CHAPTER 2

MODELLING AND ANALYSIS OF
DIGITAL BEAMFORMING ALGORITHM

2.1. SMART ANTENNA BASICS

Smart antenna refers to a system of antenna arrays with smart signal processing algorithm which is used to calculate beam forming vectors, to track and direct the beam towards the mobile user (Jeffrey Reed 2002). A smart antenna is a digital wireless communication antenna system that takes the advantage of diversity effect at the source (transmitter), the destination (receiver), or both. In conventional wireless communications, a single antenna is used at the source, and another single antenna is used at the destination. Such systems are vulnerable to problems caused by multipath effects (Simon Haykins, 2002) such as fading and inter symbol interference (ISI). In a digital communication system, multi-path fading and delay spread lead to inter symbol interference (ISI) and co-channel interference (CCI). The use of smart antennas can reduce or eliminate these problems resulting in wider coverage and greater capacity. Most specifically, the features and benefits of the smart antenna system include signal gain, interference rejection, increase of coverage and capacity.

Smart antenna systems are customarily categorized as switched beam, phased array, and adaptive array systems. Switched beam antennas are cheap, but inflexible and use multiple small, immobile sub sectors. Base Station selects one sub sector to use, based on strongest signal it receives. It suffers
from limited gain. Dynamically Phased Array/beam steering uses multiple small, immobile sub sectors. It suffers from multipath interference. Whereas, adaptive antenna array tracks the Direction of Arrival (DOA) and steers the beam automatically towards the mobile user. Adaptive antennas origin in radar applications some 40 years ago, and modern radar systems are motivated the research in the area of mobile communication during the last decades. While the requirements and the applicability are different in radar and mobile communication applications, the solutions to key problems were quite similar in both fields of research.

Adaptive antenna array system in its simplest form, consists of a Uniform Linear Array (ULA) which are excited by a set of amplitude and phase distributions determined by adaptive beamforming algorithm. The block diagram is shown in 2.1. The adaptive beamforming algorithm along with DOA algorithm optimizes the array output beam pattern, in such way that maximum radiated power is produced in the direction of desired mobile users, and deep nulls are generated in the direction of undesired signals representing co-channel interference from mobile users in adjacent cells.

Figure 2.1 Block diagram of adaptive array system and its radiation pattern
Adaptive antenna array technology uses a variety of signal processing algorithms to effectively locate and track several signals and to dynamically minimize interference and maximize intended signal. Various array geometries are linear, circular and planar arrays. While a fixed-beam network can choose a beam from a few predefined patterns, a fully adaptive array has the flexibility in synthesizing the radiation pattern in any given direction.

2.1.1 Wireless Multiple Access Techniques

One of the most important challenges with respect to wireless access is the limited capacity of the air interface which is due to the fact that the available transmission bandwidth is finite. Therefore, in the field of communications, the term multiple access could be defined as a means of allowing multiple users to simultaneously share the bandwidth with least possible degradation in the performance of the system. The conventional schemes are: FDMA, TDMA and CDMA. FDMA scheme provides one channel per carrier, whereas TDMA allocates different time slots to different subcarriers using the same carrier frequency and thus interleaves signals from various users in an organized manner. On the other hand, CDMA scheme is a spread spectrum method, that uses a separate code for each user. Various CDMA signals occupy the same bandwidth and appear as random noise to each other. In theory, the capacity provided by the three multiple access is the same and is not altered by dividing the spectrum into frequencies, time slots or codes (Godara, 1997). In practice, the performance of each system differs, leading to different system capacities. The SDMA scheme, also referred to as space diversity, uses an array of antennas, in which simultaneous calls in different cells can be established at the same carrier frequency. The advent of adaptive antenna array processing has the potential to combine SDMA along with TDMA, FDMA and CDMA to meet the requirements of third generation communication systems.
Orthogonal frequency multiplexing (OFDM) has emerged as a successful air-interface technique for cellular based systems. OFDM is a multicarrier modulation technique, a serial data bit stream is converted into several blocks of data to be transmitted in different, parallel and orthogonal subcarriers, subdividing the available bandwidth into narrowband subchannels. Broadband wireless systems such as IEEE 802.11 (Wi-Fi) and 802.16d (Fixed WiMAX) have adopted OFDM because of its notable advances on interference mitigating capabilities, robustness over frequency-selective channels and simplicity of implementation. OFDMA maintain the same benefits of OFDM and guarantees major scalability and MIMO compatibilities in the fourth generation cellular systems (4G). Adaptive antenna systems (AAS) may encompass different MIMO techniques such as Space-Time Block Coding (STBC), beamforming and spatial multiplexing (SM). For the open loop AAS, the multiple antennas can be used for STBC, SM or combinations. When the closed loop AAS is employed, channel reciprocity can be obtained in TDD mode, or feedback in FDD mode, the multiple antennas can be used either for beamforming or for CL MIMO by exploiting transmit antenna precoding techniques.

2.1.2 Uplink and downlink

Uplink beamforming is used to receive as much power as possible from the desired user and as little power as possible from any undesired users. Also, the downlink beamforming is used to transmit as much power as possible to the desired user and as low power as possible to any undesired users. For the application of adaptive antennas, FDD and TDD are well known methods for transmission/reception. In FDD, transmission and reception is performed at different frequencies, the radio channel is not reciprocal. Additionally, small scale fading and channel statistics are not the same in uplink and downlink. In the uplink case, the signal has already
propagated through the channel, and beamforming is performed at the place of reception. In the downlink case, beamforming has to be performed before the signal propagates through the channel. The channel information needed for uplink beamforming is available at the smart antenna base station through the pilot signal transmitted from each of the mobile terminals. However, since the channel information of the downlink is not known to the base station, the optimal parameters for the downlink beamforming are often borrowed from the results obtained during the uplink.

A promising approach for the downlink, is to adaptively multiplex user data onto an OFDM transmission system, where orthogonal time-frequency resources are given to the user who can utilize them best, the spectral efficiency will instead increase with the number of active users. To implement downlink beamforming, advanced systems like MIMO-OFDM/SDMA and LTE need the knowledge of the channel state information (CSI). This is obtained by TDD systems. In TDD system, uplink and downlink transmission are time duplexed over the same frequency bandwidth. Using the reciprocity principle it is possible to use the estimated uplink channel for downlink transmission. Novel technologies such as orthogonal frequency division multiplexing (OFDM) and Multiple Input Multiple Output (MIMO), can enhance the performance of the current and future wireless communication systems.

