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MIMO-OFDM Channel Tracking using a Dynamic ANN Topology

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Abstract—All the available algorithms for blind estimation namely constant modulus algorithm (CMA), Decision-Directed Algorithm (DDA/DFE) suffer from the problem of convergence to local minima. Also, if the channel drifts considerably, any DDA looses track of the channel. So, their usage is limited in varying channel conditions. The primary limitation in such cases is the requirement of certain overhead bits in the transmit framework which leads to wasteful use of the bandwidth. Also such arrangements fail to use channel state information (CSI) which is an important aid in improving the quality of reception. In this work, the main objective is to reduce the overhead imposed by the pilot symbols, which in effect reduces the system throughput. Also we formulate an arrangement based on certain dynamic Artificial Neural Network (ANN) topologies which not only contributes towards the lowering of the overhead but also facilitates the use of the CSI. A 2×2 Multiple Input Multiple Output (MIMO) system is simulated and the performance variation with different channel estimation schemes are evaluated. A new semi blind approach based on dynamic ANN is proposed for channel tracking in varying channel conditions and the performance is compared with perfectly known CSI and least square (LS) based estimation.

Keywords—MIMO, Artificial Neural Network (ANN), CMA, LS, CSI.

I. Introduction

MULTIPLE Input Multiple Output (MIMO) wireless technology has emerged as one of the options likely to meet the demands of ever expanding mobile communication networks. With increased spectral efficiency, MIMO architectures are useful for combined transmit receive diversity [1]. Similarly, Orthogonal Frequency Division Multiplexing (OFDM) is becoming the chosen modulation technique for wireless communications. As data rates increase, channels become frequency selective which produces inter symbol interference (ISI). One solution, though, is the use of equalizer but beyond a certain limit, its design is complex. In such a backdrop, OFDM is a viable alternative as it uses non-overlapping adjacent channels to increase spectral efficiency. It also allows multiple carriers be used to transmit different symbols with spectral overlap while ensuring co-existence of nearby signals due to orthogonality [1], [2]. MIMO-OFDM combines the advantages of both MIMO and OFDM techniques thereby achieving spectral efficiency and increased throughput. A MIMO-OFDM system transmits independent OFDM modulated data from multiple antennas simultaneously. At the receiver, after OFDM demodulation, decoding of each of the subchannels leads to the extraction of the data from all the receive antennas [2]. This goes on simultaneously for multiple channels which increases the throughput and spectral efficiency. Thus, a MIMO-OFDM system can achieve high data rates while providing better system performance by using both antenna and frequency diversity, which makes it attractive for high-data-rate wireless applications.

In MIMO systems, channel impulse responses are often assumed to be constant over a block or packet. This assumption of block stationarity on channels is valid for most fixed wireless scenarios. However, for communications in a high mobility environment, the assumption will result in considerable performance degradation since the channels vary fast and severely [3]. A major impediment in MIMO-OFDM system is the complicated receiver signal processing. Coherent detection requires knowledge of the channel. Therefore, accurate channel estimation is crucial in realizing the full potential of MIMO-OFDM.

In a MIMO system, multiple channels have to be estimated simultaneously. The increased number of channel unknowns significantly increases the efficiency and computational complexity of the channel estimation algorithm. The most common approach is training-based estimation, where a known pilot sequence is transmitted and used at the receiver to determine the channel state information (CSI). This task is accomplished by adaptive equalizers. Nonlinear adaptive filters based on a variety of Artificial Neural Network (ANN) models have been used successfully for system identification, equalization [4] and noise-cancellation in a wide class of applications. An important problem in such communication is that of channel equalization, i.e., the removal of interferences introduced by linear or nonlinear message corrupting mechanisms, so that the originally transmitted symbols can be recovered correctly at the receiver [6].

