Chapter 4

The ANFIS Based Channel Equalizer

The analysis of noise characteristics and modeling of a suitable equalizer for the non-linear time invariant mobile cellular channel is the focal theme of this thesis. This Chapter is devoted to analyze the functioning of the channel equalizer based on Adaptive Network based Fuzzy Inference System (ANFIS). It may be noted that the equalization of wireless mobile channels is a non-linear problem, so that a non-linear solution is more appropriate.

We have to design the fuzzy if-then else rules based on the channel characteristics; namely variances of signal, noise, co-channel (CCI) and adjacent channel interferences (ACI) as well as the transmitted signal (input)-received signal (output) mapping. The equalizer is a non-linear system that effectively undoes the aberrations done to the transmitted signal by the channel due to the noise and co-channel and adjacent channel interferences. Now, the modeling a non-linear system is fairly complex so that conventional methods of system identification techniques cannot be applied to find the inverse system. One possible experimental method to develop a model for indoor wireless channel (viz., the channel impulse response, CIR) is to carry out expensive channel sounding (for example, one could use the RUSK Channel sounder from RF Sub Systems, GmBH, which would cost over a hundred thousand dollars). In this thesis, we attempt to supplant the expensive channel sounding technique for mobile wireless channel (that too, not restricted to the indoor case) by simulation.

The rest of the Chapter is organized as follows. In Section 4.1, we introduce the working principle of ANFIS [24]. The methods of channel Equalizer analysis and design are reviewed in Section 4.2. The Mobile Cellular channel equalizer based on ANFIS is introduced in Section 4.3, where we consider a number of equalizers based on ANFIS, with varying parameters. Thereafter, in Section 4.4, we consider the concept of Ultra-Wide Band (UWB) systems and their equalization using ANFIS. Conclusions are made in Section 4.5.
4.1 Introduction

The system modeling techniques based on conventional mathematical tools like differential equations is not well suited for dealing with ill-defined and uncertain systems [24]. By contrast, a fuzzy inference system (FIS), employing fuzzy if–then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno [24], has found numerous practical applications in control, prediction and inference. However there are some basic aspects of this approach which are in need of better understanding. More specifically, no standard methods exist for optimally transforming human knowledge or experience into the rule base and database of a fuzzy inference system. There is a need for effective methods for tuning the membership functions (MFs) so as to minimize the output error measure or maximize performance index. In this perspective, a novel architecture called Adaptive Network based Fuzzy Inference System (ANFIS), which can serve as a basis for constructing a set of fuzzy if–then rules with appropriate membership functions to generate the stipulated input–output pairs, is taken up J.S.R.Jang [24].

4.2 Methods of Channel Equalizer Analysis and Design

Adaptive filtering has achieved widespread application and success such as control, image processing, and communication [63, 64]. Among the various adaptive filters, the adaptive linear filter is the most widely used one mainly due to its low hardware implementation cost and other properties, like the convergence, global minimum, misadjustment error and training algorithms. It can be analyzed and derived easily. The adaptive linear filtering has achieved a large amount of success in many situations. The maximum likelihood sequence estimators (MLSE) [65] are implemented using the Viterbi algorithm. The large computational complexity associated with the Viterbi algorithm and the poor performance of the linear equalizers have led to the development of symbol-by-symbol equalizers using the maximum a posteriori probability (MAP) principle – Bayesian equalizers [20]. These Bayesian equalizers have been approximated using nonlinear signal processing techniques like artificial neural networks (ANN) [66, 67], radial basis functions (RBF) [44, 68], recurrent neural networks [69], and fuzzy filters [14, 54, 70, 71]. The study of these new techniques can provide adaptive equalizers which have the advantages of both good performance and low computational cost [70]. Fuzzy filters are nonlinear filters that incorporate linguistic information in the form of IF–THEN fuzzy rules. Fuzzy filters have been used for equalization due to their success.
in the related area of pattern classification [14, 54, 71]. Wang and Mendel [54] present Fuzzy Basis Functions (FBF) for channel equalization. Lin and Juang [70] have developed the adaptive neuro fuzzy filters (ANFF) and use it for equalization and noise reduction. This ANFF constructs its rule base in a dynamic way with the training samples. Patra and Mulgrew [71] have derived the close relationship between the fuzzy equalizers and the equalizer based on Maximum a Posteriori probability principle (MAP). Liang and Mendel [14] developed type-2 Fuzzy Adaptive Filters (TAF) and demonstrated that it could implement the Bayesian equalizer. The structures and learning algorithms of these models are both complicated and not suitable for practical implementation.

The Fuzzy Inference System (FIS)

Fuzzy if-then rules or fuzzy conditional statements are expressions of the form

\[ IF \ A \ THEN \ B, \]

where \( A \) and \( B \) are labels of fuzzy sets, characterized by appropriate membership functions [24]. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision. An example that describes a simple fact is:

\[ \text{If pressure is high, then volume is small} \]

where pressure and volume are linguistic variables, and high and small are linguistic values or labels that are characterized by membership functions [6].

