IMPROVING RECEIVED SIGNAL IN WIRELESS COMMUNICATION SYSTEMS USING EQUALIZATION TECHNIQUE WITH NEURO FILTER

Dr. Ghaidaa. K. Salih
University of Technology
Branch of Electromechanical Engineering

Abstract:

The aim of this paper is to improve the wireless communication quality by damping or removing the inter-symbol interference (ISI) phenomena in these systems. ISI imposed the main obstacles to achieve increased digital transmission rates with required accuracy. Adaptive equalization technique with least mean square algorithm (LMS) is used to reduce or suppress the unwanted signals in communication channels and combat the resulting ISI effect. Finite impulse response (FIR) filter is used as another technique incorporated with LMS algorithm and zero tap detection technique (Zero tap) to enhance the quality of the communication systems . These techniques were used to suppress echoes that arise from non-line-of-sight (NLOS) components in these wireless communication systems. This paper proposed a new model to aid the work of adaptive equalizer using Modified Elman Neural Network (MENN) as a neuro filter with the presence of ISI and Additive White Gaussian Noise (AWGN) .This neuro filter provides the basic approach to acquire signals as input data to the system from noisy signals .The scheme of proposed system in this paper can perform successful tracking without knowing prior knowledge of the signals. Simulations demonstrate the capability of proposed model to generate considerably smoother receiver in the systems that used only adaptive equalizer.

Key Words: Channel equalizer, Adaptive equalizer, Artificial neural network, Noise cancelation, Inter-symbol interference, Least Mean Square algorithm, Zero taps detection technique.

تحسين الإشارة المستلمة في أنظمة الاتصالات اللاسلكية باستخدام تقنية الموازنة مع مرشح عصبي

د.غيداء كائن صالح
الجامعة التكنولوجية/ قسم هندسة الكهروميكانيك

المستخلص :
أن الهدف من هذا البحث هو تحسين نوعية الاتصال اللاسلكي باخماد او ازالة التداخل الناجم عن ظاهرة ISI في هذه الانظمة.ان ظاهرة ISI تمثل العقبات الرئيسية لإنجاز نسب الإرسال الرقمية المتزايدة بالدقة المطلوبة. استخدمت تقنية الموازنة المتكيفة مع خوارزمية معدل التربيع الاقل (LMS) لتقليل او فصل الاشارات غير المرغوب بها في قنوات الاتصال ودحظ تاثير ISI المتبقي .استخدم مرشح نوع FIR كتقنية اخرى مجتمعة مع خوارزمية LMS وتقنية التحري Zero tap من اجل تحسين نوعية انظمة الاتصال ،هذه التقنيات استخدمت لاخماد الصدى المتولد من مركبات NLOS (non-line –of –sight) في انظمة الاتصالات اللاسلكية . اقترح هذا البحث انموذجاً جديداً يساند عمل الموازن المكيف باستخدام شبكة ايلمان العصبية الاصطناعية المعدلة (MENN) كمرشح عصبي بوجود ISI وضوضاء الاشارة البيضاء (AWGN) . يزود هذا المرشح العصبي القاعدة الاساسية لاستحصال الاشارات كبيانات ادخال الى النظام من الاشارات المشوشة . مخطط النظام المقترح في هذا البحث يمكن له ان يؤدي الى تتبع ناجح للبيانات دون معرفة مسبقة بالاشارات الداخلة للنظام . تعرض المحاكاة قابلية الانموذج المقترح لتوليد مستلم أنعم إلى حدّ كبير في الأنظمة التي تعمل فقط بتقنية الموازنة المتكيفة مع النظام .

1. Introduction

In any communication system, the signal which transmitted over a wireless channel always smeared out over time causing Inter-symbol Interference phenomena (ISI). [1]
To reduce or remove the effect of this phenomenon in receivers, an equalizer technique is used so recently wireless communication systems used a control system to maintain all mobile users' signal received at the base station nearly equal and retrieve the original signal at the receiver side with small possible error of delayed and perhaps distorted version of a previously transmitted signal. [2]
Artificial Neural Network (ANN) have been successful to prediction of chaotic data because it has the ability to train and leavened the

internal dynamical characteristics which govern data with a good characteristic. [3]
So the ability of neural network of large scale computing and its intelligent to recognized complex data with noisy features helps to controlled data by the base station. The Elman neural network (ENN) is one kind of it. [4, 5]
Needing for channel equalizers arises from the fact of interference between transmitted signals with one another with respect to the transfer function of the channel. This transfer function is varying with time in wireless communications so it is not possible to use an optimum filter for these types of channels. In order to solve this problem an equalizer is designed. Equalizer is meant to work in such a way that Bit Error Rate (BER) should be low and Signal-to-Noise Ratio (SNR) should be high. An adaptive equalizer is an equalization filter that automatically adapts to time-varying properties of the communication channel. It is a filter that self-adjusts its transfer function according to an optimizing algorithm that supporting with neural network as controller system. [6]
The LMS is introduced as a way to recursively adjust the parameters weight w(n) of a linear filter with the goal of minimizing the error between a given desired signal and the output of the linear filter. LMS is one of the many related algorithms appropriated for the task. [5]

