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Simulation of Data De-noising System using Improved PSO Software Algorithm

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Abstract: In an RF environment, noise that starts with a few references ruins the display of telecommunications systems. Non-linearity at the RF section, time-varying warm noise inside the collector radio framework, with noise through neighboring organization hubs can all contribute to the noise at the receiver of a broadband framework, such as intellectual radios. For intelligent radios, a few denoising techniques have been developed; some are used for range detection, while others are used to obtain loud signals during conversation. Less mean square (LMS) and its variants are illustrations of part of such strategies employed to eliminate noise in detected waveforms. In any case, these computations perform poorly when dealing with non-straight signals and are unable to provide a globally optimal solution for noise retraction. In this way, the use of global inquiry advancement techniques, such as developmental calculations, is taken into account for noise retraction. In this study, LMS computations are performed and their displays evaluated, together with an upgraded particles swarm optimization improved (PSO). The supplied waveform was subjected to broad recreations in which non-straight irregular noise and Gaussian noise were included. Two metrics were used to complete the presentation examination: mean square error and bit error rate. The results demonstrate that for both Gaussian and nonlinear arbitrary noise, the enhanced PSO outperforms LMS.

Keywords: Enhanced Particle Swarm Optimization (PSO), Least Mean Square (LMS), Cognitive Radio, Noise Cancellation, Adaptive Algorithm.

1. INTRODUCTION

One of the typical issues with transmission frameworks is noise, which degrades the information transfer between the modulator and the detector. Examples of noise sources include the presence of non-linearity in the RF section, time-changin warm noise inside the collector radio framework, and noise along adjacent organization hubs or RF climate. Similarly, other factors that affect the reliability of waveforms are shadowing, crosstalk, and way chance [1, 2]. Ordinary communication frameworks use stationary equipment [3] to regulate the noise, which limits performance and requires special features. However, rather than needing specifically designed equipment for signal preparation, programming-based frameworks enable reconfigurable by employing multi-reason computerized programmable devices, such as FPGAs [4].

Cognitive Radio (CR) is an example of such reconfigurable and adaptable innovations. Programming characterized radio (SDR)-based CR frameworks are full-duplex, wideband phones. Despite the earlier mentioned sources of noise, CR frameworks are impacted by certain nonlinear framework-induced noise since CR must perform several sophisticated and intricate signal handling duties throughout a broad range of recurrence groups. The blockage caused by various groups during range detection, the noise immersion of the CR beneficiary by the co-located CR transmitter operating concurrently and the recurrence band during full-duplex communication, and framework non-linearity can all contribute to noise in CR [6].

Non-slope computations, also known as worldwide inquiry optimization methods, can be used to overcome the problem of locating worldwide minima of a blunder surface. Examples of these computations are molecular swarm optimization, cuckoo search, hereditary, and artificial honey bee province (ABC). For the cycle of transformation and hybrid to unite at a constant pace, several of these computations, such as the hereditary calculation, necessitate selecting appropriate introduction esteems [11]. Finding appropriate attributes for this introduction of components is often seen as case-subordinate and evaluated using precise perceptions. By presenting focused adaptive methodologies for describing the instatement elements, a few further studies suggested further refined adaptation of these computations. [11 - 13]. The improved PSO calculation, then again, doesn't depend on a particular single variable introduction, like the progression size in angle calculations and is less complicated [14]. As far as we could possibly know, the possibility of utilizing developmental calculation based adaptive channels, explicitly for CR frameworks, has not yet been investigated. However, some exploration works proposed and carried out inclination calculations for noise abrogation in CR framework's [15 - 16]. Consequently, the effectiveness of using dynamic optimization function PSO (DOFPSO) for denoising signals in CR frameworks is investigated in this article. The research also considers DOFPSO's efficacy in comparison to the LMS calculation. Reproductions are used to simulate information transfer between two intellectual radio units in order to evaluate how each computation is presented. To replicate the framework-initiated noise in intellectual radios, both non-straight irregular noise and white Gaussian noise (AWGN) are introduced to the received signal at the receiver end. This paper's adaptive separation framework is based on an adaptive line enhancer's (ALE) framework plan, the nuances of which are discussed in the next section. This paper is arranged as follows. In section 2, a description of the system design with a structure of the two algorithms have been presented. In section 3, the results of real-time waveforms and the two algorithms are analyzed with comparison. At last, in section 4, the conclusions and future works have been illustrated.

