HF Channel Estimation for MIMO Systems based on Particle Filter Technique

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Abstract—**Data transmission even at moderate data rates through ionospheric channels is subject to impairments from severe linear distortion, fast channel time variations, dynamic propagation effects and severe fading. The overall system performance strongly depends on the effective allocation of system resources. The adequacy of the effective allocation of system resources can only be derived through accurate and efficient Channel State Information (CSI). Thus, there is a clear need for accurate, efficient techniques to Estimate CSI between pairs of High Frequency links.**

Performance analysis of Multiple Input Multiple Output (MIMO) based High Frequency (HF) channel estimation invoking Particle Filtering (PF) is presented in this paper. The significant feature of this analysis is its ability to treat Non-Gaussian noise of the HF channel. The simulation results confirm the superior performance of the PF techniques over the Recursive Least Square (RLS) in the estimation of CSI even under low SNR scenario with affordable computational complexities. Comparative performance results of various MIMO configuration such as 2x2, 4x4 relative to Single Input Single Output (SISO) have also been discussed. The results of the proposed analysis reaffirm the superiority of the PF technique over RLS in estimating the CSI even under non-Gaussian and low SNR scenario.

Index Terms—**MIMO System, Channel Estimation, HF Communication System.**

I. INTRODUCTION

The high frequency (HF) band spanning 2-30 MHz of the spectrum has been of great interest for many years for long-distance radio communications in many military and civilian applications. The non-ideal characteristics of ionospheric channels such as severe linear distortion; fast channel time variations, dynamic propagation effects, the high interference levels and severe fading impose constraints on the achievable high-data-rate of transfer over HF channel [1,2]. The increase in demand for higher capacity and reliable adaptive links over high frequency (HF) channel[1] has motivated the researchers to explore the time, frequency and spatial dimensions of signal transmission. Thus, dynamic signal transmission with multi dimensional approach has emerged as a powerful paradigm to meet these demands.

Multiple-Input Multiple-Output (MIMO) communication systems offer significant capacity gain compared to conventional Single-Input Single-Output (SISO) systems by exploiting the spatial dimension [3]. MIMO communications is an emerging technology offering significant promise for high data rates and mobility required for the next generation HF communication systems.

To achieve reliable link one has to ensure the adequate supply of real time predicted Channel State Information (CSI) for resource allocation. The impact of channel prediction can be exploited for full channel capacity during favorable channel conditions. Under channel impairment condition, the Adaptive techniques based on channel condition such as modulation, channel coding, power-control and rate-control are known to improve the performance over time-varying channels on both transmitter and receiver chains of communication system.

Recent technological advances in embedded General Purpose processor (GPP) , Digital Signal Processor (DSP) technology, Field Programmable Gate Array (FPGA) density and comtemplated signal processing compute devices are very prominising for high frequency, high date rate communiction with moderate to high reliablity they have significantly overcome some of the inherent difficulties associated with the nature of the HF communications, which had rendered receiver strutures complicated during the past [4,5,6]. The focus of the next generation HF systems is likely to be directed towards the distributed networks and mobility as well as the dynamic selection of the most appropriate channel to establish and maintain communications links retaining the Quality of Servies (QoS) intact.

In the HF environment, signals are received by the antenna array after reflection from the ionosphere, which is a dynamic and spatially inhomogeneous propagation medium. Despite the vast amount of theoretical research and simulation studies published on the subject of array signal processing [7], there are very few studies, which have dealt the performances analysis of the channel estimation under Non-linear channel and Non-Gaussian Noisy conditions. Moreover, there is a necessity and great interest to understand how more effective adaptive algorithm should be designed and optimized for different scenarios of noisy characteristics of HF channel. Considering the futuristic state of the art networking technology for HF communication system, there is an arising necessity to evolve the next generation system with MIMO configurations to improve the link reliability and spectral efficiency that would enhance the QoS. Thus, high data transmission through HF channels at a

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rate of the same order as or higher than the channel bandwidth is considered and generally requires powerful channel estimation techniques to avail channel state information for effective resources allocation.

