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NOVEL VSS-NLMS ALGORITHM FOR ADAPTIVE EQUALIZER UNDER COMPLEX DYNAMIC WIRELESS CHANNEL

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ABSTRACT

The Inter-Symbol Interference (ISI) is a challenging problem in a wireless channel that degraded communication links. One of the efficient methods to reduce the ISI is the adaptive equalizer. In the wireless channel, the ISI elimination required an algorithm with powerful computation due to the fast changing of the wireless channel properties. In this paper, a novel Selective Mapping Variable Step Size Normalized Least Mean Square (SMVSS-NLMS) algorithm has been introduced to mitigate the ISI efficiently. The SMVSS-NLMS algorithm operates by computing a mapping of weight vectors from many variable step sizes and selects the vector that gives the minimum error. The SMVSS-NLMS algorithm has been tested and compared to the Tuning-Free VSS-NLMS algorithm (TFVSS-NLMS). The simulation results have been observed under complex static and dynamic wireless channels using Binary Phase Shift Keying (BPSK) and Quadrature Phase Shift (QPSK) modulation schemes. The Bit Error Rate (BER) performance of SMVSS-NLMS considerably outperformed the TFVSS-NLMS at typical levels of signal-to-noise ratio (SNR). Moreover, the SMVSS-NLMS offered faster convergence speeds (12 iterations) and lower Mean Square Error (MSE) (-79 dB) than the TFVSS-NLMS (88 iterations, -14 dB MSE).
Keywords: *Selective Mapping, NLMS, Adaptive Equalizer, Inter-Symbol Interference, Adaptive Filter.*

1. INTRODUCTION

Adaptive systems play a key role to optimize the responses of many types of applications in response to its environments such as system identification [1,2], prediction [3, 4], noise cancelation [5,6,7,8,9,10], beamforming [11,12], line enhancer [13] and inverse system[14,15,16,17,18]. The algorithm is the core of an adaptive system, where it is responsible for fast and accurate computing to its coefficient parameters. When the digital communication systems operate at a high data rate, distortions effects will appear due to the power amplifiers, channel and other parts. A severe channel effect, Inter-Symbol Interference (ISI) has arisen when the signal's bandwidth is higher than the channel bandwidth [14, 19, 15]. The adaptive equalizer is used to transmit data through a channel accurately by mitigating the ISI distortion [20, 16]. The concept behind the non-blind adaptive equalizer is to track the time-varying characteristics of the mobile channel to take off its effect from the received signal [5]. Subsequently, the total channel and equalizer response is uniform in frequency domain [20, 6]. In general, the presence of noise in the system creates small amount of error in the filter coefficients from its optimum values. Thus, the effects of the channel still exist [21, 7]. Many adaptive algorithms try to achieve minimum misalignment and fast convergence for different applications. Some researchers focused their attention on the MSE criterion only [22, 23, 1, 24, 25], and others on BER as well as MSE criterions [17, 18, 26, 27] to test their algorithm according to an application. Raed S.H. AL-Musawi et al., in 2016, proposed the Tuning Free Variable Step Size Normalized Least Mean Square algorithm (TFVSS-NLMS). It has been used to reduce the channel impulse response effects over a static channel using BPSK modulation. The researchers also give in the literature different types of adaptive algorithms, where the most efficient algorithms have been selected for comparison. TF-VSS-NLMS has been compared with (LMS, NLMS, Kwong VSS-NLMS, Zhao VSS-NLMS, Song VSS-NLMS) algorithms. All the transmitted bits have been used in training for computing the BER and convergence rate. The results show that the TF-VSS-NLMS algorithm gives the best performance in term of MSE and BER in all SNR range.

Peng-Fei Cui et al., in 2015 combined two algorithms which are Recursive Least Square (RLS) and Least Mean Square (LMS) for indoor wireless communications. The new combination approaches fast convergence and rapid optimization for the received signal. The problem of this algorithm is that it has a poor BER performance at SNR < 9 dB [18]. Shubham Lavania et al., in 2015, have been built adaptive channel equalizer for Stanford University Interim (SUI) channels based on Artificial Neural Networks (ANN). They used two types of neural networks: Multi-Layer Perceptron algorithm (MLP) and Recurrent Neural Network (RNN) as an adaptive equalizer in the SUI channels. The algorithms that have been used to train the MLP and RNN are the Back-propagation (BP) and Real-Time Recurrent Learning (RTRL) respectively. RNN shows the best performance in term of BER. RNN has an advantage of having a good BER, but it needs more than 400 iterations to achieve the optimal state under the static nonlinear channel [26]. Minchao Li et al., in 2013, employed the average power derivation of weight for a new variable step size in adaptive equalizer filter. As well as, first order filter applied to the error signal for minimizing the effect of noise. This algorithm compared with Kwang-NLMS and classical NLMS. The results indicate an improvement in the convergence rate than Kwang-NLMS and classical NLMS but not in terms of misalignment [22]. Mohammad Shams Esfand Abadi et al., in 2011 presented four algorithms (VSS-APA, VSS selective partial update NLMS, VSS SPU APA, VSS-Selective-Regressor-APA (VSS-SR-APA)) for identifying the channel impulse response. These algorithms informed a performance enhancement regarding convergence speed and misalignment error. These algorithms require a lot of mathematical processes [23]. Silviu Ciochină et al., in 2011 have introduced an optimized NLMS based on joint optimization process. This algorithm gives a reasonable misalignment minimization for acoustic echo cancellation. This algorithm requires prior knowledge of the noise power for updating the variable step size parameter [1]. Yi Yu and Haiquan Zhao, in 2015, used Versiera Function (VF) to introduce VSS-NLMS to update the step size parameter for the system identification. The efficiency of this algorithm has been demonstrated in comparison to other algorithms regarding convergence rate and MSE. This algorithm has three settings (α, β and b) that they need to be tuned to achieve its best performance [24]. Chunhui Ren et al., in 2016, proposed a method of a combining two new algorithms, I-VSS-AP and I-VSS-NLMS that are characterized by speed and accuracy respectively under fixed environmental conditions for adaptive system identification. Depending on the mixing parameter one of the two algorithms is being selected based on the required performance parameter, accuracy or speed. Initially, the maximum error will exist. Therefore, the effect of the I-VSSAP algorithm intensifies more than the effect of the I-VSSNLMS algorithm to increase the speed, and vice versa for improving the accuracy [25]. M.A Raja and A.Shanmugam, in 2013, introduced an adaptive filter noise cancellation for enhancing the speech signal by using Variable Step Size Normalized Differential Mean Square Error (VSS-NDLMS) algorithm [8]. Mohammad Shams Esfand and Amir Agha Arzandi in 2012, used SPU-NLMS and M-Max-NLMS algorithms as channel equalizer to remove the ISI distorsion of the channel. The SPU-NLMS algorithm is compared with LMS and NLMS in term of MSE and symbol error rate (SER) versus SNR and computational complexity [14].

