A Real Time Adaptive Resource Allocation Scheme for OFDM Systems Using GRBF-Neural Networks and Fuzzy Rule Base System

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Abstract: *Adaptive Resource Allocation is a prominent and necessary feature of almost all future communication systems. The transmission parameters like power, code rate and modulation scheme are adapted according to the varying channel conditions so that throughput of the OFDM system may be maximized while satisfying certain constraints like Bit Error Rate (BET) and total power at the same time. For real time systems, it is required that the adaptive process should be fast enough to synchronize with Channel State Information (CSI) and Quality of Service (QoS) demand that change rapidly. So in this paper, we have a real time system in which once CSI and QoS is fed in as input, it gives us optimal Modulation Code Pairs (MCPs) and power vectors for different subcarriers. Using a Fuzzy Rule Base System (FRBS) we obtain MCP by giving CSI and QoS and by using Differential Evolution (DE) the power vector is obtained. This becomes an example. A Gaussian Radial Basis Function Neural Network (GRBF-NN) is trained in offline mode using sufficient number of such examples. After training, given QoS and CSI as input GRBF-NN gives Optimum Power Vector (OPV) and FRBS gives optimum MCP immediately. Proposed scheme is compared with various other schemes of same domain and supremacy of the proposed scheme is shown by the simulations.*

Keywords: *DE, OFDM, FRBS, GRBF-NN, adaptive modulation and coding, MCP.*

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1. Introduction and Related Work

Use of evolutionary computing, soft-computing and hybrid intelligent algorithm for solution of optimization problems in various fields of engineering is an emerging area of research nowadays. These algorithms are attractive due to their nonlinear nature, fast convergence and easy implementation.

Adaptive Orthogonal Frequency Division Multiplexing (AOFDM) is one of the successful candidates for many 3rd Generation (3G) and 4th Generation (4G) Systems. In this technique a single very high data rate stream is divided into several equivalent low data rate streams by using Inverse Fast Fourier Transform (IFFT). Then, these streams are modulated over different orthogonal subcarriers. Addition of suitable Cyclic Prefix (CP) makes the system Inter Symbol Interference (ISI) free.

Fuzzy system based adaptive modulation scheme for OFDM system was proposed in [24]. Turbo coded adaptive modulation was investigated by Liew *et al.* [18] and also different adaptation schemes were analyzed [15]. For single antenna OFDM systems, coded bit and power loading problem was addressed by Li *et al*. [17] using Low Density Parity Check (LDPC) codes originally motivated by [7]. Many Bit Interleaved Coded Modulation (BICM) systems have been proposed like [7, 26, 27]. Lei *et al*. [16] investigated adaptive communication using turbo codes.

An adaptive coding and modulation scheme is proposed by Bockelmann *et al*. [6], in which a bisection method was used to adapt the transmit rate. A Genetic Algorithm (GA) based adaptive resource allocation scheme was proposed by Reddy [23], to increase the user data rate, where water-filling principle was used as a fitness function. A subchannel allocation based on auction algorithm was proposed by [21], where throughput was sustained at the cost of user data rates. A novel efficient resource allocation algorithm for multiuser OFDM system using a proportional fairness based algorithm among users and to achieve good performance even with low SNR was proposed by [11].

Another interesting paper adaptive resource allocation based on modified GA and Particle Swarm Optimization (PSO) for multiuser OFDM system was proposed by [1]. An approach akin to the previous one, Ant Colony Optimization (ACO) evolutionary technique for subcarrier allocation in OFDMA-based wireless system was proposed by [8].

Adaptive subcarrier and power allocation with fairness for multi-user Space-Time Block-Coded (STBC) OFDM system was investigated in contrast to Greedy algorithm as well as water-filling principle [29]. An optimization problem for power constraints using GA to maximize the sum capacity of OFDM system with the total power constraint was investigated in [20]. Also, it was shown that GA performs better than conventional methods.