Another form of fuzzy if-then rule, proposed by Takagi and Sugeno has fuzzy sets involved only in the premise part. By using Takagi and Sugeno's fuzzy if-then rule, we can describe the resistive force on a moving object as follows:

\[ \text{If velocity is high then } force = k \times velocity^2, \]

where, again, high in the premise part is a linguistic label characterized by an appropriate membership function. However, the consequent part is described by a non-fuzzy equation of the input variable, velocity. Both types of fuzzy if-then rules have been used extensively in modeling and control. Basically a fuzzy inference system is composed of five functional blocks as shown in Figure 4.1, which are enlisted as:

1. a rule base containing a number of fuzzy if-then rules.
2. a database which defines the membership functions of the fuzzy sets used in the fuzzy rules.
3. a decision making unit which performs the inference operations on the rules.
4. **A fuzzification interface** which transforms the crisp inputs into degrees of match with linguistic values.

5. **A defuzzification interface** which transforms the fuzzy results of the inference into a crisp output.

Usually, the rule base and the database are jointly referred to as the **knowledge base**. The steps of **fuzzy reasoning** (inference operations upon fuzzy if–then rules) performed by fuzzy inference systems are:

1. Compare the input variables with the membership functions on the premise part to obtain the membership values for compatibility measures of each **linguistic label**. This step is often called **fuzzification** [24].

2. Combine, (through a specific **t-norm operator**, usually multiplication or min of the membership values on the premise part), to get **firing strength** (weight) of each rule.

3. Generate the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength.

4. Aggregate the qualified consequents to produce a crisp output. This step is called **defuzzification** [24].

Several types of fuzzy reasoning have been proposed in the literature. Depending on the types of fuzzy reasoning and fuzzy if–then rules employed, most fuzzy inference systems can be classified into three types [24]:

![Block Diagram of Fuzzy Inference System (FIS)](image-url)
1. **Type-1**: The overall output is the weighted average of each rule's crisp output induced by the rule's firing strength (the product or minimum of the degrees of match with the premise part) and output membership functions. The output membership functions used in this scheme must be monotonically non-decreasing.

2. **Type-2**: The overall fuzzy output is derived by applying $\text{max}$ operation to the qualified fuzzy outputs, each of which is equal to the minimum of firing strength and the output membership function of each rule. Various schemes have been proposed to choose the final crisp output based on the overall fuzzy output, some of them are the *center of area*, the *bisector of area*, the *mean of maxima*, the *maximum criterion* etc.

3. **Type-3**: Takagi and Sugeno's fuzzy if-then rules (TSK model) are used. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output.

Commonly used fuzzy learning rules are illustrated in Figure 4.2.

![Figure 4.2: Various Fuzzy Reasoning Mechanisms: Type-1, Type-2, and Type-3. The difference is on the consequent part.](image)

**Adaptive Network Based Fuzzy Inference System (ANFIS)**

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to these minimal restrictions, the adaptive network's applications are immediate and immense in various areas.
In this section, a class of adaptive networks which are functionally equivalent to fuzzy inference systems, are referred to as ANFIS (abbreviation for Adaptive Network based Fuzzy Inference System) are examined.

Fuzzy modeling is applied to situations where the exact mathematical model is difficult to conceive and a measurement of values associated with the variables involved is quite tedious. Even the variables we considered in the present problem (i.e. variances of signal, noise and co-channel and adjacent channel interferences) are themselves not measurable accurately. In such situations, fuzzy models are developed and used for precise estimation of the transmitted signal at the receiver side.

4.2.1 ANFIS Architecture and Functional Layers

For simplicity, we assume the fuzzy inference system under consideration has two inputs $x$ and $y$ and one output $z$ [24]. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type:

\begin{align}
\text{Rule 1: } & \text{ If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1 x + q_1 y + r_1. \\
\text{Rule 2: } & \text{ If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2 x + q_2 y + r_2.
\end{align}

then the type-3 fuzzy reasoning is illustrated in Figure 4.3(a) and the corresponding equivalent ANFIS architecture (type-3 ANFIS) is shown in Figure 4.3(b).

Node Functions

The node functions in the same layer are of the same function family as described below [24]:

1. Layer 1: Every node $i$ in this layer is a square node with a node function

$$O_i = \mu_{A_i}(x),$$

where $x$ is the input to node $i$, and $A_i$ is the linguistic label (small, large, etc.) associated with this node function. In other words, $O_i$ is the membership function of $A_i$ and it specifies the degree to which the given $x$ satisfies the quantifier $A_i$. Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^2 b_i},$$

or,

$$\mu_{A_i}(x) = \exp \left\{ - \left[ \left( \frac{x - c_i}{a_i} \right) \right]^2 b_i \right\}.$$
where \( \{a_i, b_i, c_i\} \) forms the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label \( A_i \). In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer [24]. Parameters in this layer are referred to as premise (or, antecedent) parameters.