2.1.3 Adaptive beamforming in 4G Mobile Networks

3G and 4G cellular networks are designed to provide mobile broadband access offering high quality of service as well as high spectral efficiency. The main two candidates for 4G systems are WiMAX and LTE(Carmen 2011). While in details WiMAX and LTE are different, there are many concepts, features, and capabilities commonly used in both systems.
to meet the requirements and expectations for 4G cellular networks. The physical layer of both technologies use Orthogonal Frequency Division Multiple Access (OFDMA) as the multiple access scheme together with space time processing (STP) and link adaptation techniques (LA). In particular, Space Time Processing has become one of the most studied technologies because it provides solutions to ever increasing interference or limited bandwidth (Paulraj & Papadias, 1997).

STP implies the signal processing performed on a system consisting of several antenna elements in order to exploit both the spatial (space) and temporal (time) dimensions of the radio channel. STP techniques can be applied at the transmitter, the receiver or both. When STP is applied at only one end of the link, Smart Antenna (SA) techniques are used. If STP is applied at both the transmitter and the receiver, multiple-input, multiple-output (MIMO) techniques are used. Both technologies have emerged as a wide area of research and development in wireless communications, promising to solve the traffic capacity bottlenecks in 4G broadband wireless access networks (Paulraj & Papadias, 1997).

SDMA cellular systems have gained special attention to provide the services demanded by mobile network users in 3G and 4G cellular networks, because it is considered as the most sophisticated application of smart antenna technology (Balanis, 2005) allowing the simultaneous use of any conventional channel (frequency, time slot or code) by many users within a cell by exploiting their position. OFDM combined with SDMA has been chosen as multiple access for downlink in Long Term Evolution (LTE), (Hanzo et al, 2010). In order to cope with frequency selective channels, multiple transmit and receive antennas can be readily combined with OFDM in the time domain as space-time block coded (STBC-OFDM) and space frequency block code (SFBC-OFDM) in frequency domain. OFDM-adaptive array system
beamforming can be applied to either time-domain or frequency domain. Time domain beamforming is called pre-FFT because the array processing is done before the FFT step and in the frequency domain process, beamforming is done after FFT step (Heakle and Mangoud, 2007). Borio (2006) suggests that pre-FFT applied over the whole signal, requiring only one set of weights and one FFT operator. In spite of its relative simplicity, the pre-FFT scheme offers good results in most of the wireless applications.

The quality of a wireless link can be described by three basic parameters, namely the transmission rate, the transmission range and the transmission reliability. With the advent of MIMO assisted OFDM systems, the above mentioned three parameters may be simultaneously improved. Next generation cellular systems will have to provide a large number of users with very high data transmission rates, and MIMO is a very useful tool towards increasing the spectral efficiency of the wireless transmission. Akyildiz et. al (2010) suggested that MIMO technology in LTE-Advanced are beamforming, spatial multiplexing and spatial diversity. These techniques require some level of channel state information (CSI) at the base station so that the system can adapt to the radio channel conditions and significant performance improvement can be obtained. MIMO systems may be classified based on what type of CSI can be made practically available to the transmitter. In general, transmit antenna algorithms can be classified as: space time codes (need no CSI), MRC/blind adaptive beam steering (need full CSI), adaptive beamforming algorithms (partial CSI). TDD systems gather this information from uplink, provided that the same carrier frequency is used for transmission and reception. The idea is to perform an intelligent SDMA so that the radiation pattern of the base station is adapted to each user to obtain the highest possible gain in the direction of that user. The intelligence obviously lies on the base stations that gather the CSI of each user equipment (UE) and decide on the resource allocation accordingly.
In communication systems that use OFDM and MIMO is conventionally carried out on a subcarrier basis. There are two types of BF: sub carrier wise and symbol-wise. The computational requirements are high for each antenna. Hence symbol wise BF which performs the transmit and receive BF operations in the time domain for the mitigation of co-channel interference on spatially correlated channel (Pollok 2009). A novel iterative algorithm may be incorporated at the base and mobile stations for the computation of optimum weights which further increases system's capacity and bandwidth efficiency, as well as in quality-of-service in mobile networks.

2.2 PROPAGATION CHARACTERISTICS AND CONSTRAINTS

2.2.1 Signal model

The message signal is usually modeled as discrete stochastic process which is used to analyze a sequence of data that consists of the present observation and past observation of the process. Most of the signals in the real world are random, or contain random components due to factors such as additive noise or quantization errors. For example, the sequence \([u(n), u(n-1), \ldots, u(n-M)]\) represents a partial discrete-time observation consisting of samples of the present value and M past values of the process. Its autocorrelation function is,

\[ r(n, n-k) = E[u(n)u^*(n-k)], k \quad 0, \pm1, \pm2, \ldots \quad (2.1) \]

where \(E[.]\) denotes the expectation operator and * denotes complex conjugate. This second-order characterization of the process offers two important advantages. First, it lends itself to practical measurements and second, it is well suited for linear operations on stochastic processes. The procedure for estimating the parameters of a complex sinusoid with the help of correlation matrix leads to the measurement of mean square value and auto correlation.
matrix. The correlation matrix of a discrete-time stochastic process can be defined as the expectation of the outer product of the observation vector \( u(n) \) with itself. The dimension of the correlation matrix is \( M \)-by-\( M \) and is denoted as \( R \) and it is written as:

\[
R = \mathbb{E}[u(n)u^T(n)]
\]  

(2.2)

By substituting ‘\( u(n) \)’ into equation (2.2) and by using the property defined in equation (2.1), the expanded matrix form of the correlation matrix can be expressed as,

\[
R = \begin{pmatrix}
  r(0) & r(1) & r(M-1) \\
  r(-1) & r(0) & r(M-2) \\
  \vdots & \vdots & \vdots \\
  r(-M+1) & r(-M+2) & r(0)
\end{pmatrix}
\]  

(2.3)

2.2.2 Linear and constant envelope modulation schemes

The performance and the selection of the modulation scheme of a cellular system is mainly depends on the power efficiency, spectral efficiency, adjacent channel interference, BER performance and the implementation complexity (Ali, 1999). Linear and constant envelope modulation techniques such as QPSK and GMSK are popular in the cellular environment. QPSK is predominantly noted for its spectral efficiency and it is used extensively in CDMA cellular service and DVB (Digital video broadcasting). GMSK is a constant envelope modulation scheme which avoids the linearity requirements, but the spectral efficiency is lower, and it is used in GSM, DECT and DCS. The RF band width is controlled by the Gaussian low-pass filter bandwidth and the bandwidth efficiency is less than QPSK. However, QPSK effectively utilizes bandwidth; whereas, GMSK requires more
bandwidth to effectively recover the carrier. Both QPSK and GMSK have strong features that provide a desirable cellular environment.