2. Equalization Technique:

Communication channels such as telephone, wireless and optical channels are susceptible to ISI. Without channel equalization, the utilization of the channel bandwidth becomes inefficient. Channel equalization is a process of compensating for the effects caused by band-limited channel. These disruptive effects are due to the dispersive transmission medium and the multipath effects in the radio channel. Most of the equalization applications today employ equalizers that operate symbol-by symbol. Symbol decision equalizers can be further qualified into two categories namely, the direct-modeling equalizers in which the channel model is identified explicitly, and the indirect-modeling equalizers which recover the transmitted symbols by directly filtering the channel observations, usually using the Linear Transversal Equalizer (LTE) (also known as the Finite Impulse Response filter FIR), without estimating a channel

model explicitly. The indirect-modeling approach is by far most widely used and it is considered in the present study in the context of channel interference. A typical communication system is depicted in figure (1) where the equalizer is incorporated within the receiver while the channel introduces intersymbol interference. The transfer function of the equalizer is an estimate of the direct inverse of the channel transfer function. To transmit high-speed data over a band limited channel, the frequency response of the channel is usually not known with sufficient precision to design an optimum match filter. The equalizer is, therefore, designed to be adaptive to the channel variation. The configuration of an adaptive equalizer is depicted in figure (2). That based on the observed channel output, an adaptive algorithm recursively updates the equalizer to reconstruct the output signal. In figure (1) the x(n) is a data passed over the channel, k(n) is sampled additive white Gaussian noise (AWGN) and y⁻⁻(n) is the final channel output. [7, 8]

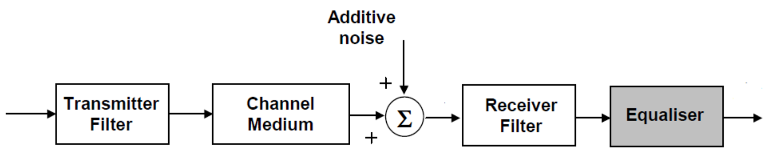

Fig (1): A Baseband Communication System [7]

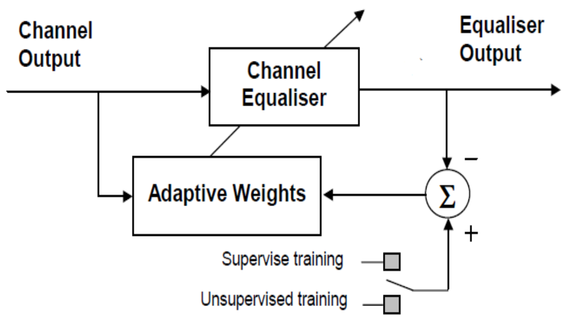

Fig (2): A Simple Channel Equalizer configuration [7]

There are two modes of equalization, supervised and unsupervised training. Supervised training employs a training sequence from a pre-stored sequence inside the receiver or embedded in the transmitted sequence. Unsupervised training, also called decision-directed equalization, employs a decision device to return the noisy estimated symbols to the actual symbols to be used to train the equalizer. Basically there are two types of equalizer structure, linear and non-linear. Decision feedback equalizers and transversal equalizers are considered linear because the internal structure is a linear combiner. While non-linear equalization is important in providing optimum performance for ill-conditioned channels that non-linear techniques require more computation and controls. ISI occurs when the symbol rate is higher than the channel bandwidth and this is driven by the bandwidth utilization efficiency in order to achieve higher data rate. When the signals are transmitted over a telephone channel, both time dispersion and additive noise is introduced. The channel response will be spread over many symbol intervals, thus causing ISI. [9]

2.1 Linear Transversal Equalizer:

A linear transversal equalizer (LTE) is shown in Figure (3). The equalizer output y(n) is the sum of weighted tap-delay inputs x(n). The equalizer can be viewed as performing an approximate inverse on a channel to balance the channel responses.

Considering the inverse of the minimum phase channel is:

$$H^{-1}(z) = 1 + 0.5^{z-1} \qquad \text{...(1)}$$

$$H(z) = c_0 + c_1 z^{-1} + c_2 z^{-2} + c_3 z^{-3} + \qquad \text{………………………..….(2)}$$

The direct inversion of equation (2) is an impractical solution because the channel is at least slow time varying and hence direct inversion will cause higher error. Instead, an adaptive equalization is required to track the time varying channel. For the transversal equalizer, its tap-delayed weights are represented by a truncation of the significant coefficients in equation (2). The resulting adaptive equalizer will then have the structure shown in figure (2). Based on the mean square error criteria, the transversal equalizer weights can be recursively estimated by an adaptive algorithm, such as the LMS algorithm, as follows:

$$W(n+1) = W(n) + e(n)X(n) \qquad \text{...(3)}$$

Where $e(n) = d(n) - y(n)$ and $X(n) = [x(n), x(n-1), \ldots, x(n-N-1))]^T$, $d(n)$ is the training signal and $W(n) = [w_0(n), w_1(n), \ldots, w_{N-1}(n)]^T$. As each weight dimension is added ,the equalization accuracy will be improved. However, higher dimensions leave the equalizer susceptible to noisy samples and it will take a long time to converge. The length of the equalizer should be in the range of $2L \le N \le 5L$ that the equalizer tap delay length (N) should be at least two times the channel delay time (L) to capture the channel response.[9]

