Beamforming Array Antenna Technique Based on Partial Update Adaptive Algorithms

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Abstract *–The most important issues for improving the performance of modern wireless communication systems are interference cancellation, efficient use of energy, improved spectral efficiency and increased system security. Beamforming Array Antenna (BAA) is one of the efficient methods used for this purpose. Full band BAA, on the other hand, will suffer from a large number of controllable elements, a long convergence time and the complexity of the beamforming network. Since no attempt had previously been made to use Partial Update (PU) for BAA, the main novelty and contribution of this paper was to use PU instead of full band adaptive algorithms. PU algorithms will connect to a subset of the array elements rather than all of them. As a result, a common number of working antennas for the system's entire cells can be reduced to achieve overall energy efficiency and high cost-effectiveness. In this paper, we propose a new architectural model that employs PU adaptive algorithms to control and minimize the number of phase shifters, thereby reducing the number of base station antennas. We will concentrate on PU LMS (Least Mean Square) algorithms such as sequential-LMS, M-max LMS, periodic-LMS, and stochastic-LMS. According to simulation results using a Uniform Linear Array (ULA) and three communications channels, the M-max-LMS, periodic LMS, and stochastic LMS algorithms perform similarly to the full band LMS algorithm in terms of square error, tracking weight coefficients, and estimation input signal, with a quick convergence time, low level of error signal at steady state and keeping null steering's interference-suppression capability intact.*

Keywords*: Beamforming Array Antenna, Partial Update Adaptive Algorithm, Full band LMS, M-max PU LMS, sequential PU LMS, periodic PU LMS and stochastic PU LMS algorithms.*

1. INTRODUCTION

In next-generation cellular communication networks, numerous antennas are used to improve spectral and energy efficiency, as well as performance against interference caused by constrained spectrum. This is possible through the use of various antenna designs, one of which is Beamforming Array Antenna (BAA). The development of 5G and upcoming wireless communication systems is anticipated to depend mainly on BAA technology [1].

Signals are correctly controlled in adaptive array beamforming at wireless communication link base stations (BSs) and mobile stations with the aim of enhancing the wireless mobile link and boosting system performance. The antenna boosts the capacity of wireless communication networks by effectively decreasing multipath fading and channel interference. This is accomplished by employing beamforming techniques to focus signal radiation in the desired direction and adapt it to the signal environment. [1, 2]. The most well-known and powerful beamforming scheme is the well-known Phased Array Antenna (PAA), which is an array of antenna elements driven by signals with well-defined phase relationships between those elements [1]. ULA with N-antenna elements required N phase shifters or other active control units. There are only a few papers in the literature that propose algorithms or techniques for reducing the number of ULA elements and thus the number of phase shifters [2-10].

To achieve high cost-effectiveness and total energy efficiency, the system can reduce the number of operational antennas for all of the cells. [2-10] The overall energy efficiency of the cell is mostly influenced by how many functioning antenna elements there are in the cell for each BS's stipulated power consumption. As novel ideas, the authors of [2] proposed the cascaded angle offset phased array antenna (CAO-PAA) and the dimensionality reduced CAO-PAA (DRCAO-PAA). They represent phase shift steering in all directions using a coefficient matrix. The dimensionality of the coefficient matrix is then lowered by reducing the number of phase shifters [2].

Other strategies for reducing the active number of antennas have been proposed [3-9], including reduced active controller-based vector synthesis. Another method is sub-array compression, which employs a different phase shifter for each sub-array. The author of [10] proposed that an adaptive algorithm (such as LMS, RLS, CG, or CMA) be connected to only a small number of the array elements located in the center of the array rather than all elements, leaving the other elements that have less of an impact on the pattern of the array unaffected by the adaptation process.

The Partial Update (PU) algorithms have gained significant attention in recent years, both in terms of research and practical applications [11-24], but they have yet to be applied to array beamforming systems. According to our knowledge, no previous studies have used adaptive partial update (PU) methods for beamforming array antennas. This study proposes using PU techniques for beamforming array antennas by proposing a new architecture system model, which was thought to be the paper's main innovation, in order to reduce the number of antennas used. Rather than connecting to the entire set of antenna elements, partial update adaptive methods will connect to a subset of them.

Then, we will be applying PU LMS algorithms such as sequential-LMS, M-max-LMS, periodic-LMS, and stochastic-LMS algorithms.

As a result, in terms of convergence time and ability to suppress interference signals via null steering, the performance of these methods will be comparable to that of full band adaptive arrays. The performance of the proposed model will then be compared to three different multipath fading propagation LTE channel models.

The reminder for this paper will be as follows: Section 2 covers beamforming theory and Partial Update LMS adaptive algorithms. Section 3 describes the proposed model's architecture. Section 4 presents simulation results, Section 5 compare results with previous work and Section 6 concludes the study.

2. BACKGROUND

2.2. BEAMFORMING ARRAY SIGNAL MODEL

The use of beamforming antennas by mobile carriers is crucial for the development of next-generation networks. Beamforming antennas dynamically shape their main and null beam directions based on the location of their connected users, in contrast to older antennas that could only transmit and receive on set radiation patterns.

Because of this, these futuristic antennas are often referred to as "beamformers" In addition to greatly enhancing the signal-to-interference-and-noise ratio (SINR) and the end user experience, beamforming antennas stand out for their ability to successfully minimize interference.

By lowering the amount of signal interference from other users, maximizing the signal strength received by each user, and transmitting beamforming aims to boost capacity. By entirely constructing the processed signals in the direction of the desired terminals and canceling the beams of competing signals, the goal of the beamforming process is to construct an antenna's radiated beam patterns.

ULA is the most commonly studied method in array signal processing due to its simplicity. Consider an N-element uniform linear antenna array (ULA), as depicted in figure 1. Let the spacing between each antenna element be d = 0.5 λ, where λ is the wavelength of incoming signals.