Two common practices of channel estimation in MIMO systems are blind and non-blind methods. Blind estimation techniques donot require training sequences but are extremely computationally intensive [5]. Among non-blind estimation methods, pilot- carrier based estimation techniques are common. These use least-squares (LS), minimum mean-square error (MMSE) and linear minimum mean-square error (LMMSE) estimators. The pilot - based channel estimation, by requiring pilot symbol bits to be inserted as training sequence along with OFDM blocks, causes waste of bandwidth. Innovative means are being formulated to tackle channel estimation and improve performance of mobile systems. One of the viable means of better channel estimation is the use of soft-computing tools like the ANN [2].

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All the available algorithms for blind estimation namely constant modulus algorithm (CMA), Decision-Directed Algorithm (DDA/DFE) suffer from the problem of convergence to local minima. Also, if the channel drifts considerably, any DDA looses track of the channel. So, their usage is limited in varying channel conditions. The primary limitation in such cases is the requirement of certain overhead bits in the transmit framework which leads to wasteful use of the bandwidth. Also such arrangements fail to use channel state information (CSI) which is an important aid in improving the quality of reception. Assuming perfect knowledge of the MIMO channel, the optimum receiver is a maximum likelihood sequence estimator (MLSE), but its complexity is prohibitive, even for low-order channels with a small number of inputs and outputs. In this work, the main objective is to reduce the overhead imposed by the pilot symbols, which in effect reduces the system throughput. Also we formulate an arrangement based on certain dynamic ANN topologies which not only contributes towards the lowering of the overhead but also facilitates the use of the CSI. Few MIMO systems, starting with the 2×2 form, are simulated and the performance variation with different channel estimation schemes are evaluated. A new semi blind approach based on dynamic ANN is proposed for channel tracking in varying channel conditions and the performance is compared with perfectly known CSI and least square (LS) based estimation. In the present work, the channel is assumed to be continuously time varying and no block fading is considered which is closer to the actual physical channel characteristics. We specifically describe the use of a semi blind approach derived using a Focused Time Delay Neural Network (FTDNN) for channel estimation of a MIMO-OFDM system. It is also extended to track the properties of the system. The FTDNN is used for one step ahead prediction of the channel coefficient which enables proper tracking of the system.

Of late, the ability of the ANN has been explored for MIMO channel estimation cases. Some of the reported works are [7]-[11]. The rest of the paper is organized as follows: Section II describes the system model. Experimental results are included in Section III. Section IV concludes the discussion.

II. System model

In a communication scheme where the channel parameters change with time, such as in a mobile environment, a training sequence must be repeated, leading to waste in the channel utilization. In these cases, equalization must be performed without training sequence. The main problem in a $M \times N$ MIMO system with LS estimation is that $M \times N$ unknowns are required to be calculated out of only N equations. Thus, the situation is underdetermined and multiple solutions for the variables may be obtained which is difficult to sort out. So, to have correct estimation, M blocks of data are required to be acquired before performing the estimation which will reduce the system throughput in a spatially multiplexed MIMO system. Again with large receiver velocity, the channel coherence time may be very small and so pilots are required to be placed in smaller intervals. In such a scenario, most of the transmitted

