CHAPTER 3

CLUSTERING SCHEMES FOR ADAPTIVE MODULATION

The basic modulation methods include: amplitude, frequency and phase based. Higher orders of modulation permit encoding more bits per symbol or period (time). The typical characteristics are listed in table 3.1.

Table 3.1 Characteristics of Amplitude, Frequency and Phase modulation

<table>
<thead>
<tr>
<th>S.No</th>
<th>Type</th>
<th>Characteristics</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Amplitude Shift Keying (ASK)</td>
<td>Amplitude variation in step with the data</td>
<td>Easily affected by noise</td>
</tr>
<tr>
<td>2</td>
<td>Frequency Shift Keying (FSK)</td>
<td>Frequency variation in step with the data</td>
<td>Noise resilient</td>
</tr>
<tr>
<td>3</td>
<td>Phase Shift Keying (PSK)</td>
<td>Phase of the carrier varies in step with the data</td>
<td>Require synchronization schemes for reception</td>
</tr>
<tr>
<td>4</td>
<td>Quadrature Phase Shift Keying (QPSK)</td>
<td>Uses four phase values 0, $\pi$, $\pi/2$, $3\pi/2$</td>
<td>Symbol/bit ratio is higher.</td>
</tr>
<tr>
<td>5</td>
<td>Quadrature Amplitude Modulation (QAM)</td>
<td>Hybrid ASK+PSK and has both amplitude and phase variations</td>
<td>Each symbol typically represent four bits</td>
</tr>
</tbody>
</table>
Figure 3.1 shows Quadrature phase shift keying where each symbol represent four bits instead of just the two bits per symbol with QPSK. Each point indicates a unique amplitude and phase of the wave (for example, point (1, 1) indicates 90 degrees and unit amplitude).

![Figure 3.1 Quadrature Phase Shift Keying]

Figure 3.2 to Figure 3.4 shows the generated signal, modulated signal and 1 dB noisy signal for PAM, 64QAM and 32 QAM respectively. In visual appearance, the signals appear similar and hence the hidden characteristics are not revealed explicitly. An automatic modulation detection scheme needs to extract these characteristics specific for different modulation and cluster identical modulation nodes for secure group communication.

![Figure 3.2 Generated signal, PAM modulated signal and 1 dB noisy signal]
Figure 3.3 Generated signal, 64 QAM modulated signal and 1 dB noisy signal

Figure 3.4 Generated signal, 32 QAM modulated signal and 1 dB noisy signal
3.1 ADAPTIVE MODULATION

The diffusion of high speed digital wireless communications has increased the need for reliable high data rate communications in variable channel conditions. Adaptive modulation techniques allow maximizing the spectral efficiency (SE) in fading channels without compromising the performance in terms of bit error probability (BEP) and bit error outage (BEO). Different order modulations allow sending more bits per symbol and thus achieving higher throughputs or better spectral efficiencies. The use of adaptive modulation allows a wireless system to choose the highest order modulation depending on the channel conditions.

In addition, adaptive modulation allows the system to overcome fading and other interference. Both QAM and QPSK are modulation techniques used in IEEE 802.11 (Wi-Fi), IEEE 802.16 (WiMAX) and 3G (WCDMA/HSDPA) wireless technologies. The modulated signals are then demodulated at the receiver where the original message can be recovered. The use of adaptive modulation allows wireless technologies to optimize throughput, yielding higher throughputs while also covering long distances.

By adjusting the transmission parameters to the momentary link quality, adaptive mechanisms aim at improving both spectral efficiency and link reliability. Nevertheless, in order to guarantee the Quality of Service (QoS) constraints from the upper layers, adaptive mechanisms implement a sub-optimal trade-off between link robustness and bandwidth efficiency.

