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A Study on Modeling of MIMO Channel by using Different Neural Network Structures

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Abstract: Recognition of Radio Channel (channel Parameters) is one of Main Challenges in Signal Transformation, and has important role in cognitive radio approach. Goal of this paper is "Channel modeling" to estimate coefficients of transmission functions affected on data being transformed in the channel. We use Multilayer perceptron(MLP) Neural Network with Back-propagation learning algorithm, block-structured Neural Network with Least Squares(LS) method(cost function) and a multilayer neural network with multiple back-propagation(MBP) learning algorithm for error estimation. These networks will be trained with received signals to be compatible with channel, then give us an estimation of these coefficients. Simulation will show that this MBP method is better than the other two method in error estimation. It has good performance and also consume less execution time. Then, we will use this network for estimating coefficients of non-linear transmission functions of actual radio channel.

Keywords: Cognitive Radio, Channel Recognition, Channel Modeling, Least Squares, Multiple Back-propagation (MBP), Neural Network, Transmission function.

I. INTRODUCTION

Today, multiple input – multiple output (MIMO) systems, with multiple antenna are noticed because of increasing in channel capacity and data rate without any increasing in band width. So for acquiring the maximum performance, we need give accurate and in-time information about channel state.

Affect of channel on transmitted signals is one of main discusses in radio channels. Channels usually have random behavior and so damaged with fading effects. This problem will cause inter-symbol interference (ISI). One of important goals is decreasing ISI, that can improve channel capacity. this estimation, is applicable in cognitive radio approach and is one of the most important challenges in this approach [1]. Other important goal of cognitive radio is to optimize transmitting and receiving of data in the radio network(cognitive network).

adaptive methods, against static methods, recognize requirements of users and allocate to them, just the resources they need. This will be cause effective use of system resource and eventually increasing the capacity of the system. So by optimal use of signal and decreasing the interference between users, this method can helps to increasing data rate and prevents the useless power consuming by users. So the quality of received signal can be improved and we need lower power for transmission of signals. This is useful in situations that we have weak signals.

In these situations, adaptive methods increase our coverable radio zone. so designing an adaptive receiver is very important in cognitive radio networks.

In this pare, we will evaluate power of mentioned neural network model, in estimation of channel parameters and eventually recognition of data that present channel state. We want to compare performance of these methods. the rest of paper is as follow: in section 2 and it's subsections we will explain the proposed method, modeling of MIMO radio channel, and also we will explain neural network inputs and outputs with respect to model. In section 3, we will explain the way of modeling of radio channel with neural networks. Section 4 involves evaluation of the neural methods. Finally section 5, involves conclusion.

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II. NON-LINEAR MODEL OF RADIO CHANNEL

Wherever Times This model involves: M inputs, a linear combiner(H) that present the propagation matrix, and L outputs that present the receiver antennas. This system involves M uncorrelated inputs with zero mean as $x_i(n), i = 1,2,\ldots\ldots, M$. Each input converted non-linearly by a converter function: $g_i(.)$. Then, outputs of this functions will be combined linearly by a matrix(H) with $M \times L$ dimensions that can varies with time. So the j[th] output of channel will be as (1) [2]-[4].

$$Y_j(n) = \sum_{i=1}^{M} h_{ji}(n) g_i(x_i(n)) + N_j(n)$$

Here, N_j is a white noise. Relation of inputs and outputs of system will be explained as (2).

$$\begin{bmatrix} Y_1(n) \\ Y_2(n) \\ \vdots \\ Y_L(n) \end{bmatrix} = H \times \begin{bmatrix} g_1(x_1(n)) \\ g_2(x_2(n)) \\ \vdots \\ g_M(x_M(n)) \end{bmatrix} + \begin{bmatrix} N_1(n) \\ N_2(n) \\ \vdots \\ N_L(n) \end{bmatrix} \qquad (2)$$

Hypothesis: here we just know the structure of the model, but we do not know the behavior of combiner matrix and blocks. Fig. 1 shows this problem.

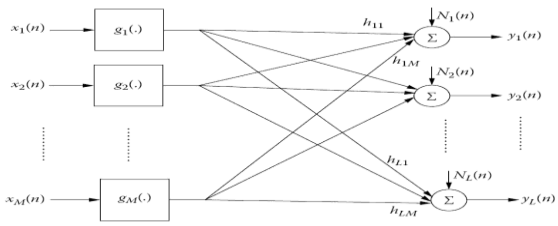

Fig. 1 non-linear MIMO system.

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III. NEURAL NETWORK PLAN(PROPOSED METHOD)

The neural network with block structure is shown in Fig. 2.

