A Study on the Basics Processes of Massive MIMO

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Abstract—Massive Multiple Input Multiple Output (MIMO) is a key technique used in 5G mobile communication systems; it aims to efficiently increase the spectral efficiency of the communication systems. Massive MIMO is a MIMO system with a massive number of antennas in the base station, it uses its large number of antennas to efficiently transmit and receive the signals between the base stations and the user equipment and maximize the spectral efficiency of the system. Massive MIMO is mainly composed of three important processes: channel estimation, uplink transmission (receive beamforming), and downlink transmission (transmit beamforming). Based on the effective channel estimation methods, the base station can process the signal to make efficient transmit and receive beamforming and provide good transmission and reception quality, which is measured by the spectral efficiency of the system. Many references present the basics of massive MIMO processes, including channel estimation, transmit beamforming and receive beamforming. This paper aims to present a cleared and concluded study on these basics massive MIMO processes. It presents different channel estimation methods and evaluates its performance based on the normalized mean square error. It also presents different receive and transmit beamforming techniques and evaluates its performance based on spectral efficiency.

Index Terms—Channel Estimation, Massive MIMO, receive beamforming, spectral efficiency, sum spectral efficiency, transmit beamforming

I. Introduction

Wireless communication technology changed the communication way which is mainly based on cellular network topology [1]. The rapid development of wireless technology leads to increase its requirements continuously [2]. The technology target is focused on the ability to improve the current wireless communication systems to meet the continuously increasing demands and to satisfy the required expectation of service quality. The development requirements, in terms of increasing data rates and system reliability, cannot be achieved by increasing the used spectrum as the spectrum is a global resource and cannot be achieved by cell densify as it has many restrictions. These requirements can be achieved by increasing the spectral efficiency of the system. Massive MIMO is a promising technology that can achieve most of the development requirements [1], [2].

Massive MIMO is a multicarrier cellular network with a certain number of cells. Each cell has a central Base Station (BS) and several User Equipments (UEs), each BS contains a massive number of antennas, approximately tens or hundreds of antennas, and communicates with several single-antenna UEs. The BS uses its antennas to process the signal in both uplink and downlink transmission sides and achieve high improvement in the spectral efficiency [1], [3], [4].

Massive MIMO includes three important processes, channel estimation, receive beamforming (receive combining) and transmit beamforming (transmit precoding). Channel estimation is the first process that provides the BS with the Channel State Information (CSI) that helps it to process the signal in both uplink (UL) and downlink (DL) transmissions. Receive beamforming, in the UL, that coherently combine the received signal from different UEs to detect the signal from the desired UE. Transmit beamforming, in the DL, control the phase of the transmitted beam to focus it to the desired UE [1], [4], [5].

This paper presents a study on basic processes of massive MIMO system and shows with simulations (using MATLAB software version R2014a) some of their performance metrics in terms of Normalized Mean Square Error (NMSE) for the channel estimation process and Spectral Efficiency (SE) for both UL and DL transmissions.

The rest of the paper is organized as follows. Section 2 presents the basic concept of cellular networks. Section 3 defines the spectral efficiency and main methods to improve it. Section 4 shows the concept and the main processes of massive MIMO which include channel estimation, uplink transmission, and downlink transmission. Finally, a conclusion is stated.

II. Cellular Network

In the cellular network topology, the coverage area is divided into cells, each cell has a fixed BS that serves a certain number of UEs as shown in Fig. 1 [1], [6],[7]. The transmission through the cellular network has two ways, the transmission from the UE to BS referred to as uplink transmission and the transmission from the BS to UE referred to as downlink transmission [1], [6], [8].

The performance of the cellular network is measured by the area throughput, which refers to the amount of information transmitted per second over a unit area and it can be expressed as following [1], [6], [7], [9]-[11].

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$$\text{Area throughput [bit/s/km2]} = B \,.\, D \cdot SE \quad (1)$$

Where: B is the channel bandwidth (Hz).

D is the number of cells in the unit area (cells per 1 km2).

SE is the spectral efficiency per cell (bit/s/Hz/cell).

According to the area throughput definition, there are three methods to improve the area throughput of the cellular network:

1. Allocate more bandwidth: this way is impractical as the frequency spectrum is a global resource that is shared among many applications.
2. Increase cell density: this way is difficult as it is hard to place more BSs due to the limitations in choosing the placed locations to avoid many risks as shadowing.
3. Increase the SE per cell: it is a more efficient way to improve the area throughput of a cellular network so that in many cases the SE per cell can be used as a major performance metric in a cellular network [1], [7], [9], [11]-[13].

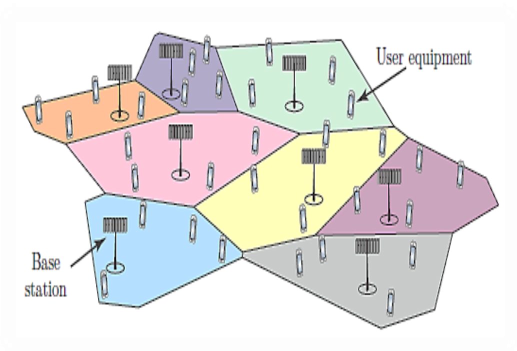

Fig. 1. Cellular network topology [6]

III. Spectral Efficiency

The area throughput of a cellular network can be improved by increasing the spectral efficiency per cell while using the same bandwidth and cell density [11].

The SE is defined as the amount of information that can be transmitted through the link between UE and BS and can be measured by [bit/s/Hz]. The sum SE is the SE of the channels from all UEs in a cell to the respective BS and measured by [bit/s/Hz/cell] [1], [9].

Consider a discrete memoryless channel with input x and output y as shown in Fig. 2, the SE is upper bounded by the Shannon capacity as follows [1], [9], [11].

$$SE \leq C = log_2(1+\ SINR) \text{ bit/s/Hz.} \quad (2)$$

where,

$$SINR = \frac{p\ |h|^2}{p_I + \sigma^2} \quad (3)$$

By substituted equation (3) in equation (2), the SE can be expressed as follow:

$$SE \leq\ log_2(1+\ \frac{p\ |h|^2}{p_I + \sigma^2}) \quad \text{bit/s/Hz.} \quad (4)$$

where: SINR is Signal to Interference and Noise power Ratio.

p is the transmitted power.

$|h|$ is the magnitude response of the channel.

$p\ |h|^2$ is the received signal power.

P_I is the interference power.

σ^2 is the variance of the noise.

