MIMO System with GA DFE-ANFIS Framework

Kandarpa Kumar Sarma and Nikos Mastorakis

***Abstract*—**Modeling multi input multiple output (MIMO) wireless channel continues to be a challenging area of research due to the stochastic nature observed in the path gains and the medium being infested with uncertainty. Traditional methods of modeling the MIMO channels have already been established to be reliable tools yet certain issues still remain in the forefront. This primarily is attributed to the fact that at some stage a prediction aspect plays a significant part where soft computing tools can play a significant part. Soft-computational approaches have been accepted as additional options as these tools learn from the environment, retain it and use the knowledge acquired for subsequent processing. The constraints observed with computational complexity of such systems are lowered by combining them with other statistical and evolutionary aids. Here, we propose such a framework designed using fuzzy systems and a variation of Recurrent Neural Network (RNN). Fuzzy systems have proven to be effective for modeling uncertainty while RNN is a derivative of Artificial Neural Network (ANN) that adopts multiple multiple feedback loops to track time-dependent variations in input patterns. Further, decision directed equalizer (DFE) based estimates of the channels are utilized for training the composite hybrid block formed around an adaptive neuro-fuzzy inference system (ANFIS). The ANFIS is constituted by fuzzified RNN (FRNN) blocks configured to model MIMO channel characteristics and optimized by a Self Organizing Map (SOM). During the fuzzification stage, a genetic algorithm (GA) block selects the most suitable set of parameters (center, slop and spread) of the Bell-membership function (MF) which contributes to the precision of the system. The proposed architecture demonstrates lower processing speed and improved precision during recovery of transmitted data through severely faded MIMO channels compared to other fuzzy based methods.
.

***Keywords*—MIMO, ANFIS, DFE, Training, RNN.**

I. INTRODUCTION

Multi input multiple output (MIMO) wireless system is a backbone of high data rate mobile communication networks though its channel estimation continues to be a challenging area. It is because of the uncertainty and stochastic beviour observed in the wireless medium resulting due to fading, interference and correlation among propagation paths and related variations. A host of traditional methods of modeling the MIMO channels have already been explored and respective potential established. Further, soft-computing approaches have been accepted as additional options as these tools learn from the environment, retain it and use the knowledge acquired for subsequent processing. Over the years, soft computing tools like Artificial Neural Network (ANN), fuzzy systems and their combinations have received attention in wireless communication. This is because of the fact that these are learning based systems. These acquire knowledge from the environment, hold back the learning and use it subsequently. The constraints observed with computational complexity of such systems are lowered by combining them with other statistical and evolutionary aids. It offers improvement in performance. Fuzzy systems provide qualitative and knowledge based mechanisms for control and decision making while ANNs are non- parametric prediction tools that have the ability to replicate biological behaviour. It provides fuzzy-based hybrid systems like neuro-fuzzy blocks the ability to acquire numeric-qualitative, expert level decision making and demonstrate greater adaptability and robustness while modeling unknown processes or situations. Such advantages of fuzzy based systems combined with ANNs are analyzed and configured for modeling wireless channels and related phenomena. Fuzzy systems along with neuro components form Fuzzy Neural System (FNS) and Neuro Fuzzy System (NFS). These are robust, adaptive and efficient systems for application as expert decision making modules suitable for a wide range of processes including dealing with the stochastic MIMO channels.

Here, we propose an approach based on a hybrid soft-computing framework designed using fuzzy systems and a variation of Recurrent Neural Network (RNN). Fuzzy systems have proven to be effective for modeling uncertainty while RNN is a derivative of Artificial Neural Network (ANN) that adopts multiple feedback loops to track time dependent variations in input patterns. Further, decision directed equalizer (DFE) based estimate of the channel is provided to the composite hybrid block formed using an adaptive neuro-fuzzy inference system (ANFIS). The ANFIS is constituted by fuzzified RNN (FRNN) blocks configured to model MIMO channel characteristics. The proposed architecture has split ANFIS blocks designed to deal with in-phase and quadrature components of received signals optimized by a Self Organizing Map (SOM). During the fuzzification stage, a genetic algorithm (GA) block selects the most suitable set of parameters (center, slope and spread) of the Bell-membership function (MF) considered for aiding to the precision of the

Kandarpa Kumar Sarma is with the Department of Electronics and Communication Technology, Gauhati University, Guwahati-781014, Assam, India. (e-mail: kandarpaks@gmail.com).

