WIRELESS SIGNAL TRANSFER METHODS FOR POWER DETECTION AND FLOW CONTROL IN AN OMNIDIRECTIONAL ANTENNA NEURAL NETWORK ALGORITHM

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***Abstract*- In this study, we implement ERNN (artificial Elman Recurrent Neural Network) for adaptive beamforming with smart antennas. The emission pattern of a uniform linear array antenna may be steered using a neural network to focus many narrow beams on the desirable users while nulling out the signals of the undesired ones. The ERNN is trained using the Levenberg-Marquardt (LM) algorithm and the Resilient Backpropagation (Rprop) method, both of which are supervised training techniques. Five elements are employed in a uniform linear array, with a distance between each member equal to half a wavelength. Since LM is considered the quickest backpropagation training method, but it consumes more memory than other algorithms, the results of training ERNN with LM and Rprop indicated that LM training resulted in superior Neural Network (NN) performance than Rprop training results.**

***Keywords*- Smart Antenna, Conventional and Adaptive Beamforming, Elman Recurrent Neural Network.**

INTRODUCTION

The requirements for optimal coverage, enhanced transmission quality, and expanded capacity in today's mobile communication system are ever-increasing. Conventional cellular systems that rely on omni-directional or sectored antennas to establish a link between the mobile user and the base station waste a lot of electricity since the radiated power isn't focused in any one direction [1,2]. There are three basic impairments that affect the mobile communication system: co-channel interference, delay spread, and multipath[3]. To overcome the limitations of existing wireless systems and to maximize transmission speed and data rate, smart antennasystems give a practical alternative. When a smart antenna system is used, it may boost system capacity by directing the most energy toward the intended receivers while blocking out unwanted signals. Benefits include increased signal-to- interference (SIR) ratios, less power consumption, and increased frequency reuse within the same cell[4,5]. Smart antennas are able to improve mobile communication system performance because of the adaptive beamforming techniques used by the signal processing unit of the smart antenna system[6,7]. In this work, an ERNN-based smart antenna adaptive beamforming model is presented for the first time. The neural network is programmed to determine the most effective weights for focusing the arrays' narrow beam patterns in the intended directions of targets and nulling out the beam in the direction of interfering sources. Fast convergence rates, increased system capacity, nonlinear properties, and adaptive learning capabilities are only some of the benefits introduced by neural network approaches for smart antenna adaptive beamforming.

2.In-Building Antenna Network

An adaptable, spatially-aware method of transmitting and receiving antenna signals, a smart antenna system consists of a network of antennas connected to a central signal processing unit. Assigning individual signals from a plethora of sources, as smart antennas can do, may greatly improve the efficiency of cellular communications networks [8]. The digital signal processing (DSP) unit of an antenna array system is the source of a smart antenna system's capabilities and intelligence. Fig.1 shows a block schematic of an M-element smart antenna system [9,10,11].

1

M

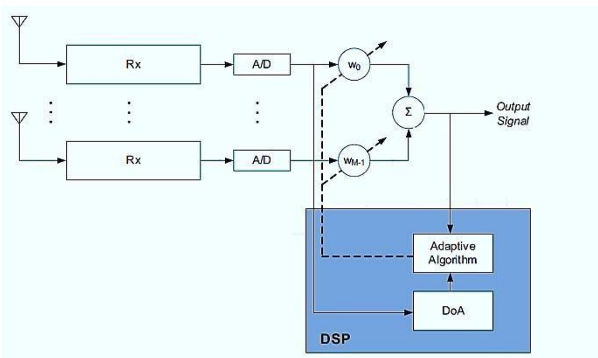


Fig1: Block diagram of smart antenna system

In this case, the DSP unit's adaptive algorithm determines the weights of the antenna array, where w0.....wM-1 are the weights of the antenna array, to direct the array's greatest radiation toward the targeted users while canceling out the interfering users. The term "DOA" is shorthand for a device that estimates the incoming signals' direction of arrival. Standard beamforming and adaptive beamforming are the two primary varieties of smart antenna beamforming.