Most digital transmitters operate their power amplifiers at or near saturation to achieve maximum power efficiency. At saturation, it poses a threat to the signal, exposing it to phase and angle distortions. These distortions spread the transmitted signal into the adjacent channel, causing interference. To resolve this issue, a filter is used to suppress the side lobes. Nyquist pulse-shaping techniques, such as the Raised Cosine (RC) filter and Gaussian filter, are used to reduce ISI. Figure 2.2 is the block diagram of generation of QPSK signal.

![QPSK modulator](image)

**Figure 2.2 QPSK modulator**

First, the system converts a bit stream into a Non-Return-to-Zero (NRZ) signal which is multiplied by an in-phase (I) and quadrature (Q) signal, keeping in mind that each carrier phase is separated by 90°. The two components are then summed to achieve the desired QPSK signal output. In order to optimize the signal, QPSK uses the RC filter. This prevents the signal from spreading its energy into the adjacent channels. Ideally, the Nyquist filter is free of ISI. However, all practical Low Pass Filters (LPF) exhibit
phase and amplitude distortions so special pulse shaping filters are needed to ensure that the total transmitted signal arrives at the receiver. As the roll-off factor of the RC filter decreases, the spectrum becomes more compact. This requires a more complex receiver at demodulation. However, since QPSK is predominantly noted for its bandwidth efficient feature, it is preferable to operate at higher values of roll-off in order to accommodate for the increasing demand for more users within a limited channel bandwidth. Nevertheless, another tradeoff is that a complex receiver is needed at the end of the filter to recover the carrier.

**GMSK modulation**

The information bits are differentially encoded, producing an NRZ (non return to- zero) symbol stream \( d(k) \) which can take the values from the set \{+1,-1\}.

As shown in figure.2.3, this symbol stream excites a transmit filter with a Gaussian impulse response and further smoothened by frequency modulator. Consequently, the pulses overlap, giving rise to phenomenon

![Figure 2.3 GMSK modulator](image-url)
known as ISI. The extent of overlap is determined by the product of bandwidth of Gaussian filter and data bit duration; the smaller the bandwidth bit time product (BT), the more the data bits or pulses overlap (Diana, 2000). A gaussian pulse is good choice of shaping function since it provides a particularly compact frequency domain spectrum which in turn eliminates the broad pattern of side lobes of a rectangular pulse (Berger, 2006). Filtering allows the transmitted bandwidth to be significantly reduced without losing the content of the digital data. This improves the spectral efficiency of the signal.

The impulse response of pre-modulation filter is,

\[ h_G(t) = \frac{\sqrt{\pi}}{\alpha} \exp\left(-\frac{\pi^2}{\alpha^2}\right) \]  

(2.4)

and the transfer function of the pre-modulation filter is,

\[ H_G(f) = \exp(\alpha^2 f^2) \]  

(2.5)

where \( \alpha \) is related to \( B_{3dB} \) by

\[ \alpha = \frac{\sqrt{\ln 2}}{\sqrt{2B}} = \frac{0.5887}{B} \]  

(2.6)

where \( B_{3dB} \) is the bandwidth of Gaussian pulse shaping filter. The sharpness of the Gaussian filter is described by BT. Common values of BT is in the range of 0.3 to 0.5 shown in figure 2.4. GMSK was simulated with a BT=0.3 as a compromise between spectral efficiency and added ISI.
The impulse response of the filter to rectangular signal of duration ‘T’ is

\[
g(t) = \frac{1}{2T} \left[ Q\left(2\pi B \frac{t - T}{2 \ln 2}\right) - Q\left(2\pi B \frac{t + T}{2 \ln 2}\right) \right]
\]  

(2.7)

where \( Q(t) \) is a function,

\[
Q(t) = \int \frac{1}{\sqrt{2}} \exp\left(-\frac{x^2}{2}\right) dx,
\]  

(2.8)

and \( B \) is the bandwidth of low pass filter having a Gaussian shaped spectrum.

As with any natural resource, it is important to make use of RF spectrum by using channel bands that are too wide. Therefore narrower filters are used to reduce the occupied bandwidth of the transmission.

Due to its linear amplification feature, QPSK is able to maintain low spectral sidelobes; thus providing good adjacent channel performance.

This is an important contribution to wireless systems because it
enables a higher channel reuse factor. Furthermore, QPSK’s importance in CDMA is evident with its efficient bandwidth use, enabling more users within a limited channel bandwidth. GMSK makes its contribution to cellular systems in communications from the mobile to the base station. In the case of uplink, power is drained significantly from the mobile, necessitating a power efficient amplifier. GMSK fulfills this need. Furthermore, due to its frequency modulating characteristics, GMSK shows a greater immunity to signal fluctuations. If most efficient bandwidth utilization and moderate hardware complexity is the key requirement, QPSK will be better choice. Out of band power, tolerance against filter parameters and non linear power amplifiers are important features, GMSK is the best solution (Mundra 1993). QPSK and GMSK each provide beneficial features, and although neither dominates the other, both contribute to the advancement of wireless telecommunication systems. Hence, the proposed system is analyzed with both of the modulation schemes.