This diagram shows how the weight vector $w=[w_1\ w_2\ \ldots w_N]^H$ can be changed to reduce errors as much as possible when iterating the array weights [25]. The signal s(n) and interferers $i_1(n), i_2(n), \ldots i_N(n)$ are received by a collection of N elements, each having N potential weights. Additionally, there is additive Gaussian noise in every element. Each of the n_{th} time samples are a representation of time.

2.2. FULL BAND LEAST MEAN SQUARES (LMS)

The LMS beamforming method is simple and widely used in wireless communication applications. As a result, this method is frequently used as an adaptive beamforming technique in a variety of applications. The weighted array output in Fig. (1) is written as follows: [25].

$$y(n)= w^H (n)\, x(n) \tag{1}$$

$$\begin{aligned} x(n) &= a_0\, s(n) + [a_1\, a_2 \ldots a_N] \,.\, [i_1(n)\ i_1(n) \vdots \\ &\quad i_N(n)]+z(n) \\ &= x_s(n)+x_i(n)+z(n) = input\ signal \end{aligned} \tag{2}$$

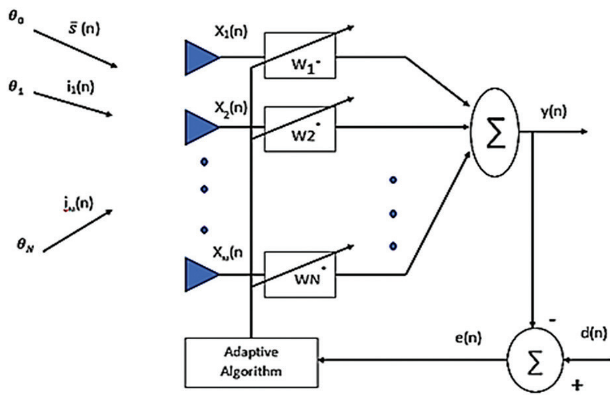


Fig. 1. Adaptive Array Beam forming System

With:

$w=[w_1\ \ w_2\ \ \ldots w_N]^T$= array weights

$x_s(n)$ = desired signal vector

$x_i(n)$ = interfere signals vector

$z(n)$ = Gaussian noise with a zero mean for each channel

$s(n)$ is desired signal

θ_0 is desired signal direction

$\theta_1 \ldots\ldots \theta_N$ is interfere signals direction

a = steering vector for θ_i direction of arrival using an N-element array.

The difference between the desired signal $d(n)$ (eq. (1)) and the output signal $y(n)$ is the error signal $e(n)$ [25]:

$$e(n)=d(n)-w^H(n)\,x(n) \tag{3}$$

The weight vector of LMS is calculated using the gradient of the cost function [1]:

$$w(n+1)=w(n)+\mu\, e(n)\, x(n) \tag{4.1.}$$

If update vector $f(n) = \mu\, e(n)\, x(n)$, then:

$$w(n+1)=w(n)+f(n) \tag{4.2.}$$

The parameter μ is a step-size directly influences the LMS algorithm's convergence in equation (4.1).

2.3. PU LMS ALGORITHMS

Processing work can be reduced during the adaptive filter update phase using a technique called partial updates (PU). In recent years, these algorithms have drawn a lot of interest from both users and researchers [23].

The partial-update approach updates only the $M \times 1$ coefficients, where $M < N$, as opposed to updating all of the N-1 coefficients. This paper considers fundamental partial update techniques such as (periodic, sequential, stochastic, and M-max) PU approaches. A general update equation can be used to characterize each PU algorithm studied in this study [14] [26]:

$$w(n+1)=w(n)+\mu\, I_M(n)\, e(n)\, x(n) \tag{5}$$

The matrix, $I_M(n)$, which is known as a weight selection matrix, represents the only distinction between PU techniques (5) and the full update LMS algorithm (4.1). It can be calculated as [14, 26]:

$$I_M(n)=\begin{bmatrix} i_0(n) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & i_{L-1}(n) \end{bmatrix},\quad i_k(n)\epsilon\,\{0,1\},\quad \sum_{k=0}^{(L-1)} i_k(n)=M \tag{6}$$

Hence, a diagonal matrix with entries of (0 or 1) makes up the weight selection matrix, where M denotes the sum of the number of 1s in the matrix indicating which M coefficients are to be updated at iteration n and the diagonal of the matrix, which has N-M zeros.

The number M, which represents how many adaptive filter weights are chosen for the update at each sampling interval, is likewise subscripted to the selection matrix. The selection matrix's diagonal elements are set to 0 or 1 in each consecutive sample interval using the procedure below: [14, 26]:

$$i_k(n)=\begin{cases} 1 & \text{if } k \in I_M(n) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Where $I_M(n)$ stands for a collection of filter weight indices with a count of M, indicating the coefficients to be modified in the nth iteration. This set's definition changes based on which PU LMS algorithm is used.

The main advantage of the partial updates in (5) is that they minimize complexity to meet hardware complexity restrictions. The slower convergence speed of partial updates could be a drawback. Partial updates might be viewed in this situation as a trade-off between computational complexity and convergence speed.

2.4. PU SEQUENTIAL LMS ALGORITHM

By updating a piece of the adaptive filter coefficients at each iteration, sequential PU reduces the computation required for the adaptation process.

For each iteration of the sequential PU approach, a portion of the coefficient vector is modified to fit the complexity restrictions [14]. The adaptive filter coefficient vector is, in this sense, "decimated" by the use of consecutive PU.

Deterministically, the coefficient subsets to be updated are chosen in a round-robin fashion. As a result, regardless of the input signal, the updates follow a periodic pattern. The coefficient selection matrix $I_M(n)$ is computed as follows: (6).

