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An Enhanced Deployment Approach of Adaptive Equalizer for Multipath Fading Channels

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Abstract
Inter-symbol interference (ISI) exhibits major distortion effect often appears in digital storage and wireless communication channels. The traditional decision feedback equalizer (DFE) is an efficient approach of mitigating the ISI effect using appropriate digital filter to subtract the ISI. However, the error propagation in DFE is a challenging problem that degrades the equalization due to the aliasing distorted symbols in the feedback section of the traditional DFE. The aim of the proposed approach is to minimize the error propagation and improve the modeling stability by incorporating adequate components to control the training and feedback mode of DFE. The proposed enhanced DFE architecture consists of a decision and controller components which are integrated on both the transmitter and receiver sides of communication system to auto alternate the DFE operational modes between training and feedback state based on the quality of the received signal in terms of signal-to-noise ratio SNR. The modeling architecture and performance validation of the proposed DFE are implemented in MATLAB using a raised-cosine pulse filter on the transmitter side and linear time-invariant channel model with additive gaussian noise. The equalizer capability in compensating ISI is evaluated during different operational stages including the training and DFE based on different channel distortion characteristics in terms of SNR using both 0.75 and 1.5 symbol duration in unit delay fraction of FIR filter. The simulation results of eye-diagram pattern showed significant improvement in the DFE equalizer when using a lower unit delay fraction in FIR filter for better suppressing the overlay trails of ISI. Finally, the capability of the proposed approach to mitigate the ISI is improved almost double the number of symbol errors compared to the traditional DFE.

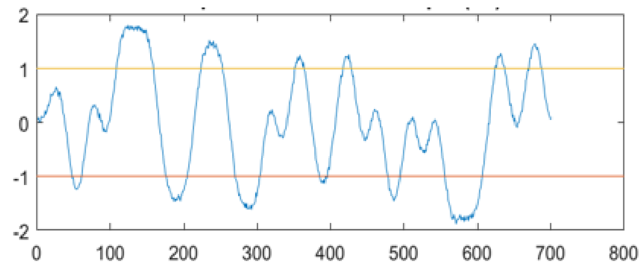
Keywords
Adaptive Equalizers, Decision Feedback Learning, Fading Channels, Signal-to-Noise Ratio.

I. Introduction

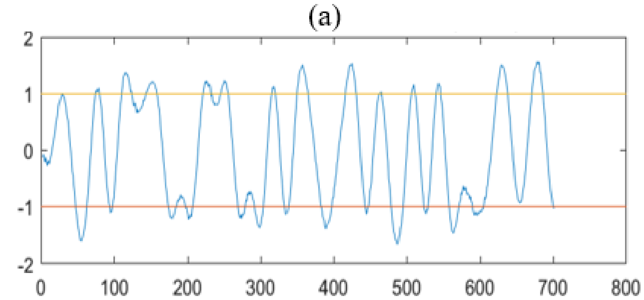
Contemporary communication systems often operate on massive data rate to fulfil the ongoing demand and quality requirement of high-definition video communications and other applications, such as big data, massive IoT, gaming, and virtual surgery. Hence, the distortion effects in wireless communications have become a dominant and challenging problematic due to dominant inter-symbol-interference (ISI) that occurs often in bandlimited channels according to Shannon theory [1–3]. Channel equalization systems are typically classified either linear or nonlinear techniques. Linear equalizers consist of simple digital architecture (i.e. finite impulse response (FIR) filter) to compensate for the static linear distortion. Linear equalizers often fail to mitigate the ISI when the channel characteristics is time-varying as in most mobile wireless communications [2, 3]. In addition, they require a huge number of parameters to mitigate sufficient ISI channel distortion. On the other hand, blind equalization techniques, such as in Lucky and Sato algorithms are more efficient and have the capabilities of adaptivity to account for both Linear and nonlinear channel distortion [4, 5]. The performance of blind equalizers in terms of convergence speed and efficiency is mostly affected by the deployed adaptation technique in minimizing the error function. Hence, the adaptation techniques are mostly researched and implemented algorithms in literature of adaptive equalizers. Example of the widely used adaptation approaches including the constant modulus algorithm, least mean squares (LMS), and recursive least-squares (RLS) [5–7]. The performance comparison of different adaptation algorithm is beyond the scope this paper since the proposed approach focuses on the operational enhancement of the decision feedback equalizer (DFE). In fact, the DFE has gained significant interests in the literature of adaptive equalizers because of the simplicity in implementation, as well as the system stability and high efficiency [8–12]. Implementation of adaptive equalizer often requires an efficient training phase that accounts for various channel characteristics, such as the nonlinearity and other effects of channel distortion [13–16]. The training mode of adaptive equalizers is normally implemented during equalizer initialization based on certain channel response. Hence, the equalizer performance can significantly degrade when the channel characteristics dramatically changes causing error propagation in DFE. This paper proposes a deployment technique for regulating the DFE training modes depending on severity of the channel distortion to improve the equalizer performance in mitigating the ISI and combating the error propagation. The coefficients of DFE are dynamically estimated to improve the adaptation convergence.

