New Algorithm for Power Control in Cellular Communication with ANFIS

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Abstract- Transmitter power is an important resource in cellular mobile radio systems. Effective power control can increase system capacity and quality of service. A commonly used measure of the quality of service is the Carrier to Interference Ratio (CIR) at the receiver. The main idea on power control schemes is to maximize the minimum CIR in each channel of system. In this paper a new adaptive neuro fuzzy distributed power control algorithm which can be used to maximize the minimum CIR among all of co-channel users, has been introduced. Simulations and results have been compared with classical method and show that intelligent control system has better performance than other existing methods.

Key-Words: - Cellular mobile communication, Power control, ANFIS, MF

1 Introduction

Good quality of conversation, high capacity of the network and low use of power are some of the fundamental goals in designing cellular radio communication systems and one of approaches to achieve these goals is the Power Control [1].

The power control is being used in the most existing cellular systems. In addition to increment the life of terminal batteries, the power control prevents the base station's receiver to be blocked when it receives an over amount of power.

In general, there are two algorithms to control the power. First, the algorithms are based on this rule that increasing the path gain will cause the power to be decreased. In the simplest and most used kind of these algorithms, the intensity of the receiving signal is remained constant, and to reach the goal path gain should be compensated completely [2]. In another kind of this structure, only some changes of path gain will be remunerated [3]. Both structures will cause a slight increase in the capacity.

The second kind of algorithms will be designed on the quality of connection which the main factor of it is the Carrier to Interference Ratio (CIR).

In [4] it has been shown that increasing the capacity by using power control provides all the users with identical qualities. One of breakdown of these algorithms is need to a central control to remain stable. So because of that, use of them in present-day applications has been limited. In this paper a method which is based on the second kind of algorithms-but with fuzzy logic-, will be introduced (Without any need of central control). The rules of this algorithm will be written by considering the transmission environment and the quality level of the received data. We will continue with ANFIS algorithm to train the system's behavior in relation to fuzzy systems and to solve the problems of fuzzy method in finding the inference rules and to design the membership functions (MF). Considering that the neural network is able to learn the behavior of the system by using input and output information, the most suitable MFs and appropriate rules in accordance to the system, will be determined automatically. Paper's Structure would be as follows:

The ANFIS structure is introduced in Sec. II. The method of learning of ANFIS is shown in Sec. III. The system model to control the power is explained in Sec. IV, in Sec. V and Sec. VI the suitable ANFIS structure system and simulation, results and comparison of represented ANFIS with other existing algorithms will be presented, respectively.

2 ANFIS Analysis

ANFIS implements a Takagi Sugeno FIS (Fuzzy Inference System) and has a layered architecture as shown in Fig.1 [5]. For simplicity, we consider an ANFIS structure with two inputs x, y and one output f [6-9].

In Sugeno model, the final result will be stated as a mathematical relation between inputs and output.

If we want to use the first order Sugeno Model, rules will be stated as follows:

Rule 1: if (x is A_1) and (y is B_1) then
($f = p_1x + q_1y + r_1$)
Rule 2: if (x is A2) and (y is B2) then
($f = p_2x + q_2y + r_2$)
Rule 3: if (x is A_3) and (y is B_3) then
($f = p_9x + q_9y + r_9$)

The depicted ANFIS structure in Fig.1 is desirable for implementing above rules.

The ANFIS architecture is not unique. Some layers can be combined and still produce the same output. In this ANFIS architecture, there are two adaptive layers (1, 4). Layer 1 has three modifiable parameters pertaining to the input MFs [10]. These parameters are called *premise* parameters. Layer 4 has also three modifiable parameters (p_i, q_i and r_i) pertaining to the first order polynomial. These parameters are called *consequent* parameters. It is important to notice that the second, third and fifth layers are fixed layers. The network training is defined as modifying of these two layers in order to achieve the desired goal.

First layer has the role of changing x, y to Fuzzy sets. In this layer Gaussian MFs are used.

