absence are also included). Furthermore, as shown in Fig.7, the NN-receiver presents a smaller BER in the Rice simulation case for  $E_b/N_0$  values ranging between 0–11 dB, only if ASK modulation is employed. Finally, as the LOS and one-path Rayleigh simulation cases are concerned, the NN-receiver achieves a comparable to the CR-receiver performance.



**Figure 5.** Performance comparison for PSK modulation (two-path Rayleigh simulation case).

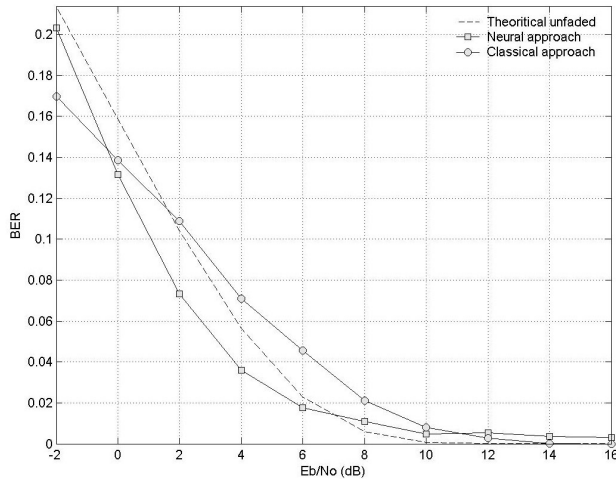


**Figure 6.** Performance comparison for QPSK modulation (two-path Rayleigh simulation case).

## 5 Conclusions and Further Work

The simulation results presented in Section 4 show that for the  $E_b/N_0$  values used, the NN-based receiver offers a better performance in comparison to that of the classical approach of a CR-receiver.

This improved performance holds in case of a two-path Rayleigh communication channel with AWGN and for all examined modulation schemes (ASK, FSK, PSK, QPSK).



**Figure 7.** Performance comparison for ASK modulation (Rice simulation case).

Furthermore, additional advantages of our digital receiver include the elimination of need for a supervisory signal to probe the radio channel and for carrier recovery (as in the case of the coherent CR).

As the NN-receiver's training is concerned, we should mention two issues for further examination [6]. The first issue is the use of continuous learning process, because this is the preferred way of learning, i.e. the receiver architecture's parameters are adjusted continuously while detection is performed at the same time. Hence, the learning process never stops and the digital receiver has a built-in capability to track statistical variations of the communications environment. The second issue is about the criterion for optimizing the design of the receiver. Although for mathematical tractability we strived for the MSE minimization, such an approach does not guarantee BER minimization, which is of primary concern for a digital communication's system performance.

In general, as many communication channels are inherently nonstationary of unknown statistics, our NN-based approach should incorporate a greater degree of adaptability to the receiver design. In particular, to deal with a nonstationary process using neural networks: the implicit effect of time has to be distributed inside the synaptic structure of the NN as described in [7], or a recurrent NN has to carry out

the learning process in a dynamic way [8], or the approach described in [9] (where three functional blocks for time–frequency analysis, feature extraction and pattern classification are involved in receiver design) has to be followed.

## Acknowledgment

This work was supported by the Greek Ministry of National Education and Religious Affairs and the European Union under the EΠΕΑΕΚ II project “Archimedes – Support of Research Groups in TEI of Crete – Smart antenna study & design using techniques of computational electromagnetics and pilot development & operation of a digital audio broadcasting station at Chania (SMART-DAB)”.

## References

- [1] S. Haykin and T.K. Bhattacharya, “Modular learning strategy for signal detection in a nonstationary environment”, *IEEE Transactions on Signal Processing*, vol. 45, iss. 6, pp. 1619-1637, June 1997.
- [2] S. Haykin and D.J. Thomson, “Signal detection in a nonstationary environment reformulated as an adaptive pattern classification problem”, *Proceedings of the IEEE*, vol. 86, iss. 11, pp. 2325-2344, Nov. 1998.
- [3] R.E. Blahut, *Digital Transmission of Information*, Addison-Wesley, New York, 1990.
- [4] J.W. Watterson, “An optimum multilayer perceptron neural receiver for signal detection”, *IEEE Transactions on Neural Networks*, vol. 1, iss. 4, pp. 298-300, Dec. 1990.
- [5] M.T. Hagan, H.B. Demuth, and M.H. Beale, *Neural Network Design*, PWS Publishing, 1996.
- [6] S. Haykin, “Adaptive digital communication receivers”, *IEEE Communications Magazine*, vol. 38, iss. 12, pp. 106 – 114, Dec. 2000.
- [7] E. Wan, “Temporal backpropagation for FIR neural networks”, *Proc. IEEE Int. Joint Conf. Neural Networks*, vol. 1, pp. 575-580, 1990.
- [8] L.A. Feldkamp, G.V. Puskorius, and P.C. Moore, “Adaptive behaviour for fixed weight networks”, *Information Science*, vol. 98, pp. 217-235, 1997.
- [9] S. Haykin, J. Nie, and B. Currie, “Neural network-based receiver for wireless communications”, *Electronics Letters*, vol. 35, iss. 3, pp. 203-205, Feb. 1999.