II. Channel Distortion

Distortion effects of ISI is a major challenge that has gained significant attention in modern generations of wireless communications. This is because the ISI affects the data transmission causing extreme degradation in bit-error rate (BER) on receiver side. In certain channel conditions, ISI distortion becomes unpredictable and it has more impact on the signal than additive gaussian noise in the communications, such as in multipath fading and time-varying channel characteristics [17–21]. The effect of ISI on symbol recovery is depicted in Fig. 1. For instance, a two-level slicer in the receiver performs 100% of symbols recovery for all peaks as shown in Fig. 1-b, but the slicer fails to detect symbols' peaks that have lower amplitude attenuated by ISI as depicted in Fig. 1-a. In communication theory, the impulse response of the transmitted pulse, channel function, and matched filter must satisfy Nyquist condition to eliminate all ISI distortion in ideal scenario as described in this section [1]. Since the pulse shaping and matched filters have static characteristics, adaptive equalizers are widely deployed dynamic solution to compensate for the time-varying characteristics of channel model. In other simple words, equalizers would enable better slicing operation (i.e decision block) in the final stage of detecting received symbols. The estimation theory of ISI is often described based on signal model of typical communication system in terms of transmitter model, channel model,



(a)



(b)

Fig. 1. Slicer operation for symbols recovery using two scenarios. (a) without ISI. (b) with ISI.

and receiver model. In baseband representation as depicted in Fig. 2, symbol waveforms are generated using pulse shaping filter on the transmitter side and channel model consists of linear time-invariant (LTI) filter with additive gaussian noise to mimic the multipath fading channel [1,2], finally a matched filter is used on the receiver side to recover the transmitted symbols. Thus, the combined impulse response $P(t)$ of the communication system is a convolution operation as follows:

$$P(t) = r(t) * h(t) * r(T-t) + n(t) * r(T-t) \tag{1}$$

where $r(t)$ is the basis function which represents the transmitter pulse shaping filter, $h(t)$ is the channel model, $n(t)$ is the additive white gaussian noise, and $r(T\text{-}t)$ is the impulse response of the matched filter on the receiver side. Thus, the received signal $y(t)$ is a convolution operation between the baseband input signal $x(t)$ and $P(t)$ as follows:

$$y(t) = x(t) * P(t) \tag{2}$$

$$y_k = p_{(0)}\, x_m + \sum_{m \neq k}^{\infty} x_m\, p_{(k-m)} + n_k \tag{3}$$

Equation (3) describes mathematically the ISI effects, for example, when one symbol is transmitted via communication channel, the convolution operation outputs series of symbols as depicted in Fig. 3. In other words, the output signal consists

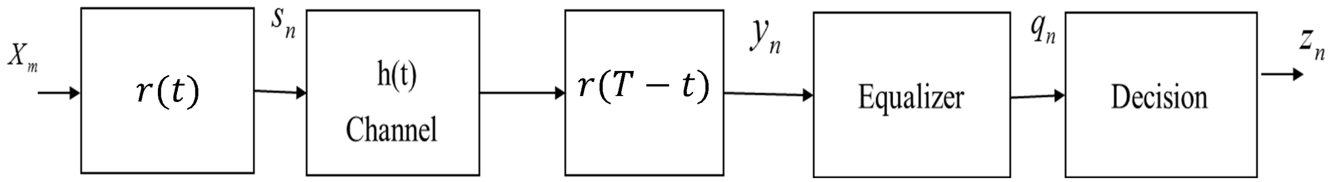


Fig. 2. A simplified modeling block diagram of typical communication system.

of the current input symbol x_m and the filtered gaussian noise plus a weighted sum of both previous and future symbols. Thuse, this term $\sum_{m\neq k}^{\infty} x_m\, p_{(k-m)}$ represents all ISI except the transmitted symbol that satisfies Nyquist criterion as follows:

$$P(nT) = \begin{cases} 1, & (n=0) \\ 0, & (n\neq 0) \end{cases} \tag{4}$$

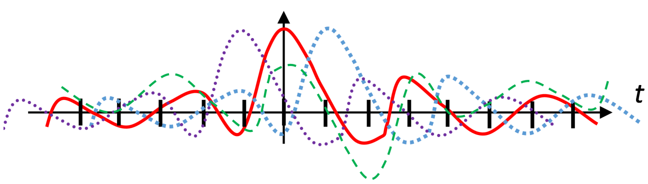


Fig. 3. The aliasing between the main received symbol in solid line and three adjacent ISI symbols in dashed/dotted lines.