For given N and M, $I_M(n)$ is not explicitly specified. Consider the distinct M-subsets of the coefficient index set (that is, subsets with M members) $S = \{1, 2, \ldots, N\}$, denoted by $(I_1, I_2, \ldots, I_C)$where $C = (N/M)$. The symbol S is the period of coefficient updates.

Suppose that $(B = N/M)$ is an integer. The sequential partial update method can then be implemented by using any B M-subsets of S. The complexity of the adaptation process can be reduced by updating M coefficients in an adaptive filter of length N at every iteration. As a result, the algorithm has a number of flaws, such as a slow rate of convergence, instability for cyclostationary input signals, and more [11-12].

2.5. PU M-MAX-LMS ALGORITHM

The M-max LMS selects M elements from the input vector $x(n)$ that cause the greatest changes in the magnitude of the filter weights. When partial updates are applied to the generic adaptive filter in (5), the result is [14]:

$$w(n+1)=w(n)+I_M(n)f(n) \tag{8}$$

Where: $f(n)$ is update vector

$$f(n)=[f_1(n), f_2(n) m \ldots, f_N(n)]^T \tag{9}$$

The entries in the selection matrix's diagonal of the coefficient selection matrix $I_M(n)$, specified in (6), are [14]:

$$i_k(n)=\{1 \quad \text{if } |f\_k(n)| \in (|f_l(n)|, M) \;\; 0 \quad \text{otherwise} \tag{10}$$

where $\max_{0\le l\le N}(f_l, M)$ represents a set of M maxima of elements f_l [26]. M-max updates are similar to sequential partial updates in that they both 'decimate' the update vector.

2.6. PU PERIODIC LMS ALGORITHM

The updating weights vector is as follows when periodic partial updates are applied to the adaptive filter coefficients in (4.2.):

$$w((n+1)S)=w(nS)+f(nS) \quad n = 0, 1, 2, \tag{11}$$

$$w((nS+i))=w(nS) \quad i = 0, 1, \ldots, S-1 \tag{12}$$

The periodic PU method decimates the coefficient update w(n) by a factor of S. The coefficients of adaptive filter update every Sth iteration at k = 0, S, 2 S, 3 S, . . ., while the coefficients of adaptive filter are held constant between updates, i.e.,

$$w(n\,S) = w(n\,S + 1) = \cdots = w(n\,S + S - 1)\,.$$

The adaptation process can calculate the update vector in S iterations due to the decimation of updates by S. As a result, the typical processing demands of each iteration are reduced by S [14].

2.7. PU STOCHASTIC LMS ALGORITHM

To implement the stochastic method, a randomized variation of the sequential approach can be used, in which the coefficient of adaptive filter subsets is chosen at random rather than in a deterministic manner [14]. The stochastic PU method employs the following coefficient selection matrix:

$$I_M(n)=[i_0(n) \cdots 0 \vdots \ddots \vdots 0 \cdots i_N(n)\;], \quad i_k(n)=\{1 \quad \text{if } k \in I_{m(n)} \;\; 0 \quad \text{otherwise} \tag{13}$$

where $m(n)$ is an independent random process.

By using stochastic PU methods, complexity can be reduced to a level equivalent to that gained by sequential PU [26], if the overheads for producing the random signal m(k) are disregarded. Moreover, the stochastic partial update algorithm surpasses the sequential partial update technique in terms of network performance [19].

3. ARCHITECTURE OF THE PROPOSED MODEL

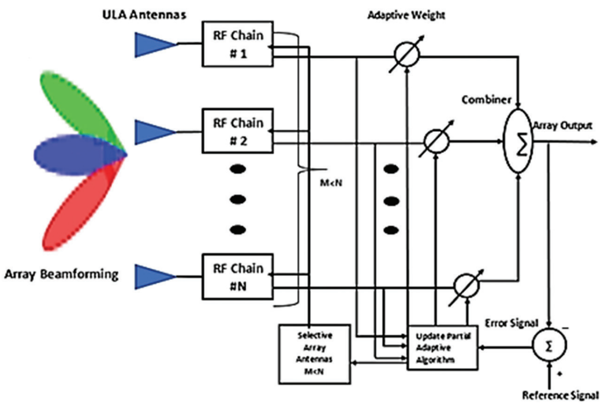
In next-generation networks with numerous antennas in the precoders and/or detectors, adaptive array beamforming is essential [27]. Next-generation networks have lower power consumption and amplifier costs due to lower power requirements of beamforming array antennas for sending signals to the intended user and cost reductions.

To achieve high cost-effectiveness and total energy efficiency, a common number of functional antennas for the system's cells might be decreased. The number of working antenna elements in the cell has a relatively significant impact on overall energy efficiency for the specified power consumption of each BS.

The most popular and effective method for providing adaptive array beamforming is the well-known phased array antenna (PAA), which is an array of antenna elements controlled by signals with well-defined phase relations between those elements [28].

A N-phased array antenna typically requires N phase shifters or other active control components. Many plans exist to reduce the use of phase shifters, but more active control units should be added as a substitute.

Although many ULA researchers have studied these issues, update partial (PU) adaptive filtering has never been used before. Fig. 2 depicts the architecture-proposing model, which employs update partial adaptive filtering to select or deselect the RF chain for each ULA element to increase or decrease the number of antennas (M), such that $M < N$.



This selection process implies that at each coefficient update, M coefficients are updated while the remaining (N-M) coefficients remain unchanged. In theory, the chosen M coefficients should change with each iteration to allow all adaptive filter coefficients to be updated over time. This reduction also has important implications, such as minimizing each antenna element's radio frequency (RF) chain and reducing the total size and weight of the antenna array system. Another critical component is to streamline signal processing and reduce the amount of storage required as fewer signals are received. As a result, the overall cost of the system is reduced.

