GWO Based Optimal Channel Estimation Technique for Large Scale Mimo in LTE Network

Rajashree A. Patil, P. Kavipriya, B. P. Patil

Abstract: The Wireless Systems Are Employed With More Number Of Antennas For Fulfilling The Demand For High Data Rates. In Telecommunication, Lte-A (Long Term Evolution-Advanced) Is A Well-Known Technology Intended For Wireless Broadband Communication Aimed At Data Terminals And Mobile Devices. Multiple Input Multiple Output (Mimo) Technology Is Used By Lte Which Is Also Known As Fourth Generation Mobile Networks To Attain Very High Data Rates In Downlink And Uplink Channels. Though The Mimo Systems In Massive Mimo Are Provided By Multiple Antennas, The Design Of The Appropriate Non-Erroneous Detection Algorithm Is A Major Challenge. Also, With The Increase In Quantity Of Antennas, The System's Spectral Efficiency Begins To Degrade. So As To Deal With This Issue, A Proper Algorithm Has To Be Utilized For Channel Estimation. The Bio Inspired Algorithms Have Shown Potential In Handling These Issues In Communication And Signal Processing. So, Grey Wolf Optimization (Gwo) Algorithm Is Used In This Approach To Estimate The Most Optimal Communication Channel. Also, The Spectral Efficiency And Data Capacity Are Enhanced Using The Presented Approach. The Proposed Approach's Performance Is Compared With The Existing Approaches. The Simulation Result Exposes That The Presented Channel Estimation Approach Is Far Better Than Existing Channel Estimation Approaches In Performance Metrics Such As Bit Error Rate, Minimum Delay, Papr, Spectral Efficiency, Uplink Throughput, Downlink Throughput And Mean-Squared-Error.

Keywords: Channel estimation, large scale MIMO, LTE, channel matrix, Wireless communication, antenna, Grey Wolf Optimization, Mean-Squared-Error and spectral efficiency.

I. INTRODUCTION

LTE is internet protocol based network that provides higher throughput, best handoff capabilities and wider bandwidth when compared with third generation networks. Increase in demand of higher data rates in mobile devices has resulted in the introduction of MIMO systems in LTE. The mobile terminal's antenna is the main key element in MIMO system that can have its effect on the overall performance of the MIMO link. LTE MIMO is capable of using the multiple path propagation that provides enhancement in the performance of the signal on using multiple antennas.

Revised Manuscript Received on October 05, 2019.

Rajashree A. Patil, Ph.D. Scholar, Electronics Dept., Sathyabama Institute of Science & Technology, Chennai
Asst. Professor, Dept of E&TC, Army Institute of Technology, Pune, India
raj_patil123@rediffmail.com
P. Kavipriya, Associate Professor. Dept. of ECE, Sathyabama Institute of Science & Technology, Chennai, India
kavipriya.ece@sathyabama.ac.in
B. P. Patil,Principal, Army Institute of Technology, Pune, India
bp_patil@rediffmail.com

Though LTE MIMO makes the system complex, it also is capable of providing some crucial enhancements in spectral efficiency and performance. An antenna technology for a wireless communication where both the source also known as transmitter and destination also known as receiver uses multiple antennas is known as MIMO (multiple inputs, multiple outputs). For minimizing the errors and for optimizing the speed of data, the antennas at the each end will combine. A large scale antenna systems is an extension of MIMO wherever the antenna at both ends (transmitter & receiver) are grouped together for attaining improved throughput and improved spectrum efficiency in a wireless communication system [1]. While using massive MIMO, it has features such as; TDD (time-division duplex) operation, Linear processing, Favorable propagation and scalable. In massive MIMO, it has the following challenges; Unfavorable Propagation, Pilot Contamination, New Designs and Standards are needed and Channel estimation for both TDD and FDD system protocols [2]. Channel estimation is one of the major challenges in a large scale MIMO. In base station (BS) it is necessary for valuing CSI (channel state information) for both protocols (TDD & FDD) for minimizing the overhead of the pilot and for improving the energy and spectral efficiency to enhance the overall performance of an large scale MIMO (massive MIMO) [3] . In TDD during the channel estimation process of uplink, the base station requires the CSI for identifying transmitted signal and that is estimated on base station with minimum k channel use. During downlink transmission in TDD, BS needs to perform precoding of the transmitted signal [4]. Based on received pilot signals, every user estimates the effective channel gains that requires minimum k channel use [5]. During the channel estimation in FDD, the BS has to perform precoding of the CSI previously communicating it to k user for downlink transmission.

The channel based received pilots are estimated by every user that requires M channel for both the transmission [6].

The BS has to decode the transmitted signal by using CSI from the k signal in the uplink transmission. Then depending on received pilot signals that require minimum k channel use, the BS estimates the channels [7]. Hence the channel estimation is required for large scale MIMO (massive MIMO) for enhancing the overall performance and increases the both energy efficiency and spectrum efficiency. In case of massive MIMO scheme, it is required for minimizing the overhead of the pilot overhead [8].

An elaborate survey has been performed for identifying the different research articles available in the literature in the area of large scale MIMO and channel estimation for analyzing the crucial contribution and its merits.

