Video Transmission Using New Adaptive Modulation and Coding Scheme in OFDM based Cognitive Radio

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Abstract

As Cognitive Radio (CR) used in video applications, user-comprehended video quality practiced by secondary users is an important metric to judge effectiveness of CR technologies. We propose a new adaptive modulation and coding (AMC) scheme for CR, which is OFDM based system that is compliant with the IEEE.802.16. The proposed CR alters its modulation and coding rate to provide high quality system. In this scheme, CR using its ability to consciousness of various parameters including knowledge of the white holes in the channel spectrum via channel sensing, SNR, carrier to interference and noise ratio (CINR), and Modulation order Product code Rate (MPR) selects an optimum modulation and coding rate. In this scheme, we model the AMC function using Artificial Neural Network (ANN). Since AMC is naturally a non-liner function, ANN is selected to model this function. In order to achieve more accurate model, Genetic algorithm (GA) and Particle Swarm Optimization (PSO) are selected to optimize the function representing relationship between inputs and outputs of ANN, i.e., AMC model. Inputs of ANN are CR knowledge parameters, and the outputs are modulation type and coding rate. Presenting a perfect AMC model is advantage of this scheme because of considering all impressive parameters including CINR, available bandwidth, SNR and MPR to select optimum modulation and coding rate. Also, we show that in this application, GA rather than PSO is better choice for optimization algorithm.

Keywords: Adaptive Modulation And Coding; Cognitive Radio; IEEE 802.16 Standard; Video Transmission; Wireless Channel.

1. Introduction

Today's with the growth of wireless systems, there is an expanding demand on real-time wireless video communications. However, transmission over Wireless channels leads to a complicated problem due to the multipath fading behaviors of the channel [1], [2] and [3]. Cognitive radio (CR) is schemed at better resource management and ameliorated data transmission technologies. Through these purposes, it is designed to amalgamate with both the introduction of Software Defined Radios (SDR) and the consciousness that machine learning. CR can be defined as a system consisting of flexible wireless system design, measurements and awareness of various parameters, including interference temperature and geo-location information [4], [5].

An Adaptive modulation and coding (AMC) can be proposed as an effective part to the CR system. AMC is a technique that selects an appropriate pair of a modulation and a channel coding rate. In [6] a Fuzzy logic based CR is proposed. In this study, using Fuzzy logic analysis, the cognitive engine controls the form of modulation and code rate in order to take care the system throughput. In [7], an AMC method for selecting the appropriate Modulation and Coding Scheme (MCS) according to the

estimated channel condition for 3G wireless system is proposed. There are several schemes for AMC, which can be found in [8-14]. In [15], an AMC scheme is proposed according to the variable power and variable-rate technique from [16] and [17]. This technique lays over a trellis code on top of the un-coded modulation.

In [18] an AMC technique is proposed using M-array phase shift keying (MPSK) modulation. Recently a resource allocation scheme is proposed for OFDMA based cognitive radio for video transmission [19], this paper performs subcarrier, bit, and power allocation for diferent cognitive users such that the sum rate of the cognitive users is increased, towards this aim, fine grain scalable (FGS) video is employed. Although this paper is near-optimal allocation scheme, it is not concern with channel coding which is inseparable part of communications systems. In the other words, channel code rate and its related ability to correct the channel errors, and also its impact on the bit-rate is not considered in optimization problem and simulation procedure. Although all of introduced AMC methods and resource allocation schemes provide acceptable performance, they are not perfect schemes for efficient CR because these schemes have not considered all involving parameters such as available bandwidth, SNR, carrier to interference and noise ratio (CINR), and Modulation order product

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code Rate (MPR), jointly, to select modulation and coding rate. Since CR, system requires a perfect scheme for AMC, in this paper, we present a perfect AMC scheme for OFDM based CR according to IEEE 802.16 [20], [21], that consider all the involving parameters. As mentioned, because of involving several parameters to determine the perfect AMC, behavior of such a function is completely nonlinear. Therefore to describe this function we propose employing the powerful Artificial Neural Network (ANN). Advantage of this scheme is considering parameters including CINR, available bandwidth, SNR, and MPR to select optimum modulation and coding rate. Consequently, the system presents a perfect and powerful decision to select optimum modulation and coding rate. This paper is organized as follows: in section 2 and 3, a briefly of OFDM based CR and H.264 video coding are presented respectively. In section 4 two recent AMC model are summarized. In section 5, our proposed scheme is detailed. Finally in section 6, our simulation setting is introduced and in section 7 simulation results are presented.

2. OFDM Based Cognitive Radio

In the last years, researchers have established an efficient inter-relation between software and radio systems. This has permitted for faster advancements and has provided wireless communication instruments more flexibility and the capacity to transmit and receive using a multiplicity of protocols. Mitola in [4] captured the definition of an SDR one step further and pictured a radio which could take decisions to the network, modulation and coding parameters based on its surroundings, and called as "smart" radio the CR. Implementation of OFDM into CR comes up as a new aspect and challenges to system design.