Nikos Mastorakis is with the Technical University Sofia, Bulgaria (e-mail: mastor@tu-sofia.bg).

system. The proposed architecture demonstrates lower processing speed and improved precision during recovery of transmitted data through severely faded MIMO channels compared to other fuzzy based methods.

An account of some applications of fuzzy systems in communication is provided in [1]. One of the earliest reported applications of fuzzy systems in wireless communication is described in [2]. It reports the use of a recursive least square (RLS) fuzzy adaptive filter for non-linear channel equalization. A work of similar nature that can also be considered to be among the few earliest reported is [3]. It deals with a fuzzy based channel equalization problem. Another work [4], reports the use of fuzzy systems to perform channel estimation in CDMA based wireless communication. A simple method reported in [5] shows that data sequence and estimates of the channel condition can be carried out at the same time using the Viterbi algorithm and fuzzy logic for the convolutional code. After a fixed number of decoding steps, the fuzzy logic unit reads the branch metric value of the survivor and the difference between maximum and minimum survivor path metric values at the Viterbi decoder and estimates the channel condition with the signal-to-noise ratio (SNR). The proposed method enables the channel estimation regardless of what kinds of modulator and demodulator are used. Another work refereed in [6] presents the equalization of channel distortion by using NF network. The structure and learning algorithm of NFS network have been described. Using learning algorithm of NFS network an adaptive equalizer have been developed. The developed equalizer recovers transmitted signal efficiently. The use of NFS equalizer in digital signal transmission allows decreasing training time of parameters and the complexity of network. Some other works are [7] - [10]. Use of fuzzy logic as the core of the reasoning engine to determine different parameters used by the WiMAX system is reported in [11]. This work focuses on one of the main functions of the reasoning engine i.e. determination of the channel type and the number of pilots used for channel estimation. Anther work introduces an Adaptive Neural Fuzzy Channel Equalizer (ANFCE) based on Adaptive Neural Fuzzy Filter (ANFF) [12]. The ANFF is a five layer ANN which is able to use the expert knowledge in its structure. The structure and parameters of this network are adjusted according to the training data and the available expert knowledge. A work cited in [13] proposes a computationally efficient NFS based equalizer for use in communication channels. This equalizer performs close to the optimum maximum a-posteriori probability (MAP) equalizer with a substantial reduction in computational complexity and can be trained with a supervised scalar clustering algorithm. To evaluate the performance of this system, the authors use BER and mean square error (MSE) criteria. The authors report the design of a feedforward ANN based approach for multipath Rayleigh channel estimation in a MIMO set-up [14]. The work [15], reports the use of a fuzzy MLP for application in stochastic MIMO channels. In [16], authors propose a FNS based MIMO channel modeling while in [17] the authors explore the usefulness of NFS or FNS for such applications. The use of an ANFIS based system for MIMO channels is reported in [18] where the authors use a Kalman filter for providing the training reference to the fuzzy system. In [19], the authors discuss about the used of GA aided technique for optimization of channel estimated obtained using an ANFIS system. In [20], the application of RNN blocks in MIMO channel estimation has been discussed. In all the above mentioned cases, the reported works have concentrated either on ANN, NFS or FNS learning and decision making approaches with the focus to improve performance of such systems with applications in time-varying wireless channels. These works have highlighted how ANN and fuzzy based systems are able to deal with the uncertainty observed in wireless channels and also track minute variations which are created due to the time dependent nature of such channels.

The rest of the paper is organized as follows. Section II introduces the conceptual framework of using fuzzy based approaches for modeling MIMO channels. The proposed GA aided ANFIS system for modeling MIMO channels is explained in Section III. Experimental details are covered in Section IV. Section 5 concludes the description.