2. **Layer 2**: Every node in this layer is a circle node labeled \( \Pi \) which multiplies the incoming signals and sends the product out [24]. For example,

\[
w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2.
\]  

(4.6)

Each node output represents the firing strength of a rule. In fact, other \( t \)-norm operators those perform generalized AND can be used as the node function in this layer.

3. **Layer 3**: Every node in this layer is a circle node labeled \( \land \). The \( i^{th} \) node calculates the ratio of the \( i^{th} \) rule’s firing strength to the sum of all rules’ firing
strengths:
\[ \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \quad (4.7) \]
For convenience, outputs of this layer will be called normalized firing strengths.

4. **Layer 4**: Every node \( i \) in this layer is a square node with a node function:
\[ O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \quad (4.8) \]
where \( \bar{w}_i \) is the output of layer 3, and \( \{p_i, q_i, r_i\} \) is the parameter set. Parameters in this layer will be referred to as consequent parameters [24].

5. **Layer 5**: The single node in this layer is a circle node labeled \( \sum \) that computes the overall output as the summation of all incoming signals, i.e.,
\[ O_i^5 = \text{overall output} = \sum \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (4.9) \]

### 4.3 Mobile Channel Equalizer Based on ANFIS

Since the equalization of mobile cellular channel, which is basically a non-linear time-variant system, is a non-linear problem, a solution using the ANFIS is most suitable for it. Here again, we have to choose a channel model as in Chapter 3, where we considered a FAF for channel equalization. For the ANFIS based equalizer, we use a type-3 TSK FIS with Gaussian membership functions. For a practical case, we choose five/seven rules for the input variables, each with a Gaussian membership function given by:
\[ \mu_{GA}(x) = \exp \left\{ - \left( \frac{x - c_i}{a_i} \right)^{2b_i} \right\} \quad (4.10) \]
where \( \{a_i, b_i, c_i\} \) is the parameter set. For a channel with 6 co-channels, (i.e., \( N = 7 \)), we can consider the ANFIS equalizer as having 7 components in its input (plus the AWGN in the channel) and one output, which is connected to the ANFIS equalizer and detector, as shown in Figure 4.4.

#### 4.3.1 Simulation of Channel Equalizer Using MATLAB

It is found that wireless channel can be modeled as non-linear time-variant (NLTV) when the duration of observation window is fairly long or as non-linear time-invariant (NLTI) when the duration of observation window is short. This fact is established by simulation, as it is a hard problem to obtain a rigorous mathematical proof.
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Conventional channel models available in recent literature were studied to arrive at a suitable paradigm for the wireless channel, consisting of the different variables and parameters. This also enabled us to understand the inadequacies of existing mathematical models for wireless channels.

The fuzzy if-then rules are generated by the Adaptive Neuro-Fuzzy Inference System (ANFIS) based inverse system (to the channel) which effectively acts as an adaptive equalizer at the receiver side. The ANFIS automatically generate the rule base from a set of input-output data vectors. This is achieved by minimizing the error between actual input signal (at the transmitter of the wireless system) and the estimate of the input (at the receiver).

In the simulation, we assume that the external input to the ANFIS equalizer is the output of the channel, which is the sum of the desired channel output plus the weighted sum of the co-channel outputs and the Gaussian noise, which is assumed to be AWGN, with zero mean and standard deviation up to 0.8. In the ensuing sections, we use the following definitions for Signal-to-Noise Ratio (SNR), Signal-to-Interference Ratio (SIR) and Signal-to-Interference Noise Ratio (SINR) [53].

\[
SNR = 10 \log_{10} \frac{\sigma_s^2}{\sigma_n^2} \tag{4.11}
\]

\[
SIR = 10 \log_{10} \frac{\sigma_s^2}{\sigma_i^2} \tag{4.12}
\]

\[
SINR = 10 \log_{10} \frac{\sigma_s^2}{\sigma_i^2 + \sigma_n^2} \tag{4.13}
\]

where \(\sigma_s^2\), \(\sigma_i^2\), and \(\sigma_n^2\) are the variances of the signal, AWG noise, and the co-channel and adjacent channel interferences (put together) signal respectively. The output of the
The ANFIS based channel equalizer is given to a limiter to clip the output levels to limiting values of +1 or -1. The different parameters of the various simulation setups are as tabulated in Table 4.1. The library function, `anfis`, available in the Fuzzy Logic Toolbox of MATLAB® version 7.0 is used extensively in all simulations.

In Table 4.1 on simulation parameters for various ANFIS, the first digit in the ANFIS type (column 1) indicates the number of inputs to the ANFIS structure (as the 1 in ANFIS-115), and the following digit(s) indicate the number of fuzzy rules for each input(s). The last column indicates the total number of fuzzy rules for the entire ANFIS. The number of outputs is one in all cases.