The cognitive engine is responsible for making the intelligent decisions and configuring the radio. The spectral opportunities are recognized by the decision unit based on the information from policy engine as well as local and network spectrum sensing data. The local spectrum sensing unit processes spectrum knowledge and then recognizes certified users accessing the spectrum and their signal setting such as bandwidth and power level, and disclose spectrum opportunities that can be utilized by CR. CR decisions contain selecting the suitable channel coding, modulation, operation frequencies, and bandwidth. At this stage, OFDM technology gets the best performance over other similar transmission technologies with its flexible features. By only changing the configuration parameters of OFDM, it can optimize the transmission relying on the environmental characteristics.

## 3. H.264 Video Coding Paradigm

The joint project of ITU-T and ISO/IEC leads to developing the video coding design with the high coding efficiency which is called H.264/ advanced video coding (AVC) [22]. The primary goal of designing the H.264/AVC is to develop a simple and genuine video coding structure with improved compression performance. Currently, it becomes the standard of video coding because of the best performance in terms of its rate-distortion compared with the previous standards in the wireless networks.

In H.264, a set of video frames are transmitted in which each frame is partitioned to several macro-blocks. Each macro block (MB) comprises a motion vector (MV). The coding process of the first frame (I frame) of a video sequence is called "intra" coded in which 2D-DCT is applied on the MBs. Then the resulting coefficients are quantized and transmitted. The coding process of other remaining frames (P frames) of a video sequence, is called "inter" coded. Inter coding uses motion compensation which is the prediction of the current frames based on previous frame by employing motion estimation (ME) part. The Inter prediction encoding process consists of ME and providing the motion data transmitted as side information. Next, 2D-DCT is applied on the residual of the prediction (error of prediction) which is the difference between the original and the predicted block. Then resulting coefficients are quantized and transmitted. Finally, the quantized transform coefficients are entropy coded and transmitted together with the side information. The high coding efficiency of H.264 can be achieved by advanced coding tools such as multiple reference frames, variable block size and quarter-pixel accuracy ME [23].

4. Recent AMC Schemes

AMC schemes are widely considered and investigated in wireless communication systems in the recent literatures [6-19]. In this paper, we concentrate on two efficient AMC schemes presented in [30]. These AMC schemes are called Channel State scheme and Error state scheme. These schemes are the only recent benchmarks possible which are based on a slot allocation.

Channel State scheme is designed to adapt the modulation and coding scheme (MCS) after deriving an estimation of the channel behavior in terms of attenuation coefficient, α.
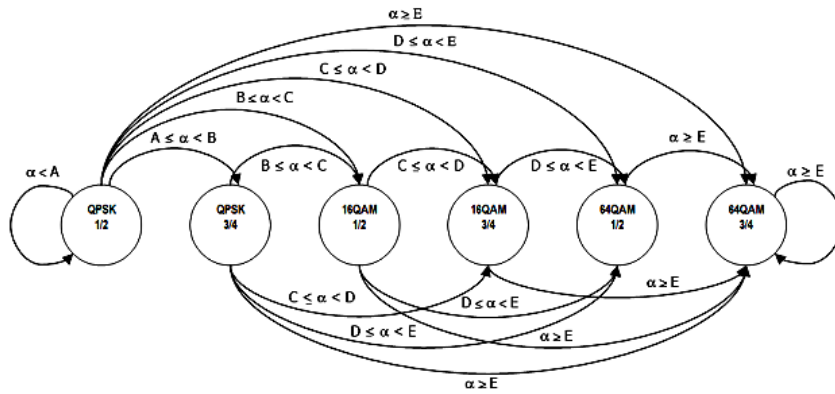
(a) Moore's state machine for channel state techniques.
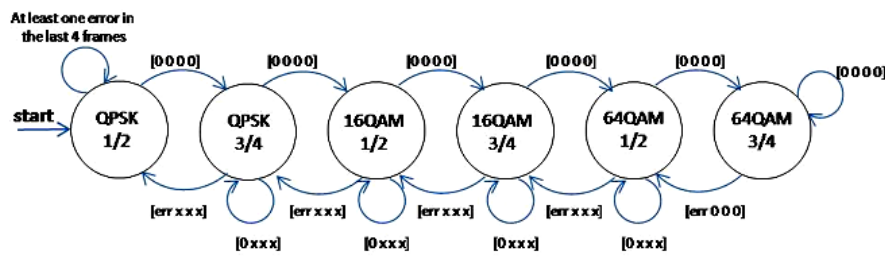
(b) Moore's state machine for error techniques.

Fig.1. Moore's state machines: 0=correct frame, err=error frame and x=any frame [30].

Over a slot, attenuation coefficient is compared with suitable thresholds, due to determination of the MCS to be used in the next frame. In Fig. 1a, Moore's state machine of this scheme is shown for the case of five thresholds A, B, C, D and E where A is the lowest threshold value [30]. In this scheme, two algorithms named Maximum Throughput (MT) and Target BLER have been proposed. The MT algorithm is designed to maximize the overall link throughput by selecting the proper MCS for each SNR value. As a result, this algorithm is not suitable for such services that are sensitive to the error probability [30], e.g., our application, real-time video communication. The other algorithm is TBLER designed based on keeping the error rate below a target constraint. This algorithm is more suitable for such services that are sensitive to the error probability. More details can be found in [30].