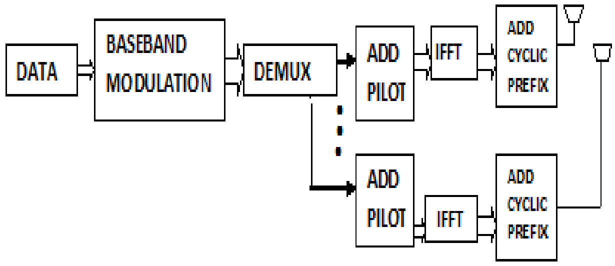

Fig. 1. Transmitter Block

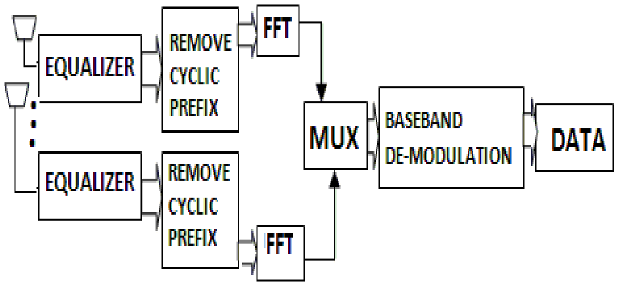

Fig. 2. Receiver Block

symbols will be pilots or training data and actual data rate achieved will be poor. Again in most of the literature, the channel is assumed to be held constant during the pilot interval and also within the pilot sequence, which is not the case in practical situations.

The block diagram of a special multiplexed MIMO system with time domain equalizer is given in Figure 1 and Figure 2. Considering a $M \times N$ MIMO system where M is the total number of transmitting antennas and N is the number of receiving antennas, the system shown in Figures 1 and 2 depicts the sub-blocks constituting the framework. The input series of bits are passed through the baseband modulator and then demultiplexed into two parallel streams of bits. Each of the baseband symbols are converted to parallel blocks and are passed through the OFDM modulator blocks which are then fed to the antennas after parallel to serial conversion. The transmitter block is shown in Figure 1. The receiver processes the data in a completely reverse order to get the bit stream. The receiver block is shown in Figure 2.

The received symbol r_k^i from the receiver antenna i (with i=1,2,.,N) at discrete time index k is

$$r_k^i = \sum_{i=1}^{n} h_k^{i,j} * s_k^j + w_k^i \tag{1}$$

where s_k^j is the transmitted symbol from the j^{th} antenna in time index k, w_k^i is the AWGN in the i^{th} received element, and $h_k^{i,j}$ is the channel coefficient between j^{th} input and i^{th} output antenna which is a complex number with Rayleigh distributed envelop. Therefore, at each time step $M \times N$ channel coefficients must be estimated for a flat fading channel that varies faster with higher Doppler shift. The autocorrelation

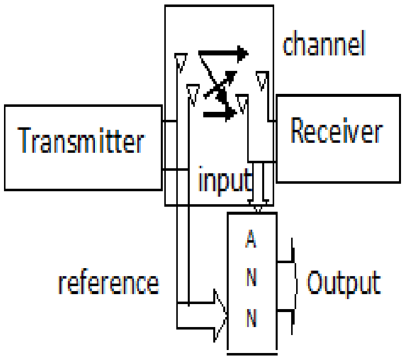

Fig. 3. System Model

sequence of the coefficients are given by

$$E\{h_k^{i,j}[h_k^{i,j}]^*\} \cong J_0(2\Pi f_D^{i,j} T\|k-l\|) \quad (2)$$

where $J_0\{\cdot\}$is the zero-order Bessel function of the first kind, superscript $*$ denotes the complex conjugate, $f_D^{i,j}$is the Doppler frequency shift for the m^{th} path between the j^{th} transmitter and the i^{th} receiver, and T is the duration of each symbol. In matrix form, eq. 1 can be written in matrix form as

$$r_k = H_k S_k + W_k \quad (3)$$

where r_k is the received vector, H_k is the channel matrix and S_k is the transmitted symbol in the time index k, and W_k is the vector with independent and identically distributed AWGN noise with variance σ_w^2 . For a 2×2 MIMO system H is represented as

$$H = \begin{pmatrix} h11(k) & h12(k) \\ h21(k) & h22(k) \end{pmatrix} \quad (4)$$

The system model for the work is shown in Figure 3. The application of the ANN for the proposed MIMO channel tracking considers multiple aspects. The first is the training, next is the validation and finally checking of the robustness of the ANN structure under a range of channel conditions. The training is carried out by using signal inputs from the transmitter section. The set-up is so constituted that it can tackle any estimation problem despite the presence of irregularities with no parametric dependence. The learning algorithm used for training considers mean square error (MSE) convergence as a factor to ascertain the level of learning which the ANN has acquired within the stipulated number of epochs or adaptation goal.