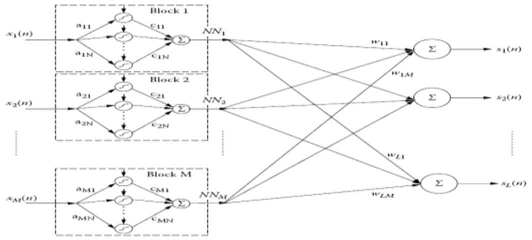

Fig. 2 neural structure of system

This structure involves M neural network blocks. Each block K has a scalar input as $x_k(n), k = 1,2,...., M$, N neuron and a scalar output as (3).

$$NN_k(n) = \sum_{i=1}^{N} C_{ki} f(a_{ki} x_k(n) + b_{ki}), k = 1,2...., M \quad (3)$$

Here, f is activation function of network(sigmoid), and coefficients b_{ki}, C_{ki}, a_{ki} are output weights in i[th] neuron at k[th] block, bios and input weights. Output NN_k of k[th] block linked to j[th] system output through weight w_{jk} . j[th] system output expressed by (4) [2]-[5].

$$S_j(n) = \sum_{k=1}^{M} w_{jk} NN_k(n), j = 1,2,..., L \quad (4)$$

The final matrix form of system will be explained as (5).

$$\begin{bmatrix} S_1(n) \\ S_2(n) \\ \vdots \\ S_L(n) \end{bmatrix} = W \times \begin{bmatrix} NN_1(x_1(n)) \\ NN_2(x_2(n)) \\ \vdots \\ NN_M(x_M(n)) \end{bmatrix} \quad (5)$$

A. *final adaptive system*

In supervised learning, input vector for MIMO and proposed neural network will be same. In each iteration, the parameters of neural network updated for minimizing the cost function. This function is explained as sum of squared errors between unknown system outputs and corresponding model outputs. These values have shown in (6) and (7) [6].

$$J(n) = \sum_{j=1}^{L} \left(e_j(n)\right)^2 \quad (6)$$

$$e_j(n) = Y_j(n) - S_j(n) \quad (7)$$

For more information about updating Equations of weights and coefficients can refer to [2]. So, the final adaptive system is shown in Fig. 3.

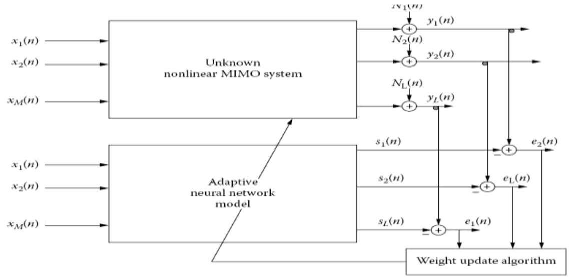

Fig. 3 adaptive system diagram

The most important problem in this model is minimizing the cost function. The coefficients of neural network blocks will be updated based on this value. So if neural network outputs are near the actual value in real channel, coefficients of neural blocks will be computed more accurately and the function $g_i(.)$ will be computed better. also the converging speed of neural networks is very important. Now, we have to improve this error by multiple back-propagation learning algorithm, implemented on multilayer neural network.

IV. EVALUATION OF PROPOSED METHODS

Here, we compute the sum of squared errors between desired outputs and network(obtained) outputs, using Equations described before. Also, we must find new approach for improving estimation of the error and other coefficients, to give a good formula for transmission functions($g(.)$). In Next section we will do this.

A. *Simulation results on neural methods*

In this section, we will improve the accuracy of estimation process, with implementing the multilayer neural network with MBP learning algorithm. In this method, We use the Root Mean Square Error(RMSE) instead of sum of squared errors used in block-structured and MLPNN methods.

In adaptive-neural planning of radio channel, we will implement the inverse computation from end of process to the beginning. The method is as follows: first we put S_j s as outputs of real radio environment. Then, design a network that estimate the NN_k s as outputs, related to values of S_j and give the weights of the network. Then, in the same manner we will design a new network and give it the NN_k s as outputs and X_i s as input, to estimate the coefficients of the network(a_{ij}, b_{ij}, c_{ij}).

We select inputs as binary data. then by selection of good values for neural network parameters we can give little time for learning stage. each column in input matrix of symbols, displays data transmitted by one of transmitter antennas. Network involves 100 inputs(matrix S) and 10 outputs(vector Y). Block-structured network has M inputs, and N neurons in each block. This is equal to a MLP with MN neurons. During neural network training, noise will added in percent form to inputs and correlated with them. Then network will affect these noises to the process. more important simulation parameters are shown in table (1).

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These coefficients are as weights of inner links of neural blocks of the second network.