In the Error state scheme, the MCS changes in function of the number of detected frames with errors. In Fig. 1b, Moore's state machine of this scheme is shown, under the assumption of an error depth equal to four frames [30]. In this algorithm, transitions are permitted only for neighbor states (e.g., from QPSK 3/4 to 16QAM 1/2 and backwards but not from QPSK 3/4 to 16QAM 3/4). The transitions observe the following rules [30]:

1) A transition to a more efficient state happens only if all the last four frames are without errors (when we are the most efficient state (i.e., 64QAM 3/4) we still remain in that state).

2) A transition to less efficient state happens only if the last frame has at least one error (when we are in the less efficient state (i.e., 4QAM 1/2) we still remain in that state).

3) The state remains the same if the last frame is without errors independently from the previous three.

5. The Proposed Scheme

Since our proposed AMC scheme is based on population algorithms and Artificial Neural Network (ANN), we present a brief description of them and their application in our proposed scheme.

5.1 Population Based Algorithm

5.1.1 Genetic Algorithm

GA as a stochastic optimization technique generates solutions to optimization problems using methods such as mutation, crossover, selection, and inheritance inspired by natural evolution. In this kind of techniques; information of each generation is passed on to next generation by chromosome. Each chromosome includes gens; also, each gen demonstrates a particular characteristic or manners [24]. In GA's method, the primary populations are firstly produced based on necessities of the problem, following that, objective function is estimated and in order to achieve best solution, in regeneration step, parents create children. In this step, some activities are happening such as crossover and mutation. Therefore, the best solution is obtained during determination and essential iterations.

5.1.2 Particle Swarm Optimization (PSO)

PSO simulates the behaviors of bird gathering. In the PSO algorithm, each single solution is considered as a "particle" in the search space. Fitness value computes for all the p particles. The p particles are "flown" by way of the problem space by following the present optimum p particles. PSO is initialized by a group of arbitrary p particles (as we know, particles are solutions). Then, it investigates for optimal solution by renewing generations. In each iteration, each p particle is renewed by following two "best" values. The first one is the best solution which it has been obtained so far. This value is well known as "pbest". Another "best" value that is tracked by the p particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is a global best called "gbest" [26-28].

After discovering the two best values, the particle renews its velocity and positions based on the following equations.

$$V_{new} = X \times (V_{old} + \phi_1 \times (P_{Pb} - X_{cs}) + \phi_2 \times (P_{gb} - X_{cs}))$$
(1)

$$X_{new} = X_{old} + V_{new}$$
(2)

$$X = \frac{2k}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}} \quad for \ \varphi > 4, \quad k \in (0,1)$$
(3)

Where, ϕ_1 and ϕ_2 are random numbers uniformly distributed in the range (0, $\phi/2$) and X is the constriction coefficient.

5.2 Artificial Neural Network (ANN)

ANNs are one of the most influential branches of artificial intelligence. Generally, it is used for description of non-linear functions, like the function of this paper. ANNs are categorized into two major groups based on learning algorithm, supervised and unsupervised learning. In supervised learning, input and desired output are presented as learning data and ANN is trained using them. In unsupervised learning, target outputs are not present and ANN can only cluster input data and when new data input, it can assign it into the corresponded cluster [25].

5.2.1 Neural Network Structure

The neural network used in this paper is a multilayer perceptron neural network. The weights and biases are the variables of the optimization algorithm. Firstly, matrix of weights and biases indicating initial position of particles for PSO and chromosome for GA are prepared as follow:

$$Weight = [w_1, w_2, ..., w_i], \quad Biase = [b_1, b_2, ..., b_i]$$
(4)

Where, w denotes weights and b denotes biases. Also for structure of ANN with 2 hidden layers we have:

$$\underline{f_1} = \underline{W}_1 \times X + b_1$$
(5)

$$\underline{\sigma_1} = \log sig(f_1)$$
(6)

$$\underline{f_2} = \underline{W}_{L2} \times \underline{\sigma_1} + b_2$$
(7)

$$\underline{\sigma_2} = \log sig(f_2)$$
(8)

$$\underline{f_3} = \underline{W}_{L3} \times \underline{\sigma_2} + b_3$$
(9)

$$\underline{\sigma_3} = \log sig(f_3)$$
(10)

Where, $\underline{X}$ is vector of input data $\underline{W}_{L1}$, $\underline{W}_{L2}$ and $\underline{W}_{L3}$ are weights between input and first layer, between first layer and second one and between second layer and third one, respectively. b1, b2 and b3 are biases related to first layer, second layer and third layer, respectively. Finally, $\underline{\sigma}_3$ is actual output of network and MSE is value of subtraction of actual output and target output. This value is fitness value of GA and PSO, therefore the proposed algorithm will change weights until MSE becomes minimum in next iterations. MSE function is given by Eq. (11)

$$MSE = \frac{1}{L} \sum_{i=0}^{L-1} (Y_{output\_ANN} - Y_{target\_output})^2$$
(11)

Where, Y_{output_ANN} is the out-put of model and Y_{target_output} is expected out-put of the model. There is different methods to train (or in other words, to update weights and biases) which most of them employ analytical and mathematical based methods, such as back propagation and gradient descent. In this paper, to optimize the function representing relationship between inputs and outputs of neural network GA and PSO are used to optimize the function.