2.2.3. Wireless channel

Free space propagation occurs when a unique direct signal path exists between a transmitter and a receiver. Reflection, refraction, diffraction and scattering determine the presence of many signal replicas at the receiver, leading to the phenomenon referred to as multipath. Besides, the complexity of the scenario is increased by the effects due to mobility, which cause short term fading and long term fading of the received signal. In a multipath scenario, each signal component is characterized by its amplitude, phase shift, delay and direction of arrival (DoA). When there is no direct path between transmitter and receiver, the entire received field is due to multipath. The inphase component, $x_I(t)$ and the quadrature component, $x_Q(t)$, of the incoming signal is modeled as complex Gaussian random process. These two processes have zero mean because of the absence of LOS between transmitter
and receiver. The channel is modeled in complex base band signal as
\[ c(t) = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} A_i e^{j(2\pi f_c t + \varphi_i)} \] where ‘\( A_i \)’ is the amplitude of the \( i^{th} \) complex sinusoid and \( \varphi_i \) is the random phase uniformly distributed from zero to \( 2\pi \), ‘\( f \)’ is the Doppler frequency shift. Thus the statistics of the envelope \( \sqrt{(x_i^2(t) - x_0^2(t))} \) follows a Rayleigh distribution,

\[ \zeta_{FAD}(z) = \begin{cases} \frac{2z}{P_{tx}} e^{-\frac{z^2}{P_{tx}}} & \text{for } z \geq 0 \\ 0 & \text{otherwise} \end{cases} \] (2.9)

Figure 2.5& 2.6 shows the absolute power of a Rayleigh fading channel taken over 2000 samples over a frequency selective channel with Doppler frequency of 10Hz and 100Hz respectively.

![Figure 2.5 Rayleigh fading with a maximum Doppler shift of 10Hz](image-url)
Experimental studies have shown that Rayleigh fading is a proper model for heavily built-up urban environment, characterized by the presence of rich scattering and absence of LOS between the communication nodes.

![Figure 2.6 Rayleigh fading with a maximum Doppler shift of 100Hz](image)

### 2.2.4 Vector Channel modeling

For design, simulation, and planning of wireless systems, the physical process by which the signals are received at the array may be modeled as narrowband or broadband.

**Narrow band Array**

It is important to recognize the narrowband model to describe the difference in the signal received at one antenna relative to another antenna. Consider a situation where a plane wave is received at multiple antennas as shown in figure 2.7. In this two-dimensional representation, the signal observed at one antenna will be delayed version of the signal observed at some other antenna. Let antenna ‘1’ be the reference antenna. The signal
observed at this antenna is given by,

$$\tilde{x}_1(t) = G_1(\phi) \tilde{r}(t) + \tilde{n}_1(t)$$  \hspace{1cm} (2.10)$$

where $\tilde{r}(t)$ is the incident signal and $\tilde{n}_1(t)$ is the measured noise for the first antenna. The quantity $\phi$ denotes the plane wave’s direction of arrival (DOA) and $G_1(\phi)$ is the gain for the first element at DOA $\phi$. The signal observed at the $k^{th}$ antenna is

$$\tilde{x}_k(t) = G_k(\phi) \tilde{r}(t + \tau_k) + \tilde{n}_k(t)$$  \hspace{1cm} (2.11)$$

where $\tau_k$ is the time difference of direction of arrival (TDOA). From figure 2.7,

$$\tau_k = \frac{d_k \sin \phi}{c}$$  \hspace{1cm} (2.12)$$

where $d_k$ is the separation of the first and $k^{th}$ antennas and ‘c’ is the velocity of the incident wave. Therefore, for sufficiently small values of $\tau_k$,

$$r(t + \tau_k) \approx r(t)$$  \hspace{1cm} (2.13)$$
The above equation is called the narrowband array approximation. The phase shift is in terms of the signal carrier wavelength $\lambda_c$,

$$\phi_k = \phi_c \tau_k = \left( \frac{2\pi c}{\lambda_c} \right) \left( \frac{d_k \sin \phi}{c} \right) \left( \frac{2\pi d_k \sin \phi}{\lambda_c} \right)$$ (2.14)

Assuming that the received signal is in a complex base band representation, we have

$$r(t + \tau_k) = a_k(\phi) r(t), \text{ where, } a_k(\phi) = G_k(\phi) e^{j\phi}$$ (2.15)

The signal experienced at each element can be represented in vector form as

$$x(t) = \begin{bmatrix} x_1(t) \\ \vdots \\ x_M(t) \end{bmatrix} = \begin{bmatrix} a_1(\phi) r(t) + n_1(t) \\ \vdots \\ a_M(\phi) r(t) + n_M(t) \end{bmatrix}$$ (2.16)

where $a(\phi) = [1, e^{-j\omega_0 \tau_1(\theta_k)}, \ldots, e^{-j\omega_0 \tau_i(\theta_k)}]^T$ is the array steering vector towards the direction $\theta_k$. $\tau_i(\theta_k)$ is the propagation delay between the first and the $i^{th}$ element for a waveform coming from direction $\theta_k$. $n(t) = [n_1(t), \ldots, n_M(t)]^T$ is the noise vector.

**Broadband model**

The broadband beamformer structure is shown in figure 2.8. It samples the propagating wave field in both space and time and is often used when signals of significant frequency extent (broadband) are of interest (Van Veen and Buckley, 1988). The outputs are expressed as,
\[y(t) = \sum_{i=1}^{J} \sum_{p=0}^{K-1} w_{i,p}^* x_i(t - pT)\]  

(2.17)

where \(K-1\) is the number of delays in each of the \(J\) sensors channels and \(T\) is the duration of a single delay. In vector form: \(y(t) = w^H x(t)\) where

\[x(t) = [x_1(t), x_1(t - T), \ldots, x_1(t - (K - 1)T), \ldots, x_J(t - (K - 1)T)]^T\]

\[w = [w_{1,0}, w_{1,1}, \ldots, w_{1,(K-1)}, \ldots, w_{J,0}, \ldots, w_{J,(K-1)}]^T\]. The frequency response of the system with tap weights \(w_p^*, 0 \leq p \leq J\) and a tap delay of \(T\) seconds is given by,

\[r(w) = \sum w_p^* e^{-j\phi(p-1)} \quad \text{or} \quad r(\omega) = w^H d(\omega)\]  

(2.18)

Assume that the signal is a complex plane wave with DOA \(\theta\) and frequency \(\omega\). For convenience let the phase be zero at the first sensor. This implies that \(x_i(k) = e^{j\omega k}\) and \(x_i(k) = e^{j\omega(l - \Delta_i)}\), \(2 \leq l \leq J\).