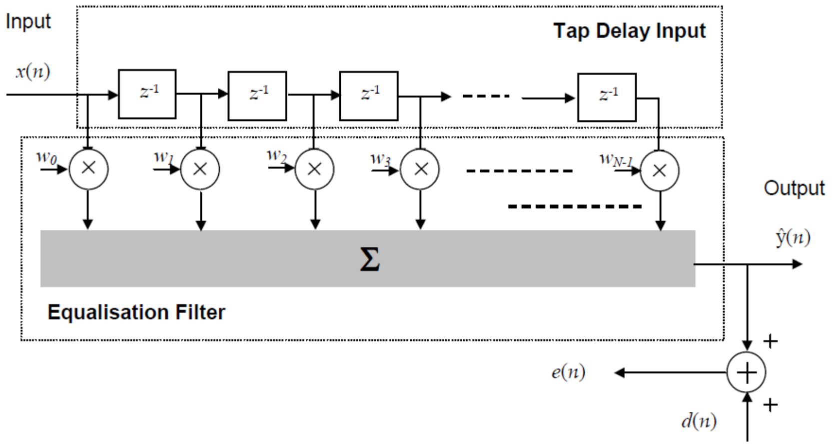

Fig (3): Transversal Linear Equalizer[9]

2.2 Decision Feedback Equalizer:

A basic structure of the decision feedback equalizer (DFE) is shown in Figure (4). The DFE consists of a transversal feed forward and feedback filter. In the case when the communication channel causes severe ISI distortion the LTE could not be provide satisfactory performance. Instead, a DFE is required. The DFE uses past corrected samples, $\bar{u}(n)$, from a decision device to the feedback filter and combines with the feed forward filter. The function of the feedback filter is to subtract the ISI produced by previously detected symbols from the estimates of future samples. Considering that the DFE is updated with a recursive algorithm; the feed forward filter weights and feedback filter weights can be jointly adapted by the

LMS algorithm on a common error signal $\hat{e}(n)$ as shown in equation (4).

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \mu\, \hat{e}(n)\bar{V}(n) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where $\hat{e}(n) = \bar{u}(n) - \hat{y}(n)$ and $\bar{V}(n) = [x(n), x(n-1), \ldots, x(n-k1-1), \bar{u}(n-k2-1), \ldots \bar{u}(n)]^T$. The feed forward and feedback filter weight vectors are written in a joint vector as:
$\mathbf{W}(n) = [w0(n), w1(n), \ldots, wk1+k2-1(n)]^T$. $k1$ and $k2$ represent the feed forward and feedback filter tap lengths respectively. Suppose that the decision device causes an error in estimating the symbol $\bar{u}(n)$. This error can propagate into subsequent symbols until the future input samples compensate for the error. This is called the error propagation which will cause a burst of errors. The detrimental potential of error propagation is the most serious drawback for decision feedback equalization. Traditionally, the DFE is described as being a non-linear equalizer because the decision device is non-linear. However, the DFE structure is still a linear combiner and the adaptation loop is also linear. It has therefore been described as a linear equalizer structure. [10, 11]

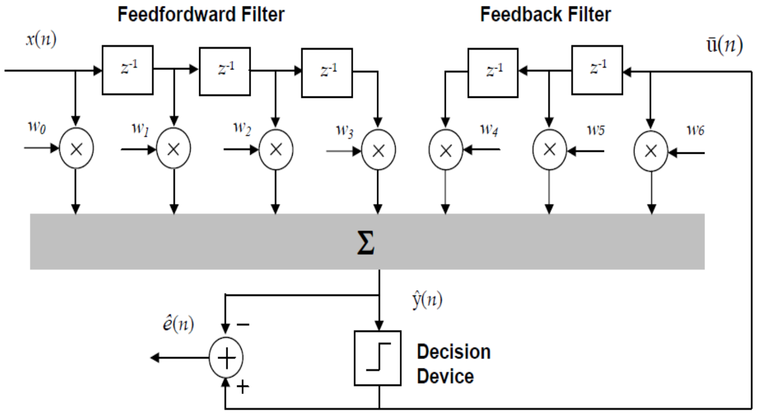

Fig (4): Decision Feedback Equalizer [10]

3:Elman Neural Network:

Reliable data transmission simple and effective interference suppression techniques needing to enhance the work of adaptive equalizers to mitigate the interference for a high-quality signal reception effects. Artificial neural networks notably Elman neural network (ENN) as one type of it, act as a control system aided the work of adaptive equalizers. Elman neural network represents as one globally feed forward locally recurrent network model .It has a set of context nodes to store the internal states. Thus, it has certain dynamic characteristics over static neural networks, such as multilayer perceptron and radial-basis function networks. The structure of the ENN is illustrated in figure (5). It is easy to find that the ENN mainly consists of four layers: input layer, hidden layer, context layer, and output layer. [12]