In this paper, we consider the problem of providing reliable estimate of CSI. If receiver system fails to yield accurate estimates of fading process, receiver performance will degrade. Current wireless systems obtain the CSI through a Pilot-Assisted Transmission which is embedded periodically along with the information-bearing symbols in each frame of transmitted data. Using the training data, the receiver is then enabled to obtain an estimate of the CSI. In order to develop a dynamic state model for the time varying wireless channel, concepts from the field of Bayesian forecasting are used for commuting CSI.

In this paper, we consider aspect of Watterson HF SISO model [8] to model HF MIMO channel. Extension of the Static AR model [10] for doppler Spectrum is characterized by Gaussian Shape. This paper describes channel estimator for different MIMO configuations under Gaussian and Non-Gaussian Noisy environment. A comparisation with Recursive least squares (RLS) based channel estimate is also considered and the results of computer-simulation tests are presented. In this paper it is demonstrated that the PF has the advantage of improved performance at low SNR and accurate estimation under noisy condition.

The brief organization of the paper is as follows. Section II presents the system description with channel model. We then present channel-estimation technique in Section III. Section IV deals with performance analysis and comparison of PF algorithms with RLS for channel-estimation under Gaussian/Non-Gaussian noise condition for various configurations. The conclusions that can be derived through the extensise simulation studies of this paper are presented in Section V.

II. SYSTEM MODEL

Figure 1 shows a typical MIMO communication system with M_t transmits antennas and N_r receiver antennas. The space-time (S-T) modem at the transmitter (Tx) encodes incoming bit stream using Alamouti's codes [2]. The information bits are modulated and the signal is mapped across space and time (M_t transmit antennas). Thereafter, the S-T modem at the receiver (Rx) processes the received signal, which is subjected to time-varying Ionospheric fading. In addition, the received signal also experiences Inter Symbol Interference (ISI) under additive Gaussian / non-Gaussian noise. The received signal will be decoded on each of the N_r receiver antennas according to the transmitter's signaling strategy. The observed signal from i^{th} receiver at the discrete time index k is

$$r_k^i = \sum_{j=1}^{M_t} h_k^{i,j}(k,\tau)s_k^j + w_k^i, \quad i = 1,....,N_r \qquad (1)$$

Where, s_k^j is the transmitted symbol at the time index k, τ is the delay variable, $h_k^{i,j}(k,\tau)$ is the channel impulse response between j^{th} transmitter and i^{th} receiver of MIMO channel with correlated Rayleigh Processes whose Doppler Spectrum is characterized by Gaussian Shape [8,9].

For simplicity $h_k^{i,j}(k,\tau)$ is written as $h_k^{i,j}$. For each time instance k, the (M_t x N_r) time-varying channel parameters have to be estimated with the following auto-correlation function

$$\left[R_h^{i,j}\right] = E\left[h_k^{i,j} h_l^{i,j^*}\right] = \exp\left[2\left\{\pi f_d^{i,j} T(k-l)\right\}^2\right] \qquad (2)$$

And normalized spectrum for each $h_k^{i,j}$ is given as

$$S_k(f) = \frac{1}{(2\pi)^{1/2} f_d^{i,j}} \exp\left[-\frac{f^2}{2(f_d^{i,j})^2}\right] \qquad (3)$$

Where superscript * denotes the complex conjugate, $f_d^{i,j}$ is the Doppler frequency shift for path between the j^{th} transmitter and i^{th} receiver, and T is the duration of each symbol.

In this paper an Auto-Regressive (AR) modeling approach is considered for the generation of correlated Rayleigh processes whose Doppler Spectrum is characterized by Gaussian Shape [8, 9]. The analysis of [10] that treats the U shaped Doppler spectrum is extended to deal with the Gaussian shape of the Doppler spread of the HF channel. The implementation model for channel estimation $h_k^{i,j}$ can be approximated by following the AR process of order L:

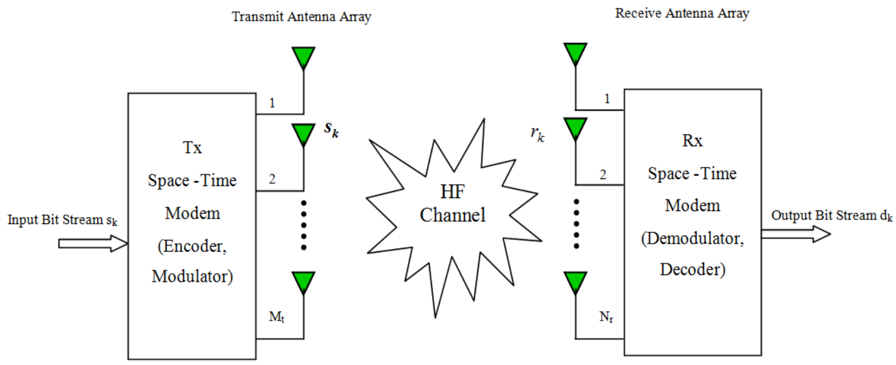

Figure 1: MIMO Communication System

$$h_k^{i,j} \approx \sum_{l=1}^{L} \alpha_{i,j,l} h_{k-l}^{i,j} + n_{i,j,k}, \qquad (4)$$

where $\alpha_{i,j,l}$ is l^{th} coefficient between j^{th} transmitter and i^{th} receiver and $n_{i,j,k}$ are zero-mean identical independent distribution (i.i.d). complex Gaussian processes with variance given by

$$E[n_{i,j,k} n_{i,j,k}^{*}] = \sigma^2_{i,j,k} \qquad (5)$$

The procedure outlined in [9] has been adopted for the optimum selection of AR channel model parameters from correlation functions $R_h^{i,j}$. The additive noise (w_k^i equation 1) can be modeled either as a complex-Gaussian distribution $p(z) = N(z:0,\sigma_w^2)$ with argument z, zero mean, and variance σ_1^2 , or as the Middleton Class-A noise model. This latter model has been used to model the impulsive noise commonly generated in wireless environment [11]. The probability density function of the noise model is given by

$$p(z) = (1-\varepsilon)N(z:0,\sigma_1^2) + \varepsilon N(z:0,\sigma_2^2) \qquad (6)$$

Where $0 \le \varepsilon \le 1$. The first component $(1-\varepsilon)N(z:0,\sigma_1^2)$ represents the ambient background noise with probability $(1-\varepsilon)$, while $\varepsilon N(z:0,\sigma_2^2)$ denotes the presence of an impulsive component occurring with probability ε. In order to maintain a constant noise variance σ^2 for a particular signal to noise ratio (SNR), the parameters ε, noise variance σ_1^2 and σ_2^2 are varied such that

$$\sigma_w^2 = (1-\varepsilon)\sigma_1^2 + \varepsilon\sigma_2^2 \qquad (7)$$

Finally in equation (7) if $\sigma_2^2 = 0$, then noise model reverts to the Gaussian distribution.

Equation (1) can be written in a matrix form for flat fading as

$$r_k = H_k s_k + w_k, \qquad (8)$$

Where r_k is the received matrix, H_k is the channel matrix, s_k is the transmitted symbol all in time index k, w_k is the matrix with i.i.d. AWGN elements with variance σ_w^2 . An equal Doppler Shift between transmitter and receiver's elements in MIMO system is assumed i.e. $f_d^{i,j} = f_d$ .With these assumption matrix coefficients of the AR model of equation (4) can be replaced by scalar coefficients. The time-varying behavior of the channel matrix can be described as

$$H_k = \alpha H_{k-1} + N_k, \qquad (9)$$

where N_k is a matrix with i.i.d. Gaussian noise elements with variance σ_n^2 , α is a AR coefficient modeled for HF Fading channel. Further, the equations (8) and (9) can also be extended to frequency selective channel.

In order to parameterize (9), for time lag (τ), the autocorrelation of the channel fading process of equation (2) is:

$$E[h_k h_{(k-\tau)}^{*}] = \exp(-2(pif_D\tau)^2)I, \qquad (10)$$

where I is the identity matrix, τ is the time lag, f_D denotes the Doppler frequency(shift). The Doppler shift is given by

$$f_D = \frac{v}{c} f_c \qquad (11)$$

where v is the mobile speed, c is the speed of light, f_c is the carrier frequency. Substituting equation (9) in equation (10) for time lag $\tau = \{0, T_s\}$ yields

$$\alpha^2 + \sigma_n^2 = 1, \qquad \tau = 0 \qquad (12)$$

$$\alpha = \exp(-2(pif_D T_s)^2) \qquad \tau = T_s \qquad (13)$$

where, $1/T_s$ are the sampling rate.
For example, if the normalized desired fading rate is $f_D T_s = 0.01$, then $\alpha = 0.998$, and $\sigma_n^2 = 3.94\times10^{-3}$.