The process of reducing the number of antenna elements in antenna arrays while maintaining their radiation pattern features close to the full band, on the other hand, has a significant impact on wireless communication systems. When the number of elements is reduced, the radiation pattern exhibits minimal distortion and is symmetric in all orthogonal planes of the array.

4. SIMULATION RESULTS

The array beamforming base station, as depicted in Fig. (2), comprises a linear antenna array made up of eight (N=8). It is assumed that the x-axis contains all of the array's elements, and that each element is d=0.5 λ units apart. Three users broadcast at a specific elevation angle, with the intended user's angle being 00 and the other two users' angles being 300 and -200, respectively. There have been 400 iterations in total. Table 1 show the simulation parameters:

Table 1. The simulation parameters

Parameter	Value
Carrier Frequency (FC)	900 MHz
Signal Frequency	200 KHz
Spacing between element (d)	0.5 λ
Type of antenna	Uniform N element linear array antenna
Number of elements	N = 8 (full band) & (M = 1, 3 , and 5 for partial band)
Channel	EPA, EVA, and ETU

Given that all algorithms tested had the same step size μ value, which was calculated automatically within the MATLAB program according to (14). It was demonstrated that using this selection criterion would produce results that were as close as possible to the full band LMS algorithm's performance. The formula in (14) is dependent on the maximum eigenvalue λ_{max} of the input correlation matrix estimation $\hat{R}_{xx}$: [24]

$$0 \leq \mu \leq \frac{1}{2\lambda_{max}} \tag{14}$$

$$\text{Step size (LMS) } \mu = \frac{1}{(4*real(trace\ R_{xx})} \tag{15}$$

Were $\hat{R}_{xx}$, can be instantaneous estimates as:

$$\hat{R}_{xx}(n) \approx \underline{x}(n)\,\underline{x}^H(n) \tag{16}$$

The crucial design parameter is the number of filters taps that must be changed with each sampling interval. In the PU-LMS algorithms, M coefficients out of the adaptive filter's N coefficients are updated at each iteration. To select the suitable value of M parameter, several values of M will used which are 1,3 and 5 respectively. Then a comparison result obtained to choose the best value of M that perform the best performance of the algorithms. Then best value for M will used for the rest of the work. The chosen M coefficient values starts at 5 then 3 , then 1 which represents the worst case [23] using EPA channel.

4.1. SIMULATION RESULTS USING EPA (EXTENDED PEDESTRIAN MODEL) LTE CHANNEL MODEL

The Extended Pedestrian is the first model. A wireless channel model (EPA) with seven pathways and a gain of [0 -1 -2 -3 -8 -17.2 -20.8] dB with a delay of [0 30 70 90 110 190 410] *1e-9 for each path [29-30]. This channel simulates small cell size and low delay spread situations found inside buildings. Fig. (3 & 4 & 5) show the error square performance for all algorithms (EPA channel) at M=1 & M=3 & M=5, respectively.

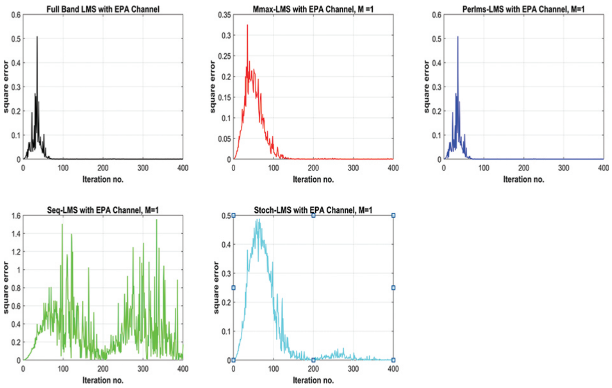


Fig. 3. Error Square performance for all algorithms (EPA channel) at M=1.

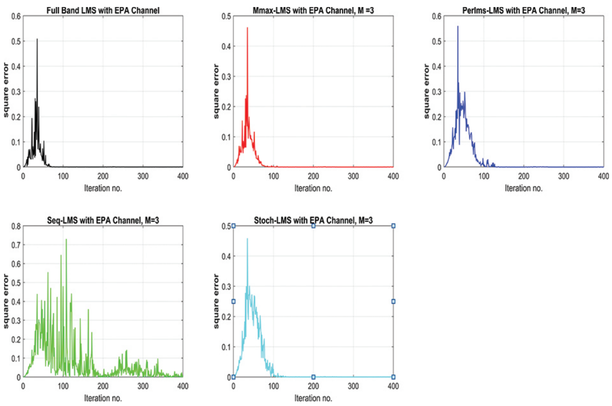


Fig. 4. Error Square performance for all algorithms (EPA channel) at M=3.

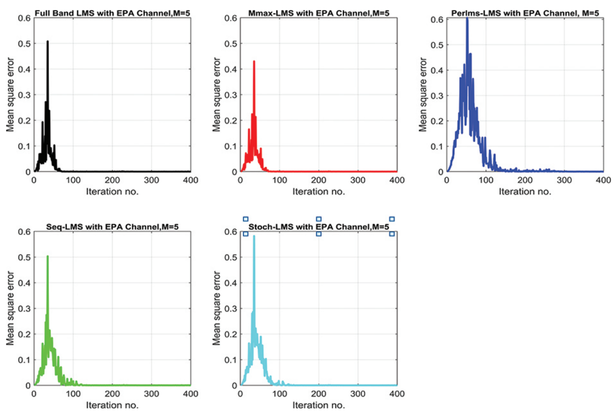


Fig. 5. Error Square performance for all algorithms (EPA channel) at M=5

Table 2 show square error convergence time comparison results for applying a different type of algorithms and EPA channel.