### Table 4.1: Simulation Parameters for Various ANFIS Based Channel Equalizers

<table>
<thead>
<tr>
<th>Type</th>
<th>Nodes</th>
<th>Linear/Non-linear Parameters</th>
<th>Fuzzy Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANFIS-15</td>
<td>24</td>
<td>10/10</td>
<td>5</td>
</tr>
<tr>
<td>ANFIS-17</td>
<td>32</td>
<td>14/14</td>
<td>7</td>
</tr>
<tr>
<td>ANFIS-115</td>
<td>64</td>
<td>30/30</td>
<td>15</td>
</tr>
<tr>
<td>ANFIS-125</td>
<td>104</td>
<td>50/50</td>
<td>25</td>
</tr>
<tr>
<td>ANFIS-25</td>
<td>75</td>
<td>75/20</td>
<td>25</td>
</tr>
<tr>
<td>ANFIS-27</td>
<td>131</td>
<td>147/28</td>
<td>49</td>
</tr>
<tr>
<td>ANFIS-35</td>
<td>286</td>
<td>500/30</td>
<td>125</td>
</tr>
<tr>
<td>ANFIS-37</td>
<td>734</td>
<td>1372/42</td>
<td>343</td>
</tr>
</tbody>
</table>

4.3.2 The Description of ANFIS Based Channel Equalizer

The Figure 4.5 shows the architecture of the proposed ANFIS based channel equalizer, for 7 fuzzy rules. The output of the communication channel is fed to the input of the equalizer, shown as \( x \) in the Figure. The output of the equalizer, shown as \( f \), feeds the receiver. The wireless channel modeling based on artificial neural networks is capable of depicting the input-output mapping existing in the equalizer system and it does provide us with an exact picture of the variables and parameters defining the system. Moreover, neural network based models do have the learning capability. The fuzzy models, on the other hand, do not possess the learning capability. Therefore, fusing together these two, we can have a model which is capable of both depicting the dynamics of the system in terms of the variables and parameters and is having the self-learning capability. The adaptability of the equalizer under purview is achieved by the learning aspect of neural network. The fuzzy reasoning (especially the TSK model used in ANFIS) maps the input to the output. We follow a first-order ANFIS with the antecedent parameters being the standard deviations of the received signal, CCI and ACI interferences (put together), and the AWGN \((\sigma_s, \sigma_t, \text{and } \sigma_h, \text{respectively})\), collectively represented as \(A_i\). The only consequent parameter is the scaling factor of...
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Figure 4.5: The Equivalent ANFIS Architecture for the Channel Equalizer. The antecedent parameters are $\sigma_s, \sigma_i$, and $\sigma_n$ (standard deviations of signal, interferences and AWG noise respectively). The consequent parameter is the scaling factor of the signal at the output, $\mu$.

The signal ($p_1$) at the output. The membership functions of $A_i$, $i = 1, 2, \ldots, 7$ are chosen to be Gaussian. Some of the rules in the fuzzy rule base can be stated as:

1. If $\sigma_s$ is very low, and $\sigma_i$ is very low, and $\sigma_n$ is very low then $y = \rho_1 s$. (4.14)
2. If $\sigma_s$ is low, and $\sigma_i$ is very low, and $\sigma_n$ is very low then $y = \rho_2 s$. (4.15)
3. If $\sigma_s$ is medium, and $\sigma_i$ is very low, and $\sigma_n$ is very low then $y = \rho_3 s$. (4.16)
4. If $\sigma_s$ is medium, and $\sigma_i$ is low, and $\sigma_n$ is low then $y = \rho_4 s$. (4.17)

The three input variables can assume any one of the 5 possible membership functions from the set, \{very low, low, medium, high, very high\}, leaving us with 125 possible combinations of rules. However, using fuzzy rule reduction techniques the total number of rules can be limited to 15 or 25. The overall output of $y$ is given by:

$$y = \frac{\sum_{i=1}^{7} [\mu_{A_i}(s) \cdot \rho_i s]}{\sum_{i=1}^{7} \mu_{A_i}(s)}$$

(4.18)

The systematic steps in the simulation of the ANFIS–27 based equalizer are as given below:
1. The standard deviations of CCI and AWGN are logarithmically varied from 0.02 to 0.8. This information is derived from literature.

2. The random binary input data (which represents the input to the channel from the transmitter) is generated and the corrupted data available at the outputs of the two multipaths due to CCI and AWGN is obtained.

3. Set the number of membership functions as 7, membership function type as “Gaussian” and the number of epochs to 80.

4. Simulate the ANFIS (which implements the equalizer) and plot the results.

The error plot of the ANFIS–125 training is illustrated in Figure 4.6. We have set the number of epochs as 80 in this case.