5.3 The Proposed AMC Model

In this scheme for cognitive Radio, at first, cognitive engine senses the spectrum using spectrum sensing unit [5]. Then it finds the white hole of spectrum. Next, because of its ability to awareness of changing in transmission environment, CR has knowledge of SNR, carrier to noise ratio (CINR), carrier to interference ratio (CIR), and Modulation order Product code Rate (MPR). Based on these parameters, it selects an optimum modulation and coding rate. We model the AMC function using ANN. Since AMC is naturally a non-liner function, ANN is selected to model this function. In order to achieve more accurate model, GA and PSO are selected to optimize the function representing relationship between inputs and outputs of ANN, i.e., AMC model. Inputs of ANN are CR knowledge parameters and the outputs are modulation type and coding rate. These parameters are calculated in following subsections.

5.3.1 Modulation Order Product Code Rate (MPR)

For DL/UL, the transmission style is precondition by the NEP (encoding packet size) and the NSCH (number of allotted slots). NEP per an encoding packet is {144, 192, 288, 384, 480, 960, 1920, 2880, 3840, and 4800}. The NSCH per an encoding Packet is {1, 480}. In Table 507, 509 [29], the numbers in the first row are NEPs, and the numbers in the remaining rows are NSCHs and associated parameters. In Table 507,509 [29] the modulation order is desirable by MOD, and it has the values of 2 for QPSK, 4 for 16-QAM, and 6 for 64-QAM. SCH points to the number of allocated slots. The bearable modulation schemes are QPSK, 16-QAM, and 64-QAM.

When the NEP and the NSCH are given, the modulation order is decided by the value of MPR (Modulation order Product code Rate).

The MPR means the effective number of the information bit transmitted bits per a subcarrier and is defined by (12).

$$MPR = \frac{N_{EP}}{48 \times N_{SCH}}$$
(12)

5.3.2 Carrier to Interference and Noise Ratio (CINR)

One imaginable technique to estimate the CINR of a particular message is to normalize the mean-squared residual error of disclosed data symbols (and/or pilot symbols) by the average signal power [29] using:

$$CINR[K] = \frac{\sum_{n=0}^{N-1}|s[k,n]|^2}{\sum_{n=0}^{N-1}|r[k,n]-s[k,n]|^2}$$
(13)

CINR[k] is the (linear) CINR for message k, s[k, n] is the corresponding detected more pilot symbol corresponding to received symbol n, and r[k, n] is the received symbol n within message k. As mentioned in previous sections, ANN can be used as a suitable model for complex processes like AMC that depends on several parameters, such as CINR, SNR and bandwidth of white hole.

5.4 Optimization Problem: Optimization of Weights and Biases by GA and PSO

As mentioned before, GA has some parameters, which should be set in initialization step, such as Population Size, Elite Count, Migration Fraction, Migration Interval, crossover, and mutation. In this method the ANN is used as an objective function in optimization. The optimization algorithm is summarized in Algorithm 1.

Algorithm 1: Optimization of AMC model

Input data: weights and biases of ANN
1) Determining parameter of GA and PSO.
2) Determining initial position and velocity randomly.
3) Evaluating fitness of chromosomes /particles.
4) Generating new chromosomes/Updating particles velocity and position.
5) Checking the stop criterion:
     If the stop criterion is met the optimum AMC model is obtained, if not, go to step 2.
Output: Optimum AMC model.

Each chromosomes of the GA represents a set of weights and biases of one ANN which may separately be an answer to the optimization problem. Depending on the adjustments, these chromosomes are transformed into new chromosomes evaluated based on the objective function. In PSO, the procedure is similar to GA optimization and the only difference is that the population is particle. For a multilayer perceptron ANN with one hidden layer that consists of n hidden unit and the network has m inputs then the output of the network can be formalized as a function of the inputs. Let's define Y

as the output of the ANN. The mathematical model of such a network defined as follow:

$$Y_{output-ANN}(x_1, x_2, ..., x_m) = \sum_{j=1}^{n} w_j f\left(\sum_{i=1}^{m} a_{ij} x_i + b_j\right)$$
(14)

Where W_j is the weight of the synapse that goes to the output neuron form the j-th neuron and a_{ij} is the weight of the synapse that goes form the input x_i to the j-th hidden neuron, b_j is the bias of the j-th hidden neuron, f is the activation function. Optimization problem is defined as follow:

$$\min\left\{\frac{1}{L}\sum_{i=0}^{L-1}\left(Y_{output\_ANN} - Y_{target}\right)^2\right\}$$
(15)

To stop the optimization process, the amount of error in training the ANN is considered to be less than 0.3%. The optimization process continues until the above condition is satisfied.