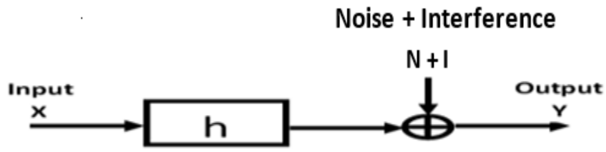

Fig. 2: Channel model [1]

There are two ways to increase the SE, increasing the SINR and obtaining an antenna array.

A. Improve SE Based on SINR

The SE can be improved based on SINR in two ways. The first way, the SE can be improved by increasing the SNR, and the second way the SE can be improved by reducing the interference ratio.

Starting from equation (4), the SE can be expressed based on both signal to noise ratio (SNR) and interference ratio ($\bar{\beta}$) as follow:

$$SE \leq\ log_2\ (1+\ \frac{1}{\frac{p_I}{p|h|^2}+\frac{\sigma^2}{p|h|^2}}) \quad (5)$$

$$SE \leq\ log_2(1+\ \frac{1}{\bar{\beta}+\frac{1}{SNR}}) \quad (6)$$

where: SNR is Signal to Noise Ratio, which means the ratio between the received signal power and the noise power.

$\bar{\beta}$ is the interference ratio, which means the ratio between the interference power and the signal power.

Based on equation (6), the SE can be enhanced by increasing SNR, which refers to increase signal power w.r.t noise power, or decreasing the interference ratio, which refers to increase interference power w.r.t signal power.

To verify this, assume two cells in the network as shown in Fig. 3, named cell 0 and cell 1, and only one UE is active per cell where each BS and UE is equipped with a single antenna. The UE in cell 0 transmits the signal to its serving BS, while the signal from the UE in cell 1 leaks into cell 0 as interference [1].

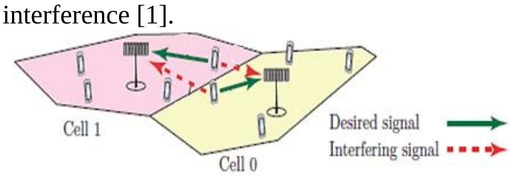

Fig. 3. Two cells network model [6]

Due to the logarithm term in the SE relation in equation (6), the exponential increase in the SNR, which refers to an increase in the transmit power, is corresponding to a linear increase in the SE. Also, due to the logarithm term in the SE relation in equation (6), the exponentially decrease in the interference ratio, which refers to a decrease in the interfering power or also refers to an increase in the transmit power, is corresponding to a linear increase in the SE.

So the highly required increase in SE can be obtained only by a great increase in the SNR term or a great decrease in the interference term, which cannot be achieved here, so this will result in an inefficient way to improve the SE by changing in SINR [1], [6], [11] as well explained in the next figure.

Fig. 4 shows the effect of both the SNR and the interference ratio $\bar{\beta}$ on the SE.

From the curve, at fixed interference ratio ($\bar{\beta} = -10$ dB) and observing the SE at different SNR, the SE = 2.585 bit/s/Hz at SNR = 10 dB and the SE = 3.446 bit/s/Hz at SNR = 30 dB. It appears that 100 times more transmit power is required to only increase SE by less than double.

At fixed SNR = 10 dB, and observing the SE at different interference ratios, the SE = 2.585 bit/s/Hz at $\bar{\beta}$ = -10 dB and the SE = 3.446 bit/s/Hz at $\bar{\beta}$ = -30 dB. It appears the same as the previous case, as the two cases refer to the increase in the signal power.

So increasing SNR or reducing interference ratio cannot achieve a great improvement in SE in cellular networks.

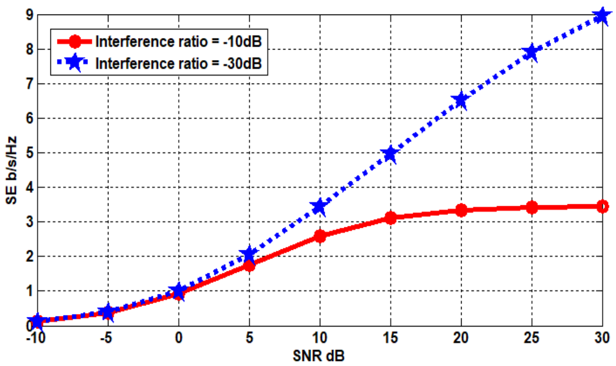

Fig. 4. Improving SE by increasing SINR

B. Improve SE using Antenna Array

An efficient way to improve the SE is by using an antenna array, where the BS uses multiple antennas to collect more energy from the received signal.

Due to the antenna array, there is an array gain, that depends on the number of BS antennas, so the SE relation, which includes the effect of the antenna array gain, can be written as follows [1].

$$\text{SE} = log_2(1 + \frac{M-1}{\bar{\beta} + \frac{1}{SNR}}) \qquad (7)$$

where: M is the number of antennas at the BS.

Fig. 5 shows the relation between the resulting SE and the number of BS antennas M. It explains that the SE is an increasing function of M, so increasing the number of BS antennas provides an improvement in the SE.

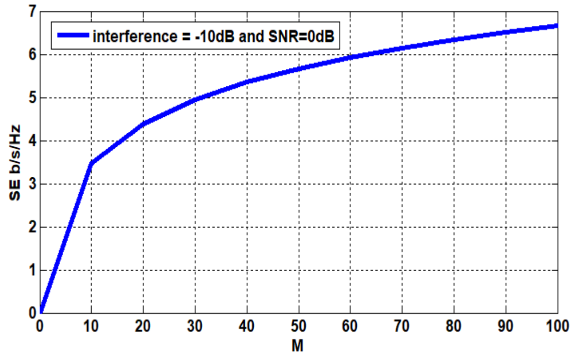

Fig. 5. Improve SE by antenna array

Also, this improvement can be magnified if there exist multiple parallel transmissions and it can be achieved by multiuser MIMO. Multiuser MIMO means that the K UEs are referred to as the multiple inputs and the M BS antennas are referred to as the multiple outputs. In multi-user MIMO, the multiple UEs (K UEs) are served at the same time in each cell so it is referred to as the sum SE [1], [11].

Due to the multiple UEs in each cell, the interference term ($\bar{\beta}$) in equation (7) will be divided into $(K - 1)$ intra-cell interference, which refers to the interference from other UEs in the same cell, and (K) inter-cell interference, which refers to the interference from all UEs in other cells. So the sum SE can be expressed as shown [1]:

$$SE = K\, log_2\ (1 + \frac{M-1}{(K-1)+K\,\bar{\beta} + \frac{1}{SNR}}) \qquad (8)$$

Fig. 6 shows the relation between the sum SE and both the number of BS antennas (M) and the number of UEs (K).