2. METHODOLOGY

A universal Cognitive Radio transceiver structure is shown in Fig. 1. The CR transmitter utilized an M-ary phase shift keying (M-PSK) modulation technique to ensure efficient bit rate analysis [1,3]. The transmitted modulated signal, x(t) is transferred through a noisy communication channel influenced with AWGN. the AWGN signal, n(t) has been additively combined with the digitally modulated information signal, and received at the CR receiver section. The received noisy signal, r(t) is then sampled as well passed to the adaptive noise cancellation scheme. In this system the ALE based filtering scheme has been implemented instead of the active noise control (ANC) filtering model, since the first utilizes single sensor while the second need a primary and reference sensor [1]. The noisy received signal, d(t) has been passed to the ALE system, with sort of delay, $z^{-\Delta}$, and result a delayed copy of y(t), denoted as: $\hat{y}(t)$ as demonstrated in Fig. 2 [1]. The noise will be suppressed after estimating the resulting output signal y(t) through updating the weight parameters W(n) of the ALE filter. This might be represented in mathematical equations as follows:

$$\boldsymbol{y}[n] = \widehat{\boldsymbol{Y}}[n]\boldsymbol{W}[n] \quad (1)$$

$$\widehat{\boldsymbol{Y}}[n] = (\hat{y}[n], \hat{y}[n-1], \ldots, \hat{y}[n-L+1]) \quad (2)$$

$$\boldsymbol{W}[n] = [W_1, W_2, \ldots, W_L]^T \quad (3)$$

Such that, L is the order of adaptive filter also, T denotes the vector transpose. As depicted in literature [3], optimal weights have been estimated when the error signal $\boldsymbol{e(t)}$, is minimized.

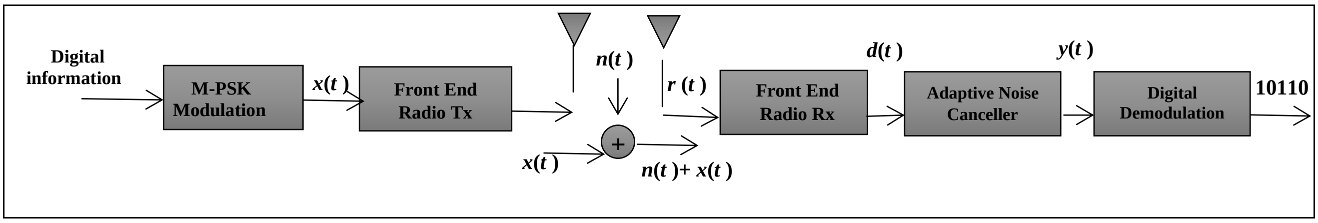

Figure1: Blok diagram of pass-band communication CR system model with noisy channel.

The error signal, $\boldsymbol{e(t)}$ might be represented as:

$$\boldsymbol{e(n) = d(n) - y(n)} \qquad (4)$$

After that, the resulting output filtered signal, $\boldsymbol{y(t)}$ is then received and analyzed using the analog-to-digital converter A/D to reconstruct the baseband bits streams utilizing the demodulation scheme.

A. DOFPSO Adaptive Noise Cancellation

One evolutionary method that relies on the stochastic global optimization technique is DOFPSO [11, 18]. In adaptive noise cancellation, DOFPSO has been utilized with the primary goal of minimizing the remaining noise signal by setting up the adaptive filter's weight coefficients optimally. As we estimate the mean square error (MSE) between the adaptive filter result signal y(n) and the input samples $d(n)$, we assess the cost function of the suggested DOFPSO method. The cost function's formulation might be computed as:

$$C_{i,k} = \frac{1}{N}\sum_{n=1}^{N} e_{i,k}(n)^2 \qquad (5)$$

where $e_{i,k}$ is the error waveform at the kth iteration for the ith particle, also N defined as the input samples number of the ALE filter [1]. By referring to Eq. (1), the resulting signal , y(n) is obtained from updating ŷ(t) using the filter weight coefficients, W(n) supplied via the DOFPSO algorithm to the adaptive filter. From the other hand, the modified PSO, named as DOFPSO will act initially in a similar methodology as the ordinary PSO, such that by initializing a group of particles, and setting every location and initial velocity to zero [1,2]. The location vector will define the weights coefficients, and initialized as N values of random solutions, such that:

Wi (n)=[W1, W2, … , WL] (6)

Where i=1, 2, 3, …. , N. Beside the primary set of the particles locations, amounts of the cost function, $C_{i,k}$ are calculated, for N parameters and k repetitions. Now by defining PBestCost as the specific value of the particle position that produce the cost function $C_{i,k}$ to minimum value [1,2]. The velocity of the ordinary PSO of of N particles for k iterations is specified as [1]:

vi,k=vi,k-1 + c1r1 (PBestCost –wi,k-1) + c2r2 (PGlobalBest - wi,k-1) (7)

Where, c1 , c2 are the learning coefficients, vi,k , wi,k-1 are the r1 r2 are uniformly distributed arbitrary amounts distributed random sums throughout the length of 0 to 1. Locations of the i^{th} parameters and at the k^{th} repetitions have been updated utilizing:

wi,k= wi,k-1 + vi,k (8)

At the kth iteration, the location PBestCost considered as the local best location, also PGlobalBest is the global better location amongst the ith iterations. These processes will be repeated till the algorithm assembles to a global optimum answer or a maximum account of repetition is attained.

Now, the DOFPSO algorithm will act based on the ordinary PSO algorithm such that to choose optimal initial values of the particles positions as well velocities according to the formula given by [2]:

xi (0) = (Xmax -Xmin) × rand () (9)

wi (0) = (Xmax -Xmin) × rand () (10)

where rand () is an arbitrary random number ranges from (0 to 1). By applying Eq. 9 and 10, an optimization of the initial values of the particles positions and velocities, xi (0), and wi (0) will be obtained. This optimal initialization will exclude the dependency of Eq. (7) on PBestCost so that, we could further exclude the effect of the learning coefficients c1 , c2 as well as the uniformly distributed random amounts r1 r2 , in Eq. (7) [2]. Hence Eq. (7) will be rewritten such as:

vi,k= + PGlobalBest - wi,k-1 (11)

consequently Eq. (8) will also rewritten as:

wi,k= wi,k-1 + s × vi,k (12)

where, s is an integer accelerator factor utilized to speeding the convergence of the weights through reducing time required to reach the local optimal [1,2]. Un like to PSO algorithm, there will be no calculations for the PBestCost and it will be not considered as the local best location at the kth iteration, due to effect of the influence of the optimum initial particles position and velocities. On the other hand, PGlobalBest will still be considered as the global best position amongst the ith iterations. Until the algorithm converges to a global optimal solution or a maximum limit of iteration is reached, these procedures will be repeated. Therefore, as shown in the flowchart of Fig. 3, these procedures will be continued until convergence to a global optimal response or a maximum range of repetition is achieved by the algorithm.