As the ANFIS implementation in MATLAB do not lend itself to observe the updation of antecedent and consequent parameters, while training is under progress, we can consider the training error as a reliable pointer to the step wise updation of the above parameters. The ANFIS-125 consists of one input, and one output, and 25 fuzzy

![Figure 4.6: The Error Plot of Training of ANFIS–125; Generated Using MATLAB Fuzzy Logic Toolbox: Number of Inputs = 1, Number of Outputs = 1, Total Number of Fuzzy Rules = 25. Type of Membership Function: Gaussian, and Number of Epochs = 80.](image)
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rules for each membership functions. The fuzzy membership functions are chosen to be Gaussian.

4.3.3 The Results of Simulations

The simulated output of the channel, which is the input to the ANFIS based channel equalizer, along with the training data is shown in Figure 4.7. The output of the channel (received signal), which is a non-linear combination of the signal, the co-channel signals, and the AWG noise, is a random waveform taking values around +1 and −1, as seen from the simulated waveform.

![Training Data Pair for ANFIS-125 and ANFIS-127](image)

Figure 4.7: The Training Data Pair for ANFIS–125 Equalizer Simulation. (a) The Channel Output Signal. (b) The Training Data to the ANFIS–125 Equalizer, which is the Expected Output.

The equalized, output after thresholding, will be very much identical to the training data as shown in Figure 4.8. The simulation results for ANFIS–125 (with one input and
25 membership functions), and ANFIS–127 (with one input and 27 membership functions) for 2048 channel output-training data pairs are shown in Figure 4.8, as a plot of the time domain response.

Results for other combinations of number of inputs and membership functions,

![Training Data for ANFIS-125 and ANFIS-127](image1)

![Simulation Results for 1 input and 25 membership functions](image2)

![Simulation Results for 1 input and 27 membership functions](image3)

Figure 4.8: Simulation Results for ANFIS–125, and ANFIS–127 Equalizers for 2048 training data pairs, showing the time domain response. The plots represent the output of ANFIS–125, and ANFIS–127 Equalizers with an attached hard thresholding detector.

as listed in Table 4.1, are found to be similar. The processing times in each case for 1024 training data pairs are tabulated in Table 4.2.¹

In one of the simulations, the standard deviation of CCI and AWGN are logarithmically varied between 0.02 and 0.8 and simulation is run on a total of 2048/4096 training data pairs. The results are shown in Figure 4.9, as a plot of \( \log(BER) \) at output of the equalizer versus SINR in dBs. The SINR is varied from \(-10dB\) to \(30dB\). It is

¹The simulations were run on a Personal Computer with Intel Pentium 4 CPU running at 2.6 GHz and 512MB RAM, using MATLAB version 7.0 software.
Table 4.2: Simulation Time for ANFIS with 1024 training data pairs

<table>
<thead>
<tr>
<th>ANFIS Type</th>
<th>Number of Epochs</th>
<th>Time in Seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANFIS-15</td>
<td>20</td>
<td>0.84</td>
</tr>
<tr>
<td>ANFIS-17</td>
<td>20</td>
<td>1.04</td>
</tr>
<tr>
<td>ANFIS-115</td>
<td>20</td>
<td>2.34</td>
</tr>
<tr>
<td>ANFIS-125</td>
<td>20</td>
<td>5.50</td>
</tr>
<tr>
<td>ANFIS-25</td>
<td>20</td>
<td>7.85</td>
</tr>
<tr>
<td>ANFIS-27</td>
<td>20</td>
<td>26.80</td>
</tr>
<tr>
<td>ANFIS-35</td>
<td>20</td>
<td>558.80</td>
</tr>
<tr>
<td>ANFIS-37</td>
<td>20</td>
<td>4255.64</td>
</tr>
</tbody>
</table>

evident from the plots that the \( \log(BER) \) versus \( \text{SNR} \) performance is improving as we increase the number of rules, consistently.

Then, in another simulation, the \( \log(BER) \) at output of the equalizer is calculated for standard deviation of noise varying from 0.02 to 0.8, and the for two versions of ANFIS Equalizers (ANFIS-115 and ANFIS-125) for 2048/4096 training data pairs and standard deviation of AWGN fixed at 0.42, and the results are plotted in Figure 4.10. In this case, we can observe that the \( \log(BER) \) reduces as the \( \text{SIR} \) in dB increases, consistently. Also, when the number of training data pairs is increased, there is a marginal improvement in performance.

The performance for the above ANFIS pairs, as regards \( \log(BER) \) at output of the equalizer versus \( \text{SNR} \) in dBs for standard deviation of co-channel interference signal fixed at 0.08, is given in Figure 4.11. Note that in this case, ANFIS-115 fails to converge and hence there is no variation in performance even when the \( \text{SNR} \) is as high as 35dB. Again, the performance is marginally better, when the number of training data pairs are increased.