Analysis and performance evaluation of a novel SMVSS-NLMS algorithm for channel equalizer has been introduced in term of filter length (N), MSE and BER under both static and dynamic complex channels. In addition to using BPSK, the QPSK modulation has been utilized for the transmitting data to guarantee the performance of the algorithm when the signal is complex. In comparison with literature, the novel variable step size does not require search time or computational formula that restricts step size values to give speed and accuracy together in different environments, where the step size strategy is using Selected Mapping method to pick up the weight corresponding to the minimum error. The outlines of this paper are arranged as follows: section 2 describes the basis of the adaptive filter and the wireless channel. Section 3 provides analysis performance for the proposed as well as TFVSS-NLMS algorithms. Section 4 will compared the performance results of the proposed algorithm concerning with TFVSS-NLMS. Section 5 will give the conclusions.

2. OVERVIEW

The adaptive channel equalizer schematic is shown in Figure (1). X (i) is the input signal to the adaptive filter, where i is the time index as in eq(1). u(i), h(i) and n(i) are a multi-level complex digital modulated transmitted signal, the collective impulse response of transmitter, radio channel and Radio Frequency (RF) - Intermediate Frequency (IF) receiver channel and noise signal respectively. The interest signal has arrived with a set of ISI and noise as mentioned in Eq. (1). The scenario of the adaptive equalizer tries to mitigate the term of ISI as much possible [28, 29].

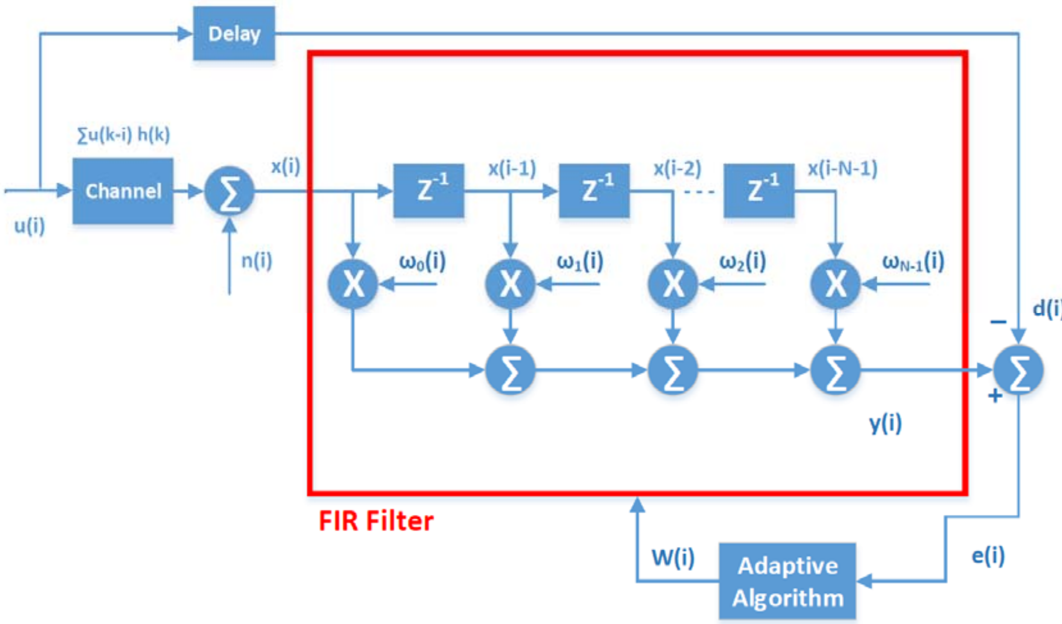

Figure 1: The Block Diagram Of The Adaptive Equalizer Application In The Presence Of Noise.

2.1 Wireless Dynamic Channel Model

The channel impulse response specified with time-varying parameters is symbolized as $h_k(i)$. This model has been implemented in a form of three-tap complex FIR filter with dynamic coefficients that represent the multipath and ISI behaviors [2, 30]. The block diagram of the channel impulse response model is shown in Figure (2).