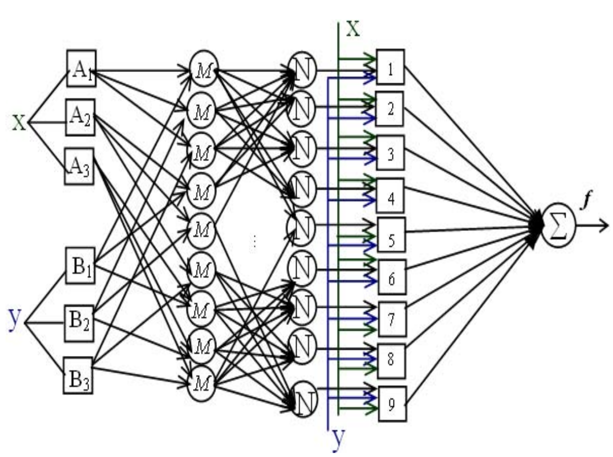

Fig. 1. The ANFIS structure

$$o_i = \mu_{A_i}(x) = gaussmf(\sigma_i, c_i) \quad i = 1,2,3$$
$$o_i = \mu_{B_i}(x) = gaussmf(\sigma_i', c_i') \quad i = 4,5,6 \qquad (1)$$

In (1) O_i , i = 1, 2, 3... 6 is the symbol of the first layer output. As a mentioned above, the parameters of this layer are known as premise parameters.

The nodes of second layer of this model are labeled M to indicate that they play the role of a simple multipliers. The output of each node in this layer (w_i) represents the firing strength of each rule.

The output of *i*th node from the third layer equals the *i*th rule Firing Strength, divided by all firing strengths' sum. The outputs of this layer are known as Normalized Firing Strength.

$$\bar{w}_i = \frac{w_i}{\sum_{i=1}^{9} w_i}$$

The forth layer's output (f_i) is consisted of the multiplication of the final result first order Sugeno fuzzy model by $\bar{w}_i$.

$$f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1,2,\ldots,9$$

And finally at the fifth layer which is an adder node, the resulted outputs of the forth layer are added together, until the final output is attained.

$$f = \sum_{i=1}^{9} f_i$$

3 Hybrid Learning Rules

If we assume the premise nonlinear parameters are fixed, the final result can be written as a linear combination of consequent linear parameters.

$$f = \sum_{i=1}^{9} f_i = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 \\ \cdots + (\bar{w}_9 x)p_9 + (\bar{w}_9 y)q_9 + (\bar{w}_9)r_9 \qquad (2)$$

Regarding this fact that equation (2) is linear in terms of the consequent parameters, so the LSE (Least-Squares Estimation) method can be used to train the parameters. In addition, to train the first layer parameters, the Back propagation can be used.

In forward path, after calculation the output of nodes to the forth layer, to calculate linear parameters vector, $\theta = [p_1, q_1, r_1, \ldots, p_9, q_9, r_9]$ which in this example is a 27-element vector, we use recursive LSE with the following form:

$$\alpha_{k+1} = \alpha_k - \frac{\alpha_k a_{k+1} a_{k+1}^T \alpha_k}{1 + a_{k+1}^T \alpha_k a_{k+1}} \qquad (3)$$

$$\theta_{k+1} = \theta_k + \alpha_{k+1} a_{k+1}(d_{k+1} - a_{k+1}^T \theta_k) \quad k = 0,1,2,\ldots,N-1 \qquad (4)$$

In which d_{k+1}, is *(k+1)*th desired training output. If we assume the relation between final output and vector θ, as $f = A\theta$ then a_{k+1}, the *(k+1)*th row of matrix A, can be calculated as follow:

$$a_{k+1}^T = [\bar{w}_1^{k+1} x^{k+1}, \bar{w}_1^{k+1} y^{k+1}, \bar{w}_1^{k+1} \\ ,\ldots, \bar{w}_9^{k+1} x^{k+1}, \bar{w}_9^{k+1} y^{k+1}, \bar{w}_9^{k+1}] \qquad (5)$$

In the equation (5) the superscripts, indicates the number of training set or the output number produced by training set. In addition N is the count of training data. In other words, it has been supposed that there are *N* numbers of training sets in the form of (x^i, y^i, f^i), $i = 1, 2, \ldots, N$ and α is a square matrix with rows and columns with the same size as vector θ. To begin we assume that θ_0 is equal to zero vector and α_0 is equal to βI, which β is a big and positive number.