II. MIMO Channel Modeling using Fuzzy-based Approach

Fuzzy systems in NFS form provide certain advantages for which it has been considered as the primary system for MIMO channel estimation. The decision making mechanism of such a system is considered here in this work. The critical aspects about the NFS are its ability to follow subtle variations in the stochastic wireless channel and the ease of design and

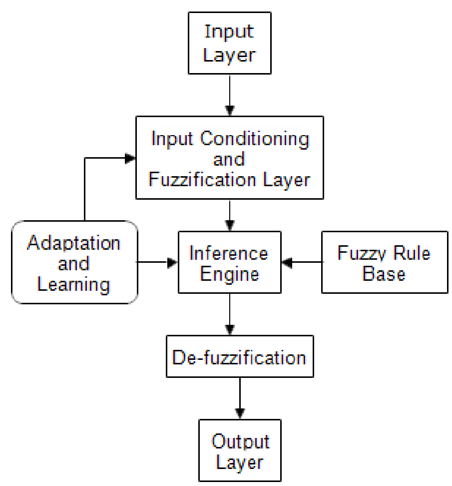

Figure 1: Different stages of a fuzzy based system

implementation of the fuzzy inference system using a traditional ANN in feed forward (FF) form. The key components of a fuzzy-based system are fuzzification, inference and defuzzification stages which is shown in Figure 1. The NFS relates a crisp input to a corresponding output, hence requires fuzzification and de-fuzzification stages.

A $m \times n$ linear MIMO system with outputs $x_1, x_2, \cdots, x_n$ and inputs $s_1, s_2, \cdots, s_m$ can be expressed as $x_1 = f_1(s_1, s_2, \ldots, s_m)$, $x_2 = f_2(s_1, s_2, \ldots, s_m)$, …, $x_n = f_n(s_1, s_2, \ldots, s_m)$ where $f_i(.)$ represents a transformation function at the i^{th} receiver end. It also denotes the non-linear variations in the channel which the transmitted signals acquire while propagating through it. The function $f_i(.)$ also encompasses the phase shifts and fading encountered in the wireless channel due to multipath propagation.

The MIMO channel input-output relationship is expressed as

$$x_n = H(n)s(n) + v(n) \qquad ------(1)$$

where x is an $\mathrm{M} \times 1$ vector with $x_i(n), i = 1, 2..., \cdots M$ as the elements, $s(n)$ representing the signal symbols, $v(n)$ denotes additive background noise with $\mathrm{H}(\mathrm{n})$ being the M x N channel matrix which maybe Rayleigh, Rician and Nakagami multipath fading. A fuzzy-based system implemented using a ANN framework adopted to model MIMO channel is shown in Figure 2.

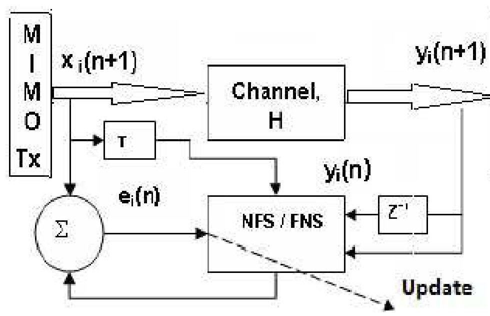

Figure 2: Fuzzy system based channel estimation

Table 1: Linguistic steps used to condition the inputs

Sl. no.	State	Notation
1	Negative Large	NL
2	Negative Medium	NM
3	Negative Small	NS
4	Close to Zero	CZ
5	Positive Large	PL
6	Positive Medium	PM
7	Positive Small	PS

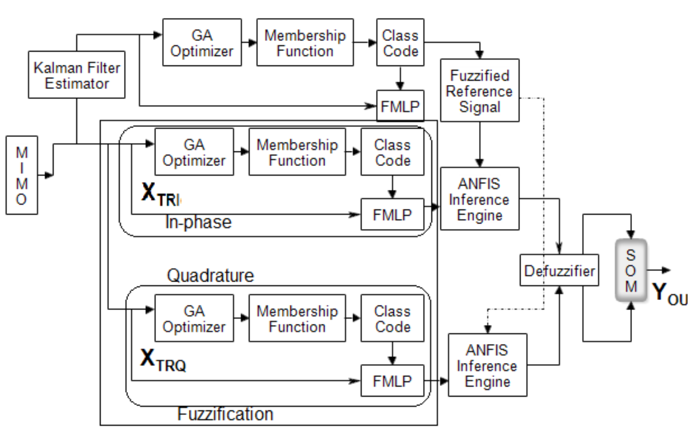

Figure 3: System model of proposed GA aided Split-ANFIS approach

III. Proposed MIMO Channel Modeling Using GA Assisted DFE- ANFIS

The block diagram of the proposed split ANFIS based framework for MIMO channel modeling is shown in Figure 3. The following sections provide the relevant details considered while formulating input conditioning norms, inference rule sets and the design issues considered for the proposed fuzzy-based approach.