A final comment that illustrates the suitability of the channel model is in order. By projecting (9) for τ time steps into the future, the expected value of a future channel state conditioned on the current value is given by

$$E[h_{(k+\tau)} | h_k] = \alpha^\tau h_k \qquad (14)$$

For α value near one, then $h_{(k+\tau)} \approx h_k$, i.e., the best guess about a future estimate is the current estimate. Note that this is precisely what is assumed by sending periodic training codes over the wireless channel; once the channel has been estimated; it is assumed to remain approximately constant until the next set of training data is sent. Significant changes over longer periods of time are expected. Since the emphasis of the paper is on short-term prediction, we have not considered the effect of long-term variation.

III. CHANNEL ESTIMATION

Channel Predictions of ionospheric propagation are typically very costly in either time or memory or both. Most of the available channel estimation schemes are based on either Least Mean Square (LMS) algorithm or one of the Kalman based RLS algorithms as means for tracking the HF link. A Kalman filter assumes that the channel performs a degree-1 Markov process on the signal [4,6], which is a valid assumption for both time invariant and random-walk channels. Thus, a Kalman filter is optimum for either of the two channel conditions, in the sense that it can give the minimum mean- square error in the adaptive adjustment of the receiver. Typical HF channel cannot be modeled as degree-1 Markov process, and computer-simulation tests have, in fact, confirmed that the conventional Kalman filter, together with its more recent developments is not optimum for a typical HF channel [4, 6]. Further the Kalman filter is limited to Gaussian stationary process but HF channel is subjected to Non-stationary, time varying and Non-Gaussian noise Environment [4, 6].

In view of these considerations, an alternative approach is to develop dynamic channel estimation for the HF channel, invoking the principle of Bayesian forecasting. Bayesian forecasting deals with the optimal learning and prediction of different classes of dynamic models [15]. Based on the concept of sequential importance sampling and the use of Bayesian theory, PF is particularly useful in dealing with non-linear and Non-Gaussian scenarios [15, 17, 19]. This paper proposes a study that would enable the adaptive channel Prediction based on PF to counter the presence of Non-Gaussian and Non-linear Channel characteristics of HF Channel. The expected improvement in the receiver performance in lieu of the use of the PF in the predictor algorithm is evaluated through the system parameters like data rate and reliability. The idea of implementing the PF concept is to enable the receiver to acquire the CSI through training data and improve the receiver performance despite the presence of Non-linear and Non-stationary channel characteristics.

One of the main objectives of this paper is to propose the adaptive HF channel estimation using PF. The implementation of proposed adaptive algorithm starts with Preamble/Training mode that is used to acquire initial estimates, after which it reverts to a correction for data mode. In the training mode, the receiver has the precise information of transmitted symbols. The channel estimation is performed using RLS and PF with Extended Kalman Filter (PF-EKF) as a variant for channel estimation during training mode. The RLS and PF – EKF algorithms are discussed in the following section.

A. Recursive Least Squares (RLS) based Channel Estimation

RLS is a low complexity iterative algorithm commonly used in estimation /equalization and filtering applications which is independent of the channel model [20,21]. The only parameter in the RLS algorithm that depends on the rate of channel variation is the forgetting factor that can be empirically set to its optimum value. In this paper, the RLS algorithm is used as a reference channel estimator to compare the performance of channel estimation based on Particle Filtering (PF).

RLS algorithm is derived for MIMO channel tracking using the analysis detailed in [12]. In training mode of the channel estimation, RLS algorithm can be summarized as follows:

i) Initializing the parameters,

$$R_0 = 0_{N_r \times M_t}, \quad Q_0 = \delta I_{M_t}, \tag{15}$$

Where δ is a arbitrary very large number and I_{M_t} is the $M_t \times M_t$ identity matrix

ii) R_n and Q_n are updated for each iteration, as follows,

$$R_n = \lambda R_{n-1} + r_n s_n^H, \tag{16}$$

$$Q_n = \lambda^{-1} Q_{n-1} - \frac{\lambda^{-2} Q_{n-1} s_n s_n^H Q_{n-1}}{1 + \lambda^{-1} s_n^H Q_{n-1} s_n} \tag{17}$$