From the curve in Fig. 6, the same observation as in Fig.5, the SE is an increasing function with the number of BS antennas. In addition to it, the SE has a great improvement in the case of multi-users.

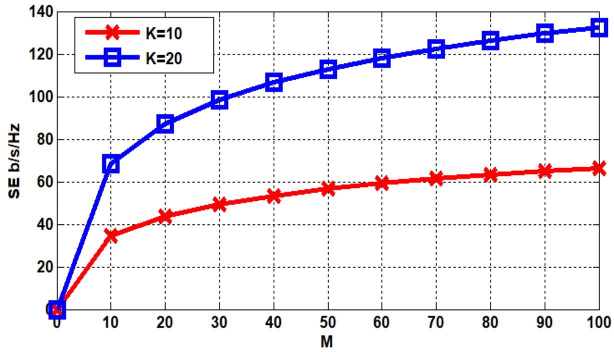

Fig. 6. SE for Multi-User MIMO

Also by observing Fig. 5 and Fig. 6 together at a constant number of BS antennas (M=100), the SE values at different number of UEs will be as follow: SE=6.657 for K=1, SE=66.44 for K=10 and SE=132.6 for K=20, so these values mean that the SE at each time approximately multiplied by the number of UEs K. This reason is due to that, according to equation (9), the SE is proportionally affected by K outside the logarithm relation and inversely affected by K inside the logarithm relation. So that the effect of K inside the logarithm relation can be neglected and only the effect of K outside the logarithm relation will affect the resultant SE.

From the previous discussion, the SE cannot be efficiently enhanced by improving SINR, but it can be efficiently enhanced by increasing the number of BS antennas and the number of UEs. Therefore, the SE can be greatly improved with the concept of multiple antenna BS that serve multiple UE with a single antenna, which is referred to as Massive MIMO technology.

IV. Concept of Massive MIMO

A massive MIMO network can be described as a multicarrier cellular network with L cells, each BS equipped with a large number of antennas $M >> 1$ and each BS communicates with single antenna K UEs with antenna-UE ratio $M/K > 1$ [1], [14], [15].

Massive MIMO has two transmission links. Uplink transmission where the signals are transmitted from UEs to BSs, the BS performs receive beamforming by selecting a receive combining vector that enables the BS to coherently combine the received signals from all antennas to extract the signal from separated UE, and this receive combining vector is based on the CSI from the channel estimation process. And downlink transmission where the signals are transmitted from BSs to UEs, the serving BS performs transmit beamforming by sending a separate signal to each UE using transmit precoding vector which determines the spatial directivity of the signal and this transmit precoding vector is also based on the CSI from the channel estimation process [1], [6].

The massive MIMO technology contains three main processes:

1. Channel estimation

The channel estimation process is performed to identify the main characteristics of the channels between BS antennas and each UE.

2. UL transmission (Receive combining)

During the uplink transmission, the receive combining vector is selected based on the CSI and used to coherently combine the received signals from all UEs at the BS.

3. DL transmission (Transmit precoding)

During the downlink transmission, the transmit precoding vector is selected based on the CSI and used to direct the signal from the BS spatially to each UE [1], [6].

A. Channel Estimation

The channel estimation process is essential for the efficient use of the massive number of antennas in massive MIMO. It is efficient to know the Channel State Information (CSI) in both uplink and downlink paths of transmission [16].

The main method for the channel estimation is the pilot sequence (pilot signaling). The pilot sequence is used to estimate the channel by transmitting a predefined sequence from every antenna in the network to estimate its corresponding channel characteristics [1], [16], [17].

The pilot signaling process in UL transmission requires K pilot signals, to be transmitted from K UEs, to estimate the channels in the UL. The pilot signaling process in DL transmission requires M pilot signals, to be transmitted from M antennas BS, to estimate the channels in the DL [1], [16].

Pilot signaling can be performed in two techniques, the TDD technique or the FDD technique.

1- TDD Technique:

Time Division Duplex (TDD) technique is used when the UL transmission and DL transmission are separated in the time domain as shown in Fig. 7, so their channel responses are reciprocal to each other [2], [3], [13], [15], [18], [19] or the channel response of the DL is transposed version of the channel response of the UL, the transpose version of the channel refers only to the reversing direction [13], [20]. So that the channel characteristics can be estimated in one transmission direction and then used in both transmission links, for simplicity the BS using only K UL pilot signals in this technique [1]. Using the TDD technique, the K UEs transmit K UL pilots and the channel estimation is performed on the BS based on these pilots. Then the BS uses this estimated channel to receive the UL signals as well as to transmit the DL signals [20].

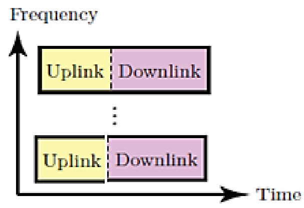

Fig. 7. TDD technique [1]

2- FDD Technique:

Frequency Division Duplex (FDD) technique is used when the UL transmission and DL transmission are separated in the frequency domain as shown in Fig. 8, so the UL and DL channels are different and not reciprocal to each other. As a result, the pilot sequences must be sent in both UL and DL separately. In UL, the UEs transmit pilot sequences, which are related to the number of UEs, to the BS to be able to estimate its channels. In DL, the BS transmits pilot sequences, which are related to the number of BS antennas, to the UEs then the UEs must feed them back to the BS where their channels can be estimated [20].

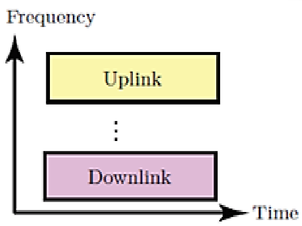

Fig. 8. FDD technique [1]

So, the pilot sequence based on the FDD technique includes M pilot sequences in the DL path, from BSs to

UEs, and K pilot sequences plus M feedback sequences in the UL path, from UEs to BSs. And with increasing the number of BS antennas, which deals with the concept of massive MIMO, the overhead due to pilot signaling will increase. So the massive MIMO prefers to operate with TDD technique to minimize the pilot overhead [1], [21].

a. Channel Estimation based on TDD UL Pilot Transmission

Massive MIMO operates in TDD to minimize the pilot overhead by transmitting the pilots only in the UL, where the pilot sequence number is only proportional to the number of UEs *(K)*. As the pilot sequence is not dependent on the number of the BS antennas (*M*), the estimation quality can be enhanced by increasing the number of BS antennas without increasing the pilot overhead [22], [23].