5.5 The Structure of Proposed AMC Scheme and Optimization Results

In this paper, we use Multilayer perceptron ANN for finding the function of AMC. Based on the five input parameters (UL/DL, SNR, CINR, available Bit-Rate, MPR) and two outputs (type of modulation and channel code rate), we utilize an ANN which has five inputs, two outputs, and 2 hidden layers. First layer has 10 neurons and second layer has 8 neurons. The modulation order (1 for BPSK, 2 for QPSK, 4 for 16-QAM, and 6 for 64-QAM) will be set for all the allowed transmission formats as shown in Table 507 of [29] (Note in this paper we consider BPSK modulation for low SNR transmission environments). For training the system, we use Table 507-Transmission format and modulation level for DL, [29], Table 509-Transmission format and modulation level for UL, [29], Table B.4 OFDM 256-FFT raw bit-rates (Mb/s), [29] CNR is the normalized Carrier to Noise Ratio (per sub-carrier) for the given modulation, Table-308 of [29]. We combine these tables into two tables. The resulting tables are given in Tables 2 and 3. The Table 2, is for uplink transmission and the Table 3, is for downlink transmission. As mentioned in previous sections, ANN can be used as a suitable model for complex processes. Since AMC involves nonlinear and complicated features (the function representing AMC has multi-input variables and multi-output variables), accurate prediction of the behavior of this process is great significance. In this paper, the proposed method has three major steps. In first step, the function which represents the model of AMC is presented, in the second step, trained ANN with GA has been used to presents an efficient and optimum model for AMC. In third step, trained ANN with PSO has been used to present an efficient and optimum model for AMC. We use Table 2 and Table 3 to train and test the ANN, ANN-GA and ANN-PSO.

80 percent of this data table is used for training and 20 percent is used for test. In this paper we employ multilayer perceptron ANN which has five inputs, two outputs, and 2 hidden layers. First layer has 10 neurons

and second has 8 neurons. It should be mentioned that in our scheme the input parameters of ANN have the same importance. GA parameters set as; maximum number of iterations, Max-It=100; population size, N-pop=50; crossover percentage, P-crossover = 0.7; number of parents is calculated by following formula:

N-crossover = round (P-crossover * N-pop / 2) * 2, mutation percentage, P-mutation = 0.2; number of mutants, N-mutation = round (P-mutation*N-pop). PSO parameters set as; maximum number of iterations Max-It=100; swarm population size, N-pop=50; $\phi_1 = 2.05$; $\phi_2 = 2.05$. Based on the presented settings the training procedure of ANN, ANN-GA and ANN-PSO is performed. The simulation results are shown in Fig.2, Fig.3 and Fig.4 respectively. Fig.2 shows training procedure of ANN. It achieves the best validation in 0.0053 in epoch 8, in this epoch MSE train is 0.0031. Next, we use GA and PSO to optimize the ANN. As shown in Fig.3, after 100 generation, GA optimizes the ANN and, as a result, it achieves the best in 0.001 (MSE=0.001). Also as shown in Fig.4, PSO achieves the best in 0.0022 (MSE=0.0022). Finally, resulting mean errors have been reported in Table 1. It is observed that ANN-GA is the optimum algorithm for representation of function of AMC because of its lower minimum mean error
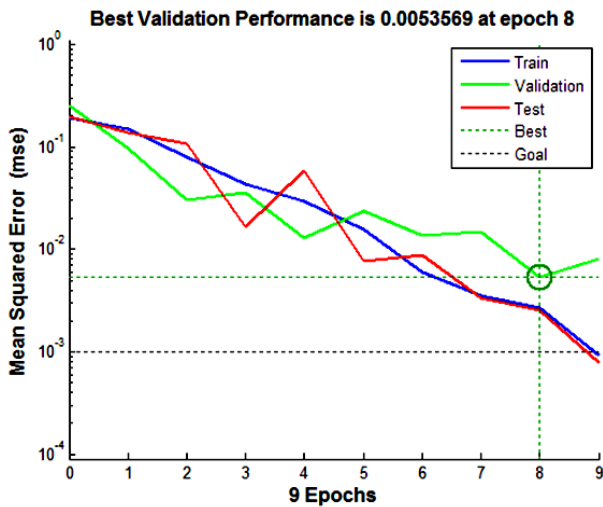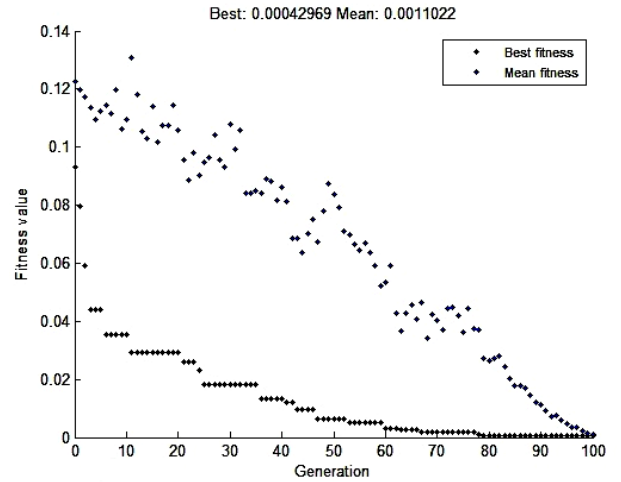

Fig.3. Optimized ANN simulation for AMC using GA
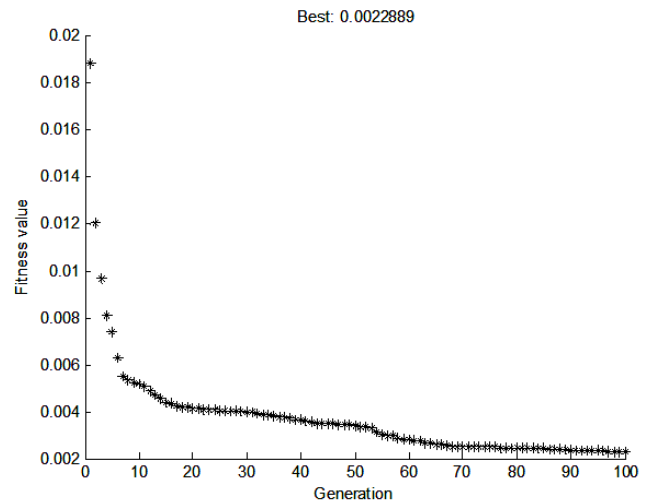