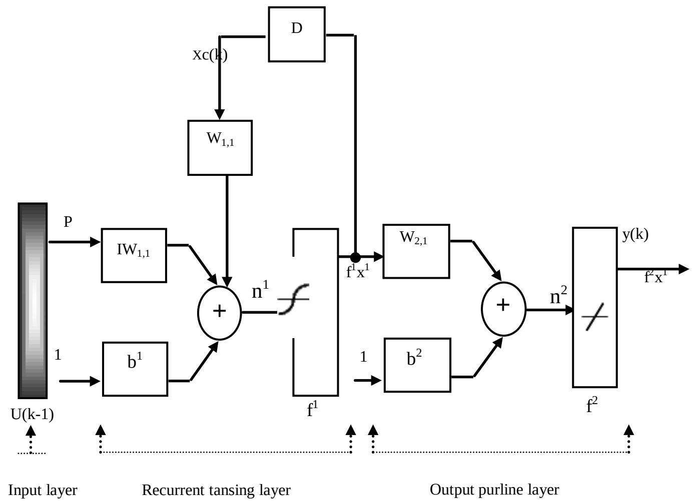

Fig (5): The Main Topology of Elman Neural Network [12]

The connecting layer is used to memorize the output of the hidden layer unit .This connecting can be regarded as one-step time delay operator. It can be considered as especial type of feed forward neural network with additional memory neurons and local feedback. The

context nodes make ENN sensitive to the history of input data, which is essentially useful in dynamic modeling. [3]
Suppose there are M,N,L, the number of the node in the input, output and hidden layers respectively ($w_{1i,j}$) is the weight that connects node (i) in the input layer to node (j) in the hidden layer while the weight that connects node i in the hidden layer to node j in the output layer $w^3_{i,j}$ is the weight in the connected context node i to node j in the hidden layer u(k-1) represents the outputs of the neural network ,$x_j(k)$ represents the outputs of the connecting layer, and $y_j(k)$ represents the outputs of neural networks.[13]
Then:

$$x(k) = f(w^2_{i,j} x_c(k) + w^1_{i,j} u(k-1)) \quad \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$x_c(k) = x(k-1) \quad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

$$y(k) = g(\ w^3_{i,j} x(k)) \quad \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

In which f represents the transfer function of hidden layer. S type function is commonly used and can be defined as :

$$f(x) = (1 + e^{-x})^1 \quad \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

g is the transfer function of the output target and it is usually a linear function of the output layer and it is usually a linear function, z^{-1} is a unit delay .
i=1,2,………M and j=1,2,………..N
The weight of ENN can be written as in equation (9):

$$E = \sum_{k=1}^{m} (t_k - y_k)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots(9)$$

In which t_k are the output vectors of the object. [13]

4: System Model:

Although the Elman neural network has found in various applications and time series prediction, its training and converge speed are usually very slow and not suitable for time critical applications, such as on-line system identification and adaptive control. To over come this difficulty our paper used modified Elman neural network (MENN) which is applied successfully to dynamical system identification. [14]
MENN is proposed by adding new adjustable weights that connect the context nodes with output nodes as in block diagram of figure (6). Figure (7) shoes the main structure of MENN that have two loops,

one is a feed-forward loop and the other is a feedback loop. The feed forward loop of this network consists of input layer, hidden layer, context layer and output layer. The feedback loop consists of context layer and hidden layer. Different from feed-forward neural networks which only utilize static mappings, the MENN can be regarded as a dynamic system itself.

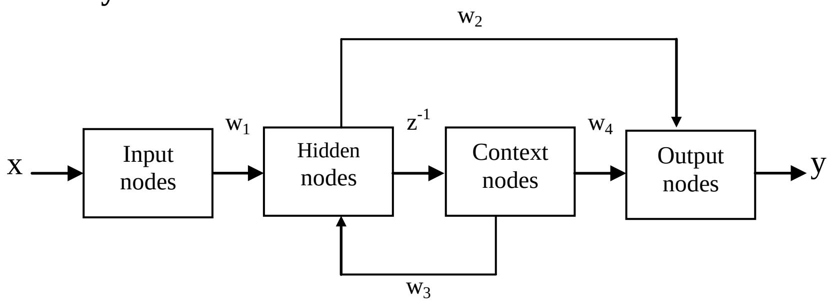

Fig (6): Block diagram of the modified Elman neural network [14]

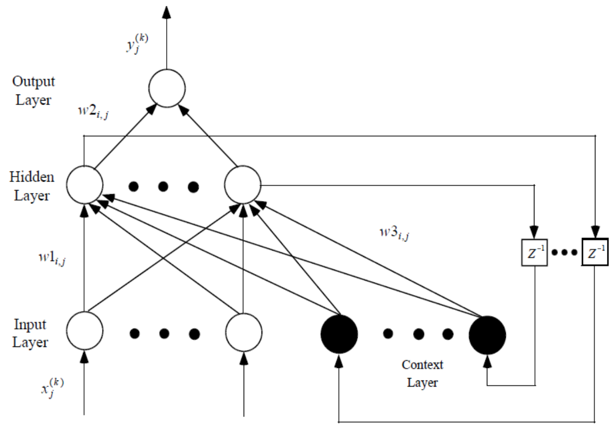

Fig (7): The Basic Structure of Modified Elman neural network [12]

MENN distinguished an approximation and generalization capability that is suited to be utilized as a filter added to work of equalization filter which operates symbol-by symbol. The structure will enhance equalization work and give a system the fast convergence speed and dynamical characteristics (due to the fact that each training epoch uses w_4, the learning speed of MENN can be improved.[14]) as shown in figure (8).

