

# Intelligent Decision Modeling for Communication Parameter Selection via Back Propagation Neural Network

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**Abstract.** Decision-making ability plays a key role in the cognitive radio system. The decision-making engine is expected to decide a suitable radio configuration (modulation mode, coding mode, coding rate, etc.) according to the complex and varying radio environment. In this paper, we propose a decision-making method for the Orthogonal Frequency Division Multiplexing (OFDM) communication system. Through this method, we can select waveform parameters for any channel condition to achieve optimal communication performance via the Back Propagation (BP) Neural Network (NN) regression. The simulation results illustrate the proposed method can provide a reasonable decision surface with various wireless channel condition.

**Keywords:** Neural Network · Decision making · Cognitive radio  
Intelligent radio

## 1 Introduction

Since Mitola proposed the concept “Cognitive Radio (CR)” in 1999 [1], most of the current CR researches were mainly focusing on spectrum sensing, dynamic spectrum access, etc., to solve the ever-increasing spectrum shortage problem [2, 3]. However, when the CR was proposed by Mitola, he has emphasized the importance of the intelligent learning and decision-making characteristics for the cognitive radio [1]. Intelligence should be a core characteristic of cognitive radio. So the next generation of intelligent radio should have the capacity to sense, learn and adapt to the complex electromagnetic environment.

The main function of “learning” in CR is making decision. Optimization based decision-making algorithm has been widely exploited in current researches of intelligent decision-making, and the typical one is Genetic Algorithm (GA). GA is used to search the best system parameters within the given feasible domain according to the designed performance objective function [4]. Christian James Rieser pioneered a biometric-based cognitive radio model (Bio-CR) first [5], and in his doctoral thesis he elaborated on the use of GA to achieve the optimization of cognitive radio configuration parameters. Since then many scholars have

made improvements on this basis, but mainly focused on the improvement of the algorithm performance, such as using the binary quantum particle swarm optimization [6], hybrid binary particle swarm optimization [7], differential evolution [8], bacterial foraging optimization [8] and so on. Note that, when using these optimization algorithms, it requires a multi-objective function of communication performance calculated by the accurate theoretical formula. So these methods only work under the assumption of Additive White Gaussian Noise (AWGN) channel. But when the channel environment is not clear or more complex, we can not get accurate calculation formula. And every time we use an optimized way to make decision, we must spend a lot of time and computing resources.

Another kind of typical intelligent decision-making methods is based on learning (knowledge) [4]. CR system need to analyze and learn from the historical cases through the method of machine learning, dig out potential rules and knowledge, summarize the rules of knowledge, and then make decision based on the rules and knowledge obtained. Related learning algorithms include Neural Networks [9, 10], Support Vector Machines (SVM) [11], Bayesian networks [12], etc. [13, 14]. At present, this kind of research is still in the infancy.

In this paper, we propose a novel decision-making method to estimate the best modulation type and coding rate OFDM wireless system. In the proposed method, we collect the training sample by sending several training sequence from the transmitter, and utilize these samples to train a Back Propagation (BP) Neural Network (NN) regression model. Last, the fine-trained BP-NN model provide the decision surface which corresponds to the given wireless channel.

## 2 BP Neural Network

BP-NN is a multi-layer feed-forward NN ordinarily which is trained by the BP algorithm [15, 16]. It can achieve the minimum error sum of square by regulating the weight value and threshold value [16]. A basic BP-NN model is shown in Fig. 1.

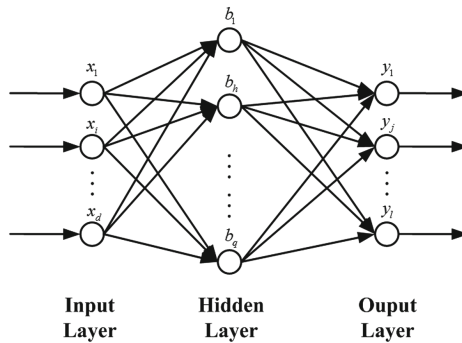


Fig. 1. A basic BP-NN structure including input layer, hidden layer and output layer.