II. RELATED WORKS

In a large scale MIMO (LS-MIMO), a major issue is that the availability of pilot sullying instigated inter-cell interference (ICI) known as channel estimation. For reducing the error during channel estimation process and improvement in performance, Lv, T., et al. [9] had developed a semi-blind channel estimator (SBCE) which is subspace-based. Here uncorrelated channels are considered. The developed SBCE first gauges the segment space of the network and after that gauge the channel framework as for ideal pilots. Due to this, ICI is reduced because of complete removal of the intra cell interference. The optimum pilots are designed by relying on Zadoff–Chu sequences. Hence the channel estimation errors are minimized and observed enhancement in presentation of LS-MIMO.

In rapid railroad correspondence framework, due to mobility decrease, pilot overhead occurs in preparing based LS-MIMO while channel estimate. For minimizing overhead of pilot during channel estimation in LS-MIMO of high speed communication system, Li, T., et al. [10] had developed a new channel estimation structure, position assisted. This estimation overhead in the system of high speed railway communication will be mostly minimized with the use of position information and the joint spatial-temporal correlation. Then using the developed scheme of position-aided channel estimation when the transmitters moving speed varies, the system throughput remains invariant and for the system with conventional training, there is quick degeneration of throughput on the increment of speed. A framework is also developed to optimize the parameters such as power allocation, antenna size and training interval for the developed training system. Hence from the simulation result, the system throughput does not degenerate considerably even the mobility increases and thus reduction in the pilot overhead during the channel estimation in the training based LS-MIMO of extraordinary speed railway communication system.

In LS-MIMO, because of huge quantity of channel coefficients to be estimated during doubly selective (DS) channel estimation which was a challenging task which leads to pilot overhead in the system. To overcome these challenges, Gong, B. et al. [11] had developed a DS channel estimation structure which created on block distributed compressive sensing (BDCS) and innovative pilot design procedure, block discrete stochastic optimization (BDSO). The basis expansion model (BEM) coefficients' common sparsity has to be analyzed on every BEM orders and every transmitting receiving antenna pair within delay area. The BDSO pilot pattern combines the structure that is superimposed and the guard pilot setting which reduces the pilot overhead by reflecting various transmit antennas' superimposed pilot positions. The developed BDCS structured sparsity results in the minimization of the overhead of the pilot and increase the accuracy of estimation. Moreover it contributes to improve the spectral efficiency and performance gain. By using the MATLAB simulation, the results shows that the developed method had reduced the pilot overhead during LS-MIMO's channel estimation and increases the parameters such as estimation accuracy, spectrum efficiency as well as performance gain as analyzed with the supplementary channel estimation technique.

In LS-MIMO with full duplex relay, the accurate estimation of channel will be the difficult task due to the interference. To overcome these two channel estimation problems, Xiong, X et al. [12] had address estimators for both the relay and Base station (BS) of the large scale MIMO system. Sparsity and steadily-changing channel characteristics during beam area are achieved by the estimator for Base station (BS). After that the possibility of correctly differentiating the interfering direct-link and desired channels are been analyzed. For the relay estimator, the self-interference (SI) and user to relay channels in maximum-likelihood (ML) principle built on Expectation Maximization (EM) algorithm are estimated at the same time. From the numerical analysis which results, probability of correct distinction is analyzed using the direct link interference. Hence it is concluded that the estimation of channel for a LS-MIMO scheme by full duplex relay is accurate for both the developed estimators through their performance analysis.

The accuracy of channel estimation for both the data-aided estimators in a pilot contaminated scenario and existing pilot based estimator is difficult task that heavy overhead in massive MIMO (multiple-input multiple-output). To overcome this, Mawatwal, K. et al. [13] had developed a channel estimator based on semi-blind iterative space-alternating generalized expectation (SAGE) maximization. Any prior details on the interfacing cells and extra pilots' large scale fading coefficients during the improvement of channel accuracy are not required. From single iteration, the developed method shows the improvement in a pilot contaminated scenario in both the existing data-aided and pilot based estimators. Hence by using the developed method, the channel is estimated accurately by avoiding heavy overhead in the massive MIMO system.

In Massive MIMO systems, for scaling up multi-user MIMO exact channel estimation is essential to provide significant enhancement in energy and spectral efficiency. The following criteria are been obtained in this paper, such as; to ease the process of estimating the channel, using Zadoff-Chu (ZC) sequences, a uplink training scheme has been obtained, by using the method of minimum-variance unbiased estimator (MVUE), the MMSE channel estimator would be replaced and the interference in addition with noise power term would be estimated, an analytical MSE expression for the developed method was derived and finally get the detailed analysis over the developed estimator using simulation results. To achieve the accurate channel estimation in pilot contaminated multipath multi cell massive MIMO TDD systems, F. DeFigueiredo et al. [14] had developed a practical and simple channel estimator. The developed estimator was addressed without having early knowledge about noise power under the performance of moderate to strong pilot contamination and large scale fading coefficients of inter cell. In addition to this approximate analytical MSE (mean square error) articulation for developed estimator was also derived. Hence the developed estimator performs asymptotically and has least MSE concerning multipath coefficients during accurate channel estimation and quantity of antennas in this system.