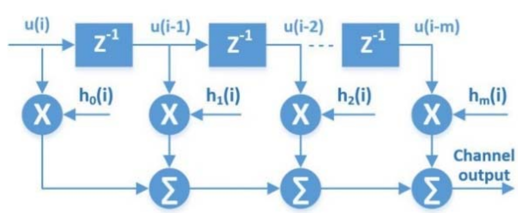

Figure 2: Wireless dynamic channel model based on digital FIR filter.

The transmitted signal will be affected by the dynamic channel as described in a Matlab code below:

```
X = zeros(m+1,1);      % tap delay of channel
Rx=zeros(1,L);         % received signal
for i=1:L              %  L: length of the signal
h=[0.1*rand(1)+0.4,-j*(0.1*rand(1)+0.1)
,0.05*rand(1)+0.15];        % time-varying channel
parameters
X(2:end)= X(1:end-1); % shift register of the FIR
filter
X(1)=u(i);                % u: transmitted signal
Rx(i)=b*X;
end
. x=awgn(Rx,Es_over_No) % Additive white
Gaussian Noise Channel
```

Equation (1) gives the mathematical model to the wireless dynamic channel [17].

$$x(i) = \underbrace{u(i)h_o(i)}_{interest\ signal} + \underbrace{n(i)}_{Noise} + \cdots \underbrace{\sum_{k=1}^{m} u(i-k)h_k(i)}_{Inter\ symbol\ interference} \quad (1)$$

$$y(i) = \sum_{i=0}^{N-1} \omega(i)\ x(i) = \boldsymbol{W}(i)^H X(i) \quad (2)$$

$$e(i) = d(i) - y(i) \quad (3)$$

$$\boldsymbol{W}(i+1) = \boldsymbol{W}(i) + \mu\Delta\boldsymbol{W} \quad (4)$$

Where m is the number of interference symbols.

2.2 Adaptive Equalizer Model

The equalizer output y(i), as mentioned in Eq. (2), is the multiplication of the input samples signal x(i) and the filter coefficient ω(i) [9, 13]. Where:

X(i)=[x(i) x(i-1) x(i-2) x(i-N+1)], is the input vector, N is the size of the transversal adaptive filter, W(i) =[ω_0 (i) ω_1 (i) ω_2 (i)…$\omega_{(N-1)}$ (i)]^H is the weight coefficient of the adaptive filter equalizer. The superscript ^{H} denotes Harmison operator. The error signal is calculated by subtracting the output signal y(i) from the delayed version of transmitted signal d(i) as given in Eq. (3). Finally, at each iteration the weight updated is computed as expressed in Eq(4)[20,17]:

Where μ is the step size stability control factor. The condition of μ that obtains a stable weight updating process is {0 < μ < 1/(tr[R])}. Where: tr[R]=(N+1) E[X(i)^2]. In which, R is the auto-correlation matrix of the input signal [31]. And ΔW is a correction parameter for updating the filter coefficients. There are common algorithms used for modifying the VSS are LMS and NLMS algorithms which are described in [17, 11, 32, 5, 8].

3. ADAPTIVE ALGORITHMS

In this section: the TFVSS-NLMS algorithm and the proposed algorithms will be discussed. The adaptive algorithms for the linear combination filter use the MSE as a cost function to minimize the Misalignment. Many algorithms that presented in the literature of this paper and the literature in [17] try to introduce competitive specifications in term of complexity, convergence rate and MSD. TFVSS-NLMS algorithm that overcomes many of them in term of performance, sophistication or both of them [17].

3.1 TFVSS-NLMS Algorithm

TFVSS-NLMS Algorithm uses the steepest descent method for updating the weight vector to minimize the MSE as expressed in Eq.(5).

$$MSE = E[e^2(i)] \tag{5}$$

For this algorithm, the step size introduced as a variable step size that it is inversely proportional to a non-linear formula with the input signal X (i) and given as Eq. (6). So that, it will govern the error sharpness effects on the weights. The final modified variable step size is given as Eq. (7). Subsequently, the weight coefficients updated as in Eq. (8). The most significant property of TFVSSNLMS algorithm over the variable step size algorithms family is that it doesn't require any adjustment to the parameters to reach the satisfactory performance [17].

$$\mu(i) = \frac{1}{\left\{\sum_{k=0}^{N-1} \sqrt{|x(i-k)|}\right\}} \tag{6}$$

$$\mu_{TFVSS}(i) = \frac{\mu(i)}{\{x(i)^H x(i)\}+\epsilon} \tag{7}$$

$$w(i+1) = w(i) + \mu_{TFVSS}(i)\, x(i) e(i) \tag{8}$$

3.2 Proposed SM-NLMS algorithm

The variable step size parameter plays a vital role in the stability of the algorithms that they are based on the steepest descent method. Therefore, these algorithms have been distinguished by providing a time-varying step size equation for optimum performance. In the case of the NLMS algorithm, the optimum value for μ in the absence of interference and noise (n(i)=0) is equal to 1. But when there is noise, it will be calculated from Eq. (9) [33].

$$\mu_{opt} = \frac{E[|True\ error|^2]}{E[|actual\ error|^2]} \tag{9}$$

The SM-NLMS algorithm surpasses the problem that exists in most types of VSS algorithms by using multiple step size to calculate the weights in a mapping form. Then, the optimum weights have been selected for the next iteration in this process. The fitness function for assigning the optimum weights is based on the minimum error that is provided for each variable step size as in Eq. (27). The procedure of this method is implemented in a parallel form.