A. Input Conditioning

The sample set considered includes 2 × 2 and 4 × 4 MIMO set-ups with orthogonal frequency division multiplexing (OFDM) data sets for different AWGN values like −3dB, 1 dB and 3 dB. This is done for the Gaussian, Rayleigh and Rician faded channels with different signal conditions with SNR values varying between −10 to 10 dB. The samples are subjected to a few linguistic steps as shown in Table 1. The inputs are also associated to the following set of norms:

$$\begin{aligned} f(x) &= NL, -0.66 \le x < -0.99; \\ &= NM, -0.33 \le x < -0.66; \\ &= NS, 0 < x < -0.33; \\ &= CS, \quad x = 0; \quad ------(2) \\ &= PL, 0.66 \le x < 0.99; \\ &= PM, 0.33 \le x < 0.66; \\ &= PS, 0 \le x < 0.33; \end{aligned}$$

B. GA-aided Parameter Selection for Fuzzification

The GA block receives estimates from the DFE which provides initial and fast estimates of the signals used for training the ANFIS blocks. The DFE uses a few pilot carriers from the signal block to provide a reduced size but near true copy of the transmitted data. It serves as the support to the training stage of the ANFIS. During the fuzzification process, the Bell MF is used. This MF provides smooth and non-linear functions optimally approximating the real world signals and are also suitable for learning systems like ANN. The Bell MF has three parameters namely slope, spread and center the selection of which is always a tedious process requiring a trial and error mechanism. Here, GA is used to select these three parameters such that an optimal set of these parameters are obtained. The steps involved in the GA assisted selection of the three parameters are shown in pseudo code form in Algorithm 1. The GA-aided block helps to increase the precision and the overall processing time of the system which is evident in the results explained in subsequent sections. For the three parameters, the mean square error (MSE) of the ANFIS system is taken as the fitness criteria. The set of values for which the best MSE is obtained at shortest time is considered to be the optimum set of slope, spread and center for the Bell MF. For different center values a search of 2000 integer values of slope and 500 non-zero values of spread are used to run the GA optimization. Four numbers of MFs are used in the fuzzification stage to generate the training, validation and test data.

C. Inference Rule Set

Two sets of inference rules are formulated. One set is shown in Table 2. The first set has less number of intermediate states while the second one contains more steps to facilitate finer classification and provide better precision.

Algorithm 1 GA in simplified form

1: [Start] Generate random n chromosomes (likely solutions)
2: [Fitness] Evaluate fitness f(x) of each chromosome x
3: [New population] Create repeating following steps
4: **while** Until the new population is complete **do**
5: [Selection] Select two parent chromosomes from a population according to their fitness
6: [Crossover]
7: **if** Crossover probability **then**
8: Generate new offspring
9: **else**
10: Offspring is an exact copy of parents
11: **end if**
12: [Mutation] With a mutation probability, mutate new offspring at each locus (position in chromosome);
13: [Accepting] Place new offspring in a new population
14: **end while**
15: [Replace] Use new generated population for a further run of algorithm
16: [Test] If the end condition is satisfied, stop, and return the best solution in current population
17: [Loop] Go to step 2.