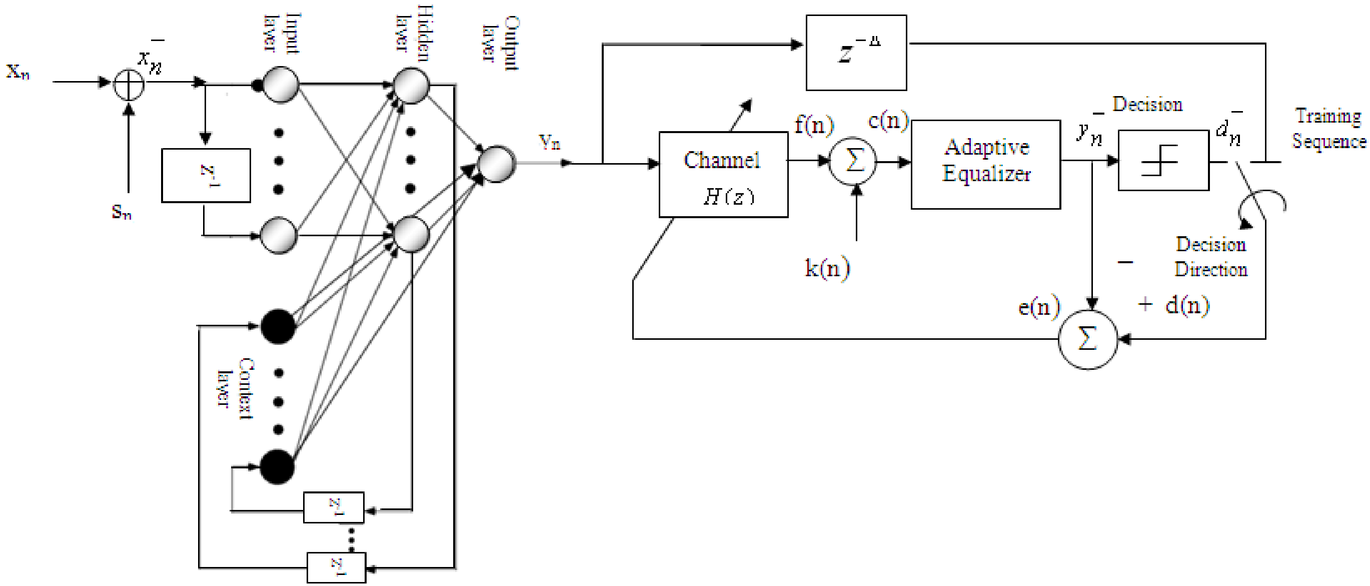

Fig (8): Neuro filter with adaptive equalizer used in proposed model

The training data for the neuro filter consists of (x_n) as the input signals passed over the ISI channel. The objective of neural network is to filter the measurement signal from noisy signal so, (x_n) corrupted by the external noise (S_n) and (y_n) as the neuro filter output that represent the transmitted data (which is known during the training phase). ($z^{-\Delta}$) is a delay function of the delayed version to the same signal that transmit to the adaptive filter and $d(n)$ is the delayed signal. $\bar{y}_{(n)}$ is the output signal from the adaptive filter and e(n) is the error signal between $d(n)$ and $\bar{y}_{(n)}$. The adaptive filter iteratively adjusts the coefficients to minimize $e(n)$ .After the power of e(n) converges, $\bar{y}_{(n)}$ is almost identical to $d(n)$,which means the resulting adaptive filter coefficients to compensate for the signal distortion. During the adaptation of the neural network, it will gradually learn to reduce the measurement noise of ISI. During the adaptation of the neural network, it will gradually learn to reduce the measurement noise s_n, and recover the primary signals x_n.The training procedure stops when an acceptable error level between the output of the neural network and the reference output is reached.

$$\bar{x}_n = x_n + s_n \qquad \text{.......................................(10)}$$

The objective of MENN is improving the input data x_n and filter the measurement noise signals that affected by ISI phenomena then send its output signals to the equalizer which is simultaneously filters the noise remaining in its work. Channel modeled by Finite Impulse Response (FIR) filters as FIR filter with frequency response H (z) as :

$$H(z) = \sum_{m=1}^{N} h_m z^{-m} \qquad \text{..(11)}$$

The impulse response of the channel equalizer combination is as close to ($z^{-\Delta}$) as possible, where (Δ) is a delay and c(n) is the distorted output signal which is corrupted by Additive White Gaussian Noise (AWGN) k(n) of zero mean and variance (σ_n^2).$y(n)$ assumed to be uncorrelated with k(n). The overall channel observation can thus be written as:. Adaptive channel equalization system decodes the signal in decision-directed phase.