A plot of the performance of two different ANFIS structures (average BER at the output of the equalizer versus \( \text{SNR} \) and standard deviation of BER at the output of the equalizer versus standard deviation of AWGN) based on 100 Monte-Carlo (MC) simulations is given in Figure 4.12 for ANFIS-115 and ANFIS-125 structures. 4096 training data pairs are used in the simulation. The \( \text{Mean}(BER) \) versus \( \text{SNR} \) performance improve consistently, as the \( \text{SNR} \) increases. The \( \text{std}(BER) \) versus \( \text{SNR} \) performance, on the otherhand, deteriorates as the \( \text{std}(\text{AWGN}) \) increases, consistently. Performances are marginally better for ANFIS-125 based equalizer.

4.3.4 Interpretation of Results and Observations

The following observations are made based on Figures 4.9, 4.10, 4.11 and 4.12 and Tables 4.1 and 4.2 as well as results of simulations with less number of data pairs:
1. With more number of training data pairs, BER at the output of the equalizer is reduced. This is due to the fact that the ANFIS gets optimally tuned with more training data pairs.

2. As shown in Figure 4.9, performance of all ANFIS Equalizers w.r.t. $\log(BER)$ at the output of the equalizer versus SINR, is nearly identical. When the SINR is above $-10dB$, practically the $\log(BER)$ becomes close to zero. However, ANFIS-125 performs slightly better than other structures.

3. The performance of ANFIS-125 w.r.t. $\log(BER)$ at the output of the equalizer versus SIR is almost identical with 2048 or 4096 data pairs. However for ANFIS-115, performance is slightly poor.

4. As it is shown in Figure 4.11, the performance of ANFIS-125 w.r.t. $\log(BER)$ at the output of the equalizer versus SNR is almost identical with 2048 or 4096...
data pairs. However for ANFIS-115, performance is very poor even at a SNR of 35dB. This is due to the fact that equalizer model with ANFIS structure fails to perform when the number of rules is 15. The AWGN overwhelms the signal, when number of rules for the ANFIS is 15 or less.

5. For MISO or MIMO systems, increasing the number of membership functions is the option for accurate system modeling, since in these cases number of inputs applied to the ANFIS is two or more, and hence it will not be optimal to increase the number of internal inputs in ANFIS.

6. An optimal ANFIS structure can be obtained based on the training time and the maximum error that can be tolerated. As indicated in Figure 4.12, at higher values of standard deviation of AWGN, and that of standard deviation of BER will be less...
Figure 4.11: Simulation Results: Logarithm of BER at output of the equalizer (varies from 0 to 0.35) versus SNR in dBs (varies from 0 to 35) for 2048/4096 training data pairs with Standard Deviation of CCI fixed at 0.08.

with more number of membership functions. Hence standard deviation of BER at the output of the equalizer can be yet another criterion in selecting a particular ANFIS structure.

We will now consider the equalization of Ultra-Wide Band (UWB) systems using ANFIS in the following section.

4.4 Equalization of Ultra-Wide Band (UWB) Systems Using ANFIS

The Ultra-Wide Band (UWB) is an emerging wireless technology that has recently gained much interest from the communication research and industry. UWB systems possess unique characteristics and capabilities that make them suitable for short-
4.4.1 Introduction to Ultra-Wide Band (UWB)

The UWB systems use signals that are based on repetitive transmissions of short pulses formed by using a single basic pulse shape. The transmitted signals have an extremely low power spectral density and occupy very large bandwidth of several GHz. Thus the UWB systems can operate with negligible interference to the existing radio systems. UWB can provide very high bit rate, low-cost, low-power wireless communication for wide variety of systems: personal computer, TV, VCR, CD, DVD, and MP3 players [72, 73].

UWB radars, which are mainly of interest for military applications, and UWB
communications systems, which also have military applications, are nowadays mainly driven by commercial applications. UWB communications gained prominence with the groundbreaking work on impulse radio by Win and Scholtz in the 1990s [74], and received a major boost by the 2002 decision of the US frequency regulator (Federal Communications Commission, FCC) to allow unlicensed UWB operation.

As per FCC recommendations, UWB systems have the following characteristics:

- They have a relative bandwidth that is larger than 25% of the carrier frequency and/or an absolute bandwidth more than 500 MHz.
- They occupy a frequency band of 3.1 GHz to 10.6 GHz.
- FCC have recently allocated 7.5 GHz of spectrum for unlicensed commercial UWB communication systems.
- Maximum radiated power is 75 mW/MHz (-41.32dBm/MHz) [72].

The following are the significant merits of UWB:

1. Accurate position location and ranging, due to the better time resolution.
2. No significant multipath fading due to better time resolution.
3. Multiple access due to wide transmission bandwidths.
4. Possibility of extremely high data rates.
5. Covert communications due to low transmission power operation.
6. Possible easier material penetration due to the presence of components at different frequencies.