3.2 SPECTRA OF DIGITAL MODULATION SIGNALS

In this section, the spectra of different digital modulation signal schemes are analyzed for their power spectral variations. The schemes chosen for study are BPSK, QPSK and MSK. Figure 3.5 shows the BPSK, QPSK and the MSK waveforms. The power spectral plots are shown in Figure 3.6.
3.3 POWER CONSTRAINTS

The instantaneous rate requirement of different traffic types (e.g., voice, video, and data) in the current frame, (if any) is taken into account. Let $X$, $Y$, and $Z$ denote the number of active links in a cluster, the number of subcarriers available in a cluster, and the number of timeslots (i.e., DATA slots) in a frame, respectively. The resource allocation optimization problem involves the selection of the best element i.e the maximizing function calculated by systematical computation approach.

\[
\max \sum_{x=1}^{X} (U_X(R_x(a, p))). \tag{3.1}
\]

subject to $R_x(a, p) >= R^d_y, \forall y \tag{3.2}$

\[
\max \sum_{y=1}^{Y} (P_{x,y} = P_{x,max}), \forall_{y,l} \tag{3.3}
\]

Here, $U_x$ is the utility function of the $X$ link. $R_x(a, p)$ represents the actual aggregate transmission rate of the frame allocating the $Y$ subcarriers to all the active links in the cluster. The transmit power over all the sub carriers in the transmitter link is indicated by ‘p’. The maximum power constraint of the transmitter and the channel gain should be
indicated for all the links. By using the resources allocated, the particular content of data should be transmitted without any loss and interruption.

### 3.3.1 COMBINED KKT-GA RESOURCE ALLOCATION

Karush-Kuhn-Tuker (KKT) algorithm first uses uniform power allocation over all the subcarriers, allocates subcarriers based on the optimal subcarrier allocation criterion, re-allocates the subcarriers until all the system constraints are met and finally performs water-filling for power re-allocation. In a multi-carrier communication system, each channel can carry a signal under noise condition considering maximizing the transmission rate and minimizing the total power consumption. The KKT algorithm finds the solution for optimization problems constrained to one or more inequalities. This algorithm follows some necessary conditions while finding the solution: (i) Feasibility (ii) Direction which improves the objective (iii) Complementary slackness (iv) Positive Lagrange multipliers. The time complexity of the Cheng’s KKT-driven algorithm is of the order $O(\text{XYZ})$. Despite low complexity, this approach is only suboptimal, because it considers three resource dimensions (i.e., power, subcarrier, and time) individually in succession. In this work, the algorithm is used for allocation process for the optimal allocation of a node to the server (cluster header) based on the above three resource dimensions power, subcarrier and time.

In this work, the focus is to perform the data communication without any packet data loss and sustain system implementation in the best manner. In this research, a hybrid Cheng’s KKT driven and GA-based resource allocation scheme is used.

### 3.4 SECOND-ORDER STATISTICS

The theoretical background for the different approaches are introduced. The autocorrelation function or sequence of a stationary process, $x(n)$ is defined by,
where \( E\{\cdot\} \) denotes the ensemble expectation operator. The power spectrum is formally defined as the Fourier Transform (FT) of the autocorrelation sequence (the Wiener-Kintchine theorem) is given by,

\[
P_{xx}(f) = \sum_{m=-\infty}^{\infty} R_{xx}(m) \exp(-j2\pi fm)
\]

(3.5)

Where \( f \) denotes the frequency. An equivalent definition is given by

\[
P_{xx}(f) = E\{X(f)X^*(f)\}
\]

(3.6)

Where \( X(f) \) is the Fourier Transform of \( x(n) \)

\[
X(f) = \sum_{n=-\infty}^{\infty} x(n) \exp(-j2\pi fn)
\]

(3.7)

A sufficient, but not necessary, condition for the existence of the power spectrum is that the autocorrelation be absolutely summable. The power spectrum is real valued and nonnegative, that is, \( P_{xx}(f) \geq 0 \); if \( x(n) \) is real valued, then the power spectrum is also symmetric, that is, \( P_{xx}(f) = -P_{xx}(f) \).