A scheme for resource allocation in downlink Multiple Input Multiple Output (MIMO) OFDMA with proportional fairness was proposed in [11] where dominant Eigen channels obtained from MIMO state matrix are used to achieve low complexity. This scheme provides much better capacity gain than static allocation method. A PSO based Adaptive multicarrier cooperative communication technique which utilizes relay node for subcarrier in deep fade to improve the bandwidth efficiency was proposed by [9] where centralized and distributed versions of PSO were investigated. A low complexity subcarrier and power allocation technique based upon GA to maximize the sum of user data rates in MIMO-OFDMA system was proposed in [25].

Al-Janabi *et al.* [2], proposed a bit and power allocation strategy for Adaptive Modulation Coding (AMC) based MIMO-OFDMA WiMAX system. Another GA based efficient real-time subcarrier and bit allocation for multiuser OFDM transmission technique was proposed in which overall transmit power was minimized under user constraint [10]. A subcarrier-chunk based technique in which resource allocation problem for the downlink of OFDMA wireless systems was proposed in [22].

A Quality of Service (QoS) based performance and resource management scheme in 3G wireless network for realistic environments is presented by [30]. An intelligent approach for data collection in Wireless Sensor Network (WSN) was presented by [19].

Adaptive coding and modulation scheme with fixed transmit power by Atta-ur-Raman *et al.* [3] proposed a Fuzzy Rules Base System (FRBS) for finding suitable Modulation Code Pairs (MCPs) for subcarriers given the QoS demand and Channel State Information (CSI) of all subcarriers. Same strategy while using Product Codes as coding scheme was proposed in [5]. A combined approach to adaptive coding, modulation and power was proposed by Atta-ur-Rahman *et al.* [4] in which FRBS was used for choosing modulation code pair while power vector for subcarriers was optimized by using two different algorithms, Water filling algorithm and GA.

In this paper, we have a real time system in which once we feed in CSI and QoS as input, the system gives us optimal MCP for different subcarriers and the power vector. Using the FRBS suggested in [3, 4], we first find out the MCP after feeding in CSI and QoS required. Then, using Differential Evolution algorithm, we get power vector for particular situation. This gives us one example. We build up many examples for various values of CSI and QoS. Having formulated these examples, we train a Gaussian Radial Basis Function Neural Network (GRBF-NN) with different CSI and QoS as input and their corresponding power vectors as desired output. All this training is done offline. Now, once training is over, given CSI and QoS for subcarriers, we immediately get MCP from FRBS and power vector from trained GRBF-NN.

The remainder of this paper is organized as follows: In section 2, system model is introduced. Performance of different codes in conjunction with different modulations is presented in section 3. The results of section 3 are used in section 4 to formulate a constrained optimization problem. In section 5 a brief introduction to FRB is given that is used to solve the optimization problem formulated in previous section. Section 6 contains the introduction to Differential Evolution (DE) algorithm; Section 7 contains the proposed GRBF-NN scheme, performance comparison of this scheme with various other famous adaptive schemes with and without FRBS is given in section 8 while section 9 concludes the paper.

2. System Model

The system model considered is OFDM equivalent baseband model with N number of subcarriers. It is assumed that complete CSI is known at both transmitter and receiver. The frequency domain representation of system is given by:

$$r_k = h_k \cdot \sqrt{p_k} \cdot x_k + z_k \,;\, k = 1, 2, \ldots\ldots, N \tag{1}$$

Where r_k, h_k, $\sqrt{p_k}$, x_k and z_k denote received signal, channel coefficient, transmit amplitude, transmit symbol and the Gaussian noise of subcarrier $k = 1, 2, \ldots, N$, respectively. The overall transmit power of the OFDM system is $P_{total} = \sum_{k=1}^{N} p_k$ and the noise distribution is complex Gaussian with zero mean and unit variance. It is assumed that signal transmitted on the k^{th} subcarrier is propagated over an independent non-dispersive single-path Rayleigh Fading channel and where each subcarrier faces a different amount of fading independent of each other. Hence, the channel coefficient of k^{th} subcarrier can be expressed as:

$$h_k = \alpha_k e^{j\theta_k} \,;\, k = 1, 2, \ldots\ldots, N \tag{2}$$

Where α_k is Rayleigh distributed random variable of k^{th} subcarrier, and the phase θ_k is uniformly distributed over $[0, 2\pi]$.