In Massive MIMO, estimation of direct in multi cell interference limited cellular network will be the major issue due to pilot contamination effect that leads to lag in overall performance of the system. To overcome this, a novel coordinated covariance-aided channel estimation framework method was developed by Yin, H. et al. [15] which manages these problems by empowering low-rate coordination among compartments amid phase of channel estimation. This developed approach has two key ideas namely; dormant side-information lying's exploitation and the user channels' order statistics. The developed coordinated approach optimizes the covariance matrices' utilization so as to attempt and fulfill non-overlapping AOA (angle-of-arrival) constraint. Using this approach, the pilot contamination effect will be removed which leads to improvement in overall performance in the large scale multiple antenna system due to accurate estimation of direct in multi cell interference limited cellular network. By simulating the parameters such as; Cell edge SNR, Cell radius, Distance from a user to its BS, Number of user's per-cell, Carrier frequency, Path loss exponent, Number of paths, Antenna spacing and Pilot length, the developed approach performs better and enhances the overall functionality of the massive MIMO system as compared with other channel estimation approaches.

Computational complexity is a noteworthy test in a massive MIMO system. It minimizes spectral efficiency and performance of estimation. To overcome this challenge, Shariati, N. et al. [16] had developed a lot of low multifaceted nature estimators namely; Bayesian channel estimator and coined Polynomial ExpAnsion CHannel (PEACH) estimator are developed for self-assertive channel and impedance insights. By approximating the converse by an L degree matrix polynomial, developed estimators minimize square complexity. To minimize MSE of estimation, coefficients of the polynomial are optimized. When providing a reasonable MSE by the developed estimators in the large scale MIMO system, it was proven that the developed estimator has performed better than the conventional estimators for floating-point operations (FLOPs). In addition, for maintaining a certain normalized MSE, the L degree matrix polynomials do not want to scale with the dimensions of system. In realistic scenarios, while analyzing with different interference, the relative MSE loss is smaller by utilizing the PEACH estimators with low complexity. Since the PEACH estimator does not suite for high pilot power noise-limited scenarios, a low-complexity diagonalized estimator is used in the regime. Hence by utilizing the developed method through numerical analysis, the computational complexity in a massive MIMO will be reduced and high robustness is attained for the matrices of large dimension.

III. PROPOSED METHODOLOGY

The optimal channel estimation can be utilized for efficient data transfer in LTE MIMO system. So as to estimate the channel, Grey Wolf optimization algorithm is used. The optimal channel in which the large amount of data can be transmitted in lesser time is estimated by selecting the channel with lowest mean squared error. The proposed approach is detailed in this section.

A. System Model:

Figure 1 shows the system model of architecture. There are two parts of the MIMO such as receiver and transmitter. In MIMO systems, there are more than one input and output. This requires multiple antennas on either side. The system model has 8x8 uplink and 16x16 downlink MIMO systems. There are 8 transmitting antennas and 16 receiving antennas. This provides many channels through which the data can be transferred. The antennas on transmitter side are represented as T and the antennas on the receiver side are represented as R. One antenna on receiver side is capable of establishing individual channel to all the antennas on receiver side and vice versa. These channels are known as channel matrix. The host computer can establish communication among these receiver and transmitter antenna using gigabit Ethernet switch. The transmitters are connected among themselves through MIMO cable. The receivers also are connected through MIMO cable through which the data flows.

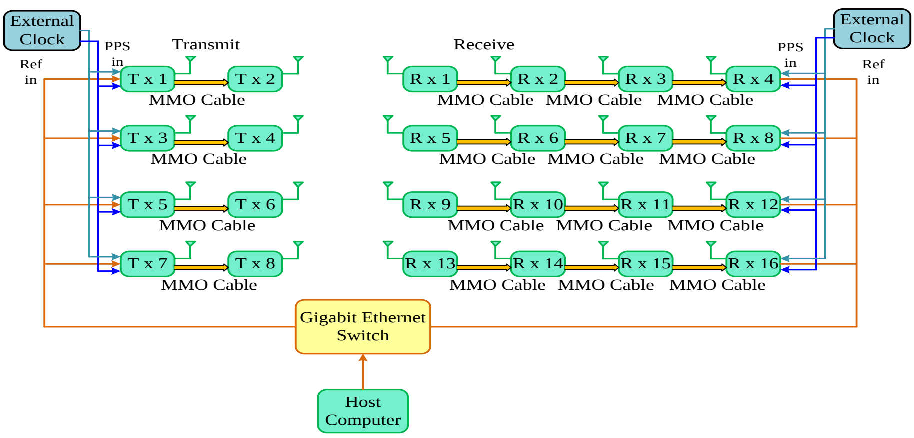

Figure 1: System model of MIMO architecture

B. Overview:

Here, the channel estimation is performed using the Grey Wolf Optimization algorithm. In this algorithm, depending on the mean square error, the objective function is formulated for selecting the optimal channel to transmit signal. The channel is selected based on the Peak to Average Power Ratio, Throughput, bit error rate and minimum delay. The mean square error is evaluated to determine variations among the signal transmitted from the transmitter and the end signal on the receiver. This is utilized to choose the best channel for 16x16 MIMO in downlink and 8x8 MIMO in uplink with minimum MSE. The robustness of presented technique remains analyzed and the overall performance of projected approach is equated with obtainable approaches.