Table 2. Square error convergence time comparison EPA channel

Type of algorithm	Convergence time at iteration number		
	M=1	M=3	M=5
Full band-LMS(N=8)	60	60	60
M max-LMS	110	70	60
Periodic-LMS	60	100	110
Sequential-LMS	400	200	70
Stochastic-LMS	150	100	70

Fig. (6 ,7, and 8) show the performance for different values of M in terms of output estimation signal when the input desired signal is a pure sinewave.

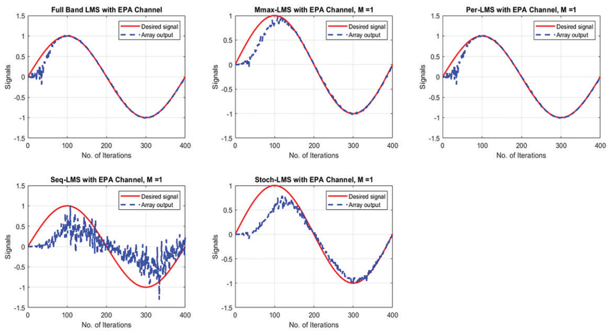


Fig. 6. Array output and desired signals of algorithms for EPA channel model, at $M = 1$

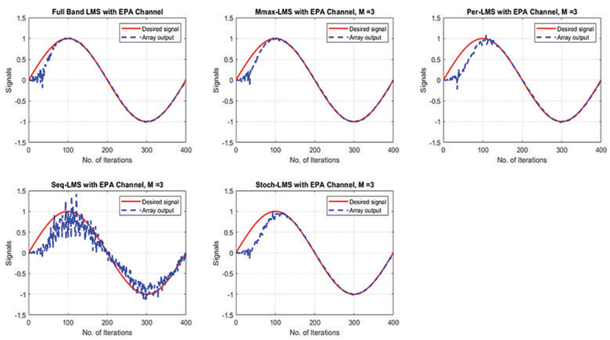


Fig. 7. Array output and desired signals of algorithms for EPA channel model, at $M = 3$

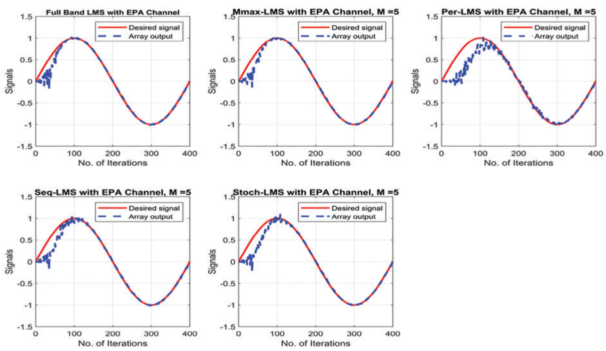


Fig. 8. Array output and desired signals of algorithms for EPA channel model, at $M = 5$

Table 3 show convergence time of estimation array output performance comparison of algorithms.

Table 3. Convergence time comparison of estimation array output over EPA channel

Type of algorithm	Convergence time at iteration number		
	M=1	M=3	M=5
Full band-LMS(N=8)	60	60	60
M max-LMS	100	70	60
Periodic-LMS	60	100	115
Sequential-LMS	Very slow	110	80
Stochastic-LMS	150	100	80

Convergence times and estimate accuracy of *M-max* algorithm are best at M=3,5, but decrease at M=1. In contrast, periodic algorithm provides reliable estimates at M=1, but starts to degrade around M = 3,5. In addition, the Stochastic method provides reliable forecasts when M=5, but it degrades when M=1, 2, or 3. The algorithm Sequential PU LMS decreases when M is equal to 1 and 3.

Fig. 9. shows the array pattern for algorithms when M equals 5.

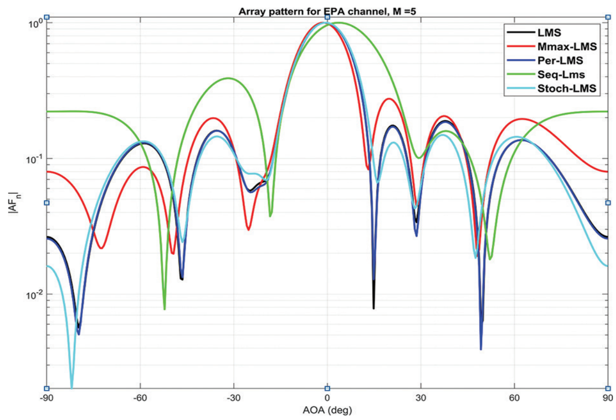


Fig. 9. The array pattern for algorithms with EPA channel model, M equals 5 elements

It is evident that in terms of steering the primary beam in the desired direction (0º) and nulling the beam in the direction of interference (-20º, 30º), for (M=5) the array structure of PU LMS algorithms is semi-similar to that of the full band LMS, except for the sequential PU algorithm.

We found that when the number of antennas was set to 5, the results were good and were more similar to the full band results than the other two options i.e., M=1 and 3.

4.3. SIMULATION RESULTS USING EVA (EXTENDED VEHICULAR MODEL) LTE CHANNEL MODEL

Extended Vehicular (EVA) was the paradigm for the second LTE channel. A wireless channel model (EVA) with nine pathways and matching gain values of [0 -1.5

-1.4 -3.6 -0.6 -9.1 -7 -12 -16.9] dB and [0 30 150 310 370 710 1090 1730 2510] *1e-9 for each path. This channel features a medium delay spread model and reflects metropolitan areas with big cells [29-30].