Where superscript H denotes the conjugate transpose operator and λ is the forgetting factor, which is $0 < \lambda \le 1$. The optimum value of λ is dependent on the Doppler frequency shift and λ is chosen empirically. R_n is Cross Correlation between received signal r_n and transmitted signal s_n. Q_n is inverse auto correlation of transmitted signal s_n.

iii) Channel matrix estimation $\hat{H}_n$ is performed using the updated R_n and Q_n

$$\hat{H}_n = R_n Q_n \tag{18}$$

For next snapshot of channel matrix estimation $\hat{H}_n$ has to proceed from step (ii)

B. Particle Filter (PF) based Channel Estimation

Particle filtering is a sequential Monte Carlo methodology where the basic idea is the recursive computation of relevant probability distributions using the concepts of importance sampling and approximation of probability distributions with discrete random measures. In this paper, PF is used for adaptive channel estimation to counter the presence of Non-Gaussian characteristics of HF Channel. This section describes the formulation of HF channel estimation based on PF Algorithm.

A general state space representation of baseband communications model for a fading channel can be written as [13]:

$$\begin{aligned} x_t &= f_t(x_{t-1}, u_t) \\ y_t &= s_t^T h_t + v_t \end{aligned} \tag{19}$$

Where y_t is the discrete time signal, received at the receiver x_t *is* the state of the system composed of vectors of transmitted symbols s_t, h_t is coefficient of fading channel

The state varies in time according to a known function f_t. It describes a Markov process driven by the additive channel noise u_t and v_t.

From the received signal y_t, the channel is estimated or the transmitted symbols are detected sequentially.

This implies obtaining estimates of $p(h_t, s_t | y_{0:t})$, where $y_{0:t} = \{y_0, y_1, y_2 .....y_t\}$. The signal y_t of equation (19) can be rewritten as

$$y_t = x_t h_t + v_t \tag{20}$$

Where x_t forms state sequence, which consists of transmitted symbol $\mathbf{s}_t$ and transition vector **F,** y_t forms observation Sequence. Each state of y_t is represented by the previous M channel coefficients (information).

An important objective of the recursive estimation is to infuse a level of confidence in accepting the validity of the channel coefficient h_t at time *t*, taking the past values of the given the data, $y_{1:t}$ up to time *t*. Thus recursive estimation demands the probability density function (pdf) $p(h_t, x_t | y_{0:t}),$.

It is assumed that the initial pdf is of the form $p(h_0|y_0) \equiv p(h_o)$ .The pdf $p(h_t|y_{1:t})$ may be obtained recursively in two stages, namely the prediction and the update.

The prediction stage involves using the system equations (19) and (20) with the assumption that pdf $p(h_{t-1}|y_{1:t-1})$ at time $t-1$ is available. The state h_t will evolve over time t via the Chapman–Kolmogorov equation

$$p(h_t|y_{t-1}) = \int p(h_t|h_{t-1})\, p(h_{t-1}|y_{t-1})\, dh_{t-1} \tag{21}$$

Where $p(h_t|h_{t-1})$ describes how the state density evolves with time t, and is defined by the state equation. When the current observation y_t becomes available, prior pdf of equation (21) gets updated via Bayes' rule, resulting

$$p(h_t|y_t) = \frac{p(y_t|h_t)\, p(h_t|y_{t-1})}{\int p(y_t|h_t)\, p(h_t|y_{t-1})\, dh_t} \tag{22}$$

Where $p(y_t|h_t)$ is the *likelihood* of receiving the observation y_t, given the state h_t. The likelihood is determined by the equation (20). The denominator term in (22) is necessary in order to keep the new estimate of the posterior properly normalized such that $\int p(h_t|y_t)\, dh_t = 1$ for all t. From the distribution function of equation (22), channel estimate $\hat{h}_t$ can be obtained. In order to recursively evaluate the updates, the method of *Importance Sampling,* is utilized, which is a common Monte Carlo (MC) method for sequential MC filters [13,14,15].