In this phase, the adaptive channel equalization system decodes the signal and $\bar{y}_{(n)}$ produces a new signal, which is an estimation of the

signal *y*(*n*) except for a delay of *Δ* taps .the error signal of this phase can be calculated by:

$e(n) = d(n) - y^{-}(n)$ ……………………………..(12)

The LMS algorithm is used to adapted channel estimated because:

- **LMS tends to reject the noisy data due to the smoothing action of the small step size parameter.**
- **LMS can track slowly varying systems, and is often useful in non-stationary environments.**
- **LMS error function has a unique global minimum, and hence the algorithm does not tend to get stuck at undesirable local minima.**
- **LMS is computationally simple (m multiplications and m additions per iteration) and memory efficient . (Only one m-vector must be stored).**
- **LMS convergence is often slow (it may take hundreds or thousands of iterations to converge from an arbitrary initialization). [15]**

LMS search iteration operates in filter output :

$y^{-}(n) = w.y(n)$ …………………………….(13)

Were $w(n)$ **is the filter weight &** $y^{-}(n)$ **is the filter output.**

Error estimated as in eq.(12)

Tap weight adaptation is:

$w(n+1) = w(n) + e(n)\mu.\, x(n)$ …………………………….(14)

Were $w(n+1)$ **is the update weight, (μ) is the step size.**

(*n* +1) = estimate of tape weight vector at time (*n* +1) and if prior knowledge of the tape weight vector (*n*) is not available, set (*n*) = 0

$f(n) = y(n) * H(z)$ ……………………………….(15)

$c(n) = f(n) + k(n)$ ……………………………….(16)

$\delta s^2 = E(f^2(n))$ **&** $\delta c^2 = E(c^2(n))$ **where E[.] is the expectation operator**

The Signal to Noise Ratio (SNR) given by:

$SNR = \delta s^2 / \delta n^2$ …………………………….(17)

The Signal to Interference Ratio (SIR) defined as:

$SNR = \delta s^2 / \delta c^2$

And finally the Signal to Interference to Noise Ratio (SINR) given by:

$SINR = \delta s^2 /(\delta n^2 + \delta c^2)$ ……………………………….(18)

In order to ensure good asymptotic performance, the length of the LMS adaptive FIR filter must be sufficient to cover the impulse response of the unknown channel however; this may lead to increased computational complexity when the impulse response of the unknown channel is 'long'. The computational complexity becomes excessive because it consists of many" inactive" or zero regions interspersed by active regions. In the effort to reduce the complexity, the inclusions of detection technique in the adaptation algorithm will be adopted. This enables the echo canceller to effectively estimate only the taps in the active regions of the echo path impulse response. By applying this technique, computational efficiency as well as the asymptotic performance can be expected to improve. The 'active' taps of a time - invariant channel with the white input signals can be detected by formula: [16]

$$C_k(s) = \frac{\sum_{i=1}^{s}(v_i u_{i-k+1})^2}{\sum_{i=1}^{s}(u_{i-k+1})^2} \qquad \ldots\ldots(19)$$

Where $C_k(s)$ **indicates the activity measure of the k-tap in the FIR channel at time instant (s) or at s-th iteration.**

$$C_k(s) > \sigma_\upsilon(s)^2 \ln(s) \qquad \ldots\ldots (20)$$

Where $\sigma_\upsilon(s)^2$ **is the variance of v(i) which may be estimated by:**

$$\sigma_\upsilon(s)^2 = \frac{1}{s}\sum_{i=1}^{s} v(i)^2 \qquad \ldots\ldots (21)$$

With the activity measure and the active tap threshold, we can then determine whether the tap is active or inactive, then only those detected active taps are estimated via the LMS tap weight adaptation using the following logic:[17]

$$\textbf{\textit{If}}\ C_k(s) > \delta_v(s)^2 \ln(s)\ \textbf{\textit{then}}\ w(n+1) = w(n) + e(n)\mu.\,x(n) \qquad \ldots\ldots (22)$$

The accuracy of this criterion improves with increasing the number of input samples(s). A tap detected as inactive will be described and hence not included in the calculation of the channel estimates.

Therefore the activity measure is used to detect the position of the active taps in the channel while the LMS algorithm determines the strength of the active taps.

5. Simulation Results:

This section focuses on the results that obtained from Matlab simulations. Results are conducted for the incorporation standard LMS algorithm with zero tap detection for the proposed model shown in figure (8). In order to test the effectiveness of this model, we compare its performance with and with out the effect of MENN .All simulations are assumed to have a time invariant unknown communication channel by using two channels with (40) taps for each channel (channel model (1) has 5 active taps & 35 inactive taps, channel model (2) has 8 active taps & 32 inactive taps).Simulation results considered is based on the asymptotic performance and convergence speed. The LMS step-size was constant and a zero mean white Gaussian signal 0.01 respectively.

Figure (9) shows the simulation results of the proposed model of figure (8) without effect of MENN. The model works with asymptotic error of [(unknown channel-channel estimation) ^2] for two channel models. Before the convergence and in training sequence, the asymptotic error of the channel model (1) is 10^0 while the asymptotic error of the channel model (2) is 10^1. This is because the channel model (2) has more number of active taps that lead to increase asymptotic error but after convergence the two channel models have approximately the same asymptotic error is10^{-3} .