D. ANFIS based Inference Engine formed using FRNN

The ANFIS based inference engine formulated to implement the norms shown in Table 2 is formed by FRNN blocks. The ANFIS is in split form to deal with real and quadrature components of the input patterns. The fuzzified inputs are passed on to the ANFIS which decides upon the class-wise discrimination by finding a best match of the cluster codes. The FRNN is formed by multiple layers of fuzzy recurrent neuron (FRN) units (Figure 4). The inputs, weights and outputs are all fuzzified. The FRNN system has multiple layers. The first receives the fuzzified inputs. Each node in this layer is formed by a FRN. With fuzzy inputs, weights and outputs, the training process is carried out by a gradient descent back-propagation algorithm with Levenberg-Marquardt (LM) optimization. These FRNs track the real and quadrature components applied with time-varying segments and capture the subtle variation in magnitudes. Each neuron in the fuzzification layer represents a fuzzy term of the input linguistic variables of which multiple sets have been taken. The learning process makes bi-directional flow of the samples from the output to the preceding layers which carry out an adaptive modification of the connectionist links between the FRNs. The inference rules for the ANFIS system to perform MIMO channel estimation is fixed by considering transmit-receive conditions. Table 2 shows one set of inference rules taken to perform the training of the ANFIS estimator which is later taken for making decisions. For a given set of inputs from the MIMO set- up to the ANFIS estimator, the x_i values generated produces the predicted set of transmitted signals from which the inference of the channel coefficients are obtained. The specific set of values that xi holds, determines the inference regarding significant or correlated channel coefficients as specified in the inference logic shown in Table 2. Appropriate encoding schemes are generated for implementing the inference rules which are executed by FRNN blocks with split activation for in-phase and quadrature components. The output decisions in fuzzy form are optimized by a SOM. SOM is a special ANN that works by resorting to unsupervised learning which enables it to group data according to closely matching attributes. The role played by the SOM blocks in the formation of the GA aided split ANFIS is significant due to the fact that the result generated is an optimized one. For a given window of N-sec.s several sets of output are generated. The optimization process carried out by following the competitive learning algorithm of the SOM selects the best set of results at the end of training iterations. As a result, the FRNN based ANFIS blocks show excellent capacity to deal with time variation observed in MIMO transmissions. The fuzzy based method to model stochastic MIMO channels is implemented in an ANFIS form of which the fuzzy rules can be either based on the Takagi-Sugeno or the Mamdani model. The Mamdani model is used in this case as it is found to be better suited for practical applications. A multiplier forward feedback type ANN of five layers formed by FRN blocks, as shown in Figure 5 is used. The first layer receives different fuzzy inputs. The second layer facilitates the implementation of the system's rules and ensures adaptive behaviour. The triggering ability of the network is ensured by the third layer. The inference process is carried out in the fourth layer and the defuzzification process takes place in the fifth layer. The processing blocks in the ANFIS block are formed by FRN units which can tackle time-varying input with fuzzified forms of patterns and targets. The training of the ANFIS system is carried out in two phases-first, a forward pass and then a backward cycle during which the weights and other network parameters are updated. All the decision making regarding the classification and judging the difference between actual and desired response is carried out by the inference layer where multiple sets are implemented to check the effectiveness and performance derived. The response of the system is de-fuzzified by the next layer which is evaluated as per the decision risk functional norm.

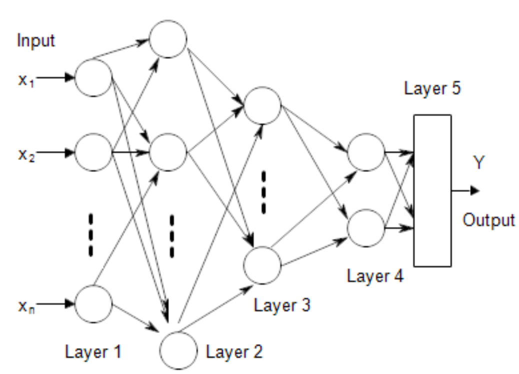

Figure 5: ANFIS block for the Mamdani model used for the MIMO modeling

Table 2: Inference rule for training FNS based MIMO channel estimator

Case	y_i		y_T Inference	$\hat{h}$ Inference
	Max.	Min.		
1	1	0.1	$y_T = \sum y_i h_{ii} + 0.1\sum y_i h_{ij}$	$0.99\sum h_{ii} + 0.1\sum h_{ij}$
2	0.9	0.1	$y_T = 0.9\sum y_i h_{ii} + 0.1\sum y_i h_{ij}$	$0.9\sum h_{ii} + 0.1\sum h_{ij}$
3	0.7	0.3	$y_T = 0.7\sum y_i h_{ii} + 0.3\sum y_i h_{ij}$	$0.7\sum h_{ii} + 0.3\sum h_{ij}$
4	0.5	0.5	$y_T = 0.5\sum y_i h_{ii} + 0.5\sum y_i h_{ij}$	$0.5\sum h_{ii} + 0.5\sum h_{ij}$
5	0.3	0.5	$y_T = 0.3\sum y_i h_{ii} + 0.7\sum y_i h_{ij}$	$0.3\sum h_{ii} + 0.7\sum h_{ij}$