3.CIRCUIT-BASED BEAMFORMING

The signals coming from various directions are analyzed usingpredetermined weights in a traditional beamforming smart antenna. The term "spatial matched filter" was coined because it "matches" the incoming signal from the desired direction with an equal and opposite "null" from all other directions[12]. To avoid adjusting the optimal weight over time, fixed weight beamforming assumed the angle of arrival of received signals would remain constant[2]. Antenna arrays may use a variety of fixed-weight beamforming algorithms, including the Minimum Mean-Square Error (MMSE), Maximum Signal-to-Interference Ratio (MSIR), Minimum Variance (MV), and Maximum Likelihood (ML) approaches. There is a block schematic of a fixed-weight beamformer in Fig .2[13].

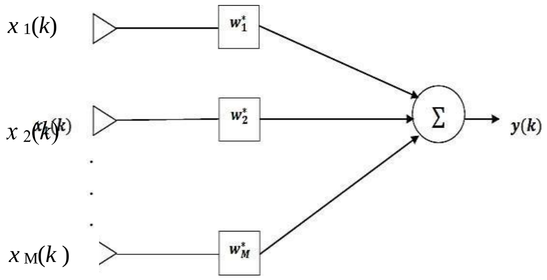


Fig 2: Fixed weight beamformer

the following form may be used to express the antenna array'sweighted output[8]:

$(k)=w^H.x(k)$ (1)

Where neural network may be identified by three distinct characteristics:

1. Architecture, or the network topology of how neurons are connected.
2. The algorithm for training or learning, which determines how connection weights are determined.
3. When a node receives certain input values, the activation function is the function that produces an output based on those inputs. [17].

Recurrent Neural Network (RNN)

One subset of artificial neural networks is called a "recurrent network." Regularized NNs may have one or more hidden layers. As can be seen in Fig.4, the primary distinction between feed forward and feedback networks is the presenceof one or more feedback loops. There are a variety of ways in which the feedback loop might manifest itself between any pair of neurons or between any two layers. Delay elements of

$(k) = a\ s\ (k\ )+[a\ \ a\ \ .....a\ \ ].[\ \mathrm{i}\ \ (k)\ \mathrm{i}\ \ (k)\ ..\mathrm{i}(k)]^{\mathrm{T}} + \mathrm{n}(k)$

length z1 are often present. Large numbers of feed forward

0 1 2

N 1 2

and feedback links give recurrent networks their complicated

$=x(k)+x\text{i}(k)+n(k)$ (2)

$w = [w1\ w2\ \ldots.wM]^{T}$ = weights of Array

$x(k)$ = desired vector of signal

$x(k)$ = vector of interfering signals

(k) = zero mean Gaussian noise for each channel

$a\text{i}$ = steering vector of M-element array for θi direction ofarrival

4.Refining Beams in Real Time

In adaptive beamforming, the received signals at each antennaelement are multiplied by complex weight vectors to adjust the amplitude and phase of the received signals to focus the beam on the targeted users while canceling out the interference from other sources. The output of an antenna array is the sum of the signals received by its many components. Traditionally, this has been done by minimizing the MSE [14] between the observed output of the array and the intended output. Block schematic of an adaptive beamformer is shown in Fig. 3.