C. GWO Based Channel Estimation:

MIMO systems have attained considerable attention in the past two decades. Since they increase the capacity and reliability of the communication systems, they have been employed in many wireless standards. Early studies on MIMO systems were on end-to-end MIMO where 2 systems with many antennas transmitting datawith each other. For an MIMO-OFDM scheme, channel transfer function next to various subcarriers seems unequal for time and frequency domains. So, dynamicchannel estimation is very much needed. Here the best channel is estimated using Grey Wolf Optimization. The propertiesof Grey wolf onto searching and prey chasing is carried out in this algorithm.Grey wolf is generallyincorporated to the Candidate group and they are classified as predators. Generally, five to twelve members of wolves are averagely incorporated in a group. The whole group is known as pack. The group contains the most stringent leading hierarchy. The pack leaders can be both male and female. There are four classifications of the pack, they are detailed as; alpha (α), beta (β), delta (δ) and omega (ω). In the proposed part, the GWO algorithm's numerical articulation is detailed. Based on the design of GWO algorithm, the fitness solutions can be represented equally alpha (α), then second best arrangement is represented as beta (β) furthermore, the third best arrangement is termed as delta (δ).Other up-and-comer arrangements are represented equally omega (ω). In this algorithm, objective function of selection of optimal channel is depending upon the Mean Squared Error (MSE). The steps involved in channel estimation based on GWO are provided below.

1 *Initialization*

Solution initialization is one of the primary processes in optimization. Here, the channels are initialized with the Bit Error Rate, Minimum delay, PAPR, spectral efficiency, Uplink throughput, downlink throughput and Mean-Squared-Error as the parameters. To optimize these parameters, a random population of solution is created by GWO. Here, the candidate solution is the channel matrix. The initialized solution is given in equation (1).

$$Y = \{Y_1, Y_2, Y_3, \ldots\ldots, Y_i\} \tag{1}$$

Here, Y represents the candidate solution.

2 *Fitness evaluation:*

After the solution initialization, the fitness is evaluated. One of the main aspects of every optimization algorithm is selection of the appropriate fitness parameter. The fitness evaluation is used to determine the effectiveness of the candidate solutions. The fitness is calculated for all the solutions. Here, the Mean squared error is considered as the main criterion for fitness evaluation. The MSE is calculated using equation (2) and the fitness is calculated using equation (3).

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(R_i - \hat{R}_i\right)^2 \tag{2}$$

Where, the signal sent from the sender is represented by R_i and the signal at the system's receiver end is represented by $\hat{R}_i$.

$$fit_i = Min\{MSE\} \tag{3}$$

3 *Updation:*

a) Fitness based solution Separation

The solutions are separated after the calculation of fitness calculation. Let G_α be the initial best fitness solutions, G_β be second best solution and finally G_δ be the third best fitness solution.

b) Encircling prey

The hunting is guided by α, β and δ and these three candidates are trailed by ω. The prey is initially encircled so as for the pack to hunt it. The solution is selected in this step using equation (4)

$$W(s+1) = W(s) - \vec{Z}.\vec{J} \tag{4}$$

$$\vec{J} = |\vec{B}.W(s+1) - W(s)| \tag{5}$$

$$\vec{Z} = 2\vec{z}q_1 - \vec{z} \text{ and } \vec{B} = 2q_2 \tag{6}$$

Here, the iteration number iss, the position of prey is *W(s)*, the coefficient vector are *Z, B*, $\vec{z}$ is linearly reduced to 0 from 2 andRandom vector [0, 1] are represented by s_1, s_2.

c) Hunting

For scientifically replicating the grey wolf's hunting activity, a consideration is made such that the alpha, beta & delta hold the effective dataon the possible location of the prey. As a solution, the initial3best solutions gottill that point are stored and theremainingsearch agents are needed to study their locations allowing the best search agent to belocated. For recurrence, $W(s+1)$ the novel solution is assessed with the assistance of the equation (7).

$$\vec{J}^{\alpha} = |\vec{B}_1.G_{\alpha} - G|, \quad \vec{J}^{\beta} = |\vec{B}_2.G_{\beta} - G|, \quad \vec{J}^{\delta} = |\vec{B}_3.G_{\delta} - G| \tag{7}$$

$$G_1 = G_{\alpha} - \vec{Z}_1.(\vec{J}^{\alpha}),\ G_2 = G_{\beta} - \vec{Z}_2.(\vec{J}^{\beta}),\ G_3 = G_{\delta} - \vec{Z}_3.(\vec{J}^{\delta}) \tag{8}$$

$$G(s+1) = \frac{G_1 + G_2 + G_3}{3} \tag{9}$$

The conclusion can be made that the final position would be in arbitrary location that includes a unique circle, utilizing alpha, beta, and delta's pointsin the search space. Also, alpha, beta &delta estimatethe prey's locationand the remaining wolves announce their locationsnearby the prey arbitrarily.

d) Attacking prey (exploitation) and Search for prey (exploration)

With the assistance of parameters a and A's adaptive values, exploration and exploitation are secured. The parameters a and A's adaptive valuesallowGWO to casually move among exploitation and exploration. Ondecrement of Z, one half of the repetitions are assigned forexploration (|A| > or = 1) and the half remaining are assigned forexploitation (|Z|<1). The GWO has just two primaryparameters needed to be accustomed (a and B). The GWO algorithm is observed to be small as likely with the humblestoperators to be accustomed. Until the highest quantity of iteration is achieved, the procedure will be sustained. Finally, depending on the fitness value, the optimal solutions are chosen.