The error square performance of each algorithm is shown in Fig. 10 for EVA channel. This figure demonstrates that in terms of convergence rate and minimum error level in the steady state region, the performance of the *M-max*, Periodic, and Stochastic PU LMS algorithms is comparable to that of the respective full band LMS algorithms. In contrast, the performance of the sequential PU LMS algorithm has little more than them because of slow convergence rates and high steady state error levels. This decrease occurred as a result of the demand for more iterations (> 400 iterations) and for step size parameter selection by trial and error.

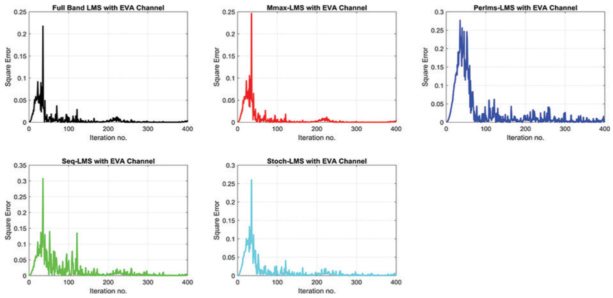


Fig. 10. Error Square performance for all algorithms (EVA channel)

Table 4 show the summary results for applying a different type of algorithms over EVA channel.

Table 4. Square error convergence time comparision (EVA channel)

Number of elements of antenna	Type of algorithm	Convergence time at iteration number
8	Full band-LMS	40
5	M max-LMS	40
5	Periodic-LMS	70
5	Sequential-LMS	150
5	Stochastic-LMS	50

Fig. 10. depicts the estimation output signal. It is evident that the *M-max*, Sequential and Stochastic PU LMS algorithms have accurate estimates, but they decline for the Periodic PU LMS algorithm.

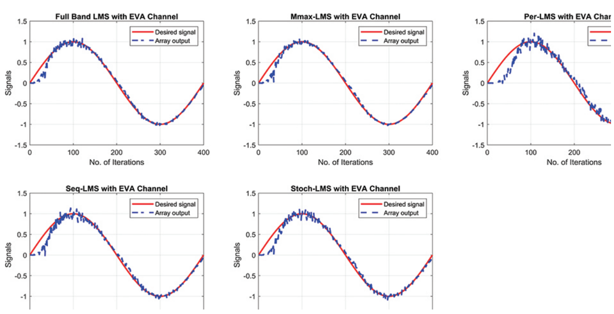


Fig. 11. Array output and desired signals of algorithms for EVA channel model

Table 5 show convergence time comparison when using EVA channel:

Number of elements of antenna	Type of algorithm	Convergence time (Iteration number)
8	Full band-LMS	40
5	M max-LMS	45
5	Periodic-LMS	80
5	Sequential-LMS	50
5	Stochastic-LMS	45

4.3. SIMULATION RESULTS USING ETU (EXTENDED TYPICAL URBAN MODEL) LTE CHANNEL MODEL

The third channel was the Extended Typical Urban Model (ETU) wireless channel model, which is used to simulate urban settings with large cells and has significant delay spread situations [14]. There are nine pathways in this channel model, each having a gain of [-1 -1 -1 0 0 0 -3 -5 -7] dB and a matching delay of [0 50 120 200 230 500 1600 2300 5000] *1e-9 [29-30].

The error square performance of each algorithm is shown in Fig. 12. This figure demonstrates that in terms of convergence rate and minimum error level in the steady state region, the performance of the M-max, Periodic, and Stochastic PU LMS algorithms is comparable to that of the respective full band LMS algorithms. In contrast, the performance of the Sequential PU LMS algorithm has little more than them because to slow convergence rates and high steady state error levels. This decrease occurred as a result of the demand for more iterations (> 400 iterations) and for step size parameter selection by trial and error.

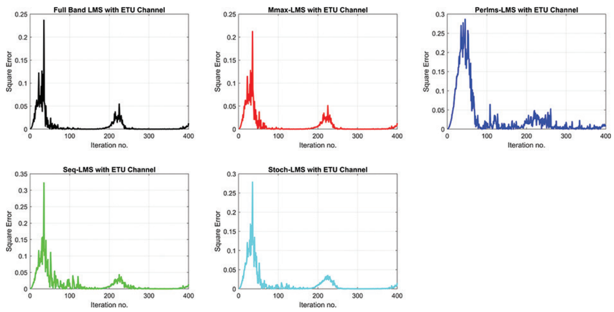


Fig. 12. Error Square performance for all algorithms (ETU channel)

Table 6 show the summary results for applying a different type of algorithms and ETU channel.

Table 6. Convergence time comparison of square error curves (ETU channel)

Number of elements of antenna	Type of algorithm	Convergence time (Iteration number)
8	Full band-LMS	45
5	M max-LMS	46
5	Periodic-LMS	80
5	Sequential-LMS	55
5	Stochastic-LMS	47

Fig. 13 depicts the accurate estimates output signal using M-max, Sequential and Stochastic PU LMS algorithms, but they decline for the Periodic PU LMS algorithm.

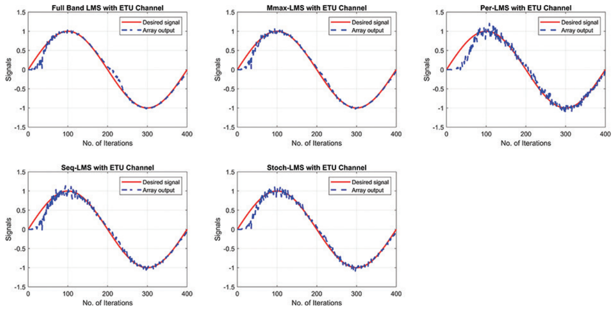


Fig.13. Array output and desired signals of algorithms for ETU channel model

Table 7 show convergence time comparison when using ETU channel.