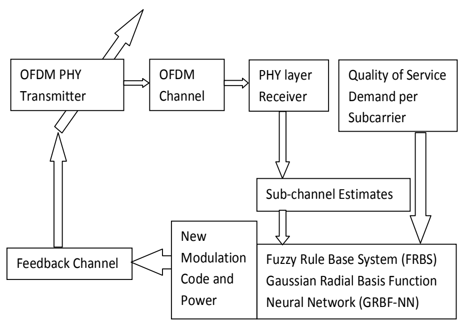

Figure 1. Brief diagram of proposed system.

A brief diagram of proposed system is given in Figure 1. Once the signal is received from OFDM channel, channel estimates CSI and QoS demand per subcarrier is fed into adaptation block which suggests the parameters for the next transmission interval. These parameters are sent to PHY layer transmitter via a feedback channel.

3. Coding and Modulation

Components of the proposed system model are described below.

3.1. Coding Schemes

Non recursive convolution codes are used for coding scheme in this paper. The code rates taken from the set *C = {1/4, 1/3, 1/2, 2/3, 3/4}* with constraint length 3. For decoding, standard Soft Output Viterbi Algorithm (SOVA) decoder is used [14] while proposed FRBS is used for adapting optimal code rate.

3.2. Modulation Schemes

As modulation scheme for adaptive modulation Quadrature Amplitude Modulation (QAM) is used, with rectangular constellation. The modulation symbols are taken from the set *M = {2, 4, 8, 16, 32, 64, 128}*. FRBS is used for adapting optimal modulation symbol.

3.3. Power Distribution

Power distribution or the loading algorithm is the main contribution of this paper. For this purpose a GRBF-NN is proposed. Moreover, the proposed scheme is compared with other loading algorithms like Water-filling and GA etc., and also with fixed power case.

For experimentation the sequence of operations is carried out in same way as given in the Figure 2.

The transmitted signal is first encoded using standard feed-forward convolutional encoder having code rate from the set *C* and then the encoded signal is modulated using the elements of QAM from the set *M*. In this way we have following possible pairs of coding and modulation by cross product of sets *C* and *M*, which yields:

$$P = C\text{x}M = \{(c_i, m_j) \mid \forall c_i \in C \wedge \forall m_j \in M\} \qquad (3)$$

Then, graph for each pair is obtained over an Additive White Gaussian Noise (AWGN) channel. The selection of this channel is suitable in a sense that it reflects the proper relationship between Signal to Noise Ratio (SNR) and data rate achievable under a specific target Bit Error Rate (BER). And other channel characteristics like fading types etc., can be compensated easily. Some of these graphs are depicted in the Figures 3, 4 and 5 with rate 1/4, 1/3 and 1/2 respectively. Each curve in these figures represents performance of a specific modulation and code pair. This information will be used in FRBS rule base in subsequent sections. These graphs are plotted in MATLAB 7.8.0.

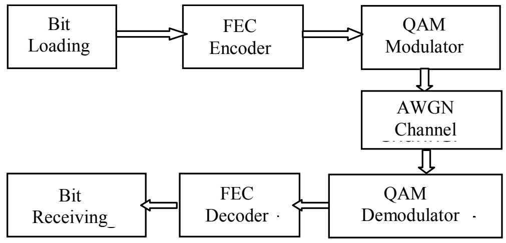

Figure 2. Brief diagram of simulations.

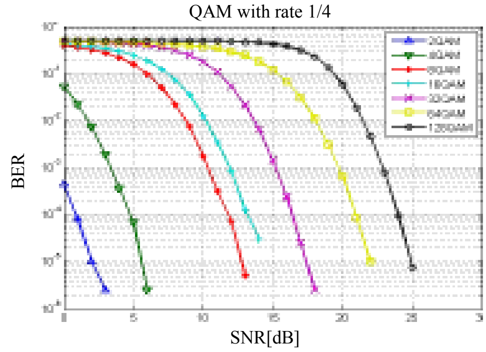

Figure 3. BER comparison of different QAM modulations using rate 1/4 convolutional codes.