4 Termination criteria:

Only when the highest quantity of iteration is reached, the algorithm's execution is discontinued and the solution that is having the best fitness value is chosen as the optimal channel.

Algorithm1: Channel estimation in MIMO using GWO

Input: Random channel states (E_i)

Output: Selected optimal channel in MIMO

1. Initialization of random initial channelspopulation
2. Fitness evaluationusing equation (3)
3. Initialize parameters z, Z and B
4. **While** the end criterion is not satisfied
5. **For** each search agent
6. Current search agent's position updationusing equations (4) to (9)
7. **End** for
8. Update z, Z and B
9. Calculate the channels' fitness
10. Update the first, second and third best solution
11. **End** while
12. Return optimal channel

IV. RESULT AND DISCUSSION

MATLAB has been used as the platform for implementation of the presented approach and the implemented results were analyzed.All the compared approaches' result and the Performance of all these approaches on all their performance metricsaredepicted in the diagrams and detailed autonomously in this section. In this approach, the 8x8 uplink antenna and 16x16 downlink antennas are used. The approach is carried out with 64-QAM carrier modulation and 1024 of FFT size. The total sub-carriers used are of 256 and the cyclic prefix length is 4.63μs. The simulation parameters along with their values are appeared in Table 1.

Table 1: Simulation parameters

Simulation parameters	
Parameter	**Value**
Carrier modulation	64-QAM
Up-link Antennas	8x8
Downlink antennas	16x16
Number of sub-carriers	256
Cyclic prefix length	4.69 μs
FFT Size	1024

A. Performance Metrics:

The presented approach's performance is calculated and analyzed along with existing approach for the following performance metrics.

Bit error rate:

The quantity of bit errors per unit time is known as bit error rate (BER). The bit error rate can be calculated by dividing overall quantity of transmitted bits during an observed interval of time. BER is calculated in ratio, hence it has no unit and expressed as a percentage. Transmission channel noise, distortion, interference, wireless multipath fading, attenuation, bit synchronization problems, etc., can be influential on BER.

Spectral efficiency:

The spectral efficiency depends on the rate of data that can be transmitted in the bandwidth provided in the structure of exacting communication. It is evaluated in bit per symbol as shown in equation (10).

$$R.D = \frac{S}{A.V * B} \tag{10}$$

Where,

R.D= spectral efficiency
S= overalldata channels in the communication system
A.V= bandwidth
B= coverage

Uplink Throughput:

Uplink throughput measures the rate at which the data is sent from the transmitter successfully. It is taken in to account as the primary feature for attaining maximum bandwidth in Gb/s. Ithas to be high for the network to be considered as effective.

Downlink Throughput:

Downlink throughput is considered a little more important than uplink because of the additional antennas for downlink (16*16) which varies from uplink. It is the measure of rate at which the data is successfully received on the receiver side. The downlink throughput is calculated in Gbps.

Complementary Cumulative Distribution Function (CCDF) of PAPR:

From a signal of time domain, CCDF evaluates the power complementary cumulative distribution function. The time consumed by a signal above or equvialent to the aversage level of power of the measured signal or probability of signal power being above the average power level can be determined by CCDF curve. The prominent information on the qualified signals in the structure of OFDM is provided by Complementary Cumulative Distribution Function (CCDF) curves. Likewise, the peak to regular power data is furnished via the division exclusive mandatorily.One among the commonly utilized parameter for evaluating PAPR reduction is the PAPR's CCDF.

Minimum delay:

The common obstruction in between the dissemination and postponement that is enclosed by the signal that travels on various courses will be encompassed by the wireless system signals.The overall time takenby a single packet to reach the destination is known as delay.The overall time consumed by a bit of data to move over a system starting with one hub then onto the next node is considered as the delay of a network.Minimum delay has to be attained in the network to be effective in communication. The minimum delay is calculated in the unit of seconds.

*B. **Performance Evaluation:***

The BER diagram of the presented and existing approachesareprovided in Figure 2. The presented approach's BER is constantly lower than existing procedures. This shows the effectiveness of the presented approach on every possibility.Figure 2 clearly shows that the presented approach's BER is constantly lower when compared with that of the existing approaches. The presented approach's BER decreases rapidly when the SNR value is increased.

Figure 3 shows spectral efficiency for the proposed and existing approaches. Initially spectral efficiency of proposedapproach is more than existing approaches. In the same way, throughout the whole process, the spectral efficiency of the presentedtechnique is more than the compared approaches. It can be clearly known from Figure 3 that the efficiency of every compared technique consistently keeps improving throughout the iterations. By observing the graph, it can be concluded that the proposed approachhas attained the desired spectral efficiency.