In backward path to train the premise parameters, with keeping the linear parameters as constant values, we define an error function with the following form, using back propagation method:

$$E^i = \frac{1}{2}(d^i - f^i)^2$$

In which di is the desired output for ith training input group and fi is the real output of network with these inputs. So according to the gradient descent we have:

$$\frac{\partial E^i}{\partial f^i} = f^i - d^i \quad i, j = 1, 2, \cdots, N \tag{6}$$

$$\frac{\partial E^i}{\partial \overline{w}_j} = \frac{\partial E^i}{\partial f^i} \cdot \frac{\partial f^i}{\partial \overline{w}_j} = (f^i - d^i)(p^i_j x^i + q^i_j y^i + r^i_j) \underline{\underline{\Delta}} k^i_j \tag{7}$$

$$\frac{\partial E^i}{\partial w^i_j} = \frac{\partial E^i}{\partial \overline{w}^i_1} \cdot \frac{\partial \overline{w}^i_1}{\partial w^i_j} + \cdots + \frac{\partial E^i}{\partial \overline{w}^i_9} \cdot \frac{\partial \overline{w}^i_9}{\partial w^i_j} = \frac{1}{(\sum_{j=1}^{9} w^i_j)^2} [k^i_j \sum_{\substack{|l=1| \\ l \neq j}}^{9} w^i_l - \sum_{\substack{|l=1| \\ l \neq j}}^{9} k^i_l w^i_l] \underline{\underline{\Delta}} h^i_j \tag{8}$$

$$\frac{\partial E^i}{\partial o^i_1} = \frac{\partial E^i}{\partial w^i_1} \cdot \frac{\partial w^i_1}{\partial o^i_1} + \frac{\partial E^i}{\partial w^i_2} \cdot \frac{\partial w^i_2}{\partial o^i_1} + \frac{\partial E^i}{\partial w^i_3} \cdot \frac{\partial w^i_3}{\partial o^i_1} = h^i_1 o^i_4 + h^i_2 o^i_5 + h^i_3 o^i_6 \underline{\underline{\Delta}} \Delta^i_1 \tag{9}$$

$$\frac{\partial E^i}{\partial o^i_2} = h^i_4 o^i_4 + h^i_5 o^i_5 + h^i_6 o^i_6 \underline{\underline{\Delta}} \Delta^i_2 \tag{10}$$

Hence:

$$\frac{\partial E^i}{\partial o^i_j} = \underline{\underline{\Delta}} \Delta^i_j \tag{11}$$

As mentioned before, in the first layer the Gaussian MF is being used:

$$G(x) = gaussmf(\sigma, c) = \exp[-\frac{1}{2}(\frac{x-c}{\sigma})^2] \tag{12}$$

From (12) will be proved that:

$$\frac{\partial G(x)}{\partial x} = G_1(x) = -\frac{(x-c)}{\sigma^2} G(x)$$
$$\frac{\partial G(x)}{\partial \sigma} = G_2(x) = \frac{(x-c)^2}{\sigma^3} G(x) \tag{13}$$
$$\frac{\partial G(x)}{\partial c} = G_3(x) = \frac{x-c}{\sigma^2} G(x)$$

It is therefore possible to write:

$$\begin{cases} \frac{\partial E^i}{\partial \sigma_j} = \frac{\partial E^i}{\partial o^i_j} \cdot \frac{\partial o^i_j}{\partial \sigma_j} = \Delta^i_j G_2(x^i) \\ \frac{\partial E^i}{\partial c_j} = \frac{\partial E^i}{\partial o^i_j} \cdot \frac{\partial o^i_j}{\partial c_j} = \Delta^i_j G_3(x^i) \end{cases} \quad j = 1, 2, 3 \tag{14}$$

$$\begin{cases} \frac{\partial E^i}{\partial \sigma'_j} = \frac{\partial E^i}{\partial o^i_j} \cdot \frac{\partial o^i_j}{\partial \sigma'_j} = \Delta^i_j G_2(x^i) \\ \frac{\partial E^i}{\partial c'_j} = \frac{\partial E^i}{\partial o^i_j} \cdot \frac{\partial o^i_j}{\partial c'_j} = \Delta^i_j G_3(x^i) \end{cases} \quad j = 4, 5, 6 \tag{15}$$