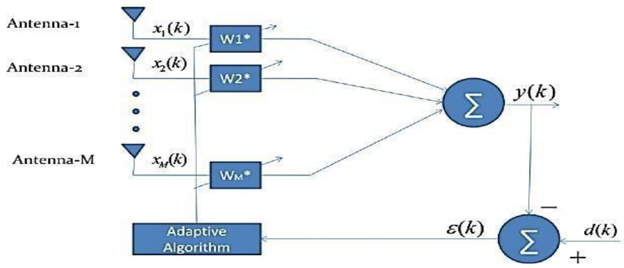


Fig 3: Adaptive beamformer

5.Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are a kind of AI software that attempts to represent the brain's operations and structure mathematically. Biological neural networks were the inspiration for the term "artificial neural nets," which serves to differentiate between computer-based and biological neural network systems. Applications of ANNs in the medical, industrial, and financial sectors are all on the rise[15]. Likewise, the nervous system networks are popular in the area of signal processing due of their quick convergence rates, general-purpose character, and capacity to retain the experimental information and make it accessible[16]. A dynamics. System identification, intelligent control, and other dynamical system applications are only some of the many uses for recurrent networks[17]. The layers with feedback connections may employ their prior activation in their previous behavior, as shown by the unit delay element of the feed- back loops, demonstrating that the RNN has local memory properties. Therefore, at each moment, the network's output may be computed by forward-propagating the input pattern through the NN and backward-propagating the recurrent activations to a context layer that can replicate the activation pattern from the output layer. The most popular recurrent neural networks were developed by Jordan and Elman [18, 19, 20]. Jordan's network is completely recurrent (all existing neurons' outputs are utilized for feedback), while Elman's is only partly recurrent.

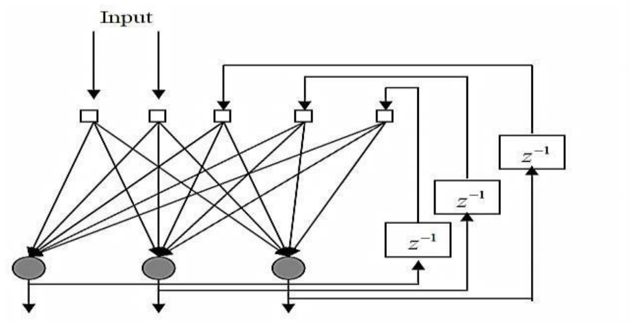


Fig 4: Recurrent neural network

6.Model in Math Of A Linear ArrayWith Constant Span

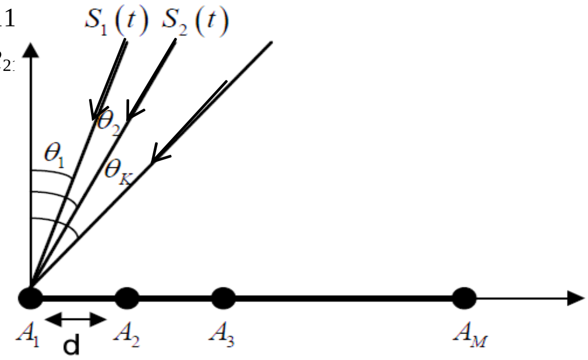
A Uniform Linear Array (ULA) with M(M>K) omnidirectional antenna elements spread by distance d from directions 1,2, K1,which lie between [-90,90], is expected to

receive K narrow-band incoherent plane waves. Figure 5 depicts the geometrical make-up of a linear array antenna.

The following signals are created to be received by the Melements of the antenna array system:

$R11$

R_{2}



$R12$ ……. . $R1M$

R_{22} … … … R_2 M 1

Rxx= E{X(k)X(k)^H} =

Fig 5: Geometry of linear array antenna

(13)

· I

I ·

L$RM1$ $RM2$ … … . .

RMM

where H refer to conjugate transpose, then the first row of the correlation matrix Rxx is taken to be as the input of neural network since it contain adequate information about the received signal as:

Z=[R11 R12...R1M] , then the input vector is normalized

to be more suitable as input of neural network :

$$B = \frac{Z}{\|Z\|}$$

(14)

the received signal at Mth antenna element is calculated by[11]:

and because the neural network does not operate with complex number ,therefore the real and imaginary part of eachelement in B vector is taken , so the dimension of B vector

$Xi(k) = \sum^{K}_{m=1}$

i=1,2,……M

$sm(k)\ e^{-j(i-1)km} + ni(k)$ (3)

will be twice (1x2M).The target output of neural network is

generated from the weight equation of Minimum VarianceDistortionless (MVDL) beamformer. The weights that

where :sm are the steering vector of signals received from i[th] sensor, ni (t) is the noise received at each element of array antenna and $k = \omega0\ d$ sin (θ)

m c m

generated from MVDL beamformer can provide optimal beamforming and steer the main beam of radiation pattern toward desired users and nulling undesired users in optimal

form. The antenna array weight based on MVDL beamformeris given in eq.(15)[21].