\(\Delta_i(\theta)\) represents the time delay due to propagation from the first to the \(l^{th}\) sensor. Substitution into eqn 2.17 results in the beamformer output

\[y(k) = e^{j\omega k} \sum w_{i,p}^* e^{-j\omega(l - \Delta_i(\theta))} = e^{j\omega k} r(\theta, \omega)\]  

(2.19)

where \(r(\theta, \omega)\) is the frequency response represented in the vector form as \(r(\theta, \omega) = w^H d(\theta, \omega)\).
2.2.5 Channel State Information (CSI)

In wireless communication, channel state information (CSI) refers to known channel properties of a communication link. CSI needs to be estimated at the receiver and usually quantized and fed back to the transmitter. Therefore, the transmitter and receiver can have different CSI. Since the channel conditions vary, instantaneous CSI needs to be estimated on a short term basis. A popular approach is called training sequence, where a known signal is transmitted and the channel matrix H is estimated using the combined knowledge of the transmitted and received signal. In multi antenna communication, the receiver can accurately track the instantaneous state of the channel from pilot signals that are typically embedded within the

Figure 2.8 Broad-band beamformer structure
transmissions. In practice, the CSI available at the transmitter is subject to errors caused by limited channel state feedback, estimation errors, short channel coherence time etc. The system model of channel estimation is shown in figure 2.9.

![Figure 2.9 Channel state information-system model](image)

Channel estimation is done at the receiver during the training phase. The estimated channel values are also feedback to the transmitter. The transmitter adapts the beamforming vector based on the predicted channel values. The delay involved in the feedback and the time varying nature of the wireless channel together lead to a different channel at the time of transmission than the channel that is feedback. Therefore, the adaptation at the transmitter is done based on the past channel values.

The idea behind channel prediction is to use past and present channel samples to predict future power level of the Rayleigh channel. In a narrowband flat-fading channel, the system is modeled as

\[ y = Hx + n \]  \hspace{1cm} (2.20)

where ‘y’ and ‘x’ are the receive and transmit vectors, respectively, and ‘H’ and ‘n’ are the channel matrix and the noise vector, respectively. Since the channel conditions vary, instantaneous CSI needs to be estimated on a short-term basis. A popular approach is so-called training sequence (or pilot
sequence), where a known signal is transmitted and the channel matrix \( H \) is estimated using the combined knowledge of the transmitted and received signal. Wajid (2009) suggested downlink beamforming using perfect instantaneous and covariance based CSI are the suitable methods to estimate CSI. In practice, the CSI available at the transmitter is subject to errors caused by limited channel feedback, estimation errors and short channel coherence time etc. Generally, there are two types of channel estimators: Least squares estimators (LSE) and Minimum mean square estimator (MMSE).

LS is a simple method for estimation and it is used as an initial step. Yucek (2007) suggests least squares (LS) method for OFDM signal, whose LS estimate of the channel frequency response \( H \) can be calculated using the received signal and the knowledge of the transmitted symbols as,

\[
\hat{H}_{\text{LS}}(k) = \frac{Y(k)}{X(k)} = H(k) + \frac{W(k)}{X(k)}
\]  

(2.21)

If the channel and noise distributions are unknown, then the least-square estimator (also known as the minimum-variance unbiased estimator) is,

\[
H_{\text{LS-estimate}} = YP^H (PP^H)^{-1}
\]  

(2.22)

where \((\cdot)^H\) denotes the conjugate transpose and the training matrix \( P = [P_1,\ldots,P_N] \).

The received SINR of the \( i \)th user can be written as

\[
\text{SINR} = \frac{w_i^H R_i w_i}{\sum_{l \neq i} w_i^H R_l w_i + \sigma_i^2}
\]  

(2.23)
where $R_i = E\{H_iH_i^H\}$ is the downlink channel covariance matrix for the $i^{th}$ user. If the channel co-variance matrix assumed to be perfectly known, the downlink beamforming is subjected to the condition:

$$
\min \sum_{k=1}^{K} \|w_k\|^2 \geq \frac{\sum_{l=1}^{K} w_l^H R_i w_l}{\sum_{l=1}^{K} w_l^H R_i w_l + \sigma_i^2} \geq \gamma_i
$$

(2.24)

where $\gamma_i$ is the minimum acceptable SINR for the $i^{th}$ user. $\|\|$ denotes the Euclidean norm of a vector.

MMSE is another method, very widely used in the OFDM channel estimation. It uses additional information like the operating SNR and the channel statistics. For a system of model $y = Ax + w$, MMSE of the variable $x$ is given by, $\hat{x} = R_{xy} R_y^{-1} y$ where $R_{xy}$ is the cross co-variance between variables $x$ and $y$. When $\hat{x}$ is applied to the OFDM channel estimation,

$$
\hat{H}_{MMSE} = R_{hh} (R_{hh} + \sigma_w^2 (XX^H)^{-1})^{-1} \hat{H}_{LS}
$$

(2.25)

can be obtained. Here, $H_p$ is the channel frequency response (CFR) at the pilot subcarriers, $R_{hh}$ represents the cross-correlation between all the subcarriers, $R_{hh}$ represents the auto-correlation between the pilot subcarriers. For simulation, a total number of 1024 subcarriers are considered. Out of which, 896 are data and 128 are pilots. The MSE performance of both LS and MMSE are discussed in chapter 3.

2.2.6 ISI Mitigation

To mitigate the ISI in multipath scenario, adaptive equalization is necessary in TDMA based systems. The narrowband and wideband time division multiple access (TDMA) digital cellular systems require adaptive
equalization at the demodulator to combat the ISI resulting from the time-variant multipath propagation of the signal through the channel. Whereas, OFDM is the promising technique to combat multipath in receiver.

### 2.2.6.1 Equalization

An equalizer is a compensator for channel distortion. For communication channel in which the channel characteristics are known or time varying, optimum transmit or receive filters can not be designed directly. For these cases, an equalizer is needed to compensate for the ISI created by the distortion in the system. There are three types of equalization methods commonly used: Maximum Likelihood (ML) detection, Linear equalization, Non linear equalization. Linear equalizers are easy to implement and effective where the ISI is not severe (using Zero forcing rule or mean square error criterion). Adaptive equalization will be needed to overcome the severe ISI affecting transmission at high data rate rates. In addition to the ISI due to multipath, spectrally efficient GMSK introduces considerable amount of controlled phase ISI. Hence, the LMS or Gradient equalizer is used to implement adaptive equalization. It is a stochastic gradient optimization algorithm based on traditional optimization technique called method of Steepest Descent. The LMS algorithm is basically a simplification of the Method of Steepest Descent, where instantaneous values are used instead of actual values. The weight update equation,

\[
w[n+1] = w + \Delta e[n] * Y'[n] \tag{2.26}
\]

where \( Y'[n] = [Y((n-M)T), \ldots, Y(0), \ldots, Y((n+M)T)]^T \) represents the tap-inputs at the time instant(or iteration). The error \( e[n] \) is computed from the equalized output using either a training sequence or the decoded output as reference.
\[ \varepsilon[n] = A_n - y_{eq}[n] \] (2.27)

where \( y_{eq}[n] \) is the equalized output, \('A_n' are uncorrelated symbols, \( y_{eq}(n) = w[n]^H Y[n] \). The mean square error of LMS adaptive equalizer is, \( MSE = E[(A_n - Y_{eq}(n))^2] \). The block diagram of implementing this algorithm is shown in figure 2.10. The simulation results are discussed in chapter 3.