After retrieving the former equations, the first layer training relation can be expressed as follow:

$$\begin{cases} \sigma_{j,new} = \sigma_{j,old} - \eta_\sigma \frac{\partial E^i}{\partial \sigma_j} \\ c_{j,new} = c_{j,old} - \eta_c \frac{\partial E^i}{\partial c_j} \end{cases} \quad j = 1, 2, 3 \tag{16}$$

$$\begin{cases} \sigma'_{j,new} = \sigma'_{j,old} - \eta_{\sigma'} \frac{\partial E^i}{\partial \sigma'_j} \\ c'_{j,new} = c'_{j,old} - \eta_{c'} \frac{\partial E^i}{\partial c'_j} \end{cases} \quad j = 4, 5, 6 \tag{17}$$

In (16) and (17) $\eta_c, \eta_\sigma, \eta_{c'}, \eta_{\sigma'}$ are the learning coefficients of c, σ, c', σ' parameters, respectively that are positive and small numbers in the range of [0, 1].

4 System Model

In this section, although we discuss the Uplink power control, with a little change all the results are valid for downlink, too. We assume a usual radio system with *N* channels. The number of mobile units that use a channel is *M*. We assume that there are different orthogonal channels and the units that use different channels don't have any interference with each other. We denote the transmitted power

of ith mobile unit which is communicating with jth base station and the link gain of jth mobile unit to ith base station with P_i and G_{ij}, respectively.
All the G_{ij} s are positive numbers and can get any value at the range of 0 to 1.

If v_i be the received noise at the ith base station, the CIR of the ith mobile unit at its own base station place can be achieved from the following equation:

$$\gamma_i = \frac{p_i}{\sum_{\substack{j=1 \\ j\neq i}}^{M} p_j A_{ij} + \eta_i} \tag{18}$$

Where $\eta_i = \frac{v_i}{G_{ii}}$. In fact η is an M dimensional vector which the ith element of it, is η_i. To simulate, η is eliminated in comparison with interference. And also $A = \{A_{ij}\}$ is an $M*M$ matrix which is defined as follow:

$$A_{ij} = \begin{cases} \frac{G_{ij}}{G_{ii}} & i \neq j \\ o & i = j \end{cases} \tag{19}$$

It can be proved that in order to have an irreducible matrix, at least one row of it, should contain more than one zero element. Considering the definition of the Matrix A, this matrix is none-negative and can be irreducible. Hence to express the characteristic of Matrix A we can use O.Perron, G.Frobenius theorem [11-14].
This theorem tells that if A is a none-negative irreducible M*M matrix with the eigenvalues $\{|\lambda_i|\}_{i=1}^{M}$, then:

1. A Matrix has a real positive eigenvalue λ^* equal to $\lambda^* = \max\{\{|\lambda_i|\}_{i=1}^{M}\}$.
2. Eigenvalue λ^* has an eigenvector p^* whose elements are positive.

Therefore, there would be a λ* which can be reached by all the mobile units [15-19].

In fuzzy power control structure, fuzzy MFs for power and CIR can be obtained by using try and error method. ANFIS is used to optimize the operation of the former algorithm. In this algorithm, inputs will be $p_i^{(n)}$ and $\lambda_i^{(n)}$ and the output will be power in the next iteration, means $p_i^{(n+1)}$.

4.1 Fuzzy structure

In fuzzy structure, mobile units correct their power levels individually, iterative and simultaneously in discrete time levels by using fuzzy system ρ. In ith cell, power level which will be used in the next iteration will be defined by the means of CIR and current power level means p_i. Both of the two parameters should be measured locally in the cell, by the mobile units and the base station. The system therefore has two inputs and one output [21]. Determining the fuzzy system ρ has 3 stages which are fuzzification, inference operation and unfuzzification.