(4)

$^{-1}$

d

$W = \underline{Ad\ R}\ xx$(15)

where: d , is the distance between the array elements, ω0 is the angular frequency and c refer to the light speed in free space.
The formula of the received signal can be written in matrix form as :

$X(k)$=A$S(k)$+$N(k)$ (5)

Where:

A is array steering matrix toward the direction of theincoming signal and is given by:

A=[a(θ1),a(θ2)…….a(θk)] (6)

a(θm)=[1 e^{-jkm} e^{-j2km}…….$e^{-j(M-1)km}$] (7)

$X(k)$=[$x1(k)$ $x2(k)$……$xm(k)$]^T (8)

$N(k)$=[$n1(k)$ $n2(k)$ …… $nm(k)$]^T (9)

$S(k)$=[$s1(k)$ $s2(k)$ ……… $sm(k)$]^T (10)array output y can be given as follows:

$y(k) = w^H \cdot X(k)$ (11)

where:

w =[$w1$ $w2$ …. wM]^T (12)

w:weight vector of antenna array.

7.PROCEDURE FOR FORMED BEAMS

Using a neural network for multiple antenna beamformingentails two stages:

Start of the Training Process

The input and output pairs of an artificial neural network are created (preprocessed) at this stage so that the network may betrained on them, with the weights being saved after optimal training performance has been reached. Before, the initial correlation matrix.

op A ^{H} R $^{-1}$ A

d xx

Where Ad refer to the steering vector of K desired signals received by antenna array with M elements. The neural network training process is shown in Fig.6.

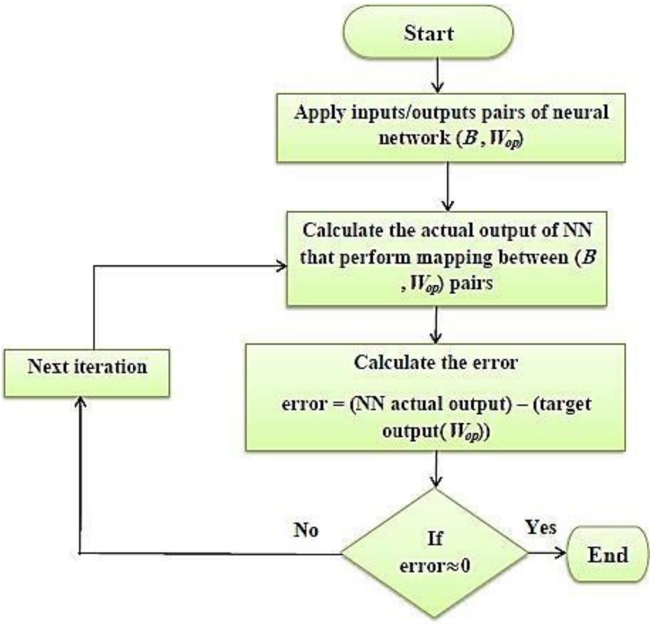


Fig 6: Training process of neural network

Upon achieving the optimal training performance, as seen in Fig.6, the network's weights are stored. To estimate the outputof data samples that were not used during training, the network will utilize these weights (unseen data sample). It should be noted that the network requires several trainingiterations to achieve optimal training performance, and that the stored iterations may be used later. Weights in a neural network represent the data-driven expertise the system has acquired over time..

Execution Phase

Here, the neural network uses its previously acquired empirical knowledge to make an educated guess as to the output (optimum weight (Wop)), based on the characteristics of newly received signals that were not present during training (the network was not trained on these signals). The neural network receives as its sole input the B vector from eq(14), and it uses this information to make its weight estimates. Antenna array systems employ these "weights" to focus many narrow beams in the desired directions while canceling out radiation in the interference'sdirection.