Assuming a Linear Time-Invariant (LTI) channel, the coherence block τ_c in which the channel response is constant, is divided into three parts: τ_p pilot sequence, followed by τ_u uplink data then τ_d downlink data as shown in Fig. 9 [17], [24].

Fig. 9. The coherence block [1], [5]

If two or more UEs use the same pilot sequences, the estimated channels for these UEs will be contaminated or correlated with each other which is referred to as pilot contamination [1], [25]-[27]. The pilot contamination reduces the channel estimation quality and causes the estimated channels dependent on each other so the BS will not be able to eliminate the interference from the UEs that use the same pilot sequences as the intended UE [1], [25] and it will produce a bad effect on the resultant SE of the massive MIMO [26]. To avoid this interference, the used pilot sequences must be orthogonal to each other [20].

For the pilot sequences to be orthogonal, they must satisfy two constraints, the amplitude of each element in the pilot sequence must be unity and all pilot sequence must be mutually orthogonal with each other as shown in the following equations [1]:

$$\left|\phi_{i,j}\right| = 1 \tag{9}$$

$$\phi^H \phi = \tau_p I_{\tau_p} \tag{10}$$

where: τ_p is the pilot sequence length.

ϕ is the τ_px τ_p pilot sequence matrix.

$\Phi_{I,j}$ is the ith row and jth column in the pilot sequence.

I_{τ_p} is τ_px τ_p identity matrix

Walsh Hadamard matrix and discrete Fourier Transform are two ways to create pilot sequences that satisfy the required constraints. The Walsh Hadamard matrix elements equal 1 or -1, so it is suitable for any application based on BPSK modulation. The discrete Fourier Transform matrix elements are not equal to 1 or -1, so it suitable for any application based on any modulation form [1].

Although it is impossible to assign orthogonal pilot sequences to all UEs in all cells, each BS can allocate orthogonal pilot sequences to its related UEs [1]. So the effect of pilot contamination can be limited by using a certain pilot reuse factor which means assigning orthogonal pilots to a certain cell with respect to others. For example, if the reuse factor equals one, it means assigning orthogonal pilots to all UEs in one cell and reuse it in all other neighboring cells, this will reduce the inra-cell interference which mainly has high effect than the inter-cell interference [15], [28].

To ensure achieving orthogonal pilot sequence to each UE, in one cell, the length of this orthogonal pilot sequence will be at least equal to the number of UEs. As the number of pilots is related to the number of UEs, in massive MIMO the number of UEs is smaller than the number of BS antennas [25].

To explain the channel estimation process, let there are L cells, each cell has one BS and K active UEs. The channel estimation process follows the next sequence:

At transmitter: each UE transmits a pilot sequence, ϕ_{jk}, this pilot sequence is scaled by the UL transmit power as $\sqrt{P_{jk}}$. Then transmitted through the channel as the signal s_{jk} over τ_p UL samples [1].

$$s_{jk} = \sqrt{p_{jk}}\, \Phi_{jk}^T \tag{11}$$

where: s_{jk} is the transmitted signal from UE k in cell j.

P_{jk} is the power at UE k in cell j.

Φ_{jk} is the pilot sequence for UE k in cell j.

At receiver: the received UL pilot signal at BS j, Y_j^p, which includes the transmitted signal from all UEs at the required cell, plus the interference from other UEs in other cells, plus the noise [1].

$$Y_j^p = \sum_{k=1}^{K_j} \sqrt{p_{jk}}\, h_{jk}^j \Phi_{jk}^T + \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} \sqrt{p_{li}}\, h_{li}^j \Phi_{li}^T + N_j^p \tag{12}$$

where: Y_j^p is the received pilot signal at BS j.

N_j^p is the noise at BS j.

P_{li} is the power at UE i in cell l.

Φ_{li} is the pilot sequence for UE i in cell l.

h_{jk}^j is the channel between the UE k in cell j and the BS j.

h_{li}^j is the channel between the UE i in cell l and the BS j.

This received signal will be used to estimate their channel responses, by multiplying it with the conjugate of the pilot sequence that related to the required channel to be estimated. Let the channel of UE k in cell j is the required channel to be estimated, so multiply Y_j^p by the conjugate of ϕ_{jk}.

$$y_{jjk}^p = Y_j^p\ \Phi_{jk}^*$$
$$=\sqrt{p_{jk}}\ h_{jk}^j \Phi_{jk}^T \Phi_{jk}^* + \sum_{\substack{i=1 \\ i\neq k}}^{K_j} \sqrt{p_{ji}}\ h_{ji}^j \Phi_{ji}^T \Phi_{jk}^*$$
$$+ \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} \sqrt{p_{li}}\ h_{li}^j \Phi_{li}^T\ \Phi_{jk}^* + N_j^p \Phi_{jk}^* \quad (13)$$

where: y_{jjk}^p is the signal that is used to estimate the channel between the UE k in cell j and the BS j.

After this multiplication, the resultant signal y_{jjk}^p, which is used to estimate the required channel, consists of four terms. The first term refers to the desired UE estimated channel, the second term refers to the intra-cell interference from other UEs in the same cell, the third term refers to the inter-cell interference from other UEs in other cells and the fourth term refers to the noise term.

If the pilot sequences of two UEs are orthogonal, so ${\phi_{li}}^T {\phi_{jk}}^* = 0$. Then the corresponding interference term equals zero and does not affect the estimation process.

Based on the resulting signal y_{jjk}^p , the channel estimated vector will be created according to one of the channel estimation methods, which will be mentioned below [1].

b. Channel Estimation Methods

The pilot-based channel estimation methods include Minimum Mean Square Error (MMSE), Element Wise Minimum Mean Square Error (EW-MMSE), and Least Square (LS) channel estimation methods.

The estimation quality of the channel estimation method is measured by the Normalized Mean Square Error (NMSE), where Mean Square Error (MSE) means the mean of the difference between the actual channel and the estimated channel then normalize it, by dividing MSE by the number of BS antennas (M), which means representing the MSE per one antenna, which refers to NMSE. [1], [29].

$$MSE_{jk}^j = E\left\{\left\|h_{jk}^j - \hat{h}_{jk}^j\right\|^2\right\} \quad (14)$$

$$NMSE_{jk}^j = \frac{E\left\{\left\|h_{jk}^j - \hat{h}_{jk}^j\right\|^2\right\}}{M} \quad (15)$$

where: MSE_{jk}^j is the MSE of the channel between UE k in cell j and BS j.