During the training phase, weights of the different links in the network will be estimated and we can use these coefficients and weights for estimating the form of cost(error)function and also acquire the form of activation functions in nodes of the neural network, that are our final goal.

First, we generate random numbers with normal(Gaussian) distribution. Because, signals(data) transformed in radio environment, usually have this pdf or distribution[1,2]. for example, we will have the following data in table (1).

TABLE I. Some Inputs With Gaussian Distribution

-0.1867	0.7258	-0.5883	2.1832	-0.1364
0.1139	1.0668	0.0593	-0.0956	-0.8323

Then we make a file with such data to train the neural network. After identifying inputs and outputs of multilayer neural network, as described above, we will train the network, so that it can estimate the real output with 95% accuracy. So the weights of network will be obtained more suitable, and we will compute the function $g(.)$ better, because we compute NN_k s based on MBP training method and it helps us to guess the coefficients of the function more accurately. After estimating the NN_k s, we will compute the (a_{ij}, b_{ij}, c_{ij}) coefficients based on (3). Then we will compute the sum of squared difference between values obtained from (3) and values of NN_k s obtained from neural network learned by multiple back-propagation method. During computation of this error, we will compute the (a_{ij}, b_{ij}, c_{ij}) coefficients. So the Fig. 4 shows our overall method.

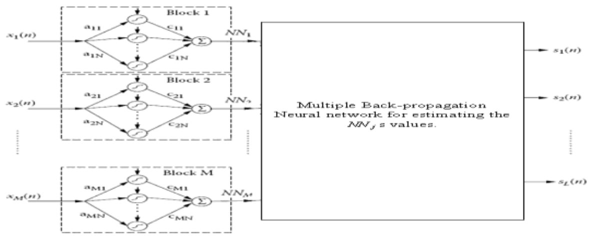

Fig. 4 method layout in estimating process

The outputs of multiple back-propagation neural network displayed in Figs. 5 to 8.

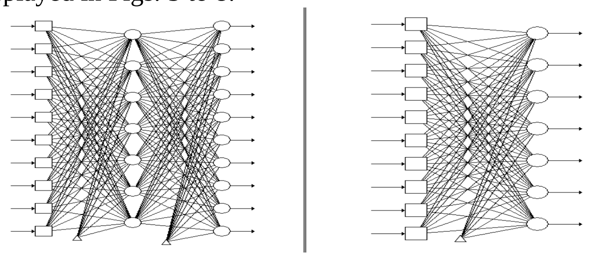

Fig. 5 multiple back-propagation architecture

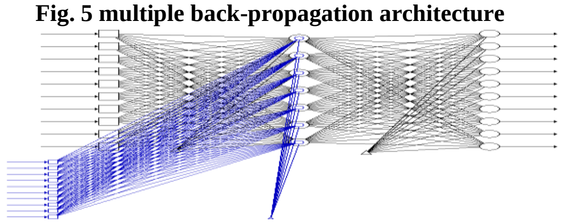

Fig. 6 architecture of network during learning phase

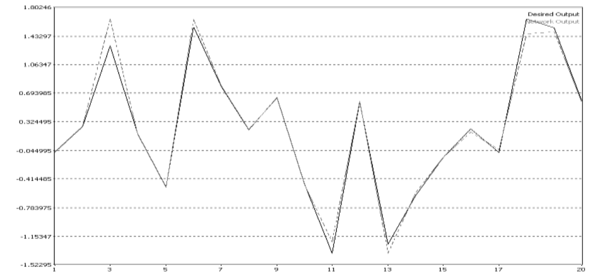

Fig. 7 root mean square error curve. Desired output (solid) and network output(dashed)

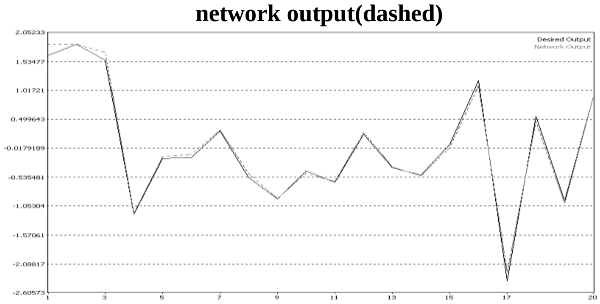

Fig. 8 root mean square error curve. desired output(solid) and network output(dashed)

Below figures are corresponding MBP neural network outputs.

As an Example, we will display two cases that are good estimations of radio channel, based on MBP learning algorithm. These have shown in tables (2) and (3).