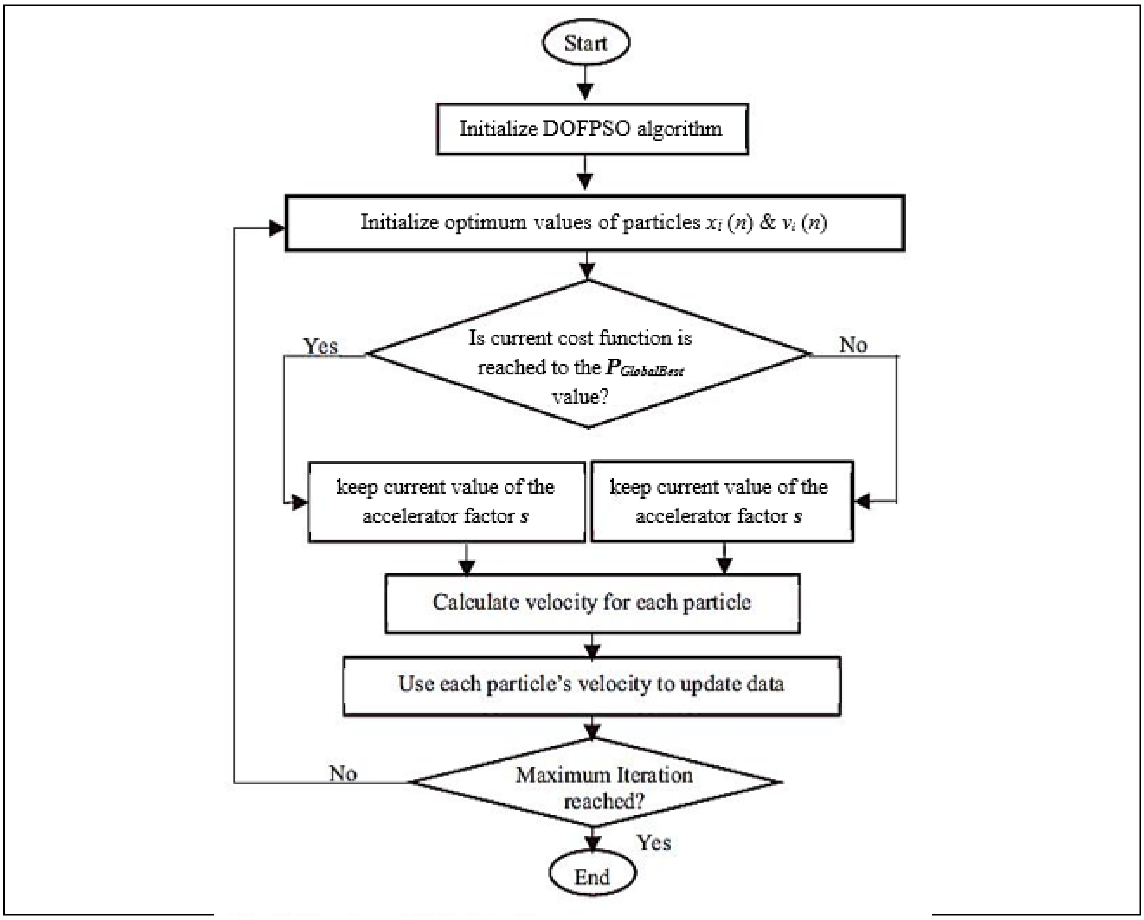

Figure3: Flowchart of the DOFPSO algorithm.

B. LMS Adaptive Noise Cancellation

The least mean square LMS is a gradient descent method that follows the gradient's negative in order to converge to the desired local minimum. It has been initialized among a certain number. In order to determine the propensity of the negative fall from one point to another, LMS utilizes a step length that might be explained as the directing element. An LMS weight update might be written like:

$$W(n+1) = W(n) + \mu\, e(n)\, \hat{Y}(n) \qquad (13)$$

Such that, μ is the step length with W (n) is the weight vector, which together regulate the LMS convergence speed. To get the best convergence rate, it is preferred to choose a step size with modest values in order to decrease the total error plane or the error sampled waveform [12]. One of the most crucial operational requirements of an adaptive algorithm is the optimization of the step size. According to Eq. (1), the updated filter coefficients are thus used to estimate the resultant waveform. Fig. 4 shows the LMS algorithm flowchart.

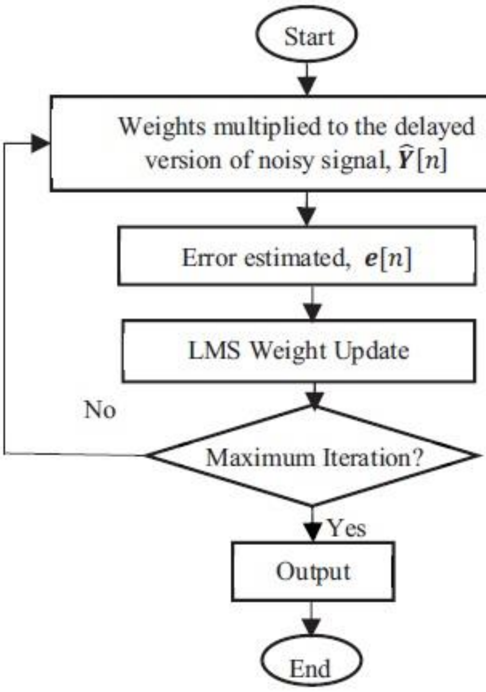

Figure 4. Flowchart of Least Mean Square algorithm [1].