The higher-order moments are natural generalizations of the autocorrelation, and cumulants are specific nonlinear combinations of these moments. The first-order cumulant of a stationary process is the mean \( C_{1x} := E\{x(t)\} \). The higher-order cumulants are invariant to a shift of mean. Hence, it is convenient to define them under the assumption of zero mean. If the process has nonzero mean, then subtract the mean, apply the following definitions to the resulting process. The second-order cumulants of a zero-mean stationary process are defined by

\[
C_{2x}(k) = E\{X^*(n)x(n + k)\}
\]

(3.8)

The first-order cumulant is the mean of the process; and the second-order cumulant is the auto covariance sequence. Note that for complex processes, there are several ways of
defining cumulants depending upon which terms are conjugated. The zero-lag cumulants have special names: $C_{2x}(0)$ is the variance and is usually denoted by $\sigma_x^2$.

### 3.5 STRUCTURED LEARNING BASED CLASSIFIER (SLBC)

A set of related structured learning methods (ex: Support Vector Machine (SVM)) analyzes the data and recognize the patterns that can be used for classification and regression analysis. The standard learning based classifier is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one “target value” (class labels) and several “attributes” (features). SLBC has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basic functions are automatically obtained during training. The performance of SLBC largely depends on the kernel.

SLBC is essentially a linear learning machine. For the input training sample set

$$\{(x_i, y_i), i = 1 ... n, x \in R^n, y \in \{-1, +1\}\}$$  \hspace{1cm} (3.9)

the classification hyperplane equation is let to be

$$\omega \cdot x + b = 0$$  \hspace{1cm} (3.10)

thus the classification margin is $2 / |\omega|$. To maximize the margin, that is to minimize $|\omega|$, the optimal hyperplane problem is transformed to quadratic programming problem as follows,

$$\begin{align*}
\min \Phi(\omega) & = \frac{1}{2} (\omega, \omega) \\
\text{s. t. } y_i ((\omega \cdot x) + b) \geq 1, & \quad i = 1, 2 .... l
\end{align*}$$  \hspace{1cm} (3.11)

After introduction of Lagrange multiplier, the dual problem is given by,
According to Kuhn-Tucker rules, the optimal solution must satisfy

$$\alpha_i(y_i((w \cdot x_i) + b) - 1) = 0, \quad i = 1, 2, \ldots, n$$

(3.13)

That is to say if the option solution is

$$\alpha^* = (\alpha_1^*, \alpha_2^*, \ldots, \alpha_i^*)^T, \quad i = 1, 2, \ldots, n$$

(3.14)

Then

$$w^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$$

$$b^* = y_i - \sum_{i=1}^{n} y_i \alpha_i^* (x_i \cdot x_j), \quad j \in \{j | \alpha_i^* > 0\}$$

(3.15)

For every training sample point $x_i$, there is a corresponding Lagrange multiplier. And the sample points that are corresponding to $\alpha_i = 0$ don’t contribute to solve the classification hyper plane while the other points that are corresponding to $\alpha_i > 0$ do, so it is called support vectors. Hence the optimal hyper plane equation is given by,

$$\sum_{x, \in SV} \alpha_i y_i (x_i \cdot x_j) + b = 0$$

(3.16)

The hard classifier is then,

$$y = sgn \left[ \sum_{x, \in SV} \alpha_i y_i (x_i \cdot x_j) + b \right]$$

(3.17)
For nonlinear situation, SLBC constructs an optimal separating hyperplane in the high dimensional space by introducing kernel function \( K(x,y) = \phi(x) \cdot \phi(y) \), hence the nonlinear SLBC is given by,

\[
\begin{align*}
\min \phi(\omega) &= \frac{1}{2} (\omega, \omega) \\
\text{s.t. } y_i \left( (\omega \cdot \phi(x_i)) + b \right) &\geq 1, \ i = 1, 2, ..., l 
\end{align*}
\]

(3.18)

And its dual problem is given by,

\[
\begin{align*}
\max L(\alpha) &= \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \\
\text{s.t. } \sum_{i=1}^{n} y_i \alpha_i &= 0, \ 0 \leq \alpha_i \leq C, \ i = 1, 2, ..., l
\end{align*}
\]

(3.19)

Thus the optimal hyperplane equation is determined by the solution to the optimal problem. A SLBC classifier can predict the input data into two distinct classes. However, it can be used as multiclass classifiers by treating a K-class classification problem as K two-class problems. This is known as one Vs rest or one Vs all classification.