4.4.2 Conventional Channel Models for UWB

Conventional wideband channel models discussed in Chapter 2 cannot be adapted as such to UWB due to the following reasons:

1. The signal conditioning problems associated with the wideband technology becomes more severe, in the case of UWB. This includes co-channel interference (CCI).
2. Rapid synchronization and acquisition is required for UWB.
3. Propagation models more complex in multipath environments and do not allow for direct extension of narrow band.
Table 4.3: Environments and Ranges for UWB Systems

<table>
<thead>
<tr>
<th>Environment</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indoor residential</td>
<td>1 - 30m</td>
</tr>
<tr>
<td>Indoor office</td>
<td>1 - 100m</td>
</tr>
<tr>
<td>Body Area Network (BAN)</td>
<td>0.1 - 2m</td>
</tr>
<tr>
<td>Outdoor peer to peer</td>
<td>1 - 100m</td>
</tr>
<tr>
<td>Outdoor base station scenario</td>
<td>1 - 300m</td>
</tr>
<tr>
<td>Industrial Environments</td>
<td>1 - 300m</td>
</tr>
<tr>
<td>Emergency Communications</td>
<td>1 - 50m</td>
</tr>
</tbody>
</table>

Table 4.4: IEEE 802.15.3a Standard Summary Requirements

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bit Rate (PHY-SAP)</td>
<td>110 and 200 Mbps</td>
</tr>
<tr>
<td>Range</td>
<td>30ft and 12ft</td>
</tr>
<tr>
<td>Power Consumption</td>
<td>100mW and 250mW</td>
</tr>
<tr>
<td>Bit Error Rate (BER)</td>
<td>$1 \times 10^{-3}$</td>
</tr>
<tr>
<td>Co-located Piconets</td>
<td>4</td>
</tr>
<tr>
<td>Interference Capability</td>
<td>Robust to IEEE Systems</td>
</tr>
<tr>
<td>Co-existence Capability</td>
<td>Reduced Interference to IEEE Systems</td>
</tr>
</tbody>
</table>

4. The better time resolution of UWB results in different multipath components arriving at the receiver at different delays and angles, which create a dynamic and extended Channel Impulse Response (CIR).

Typical environments and ranges for UWB are given in Table 4.3.

The Modified SV/IEEE 802.15.3a Model

The Modified Saleh-Valenzuela (SV) Model (SV/IEEE 802.15.3a model is commonly used to model UWB channels [72]. The model is developed by the IEEE 802.15.3a standardization group for UWB communications systems in order to compare standardization proposals for high data rate wireless PANs. Due to this purpose, the environments considered are office and residential indoor scenarios with a range of less than 10m [72]. Requirements of this model are summarized in Table 4.4.

The 802.15.4a Model for High Frequencies (4a HF)

The 802.15.4a standardization group has recently been developing a standard for UWB systems with low data rates and geolocation capabilities for sensor networks. The 802.15.3a models do not cover many of the ranges and environments envisioned for these applications, so that new models had to be developed. In addition, it is decided to
take into account several effects that were neglected in the 15.3a models. The resulting model for the $3 - 10GHz$ range is a generalized SV model with parameters defined for residential indoor, office indoor, industrial, outdoor, and farm environments. For each of those environments, LOS and NLOS is distinguished, with the exception of farm environments, where only NLOS situations are modeled. The models are based on measurement campaigns, again with the exception of the farm environment, which is based on simulations only. Several of the underlying measurements do not cover the full $3 - 10GHz$ range, restricting the validity range of the models [72].

The 802.15.4a Model for Low Frequencies (4a LF)

In addition to the $3 - 10GHz$ range, the IEEE 802.15.4a group have also developed a model for the frequency range from $100 - 960MHz$ [72]. For this frequency range, only the office NLOS scenario is considered, since this is the only scenario where measurements are available. The chosen model is essentially the model of [75], namely a dense channel model with a single, exponentially decaying cluster. The decay constant is modeled as a deterministic variable that increases with distance as $(d/10m)^{0.5} \times 40ns$ (note that this is a deviation from the original model of [75]. This equation gives the same delay spread as [75] at $10m$ distance. The distance exponent is chosen as a compromise between the results of [75] (no distance dependence) and the results of [76] that shows a linear increase with distance. The first path has enhanced amplitude. The path gain follows a simple $d^{-n}$ law, where $n$ is the propagation (path gain) exponent.

Channel Covariance Matrix (CCM) Formulation

Shadow-fading fluctuations of the average received power are known to be log-normally distributed. Recently, for macrocell scenarios, the fluctuations in delay and angle spread are shown to behave similarly [73]. The reason is that these quantities are sums of powers of individual sub-paths times the square of their corresponding delay times or angles. Since the powers are log-normally distributed and sums of log-normal variables are (approximately) log-normal [77], this implies that angle-spreads and delay-spreads have log-normal distributions. This motivation of how angle spread and delay spread are log-normally distributed also suggests that they will be correlated with shadow fading and each other. Let us assume that $X_{1n}, \ X_{2n}, \ X_{3n}, \ldots$ are zero-mean, unit-variance Gaussian random variables, representing the signals received
at base station \( n \). Then we define:

\[
\begin{align*}
\rho_{DA} &= E[X_{1n}, X_{2n}] \\
\rho_{DF} &= E[X_{2n}, X_{3n}] \\
\rho_{AF} &= E[X_{1n}, X_{1n}] \\
\zeta &= E[X_{3n}, X_{3n}]
\end{align*}
\]  