The idea of importance sampling is to represent the required posterior density function by a set of weighted particles:

$$p(h_t|y_t) \approx \sum_{l=1}^{L} w_t^l\, \delta(h_t - h_t^l) \tag{23}$$

Where L is the number of particles, δ(·) is the Dirac delta function, h_t^l is the state of particle at time t.

The weights w_t^l are normalized such that at each time t.

$$\sum_{l=1}^{L} w_t^l = 1\,. \tag{23a}$$

As the number of particles increases to the larger value, the approximation in (23a) converges to the true posterior pdf.

New particles are drawn from a known distribution referred to as the *proposal distribution.*

$$h_t \sim q(h_t|h_{t-1}^l, y_t) \tag{24}$$

In order to increase the sampling efficiency, this paper considers the Extended Kalman Filter as the proposal distribution [12].

Following the selection of the particles from (24), the weights for $l = 1.......L$ at time t are sequentially updated as follows [13]:

$$w_t^l = w_{t-1}^l\, \frac{p(y_t|h_t^l)\, p(h_t^l|h_{t-1}^l)}{q(h_t^l|h_{t-1}^l, y_t)} \tag{25}$$

To monitor the degeneracy of weight or sample impoverishment, a suggested measure called the *effective sample size* is adopted as defined in [18],

$$\hat{N}_{eff} = \frac{1}{\sum_{l=1}^{L} (w_t^l)^2}, \tag{26}$$

Whenever $\hat{N}_{eff}$ is below a predefined threshold N_T (typically N_T = 2/3 L), a resampling procedure is performed. Specifically, particles with low weights are discarded to form a subset of particles $\{h_t^p\}$. New particles $\{h_t^l\}$ are generated by resampling with replacement particles from the subset $\{h_t^p\}$ with probability $\Pr(h_t^l = h_t^p) = w_t^p$ to keep L constant. The weights must now be normalized by resetting them to $w_t^l = 1/L$. In a sequential filtering framework, the resampling procedure is almost inevitable; however, it also introduces increased random variation into the estimation procedure.

PF Channel Estimation algorithm can be summarized as follows:

For time steps t, t + 1, t + 2…

i. Starting from posterior estimate for time t - 1: $N(m_{t-1}, P_{t-1})$ and $p(h_{t-1}|y_{t-1})$ with mean m_{t-1} and variance P_{t-1}.

ii. Update the prior distribution and perform prediction.

$$N(m_{t-1}, P_{t-1}) \rightarrow N(\hat{m}_t, Q_t) \tag{27}$$

Where estimated mean , $\hat{m}_t = m_{t-1}$ (28)

$$R_t = P_{t-1} + \sigma_v^2 I \tag{29}$$

$$Q_t = R_t + \sigma_u^2 I \tag{30}$$

$u_t = \mathrm{N}(0, \sigma_u^2)$ is process noise.

$v_t = \mathrm{N}(0, \sigma_v^2)$ is measurement noise

iii. Posterior estimate for time t:

$$N(m_t, Q_t) \rightarrow N(m_t, P_t)$$

Where, $m_t = \hat{m}_t + R_t Q_t^{-1}[\hat{h}_t - (\hat{h}_{t-1} + \hat{m}_t)]$ (31)

$$P_t = R_t Q_t^{-1} \sigma_u^2 \tag{32}$$

Using convergence results for the limiting behavior of the recurrence relations equations (27) through (30) can be modified and it can be shown that

$$t \to \infty, \begin{cases} K_t \overset{\Delta}{=} R_t Q_t^{-1} \to K \\ P_t \to P = K\sigma_u^2 \end{cases} \tag{33}$$

$$K = \frac{\alpha\left(\sqrt{1+4/\alpha}-1\right)}{2} I = \xi I \tag{34}$$

$$\alpha = \frac{\sigma_v^2}{\sigma_u^2} \tag{35}$$

ξ is referred as the rate of adaptation and takes the value $0 \le \xi \le 1$.

iv. Once m_t and P_t are found out, the channel estimation h_t is performed using the method of importance sampling to predict the state density by propagating particles ℓ = 1, ..., L, from time $t-1$ to t using equations (31) and (32),

$$h_t^l = h_{t-1}^l + \mu_t^l + n_t^l \tag{36}$$

Where $\mu_t^l = \mathrm{N}(m_t, P_t)$, n_t^l = noise variance.