The summery of SM-NLMS algorithm described as Eq. (10-20).

$$y(i) = \mathbf{W}^H \boldsymbol{X}(i) \tag{10}$$

$$e(i) = d(i) - y(i) \tag{11}$$

$$\mu_p = \frac{\varepsilon_p}{\boldsymbol{X}(i)^H \boldsymbol{X}(i)} \tag{12}$$

$$\mathbf{W}_p(i+1) = \mathbf{W}_p(i) + \mu_p\, e(i)^* \boldsymbol{X}(i) \tag{13}$$

$$y_p(i) = \mathbf{W}_p(i+1)^H \boldsymbol{X}(i) \tag{14}$$

$$e_p(i) = d(i) - y_p(i) \tag{15}$$

$$\mathbf{e}_T = [e_1(i)\ \ e_1(i) \ldots\ldots e_p(i)] \tag{16}$$

$$\mathbf{W}_T = [\mathbf{W}_1(i+1)\ \ \mathbf{W}_1(i+1) \ldots . \mathbf{W}_p(i+1)] \tag{17}$$

$$L = find(|\mathbf{e}_T| = \min(|\mathbf{e}_T|)) \tag{18}$$

$$\mathbf{W}_{opt} = \mathbf{W}_T(L)] \tag{19}$$

$$y_{opt}(i) = \mathbf{W}_{opt}{}^{H}\ \boldsymbol{X}(i) \tag{20}$$

Where: p is integer value referring to the number of individuals that have been used. e_T is the vector value of the fitness function, W_T is total updated weight, L is the location of the minimum value of e_T, W_{opt} is the best candidate for the next iteration.

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The parallel computation of this algorithm will save more time besides, it is efficient. Also, when the number of mapping size is increased, the ability of the algorithm to move between the steps will increase, making it superior to the Gradient Noise Amplification (GNA), stable, fast and accurate in processing.

Table1: comparison between the SMVSS-NLMS and other algorithms in concerning with computational complexity.

name	Multiplier	Sum	exponent	Root square	Min.	Abs	Div.
NPVSS [34]	3N+6	3N+6	0	2	0	0	2
NVS-NLMS[35]	3N+6	3N+6	0	0	0	0	2
NEW-NPVSS[36]	5N+16	5N+10	0	1	0	0	2
Yu-VSS-NLMS [37]	5N+9	5N+7	1	0	0	0	2
SPU-NLMS [14]	N+SL+2	N+SL+2	0	0	1	0	1
TFVSS-NLMS [23]	3N+1	4N-2	0	N	0	N	2
Proposed SM-NLMS	2N(1+P)+P	2N(1+P)-P-1	0	0	1	0	P

- Where S: the blocks with the largest square-Euclidean norm, L: length of the filter coefficient in each block.

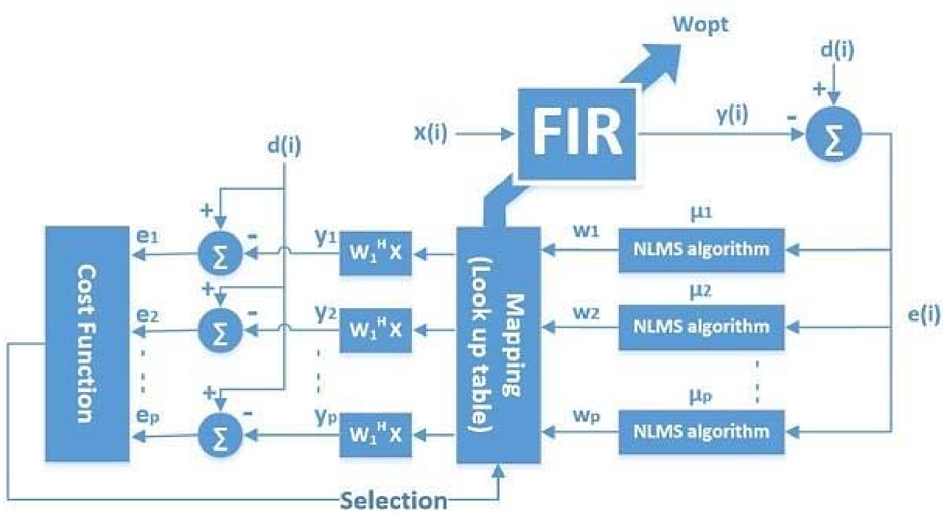

Figure 3: The General Block Diagram Of The Proposed SMVSS-NLMS Algorithm.

Table 1 gives the computational complexity of the proposed algorithm in comparison with other algorithms [17, 33, 34, 35, 36] regarding Multiplier addition, exponent, Root square, minimum, Absolute, and division. The proposed algorithm does not require square root as: TFVSS-NLMS and NEW-NPVSS. And it does not need an exponential competition as Yu-VSS-NLMS. The number of multiplications and additions in the proposed algorithm is higher than other algorithms. This is because of using many branches. The Figure 3 illustrates the implementation steps of the proposed algorithm for channel equalization.

4. SIMULATION RESULTS

In this section, the MATLAB simulation results have been presented for the proposed algorithm, as well as make a comparison with TFVSS-NLMS algorithm to measure its essential aspects. BPSK and QPSK modulations have been used for data transmission under static and dynamic channel models that described in section 2. BER and MSE are computed to show the enhancement of the SMVSS-NLMS algorithm in the comparison. The BER has been calculated regarding energy symbol to noise spectrum ratio (E_S/N_O) with a typical range between 0- 40 dB. 1Mega symbol is transmitted to calculate each BER point. Also, the 1Mega symbols are divided into 1000 frames, and the weights are reset at the beginning of each frames to give a reliable BER calculation. One hundred bit is injected into each frame as a BPSK training sequence. The other parameters of this experiment have been summarized in Table (2).