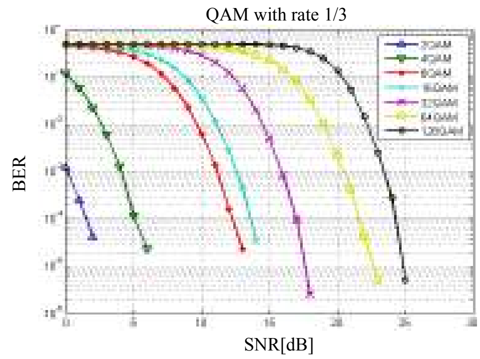

Figure 4. BER comparison of different QAM modulations using rate 1/3 convolutional code.

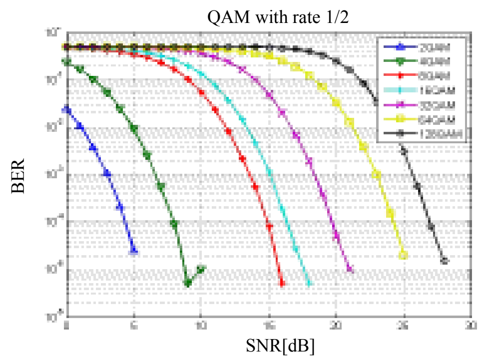

Figure 5. BER comparison of different QAM modulations using rate 1/2 convolutional code.

4. Rate Optimization

In order to maximize the data rate for OFDM systems, the constrained optimization problem may be stated as, "Maximize the overall data rate of OFDM system such that BER and transmit power remains constrained." Mathematically:

$$\begin{aligned} &\max \quad R_{Total} = \frac{1}{N}\sum_{i=1}^{N} r_i \\ &s.t, \\ &BER_i \le BER_{QoS_i} \\ &and \\ &P_{Total} = \sum_{i=1}^{N} p_i < P_T \end{aligned} \tag{4}$$

Where $r_i = (\log_2(M))_i R_{C,i}$ is bit rate of i^{th} subcarrier, which is a product of code rate $R_{C,i}$ and modulation order $(\log_2(M))_i$ used at i^{th} subcarrier, P_T is the available transmit power and $BER_{QoSi,}$ is target BER that depends upon a specific QoS request or application requirement over i^{th} subcarrier, while N is number of subcarriers in OFDM system.

From the results obtained in section 3, those code-modulation pairs that fulfill different BER demands depending upon different QoSs i.e., $BER_T = 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}$ *etc.*, are obtained. This is done by drawing straight lines on the graphs as shown in Figures 3-5 on certain BER points QoS like 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}. This is shown in Figure 6.

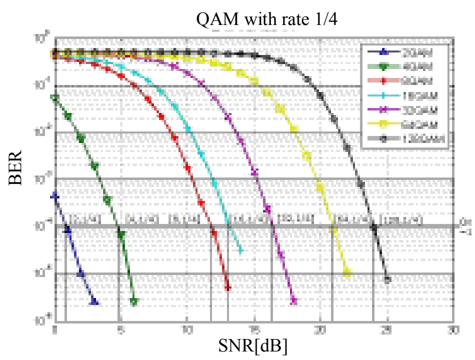

Figure 6. Process of obtaining modulation code pair under specific QoS.

Then, the points of intersection of these lines and the curves (representing a code and a modulation) are noted that gives the appropriate SNR value. So, the information obtained can be expressed as "for a given SNR and specific QoS which modulation code pair can be used". In order to obtain more granularity BER points are even quantized. In this way there are about five hundred pairs are obtained from the graphs. This table after completion is used as a starting point for generation of look-up table for the FRBS. Without loss of generality we can say that this table represents a function (mapping) in which the throughput can be expressed in terms of BER, transmit power and SNR:

$$R = MCP = f(SNR, BER, P) \tag{5}$$

The mapping shown in Equation 5 is a non-convex function that cannot be optimized using convex optimal techniques unless it is made convex according to [9]. However, this function is optimized by the proposed FRBS described in next section. The steps involved in creation of FRBS are described in the flowchart given in Figure 7. The brief description of each phase of the flowchart is given below:

- *Data Acquisition*: Data is obtained from the graphs obtained in section 3 in the form of Input/Output (IO) pairs.
- *Rule Formulation*: Rules for each pair are obtained by the appropriate fuzzy set used. That is by putting complete pair in IO set and a rule generated for each pair.
- *Elimination of Conflicting Rule*: The rules having same IF part but different THEN parts are known as conflicting rules. This appears when more than one MCP is available for given specification.
- *Completion of Lookup Table*: Look up table is complete in a sense that there exists a rule for every situation.

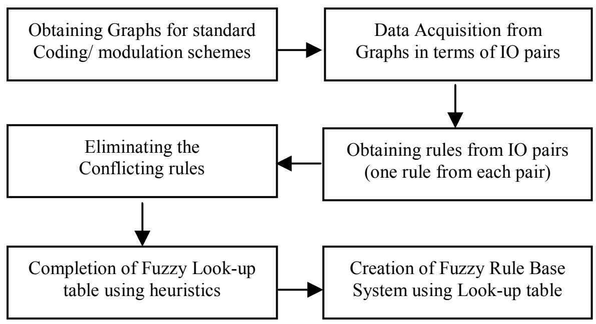

Figure 7. Fuzzy rule base system flowchart.

5. Fuzzy Rule Base System

A FRBS is used to optimize the cost function given in Equation 4. It will be decided that which modulation code pair is suitable for a specific subcarrier based upon the individual CSI at the subcarriers and the QoS demand. The rules are of the form:

$$(x_1^p, x_2^p; y^p);\ p = 1, 2, 3 \ldots N \tag{6}$$

Where x_1^p represents received SNR, x_2^p represents required BER QoS and y^P represents the output MCP suggested by FRBS, so a rule can be narrated as:

{If ($x_1$is L1 and $x_2$is Q7) Then y is P2}

Following is the brief description of different components of FRBS used. Design of the FRBS is carried out in MATLAB 7.8.0 standard Fuzzy System Toolbox.

5.1. Fuzzy Sets and Fuzzifier

Sufficient numbers of fuzzy sets are used to cover the input output spaces. There are two input variables received SNR and Minus Log Bit Error Rate (MLBER) that represents a QoS. The reason taking MLBER is because BER of a required QoS is given by 10^{-2}, 10^{-3}, 10^{-4} *etc.,* while the range of fuzzy variable should be equally spaced and quantifiable. So, to get this, following operation is done first:

$$\begin{aligned} MLBER &= -\log(BER) \\ BER &= 10^{-q} \\ MLBER &= -\log(10^{-q}) = q \end{aligned} \tag{7}$$

There is one output variable that is MCP. Standard triangular fuzzifier is used with AND as MIN and OR as MAX.

5.2. Rule Base

Rule base contains rules against all the IO pairs. As there are thirty-one sets (L0 to L30) for first input variable named SNR and about sixteen sets (Q1 to Q16) for input variable MLBER, hence there are 496 rules in rule base. Rule base is complete in the sense that rules are defined for all possible combinations of input space.

5.3. Inference Engine and De-Fuzzifier

Famous Mamdani Inference Engine (MIE) is used that will infer which input pair will be mapped onto which output point. Standard Center Average Defuzzifier (CAD) is used for defuzzification.