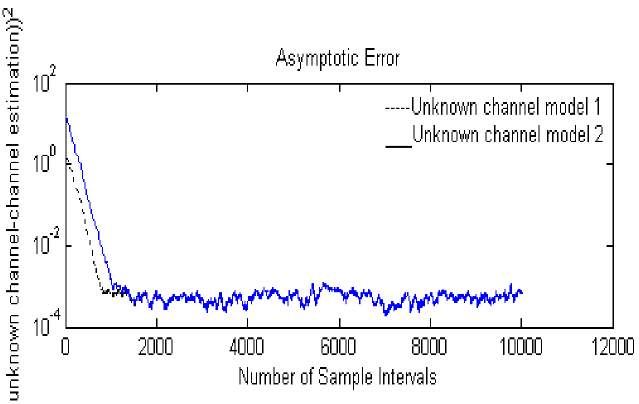

Fig (9): Asymptotic error

Figure (10) shows the asymptotic error of two channel models after convergences which have approximately same asymptotic error at 10^{-4}. This type of algorithm gives some improvement of the asymptotic performance than asymptotic error in normalized LMS

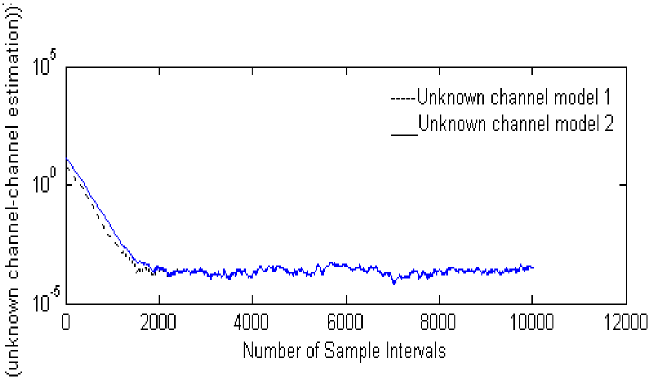

Fig (10): Asymptotic error in standard LMS

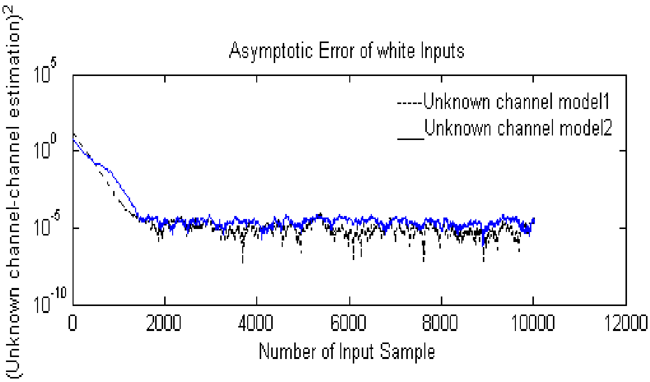

Fig (11): Asymptotic error with standard LMS and zero tap detection

Figure (12) shows the asymptotic performance of two channel models in the same model shown in figure (8) adding to it the effect of MENN. The simulation results show asymptotic error of channel model (1) is 10^{0} and asymptotic error of channel model (2) is 10^{1} (to the same reason of taps numbers that each channel have it) but after convergence the two channel models have approximately the same asymptotic error of 10^{-7}.This because the advantageous capabilities of MENN for learning from training data, recalling memorized information, and generalizing to the unseen patterns. These

capabilities do show great potential in such application areas of signal processing.

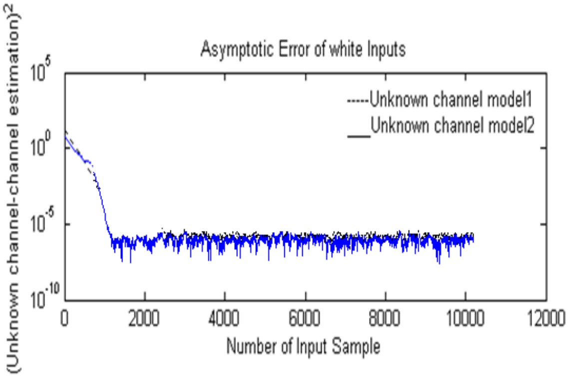

Fig: (12): Asymptotic error with effect of MENN

Figure (13) shows the asymptotic error of two channel models with the effect of MENN. It is clear that each channel models have approximately same asymptotic error at 10^{-8} after convergences. Compared with simulated results of figure (10) using MENN with this type of algorithm gives some improvement of the asymptotic performance than asymptotic error in normalized LMS.