4.1 Complex Static Wireless Channel

This section introduces the suitable filter length (N) that offers adjustment between the complexity and the performance. Secondly, the MSE performance will be computed to indicate the speed and the accuracy of the algorithms. Thirdly, the effects of μ on the algorithm behaviors over the adaptation processes that guarantee the stability are computed to give an explicit evaluation. Finally, The BER vs. SNR behaviors are calculated at the different noise level.

Table (2): the summary of parameters of the experiment.

Parameter	Description
Static Channel response	$h(n)=0.4\delta(n)-j0.1\delta(n-1)+ 0.15\delta(n-2)$
Dynamic channel response	$h(n)=a*(0.4\delta(n)-j*0.1\delta(n-1)+ 0.15\delta(n-2))$
a	Random variable with standard deviation= 0.1.
BPSK training data	100 bit/frame
# of samples/bit	1 sample
AWGN Channel	Yes
The step size control parameters P=3	$\varepsilon_1=0.05$, $\varepsilon_2=0.01$, $\varepsilon_3=0.001$
P=4	$\varepsilon_1=0.1$, $\varepsilon_2=0.05$, $\varepsilon_3=0.01$, $\varepsilon_4=0.001$
P=5	$\varepsilon_1=0.2$, $\varepsilon_2=0.1$, $\varepsilon_3=0.05$, $\varepsilon_4=0.01$, $\varepsilon_4=0.001$

4.1.1 BER vs. filter length

The optimum filter length and the variable step size are the two essential aspects that fulfill the satisfactory performance of an algorithm. The proposed algorithm is analyzed with P=3, 4 and 5 to demonstrate the comparison between the computational complexity and the optimum performance. In SNR = 20dB, Figure (4) shows the BER vs. N behavior of the proposed algorithm in compared with TF-VSS-NLMS algorithm using QPSK modulation. The SM-VSS-NLMS algorithm reaches the maximum satisfactory performance at N=6 and P=4. So that these parameters have been selected to calculate the BER for other modulation schemes and MSE performance. Obviously, the VSS-NLMS is vastly overcomes TFVSS-NLMS at all N values.

4.1.2 MSE performance

The MSE performance has been analyzed for each algorithm in dB using QPSK modulation under noise-free complex static channel as in Figures 5-6. Three frames with length 200 bit are transmitted over the channel to examine the MSE behavior of SMVSS-NLMS and TFVSS-NLMS.

The SM-VSS-NLMS algorithm has been analyzed with step size values = [1.05 1 0.96 0.951] as shown in Figures 5. The MSE of the proposed algorithm has been calculated after taking twenty reading. The convergences speed reached to steady state after 12 iterations, and the misalignment value fluctuates around -79 dB.

In TFVSS-NLMS algorithm, the μ=1 has been selected to agree with the condition in Eq. 10 when the channel is noise free to calculate the MSE performance at the optimum situation. The result in Figure 6 shows that the TFVSS-NLMS algorithm gives slower convergence speed and lower accuracy than the proposed algorithm under the same conditions. The convergence rate is reached to -14.6 dB after 88 iterations. It's evident that the TFVSS-NLMS is suffering from degradation in its performance under the complex wireless channel.

4.1.3 Step Size Analysis

The variable step size has been evaluated at different values of SNR (0 to 30 dB). At a low level SNR, the proposed algorithm delivers a small step size, and it is increased as SNR increased to be consistent with the condition in Eq. 10 as depicted in Figure 7. Whereas, the μ of the TFVSS-NLMS algorithm does not submit to Eq. 10 because the channel is complex as illustrated in Figure 8.

4.1.4 BER vs. SNR performance

Figure 9 gives the BER comparison of the SMVSS-NLMS with TFVSS-NLMS algorithm using BPSK. As expected, both algorithms deliver approximately the same performance at SNR below 9 dB. The SMVSS-NLMS algorithm delivers significantly better performance as compared with TFVSS-NLMS algorithm at SNR >9 dB. The variable step size of the proposed algorithm are = [0.1 0.05 0.01 0.001]. The best BER performance of TFVSS-NLMS algorithm achieved at μ=0.01, and this is making the step size needed to be tuned. While the proposed algorithm has a suitable verity of step size for different levels of SNR values.

The Figure 10 present QPSK performance using SMVSS-NLMS and TFVSS-NLMS algorithms. At SNR value more than 10, the SMVSS-NLMS exceed the TFVSS-NLMS, and the improvement is increased around 5 dB as SNR increased.

4.2 Dynamic Complex wireless Channels

In this section, the proposed algorithm has been compared with TFVSS-NLMS algorithm in term of

BER vs. SNR under the dynamic complex wireless channel (presented in table (2)) and exanimate the performance of the algorithm to wireless transmission purposes. BPSK and QPSK modulation are both used in this case to transmit data.

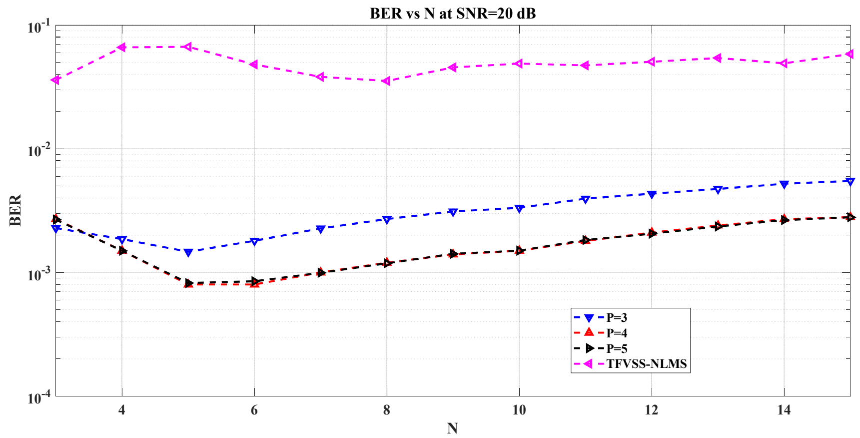

Figure 4: BER Vs. Filter Length Performance Under The Static Complex Wireless Channel.