The SLBC classifier implementation is standard implementation. In the MATLAB environment the LIBSLBC software is used. LIBSLBC is integrated software for support vector classification, regression and distribution estimation. It also supports multi-class classification.

### 3.6 PLL STRUCTURE WITH INCREASED GAIN

The input signal of a common gate may be a current and a transistor in a common-source arrangement converts a voltage signal to current signal. The cascade of a Common Source (CS) and a Common Gate (CG) stage is called a “Cascade” topology. It provides many useful properties.
In Figure 3.7, M1 generates a small signal drain current proportional to $V_{in}$ and M2 simply routes the current to $R_d$ (Drain Resistance). In Figure 3.8, the transistor, M1 is the input device and M2 is the cascade device.

**Figure 3.7 Cascade stage**

It can be noted that in this example, M1 and M2 carry equal currents. As per the bias conditions of the cascade, if M1 to operate in saturation then the voltage at node X is, $V_x \geq V_{in} - V_{th}$ (Where $V_{in}$ is the input voltage and $V_{th}$ is the thevenin voltage) and both M1 and M2 are in saturation, then $V_x$ is determined primarily by

$$V_{b}; \quad V_x = V_b - V_{gs2}$$  \hspace{1cm} (3.20)

Where $V_b$ is the body bias voltage and $V_{gs2}$ is the gate to source voltage of M2.

Thus, \hspace{1cm} $V_b - V_{gs2} \geq V_{in} - V_{th1}$ \hspace{1cm} (3.21)

Where $V_{gs2}$ is the gate to source voltage of M2.

$V_{in}$ is the input voltage.

$V_{th1}$ is the thevenin voltage of M1.
And hence $V_b > V_{in} + V_{gs2} - V_{th1}$ \hfill (3.22)

**Figure 3.8 Equivalent Cascade Stage**

For $M_2$ to be saturated

\[ V_{out} \geq V_b - V_{th2} \] \hfill (3.23)

\[ V_{out} \geq V_{in} - V_{th1} + V_{gs2} - V_{th2} \] \hfill (3.24)

If $V_b$ is chosen to place $M_1$ at the edge of saturation, the minimum output level for which both transistors operate in saturation is equal to the overdrive voltage of $M_1$ plus that of $M_2$. In other words, addition of $M_2$ to the circuit reduces the output voltage swing by at least the overdrive voltage of $M_2$. Also say $M_2$ is stacked on top of $M_1$.

The large-signal behavior of the cascade stage shown in Figure 3.9 is analyzed, as $V_{in}$ goes from zero to $V_{DD}$. For $V_{in} \leq V_{th1}$, $M_1$ and $M_2$ are off, $V_{out} = V_{DD}$ and

\[ V_x = V_b - V_{th2}. \] \hfill (3.25)
To understand the effect of cascade on $R_{out}$, the following illustration is described and mentioned below.

From the discussion of source degenerated common source (CS) amplifier a small signal equivalent circuit is developed, which includes the effect of body bias as shown in Figure 3.10

Since the current through $R_s$ is equal to $I_x$.

\[ V1 = - I_x R_s \] and the current flowing through $R_o$ is given by

\[ I_x - (g_m + g_{mb}) V1 = I_x + (g_m + g_{mb}) R_s I_x \] \hspace{1cm} (3.26)

Where $g_m$ is the transconductance, $g_{mb}$ is the transconductance due to body bias transistor and $R_s$ is the source resistance.