3. SIMULATION & RESULTS

MATLAB was used as a stage to execute DOFPSO with LMS algorithms. For all reenactments, the piece packet is provided to generate a signal of $H=10^4$ tests as well regulated utilizing M-PSK scheme along M=2. At the recipient, AWGN with non-direct irregular noise were also summed to the sent waveform, and it was then sifted using DOFPSO in addition to LMS algorithms. Two measurements were employed to compute also look for the efficiency of two calculations: bit error rate (BER), which is detailed as the sum of pieces in error isolated by the overall value of moved pieces through a focused period span:

$$BER = \frac{Number\ of\ Corrupted\ Bits}{Total\ Number\ of\ Transmitted\ Bits} \qquad (14)$$

The mean of squares of the errors or divergences, or the variance amidst the noisy wave and the filter-generated wave, is known as the mean square error (MSE). It is explained as:

$$:\mathrm{MSE} = \sum_{l=1}^{N}\left(\frac{\text{Noisy Signal}}{\text{Output Filtered Signal}}\right)^2 \qquad (15)$$

Where, N denotes the domain of the reconstructed wave. The real-time waves determined along the simulated scheme of both the transmitter and receiver units with samples of MSE and BER results for DOFPSO and LMS have been illustrated in Fig. 5 through 8. As previously mentioned, the main deficiencies of LMS algorithm is its inferior response with non-linear waveforms. Therefore, for waveforms corrupted through both AWGN as well as non-linear random noise, an equivalent simulations have been produced. Furthermore, multiple frequency ranges have been implemented to simulate the M-PSK modulation technique utilized for the CR’s dynamic frequency connection capacities. Such frequency ranges are taking values of; 2.4GHz, 5.8 GHz and 60 MHz to cover both licensed as well as unlicensed frequency bands utilized by CR schemes to investigate the performance of the LMS and DOFPSO algorithms.

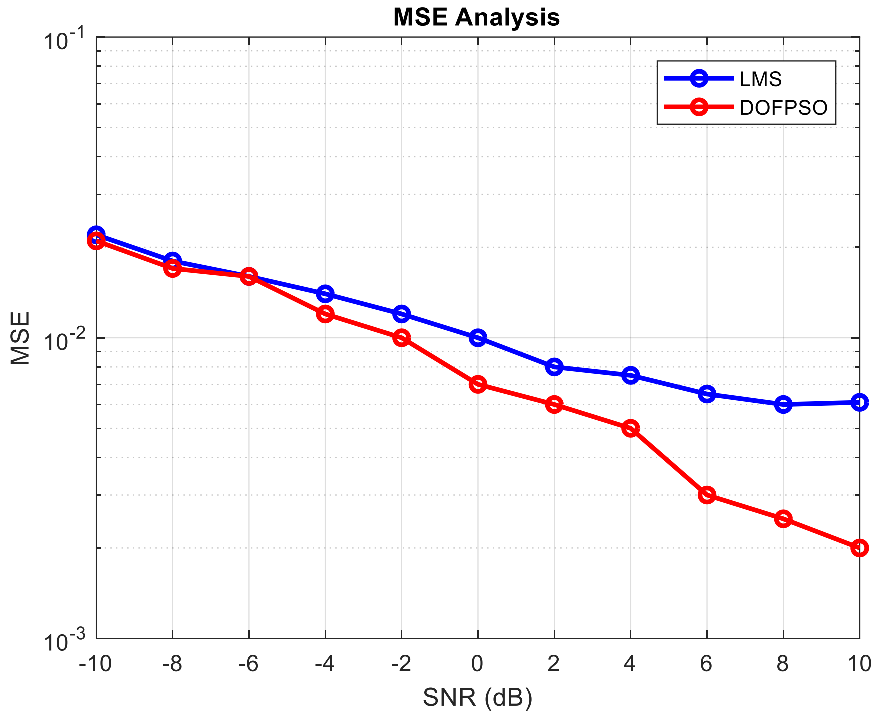

Figure 5:DOFPSO and LMS for altering SNR constraints.