III. Adaptive Equalizers

The traditional architecture of adaptive equalizers consists of digital filters (FIR/IIR) and adaptive algorithm, such as LMS/RLS for dynamically estimating the filter coefficients to compensate for time-varying channel distortion. Therefore, the equalizer performance is specified by the filter design (i.e type and number of coefficients) and the convergence speed/accuracy of the used adaptive algorithm. FIR filter is a popular solution in adaptive equalization because it is always stable design, linear in parameters, and simple in implementation. Similarly, LMS algorithm is a widely adopted approach in adaptive equalizers because of its computational efficiency and design simplicity [4–7]. The integration of LMS and FIR filter results in nonlinear equalizer model because the FIR coefficients become dynamic based on the channel characteristics. This property enhances the equalization to account for both linear and nonlinear channel distortion. However, the training mode in adaptive equalizers is crucial in coefficient estimation especially during the decision feedback training mode. For instance, DFE uses the feedback symbols from slicer as a desired output symbols enable coefficient estimation based on adaptive technique, such as in LMS. Therefore, the problem of possible existing error symbols in the feedback block has significant impact on coefficient estimation causing error propagation which often leads to substantial degradation and distortion, especially during high-rate data transmission due to the increase in channel delay spread [13–16]. Finally, the two different training scenarios in adaptive equalizers are described in the next sections.

A. Decision Directed-Learning

Decision directed-learning (DDL) is a training mode using a predefined sequence of the transmitted symbols over the communication channel. The DDL technique performs well when communication channel is statistically stationary that exhibits time-invariant characteristics. The Lucky equalizer as depicted in Fig. 4. is a popular example that is initialized (i.e feedback switch off) based on DDL approach for estimating the coefficients of the digital wiener filter [17–19]. During the training mode, a time-delayed version of the same transmitted symbols is used as a desired response $d(n)$ for coefficients estimation of the equalizer as presented in (5) based on normalized least-mean squares (NLMS) algorithm [4].

$$\widehat{\mathbf{w}}(n+1) = \widehat{\mathbf{w}}(n) + \mathbf{u}(n)e(n)g/\|\mathbf{u}(n)\|^2 \tag{5}$$

where $\hat{\mathbf{w}}(n)$ is a vector of the filter coefficients at time index n, $\mathbf{u}(n)$ is a vector of the symbols on the equalizer input, g is the learning rate, and $e(n)$ is the residual error which is calculated as follows:

$$e(n) = d(n) - \widehat{y}(n) \tag{6}$$

$$\widehat{y}(n) = \widehat{\mathbf{w}^{\mathbf{T}}}\mathbf{u}(n) \tag{7}$$

where $\widehat{y}$ is a vector of the equalizer output symbols.

B. Decision Feedback Equalizer

The adaptive equalizer employs a reinforcement learning technique when the equalizer output is switched from the desired response during the training mode to the decision feedback output under the assumption that the output symbols of the decision block (i.e. slicer) have more than 75% error-free symbols. Therefore, the equalizer converges only for initial

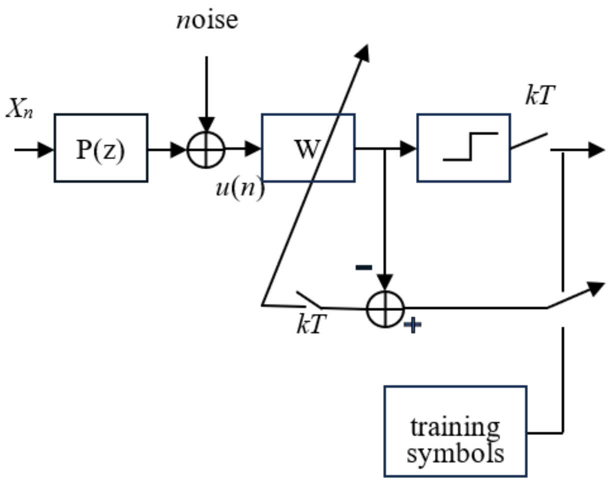


Fig. 4. Block diagram of the Lucky equalizer.

errors less than 25% of the total sequence of the output symbols [1, 2]. The error symbols between the equalizer input and the decision-block output are directly proportional to the channel distortion and LMS convergence rate which is an important factor that specifies the performance of the equalizer in mitigating ISI. The NLMS algorithm is used in the proposed DFE architecture for estimating the equalizer coefficients because it has the following advantages over the LMS:
1) The rate of convergence is significantly faster than the standard LMS algorithm.
2) The NMLS combats the effect of the gradient noise when the error, number of model's coefficients, or the symbol input amplitude are large [1–4].