$NMSE_{jk}^j$ is the NMSE of the channel between UE k in cell j and BS j.

h_{jk}^j is the actual channel between UE k in cell j and BS j.

$\hat{h}_{jk}^j$ is the estimated channel between UE k in cell j and BS j.

1. MMSE Channel Estimation

Based on the pilot sequence, the MMSE channel estimation method estimates the channel of the required UE, by using the y_{jjk}^p signal, which previously gets from the multiplication between the received signal at the BS and the conjugate of the intended UE pilot sequence. The y_{jjk}^p signal is then multiplied by two matrices, the first matrix R_{jk}^j which refers to the correlation matrix of the required UE and the second matrix Ψ_{jk}^j which represents the inverse of the correlation matrices of UEs that use the same pilot as the intended UE plus the noise term. The MMSE channel estimator can be expressed as [1]

$$\hat{h}_{jk}^j = \sqrt{p_{jk}} R_{jk}^j \Psi_{jk}^j\ y_{jjk}^p \quad (16)$$

and,

$$R_{jk}^j = E\left\{h_{jk}^j \left(h_{jk}^j\right)^H\right\} \quad (17)$$

$$\Psi_{jk}^j = \left(\sum_{j',k'} p_{j'k'}\, \tau_p\, R_{j'k'}^j + \sigma_{UL}^2\, I_{M_j}\right)^{-1} \quad (18)$$

where: Ψ_{jk}^j is M x M matrix represents the inverse of correlation matrices of all UEs that use the same pilot as the intended UE plus noise term.

R_{jk}^j is M x M correlation matrix of the channel between UE k in cell j and BS j.

$R_{j'k'}^j$ is M x M correlation matrix of all UEs that use the same pilot as UE k in cell j.

σ_{UL}^2 is the variance of the noise in the UL.

I_M is M x M identity matrix.

As explained in equation (16), the MMSE channel estimation depends on the full channel statistics and takes into account the interference and noise terms, so it can suppress the interference and the noise and minimize the MSE between the actual channel and the estimated channel. Therefore, MMSE channel estimation is the most accurate channel estimation method and provides the best estimation quality [1], [30], [31].

On the other side, MMSE is the more complex method as it needs to know not only the correlation matrix of the intended channel but also the correlation matrices of all UEs that use the same pilot sequence as the intended one and its matrix inversion [30], [31], [32], [33].

2. Element-Wise MMSE Channel Estimation

The EW-MMSE estimation method reduces the complexity than the MMSE as it depends only on the main diagonal elements of the channel correlation matrices, R_{jk}^j and Ψ_{jk}^j. The EW-MMSE method estimates each element of the channel vector separately regardless of the correlation between these elements. The EW-MMSE channel estimator can be expressed as [1]:

$$\left[\hat{h}_{jk}^{j}\right]_m = \sqrt{p_{jk}}\left[R_{jk}^{j}\right]_{mm}\left[\Psi_{jk}^{j}\right]_{mm}\left[y_{jjk}^{p}\right]_m \tag{19}$$

where: m is the element index in the channel vector.

$\left[\hat{h}_{jk}^{j}\right]_m$ is the m^{th}element in the channel vector $\hat{h}_{jk}^{j}$.

$\left[R_{jk}^{j}\right]_{mm}$ is the m^{th} row and m^{th} column element of the correlation matrix R_{jk}^{j}.

On the other side, the EW-MMSE provides higher NMSE than the MMSE case [1].

3. LS Channel Estimation

The LS channel estimation is simpler than other methods as it depends only on a division operation, the y_{jjk}^{p} signal is only divided by the pilot sequence length. LS method does not require any statistical information about the channel [1], [31]. The LS channel estimator can be expressed as [1]

$$\hat{h}_{jk}^{j} = \frac{1}{\sqrt{p_{jk}\,\tau_p}}\, y_{jjk}^{p} \tag{20}$$

The estimation based on the LS method is more sensitive to the noise effect as LS does not take into account the effect of the noise [30], [31]. The LS method provides the highest NMSE than other methods [1].

To verify and compare the performance of the previous three-channel estimation methods, the following curve represents the NMSE of the three methods versus the effective Signal to Noise Ratio (Effective SNR). The effective SNR refers to the SNR including the pilot processing gain (τ_p).

where:

$$Effective\ SNR = SNR * \tau_p \tag{21}$$

In the simulation, the NMSE of the channel estimation methods is verified using pilot transmission simulation. During the simulation, assume the network consists of L = 16 cells, each cell contains a central BS with M = 100 antennas which serve K=16 UEs.

The simulation started by generating random channels and spatial correlation matrices between all UEs and BS antennas, and generate random pilot sequences based on the Walsh Hadamard matrix, each pilot sequence assign to each UE as transmitted signal, then pass it through the generated channels. Finally, perform the channel estimation process as the previous methods and compare the actual channels by the estimated ones to calculate the NMSE in each method.

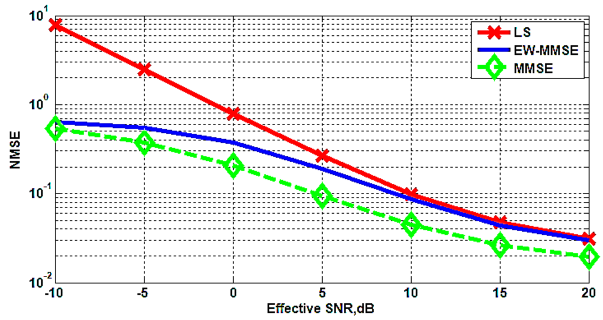

Fig. 10. NMSE for different channel estimation methods

From Fig. 10, the MMSE has the best performance according to the smallest NMSE. The EW-MMSE has higher NMSE than the MMSE, but lower than the LS method. Finally, the LS method has the lowest performance as it doesn't consider the noise effect, but at high SNR, where the effect of noise can be neglected, the performance of LS will be closer to the EW-MMSE.

B. Uplink Transmission (Receive Beamforming)

In uplink transmission, each UE transmits its data to the respective BS as shown in Fig. 11. The BS requires to separate the multiple received signals from different UEs which is called receive beamforming [9], [19]. The BS detects the signal from certain UE by using the receive combining (receive beamforming) vector that is related to the estimated channel of that UE [5], [34], [35]. So that, the BS first listens to the pilot sequence to estimate the channel then uses it to construct the receive combining vector, which will be used to extract the received signal that corresponding to that UE [36], [37]. Each UE has its receive combining vector which depends on its estimated channel to be able to coherently combine the desired signal, and also depends on other estimated channels to be able to suppress the interference from them [1], [17],[37], [38].