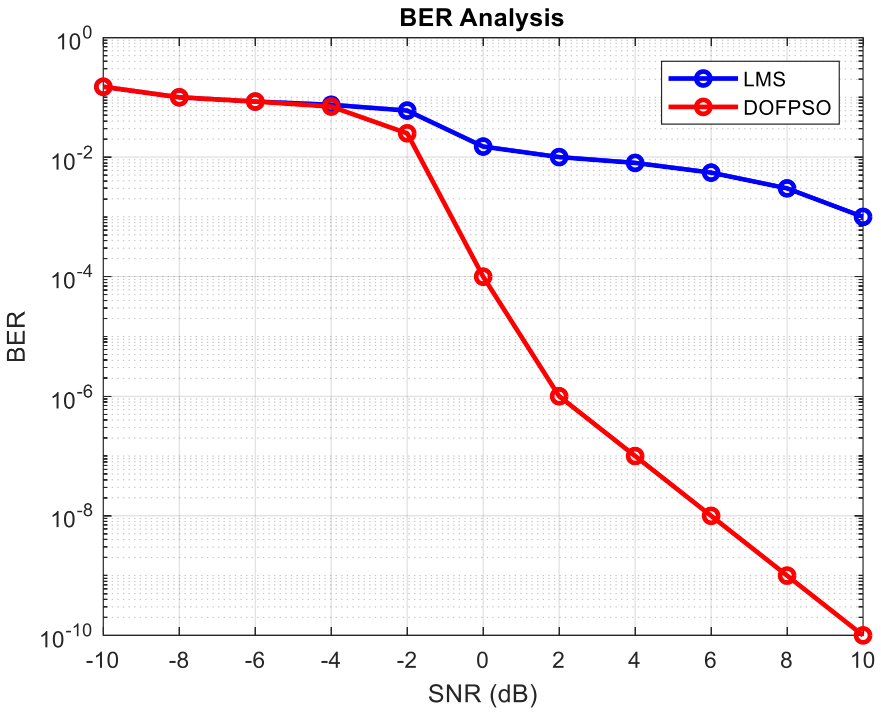

Figure 6. BER of LMS and DOFPSO for noisy waveforms based on AWGN.

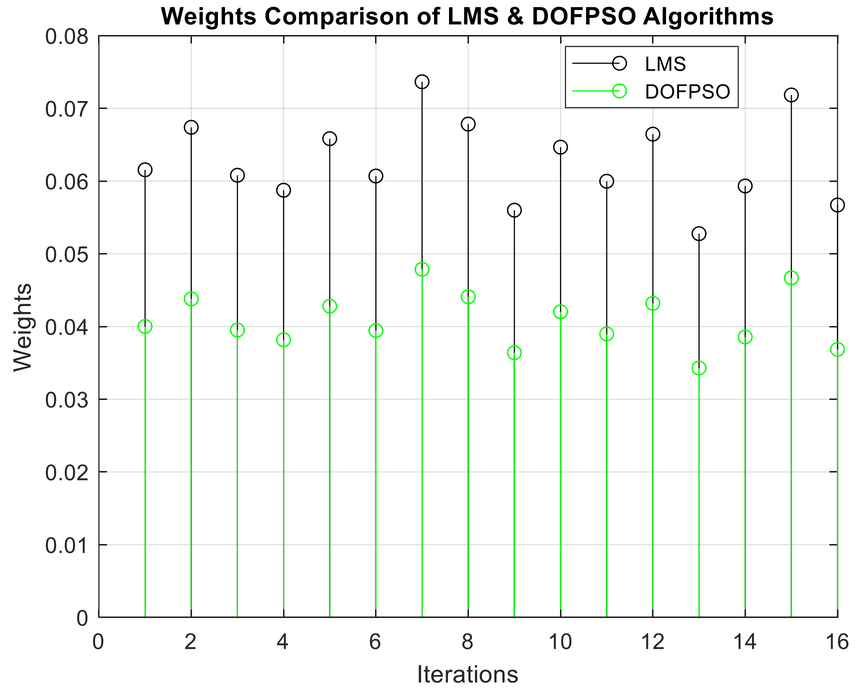

Figure 7:Adaptive filter weights coefficients for both DOFPSO and LMS algorithms.