IV. EXPERIMENTAL CONSIDERATIONS AND RESULTS

The experiments are carried out using a set of samples which are accumulated for 2 × 2 and 4 × 4 MIMO- OFDM set-ups for Gaussian, Rayleigh and Rician faded channels with signals having SNR values varying between −10 to 10 dB. During testing, inputs from the receiver side estimates channel coefficients and compares them to the DFE generated values for a frequency range of 0.9 Ghz to 5 GHz. A standard set of six rules gives optimal performance but experiments are carried out to see the effect of variation of the inference stage. The implementation of the inference engine using six set of rule shows a dependence on the network structure adopted for the purpose.

Table 3 summarizes performance variations observed in case of the ANFIS with change in the network structure adopted for the implementation of the inference engine [18]. Four different ANFIS structures are used to implement the inference rules. While all the networks using six inference rules generate a MSE convergence between 0.51×10^{-5} and 0.91×10^{-5}, the value comes down significantly to a range of 0.048×10^{-5} to 0.071×10^{-5} with nine inference rules. With more inference rules, the networks learn better and approach the level of optimality with greater closeness. It amounts to an improvement but this happens at the cost of greater processing time with improvement of precision marginally. But this marginal improvement in precision provides improvement in overall system performance.

Table 3: Effect in performance due to variation in network structure adopted for implementation of inference engine

Network Size	No. of rules	MSE × 10^{-5}	Epochs	Precision in %
20-32-43-28-16-4 (N1)	6 9	0.91 0.062	45 121	94.4 95.2
20-36-43-30-15-4 (N2)	6 9	0.67 0.051	47 119	95.2 95.8
20-38-43-40-20-4 (N3)	6 9	0.68 0.071	49 119	95.4 96.0
20-40-43-50-25-4 (N4)	6 9	0.51 0.048	46 121	94.9 95.1
20-42-43-50-30-4 (N5)	6 9	0.53 0.071	56 122	95.1 95.3

The standard, GA-aided and DFE-GA aided ANFIS configurations are tested for a VOIP based voice and digital video broadcast using a 4 × 4 MIMO wireless set-up infested with Rayleigh fading [16]. The VOIP voice grade transmissions involve 128-bit size OFDM data blocks of around fifty while the digital video broadcast involves over a thousand 6400-bit transmissions. These data blocks are used to train the ANFIS and GA-ANFIS systems. The results derived are also compared with that reported in [18]. Network complexity of the DFE-GA ANFIS system increases marginally but it lowers processing time and number of epochs required to reach the desired convergence goal. The results derived are summarized in Table 4. With a little rise in the design complexity, the proposed DFE-GA aided split ANFIS system contributes significantly to better quality reception in stochastic MIMO channels. Also there is a training latency but the validation and testing periods are considerably faster. Therefore, a fully trained system shows comparable processing time to that of statistical techniques but with better precision and reliability. Further, the training latency observed in the proposed approach can be lowered by using specialized hardware. This establishes the effectiveness of the proposed system.

V. CONCLUSION

Here, we proposed an ANFIS based system for stochastic MIMO channel modeling supported by a DFE and GA optimizer block. The system constituted by FRNN blocks use GA optimization in selecting suitable sets of parameters provided by the DFE for MFs which perform the fuzzification. The ANFIS in split form tracks variations in the MIMO channel. The composite structure is capable of tracking time varying behaviour in the MIMO channel and contributes significantly towards improvement in the quality of reception of data transmitted through severely faded MIMO channels.

REFERENCES

[1.] M. Erman, A. Mohammed and E. Rakus-Andersson , "Fuzzy Logic Applications in Wireless Communications", in Proceedings of IFSA-EUSFLAT, pp. 763-767, Lisbon, Portugal, 2009.

[2.] L-X Wang and J. M. Mendel, "An RLS Fuzzy Adaptive Filter with Applications to Nonlinear Channel Equalization", in Proceedings of 2nd IEEE International Conference on Fuzzy Systems, vol. 2, pp. 895-900, San Francisco, USA, 1993.