(4.19) (4.20) (4.21) (4.22)

In particular, \( \sigma_{SF,n} \) (variance of shadow fading component w.r.t. to base station, \( n \)) is negatively correlated with \( \sigma_{DS,n} \) (variance of delay spread) and \( \sigma_{AS,n} \) (variance of angle spread), while the latter two have positive correlations with each other. It should be noted that this relationship does not hold for the angle-spread at the mobile since the different paths with distinct angles do not necessarily lead to such pronounced differences in the delays. These correlations can be expressed in terms of a covariance matrix \( A \), whose \( A_{ij} \) component represents the correlations between \( X_{ii} \) and \( X_{jj} \), with \( i, j = 1, 2, 3 \). Note that the matrix \( A \) is symmetrical.

Measurements of cross-correlations of these parameters between different base-stations are more difficult. In particular, only correlations between shadow-fading components have been adopted. These correlations are assumed to be the same between any two different base-stations and are denoted by \( \zeta \). For simplicity and due to lack of further data, the cross-correlation matrix between the \( X_{in} \) triplet \((i = 1, 2, 3)\) of different base-stations are assumed to be given by the following matrix \( B \).

\[
A = \begin{bmatrix}
1 & \rho_{DA} & \rho_{DF} \\
\rho_{DA} & 1 & \rho_{AF} \\
\rho_{DF} & \rho_{AF} & 1
\end{bmatrix}, \quad B = \begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & \zeta
\end{bmatrix}
\]

(4.23)

Simulation of an ANFIS Equalizer for UWB based on CCM

The following extended channel covariance matrix was used in the simulations.

\[
A = \begin{bmatrix}
1 & 0.8 & -0.7 & 0.6 \\
0.8 & 1 & -0.6 & 0.5 \\
-0.7 & -0.6 & 1 & 0.5 \\
0.6 & 0.5 & 0.5 & 1
\end{bmatrix}, \quad A' = \begin{bmatrix}
1 + \alpha & 0.8 + \beta & -0.7 + \gamma & 0.6 + \delta \\
0.8 + \beta & 1 + \alpha & -0.6 + \epsilon & 0.5 + \zeta \\
-0.7 + \gamma & -0.6 + \epsilon & 1 + \alpha & 0.5 + \zeta \\
0.6 + \delta & 0.5 + \epsilon & 0.5 + \zeta & 1 + \alpha
\end{bmatrix}
\]

(4.24)

\( A' \) indicate the modified CCM corrupted by CCI and AWGN. We use an ANFIS with the following parameters in the equalizer:

- One-input One-output ANFIS.
- 20 Rules.
- Gaussian membership functions.
• Maximum Spread in CCM parameters is 0.5 (0.1:0.1:0.5)

The structure of the ANFIS is given in Figure 4.13. The simulation results are given in

![ANFIS Model Structure](image)

Figure 4.13: ANFIS Model Structure Used for UWB Channel Equalization: Number of Inputs=1, Number of Outputs=1, Number of Rules=20, and Type of Membership Function- Gaussian.

Figure 4.14. It shows that the ANFIS model is capable of estimating the CCM parameters with almost negligible error.

### 4.4.3 Conclusions on ANFIS based Equalizer for UWB

The following conclusions can be made based on results of simulations:

1. As the spread in CCM parameters increases, error in estimate of CCM parameters by the ANFIS network increases.
2. Estimation of the CCM is better when the spread in parameters is small.
3. More number of trials improve the estimate and minimizes the error.
4. The ANFIS based equalizer, which is successfully applied to wideband channels, can be adapted for UWB channels as well.
Figure 4.14: Results of Simulation—ANFIS Equalizer for UWB Channels: The results of varying number of trials are indicated by varying line thicknesses. Note that results improve as the number of trials increases.

4.5 Conclusion

In this chapter, we considered an alternative solution to the non-linear channel equalization problem. Several ANFIS equalizer structures are considered, with varying number of inputs and membership functions. It was found that the BER versus SINR performance of all of them were almost the same. However, at low values of SNR, ANFIS structure with more number of nodes (or more number of rules) performed slightly better. But as the number of nodes in the ANFIS structure was increased, convergence time was also increased, as evident from Table 4.2. The number of nodes in the ANFIS structure is a function of the number of inputs, membership functions and outputs. The time for convergence increases as the number of inputs or membership functions increases.

It is also shown that equalizers based on ANFIS can be suitably adapted for UWB channels as well. A co-variance matrix (CCM) formulation was used to model the UWB channel. It was shown that the estimate of the CCM was better when the spread in parameters was small.