4.2 Fuzzy sets

To design the fuzzy transmission function as simple as possible, the number of fuzzy levels will be taken small. Two fuzzy sets will be defined; one of them for power level and another for CIR. Transmitted power will be normalized between 0 and 1 and for fuzzification of that, 3 fuzzy sets with the Gaussian MF HP (High Power), MP (Medium Power) and LP (Low Power) will be considered as illustrated in Fig. 2.

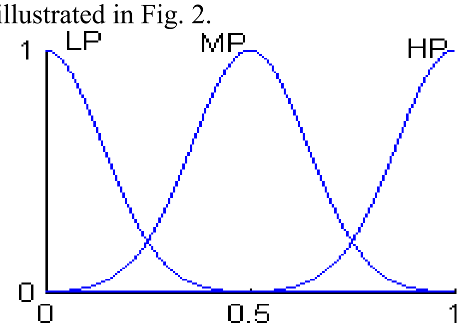

Fig. 2. Power membership function

Also for CIR, the Gaussian MF has the same form of Fig. 2 which is contained of 3 fuzzy sets LI (Low Interference), MI (Medium Interference) and SI (Sever Interference).

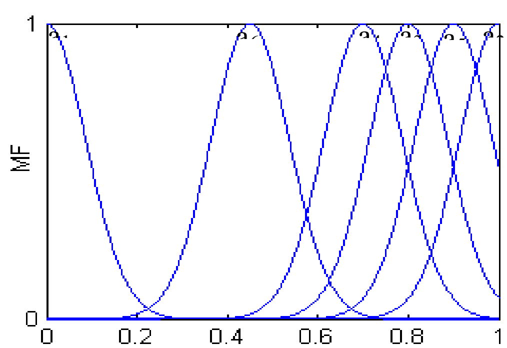

Fig. 3. Output membership function

For output membership the Gaussian function will be selected as shown in Fig. 3.

4.3 Fuzzification

If we assume that in the *i*th cell and at the *n*th iteration, the power level is $p_i^{(n)}$ and the corresponding CIR is $\lambda_i^{(n)}$ then the input ($p_i^{(n)}$, $\lambda_i^{(n)}$) would change to the following 6-element vector:

$$(\mu_{HP}(p_i^{(n)}), \mu_{MP}(p_i^{(n)}), \mu_{LP}(p_i^{(n)})$$
$$, \mu_{SI}(\lambda_i^{(n)}), \mu_{MI}(\lambda_i^{(n)}), \mu_{HI}(\lambda_i^{(n)}))$$

This operation is a mapping from 2-dimensional space to a 6-dimensional one.

4.4 Inference Operation

One inference rule would be allocated for each input of the fuzzy system. Noticing the MFs, 9 fuzzy rules will be written for the system. Means one 9-element vector $(a_1, a_2, \ldots, a_9)$ will be created that a_k is the degree of a rule which is fired by minimum inference. The Inference Operation is a mapping from 6-dimensional space to 9-dimensional. The resulted heuristic of designing fuzzy rules is as follows:

I. If (CIR is SI) and (Current Power is LP) then we will try to decrease the interference and to use high power.
II. If (CIR is SI) and (Current Power is MP) then we will increase the power more than MP.
III. If (CIR is SI) and (Current Power is HP), probably the situation is deep fade and in order to have no interference with others, we should use a lower power.

And the other fuzzy rules have been written in table 1.

Table 1
Fuzzy Rules

CIR / Power	SI	MI	LI
LP	a2	a3	a1
MP	a3	a4	a6
HP	a1	a5	a7

4.5 Unfuzzification

The power level at the next iteration is calculated by standard unfuzzier. Indeed, power at the next iteration is calculated with equation (20).

$$p_i^{(n+1)} = \frac{\sum_{k=1}^{9} a_k c_k}{\sum_{k=1}^{9} a_k} \tag{20}$$

a_k is the degree of every rule which has been fired at the *n*th iteration. And c_k is the average of output region which is inferred due to the mentioned rules.