Figure 7 depicts the proposed ERNN model, which consistsof three layers with a context unit; the input and output layers each have three nodes (the same number as the samples used for training), while the hidden layer has five nodes determined by trial and error. ERNN uses tan sigmoid transfer functions as activationfunctions in both the hidden and output layers. These two supervised training algorithms—the Levenberg-Marquardt (LM) method and the Resilient backpropagation (Rprop) algorithm—are used to teach

ERNN.
The ERNN model, or Elman Recurrent Neural Network, is shown below.:

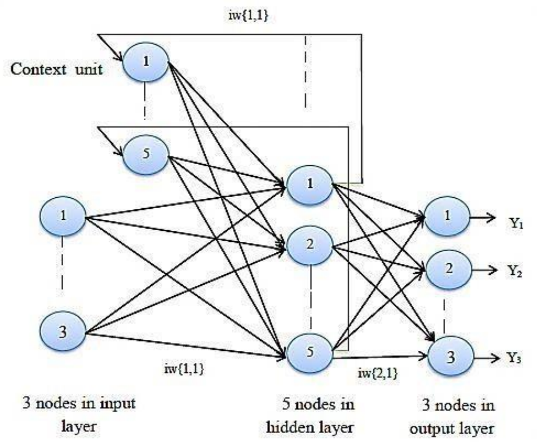


Fig 7 : Elman Recurrent neural network

where iw1,1 is the matrix of weights connecting the hidden layer to the context unit and iw2,1 is the matrix of weights connecting the output layer to the hidden layer; Y1, Y2, and Y3 are the ERNN outputs. In addition, the input/output pairs (B, Wop) needed to train the ERNN with the necessary weightvectors are created. If the ERNN is trained on the signals that arrived at [-90o, 0o, 90], the network is able to predict the weights of all unseen signals between the range [-90o,90o]. As soon as the network reaches its peak training performance, the weights vectors (iw1,1 and iw2,1) are stored, and thenetwork is sent to the test with unseen incoming signals (Wop). The antenna array system's beam pattern may be calculated using the following equation of array factor after the results of the artificial neural network training have been obtained:

$AF = |Wop(k)\, e^{-j(i-1)a(k)}|$ (16) $i=1,2\ldots..M$

where a(k) is the searched angle between (-900, 900) witha step size of (-90, 90) = 1..

8.Results and Discussions

For a uniform linear array with (M=5) and element spacing d=u / 2, we simulate the ERNN-based smart antenna beamforming and provide the results. The following supervised methods were used to train ERNN:

Levenberg-Marquardt (lm) Training

The best training phase performance for ERNN was [1.121938e-14] at epoch 38, with best validation performance equal to [1.682442e-14] and best test performance being [3.363946e-14]. This was achieved using the Levenberg- Marquardt (LM) algorithm and five hidden neurons.

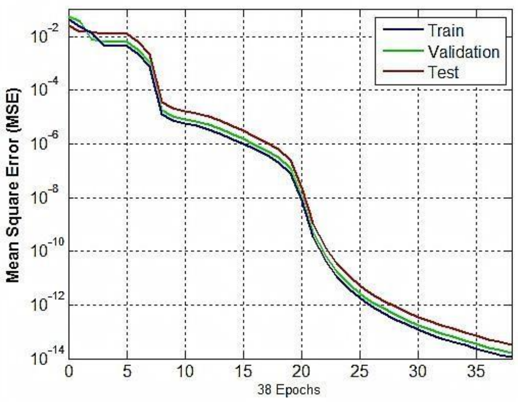
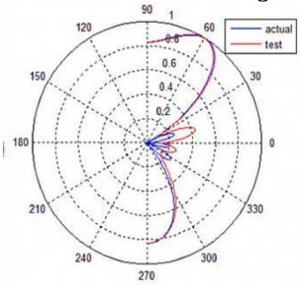


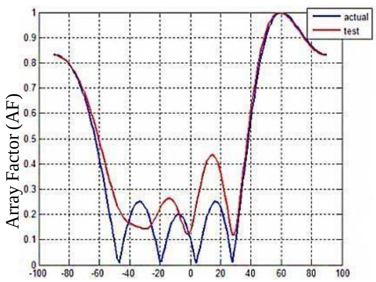
Fig 8: Performance of ERNN trained by LM algorithm

Following the completion of the LM-based ERNN training phase, the network was put through its paces by being exposed to some novel, previously unheard signals. Figure 9 is a linear and polar depiction of the beam pattern (uniform Array factor (AF) with respect to Angle Of Arrival (AOA)) for a newly arriving signal with a Direction Of Arrival (DOA) of 30 degrees (based on MVDL beamformer). Antenna beam pattern based on ERNN trained by LM method has a side lobe level that is around 0.05 higher than the true value.