The uplink throughput for the proposed and existing approaches has been shown in Figure 4. The approaches' uplink throughputisobservable from the graph and it shows theproposedapproach's throughput is muchhigher than the existing ones. When the data bandwidth is low, the throughput of proposed approachis lower at the same time and it is greaterwhen compared withexistingapproaches. Throughout the transmission, the throughput of proposed approach increases consistently than existingapproaches.

Downlink throughput of the proposed and existingapproaches is shown in Figure 5. It can be clearly seen in the figurethat the proposedapproach's throughput is higherwhen compared withexistingapproaches. Also, downlink throughput has been constantlyhigher and also throughout the iteration, the proposedapproachhas achievedgreater throughput than existingapproaches. From the graph, it is shown that the proposed approach is efficient in terms of downlink throughput.

Figure 6 shows the CCDF graph for the proposed and existingapproaches. At the early points of SNR values, the PAPR is lower for the proposed approach. The difference between the proposed and existing approaches gets smaller in the middle.On observing the figure, it is clear that there is more deviation among proposed approach's CCDF graph and the compared approaches' CCDF graphs.But at the end, the proposed approach has lower PAPR value than existing approaches.

The proposed and existing approaches'graph for minimum delay is shown in Figure 7. Initially, the delay of the proposed approach is as same as the existing approaches. But on further SNR values, the delay of the proposed approach can be seen getting lower than the existing approaches.

Figure 8 shows the MSE of the proposed and existing approaches. It can be known from the graph that the proposed approach's MSEhas been lower when compared with the existing approaches throughout the various SNR values.

The performance of projected and obtainable approaches for all the presentation parameters when the SNR value is 6dB have been compared and depicted in Table 2.Using this table it can be easily compared to identify which approach has performed more effective than others in terms of BER, spectral efficiency, upload throughput, download throughput, PAPR, minimum delay and MSE at a common SNR value.

From the table, it has been observed that the proposed approach has performed better than compared approaches in all the mentioned performance parameters.