So that, the performance of uplink transmission depends on the channel estimation process and the receive combining vector, and the performance of UL transmission is measured in terms of the sum SE [39].

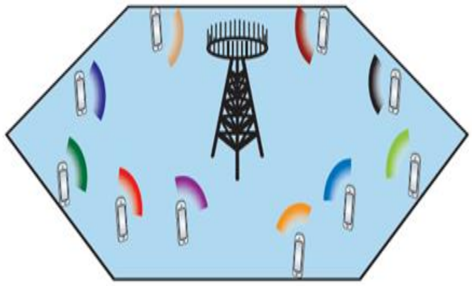

Fig. 11. UL transmission [5]

To explain UL transmission, let the received UL signal at BS j, which include all UE's signals, can be expressed as follow [1], [6]:

$$y_j = \sum_{l=1}^{L}\sum_{k=1}^{K_l} h_{lk}^{j}\, s_{lk} + n_j \tag{22}$$

where: y_j is the received signal at BS j from all UEs in all cells.

The received signal y_j can be extended to the received signals from UEs in cell j, which contain the intended UE, and the received signals from other UEs in other cells, plus the noise term, as follow [1].

$$y_j = \sum_{k=1}^{K_j} h_{jk}^{j}\, s_{jk} + \sum_{\substack{l=1\\ l\neq j}}^{L}\sum_{i=1}^{K_l} h_{li}^{j}\, s_{li} + n_j \tag{23}$$

Then the BS selects the receive combining vector related to the intended UE and correlates the received signal with that receive combing vector, to be able to extract the received signal related to that UE, as shown below [1], [6], [35].

$$v_{jk}^H y_j = v_{jk}^H h_{jk}^j s_{jk} + \sum_{\substack{i=1 \\ i\neq k}}^{K_j} v_{jk}^H h_{ji}^j s_{ji} + \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} v_{jk}^H h_{li}^j s_{li} + v_{jk}^H n_j \tag{24}$$

where: v_{jk} is the receive combining vector for UE k in cell j.

From equation (24), the L.H.S refers to the received signal at BS j correlated by the receive combining vector of the intended UE, and the R.H.S contains the required signal from the intended UE, the intra-cell interfering signals, the inter-cell interfering signals, and the noise term.

Also, this relation can be rewritten by replacing each channel with the estimated channel and the error due to the channel estimation process as follow.

$$v_{jk}^H y_j = v_{jk}^H \hat{h}_{jk}^j s_{jk} + v_{jk}^H \tilde{h}_{jk}^j s_{jk} + \sum_{\substack{i=1 \\ i\neq k}}^{K_j} v_{jk}^H \hat{h}_{ji}^j s_{ji} + \sum_{\substack{i=1 \\ i\neq k}}^{K_j} v_{jk}^H \tilde{h}_{ji}^j s_{ji} + \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} v_{jk}^H \hat{h}_{li}^j s_{li} + \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} v_{jk}^H \tilde{h}_{li}^j s_{li} + v_{jk}^H n_j \tag{25}$$

where: $\tilde{h}_{jk}^j$ is the error due to the estimation of the channel between UE k in cell j and BS j.

In the R.H.S of equation (25), only the first term represents the intended received signal based on the estimated channel, and all other terms act as interference and noise terms. The interference term includes the signal due to the unknown part (error part) of the intended UE channel, the intra-cell and inter-cell interference. Finally, the last term is the noise term.

Then the performance is measured according to the value of the Spectral Efficiency, which is mainly based on the Signal to Interference and Noise Ratio. The SINR can be deduced based on the R.H.S in equation (25), where the first term refers to the signal term, and all other terms refer to the interference plus noise term, only by a small change in replacing the error in the channel estimation by its correlation matrices, so the SINR can be written as following [1].

$$SINR_{jk}^{UL} = \frac{p_{jk} \left| v_{jk}^H \hat{h}_{jk}^j \right|^2}{\sum_{l=1}^{L} \sum_{\substack{i=1 \\ (l,i)\neq(j,k)}}^{K_l} p_{li} \left| v_{jk}^H \hat{h}_{li}^j \right|^2 + v_{jk}^H \left(\sum_{l=1}^{L} \sum_{i=1}^{K_l} p_{li} C_{li}^j + \sigma_{UL}^2 I_M \right) v_{jk}} \tag{26}$$

$$C_{li}^j = \tilde{h}_{li}^j \left(\tilde{h}_{li}^j \right)^H \tag{27}$$

where: $SINR_{jk}^{UL}$ is the Signal to Interference and Noise Ratio at UE k in cell j through UL.

C_{li}^j is the M x M correlation matrix of the error in the channel estimation $\tilde{h}_{li}^j$.

Then, the SE and the sum SE can be expressed as follow.

$$SE_{jk}^{UL} = \frac{\tau_u}{\tau_c} E\{ log_2 (1 + SINR_{jk}^{UL}) \} \tag{28}$$

$$sum\ SE = \sum_{k=1}^{K_j} SE_{jk}^{UL} \tag{29}$$

where: SE_{jk}^{UL} is the Spectral Efficiency achieved at UE k in cell j through UL.

$\frac{\tau_u}{\tau_c}$ is the UL data portion from the total coherence block.

$sum\ SE$ is the Spectral Efficiency of all UEs in cell j.

There are many methods to create the receive combing vector which leads to maximizing the SINR and SE, so provide good reception quality. The different receive combining methods shown below will trade-off between the complexity and the resultant sum SE [1].

a. M-MMSE Combining

The Multicell Minimum Mean Square Error (M-MMSE) combining vector is the optimal one that can be able to maximize the SINR and SE to provide the best performance [37], [38], [40]. The M-MMSE combining vector depends on the estimated channels in the intended cell and all other cells, or it depends on the full channel estimations characteristics and takes into consideration the noise effect. Therefore, it can suppress the intra-cell interference as well as the inter-cell interference and the noise [5], [36]-[38]. The M-MMSE combining vector is defined as following [1]:

$$v_{jk} = p_{jk} \left(\sum_{l=1}^{L} \sum_{i=1}^{K_l} p_{li} \left(\hat{h}_{li}^j \left(\hat{h}_{li}^j \right)^H + C_{li}^j \right) + \sigma_{UL}^2 I_{M_j} \right)^{-1} \hat{h}_{jk}^j \tag{30}$$

Also, the M-MMSE can be expressed for all UEs in cell j in matrix form, by combining the channels for all UEs in cell j and their power in matrix forms, as follow:

$$v_j^{M-MMSE} = \left(\sum_{l=1}^{L} \hat{H}_l^j P_l \left(\hat{H}_l^j \right)^H + \sum_{l=1}^{L} \sum_{i=1}^{K_l} p_{li} C_{li}^j + \sigma_{UL}^2 I_M \right)^{-1} \hat{H}_j^j P_j \tag{31}$$

where: $\widehat{H}_l^j$ is the estimated channels for all UEs in cell j in matrix form, each column represents a channel for one UE.