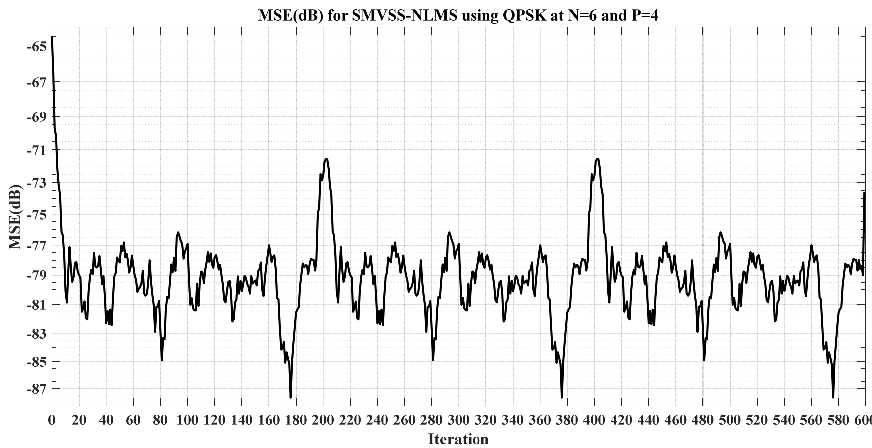

Figure 5: The MSE Performance Of SMVSS-NLMS Algorithm Under The Noise-Free Static Complex Wireless Channel.

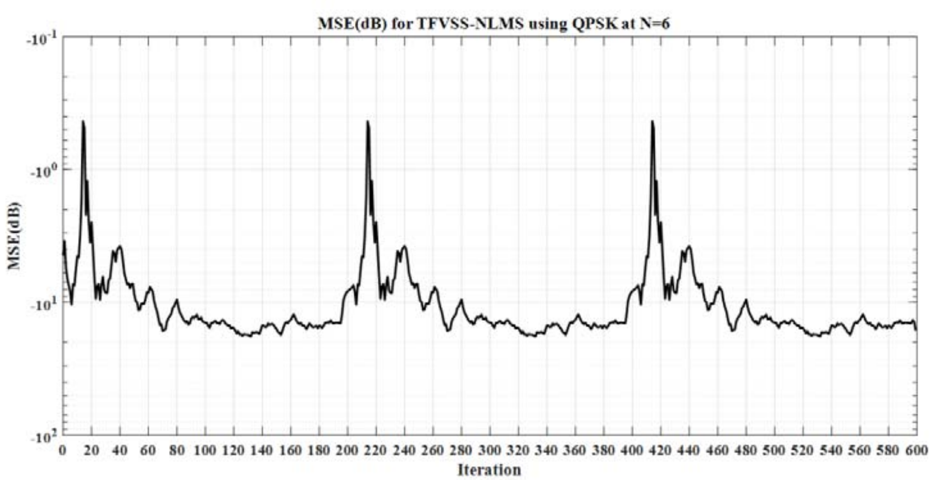

Figure 6: The MSE Performance Of TFVSS-NLMS Algorithm Under Noise Free Static Wireless Channel

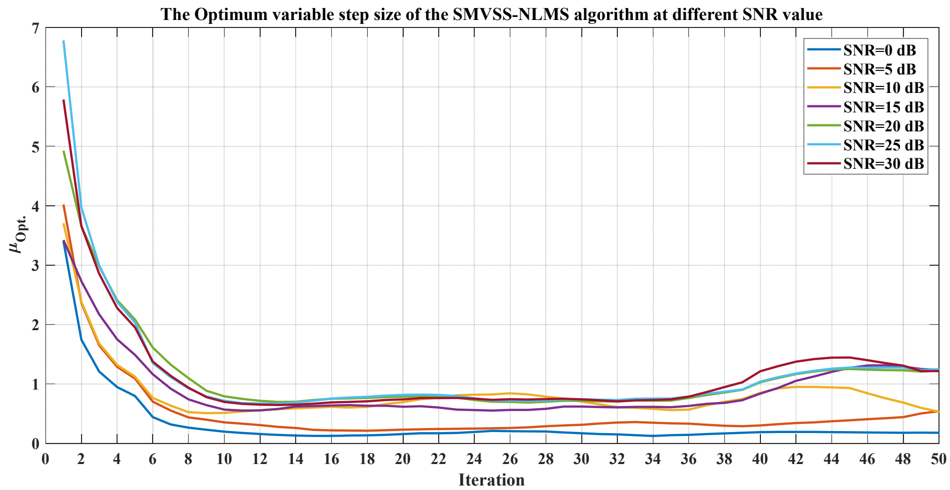

Figure 7: Relationship Between The μ Vs Adaption Time At P = 4 And N=6 For SMVSS-NLMS Algorithm.