A. *LS Solution*

The standard solution to the LS channel estimates is expressed as

$$\widehat{H}_k = [(r_k^p)^H * r_k^p)]^{-1} * (r_k^p)^H * S_k^p \quad (5)$$

where r_k^p is the received pilot sequence, S_k^p is the transmitted pilot and $\widehat{H}_k$ is the estimate of the channel matrix. The recovered symbols are given by

$$\widehat{s}_k = \widehat{H}_k^{-1} * S_k \quad (6)$$

where $\widehat{s}_k$ is the estimate of the transmitted symbol S_k .

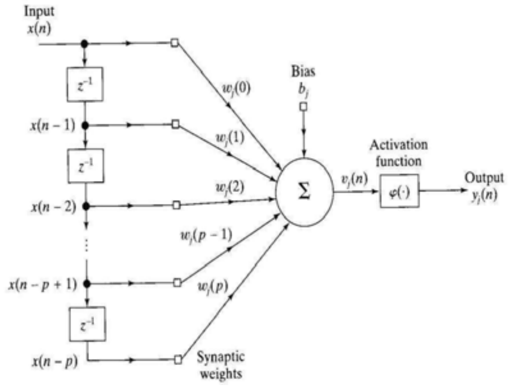

Fig. 4. Structure of a Focussed Time Delay Neural Network

TABLE I
ANN CONFIGURATION

Item	Details
ANN Type	FTDNN
Training Type	LM BP
ANN Layer Set-up	Input layer- 8 neurons Hidden layer- 5 neurons Output layer- 1 neuron
MSE goal	10^{-3}
Average epochs	10 to 100
Random trials	15 each

B. *FTDNN Based Estimation*

Focused Time Delay Neural Network (FTDNN) is a class of dynamic ANNs which consists of a feedforward structure with a tapped delay line at the input. Dynamic ANNs are able to capture time varying properties of transmitted signals through a MIMO set-up. Such networks are capable of dealing with variations and fading seen in the mobile environment [7]-[12]. One significant feature of the FTDNN is that it does not require dynamic back propagation to compute the network gradient. This is because the tapped delay line appears only at the input of the network, and contains no feedback loops or adjustable parameters. For this reason, this network trains faster than other similar networks [13]. In dynamic networks, the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. So, FTDNN is suitable for using in time series prediction. The structure of the FTDNN, we are using is shown in Fig 4.

FTDNN is used for one step ahead prediction of the channel coefficient. The approach is a semi blind approach. The FTDNN used in the process is configured to have 3 layers with 8 input and 5 hidden neurons and 1 output neuron. Training is done with Levenberg-Marquardt (LM) backpropagation (BP) training algorithm. Simulation is performed in a 2×2 MIMO system with flat fading and time varying Rayleigh distributed channel coefficients generated with Jack's model. The ANN configuration used for the work is summarized as in Table I.