And with the former explanations, the definition of the fuzzy system ρ is completed.

5 ANFIS Network Structure

The ANFIS Network Structure which is used in the simulations is the same structure which has been discussed in Sect. II, with this explanation that the inputs of structure are Power and CIR at the time n (means *n*th iteration) and the output is the Power at the time $n+1$. It is crucial to notice that the optimized output values which is needed in the hybrid Learning Algorithm to train the first layer parameters (nonlinear parameters), would be assumed as the same P^* vector which the definition and obtain approach of it, was shown at the O.Perron, G.Frobenius theorem.

6 Simulation and Results

We assume a symmetrical and fixed allocation strategy for channel that separates the cells into K channel groups. The cells that use identical frequencies are placed symmetrically in a hexagonal region.

The model which is widely accepted in the cellular communication systems for transmission of signals has been shown in (21) that after averaging over the fast fading, the receiving power is defined as follow:

$$p_r = p_t . r^{-\gamma} . 10^{(A/10)} \tag{21}$$

Which P_t is the power of transmitted signal, r is the distance between mobile unit and base station, γ is the transmission constant and A shows the slow fading which will be assumed as a random normal variable with zero average and standard deviation σ. In the simulations, we will assume that $\gamma=4$ and $\sigma = 6\ dB$.

We simulate the proposed ANFIS structure with the classical approaches DPC [20], DBA and FDPC [21] in the cellular radio system with $k=7$(iteration pattern). We assume that there are 16 co-channel users in this system which are using in a single common channel ($M=16$) and also the cells radius is $R=5km$.

The operation of FDPC and also ANFIS-PCA with DPC and DBA algorithms is shown in Fig. 4.

In this figure it is obvious that FDPC converge to CIR less than DPC but FDPC has this desirable specification that the used power level in mobile units is usually limited in the Normalization Boundary *[0.001,1]*.

In FDPC structure, the main factor is that the transmitted power should be in an applicative boundary which can not be reached by other DPC and DBA structures.

As mentioned before, in fuzzy control structure, using try and error the fuzzy MFs will be achieved for the Power and CIR. To optimize this Algorithm, we therefore use ANFIS. The ANFIS algorithm with p_i^n and γ_i^n as inputs, will obtain the Power at the next iteration, means $p_i^{(n+1)}$.

From the Fig. 4 it is obvious that in ANFIS algorithm, the minimum value of CIR converges to optimized value at the second iteration. In addition to the fuzzy advantages of this method, a fast converge will be created. In fact, comparing to other ANFIS methods, this is the fastest way for the minimum of CIR to get to the value of γ^*. For example it is possible to see that in the DPC method, we need at least *20* iterations to get to the value of γ^*; but in this method we will get to this value at the second iteration.

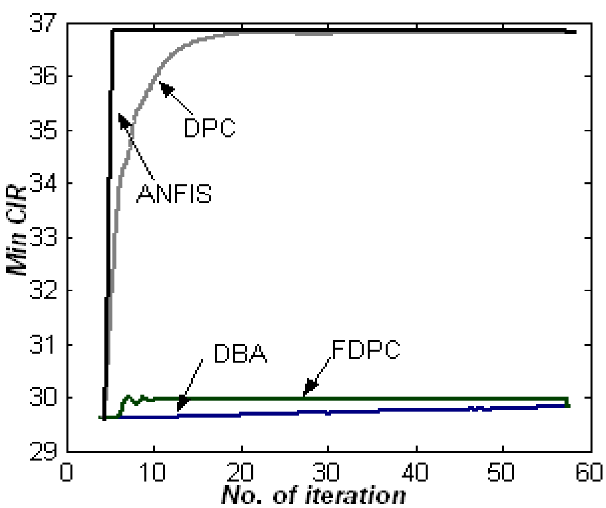

Fig. 4. The comparison ANFIS with other methods

7 Conclusion

In this paper, a new method based on Adaptive Neuro FIS (ANFIS) for power control in cellular radio communication is described. The simulation results show that the proposed method provides the fastest convergence among the former. Indeed, ANFIS at the iteration 2 gets the optimized value, means λ^*.

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