The BP training process can be described as follows [15,16]:

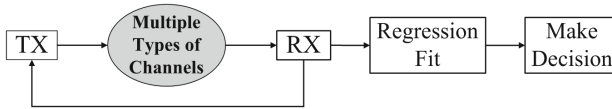
**Forward propagation stage:** The input signal from the input layer propagates through the hidden layer to the output layer, and the weight value and threshold value are fixed. At this stage, the state of each neuron will only affect the next layer of neurons.

**Back propagation stage:** The error signal is generated by comparing the real output with the desired output. Then the error signal propagates layer-by-layer in the opposite direction. At this stage, the network parameters are continuously regulated by the feedback error. It makes the real network output value closer to the expected one.

The main advantage of BP-NN is that it has strong nonlinear mapping ability [16]. Theoretically, as long as the number of hidden neurons is sufficient, a three-layer BP-NN can approximate a nonlinear function with arbitrary precision.

### 3 Design of Decision-Making Model

In our method, the objective function is constructed based on the Shannon-Hartley law [17]. It's an evolution of the channel capacity function. And our goal is to find the modulation and coding mode which maximizes the objective function with BP-NN regression. The maximum means the system communication performance is optimal to some extent [17]. The system process is shown in Fig. 2.



**Fig. 2.** Decision-making system flow chart.

First, we set up a complete OFDM communication system, modulation modes include binary phase shift keying (BPSK), 4-quadrature amplitude modulation (QAM), . . . , 128-QAM, coding mode uses the BCH block code (coding rate from 0 to 1). The main parameters of our OFDM system are shown in Table 1.

**Table 1.** Main parameters of OFDM system.

Parameter	Value
Available subcarriers	128
Used subcarriers	64
Cyclic prefix	32
Baseband frequency	10 MHz

Select as many channel models as possible to simulate (eg.: AWGN, Rayleigh fading, Rician fading, Plus interference). The objective function related to the modulation-coding modes is defined as follows:

$$c = f(\text{rate}) \times f(\text{ber}) \quad (1)$$

Here:

$$f(\text{rate}) = \log_2(M) \times r_c \quad (2)$$

$$f(\text{ber}) = -\log_{10}(\text{ber}) \quad (3)$$

where  $M$  denotes the modulation order,  $r_c$  means the coding rate,  $\text{ber}$  represents the bit-error rate,  $\text{rate}$  means the data-transmitted rate.

After that, we choose different values of various channel environment parameters, such as Signal-to-Noise Ratio (SNR), Doppler shift, etc., to collect a large number of sample data in each channel model.

Use BP-NN to regress the objective function  $c = f([M, r_c], \mathbf{w})$  (where  $\mathbf{w}$  is the channel environment to be regressed). The fitted surface reflects the relationship between transmission performance and different modulation-coding modes in current channel environment. The vertex of the surface means the value of modulation-coding mode which maximizes the objective function.

And we make two constraints to  $\text{ber}$  as follows:

When  $\text{ber} < 10^{-6}$ , consider that the bit error rate reaches the ideal state, record it as  $10^{-6}$ .

When  $\text{ber} > 0.1$ , consider that the bit error rate is beyond the scope of tolerance, record it as 1.

## 4 Simulation Results and Analysis

We only select partial modulation-coding modes to regress and compare the fitted surface with the one obtained by mapping all modulation modes (including BPSK, 4-QAM, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 128-QAM) and coding-rate modes (including (8, 15, 22, 29, 36, 43, 50, 64, 71, 78, 92, 127)/127) directly. If the trend is consistent, it verify the correctness of fitting.

The fitted surfaces are shown in Fig. 3. For the convenience of observation, we will use contour lines instead of three-dimensional figure in the following space.