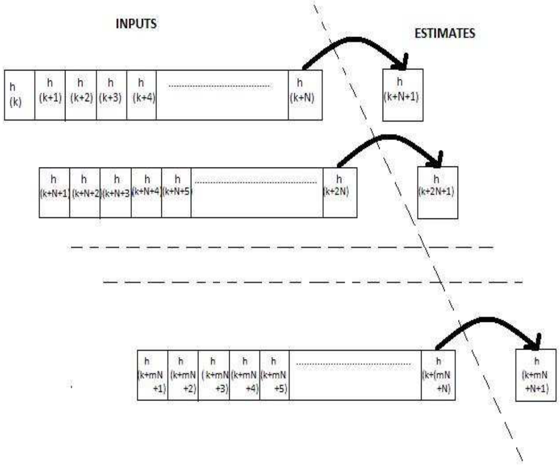

Fig. 5. Representation of the training and testing steps

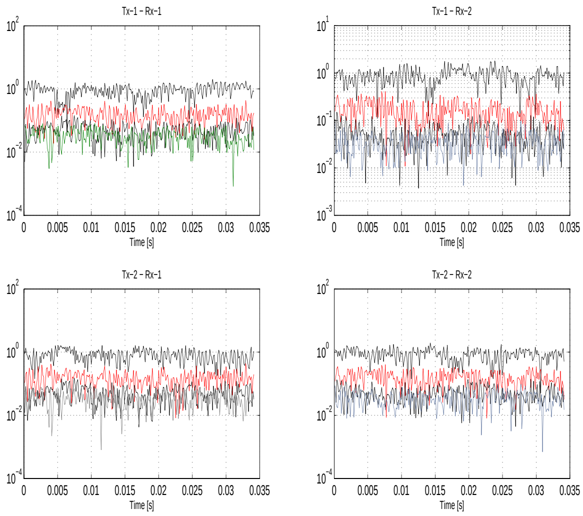

Fig. 6. MIMO waveforms for ITU pedestrian channel with delay between 100 to 500 ns and average power distributed between 0 to -20dB.

C. *Preparation of the training data*

On startup, the system will be in the training mode and channel state information for N time steps will be acquired by using LS estimation technique. The FTDNN will be trained by CSI of k time steps out of the total acquired CSI of N time steps to predict the CSI of $(k+1)^{th}$ time step in an incremental basis to cover the whole acquired information of N time steps. In our work, the parameter values for N and k were taken to be 6400 and 8 respectively and it was found that the FTDNN offers good tracking performance. The whole training scheme is shown diagrammatically in Fig 5. Separate networks are configured to be trained with real and imaginary parts of the received signal in the training mode. The fading conditions considered are of Rayleigh, Rician and Nakagami type. Also considered are ITU pedestrian and vehicular channel parameters to see the effectiveness of the proposed approach. A set of MIMO transmission involving ITU pedestrian channel is shown in Figure 6. The parameters as given in Table II are used for deriving the channels.

III. Experimental Results

Performance of each of the schemes is evaluated in terms of the phase and magnitude tracking of the channel variation, symbol error rate (SER), bit error rate (BER) and benefits derived with scaling up of antenna configuration compared to a 2×2 framework. Evaluation of the systems is performed

TABLE II
PARAMETERS USED FOR SIMULATING CHANNELS WHICH INCLUDE RAYLEIGH, ITU PEDESTRIAN AND ITU VEHICULAR TYPES

Parameter	Details
Antenna configuration	2×2, 2×3 3×2, 3×3 3×4, 4×3 4×4
Antenna gap	$0.1\lambda, 0.2\lambda, 0.3\lambda, 0.5\lambda$
Chip rate	2-4 MHz
Carrier frequency	2-5 GHz
Vehicular speed	40, 60, 120 kmph
Doppler shift	$\frac{Speed \quad in \quad mps}{Wavelength, \lambda \quad in \quad m}$
Samples	maximum 100000
ITU pedestrian	Av. power, 0 to -25dB Relative delay, 0 to 900nS
ITU vehicular	Av. power, 0 to -20dB Relative delay, 0 to 500nS, 700nS to 1μS, 1.5 to 3μS

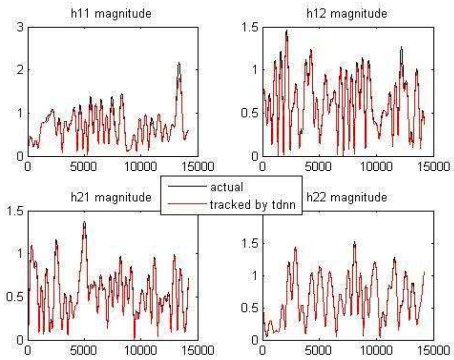

Fig. 7. Magnitude tracking performance using FTDNN with Doppler shift 120 Hz and 12800 symbols