C. Improved Architecture of DFE

The improved DFE is shown in Fig. 5 which consists of the typical architecture of DFE with additional adaptive FIR filter on the decision feedback branch for efficiently subtracting trailing ISI [12]. In other words, the improved DFE makes use of prior decision output for estimating current symbol as described by (8)-(11) as follows:

$$\mathbf{Z}_k = \sum_{n=0}^{m-1} w_n \, y_{k-n} \; - \sum_{n=1}^{N} b_n \, \hat{x}_{k-n} \tag{8}$$

where $\mathbf{Z}_k$ is the residual symbols between the output of the feedforward and the feedback filters. Equation (8) can be represented in a matrix form as follows:

$$\mathbf{Z}_k = \begin{bmatrix} w_o & \cdots & w_{m-1}\,, -b_1 & \cdots & -b_N \end{bmatrix} \begin{bmatrix} y_k \\ \vdots \\ \hat{x}_{k-n} \end{bmatrix} \tag{9}$$

$$\mathbf{Z}_k = \widetilde{\mathbf{w}}_k \overline{\mathbf{x}_k} \tag{10}$$

where $\widetilde{\mathbf{w}_k}$ is a row vector consists of the filter coefficients; feedforward (W) and feedback (B), $\overline{\mathbf{x}_k}$ is a column vector includes the input and output symbols of the DFE. Finally, the filter coefficients can be estimated using the following NLMS approach:

$$\widetilde{\mathbf{w}}_{k+1} = \widetilde{\mathbf{w}}_k + 2g\,(\widehat{x_k} - Z_k)\,\overline{\mathbf{x}_k} / \,\|\overline{\mathbf{x}_k}\|^2 \tag{11}$$

where g is the learning rate and the term $(\widehat{x_k} - Z_k)$ represents the residual errors. Although the DFE consists of a simple modeling approach in terms of computation, the conventional DFE structure suffers from error propagation phenomenon because its operational capability depends significantly on the output symbols of the decision component block. This scenario occurs when some error symbols are sent back through the feedback filter which enhances ISI leading to degradation in BER. In some cases, error propagation leads to instability, especially in transmission scenarios of high data rate and mobile wireless communication channel. In some cases, the DFE fails to recover the correct symbols from the interference [15,16]. Thus, alternating the equalizer operational mode from the decision feedback to DDL is the most appropriate option to combat the error propagation during the operation of decision feedback as discussed in this section. The SNR is a figure of merit widely used to measure signal quality and distortion effects on the receiver side. In other words, when the SNR decreases, the ISI is proportionally increasing because the ISI increases the noise level [1, 2]. Thus, the SNR criteria is adopted in this work as indication to control the operational states of DFE using two switches as depicted in Fig. 6 and described in this section. The proposed architecture of DFE consists of two switches; one on the transmitter side and another switch on the receiver side. These switches are used for setting/resetting the operational modes from training state to online state and vice versa based on the quality of the received signal in terms of SNR. For instance, during the online mode when the SNR degrades (i.e. SNR$\leq$ SNR$_{threshold}$), the controller on the receiver side sends a narrow-band control signal (i.e pilot) requesting to re-train the DFE based on a predefined and known training symbols. A detailed operational scenario of the proposed enhanced DFE is described in algorithm 1.

In this algorithm the SNR$_T$ is initially set according to the deployed application, such as voice, video, etc for the required accurate symbol recovery. Firstly, the DFE is initialized (toggle SW1 and SW2) on the training symbols that are installed on both the transmitter and receiver side to allow the adaptation algorithm of estimating the equalizer's coefficients. After the initialization stage, the DFE is deployed (toggle back SW1 and SW2) to operate on any received signal that has SNR higher than the SNR$_T$. In case the channel distortion increases, the SNR is directly degraded on the receiver side causing increase of the error propagation (SNR$\leq$ SNR$_T$) in