Fig.4. Optimized ANN simulation for AMC using PSO
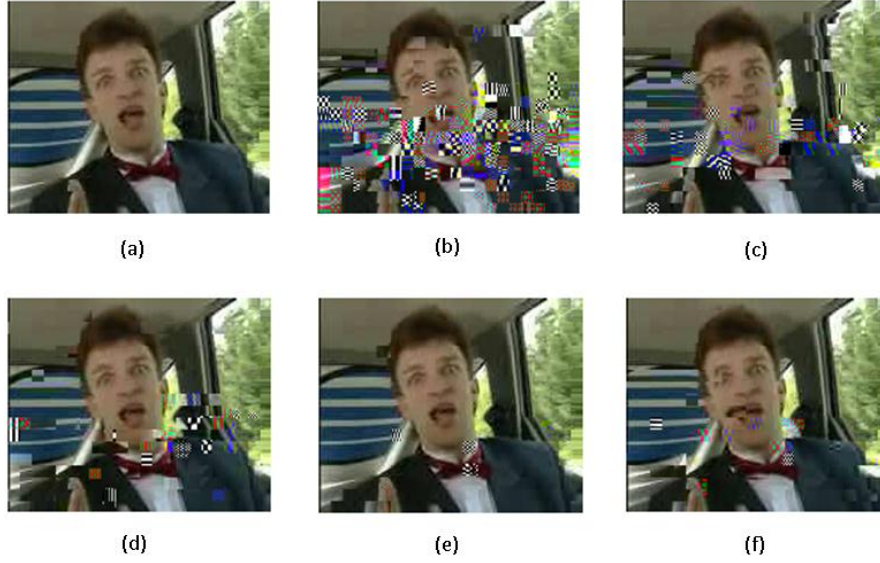

Fig.2. ANN simulation for AMC

Fig. 5: Frame of Car-phone video in the receiver after passing Rayleigh fading channel in Uplink, SNR=10.5, MPR=1.5, CINR=23.7, (a) is the coded frame 285, (b) using QAM64 and Code rate = 0.25, (c) using QAM16 and Code rate = 0.5, (d) using QAM and Code rate = 0.67, (e) QAM16 and Code rate= 0.38 and (f) using QAM and Code rate = 0.63.

5.6 About the Complexity of Proposed Scheme

There may be several numbers of algorithms to solve the same function. In terms of complexity theory, one strategy to evaluate them is to compare their performance in terms of how quickly they solve the same function. In this paper, we emphasize that the function having been considered for AMC in other literatures is imperfect because this function does not consider important parameter such as CINR, MPR and available bandwidth (i.e. they consider a simple function for AMC and design algorithms to solve it). In this paper, we present a non-linear function for AMC including all impressive parameters; also, we design a scheme according to this complex function. Since we change the AMC function, clearly, we do not deal with the same function to compare the complexity of our scheme with the other schemes presented in other literatures.

Furthermore, the proposed AMC model and its optimization algorithm (Algorithm 1) are the pre-computing procedures which are performed offline, i.e., these procedures are applied to determine the function representing AMC model. The resulting AMC model can be applied in each cognitive radio system. What the system needs to compute online is Y_{AMC}, i.e., the system just enters the inputs, x_i, in equation (16) which its parameters w_k, w_j, a_{ij} and b_j are offline prepared already. Y_{AMC} is our proposed AMC model (our model has 5 inputs, 2 outputs and 2 hidden layers):

$$Y_{AMC}\left(x_1, x_2, ..., x_m\right) = \sum_{k=1}^{h} w_k \, f_2\left(\sum_{j=1}^{n} w_j \, f_1\left(\sum_{i=1}^{m} a_{ij} \, x_i + b_j\right)\right) \quad (16)$$

As mentioned before, Y_{AMC} is the AMC model. Therefore, the complexity for our proposed AMC scheme is just related to calculating the Y_{AMC}, i.e., $O(Y_{AMC})$.

Maybe this question arises why we apply ANN in order to model the AMC function. The reason is that we require a powerful tool that can be able to model a complex and nonlinear function which has several inputs and several outputs. ANN and nonlinear regression are known as powerful tools for modeling the complex and nonlinear functions. Although nonlinear regression is a powerful tool, it is proved that ANN is more accurate than it [32]; furthermore, it is a traditional tool respect to ANN.