6. Differential Evolution Algorithm

DE is an evolutionary algorithm originally proposed by [28]. In many aspects it is comparable to GA, but the main features that makes it superior than GA, is its fast convergence rate and less vulnerability to stuck in the local minima problem which is inherent in many variants of GA. There are four main operations in DE namely initialization, mutation, crossover and selection. A flowchart of the algorithm is given in Figure 8. Description of each step pertaining to our problem is given below:

a. *Initialization*: The first power vector taken in the scheme would be taken as flat power for all subcarriers. Power vector length is equal to number of subcarriers *N*. Then, initial population is generated randomly around the initial vector, so that the power constraint remains satisfied.
b. *Mutation*: Standard mutation operation is used as described originally in the algorithm, i.e., a weighted difference of two power vectors is added to third vector.
c. *Crossover*: Standard crossover method is used to generate the trial vector.
d. *Selection*: Whether to keep a vector or not is based upon a fitness value used in greedy criterion. We have employed FRBS for this purpose, as shown in Figure 9. That is fitness equal to sum rates after applying the chosen vector to the system. Mathematically, it can be written as:

$$\begin{aligned} R &= \frac{1}{N}\sum_{i=1}^{N} r_i \\ &= \frac{1}{N}\sum_{i=1}^{N} (\log_2(M))_i \, R_{C,i} \\ &= \frac{1}{N}\sum_{i=1}^{N} FRBS(SNR_i, QoS_i) \\ &= \frac{1}{N}\sum_{i=1}^{N} FRBS(p_i\alpha_i, QoS_i) = \frac{1}{N}\sum_{i=1}^{N} MCP_i \end{aligned} \tag{8}$$

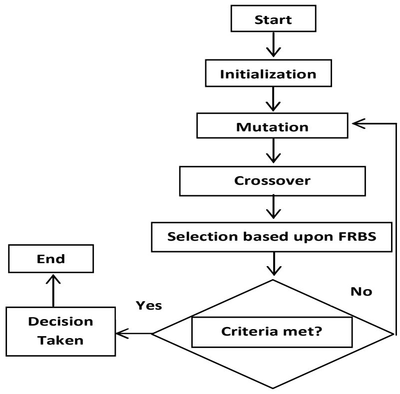

Figure 8. Differential evolution algorithm flowchart.

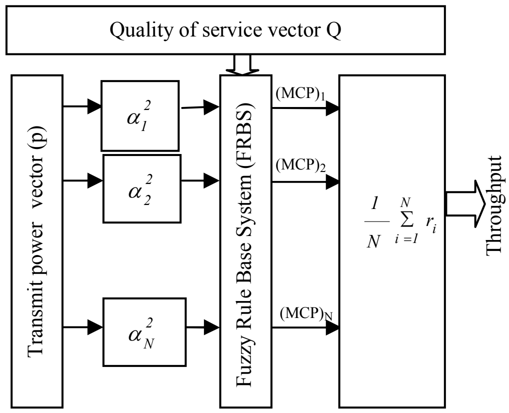

Figure 9. Fitness block for selection phase in DE.

7. Gaussian Radial Basis Function Neural Network

GRBF-NN are considered the most powerful networks for highly nonlinear systems. They are also proven to be the universal approximators [13]. In our scenario, GRBF-NN are well suited because our problem is highly non-linear, in which we need to seek the appropriate power vector based upon the given channel conditions and QoS demand per subcarrier, with a constrained overall transmit power. The schematic diagram for the proposed network is given in Figure 10.

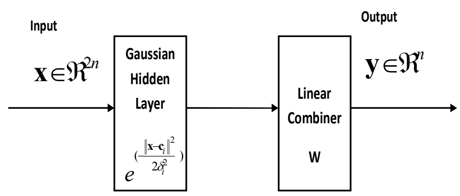

Figure 10. Block diagram of the GRBF-NN.

Following are the steps involved in construction of the network.

7.1. Example Set

In order to train the network, a large number of examples are generated by Fuzzy Rule Base System with Differential Evolution (FRBS-DE). This is done in following manner:

- Randomly pick set of channel coefficients and QoS demands per subcarrier.
- For this set find the MCP and then Optimum Power Vector (OPV) using FRBS-DE as described in section 6.
- It becomes an example that is for a certain channel coefficient vector and QoS vector which power vector is optimum $[x_i^1, x_i^2; d_i]$.
- Add example to make an example set of S in total, i.e., $[x_i^1, x_i^2; d_i]_{i=1}^S$.
- About 50,000 examples are generated in this fashion, in order to make the system robust.