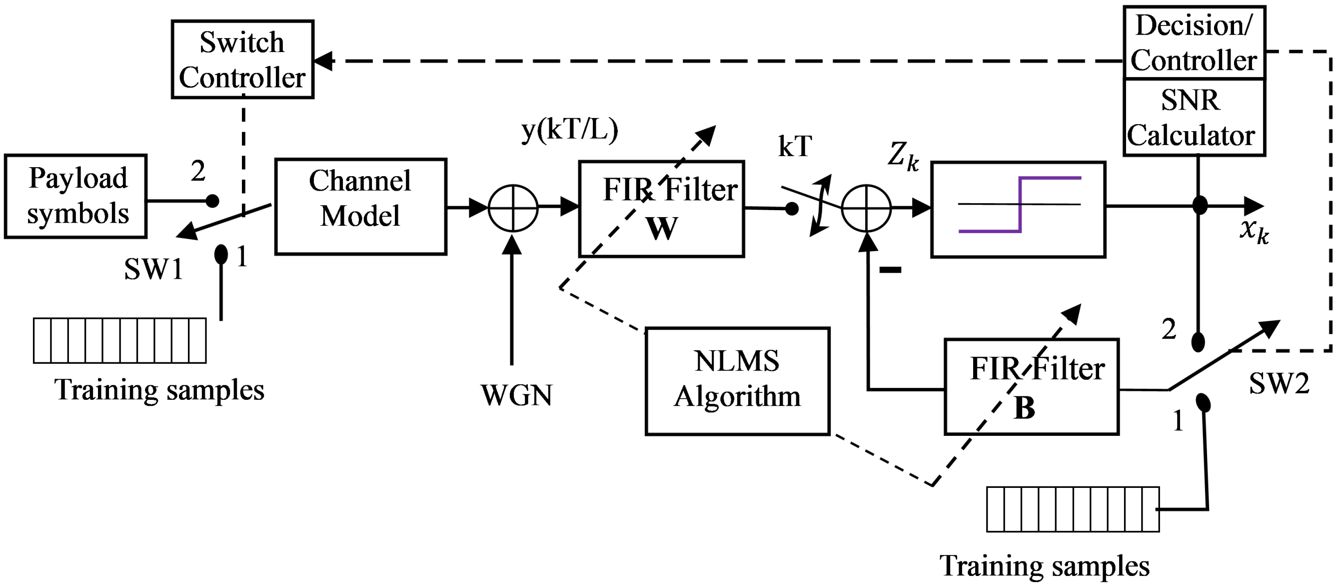


Fig. 5. Proposed adaptive architecture of DFE with controller blocks.

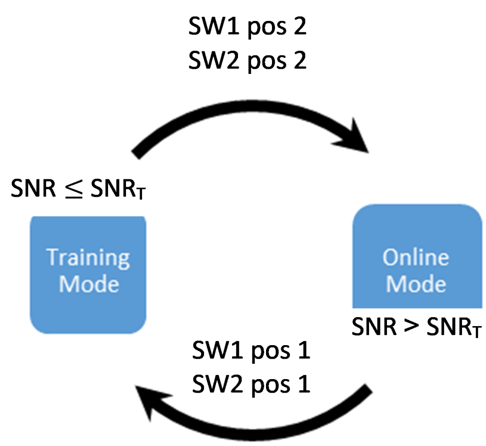


Fig. 6. A block diagram of the proposed switching scenarios between training mode and online mode.

Algorithm 1 DFE training scenario

Set SNR_T ▷ $SNR_{threshold}$
Load training symbols (x_m) on transmitter side
Load training symbols (x_m) on receiver side
Toggle SW1 to port 2 ▷ transmitting payload
Toggle SW2 to port 2 ▷ DFE mode
Start online DFE mode
Calculate SNR output on the equalizer (x_k)
While ($SNR \leq SNR_T$) **do**
Toggle both SW1 & SW2 to port1 respectively
Sync transmitted and received symbols
Start training DDL mode
Update the FIR coefficients **W**& **B**
Stop DDL training mode
Toggle both SW1&SW2 to port2 respectively
Start DFE online mode

the decision feedback and potential of failure in DFE. Hence, this algorithm is proposed to ignore the incoming symbols from the feedback branch in DFE (toggle SW1 and SW2 to port) and re-training the equalizer back based on the same training symbols during the initialized stage. Finally, the equalizer operational mode is set back to decision feedback after successful updating the equalizer's coefficients.

IV. System Simulation and Results

A simulation set-up is implemented using MATLAB software for system modeling and performance evaluation of the enhanced DFE based on the digital communications as described in Fig. 7, which consisting of a random binary generator on the transmitter side and BPSK digital modulator. A total number of 3000 random binary symbols are modulated in baseband using a raised-cosine pulses with roll-off factor of 0.25. The channel model employed in this simulation is a four-way multipath fading channel of a truncated raised-cosine function as follows:

$$h(t) = \sum_{i=0}^{3} a_i r(t-d_i) L(t-d_i T) \tag{12}$$

where $r(t)$ is a raised-cosine function as depicted in (13), $L(t)$ is a rectangular pulse of width $[-3T, 3T]$ for bandlimited truncation, a_i are the attenuation factors, and d_i are the corresponding offset of the multipath fading channel.