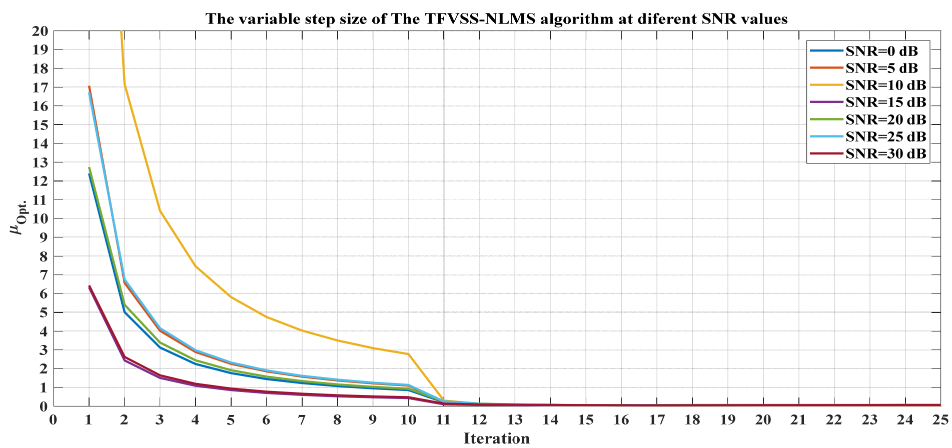

Figure 8: Relationship Between The μ Vs. Adaption Time For TFVSS-NLMS Algorithm.

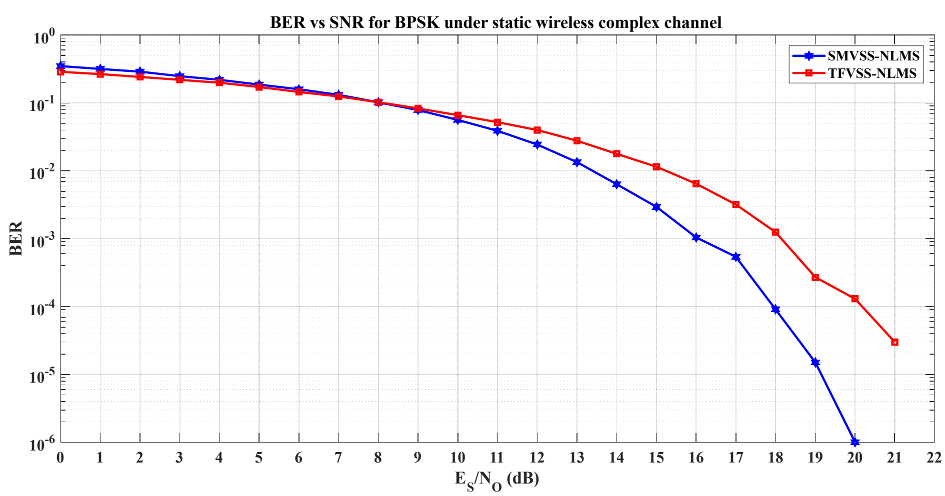

Figure 9: The BPSK Performance Of The Proposed And TFVSS-NLMS Algorithms At N=6 And P=4

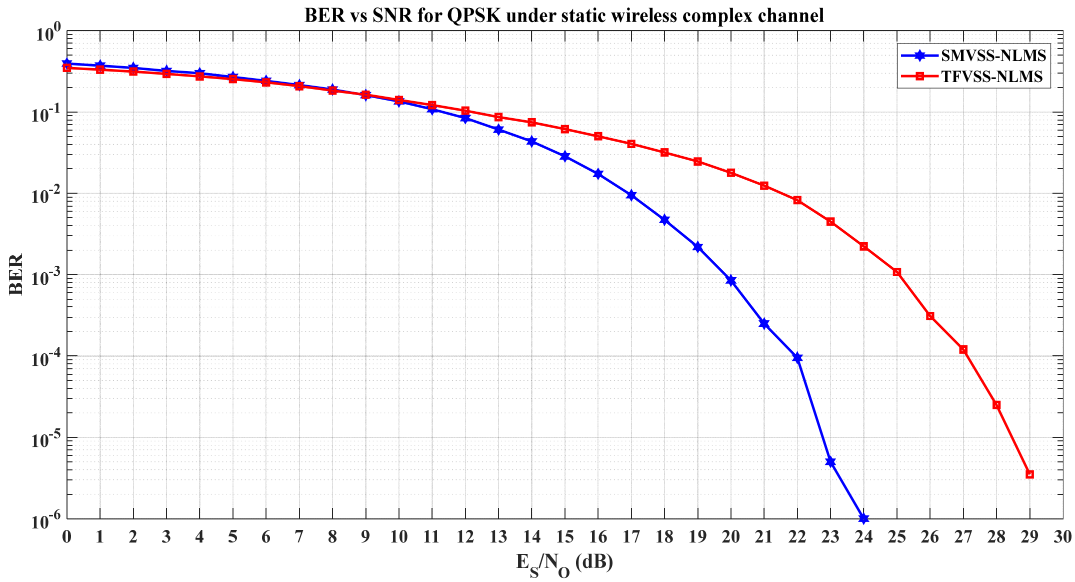

Figure 10: The QPSK Performance Of The Proposed And TFVSS-NLMS Algorithms At N=6 And P=4.

From Figure 11 the BPSK modulation has been used to measure the performance of algorithms. The performance of the dynamic channel is worse than the static channel. The proposed algorithm makes progress better at SNR > 9 dB. At SNR=20 dB, the SMVSS-NLMS algorithm gives BER = 0.012 whereas the TFVSS-NLMS offers BER=0.027. This result shows the proposed algorithm can provide the best equalization process than TFVSS-NLMS algorithm. Figure 12 shows the performance of QPSK. The TFVSS-NLMS algorithm has worsted than the performance of BPSK at all SNR values whereas the proposed algorithm delivers relative performance to the BPSK.