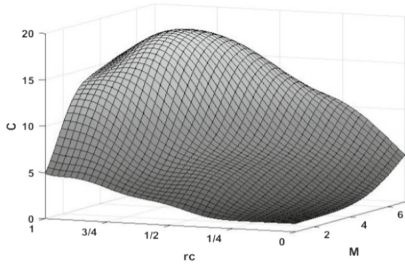
### 4.1 Simulation in AWGN Channel

As we can see from Fig. 4, when the channel is AWGN (SNR = 20 dB), capacity function approximately reaches the vertex at “128-QAM,  $R_c=1$ ”.

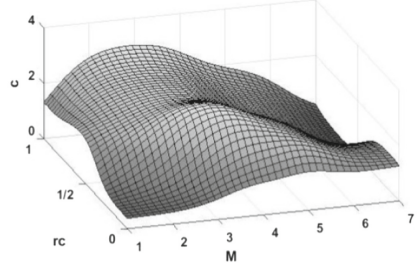
As we can see from Fig. 5, when the channel is AWGN (SNR = 10 dB), capacity function approximately reaches the vertex at “32-QAM,  $r_c=7/10$ ”.

As we can see from Fig. 6, when the channel is AWGN (SNR = 0 dB), capacity function approximately reaches the vertex at “BPSK,  $r_c=1/5$ ”.

In AWGN channels, when the SNR from 20 dB to 0 dB, the modulation-coding options from the high modulation level, large coding rate, to low modulation level, small coding rate. This is basically consistent with the theoretical speculation.

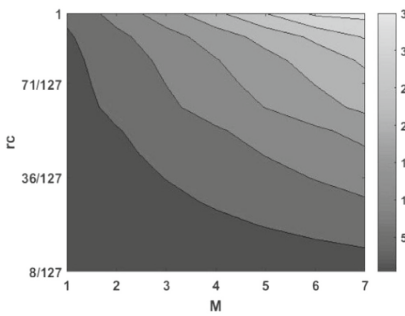


(a) Fitted surface for AWGN (SNR = 12 dB) channel.

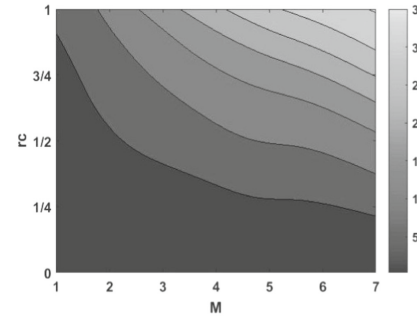


(b) Fitted surface for Rayleigh (SNR = 12 dB,  $F_d = 500$  kHz) channel.

**Fig. 3.** Fitting surface examples.

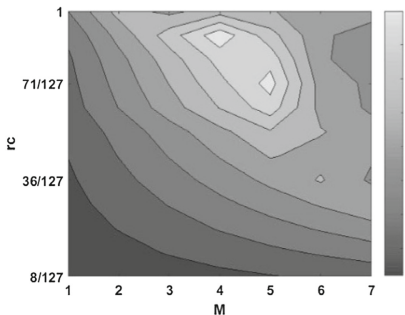


(a) Mapping all modulation-coding modes in AWGN (SNR = 20 dB) channel.

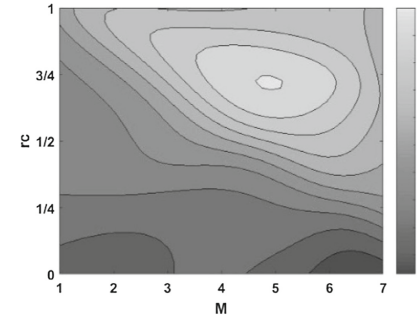


(b) Fitted figure in AWGN (SNR = 20 dB) channel.