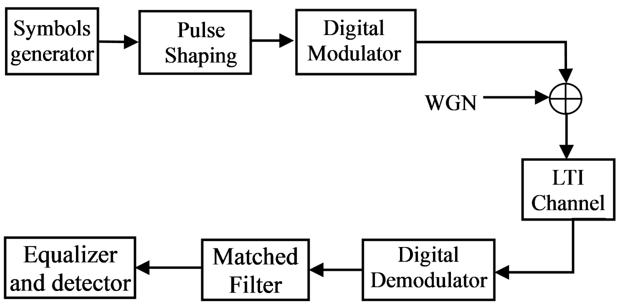


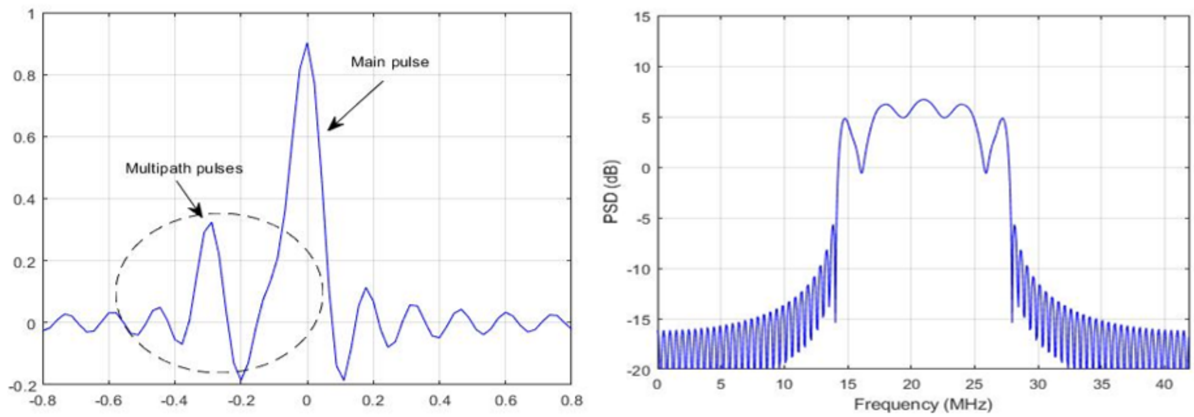
Fig. 7. Block diagram of the simulated communication system with equalizer.

In this simulation the parameters are set for severe ISI as follows:
a_0=1, a_1=0.6, a_2= –0.8, a_3=0.1, d_0=0, d_1=0.25, d_2=0.5, d_3=2. The above coefficients represent the attenuation factors (a_0, a_1, a_2, a_3) and the corresponding time dispersion (d_0, d_1, d_2, d_3) of each transmission path in the multipath channel. These parameters were chosen randomly based on rule-of-thumb proportions. For example, the main signal is travelled via the main path (i.e. shorter distance) from the transmitter to the receiver, which is normally exhibits higher magnitude. The second signal path is attenuated by factor 0.6 due to certain reflection criteria in addition the signal typically travels longer distance assuming a symbol delay equivalent to $0.25T$. Similarly, the impact of the third and fourth arrays is used in this simulation to control the severity of the channel ISI.

$$r(t) = sinc(tT)\cos(\pi\alpha tT)/(1-4\alpha^2 t^2 T^2) \tag{13}$$

where α is the pulse roll-off factor $(0 \leq \alpha \leq 1)$ and T is a symbol period. The channel impulse response is depicted in Fig. 8(a) which shows the ISI aliasing in time domain; furthermore, the channel characteristics and attenuation in the frequency domain are depicted in Fig. 8(b). The signal on the receiver side is obtained from a convolution operation between the channel model and the pulse shaping filter, and then the resulted signal is convoluted with matched-filter that has impulse response $h(t) = r(T-t)$ for optimal receiver architecture. Finally, signal demodulation and equalization operation are both applied to recover the transmitted symbols.

The communication model with DFE is simulated during the two modes; DDL and DFE to compare and monitor the equalizer performance during all the stages. The symbol synchronization between the transmitter and the receiver side is implemented using the cross-correlation function in MATLAB for accurate estimation the equalizer's coefficients. The simulated output result in terms of BER with respect to SNR is illustrated in Fig. 9, which shows significant improvement in BER (i.e more than 100 times decreases in error rate based on the same SNR) due to the obtained mitigation of ISI when the DFE is applied on the receiver side. The margin the between the theoretical ideal characteristics (blue curve in Fig. 9) and the measured BER/SNR (red curve in Fig. 9) characteristics increases proportionally due to the impact of multipath fading channel. In addition, the receiver performance in BER decaying rapidly to optimal point with respect to SNR (green curve) due to the obtained improvement using the DFE. The equalizer operation is evaluated during different time periods; before equalizer to show the error symbols, during the training mode, and during regular DFE operation mode as depicted in Fig. 10, using two different quantities of SNR and the same equalizer time spacing τ. Whereas the equalizer performs well during the DFE mode for both SNR quantities, the residual errors decrease rapidly using fewer steps during the training mode when the channel distortion is minor (i.e higher SNR). The eye diagram is another measure to describe visually the channel distortion and ISI, such that the wider the eye-openings, the higher channel capacity, and lower ISI distortion. Hence, Fig. 11 shows clearly the simulation results of symbols overlap on the receiver side at different time instance; before the equalizer, during and after the training mode of the DFE. The simulation results show a huge randomness in symbol overlap due to severe channel ISI which is compensated gradually during the training phase until obtaining the optimal results during the DFE mode. In this simulation, two different quantities of equalizer's time spacing (τ) with respect to symbol duration are used to evaluate the efficiency of DFE based on eye diagram. The compared eye diagrams with respect to the parameter τ shows clear improvement in eliminating the ISI when τ is set to $0.75T$ versus $1.5T$. This is because the equalizer model of a higher time-spacing bypasses some of ISI symbols that have lower time duration. Finally, the convergence rate of NLMS algorithm in estimating the equalizer's coefficients is depicted in Fig. 12 to investigate the adaptation's performance under different SNR. In this figure