[3.] P. Sarwal and M. D. Srinath , "A Fuzzy Logic System for Channel Equalization", IEEE Transactions on Fuzzy Systems, vol. 3, no. 2, pp. 246-249, 1995.

[4.] A. Niemi, J. Joutsensalo and T. Ristaniemi, "Fuzzy Channel Estimation in Multipath Fading CDMA Channel", in Proceedings of 11th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, vol. 2, pp. 1131-1135, London, UK, 2000.

[5.] B. Young-Bae, Y. Takama and K. Hirota, "Combined Channel Estimation and Data Decoding Based on Fuzzy Logic", IEEE Transactions on Instrumentation and Measurement, vol. 51, no. 2, pp. 342-346, 2002.

[6.] R. H. Abiyev and T. Al-shanableh, "Neuro-Fuzzy Network for Adaptive Channel Equalization", LNCS Advances in Neural Networks-ISNN 2007, vol. 4492, pp. 241-250, 2007.

[7.] J. Zhang, Z. M. He, X. Wang and Y. Huang, "A TSK fuzzy approach to Channel Estimation for OFDM Systems", Journal of Electronic Science and Technology in China, vol. 4, no. 2, 2006.

[8.] J. Wen, C. Chang, G. Lee and C. Huang, "OFDM Channel Prediction using Fuzzy Update LMS Algorithm in Time-Variant Mobile Channels", in Proceedings of IEEE 64th Vehicular Technology Conference, pp.1-5, Montreal, Canada, 2006.

[9.] J. Zhang, Z. He, X. Wang and Y. Huang, "TSK Fuzzy approach to Channel Estimation for MIMO-OFDM Systems", IEEE Signal Processing Letters, vol. 14, no. 6, 2007.

[10.] M. Nuri Seyman and N. Taspinar, "Channel Estimation based on Adaptive Neuro-Fuzzy Inference System in OFDM", IEICE Trans. Commun., vol. E91-B, no. 7, pp. 2426-2430, 2008.

[11.] H. Shatila, M. Khedr and J. H. Reed, "Channel Estimation for WiMaX Systems using Fuzzy Logic Cognitive Radio", in Proceedings of IFIP International Conference on Wireless and Optical Communications Networks (WOCN '09), pp. 1 - 6, Cairo, Egypt, 2009.

[12.]F. Gharibi, J. R. Jamjah, F. Akhlaghian and B. Z. Azami, "An improved Adaptive Neural Fuzzy Channel Equalizer", in Proceedings of 18th Iranian Conference on Electrical Engineering (ICEE), pp. 326-330, Isfahan, Iran, 2010.

[13.]P. K. Sahu, S.K. Patra, S. P. Panigrahi, "Nonlinear Channel Equalization using Computationally efficient Neuro-Fuzzy Channel Equalizer," in Proceedings of 18th Iranian Conference on Electrical Engineering (ICEE), pp. 326-330, Isfahan, Iran, 2010.

[14.] K. K. Sarma and A. Mitra, "Estimation of MIMO Wireless Channels using Artificial Neural Networks" , as part of a book titled *Cross-Disciplinary Applications of Artificial Intelligence and Pattern Recognition: Advancing Technologies*, IGI Global, PA, USA, pp. 509-545, 2011.

[15.]K. K. Sarma and A. Mitra, Stochastic MIMO Channel Modeling using FMLP based Inference Engine, International Journal of Information and Communication Technology (IJICT), vol. 5, no. 2, 2013.

[16.]K. K. Sarma and A. Mitra, Fuzzy-Neural MIMO Channel Modeling using Application Specific Membership and Inference Rule Generation, International Journal of Tomography and Simulation (IJTS), Vol. 22, no. 1, pp. 63-72, 2013.

[17.]K. K. Sarma and A. Mitra, MIMO Channel Modeling: Suitability between Neuro-Fuzzy and Fuzzy-Neural Approaches, in Proceedings of 2nd IEEE National Conference on Computational Intelligence and Signal Processing (CISP2012), pp. 12-18, Guwahati, India, March, 2012.

[18.]K. K. Sarma, "Stochastic MIMO Channel Modeling Using Split-ANFIS Framework With GA Optimization", 1st International Conference on Wireless and Mobile Communication Systems (WMCS '13), Paris, France, October 29-31, 2013.