**Fig. 4.** Relationship between objective function values and modulation-coding modes in AWGN (SNR = 20 dB) channel.

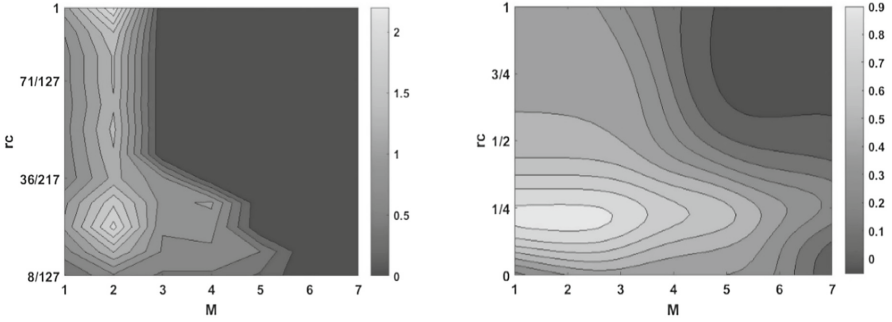


(a) Mapping all modulation-coding modes in AWGN (SNR = 10 dB) channel.



(b) Fitted figure in AWGN (SNR = 10 dB) channel.

**Fig. 5.** Relationship between objective function values and modulation-coding modes in AWGN (SNR = 10 dB) channel.

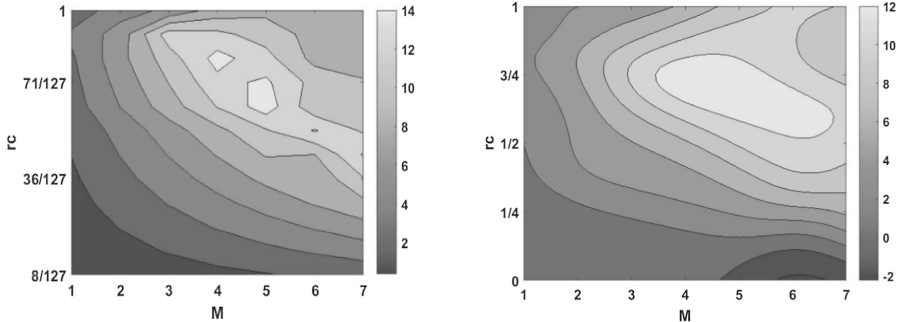


(a) Mapping all modulation-coding modes in AWGN (SNR = 0 dB) channel. (b) Fitted figure in AWGN (SNR = 0 dB) channel.

**Fig. 6.** Relationship between objective function values and modulation-coding modes in AWGN (SNR = 0 dB) channel.

### 4.2 Simulation in Other Channels

Because of the limited space, we use Fig. 7 as an example to show the fitted results for other channels.



(a) Mapping all modulation-coding modes in Rayleigh (SNR = 20 dB,  $F_d = 500$  kHz) channel. (b) Fitted figure in Rayleigh (SNR = 20 dB,  $F_d = 500$  kHz) channel.

**Fig. 7.** Relationship between objective function values and modulation-coding modes in Rayleigh (SNR = 20 dB,  $F_d = 500$  kHz) channel.

As we can see from Fig. 7, when the channel is Rayleigh-fading (SNR = 20 dB,  $F_d = 500$  kHz), capacity function approximately reaches the vertex at “32-QAM,  $r_c=5/8$ ”.

From the simulation results we can see that the trend of the fitted surface is basically the same as that of the figure mapping all modulation-coding modes, so the effect of regression is in line with expectations. The fitted surface can reflect

the channel environment. However, in the process of fitting, we find that the training of BP-NN is not consistent and it is easy to fall into the local optimum. The fit of the decision surface has uncertainties. Although we select the least mean square error one by fitting ten times, sometimes the fitted error is also large. Therefore, we suggest to use other regression algorithms, such as support vector regression (SVR) (because of the small number of input samples) in the future research.

## 5 Conclusion

In this paper, we have proposed a decision-making method based on the BP-NN regression model. We made decisions to select the most suitable communication waveform parameters in some channel environment examples. Through our model, we can make a decision and analysis for the complex, undiscovered channel. The simulation results demonstrates the correctness and applicability of the introduced model. In the future research, we will use more other machine learning algorithms to regress, analyze and contrast their regression performance to improve our method.

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