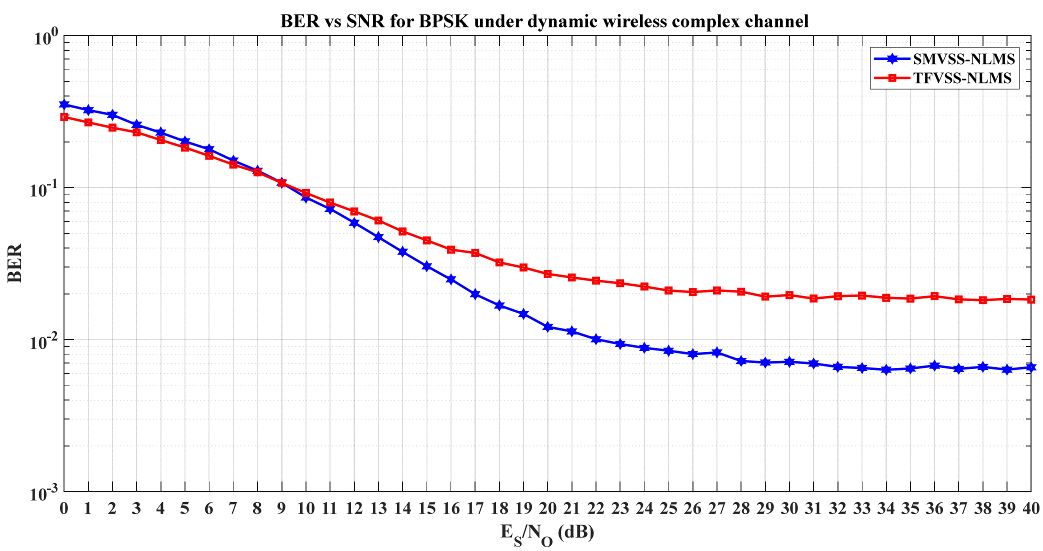

Figure 11: The BPSK Performance Of The Proposed And TFVSS-NLMS Algorithms Under Dynamic Channel At N=6 And P=4.

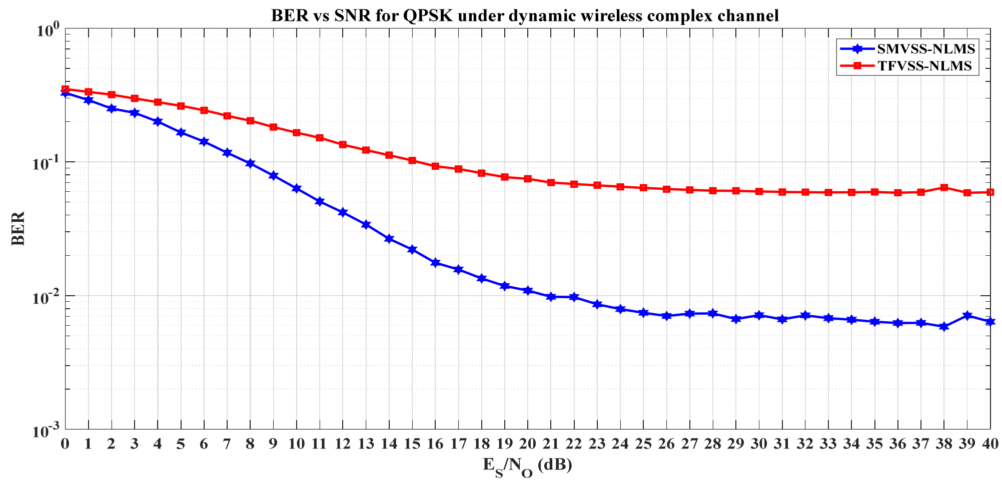

Figure 12: The QPSK Performance Of The Proposed And TFVSS-NLMS Algorithms Under Dynamic Channel At N=6 And P=4.

5. CONCLUSION

The performance of the proposed SMVSS-NLMS algorithm has been computed in various situations (static and dynamic complex channel, BPSK and QPSK modulations). The simulation results proved that the ability of the proposed algorithm is better than TFVSS-NLMS under complex channels. The SMVSS-NLMS algorithm gives direct proportion between SNR and µ (*as Figure* 7). The performance becomes higher as the size of the mapping increases and its value is more comprehensive to fit the desired SNR range without having to re-tune. Furthermore, the computational complexity of the proposed algorithm has been compared with other algorithms. It was showed that the proposed algorithm does not require complicated functions (exponential function, root, etc.), but in general, it involves some multiplication and addition processes. The effectiveness of the SMVSS-NLMS algorithm has been demonstrated in term of MSE and BER at N=6 and P=4 (*as Figure 4*). Under the noise-free complex static channel, it offers lower value of MSE (*as Figure 5*) than TFVSS-NLMS (*as Figure 6*) that gives huge failure in MSE for QPSK. The BER of the SMVSS-NLMS examination is better than the TFVSS-NLMS around 2 dB and 5 dB under static complex wireless channel with BPSK (*as Figure 9*) and QPSK (*as Figure 10*) Respectively. In the case of dynamic complex wireless channel, the SMVSS-NLMS algorithm gives BER 44% and 10% from the BER of the TFVSS-NLMS for BPSK(*as Figure 11*) and QPSK (*as Figure 12*) at SNR=20 dB respectively.

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