7.2. Training

The network is trained by the supervised learning technique using famous Least Mean Square (LMS) algorithm. The training process is shown in Figure 11. In this process an example is introduced to the network the output is compared with the desired output, consequently the error is fed back to LMS algorithm that updates the weights. Then the change in weights is updated in the network.

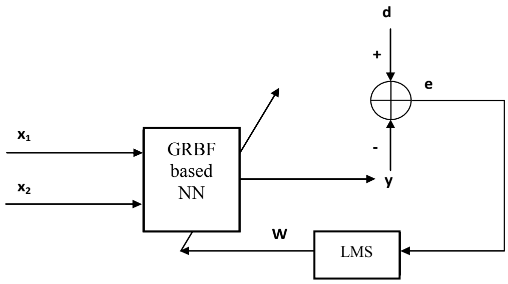

Figure 11. GRBF-NN training using LMS algorithm.

7.3. Verification

After training, the network is verified by giving same pair of inputs to network and to FRBS-DE block. The outputs of both should conform to each other.

7.4. Tool

MATLAB 7.8.0 (R2009a) Neural Network Toolbox is used to construct the proposed scheme. The parameters used are enlisted in Table 1 section 8.

8. Simulation Results

In this section proposed scheme is compared with various other schemes through the simulations and the results are shown in Figures below. The parameters used for simulations are given in Table 1.

MATLAB 7.8.0 (R2009a) is used as simulation tool for obtaining the results shown in figures below:

Table 1. Simulation parameters.

Sr.	Parameter	Value
1	Type of input	Real valued
2	Type of layers	Input, gaussian hidden layer and output layer
3	Number of subcarriers N	1024
4	Input and output size	2048×1024
5	Fitness function for DE	Fuzzy rule base system equation 7
6	Channel considered for simulation	IEEE indoor channel (WIFI)
7	Learning algorithm	Supervised LMS algorithm
8	Channel coefficients range	[0.1-0.4]
9	Quality of service (QoS)	10e-2,10e-3,10e-4 and 10e-5
10	Adaptive criterion	Fuzzy rule base system based differential evolution
11	Parameters being adapted	Code rate, modulation scheme and power

GRBF neural network is trained and then utilized for suggesting the suitable power for a given CSI and QoS demand per subcarrier. As it is explained earlier that training is based upon DE algorithm in which FRBS is used as fitness proportionate. So, the proposed scheme is compared with the following schemes:

- DE with FRBS based Adaptive, Coding, Modulation and Power (ACMP).
- Genetic algorithm + FRBS based ACMP [4].
- Water filling algorithm + FRBS based ACMP [4].
- FRBS based ACM with flat power for all subcarriers [5].
- ACMP scheme using Bisection Approach [6].

Figure 12 shows performance of proposed scheme with various QoS requests for the subcarriers. The throughput approaches to almost 5.6bit/s/Hz for the QoS 10e-2 while for value of QoS 10e-5 it is 3bits/s/Hz. This figure explains that as QoS demand increases mean the required BER is decreased the average throughput is decreased since the focus is to meet the BER threshold. On the other hand for a relaxed BER, average throughput goes high. This is because the system is suggesting MCPs that provide more data rate, which results in a high throughput. So, roughly we can say that QoS is inversely proportional to the average throughput. Similarly, for a fixed target BER average throughput is almost directly proportional to the average power per subcarrier.

Figure 13 depicts the upper and lower bounds on performance of proposed scheme. Upper bound is designated to the situation where all subcarriers have same QoS demand that is 10e-2. As this is most relaxed target BER so this will end up in MCPs with high rate, which consequently will increase the overall throughput of the system. Similarly, the assuming 10e-5 as QoS for all subcarriers would result in the lowest throughput because FRBS will suggest MCPs with low rates but better BER. Now, the average case which is more practical is when all subcarriers demands random QoS and in this way the average throughput approaches to 4.6bits/s/Hz.