Table 7. Convergence time comparison of estimation array output (ETU channel)

Number of elements of antenna	Type of algorithm	Steady state at iteration number
8	Full band-LMS	48
5	M max-LMS	48
5	Periodic-LMS	80
5	Sequential-LMS	50
5	Stochastic-LMS	50

The results of the simulation may indicate which PU LMS algorithm performs best in terms of error square and convergence time, and whether any of the PU LMS algorithms perform similarly to the full band LMS algorithm.

Periodic-partial-updates LMS are has slower convergence time than the LMS algorithm. Sequential partial updates aim to reduce computational complexity by updating a subset of the adaptive filter coefficients at each iteration. It is may not provide a satisfactory solution to the instability problem.

Stochastic partial updates are used to avoid instability issues with sequential partial updates for non-stationary inputs. Stochastic partial updates are desirable due to their stability implications.

M-max updates where the maximum absolute value of the filter coefficients is limited to a predefined value. This modification can improve the stability of the algorithm. It is the best PU LMS algorithm and comparable to the full band LMS algorithm.

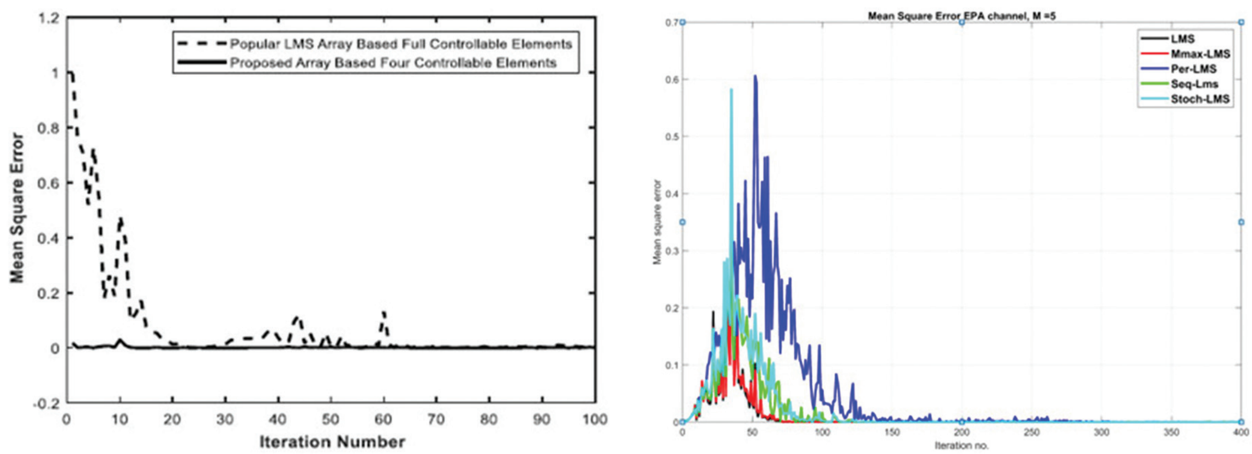
5. RESULTS COMPARISON WITH PREVIOUS WORK

Our proposed paper will compare with very related and previously published paper in 2019 [10] that used adaptive algorithms also like LMS. Before make a comparison result, Table 8 shows the main comparison points between our proposed model and [10].

Table 8. the main comparison points between our proposed methods and [10].

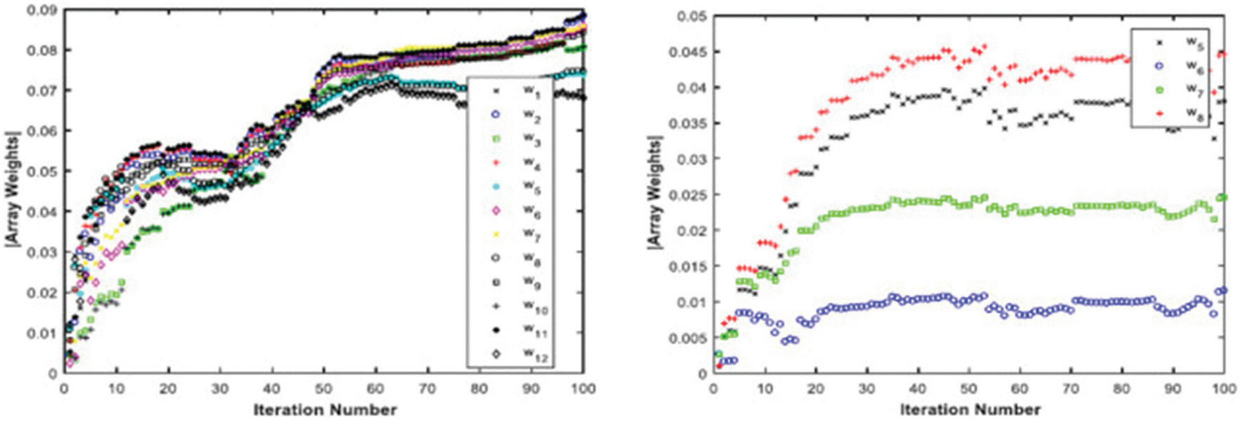
Items	[10]	Our proposed model
N and M parameters	N =12, M =4	N= 8, M= 5 ,3, and 1
Communications channel	Did not mentioned, Unknown	EPA, EVA, and ETU channels
Number of Iterations K	K=100	K=400
Step size μ	Fixed (μ= 0.006)	Automatic selectable μ eq (14)
Input desired signal (S)	Did not mentioned, Unknown	Sinewave input desirable signal
Method for Selectable number of antennas (M)	Did not mentioned how they choose M=4 out from N=12	PU algorithms (*M- max*, Periodic, Sequential, and Stochastic)
Carrier frequency (FC)	Did not mentioned, Unknown	FC = 900 MHz

Figs. (14 and 15) shows comparison results between this paper and [10].