Fig 9 : Antenna beam pattern using ERNN trained by LM algorithm (*M*=5, d=λ / 2,DOA=30º)

Linear and polar plot of new signal with DOA=60o is shown in Fig.10; the main beam is the same as the existing one, and the side lobe level is 0.18 dB higher than the existing side lobe.





Angle of Arrival (AOA) in degree

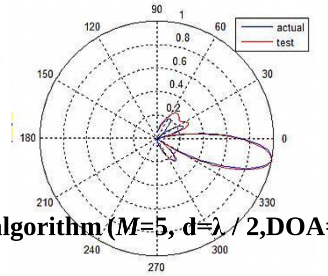
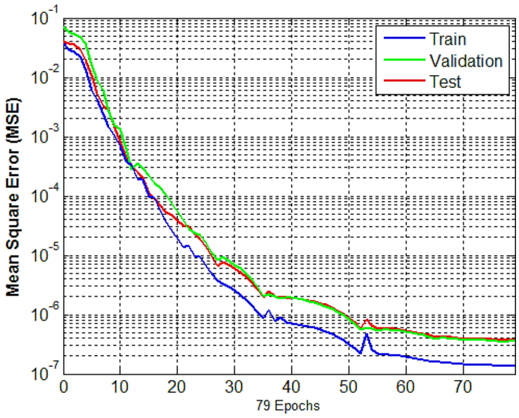


Fig 10 : Antenna beam pattern using ERNN trained byLM algorithm (*M*=5, d=λ / 2,DOA=60º)

Resilient Back-Propagation (Rprop)Training

Using the Rprop training method and five hidden neurons, ERNN training is proven to have a best phase training performance of [1.358237e-07], as seen in Fig.11. The greatest validation performance is [3.494906e-07] at epoch79, whereas the best test performance is [3.704479e-07].

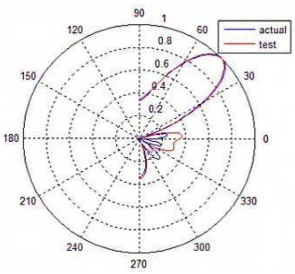


Performance/Training algorithm	LM	Rprop
Training performance	1.121938e-14	1.358237e-07
Validation performance	1.682442e-14	3.494906e-07
Test performance	3.363946e-14	3.704479e-07
epoch	35	79

Fig 11: Performance of ERNN trained by Rpropalgorithm

Good results were obtained while testing the ERNN on some novel unknown signals after the training phase based on the Rprop method was finished. As can be seen in Fig.12, the main beam of the antenna calculated using ERNN is almost equal to the real main beam. This is shown by a linear and polar plot of the beam pattern of the new incoming signal withDOA=45o. An ERNN trained with the Rprop method predicts a side lobe level of 0.12 for an antenna beam pattern, which is somewhat higher than the measured value.

Angle of Arrival (AOA) in degree



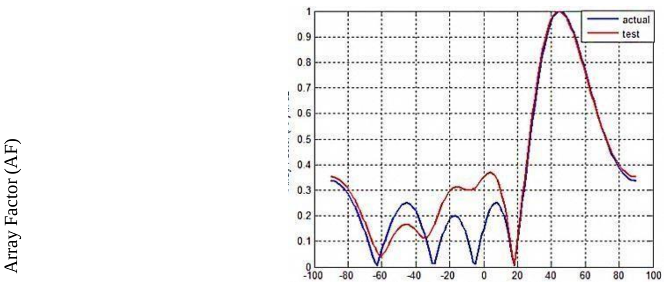
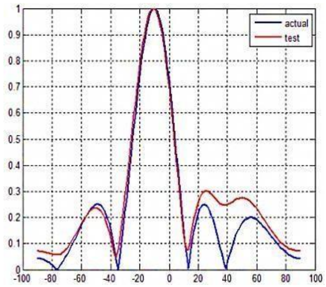


Fig 12 : Antenna beam pattern using ERNN trained byRprop algorithm (*M*=5, d=λ / 2,DOA=45º)

Figure 13 is a linear and polar plot of the newly arriving signal at DOA=-10 degrees, with a main beam that is equal to the real one and a side lobe level that is 0.05 percent higher than the side lobe of the actual beam.