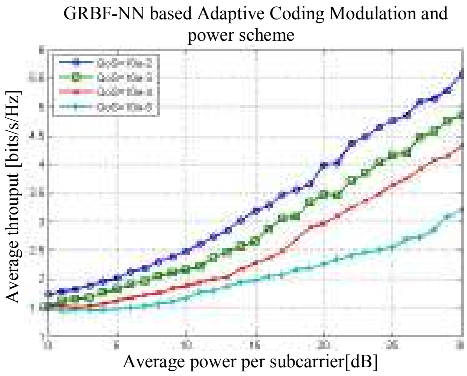

Figure 12. Comparison of DE+FRBS for different quality of service.

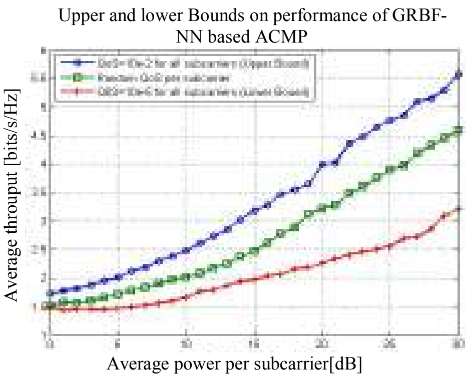

Figure 13. Upper and lower bounds on performance of proposed scheme.

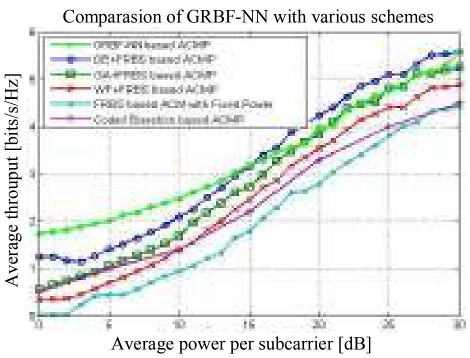

Figure 14. Comparison proposed scheme with various other schemes.

Figure 14 shows the comparison of proposed scheme with previously proposed schemes by the same author in [3, 4, 5] respectively and another scheme namely the Bisection method by [6].

Table 2. Comparison of proposed scheme.

Sr.	Scheme	Throughput [bits/s/Hz] 30dB	20dB	10dB	5dB
1	Proposed GRBF-NN	5.6	4.0	2.5	2.0
2	DE+FRBS	5.6	4.3	2.0	1.2
3	GA+FRBS	5.2	3.9	1.7	1.0
4	WF+FRBS	4.9	3.6	1.4	0.7
5	Flat FRBS	4.4	3.4	1.4	0.45
6	Bisection	4.5	2.8	1.0	1.0

Simulation results show that proposed scheme outperforms compared to all other schemes. The detailed comparison is shown in Table 2 at 30 dB, 20 dB, 10 dB and 5 dB average transmit power per subcarrier. At 30dBm transmit power, proposed scheme outperforms 0.4, 0.7, 1.2 and 1.1bits/s/Hz compare to GA with FRBS, WF with FRBS, flat power with FRBS and Bisection method respectively. The performance of proposed scheme is nearly equal to that of DE based FRBS for high values of transmitted power. This is because GRBF-NN is trained on the examples generated by DE-FRBS. But, in low power range that is 1 dB to 14 dB proposed scheme performs better than all the schemes being compared.

9. Conclusions

In this paper a real time adaptive coding, modulation and power scheme has been proposed by using a GRBF-NN. Given CSI and target BER vectors network suggests the OPV. Then, a FRBS chooses optimum MCPs for all the subcarriers. In this way jointly throughput of the system is optimized. For training of the network a number of examples are obtained by DE-FRBS. The example format is like given CSI and QoS vector what power vector is optimum. The training is done offline. Once trained, the neural network becomes a simple mapping function useful for real time applications. Comparisons show that proposed scheme performs better compare to many other schemes. The proposed scheme may be implemented for any OFDM based standard like WIFI (IEEE 802.11n), WiMAX (IEEE 802.16/E) etc.

In future, proposed scheme may be investigated for multiuser OFDM systems and MIMO wireless OFDM systems. Different channel models, modulation and coding schemes may also be investigated.

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