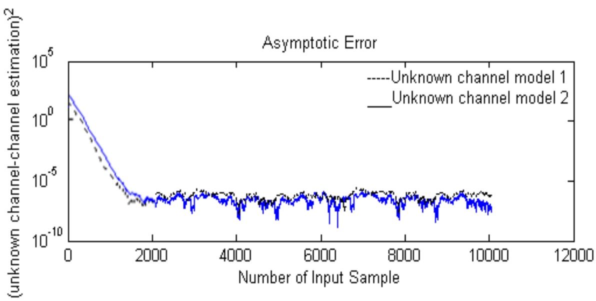

Fig (13): Asymptotic error in standard LMS with MENN

Figure (14) shows the improvement in the performance of proposed model after adding the effect of MENN with standard LMS algorithm and zero tap detection. The error is 10^{-9} of the two channel models in training sequence. MENN as a neuro filter of the model used offers better filtering performance for this specific simulated in the same model using standard and normalized LMS algorithm with out it because this technique reduce the required filter dimension that means reduce the computational complexity, which lead to improving the convergence rate and then improving asymptotic performance.

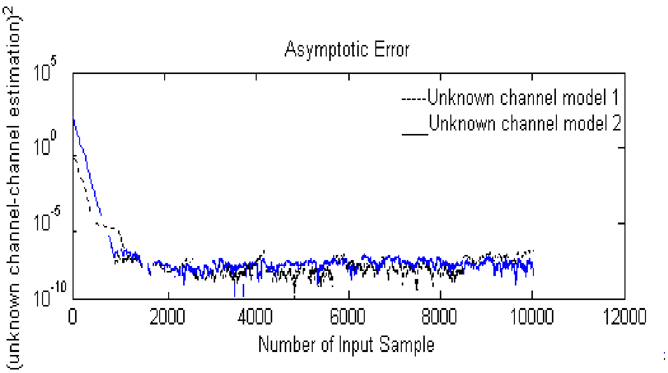

Fig (14): Asymptotic error using MENN effect with standard LMS and zero tap detection

6. Conclusions:

Adaptive filter with LMS algorithm is considered in this paper unlike most of the existing filters that capable of removing the channel distortion. The simulation results of proposed model of this paper show the performance of an adaptive filter is not dependent only on its internals structure, but also on the algorithm used to recursively updates the filter weights. Applied standard LMS algorithm with equalization of channels under white input signal conditions gives high asymptotic mean squared error and more computational burden while normalized LMS equalization of channels under white input signal conditions gives asymptotic error less than the standard LMS equalization of the channel. The LMS equalization of channels with zero tap detection technique used to reduce the computational burden due to the LMS estimation of long channels. It gives asymptotic error less than the normalized LMS equalization of channels. Artificial neural network gives the proposed model efficient in noise attenuation. The simulation results demonstrate the ability of artificial neural network to offer higher noise attenuation in the systems that work without the effect of artificial neural net. It is clear from the accuracy results that neural network can accurately predict signal processing if it given the proper data upon which to train.

References:

[1] Simon Haykin, "Communication Systems" John Wiley & Sons Inc, 2001

[2] M.G.Bellanger, "Adaptive digital Filters and Signal Analysis", Marcel Dekker,INC 1999

[3] Hech Neilson R., " Neuro Computing" Addison – Wesley Publishing Compancy 1998

[4] X. Z. Gao, X. M. Gao 1& S. J. Ovaska "A Modified Elman Neural Network Model with Application to Dynamical Systems Identification" 2 Dept of Control Engineering, Harbin Institute of Technology , 2009

[5] Shifei D.,Weikuan J.etal,"PCA-Baced Elman Neural Network Algorithm" ISICA2008pp.315-321,2008

[6] Wang Junfeng, etal "Design of Adaptive Equalizer Based on Variable Step LMS Algorithm,"3rd International on Computer Science & Computational Technology, pp. 256-258, Aug 2010.

[7] Matlab Language (R2009 a)(Toolbox),ver7.8

[8] Jhon, Wiley& Sons,Ltd, "Advanced Wireless Communications", 4G technologies, University of Oulu, Finland, 2004.

[9] J. G. Proakis, "Digital Communications", McGraw-Hill Companies, Inc NY, 4th Edition, 2000.

[10] S. Qureshi, "Adaptive Equalization," Proceedings of the IEEE, vol.73, No.9, pp. 1350-1389, Oct 2003.

[11] S. Mclaughlin, "Shedding Light on the Future of SP for Optical Recording," IEEE Sig. Process. Mag., vol. 15, No.4, pp. 83-94, May 1998.

[12] J. Elman, "Finding Structure in Time," Cognitive Science, vol. 14, pp. 189-214, 2004.

[13] Al-Alaoui, M.A etal "A Cloning Approach to Classifier Training", IEEE Transactions on Systems, vol.32, no.6, pp.746-752, 2002

[14] Hamdi A. Awad "A Novel Version of ELMAN Neural Networks for Modeling and controlling", Special Volume: Advances in Neural Networks-Theory and Applications, Watam Press,2007.

[15] S. Haykins , "Adaptive Filter Theory" , Prentice Hall ,New Jersey, 2011.

[16] Shobhna Gupta "Acoustic Echo Cancellation using Conventional Adaptive Algorithm and Modified Variable Step Size Algorithm" M.S.C Thesis 2004.

[17]] B.A.Shenoi, "Introduction to Digital Signal Processing and Filter Design" Johnwiley and sons Inc.,USA,2006

[18] A.Sadiq ,G.Kaain,"Study Effect of Step-size of LMS Algorithm in Sparse Channel Estimation" Al-mamoon college Journal ,no.20 ,2012.