[19.]K. K. Sarma and N. Mastorakis, "GA Assisted DFE-ANFIS Framework for Stochastic MIMO Channel Modeling", in Proceedings of 15th *International Conference on Neural Networks (NN14)*, Gdansk, Poland, May, 2014.

[20.]P. Gogoi and K. K. Sarma, "Kalman Filter and Recurrent Neural Network based Hybrid Approach for Space Time Block Coded-MIMO Set-up with Rayleigh Fading", 13th International Conference on Neural Netwroks (NN '12), Isai, Romania, June, 2012.

Kandarpa Kumar Sarma is currently an associate professor at Department of Electronics and Communication Technology, Gauhati University, Guwahati, Assam, India. He obtained MTech for Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati, Assam, India in 2005 and alter PhD from the same institute. His areas of interest include MIMO system, mobile and wireless communication, soft computing, speech processing, antenna design and document image analysis. He is a senior member of IEEE (USA) and fellow of IETE (India). He is an author of seven books, several research papers published in peer reviewed international journals and conference proceedings. He serves as reviewer to over thirty international journals, and has been TPC member/ reviewer of over hundred international conferences.

Prof. Dr. Nikos E. Mastorakis received his B.Sc. and M.Sc. (Diploma) in Electrical Engineering from the National Technical University of Athens (Greece) and the Ph.D. in Electrical Engineering and Computer Science from the same university. He also received the B.Sc. (Ptychion) in Pure Mathematics from the National University of Athens, Greece. He also studied Medicine in Medical School of Athens of the same university. He have served as special scientist on Computers and Electronics in the Hellenic (Greek) Army General Staff (1993-1994) and taught several courses in the Electrical and Computer Engineering Department of the National Technical University of Athens (1998-1994). He has also served as Visiting Professor at the University of Exeter, School of Engineering (UK, 1998), Visiting Professor in the Technical University of Sofia (Bulgaria, 2003-2004) while he is now Professor in the Technical University of Sofia (Bulgaria, http://elfe.tu-sofia.bg/elfe/staff.htm, http://elfe.tu-sofia.bg/elfe/curriculum4.htm and http://elfe.tu-sofia.bg/elfe/curriculum3.htm and also Professor in the department of Computer Science at the Military Institutions of University Education (MIUE) -Hellenic Naval Academy, Greece.
Prof. Dr. Nikos Mastorakis was the first that solved with several different approaches the former unsolved problem of Multivariable Factorization and published it. He was also the first scholar that completely solved the problem of stability for Multidimensional Systems using Genetic Algorithms. Also, was the first that constructed Electronic Musical Instrument with the spaces of the Byzantine music. He is an active researcher in Applied Mathematics and Computer Science (Systems Theory, Control, Optimization Theory, Algorithms Theory, Signal Processing, Robotics, Computational Intelligence). The editor of over than 200 Books and the author of 5 books, Dr. Mastorakis has published more than 600 papers (see below) in international books, journals and conferences. An active reviewer of 26 International Journals and member of the Editorial Board of 13 International Journals and Editor of International Book Series: (Editor of the series "Electrical and Computer Engineering" (WSEAS Press) and Editor of the series "Mathematics and Computers in Science and Engineering" (WSEAS-Press), Member of the Editorial Board of "Advances in Computation: Theory and Practice" by NOVA), Dr. Mastorakis has received several awards (Royal Society of England, Hellenic National Research Foundation, etc) for his academic studies and his scientific research.
Prof. Dr. Nikos Mastorakis is the Editor-in-Chief in many International Journals. He was the General Chairman in more than 30 International Conferences. He has organized more than 40 Special Sessions, 3 Workshops and has given many plenary lectures. He is also member of IEEE (Senior Member), New York Academy of Sciences, of A.F. Communications and Electronics Association, American Association for the Advancement of Science and other smaller scientific societies.
Dr. Mastorakis is a registered professional electrical and mechanical engineer. He is also Honorary Professor, University of Cluj, ROMANIA http://outstanding.wseas.us He has received the Prize of Excellence from Romanian Academy of Science, Bucharest, ROMANIA http://outstanding.wseas.us and he is also Professor at the ASEI (Military Institutes of University Education), Hellenic Naval Academy, GREECE since 1994 http://www.hna.gr