P_j is a diagonal matrix that contains the power of all UEs in cell j.

On the other hand, the M-MMSE combining vector is not frequently used due to its high computational complexity [38], [41].

b. S-MMSE Combining

The Single-cell Minimum Mean Square Error (S-MMSE) uses only the estimated channels in the intended cell, and the full channel estimations for the channels in other cells that exist in the M-MMSE vector is replaced by its expectation that based on the correlation matrices of these channels, as shown below [1].

$$v_j^{S-MMSE} = \left(\widehat{H}_j^j\, P_j\, (\widehat{H}_j^j)^H + \sum_{i=1}^{K_j} p_{ji}\, C_{ji}^j + \sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} p_{li} R_{li}^j + \sigma_{UL}^2\, I_{M_j}\right)^{-1} \widehat{H}_j^j P_j \tag{32}$$

As the S-MMSE depends on the channels in the intended cell, it can only suppress the intra-cell interference and cannot deal with the inter-cell interference [36]-[38], [42]. So, the S-MMSE is a suboptimal combining vector [40], and if there are strong interfering UEs in other cells, it will suffer from a strong inter-cell interference [1].

On the positive side the S-MMSE can be implemented in lower computational complexity than the M-MMSE, and also the effect of the intra-cell interference is important than the inter-cell interference in many situations [1].

c. RZF Combining

The Regularized Zero Forcing (RZF) combining vector has lower computational complexity than MMSE combining vectors at the cost of SE reduction [43], [44]. In RZF combining vector, the channel conditions are assumed to be good, which means the correlation between the channels is very weak and can be neglected, so the correlation matrices in the S-MMSE expression, which is represented in R_{li}^j and C_{ji}^j terms can be neglected in the RZF case. So RZF depends only on the estimated channels in the intended cells and the noise effect, as follow [1]:

$$v_j^{RZF} = \widehat{H}_j^j \left(\left(\widehat{H}_j^j\right)^H \widehat{H}_j^j + \sigma_{UL}^2\, P_j^{-1}\right)^{-1} \tag{33}$$

So, RZF combining vector can treat only with the intra-cell interference and the additive white Gaussian noise [45], [46]. The performance of the RZF combining vector can exhibit good if the channel conditions are good and the interference from other cells is weak, but generally, the channel conditions cannot be good for all UEs and the other cells interference cannot be neglected, which will affect the SE in case of using RZF [1].

d. ZF Combining

The Zero Forcing (ZF) combining vector has lower complexity than the RZF combining vector at the cost of SE reduction [43], [44] as it ignores the effect of the additive white Gaussian noise, and depends only on the estimated channels in the intended cell and doesn't take into account the noise effect as shown [4], [46], [47].

$$v_j^{ZF} = \widehat{H}_j^j \left(\left(\widehat{H}_j^j\right)^H \widehat{H}_j^j\right)^{-1} \tag{34}$$

So, ZF combining vector can suppress only the intra-cell interference [38], [45], [48], and it provides low performance in case of low SNR cases [47]. It performs well if all UEs have high SNR, but practically all UEs cannot have high SNR at the same time [1], [45].

e. MR Combining

The Maximum Ratio (MR) combining vector is the simplest combining vector that can be used, the MR combining vector needs only the estimated channels in the intended cell and neglects the existence of all interference and noise sources [4], [5], [43], [47], [48]. MR combining vector uses the estimated channel to maximize the power of the desired UE signal [45], [47], [49].

$$v_j^{MR} = \widehat{H}_j^j \tag{35}$$

The performance of uplink transmission using different combining vector methods is measured by showing the relation between the sum SE and the number of BS antennas M. The simulation is performed as follow: find the estimated channels based on the MMSE channel estimation method, then use these estimated channels to create the receive combining vectors using different receive combining methods, and finally find the corresponding sum SE at a different number of BS antennas, using the number of UEs K=10 and SNR = 10 dB.

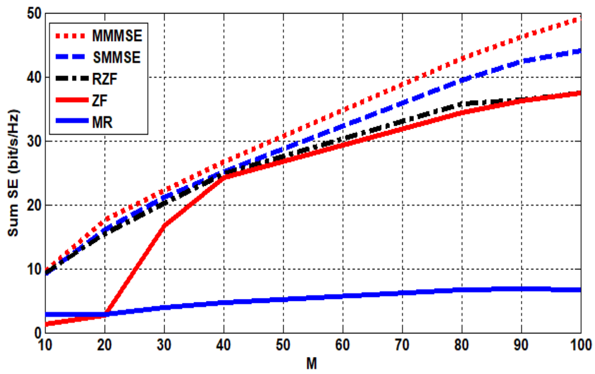

Fig. 12. UL SE for different combining vector methods

From Fig. 12, M-MMSE provides the largest SE, and the SE is reduced for other alternative methods but with lower complexity. S-MMSE provides lower SE than M-MMSE, but higher than RZF, ZF, and MR. RZF and ZF provide approximately the same performance for a large number of BS antennas (M > 50). MR provides the lowest SE but with a simpler implementation.

C. Downlink Transmission (Transmit Beamforming)

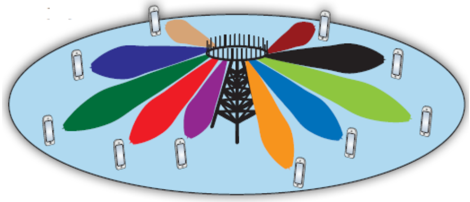

Fig. 13. DL transmission [5]

In downlink transmission, the data is transmitted from the BS to the UEs as shown in Fig. 13. The main aim in the downlink is to achieve good transmit beamforming which means the ability to direct the signal to the desired UE and minimize the interference to other UEs [1], [13], [19], [23], [49]-[51] and this can be achieved by using certain transmit beamforming vector or transmit precoding vector. The transmit precoding vector determines the spatial directivity of the transmitted signal by controlling the phase of the beam of the antennas and direct it in the direction of the intended UE [1], [9], [35], [49], [52]. As well as the receive combining vector in the uplink, the transmit precoding vector in the downlink depends on the channel estimation process [35], [53].