6. Simulation Settings

Conventional OFDM system with assuming 256 subcarriers is used in our simulation. In wireless transmission, motion causes Doppler shift in the received signal components, the Doppler frequency f_D equals to $f_c v/c$ in which v is the mobile speed, f_c is the carrier frequency and c is the light speed and equals 3×10^8. In deriving our simulations results we have focused on a wireless environment with Radio frequency carrier $f_c = 3.5$GHz Maximum available bandwidth of 10 MHz, maximum Doppler frequency $f_D = 291$ Hz (mobility terminals up to 90 km/ h). Coherence time T_c 1.03 ms. maximum delay spread equal to 20µs ITU-R vehicular channel model A, with 6 paths [33].
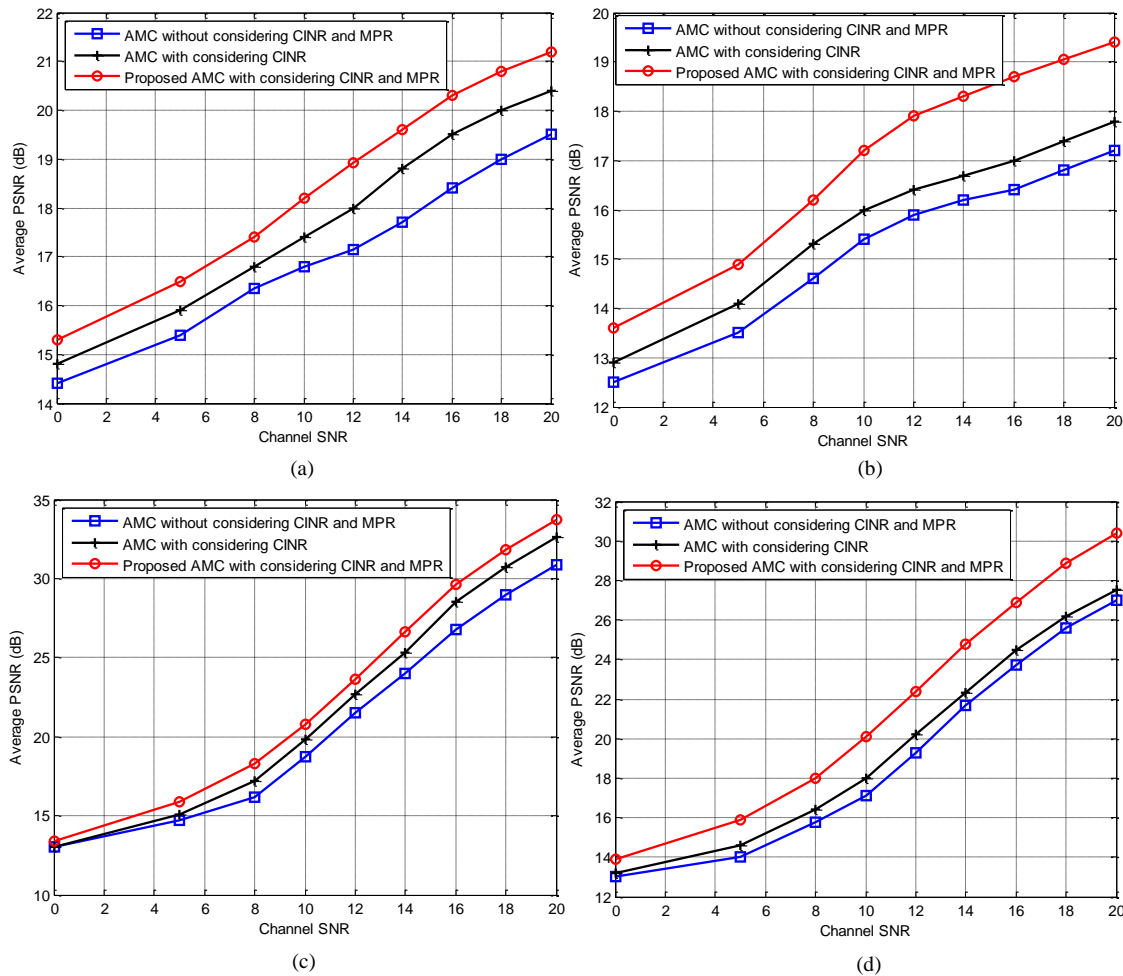
Fig. 6: Simulation result of Stefan and Foreman video transmission over Rayleigh fading channel under two conditions; first condition (I) MPR=3.85, CINR=18, and available bit-rate=6 for CR user in uplink; second condition (II) MPR=1.33, CINR=15, and available bit-rate =5 for CR user in uplink. (a) and (b) are associated with Stefan video under condition (I) and (II) respectively. (c) and (d) are associated with Foreman video under condition (I) and (II) respectively.

Simulation scenario is involved two primary users and one secondary user. All of simulations are performed using Matlab-R2011b software.

7. Simulation Resuls

In this study, Quarter pixel Common Inter-mediate Format (QCIF) resolution video sequences Car-phone video, [31], is employed as video sources to evaluate the performance of the proposed scheme, in Uplink, based on the parameters SNR=10.5, MPR=1.5, CINR=23.7. As shown in Fig.5 Frame number 285 of Car-phone video in the secondary user receiver after passing Rayleigh fading channel is as follow; (b) using QAM64 and Code rate = 0.25, (c) using QAM16 and Code rate = 0.5, (d) using QAM and Code rate = 0.67, (e) QAM16 and Code rate= 0.38 and (f) using QAM and Code rate = 0.63 are

used for transmission. As shown based on the proposed scheme the best transmission is performed using selecting the QAM16 and Code rate = 0.38.