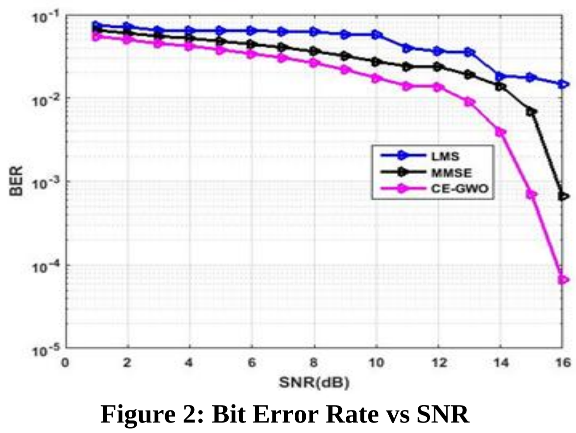

Figure 2: Bit Error Rate vs SNR

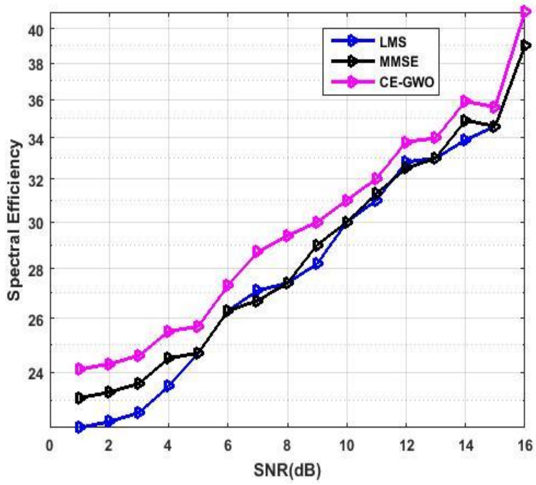

Figure 3: Spectral Efficiency vs SNR

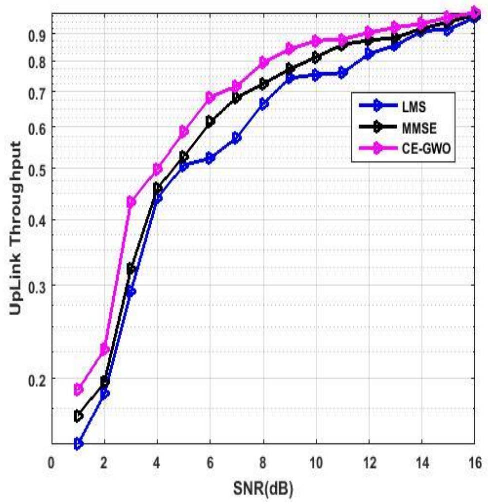

Figure 4: Uplink Throughput vs SNR

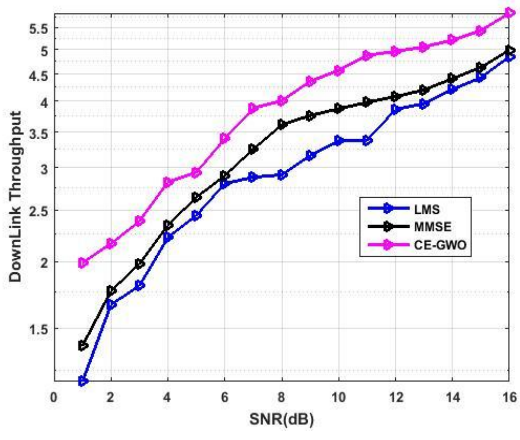

Figure 5: Downlink Throughput vs SNR

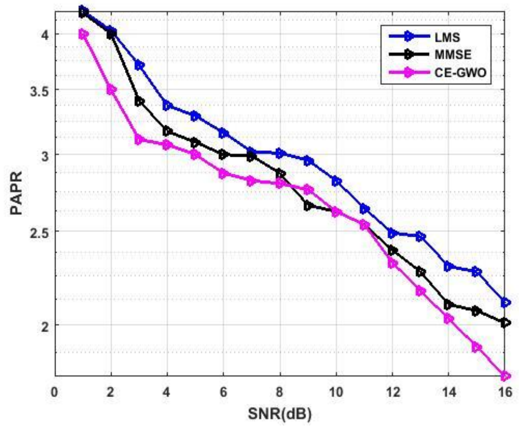

Figure 6: PAPR vs SNR

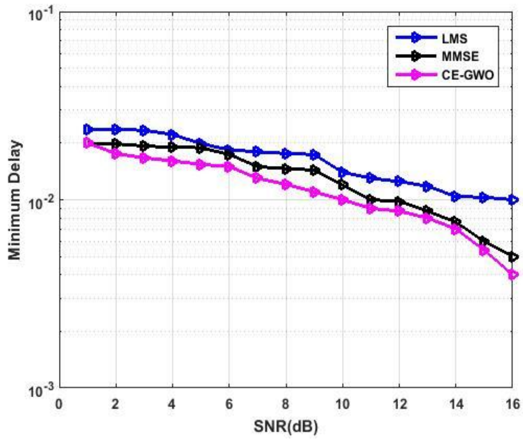

Figure 7: Minimum delay vs SNR

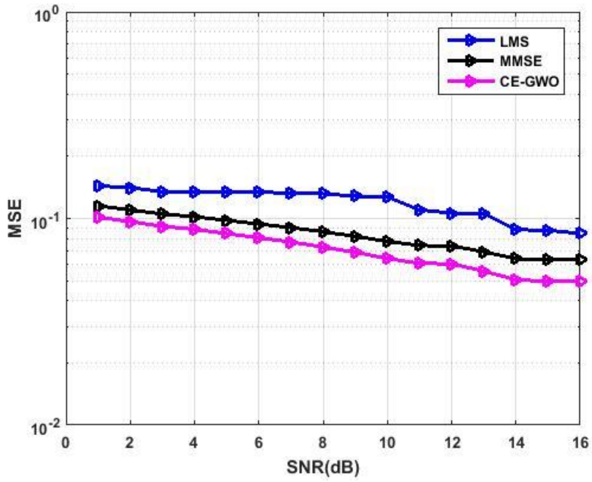

Figure 8: Mean-Squared-Error vs SNR

Table 2: Comparison of techniques for the performance parameters when SNR value is 6dB

Performance parameters	Techniques			% Improvement	
	LMS	MMSE	CE-GWO	w.r.t. LMS	w.r.t. MMSE
BER	0.0644	0.044	0.034	89%	29%
Spectral efficiency	26.3	26.3	27.3	4%	4%
Upload throughput	0.52325	0.61325	0.68325	31%	11%
Download throughput	2.8	2.9	3.4	21%	17%
PAPR	3.16	3	2.87	10%	5%
Minimum delay	0.0184	0.0174	0.015	23%	16%
MSE	0.1344	0.094	0.0806	67%	17%

V. CONCLUSION

A new technique has been proposed in this paper for channel estimation using Grey Wolf Optimization algorithm for massive MIMO in LTE network. The channels in the MIMO systems are individually analyzed and their capacities are estimated. Here, the channel is analyzed for their performance in terms of Bit Error Rate, Minimum delay, PAPR, spectral efficiency, Uplink throughput and downlink throughput. Then the optimal channel is estimated using Mean-Squared-Error value. The proposed approach has been implemented in MATLAB system. The proposed CE-GWO approach's performance is evaluated along with existing LMS and MMSE approaches in terms of their mentioned performance metrics. These results have clearly depictedthat the performance of the proposed approach's channel estimationis better than the performance of the existing approaches and has enhanced the spectral efficiency and data capacity of the massive MIMO systems in LTE network.