TABLE II. Actual(Estimated) And Desired Values Of Outputs. For Rms Less Than Or Equal To 0.02(8th Network Output)

1	-0.068000	-0.061181
2	0.265200	0.270239
3	1.304600	1.651298
4	0.170800	0.161735
5	-0.514900	-0.521619
6	1.552500	1.648412
7	0.784000	0.795220
8	0.219200	0.225313
9	0.638100	0.634395
10	-0.482700	-0.488155
11	-1.371800	-1.227736
12	0.581700	0.591573
13	-1.257300	-1.371800
14	-0.628500	-0.590850
15	-0.138800	-0.137176
16	0.235700	0.195448
17	-0.072800	-0.034270
18	1.651300	1.460015
19	1.540900	1.485762
20	0.595100	0.581982

TABLE III. Actual(Estimated) And Desired Values Of Outputs. For Rms Less Than Or Equal To 0.02(5th Network Output)

1	1.648900	1.840600
2	1.840600	1.840600
3	1.553300	1.695833
4	-1.193100	-1.177166
5	-0.202900	-0.168369

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6	-0.189000	-0.131232
7	0.292100	0.303974
8	-0.543700	-0.476278
9	-0.928800	-0.913544
10	-0.424500	-0.466781
11	-0.628400	-0.616887
12	0.236500	0.268221
13	-0.364300	-0.348500
14	-0.502100	-0.519000
15	0.052600	-0.008653
16	1.191100	1.102164
17	-2.394000	-2.236379
18	0.555600	0.465007
19	-0.957700	-1.006657
20	0.897100	0.896897

Table (4) shows performance of three methods in error estimating has done on an instance problem. These methods are: MLP and block-structured neural network with standard Back-propagation learning algorithm, and Multilayer neural network with Multiple Back-propagation learning algorithm. Here, M=10, N=10 and L(linear combiner)=10.

TABLE IV. Comparing Different Methods Used In Channel Estimation

Multiple Back-propagation MLNN	Standard back-propagation MLPNN	Block-structured NN	Method
200	454	333	Epoch
0.52	0.7	0.6	Total elapsed time
0.0096564413	0.0099948021	0.856434320	Final acquired error
1300	2100	400	parameters
87	100	100	Sigmoid transforms
270	2000	300	multiplications
302	2100	310	additions

The a_{ij}, b_{ij}, c_{ij} coefficients obtained from this method are shown in tables (5) – (7). Here, we will just show a part of total estimated coefficients and we can compute form of the $g(.)$ function using theses coefficients and (3).

TABLE V. Coefficients Of Matrix A($\lfloor a_{1j} \rfloor, j=1,\ldots,9$)

$a_{1,1}$	$a_{1,2}$	$a_{1,3}$	$a_{1,4}$	$a_{1,5}$
0.2282	0.2871	0.2720	0.0934	0.8026
$a_{1,6}$	$a_{1,7}$	$a_{1,8}$	$a_{1,9}$	$a_{1,10}$
0.0091	0.7928	0.3795	0.4652	0.3046

TABLE VI. Coefficients Of Matrix B($\lfloor b_{1j} \rfloor, j=1,\ldots,9$)

$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$
0.7693	0.6952	0.1682	0.1008	0.6088
$b_{1,6}$	$b_{1,7}$	$b_{1,8}$	$b_{1,8}$	$b_{1,10}$
0.5111	0.8295	0.2893	0.8186	0.0048

TABLE VII. Coefficients Of Matrix C($\lfloor c_{1j} \rfloor, j=1,\ldots,9$)

$c_{1,1}$	$c_{1,2}$	$c_{1,3}$	$c_{1,4}$	$c_{1,5}$
0.7280	0.6259	0.1366	0.0028	0.6472
$c_{1,6}$	$c_{1,7}$	$c_{1,8}$	$c_{1,9}$	$c_{1,10}$
0.4175	0.3416	0.5003	0.5520	0.2337

V. CONCLUSION

In section 1, we have discussed about implication of radio channel modeling by neural network. In Section 2, we explained architectures of proposed neural networks for modeling the channel. In section 3 and its subsections, we have explained the neural plan of radio channel and some alignments on its parameters. In section 4 and its subsections, proposed neural methods were evaluated, and tested with some predefined(training) data.

As conclusion we must say that: LS method used in MLPNN and block-structured neural network has simple implementation but doesn't applicable in positions that signal – to – noise ration(SNR) is low, and it's complexity is high, when channel inputs varied continuously. So it's better that concentrate all of transmission power in training sequence or define a maximum power level for each antenna.

In this paper, we have shown that MBP method has better performance than BP method, and block-structured NN method(as minimum sum of square). Overall, we did a good estimation of cost function(error function) on radio channel, with MBP structure, and we have shown that RMS error is better than other regression methods used for function estimating.

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AUTHOR PROFILE

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