for different Doppler shift condition and data lengths. Performance difference using LS with known CSI and pilot estimated CSI are evaluated using only the BER plot. The strength of our system lies in the fact that our approach is semi blind approach and pilots are used only for the starting training phase. As a result, more throughput is obtained. The true potential of a MIMO system lies in spatial multiplexing which is again computationally intensive and hence not being used. With spatial multiplexing, the data rate increases linearly with number of antennas used which is not the case with Space Time Block Code (STBC) [9] and Space Time Trellis Code (STTC). In our work, we are resorting to spatial multiplexing. Figure 7 shows a magnitude tracking using FTDNN of the channels for Doppler shift of 120Hz and 12800 symbols. Similarly, phase tracking performance using FTDNN with Doppler shift of 120 Hz and 12800 symbols is depicted in Figure 8.

A BER curve performance using the FTDNN based approach with Doppler shift 120 Hz and 12800 symbols is shown in Figure 9. Average SNR gain obtained by the proposed approach at 10^{-3} compared to LS and MMSE for Rayleigh

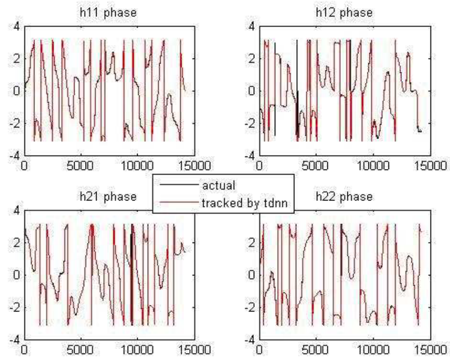

Fig. 8. Phase tracking performance using FTDNN with Doppler shift 120 Hz and 12800 symbols

TABLE III
AVERAGE SNR GAIN OBTAINED BY THE PROPOSED APPROACH AT 10^{-3} COMPARED TO LS AND MMSE FOR RAYLEIGH AND ITU VEHICULAR CHANNELS

MIMO Set-up	LS	MMSE
2×2	1.1	0.9
2×3	2.1	1.1
3×2	2.2	1.15
3×3	2.3	1.2
3×4	2.4	1.5
4×3	2.5	1.6
4×4	3.1	2.1

and ITU vehicular channels is shown in Table III. The gain is between 0.9 to 3.1 dB which is significant and leads to power saving and improved reception quality. Figure 10 shows average SER provided by the proposed approach compared to LS and MMSE methods in Rayleigh and ITU vehicular channels. The SER plot tends towards theoretical limit with better accuracy than traditional methods. Average capacity in terms of b/s/Hz achieved by the proposed approach compared to blind and non-blind methods in Rayleigh and ITU vehicular channels as shown in Table IV shows that the FTDNN is capable of capturing the time varying changes of the MIMO channel despite the range of variations observed in the propagation media.

Also, from the simulation results, it is clear that the channel is well tracked by the FTDNN both in terms of

TABLE IV
AVERAGE CAPACITY IN TERMS OF B/S/HZ ACHIEVED BY THE PROPOSED APPROACH COMPARED TO BLIND AND NON-BLIND METHODS IN RAYLEIGH AND ITU VEHICULAR CHANNELS

MIMO Set-up	Theory	Blind	Non-blind	Proposed
1×1	0.3	0.21	0.24	0.27
2×2	2.2	2.1	2.12	2.14
2×3	3.7	3.4	3.5	3.55
3×3	5.8	5.7	5.71	5.72
3×4	6.7	6.6	6.63	6.64
4×4	7.5	7.3	7.35	7.4