(a) (b)

Fig. 8. Multipath raised-cosine fading channel. (a) Impulse time response (b) Frequency domain.

the mean square-errors (MSE) criteria decays exponentially as calculated for the three different values of SNR (20dB, 15dB, 10dB). In addition, Fig. 12 shows adequate convergence rate among these values of channel SNR such that the learning curve reaches the optimal point in a faster trend (i.e within fewer iterations) when the SNR is relatively high as in blue curve compared to slower decaying trend as in black curve which requires more iteration steps to reach the optimal point. The learning rate in each iteration of the presented simulation is set to 0.01 which is relatively small for slower convergence to avoid possible estimate divergence scenario. The compared calculated ISI of the enhanced DFE approach with respect to the traditional DFE is depicted in Table I. Of the 1000 received symbols, it is observed that 37 symbols containing error in the traditional DFE compared to only 18 error symbols in the proposed enhancement architecture of DFE.

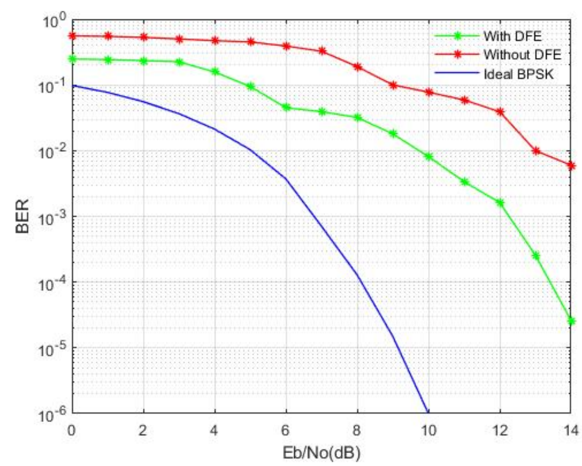


Fig. 9. Performance evaluation results of the equalizer in terms of SNR and BER.

TABLE I.
PERFORMANCE RESULTS OF ADAPTIVE EQUALIZERS IN MITIGATING ISI

Adaptive Equalizer	Symbol Error
DFE	3.7%
Enhanced DFE	1.8%

V. CONCLUSIONS

An enhanced deployment architecture of DFE has been presented in this paper. The SNR on the receiver side is monitored instantaneously to set the operational state of DFE for improving the adaptive estimation of the equalizer coefficients. The error analysis and evaluations of the adaptive equalizer have been presented during training and running modes over bandlimited 4-array multipath fading channel based on system simulation using MATLAB. The modeling theory structure of DFE was developed using the combination of wiener digital filter and NLMS algorithm for dynamic estimating of the equalizer coefficients. The proposed model is appropriate for different communication scenarios, especially in severe channel distortion that degrades the performance of DFE due to the increase in multipath fading and other aspects, such as the time-varying and nonlinear characteristics. Finally, the obtained validation results showed modeling improvement in DFE which performs well in mitigating the error symbols of ISI during the running state and converges faster using lower number of iterations.

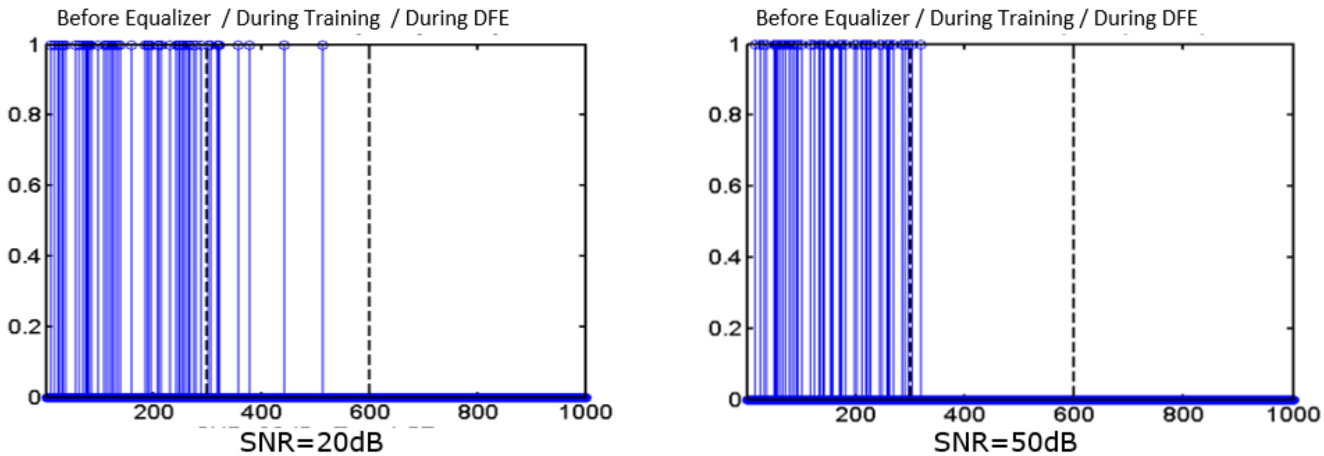


Fig. 10. Residual errors of the DFE during different operational modes.