REFERENCE

1. Biguesh, Mehrzad, and Alex B. Gershman. "Training-based MIMO channel estimation: a study of estimator tradeoffs and optimal training signals." IEEE transactions on signal processing 54, no. 3: 884-893, 2006.
2. Yoo, Taesang, and Andrea Goldsmith. "Capacity and power allocation for fading MIMO channels with channel estimation error." IEEE Transactions on Information Theory 52, no. 5: 2203-2214, 2006.
3. Jagannatham, Aditya K., and Bhaskar D. Rao. "Whitening-rotation-based semi-blind MIMO channel estimation." IEEE Transactions on Signal Processing 54, no. 3: 861-869, 2006.
4. Yang, Jiayi, Jun Tong, QinghuaGuo, Jiangtao Xi, and Yanguang Yu. "Reduced-complexity Krylov subspace methods for large-scale MIMO channel estimation." Digital Signal Processing 78: 332-337, 2018.
5. Watanabe, Koya, Shun Kojima, Takashi Akao, Masato Katsuno, KazukiMaruta, and Chang-Jun Ahn. "Modified pilot selection for channel estimation of systematic polar coded MIMO-OFDM." ICT Express 2019.
6. Guo, Changlin, Jiaming Li, and Han Zhang. "On superimposed pilot for channel estimation in massive MIMO uplink." Physical Communication 25: 483-491, 2017.
7. Xie, Zedong, Xihong Chen, and Chenglong Li. "A novel joint channel estimation and equalization algorithm for MIMO-SCFDE systems over doubly selective channels." Digital Signal Processing 75: 202-209, 2018.
8. Zhu, Fangqi, Na Wu, and Qilian Liang. "Channel estimation for massive MIMO with 2-D nested array deployment." Physical Communication 25: 432-437, 2017.
9. Lv, T., Yang, S. and Gao, H. "Semi-Blind Channel Estimation Relying on Optimum Pilots Designed for Multi-Cell Large-Scale MIMO Systems." IEEE Access, 4, pp.1190-1204, 2016.
10. Li, T., Wang, X., Fan, P. and Riihonen, T. "Position-Aided Large-Scale MIMO Channel Estimation for High-Speed Railway Communication Systems." IEEE Transactions on Vehicular Technology, 66(10), pp.8964-8978, 2017.
11. Gong, B., Gui, L., Qin, Q., Ren, X. and Chen, W. "Block Distributed Compressive Sensing-Based Doubly Selective Channel Estimation and Pilot Design for Large-Scale MIMO Systems." IEEE Transactions on Vehicular Technology, 66(10), pp.9149-9161, 2017.
12. Xiong, X., Wang, X., Riihonen, T. and You, X. "Channel Estimation for Full-Duplex Relay Systems With Large-Scale Antenna Arrays." IEEE Transactions on Wireless Communications, 15(10), pp.6925-6938, 2016.
13. Mawatwal, K., Sen, D. and Roy, R. "A Semi-Blind Channel Estimation Algorithm for Massive MIMO Systems." IEEE Wireless Communications Letters, 6(1), pp.70-73, 2017.
14. De Figueiredo, F., Cardoso, F., Moerman, I. and Fraidenraich, G. "Channel Estimation for Massive MIMO TDD Systems Assuming Pilot Contamination and Frequency Selective Fading." IEEE Access, 5, pp.17733-17741, 2017.
15. Yin, H., Gesbert, D., Filippou, M. and Liu, Y. "A Coordinated Approach to Channel Estimation in Large-Scale Multiple-Antenna Systems." IEEE Journal on Selected Areas in Communications, 31(2), pp.264-273, 2013.
16. Shariati, N., Bjornson, E., Bengtsson, M. and Debbah, M. "Low-Complexity Polynomial Channel Estimation in Large-Scale MIMO with Arbitrary Statistics." IEEE Journal of Selected Topics in Signal Processing, 8(5), pp.815-830, 2014.

AUTHORS PROFILE

Rajashree Patil, obtained her Bachelor's degree in Electronics Engineering from North Maharashtra University, India in 1999. Then she obtained her Master's degree in Telecommunication from Shivaji University, India in 2010 and pursuing Ph.D. in Electronics engineering from Sathyabama Institute of Science and Technology, Chennai. Currently, she is an Assistant Professor at the Department of Electronics and Telecommunication Engineering, Army Institute of Technology, Pune, Maharashtra, India. She is IETE life member. Her specializations include Signal processing and Wireless communication. Her current research interests are MIMO, LTE, and LTE-A.

Dr. P. Kavipriya, received her B.E degree from Bharathidasan University, in 2000 and her master degree ME (Applied Electronics) from Sathyabama University in 2005, and the Ph.D. degree from Sathyabama University, Chennai in 2015. From 2001 to 2003, she worked as a Lecturer in AVC College of Engineering, Mayiladuthurai. She is currently an Associate Professor in the Department of Electronics and Communication Engineering at Sathyabama Institute of Science and Technology. Her research interests are in WCDMA networks for wireless networks, wireless sensor networks. She has published more than 40 papers in reputed journals and conferences.

Dr B P Patil, received his Bachelor of Engineering degree in Electronics Engineering. From Amravati University, India in 1990 and Masters in engineering degree from NIT Allahabad, India in 1996. He received Ph.D. in Electronics Technology from Guru Nanak Dev Univ., Amritsar India in year 2000. Presently working as Principal, Army Institute of Technology, Pune, India. He has published 150 research papers in various international and national referred journals and conferences. He has filed 6 patents and one copy rights. He is recipient of "Sir Thomas Ward Memorial Medal" from the Institution of Engineering, Calcutta, for his best paper in E & T Journal div. for the year 1999–2000. His area of Interest includes Communication and Wireless Sensor Network.