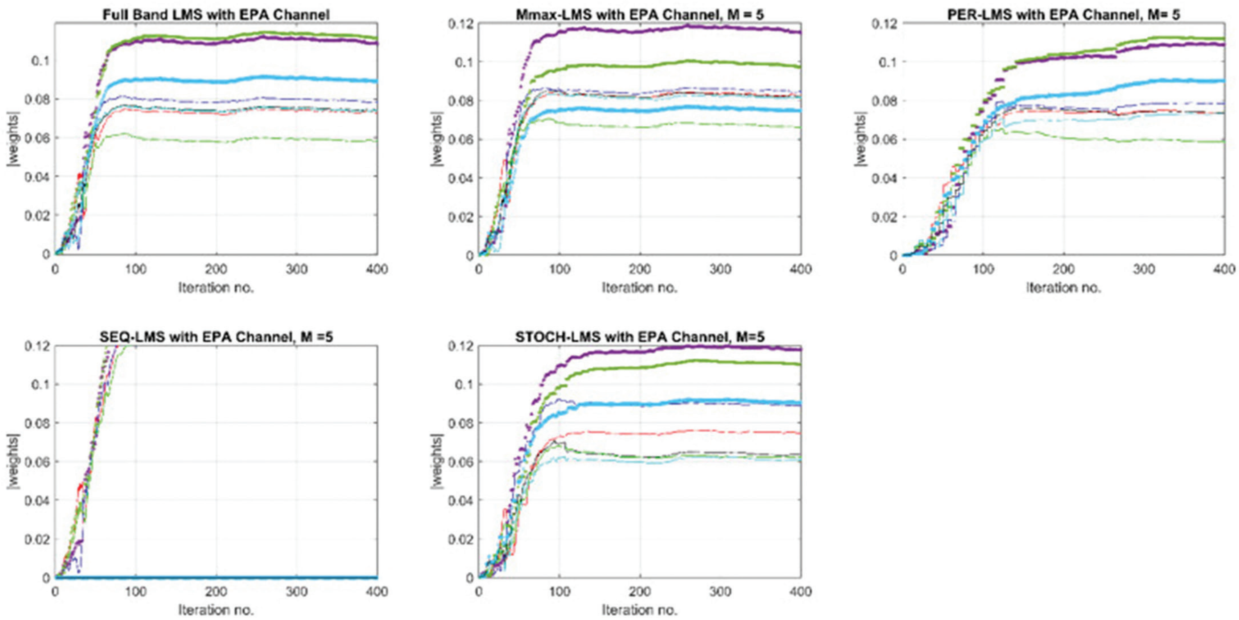


a) b)

Fig.14. MSE comparison; a) MSE [10] , b) Proposed



a)



b)

Fig 15. Weights tracking comparison; a) [10] , b) Proposed

The research methodology employed in this study for reducing the number of antennas and consequent reduction in phase shifters is deemed more effective compared to research method [10]. This superiority can be attributed to the incorporation of intelligent decision-making in our approach, wherein the selection of antennas to be reduced is guided by the principles and equations of partial modernization. In contrast, method of [9] solely focuses on selecting antennas located in the center of the matrix, without providing a rationale for this choice or considering antennas situated elsewhere within the system.

The absence of a theoretical foundation and explanation for the exclusive selection of central antennas in method of [10] stands in contrast to our methodology, which adheres to the rules and equations of modernization to inform the antenna selection process. If our method demonstrates superior effectiveness and efficiency, and the selection of fixed antennas is not arbitrary but rather adheres to the prescribed laws and regulations of each respective method, then it can be concluded that this method is superior.

6. CONCLUSION

This paper's key contribution was the first attempt to apply PU adaptable methods for selecting or choosing the number of antennas (M) by selecting or deselecting the RF chain for each element in the ULA such that $M < N$, which in turn reduced the number of active components.

The total size and weight of the antenna array system are reduced, and each antenna element's radio frequency (RF) chain is minimized as a result of this decrease in size and weight. Another crucial element is to streamline signal processing and decrease the amount of storage needed as a result of fewer signals being received. As a result, the cost of the entire system has decreased.

The performance of PU algorithms, with the exception of Sequential PU LMS, is comparable to that of the full band LMS algorithm in terms of convergence time and low level of minimal error in steady state. While the *M-Max* algorithm is significantly quicker than other PU methods, the Stochastic algorithm is considerably more reliable because it is not affected by cyclo-stationary input. When utilizing Periodic PU in the BAA system with LMS algorithm, it is sufficient to utilize a maximum of half of the coefficients. This is due to the fact that increasing the number of coefficients beyond this threshold does not result in a significant difference.

The nulling effect affects beam-forming array antenna radiation patterns. The null control was designed to emit low power in areas where unapproved listeners may be present. Adjusting excitation amplitude, phase, array distance spacing, and element number can achieve null control. Radiation patterns show a higher primary beam orientation and a lower secondary interference direction.

From simulation results, the convergence time by using the partial update (with exception of sequental one) is combarable or semicombarable to full band LMS. While convergence time of perodic PU algorithm became slow with increasing M as contrary to the others.

As for nulling, the array structure of PU LMS algorithms demonstrates clear effectiveness in directing the primary beam towards the desired direction (0°) and nullifying the beam in the direction of interference (-20°, 30°), particularly for an array size of M=5. This array structure exhibits a semi-similarity to the full band LMS, with the exception of the sequential PU algorithm. the *M-max*-LMS, periodic LMS and stochastic LMS algorithms perform similarly to the full band LMS algorithm in terms of square error (SE), tracking weight coefficients and estimation input signal, with a quick convergence time and a low level of error signal at steady state.

Additionally, the PU algorithms retain the radiation patterns' minimal distortion and symmetrical properties, which have a big impact on wireless communication systems.

The total number of coefficients required was reduced by 62% (M=5) compared to the total number used by the full update method.

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