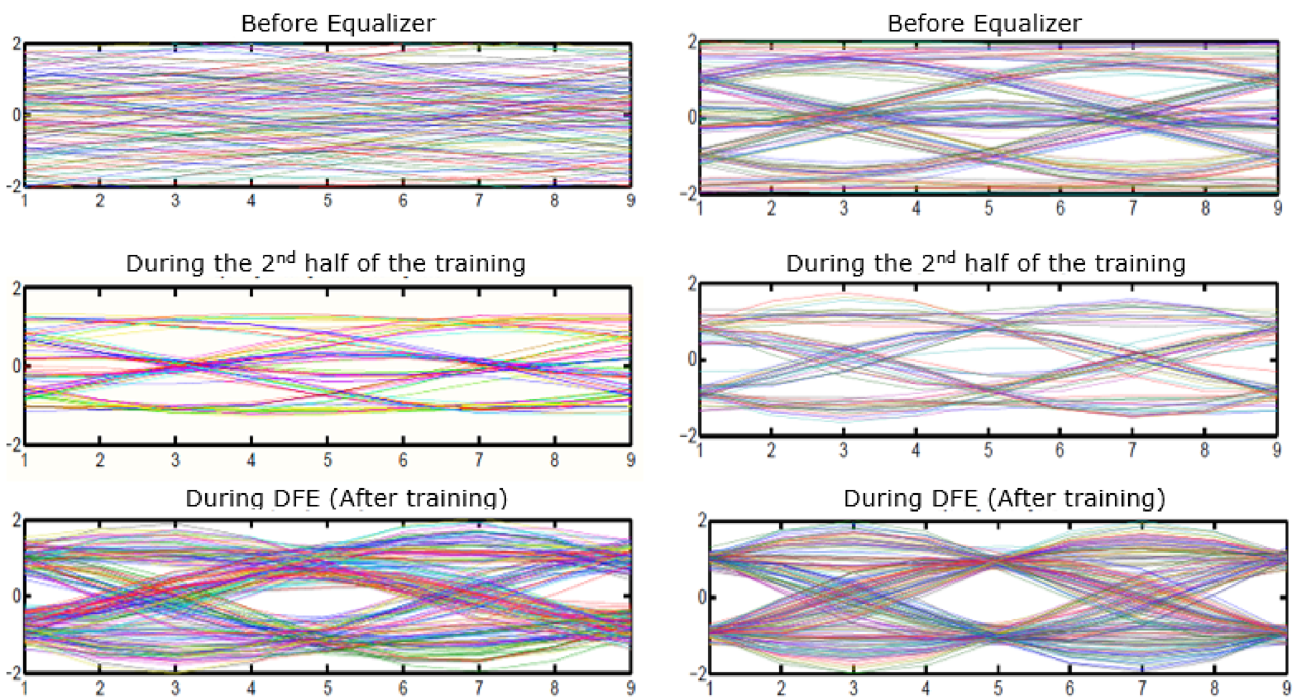


Fig. 11. Eye diagram for BPSK signal over the simulated multipath fading channel for assessing the DFE in eliminating the ISI during different scenarios. $SNR = 25dB$, $\tau = 0.75T$ (RHS) and $SNR = 15dB$, $\tau = 1.5T$ (LHS).

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CONFLICT OF INTEREST

The author has no conflict of relevant interest to this article..

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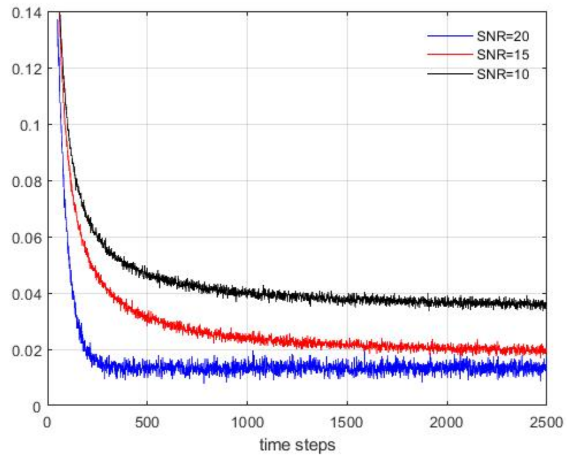

Fig. 12. Learning curves of NMLS convergence for estimating model coefficients using different channel SNR.

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