Array Factor (AF)

Angle of Arrival (AOA) in degree

Fig 13 : Antenna beam pattern using ERNN trained byRprop algorithm (*M*=5, d=λ / 2,DOA=-10º)

We can see that the LM-trained ERNN outperforms the Rprop-trained ERNN in Table(1), but the LM training technique is more memory-intensive and needs fewer epochs.

Table 1 : Comparison between the performance of ERNNtrained by LM and Rprop

Antenna array enables active based on ERNN is shown in table (2), along with the amount by which it deviates from the real value for 10 transmissions. Since the inputs/outputs pairs of the neural network (B,Wop) may contain roughly equivalent adjacent samples, and since it has been proven byexperience that this will adversely affect the weights of the algorithm network, the outcomes show that the amount of increment in the side lobe level is almost the same for LM and Rprop, but it may be different from one angle of arrival to another.

Table 2 : The amount of in the side lobe level in the beampattern of antenna array pattern based on ERNN from the actual value for 10 signals.

DOA / Training algorithm	LM	Rprop
30º	0.05	0.01
60º	0.18	0.16
45º	0.12	0.12
-10º	0.05	0.05
-20º	0.133	0.133
40º	0.18	0.18
10º	0.05	0.05
-30º	0.01	0.01
-60º	0.15	0.15
-40º	0.18	0.18

7. CONCLUSION

In this study, we implement Elman Recurrent Neural Network (ERNN) for adaptive beamforming using smart antennas. It is a back propagation training method called LM and Rprop that is used to teach ERNN. In order to maximize signal strength in the intended user directions while canceling out interference from other sources, ERNN is taught to determine the optimal weights of an antenna array. When compared to the Rprop training algorithm, LM has been shown to perform better.takes up more space in the computer's memory than comparable algorithms. Fast convergence rates, nonlinear characteristic, improve capacity of system, and adaptive learning capabilities are some of the benefits introduced bythe use of neural networks in adaptive beamforming for smart antenna systems. Future work on this technique may involve reducing the level of complexity involved in the hybridization process between the artificial neural network and antenna array, which would allow for a greater number of desired users (targets) to be served by multiple narrow beams while simultaneously canceling out interference sources.

REFERENCES:

[1] RK Jain, Sumit Katiyar and NK Agrawal, "Smart Antenna for Cellular Mobile Communication" VSRD International Journal of Electrical, Electronics & Communication, Department of Electrical & Electronics Engineering, Singhania University, Jhunjhunu, Rajasthan, INDIA, Vol. 1 (9), 2011, pp.530-541.

[2] Hung Tuan Nguyen ,"Multiple Antenna Systems for Mobile Terminals", PhD. Thesis , Department of Communication Technology., Aalborg University, Denmark, 2005.

[3] Jack H.Winters AT and T Labs, "Smart Antennas For Wireless Systems" IEEE Personal Communication, ISSN :1070-9916 February 1998,pp.23-27.

[4] Frank Gross, "Smart Antenna for Wireless Communications " , Mcgraw-hill, September, 2005.

[5] Murray, B.P. and Zaghloul, A.L. "Survey Of Cognitive Beamforming Techniques " IEEE ,Dept. of Electrical and Computer Engineering, Virginia Tech, Blacksburg,

VA, USA, ISBN:978-1-4799-3119-4 ,January 2014

[6] Nwalozie G.C, Umeh K.C, Okorogu V.N and Oraetue C.D, "Performance Analysis of Constant Modulus Algorithm (CMA) Blind Adaptive Algorithm for Smart Antennas in a W-CDMA Network", International Journalof Engineering Science and Innovative Technology (IJESIT), ISSN: 2319-5967, Volume 1, Issue 2, November ,2012 ,pp.246-254.

[7] Xu-Bao Shun and Shun-Shi Zhong, "An Adaptive Beamforming Approach Using Online Learning Neural Network", IEEE, School of Communication and Information Engineering ,Shanghai University, China , ISBN:0-7803-8302-8, June 2004 ,pp.2663-2666.