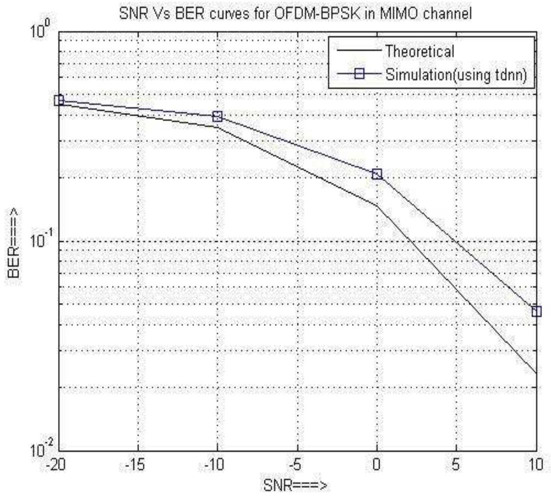

Fig. 9. SNR-BER performance using FTDNN with Doppler shift of 120 Hz and 12800 symbols

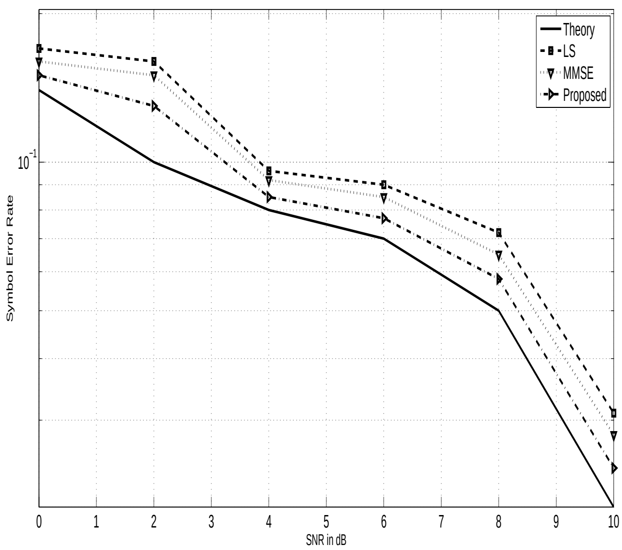

Fig. 10. Average SER provided by the proposed approach compared to LS and MMSE methods in Rayleigh and ITU vehicular channels

magnitude and phase. The phase tracking is important when we consider a constant envelop modulation scheme such as Phase Shift Keying (PSK). Both magnitude and phase tracking are parameters of importance in OFDM. Also, the FTDNN provide appropriate estimation of the channel coefficients in the MIMO set-up. The robustness of FTDNN is evident from the BER curves obtained. Although the training time of the FTDNN is an issue, it is less then the recurrent class of networks [7]-[9] due to the fact that the training algorithms used with FTDNN are simple gradient based algorithms. The training time can be further reduced with a distributed, high performance computational framework instead of a stand alone set-up. The proposed approach provides better capacity performance than blind and non-blind methods and approaches the known theoretical limits in case of a range of channel variations as shown in Table IV. In DFE equalizers, error propagation takes place and hence it is mandatory to transmit training symbols in regular interval of time so that the tracking is not lost. In case of the MLSE, optimum performance is obtained at the cost of high computational requirements. Contrary to that the FTDNN not only contributes towards preserving bandwidth, it shows better adaptive capability and speed. Further, its robustness is observed in the fact that point it restarts tracking even after an erroneous detection and repeats the cycle till a proper decision is made. This contributes towards improved precision and better reception. These aspects establish the obvious advantages offered by the proposed FTRNN based channel tracking approach designed for a MIMO-OFDM framework.

IV. Conclusion

Here, we proposed a semi blind approach derived using a FTDNN set-up for channel estimation of a MIMO-OFDM system. It has also been extended to track the properties of the system under a range of channel conditions which includes Rayleigh and certain ITU models. The FTDNN is used for one step ahead prediction of the channel coefficient which enables proper tracking of the system. Experimental results show that the proposed approach contributes towards preserving bandwidth, better adaptive capability, speed and robustness which makes is a viable option for receiver design of upcoming higher data rate mobile systems.

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