2.2.6.2 OFDM system

Orthogonal frequency division multiplexing (OFDM) is proved to be an efficient way to overcome the effects of fading channels and multipath by dividing the frequency selective channel into a number of sub-channels.
corresponding to the OFDM sub-carrier frequencies. In order to increase the spectral efficiency in OFDM systems and to promote the interference suppression in multipath channels, a multiple antenna array can be used at the receiver (Borio, 2006). In an OFDM system, the beamforming algorithm can be applied in either time domain or frequency domain. Time domain array processing has lower complexity, because only one FFT is required. Time domain beamforming is called pre-FFT beamforming because the array processing is done before the FFT step in time domain, and frequency domain beamforming can be called post FFT because the array processing is done after the FFT step in frequency domain. Post-FFT requires set of weights for each array branch, so that the total number of weights processed is equal to the number of elements times the number of sub carriers, which requires a high computational complexity. Even though, Borio and Ribeiro (2006) suggested that pre-FFT can be performed with conventional LMS, RLS and SMI algorithm with appreciable BER, the development of suitable adaptive algorithm may further improves the performance of the system.

At the transmitter (figure 2.11), the input random data is converted from serial to parallel and then mapped to any one of the modulation types (BPSK, QPSK, 16QAM, 64QAM). The obtained N samples are then passed through the IFFT block. Cyclic prefix (CP) was added to the data once the data was converted into time domain and ready to be transmitted. The addition of the CP (of lengths such as ¼, 1/8, 1/16 and 1/32) to the data before it was actually transmitted to cater the problems related to the multipath propagation and provided a resistance against ISI. The transmitted data is then fed to the channel.
In order to design an efficient wireless channel, multipath spread, fading characteristics, path loss, doppler spread and co-channel interference are the important factor to be kept in mind. As a result, the transmitted OFDM signal suffers from multipath effects and other channel effects. At the receiver, an array of antennas are deployed. The received signal is passed through a beamformer which is located before the FFT stage. The process starts with the removal of the cyclic prefix that was initially added to the transmitted signal as earlier explained in the transmitter module. After cyclic prefix removal, the data was converted back into frequency domain from the time domain using the FFT. Once the data conversion is completed, the data is passed to the de-modulator where the data is demodulated according to modulation schemes applied on the data during the transmission. The de-modulated data is analyzed and compared to the original data by Bit-Error-Rate (BER) calculator.

**Figure.2.11 OFDM Transmitter functional scheme**

**Figure.2.12 Pre-FFT beamforming scheme**
A Pre-FFT beamformer (figure 2.12) was employed as spatial processing at reception. Each replica of the received signal \( r_{k,h}[n] \) is multiplied by the conjugate of a complex weight \( w_{k,h}[n] \) and then summed up to form the spatially filtered signal \( y[n] \). In this method, the array weighting is applied over the whole signal in time domain, that is, before FFT operation. The base band sampled signal at the output of the pre-FFT beamformer is obtained by a linear combination of the components directly detected by the K elements. The array weighting process in pre-FFT scheme can be expressed, in vectorial notation, as:

\[
\mathbf{y}[n] = \mathbf{w}^H \mathbf{r}[n],
\]

where \( \mathbf{w} \) is the \( K \times 1 \) complex weight vector. In this scheme, the complex weights are determined by a suitable adaptive algorithm which minimizes the mean square error (MSE). In order to evaluate the MSE, a reference signal is needed, which is a pilot tone embedded into the OFDM frame.

\[
MSE = E \left\{ \| \mathbf{s}^T - w_k^H \mathbf{X}_k \|^2 \right\}
\]

(2.28)

The beamforming weight set \( w_k \) that minimizes the above equation and nullifies the MSE gradient and hence the performance of the system is improved.

### 2.3 DIGITAL BEAMFORMING ALGORITHMS

The increasing demand for mobile communication services in a limited RF spectrum motivates the need for better techniques to improve spectrum utilization in terms of digital beamforming algorithm. This challenging scenario involves the emerging 4G technologies like World wide interoperability of Microwave Access (WiMAX), and Long term Evolution (LTE). However, in order to satisfy the increasing demand of network capacity, the exploitation of the spatial domain of the communication channel by means of multiple antenna system is followed (Godara, 1997). This can be
a key improvement for enhancing the spectral efficiency of the wireless systems. Spatial Division Multiples Access (SDMA) cellular systems have gained special attention to provide the services demanded by mobile network users in 3G and 4G cellular networks, because it is considered as the most sophisticated application of smart antenna technology (Balanis, 2005) allowing the simultaneous use of any conventional channel (frequency, timeslot or code) by many users within a cell by exploiting their position.

Basically, Digital beamforming is the marriage of antenna technology and digital technology. Digital beamforming need a reference for the underlying principle to compare their operation’s outcome with some desired property of the received signals. This reference may be of temporal or spatial nature. Generally the goal of the adaptive beamforming is to optimize the beamformer response, so the output contains only minimal contribution due to noise and signals arriving from other than the desired signal direction. This is performed by choosing weights based on the statistics of the data captured by the array according to some optimum criterion. Adaptive beamforming method may be roughly divided into different classes according to their reference they use to adaptively determine the weights. Historically, temporal reference based algorithms were used. This class of algorithms relies on the existence of a reference or training sequence embedded within the data stream. To exploit the information and to estimate the direction of arrival, spatial reference is also needed.

2.3.1 Temporal Reference algorithms

This class of adaptive algorithms is designed to act as a spatial (or spatio-temporal in the wideband case) filter, in such a way, that complex weights are calculated directly from the statistics of the received array data. To do so, an error signal is minimized by adjusting complex weights in a continuous, iterative, or in a block-wise fashion. To adjust the weights in an
optimum way, it is necessary to know enough about the desired signal, called temporal reference. A generic adaptive beamforming system is shown in figure 2.13. Conventional adaptive beamforming algorithms such as least mean square (LMS), constant modulus algorithm (CMA), recursive least square (RLS) have been simulated and analyzed using ULA of eight elements.