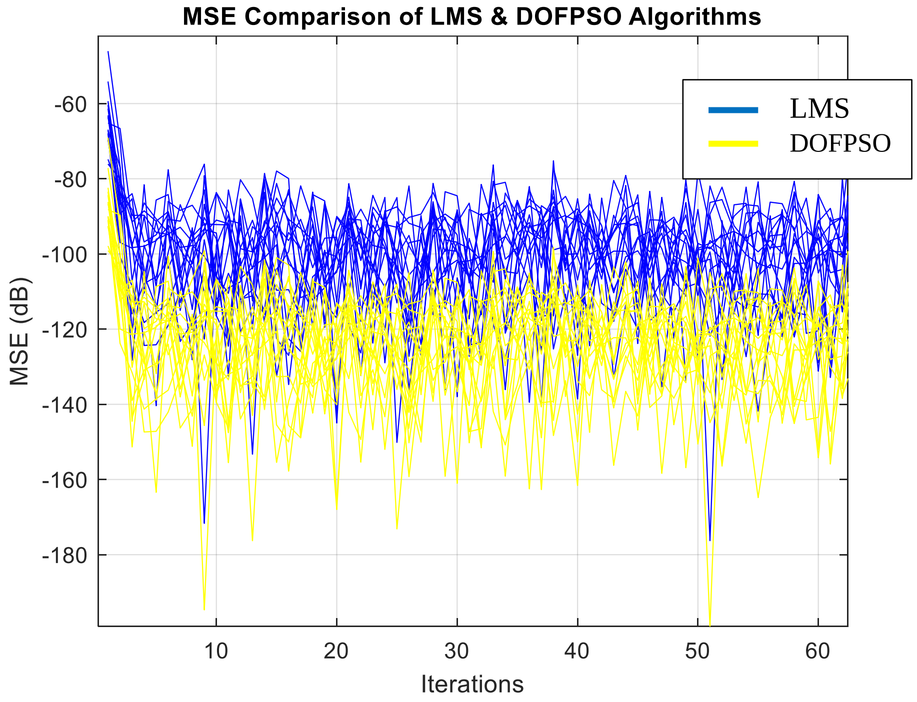

Figure 8:Adaptive weights coefficients for both DOFPSO and LMS algorithms.

Now by referring to Figure 5, it is clear that, the mean square error, MSE obtained utilizing the improved PSO algorithm (DOFPSO) has best performance of that accomplished by the LMS algorithm. Accordingly, as the signal to noise, SNR increased, the proposed DOFPSO algorithm show a noticeable enhanced MSE that the LMS one. Also, concerning Figure 6, it is further obvious the effect of the suggested DOFPSO algorithm influence over the LMS one on the resulting bit error rate BER of the reconstructed data, since by increasing the SNR of the transmitted digital signal, the overall system BER will greatly declines with DOFPSO algorithm rather than LMS technique. We could noticed that at 10 dB SNR the degradation in the BER will be reached to -100 dB using DOFPSO algorithm whereas by implementing LMS approach the BER is only touched -30 dB declination. On the other hand, we can also see from Figure 7 the effect on utilizing the proposed adaptive DOFPSO over the LMS algorithm on the adaptive filter weights coefficients. The adaptive filter weights showing better results in their amplitudes when implementing the suggested adaptive DOFPSO algorithm that that of the LMS approach. Finally, the most important result has been demonstrated in Figure 8, in which the mean square error MSE has been computed for both adaptive DOFPSO and LMS techniques. We can unquestionably measure the reduction in the MSE value calculated through utilization of adaptive DOFPSO over LMS algorithm. Table 2 illustrate a general comparison among adaptive DOFPSO and LMS algorithms.

Table 1: General comparison among adaptive DOFPSO and LMS algorithms.

Algorithm	**Complexity**	**Convergence**	**Optimization**
DOFPSO	Complex	Initial variables un affected e.g. step size	Locate Global minima
LMS	Simple	Initial variables affected	Locate Local Minima Only

CONCLUSIONS

This study describes the use of LMS algorithms in conjunction with the adaptive improved PSO (DOFPSO). By simulating actual communication methods and waveforms tainted by both Gaussian and non-linear random noise, massive simulations were put into practice. BER and MSE analysis were used to calculate and evaluate the two methods' efficiency. According to simulation data, the DOFPSO method outperforms the LMS approach in terms of expressively increased BER for Gaussian noise. By all means, DOFPSO still outperforms the LMS approach even if both algorithms exhibit declining features for nonlinear random noise. In addition, the MSE system of both methods was examined for different values of SNR. The findings show that DOFPSO's MSE is less than that of LMS against advancing SNR. Additionally, the impact of step lengths and varying particle ranges on the MSE of DOFPSO and LMS were examined. In general, this study demonstrated how the adaptive DOFPSO algorithm, when combined along AWGN with non-linear arbitrary noise, improved the performance of the CR communication system that received data..

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