The performance of downlink transmission is also measured by the sum SE, which is based on the SINR.

Here the SINR expression is similar to that in the UL case, with using the transmit precoding vectors instead of the receive combining vectors and use the DL channels instead of UL channels. In addition, the denominator of the SINR, which refers to the interference plus noise term, the interference term is expressed by subtracting the intended UE signal from the whole received signal as shown [1].

$$SINR_{jk}^{DL} = \frac{\rho_{jk}\left|E\{w_{jk}^{H}\, h_{jk}^{j}\}\right|^{2}}{\sum_{l=1}^{L}\sum_{i=1}^{K_l}\rho_{li}\, E\left\{\left|w_{li}^{H}\, h_{jk}^{l}\right|^{2}\right\} - \rho_{jk}\left|E\left\{w_{jk}^{H}\, h_{jk}^{j}\right\}\right|^{2} + \sigma_{DL}^{2}} \tag{36}$$

where: $SINR_{jk}^{DL}$ is the Signal to Interference and Noise Ratio at UE k in cell *j* through DL.
P_{li} is the power at UE *i* in cell l.
σ_{DL}^2 is the variance of the noise in the DL.
W_{jk} is the transmit precoding vector for UE *k* in cell *j*.

Then, the SE and the sum SE can be expressed as follow

$$SE_{jk}^{DL} = \frac{\tau_d}{\tau_c} log_2\left(1 + SINR_{jk}^{DL}\right) \tag{37}$$

$$sum\ SE = \sum_{k=1}^{K_j} SE_{jk}^{DL} \tag{38}$$

where: SE_{jk}^{DL} is the Spectral Efficiency achieved at UE k in cell *j* through DL.
$\frac{\tau_D}{\tau_c}$ is the DL data portion from the total coherence block.

As shown, the SE in DL depends on all precoding vectors for all UEs, in contrast to the SE in UL which depends only on combining vector for the intended UE [1].

For TDD, as the uplink channels and the downlink channels are reciprocal to each other, there is a relation between receive combining vector and transmit precoding vector which is referred to as Uplink-Downlink duality (UL-DL duality) [5], [35]. The transmit precoding vector will be designed based on the UL-DL duality and it will provide approximately the same SE in both UL and DL transmissions [1].

$$SE_{DL} = SE_{UL} \tag{39}$$

The design of the transmit precoding based on the UL-DL duality is represented by the following relation between the transmit precoding vector and the receive combining vector.

$$w_{jk} = \frac{v_{jk}}{\left\|v_{jk}\right\|} \tag{40}$$

where: $\left\|v_{jk}\right\|$ is the norm of the receive combining vector of UE *k* in cell *j*.

This relation shows that the transmit precoding vector is provided by dividing the receive combining vector by its norm, which will provide the direction of that vector, which represents the direction of the intended UE, that gives the ability to direct the signal in the intended direction.

As well as the receive combining methods, the transmit precoding vector can be provided by the optimum scheme as M-MMSE or sub-optimum as S-MMSE, RZF, ZF, and MR as mentioned previously [1]. And the transmit precoding vectors for all UEs in a certain cell can be provided based on different precoding methods as shown below.

$$w_j = \begin{cases} \dfrac{V_j^{M-MMSE}}{\left\|V_j^{M-MMSE}\right\|} \\ \dfrac{V_j^{S-MMSE}}{\left\|V_j^{S-MMSE}\right\|} \\ \dfrac{V_j^{RZF}}{\left\|V_j^{RZF}\right\|} \\ \dfrac{V_j^{ZF}}{\left\|V_j^{ZF}\right\|} \\ \dfrac{V_j^{MR}}{\left\|V_j^{MR}\right\|} \end{cases} \tag{41}$$

The following curve represents the DL SE for different precoding schemes.

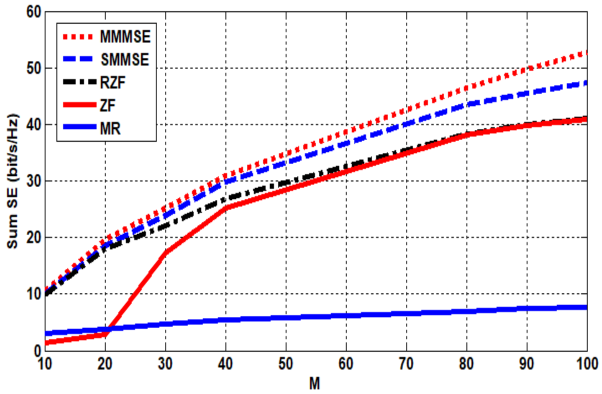

Fig. 14. DL SE for different combining vector methods

From Fig. 14, the SE in DL transmission, for different transmit precoding techniques, provide approximately the same observation as in the case of UL transmission. And the SE of DL is approximately similar to that in the UL case.

V. Conclusion

In massive MIMO, the network is divided into cells, each cell BS uses its massive number of antennas to serve multiple single-antenna UEs in such a way to maximize the SE of the network. Massive MIMO achieved its goals through its three main processes, channel estimation, receive combining and transmit precoding. The first process in massive MIMO is the channel estimation process and there are many methods for pilot sequences channel estimation as MMSE, EW-MMSE, and LS. The performance metric for the channel estimation is the NMSE and by simulation, it is proved that the MMSE method has the lowest NMSE, then EW-MMSE and LS have the highest NMSE. Based on the channel estimation, the BS can perform the receive combining and the transmit precoding processes. The receive combining aims to extract a certain UE signal from the whole received signal at the BS and the transmit precoding aims to direct the signal from BS to the intended UE. The receive combining and transmit precoding processes include different techniques as M-MMSE, S-MMSE, RZF, ZF, and MR and its performance measured by the resultant sum SE. By simulation, it is proved that the M-MMSE provides the largest SE and by reducing the complexity in other sequential techniques the SE is reduced than the optimum M-MMSE till the MR which has the simplest technique with the lowest SE. Finally, it proved that the massive MIMO concept achieve the required improvement of SE in the communication system.

Conflict of Interest

There is no conflict of interest.

Author Contributions

Marwa Abdelfatah conducted the research; Marwa Abdelfatah, Shaimaa ElSayed and Abdelhalim Zekry analyzed the data; Marwa Abdelfatah wrote the paper; Shaimaa ElSayed and Abdelhalim Zekry revised the paper; all authors had approved the final version.

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