(i) **Least Mean Square algorithm (LMS)**

One of the simplest algorithm for adaptive processing is based on least mean square (LMS) algorithm for continuous adaptation. The LMS algorithm is stated by the following equations:

\[
\text{Output vector, } y[n] = w^H[n]x[n] \\
\text{Error vector, } e[n] = d[n] - y[n] \\
\text{Weight update vector, } w[n+1] = w[n] + \mu e[n]x[n] 
\]

(2.29)

where \( x[n] \) is the input data sequence, \( y[n] \) is the output sequence, ‘\( w \)’ is the update weight vector and \( d[n] \) is the desired signal sequence. It has been shown that starting with an arbitrary initial weight vector, the LMS algorithm will converge and stay stable as long as the value of \( \mu \) is chosen as:

\[
0 < \mu \frac{1}{\lambda_{\max}}
\]

where \( \lambda_{\max} \) is the maximum eigenvalue (or trace) of the Covariance Matrix. Within the margin, the larger the value of \( \mu \), faster the convergence but less stability around the minimum value. On the other hand, smaller the value of \( \mu \), slower the convergence but the algorithm will be more stable around the optimum value. When the eigenvalues are widespread, convergence can be slow.
(ii) **Recursive Least Squares algorithms (RLS)**

The recursive least squares (RLS) algorithm offers an alternative to the LMS algorithm as a tool for solution of adaptive filtering problems. The fundamental difference between the RLS algorithm and the LMS algorithm may be stated as: The step size parameter $\mu$ in the LMS algorithm is replaced by the inverse of the correlation matrix of the input vector $x(n)$, which has the effect of whitening the tap inputs. The convergence behavior of the RLS algorithm is as follows:

i. The rate of convergence of the RLS algorithm is typically in an order of magnitude faster than that of the LMS algorithm.

ii. The rate of convergence of the RLS algorithm is invariant to the eigen value spread of the ensemble average correlation matrix of the input vector $x(n)$.

iii. The excess mean-square error of the RLS algorithm converges to zero as the number of iterations ‘$n$’ approaches infinity.

(iii) **Constant Modulus Algorithms (CMA)**

When training sequences are unavailable, blind algorithms become attractive. Generally, these techniques exploit some known property of the desired signal so that an indirect measure of the output SINR can be obtained. The constant modulus algorithm (CMA) is perhaps the most well-known blind algorithm and is used in many practical applications, because it requires no carrier synchronization (Tong 1998). In general, the CMA seeks a beamformer weight vector that minimizes a cost function of the form

$$J_{pq} = \langle (|y_n|^p - 1)^q \rangle$$  \hspace{1cm} (2.30)
The weight update equation is,

\[ w(n + 1) = w(n) - \mu e(n)x(n + 1) \tag{2.31} \]

A particular choice of \( p \) and \( q \) yields a specific cost function, called the (\( p, q \)) CMA cost function. The objective of CM beamforming is to restore the array output ‘\( y_n \)’ to a constant envelope signal.

### 2.3.2 Performance comparison of conventional algorithms

Literature suggests numerous adaptive algorithms and diversity algorithms for beamforming applications (Reed, 2006). The best algorithm for the particular array must not only account for the signal environment at hand, but also for a number of other practical considerations including synchronization, the presence or absence of array data, the computational complexity and hardware cost. Signal environment considerations include the nature of the desired signal’s channel, its SNR, number of interfering signals as well as their powers and DOAs relative to their desired signal. Hence, there is no algorithm which satisfies all the above requirements.

In this chapter, some of the blind and non-blind adaptive algorithms are analyzed based on their performance in the given channel conditions and various parameters like HPBW, percentage of power in the side lobe, null point suppression and number of iterations required to optimize the weight vectors are compared. Let us analyze one by one. LMS is simple and less complex. If the input vector and desired response are available at each iteration, the LMS algorithm is generally the best choice for many applications of adaptive signal processing (Reed, 2006).

The CMA cost function is most important since noise and interference compute the constant modulus property of the desired signal (Denno, 2004).
A potential drawback of the CMA is the capture effect. In an environment containing multiple CM signals, a CMA beamformer will typically extract the strongest signal. This may or may not be the desired signal. To extract the original signal, the successive interference cancellation is made so as to determine the original signal. The only difficulty of the RLS algorithm is the update of the inverse data co-variance matrix. The RLS computation is obtained for three different cases, i.e. high SNR (SNR = 30dB or more), medium SNR (Input SNR 10dB) and low SNR.

All the cellular mobile applications use the 120° sector for the coverage of users, hence the calculations are obtained for -60° to +60°. The various parameters such as HPBW, side lobe level, null levels and the convergence rate are calculated by assuming the desired user and the interferers are moving in the scanning sector of -60° to 60°, and they are tabulated (Tables 2.1). From the observations, LMS and RLS are found to be better compared to other conventional algorithms.

Table 2.1 Advantages and performance of conventional algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Advantage</th>
<th>HPBW (Deg)</th>
<th>Side lobe level (dB’s)</th>
<th>Null levels (dB’s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMS</td>
<td>Simple stable, low complexity</td>
<td>17-18</td>
<td>-12 to -15</td>
<td>-25 to -30</td>
</tr>
<tr>
<td>RLS</td>
<td>Update of the inverse data co-variance matrix</td>
<td>18-20</td>
<td>-14 to -15</td>
<td>-25 to -40</td>
</tr>
<tr>
<td>CMA</td>
<td>No carrier synchronization, robust to symbol timing</td>
<td>23-25</td>
<td>-12 to -18</td>
<td>-25 to -35</td>
</tr>
<tr>
<td></td>
<td>error</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wiener</td>
<td>Depends on the update of co-variance inverse matrix</td>
<td>18-20</td>
<td>-13 to -14</td>
<td>-20 to -30</td>
</tr>
<tr>
<td>MVDR</td>
<td>Minimum power contributed by noise and interference,</td>
<td>20-25</td>
<td>-13.5 to -15</td>
<td>-30 to -35</td>
</tr>
<tr>
<td></td>
<td>fixed gain, max SNR in desired directions,</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Drawbacks of conventional algorithm

Each of the conventional algorithms has its own advantage and disadvantage. From the above Table 2.1, it is understood that the HPBW is larger (Simon 2002), approximately from 17° to 25° and side lobe level is at an average of 13.5dB. The classical RLS algorithm uses the constant forgetting factor 0<\lambda<1, this achieves low misadjustment and good stability, but its tracking ability is poor. The recursive equation for updating the tap-weight vector of RLS algorithm is based on Kalman gain and posteriori error which in turn depends on forgetting factor ‘\lambda’. A smaller value of forgetting factor improves tracking, but also increases misadjustment, which could affect the stability of the algorithm. The Weiner solutions require the computation of inverse of the array correlation matrix (R_{xx}^{-1}) and the calculation of output vector. Normally, inverse matrix operation affects the convergence rate and the speed of the algorithm.