Next, to evaluate the performance of the proposed scheme and demonstrate the impact of considering CINR and MPR, two sequences Foreman and Stefan [30] are transmitted over Rayleigh fading channel in wide range of channel SNR (0-20 dB). In this simulation we consider three schemes for AMC; in the first scheme we employs AMC scheme which doesn't consider CINR and MPR, second AMC scheme which consider CINR and third AMC scheme which consider both CINR and MPR. For each video we consider two conditions; first condition (I) MPR=3.85, CINR=18, and available bit-rate=6 for CR user in uplink; second condition (II) MPR=1.33, CINR=15, and available bit-rate =5 for CR user in uplink.
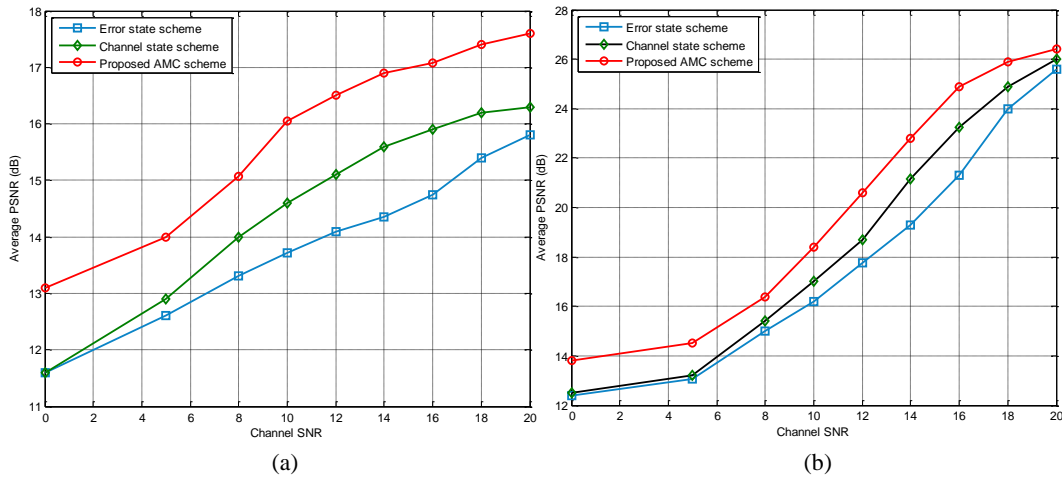
Fig. 7: Simulation results: comparing the proposed scheme with Error state scheme and Channel state scheme, (a) for Stefan sequences (b) for Foreman sequences, over Rayleigh fading channel under condition; MPR=0.25, CINR=10, and available bit-rate=4 for CR user in uplink.

As shown in Fig 6 (a-d) the proposed scheme provides higher PSNR than other two schemes. For example in second condition (II) the AMC scheme which doesn't consider CINR and MPR selects QPSK-0.5, QPSK-0.75, 16QAM-0.5, 16QAM-0.66, 16QAM-0.75, 64QAM-0.5, 64QAM-0.66 and 64QAM-0.75 in SNRs 5, 8, 10, 12, 14, 16, 18, 20 dB respectively [29], but the proposed scheme selects QPSK-0.33, QPSK-0.4, QPSK-0.5, QPSK-0.56, QPSK-0.66, 8QAM-0.66, 8QAM-0.75 and 8QAM-0.75 in SNRs 5, 8, 10, 12, 14, 16, 18, 20 dB respectively. It should be mentioned that the quality of the received video (average PSNR of video) at each Channel SNR is obtained by 15 minute running time.

Next, to compare the proposed scheme with two presented schemes, Channel state scheme and Error state scheme, two sequences Foreman and Stefan [30] are transmitted over Rayleigh fading channel in wide range of channel SNR (0-20 dB). For Channel state scheme, as the best BLER performance is obtained for the lowest target, $BLER_{target} = 10^{-3}$ [30], the target value of BLER is set to 10^{-3}. For Error state scheme, as the best BLER performance is obtained for Error state memory 3 and 4, in this simulation it is set to 4. In this simulation, Channel state scheme, TBLER algorithm, selects QPSK 1/2 and QPSK 3/4 in SNR ranges 0-15dB and 15-20dB respectively. Error state scheme selects QPSK 1/2, QPSK 3/4, and 16 QAM 1/2 in SNR ranges 0-5dB, 5-15dB and 15-20dB respectively. The proposed scheme selects BPSK 1/4 and QPSK 1/2 in SNR ranges 0-18dB and 18-20dB respectively. As reported in Fig.7, the proposed scheme offers about 1-1.5dB PSNR gain for Stefan and Foreman sequences. This is because of applying accurate AMC model which is affected by considering all effective parameters in modeling procedure, as mentioned before.

8. Conclusions

In fast changing environment, a CR system needs a perfect model for AMC. In this paper we have presented a perfect AMC model for OFDM based CR that is compliant with the IEEE.802.16. Presenting a perfect AMC model is advantage of this scheme because of considering all impressive parameters including CINR, available bandwidth, SNR and MPR to select optimum modulation and coding rate. We have modeled the AMC function using ANN because AMC is naturally a non-liner function. In order to achieve more accurate model, GA and PSO have been selected to optimize the function representing relationship between inputs and outputs of ANN, i.e., AMC model. Simulation results prove that the proposed AMC scheme presents perfect and powerful decision to select optimum modulation and coding rate and consequently provides higher quality for delivered video. Also it was shown GA is more powerful optimizer algorithm than PSO.

9. Acknowledgment

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