[8] Ahmed H. El Zooghby, , Christos G. Christodoulou, and Michael Georgiopoulos, "A Neural Network Based Smart Antenna for Multiple Source Tracking ", IEEE , TRANSACTIONS ON ANTENNAS AND PROPAGATION, Electrical and Computer Engineering Department, University of Central Florida, Orlando, FL 32816 USA., VOL8, NO. 5, May 2000,pp.768-775.

[9] Halil Yigit , Adnan Kavak and H .Metin Ertunc "Using Autoregressive and Adaline Neural Network Modeling toImprove Downlink Performance of Smart Antennas",IEEE, Department of Electronic and Computer Engineering, Kocaeli University, Izmit, Turkey, ISBN:0-7803-8599-3,June 2004,pp.165-170.

[10] Nuri Celik, , Wayne Kim, Mehmet F. Demirkol, Magdy F.Iskander, Rudy Emrick, "Implementation and Experimental Verification of Hybrid Smart-Antenna Beamforming Algorithm",IEEE, Hawaii Center for Advanced Communication, University. of Hawaii, Honolulu, HI, VOL. 5, April 2006,pp280-283.

[11] Ross D. Murch and Khaled Ben Letaief, "Antenna Systems for Broadband Wireless Access ",IEEE Communications Magazine, Hong Kong University of Science and Technology, Department of Electrical and Electronic Engineeringof Science and Technology, China, ISSN :0163-6804, April 2002,pp76-83.

[12] Heikki Koivo and Mohammed Elmusrati , "SmartAntennas",Systems Engineering in WirelessCommunications, John Wiley and Sons, Ltd. ISBN: 978- 0-470-02178-1,2009, ,pp 261-302 .

[13] Mohammad Tariqul Islam and zainol Abidin Abdul Rashid , " MI-NLMS Adaptive Beamforming Algorithm For Smart Antenna System Applications", Journal of Zhejiang University Science, Department of Electrical, Electronics and System Engineering, Faculty of Engineering, University of Kebangsaan Malaysia, ISSN 1009-3095,July 2006 pp.1709-1716 .

[14] Jian Li and Petre Stoica, "Robust Adaptive Beamforming",J OHN WILEY & SONS, INC, ISBN: 10 0-471- 67850-3,2005.

[15] D.M. Rodvold, D.G. McLeod, J.M. Brandt, P.B. Snow, and G.P. Murphy, "Introduction to Artificial Neural Networks for Physicians: Taking the Lid Off the Black Box", Wiley-Liss,Inc., Volume 46, Issue 1, January 2001, pp.39–44.

[16] A. H. El Zooghby, M. Georgiopoulos and C. G. Christodoulou , "Neural Network-Based Adaptive Beamforming for One- and Two-Dimensional Antenna Arrays", IEEE, Electrical and Computer Engineering Department, University of Central Florida, Orlando, FL 32816 USA, December 1998 pp.1891-1893.

[17] Laurene Fausett, " Fundamentals Of Neural Networks Architectures, Algorithms and Applications ",Prentice-Hall,ISBN: 0133341860, 9780133341867,1994 .

[18] Wai-Kai Chen, "Neural Networks and Computing Learning Algorithms and Applications" , SERIES IN ELECTRICAL AND COMPUTER ENGINEERING,University of Illinois, Chicago, USA), ISBN-10 1- 86094-758-1,2007.

[19] Medsker L.R. and L.C. Jain, "Recurrent Neural Networks Design And Application" ,CRC Press, Boca Raton London New York Washington, D.C, 2001.[48] Graves A., Hinton G, and Mohamed A. . ,"Speech Recognition with Deep Recurrent Neural Networks" Department of Computer Science, Toronto University, PP.1-5, 2012.

[20] Ben Krose and Patrick van der Smagt,"An Introductionto Neural Networks", 8th eddition, Amsterdam University, November 1996.

[21] Guez-Estrello , Carmen B. Rodr, and Felipe A. CruzPérez, "An Insight into the Use of Smart Antennas in Mobile Cellular Networks" , University Campus ,ElectricEngineering Department, ISBN 978-953-307-246- 3,April 2011