The unconstrained LMS is not subjected to constraints at each iteration, but it estimates the gradient of MSE quadratic error and then moving the weights in the opposite direction with respect to the gradient by a small quantity, which is determined by a constant step size. This step size largely influences the convergence characteristic of the algorithm in terms of speed and closeness to the optimal solution. The selection of a too small step size results in a lower rate of convergence. The main drawback of the LMS is its sensitivity to the convergence behavior.

Constant modulus (CMA) algorithm operates on the principle that the amplitude of the communication signal is distorted by interference and multipath fading. The main drawback of the CMA is, in hostile environment, the algorithm may incorrectly select an interferer having the same envelope of the desired signal. CMA is a gradient based algorithm which works on the
premise that the existence of interference causes fluctuation in the amplitude of the array output.

### 2.3.3 Spatial Reference algorithm

This class of algorithm estimates the direction of arrival (DOA) from the available samples. This can be done either by eigenvalue decomposition of the estimated array correlation (covariance) matrix, or by singular value decomposition of the array data matrix.

#### Direction of Arrival (DOA) algorithm

In an adaptive array antennas, to locate the desired signal, some popular direction of arrival estimation algorithms such as MUSIC and ESPRIT are used. MUSIC and ESPRIT DOA estimation algorithms provide high angular resolution and hence they are explored by various parameters of the adaptive antenna system. Literature suggests that MUSIC algorithm is highly accurate and stable and provides high angular resolution compared to ESPRIT and hence MUSIC can be widely used in mobile communication to estimate the DOA of the arriving signals.

#### Multiple Signal Classification (MUSIC) Algorithm

The MUSIC method is a relatively simple and efficient eigenstructure method of DOA estimation. This method estimates the noise subspace from the available samples by either eigenvalue decomposition of the estimated array correlation matrix or singular value decomposition of the data matrix. Once the noise subspace has been estimated, a search for ‘M’ directions is made by looking for steering vectors that are orthogonal to the noise subspace. In narrowband condition, if M signals impinge on an L
dimensional array from distinct DOAs $\theta_1, \theta_2, \ldots, \theta_M$, the array model may be written as,

$$x(t) = A(\theta)s(t) + n(t) \tag{2.32}$$

where $A(\theta) = [a(\theta_1), a(\theta_2), \ldots, a(\theta_M)]$ is the steering matrix, $s(t) = [s_1(t), s_2(t), \ldots, s_M(t)]^T$ denotes the baseband signal waveforms, and $n(t)$ is spatial white noise. The spatial covariance matrix:

$$R = E\{x(t)x^H(t)\}$$

$$= AE\{s(t)s^H(t)\}A^H + E\{n(t)n^H(t)\}$$

$$= ASA^H + \sigma^2 I \tag{2.33}$$

where $S = E\{s(t)s^H(t)\}$ is the source covariance matrix; $E\{n(t)n^H(t)\} = \sigma^2 I$ is the noise covariance matrix, that is a reflection of the noise having a common variance $\sigma^2$ at all sensors and being uncorrelated among all sensors. This is normally accomplished by searching for peaks in the MUSIC spectrum given by,

$$P_{MUSIC}(\hat{\theta}) = \frac{a^H(\hat{\theta})a(\hat{\theta})}{a^H(\hat{\theta})U_NU_N^H a(\hat{\theta})} \tag{2.34}$$

or, alternatively,

$$P_{MUSIC}(\hat{\theta}) = \frac{1}{a^H(\hat{\theta})U_NU_N^H a(\hat{\theta})}, \tag{2.35}$$

where $U_N$ denotes an $L$ by $L-M$ dimensional matrix with its $L-M$ columns being the eigen vectors corresponding to the $L-M$ smallest eigenvalues of the array correlation matrix, and $a(\theta)$ denotes the steering vector corresponding to
direction $\theta$. The signal components are orthogonal to the noise subspace eigenvectors, the denominator approaches ‘0’ for angle $\theta$, thus producing the peaks in the MUSIC spectrum. For ULA, the peak searching is efficiently replaced by a polynomial rooting problem, the resulting method is known as Root-MUSIC.

**Simulation results**

DOA estimations are simulated using MATLAB. Performance of the algorithm has been analyzed by considering mean square error for 50 trials. Figure 2.13 shows the output of MUSIC for an array of eight elements for the SOI at $85^\circ$ & $115^\circ$ and for SNR=10dB. Figure 2.14 shows the output of MUSIC for an array of eight elements for the SOI at $0^\circ$ for SNR=10dB.

![Figure 2.13](image1.png) **Figure 2.13 Response of MUSIC for SOI at $85^\circ$ & $115^\circ$**

![Figure 2.14](image2.png) **Figure 2.14 Response of MUSIC for SOI at $0^\circ$**
2.3.4 Scheme of proposed adaptive beamforming algorithm

A new beamforming algorithm becomes necessary for the fast convergence and adaptation of weight vectors in a continuous manner. The important aspects to be considered in the design of a novel adaptive beamforming algorithms are the type of modulation scheme, type of wireless channel, channel state information, and ISI mitigation due to multipath in wireless communication link. The incoming signal comprising of user information and multiple interferers occupy the same frame. The received signal is modulated and passed through the channel, the output vector is generated with initial amplitude and phase distributions. The proposed beamforming algorithm (figure 2.16) updates the weights based on the channel estimation and the signal is directed towards the DOA estimated by MUSIC algorithm. In the receiver side, the symbol is detected and the ISI is equalized by adaptive equalizer.

Figure 2.15 Scheme of proposed beamforming algorithm