Adding the voltage drops across $R_o$ and $R_s$ we have,

\[ r_o [ I_x + (g_m + g_{mb}) R_s I_x] + I_x R_s = V_x \] \hspace{1cm} (3.27)

it follows that,

\[ R_{out} = [1 + (g_m + g_{mb}) R_s] r_o + R_s \] \hspace{1cm} (3.28)
\[ \text{Gain (G)} = - g_m R_{out} \]  

(3.32)

Where \( g_m \) is the transconductance and \( R_{out} \) is the output resistance

An important property of the cascade structure is it has high output impedance. Hence, for the calculation of \( R_{out} \) of the final circuit, it is viewed as a common-source stage with a degeneration resistor which is equal to \( r_{o1} \). Thus using equation (3.31)

\[ R_{out} = [1 + (g_{m2} + g_{mb2}) r_{o2}] r_{o1} + r_{o2} \]  

(3.33)

The expression for \( R_{out} \) is given by
\[
R_{out1} = \left\{ 1 + (g_{m1} + g_{mb1})r_{o1} \right\} r_{o2} + r_{o1} \right\} \| \left\{ 1 + (g_{m3} + g_{mb3})r_{o3} \right\} r_{o4} + r_{o3} \]
\approx \left\{ 1 + (g_{m1} + g_{mb1})r_{o1} \right\} r_{o2} + r_{o1}
\quad \text{(3.35)}
\]

Where \( R_{out1} \) seen from the positive terminal of the opamp circuit.

\[
R_{out2} = \left\{ 1 + (g_{m13} + g_{mb13})r_{o13} \right\} r_{o14} + r_{o13} \right\} \| \left\{ 1 + (g_{m15} + g_{mb16})r_{o15} \right\} r_{o16} + r_{o15} \]
\approx \left\{ 1 + (g_{m13} + g_{mb13})r_{o13} \right\} r_{o14} + r_{o13}
\quad \text{(3.36)}
\]

Where \( R_{out2} \) seen from the negative terminal of the opamp circuit.

From equation (3.32) and (3.33), it is observed that, the \( R_{out} \) is increased by a factor of

\[1 + (g_{m13} + g_{mb13})r_{o13}\] \( r_{o14} + r_{o13} \]

\[\text{3.7 CLUSTERING OF SIMILAR NODES BASED ON MODULATION}\]

In the clustering process, there are no predefined classes and no examples that would show what kind of desirable relations should be valid among the data (unsupervised process). On the other hand, classification is a procedure of assigning a data item to a predefined set of categories. Clustering produces initial categories in which values of a data set are further classified during the classification process. More researches have tried to develop intelligent receivers that are capable of identifying the incoming modulation scheme and reconfigure themselves accordingly. However, these architectures support only a very limited number of constellations, thus limiting both generality and performance.

For nodal management in a network, modulation identification and clustering mechanism are employed. In a communication network, several nodes are connected together randomly. While transmitting data to the receiver, the modulation selector selects the appropriate modulation scheme. At the receiver, a modulation tracker tracks and recovers the data sent by the transmitter. The modulation tracking scheme is also
used to identify a specific node allocated with a unique but dynamically varying modulation scheme. The parameters used to identify the modulation include Signal Strength and Average response time. On completion of modulation tracking performance, clustering mechanism is performed. This can be adapted by identifying the identical nodes in the network, where the node address can differ from each other.

The nodes with varying node address in a communication network are classified as active node and idle node. The active node undergoes node scanning process before transmission of data. The identical nodes which perform same type of modulation are clustered together and handled. Different architectures and design goals/constraints have been considered in various applications of WSNs. The clustering mechanism is employed and various nodes are exploited according to its capability. In some situations, the sensor nodes are scattered randomly in a region of interest and all the nodes are not mobile or it may be location unaware which are left unattended after deployment. All nodes have similar capabilities such as processing, communication and broadcasting power level and at the beginning they have no globally unique IDs. Network-wide unique IDs are beneficial for administrative tasks, such as configuration and monitoring of individual nodes. This is also regarded as an efficient scheme in many clustering algorithms.

WSN is a package of more clusters. Each and every node in the communication networks are connected together or sprinkled all around which in turn shapes to in the multi-hop network. Grouping of similar nodes in to clusters are called clustering and this technique is employed. By similarity the nodes can be split up into small groups which are referred to as clusters for effective data combination. This clustering technique offers abundant advantages such as network scalability, network stability, minimize the magnitude of the routing table by setting up the route set up inside the clusters, preserves communication bandwidth, evades unneeded exchange of information among the nodes and reduces transparency in topology maintenance.
All the clusters available in the networks must have a cluster head for directing the other nodes to perform the data communication effectively. This cluster head must have adequate resources and it was elected by the neighboring nodes. By employing the clustering mechanism, the networks can provide bandwidth, stability and scalability. The nodes in the cluster may vary or it may be constant according to the traffic load variations. The cluster head plays an important role and this offers the resource allowance for all the lively nodes in the cluster. Also it affords the timing information to all the clusters available in the network. The cluster head employs many management policies for the networking process to enhance its existence in advance and reduces the utilization of energy during transmission. Further, this time is divided into frames. Every frame in the nodes consists of a beacon slot, control slot and data slots in a serial manner and is shown in Figure 3.11.

| Beacon slot | Control slot | Data 1 | Data 2 | ...... | Data N |

**Figure 3.11 Frame structure**

Each and every slot in the frame has their own functionality. The beacon slot in the frame provides timing and node cluster sequence which are needed for transmission in the data slots. The control slot in the frame reveals the needed information of resource allowance technique to the beacon slot for all the clusters in the network. A mesh router can be a sender, relay or receiver at different times. The mesh routers act as an Omni-directional transceiver.
3.8 PROPOSED CLUSTERING SCHEME

The clustering of the nodes is performed in the following stages:

Step 1: To classify a group of transmitting nodes into “Active” and “Idle” groups, as shown in Figure 3.12

Step 2: Among given range of Node address, identify whether the nodes are live

Step 3: Perform”Node scanning”.
Identify Group of Nodes

Identify Group of Nodes
Initialize CCMM_Count;
Set CCMM_threshold;
Initialize CCMM_Timer
Set CCMM_Maxtime

Send CCMM

Activate CCMM_Timer;
Activate CCMM_count;

If
CCMM_Count 
CCMM_threshold
  
Receive response 
Relay from node 

Terminate CCMM 
Transmission

Assign responding nodes as IDLE

If
CCMM_Timer 
CCMM_maxtime

Assign responding nodes as ACTIVE

Figure 3.12 Flow chart for node address identification

Note: CCMM-Communication and Control Message Management
3.9 MEASURING BIT ERROR RATE (BER)

A Bit Error Rate tester is a device that measures the BER for a given transmission. The BER is given by,

\[ BER = \frac{\text{Bits in error}}{\text{Total bits transmitted}} \]

The BER test setup (Figure 3.13) uses a comparator and the transmitted bits are matched in an XOR gate with the received bits.

The number of bit errors is dependent upon the amount of noise during transmission. In telecommunication transmission, the measurement of end-to-end performance is usually bit error rate (BER), which quantifies the reliability of the entire communication system from “bits in” to “bits out”. A BER is defined as the ratio of bits that have errors relative to the total number of bits received.

Figure 3.13 Bit error rate tester
3.10 REALTIME STUDY SETUP

In the chosen communication network, the data needs to be transmitted through the nodes that are identically modulated. Based on the performance of the different modulation scheme, the lane can differ and travel accordingly. The experimental setup consists of fifty nodes, with hardware set up on FL2440 board with S3C2440 ARM processor running with Linux. High speed links for interconnects with user programmable modulation schemes for a wide range of channel modeling is also supported. The implementation details are given in chapter 4 of the thesis.

3.11 CHAPTER CONCLUSION

In this chapter various modulation schemes are discussed with their characteristics. A Structured Learning Based Classifier (SLBC) is proposed for analyzing data and recognizing patterns which substantially help for classification, regression analysis and distribution estimation. In the proposed system, the signals in cognitive radio are subject to various training phase and classification phase. For nodal management in a network, modulation identification and clustering mechanisms are employed. A gain boosting charge pump for PLL design is proposed and the factor by which the gain improves is derived mathematically. Phase Locked Loop (PLL) is used to track the frequency drift and other nonlinear effects of the Voltage Controlled Oscillator (VCO) are included and an increased gain based design is presented.