IV. PERFORMANCE ANALYSIS OVER SIMULATED HF CHANNELS

Analysis of simulation results of MIMO channel estimation for both Gaussian and Non-Gaussian Noise scenario is presented. Extensive comparative studies have been carried out on MIMO HF channel estimation employing RLS and PF with EKF as proposal distribution.

A. The results of the MIMO Channel estimation simulations have been compared with the corresponding SISO HF channel. Parameters chosen for the simulation are as follows

Channel Model:

(i.) Three Independent Multi-path HF Channel using AR Filter of order 3

(ii.) The coefficient of the AR Filter is modeled as HF Fading (Gaussian Fading as discussed in section II).

(iii.) Power attenuation of 3 paths are 0, - 8, -10dB respectively.

(iv.) Doppler Spreads: 0.15, 0.5 and 1.1 Hz

Noise Model:

The noise model as given in equation (6) with $\varepsilon = 0.1$, $\sigma_2^2 = 10\sigma_1^2$.

Algorithms:

RLS and PF-EKF with particle length of 30.

MIMO Encoding Space Time Block Code (STBC) Matrix:

For 2x2 is
$$A_{2x2} = \begin{bmatrix} s_1 & -s_2^* \\ s_2 & s_1^* \end{bmatrix} \tag{37}$$

Where s_1 and s_2 is QPSK symbol. Symbol $[\, s_1 \quad s_2 \,]$ is transmitted over two antennas at time slot t_1, and Symbol $[\, -s_2^* \quad s_1^* \,]$ is transmitted over two antennas at time slot t_2.

And STBC matrix for 4x4 is

$$A_{4x4} = \begin{bmatrix} s_1 & -s_2^* & s_1 & -s_2^* \\ s_2 & -s_1^* & s_2 & s_1^* \\ s_3 & -s_4^* & -s_3 & s_4^* \\ s_4 & s_3^* & -s_4 & -s_3^* \end{bmatrix} \tag{38}$$

Where s_1, s_2, s_3 and s_4 are QPSK symbols. The Symbol $[\, s_1 \quad s_2 \quad s_3 \quad s_4 \,]$ is transmitted over four antenna at time slot t_1, similarly other column symbol is transmitted in respective time slot t_1, t_2 and t_4.

The performance improvement (BER, MSE and channel capacity) realized through various MIMO configurations such as 4x4, 2x2 has also compared with the SISO for a chosen HF channel Model.

B. Channel estimation error is analysed with error variance between the estimated channel matrix and simulated channel matrix as a performance parameter. Estimated symbol is obtained based on the estimated channel with zero force equalizer. The bit error probabilities have been estimated over 2000 data symbol long (4000 bits).

C. The extensive simulation studies have been carried out on the BER performance realized through the SISO HF Channel invoking the RLS as well as PF-EKF. The obtained simulated BER performance of the SISO HF channel has been compared with that published in [2]. As can be seen from the results of the Table I, it is evident that both the RLS and PF-EKF algorithms show improved performance relative to the method employed in [2]. In this comparison, 40000 data bits were considered as employed in [2]. However, even with reduced data bits of 4000, the simulation results continue to exhibit better performance relative to [2].

Table I. BER performance comparision with [2] against simulated result under doppler spread of 0.15 , 0.5 and 1.1 Hz for SISO HF multipath channel

Doppler Spread Hz	SNR dB	BER		
		Ref[2]	RLS	PF-EKF
1.1	5	0.8500	0.07158	0.0552
	10	0.7375	0.02837	0.0219
	15	0.6625	0.00420	0.0033
	20	0.6250	0.00135	0.0010
0.5	5	0.6250	0.06250	0.0459
	10	0.4000	0.01005	0.0063
	15	0.2500	0.00192	0.0012
	20	0.1375	0.00072	0.0005
0.15	5	0.325	0.01416	0.0051
	10	0.0775	0.00335	0.0012
	15	0.0550	0.00064	0.0002
	20	0.0325	0.00024	0.0001

D. The Channel Estimation Mean Square Error (MSE) of the SISO HF channel with varying Doppler spreads has been studied employing RLS and PF-EKF. The relative comparison of the MSE between the RLS and PF-EKF has been depicted in Figure 2, for SNR ranging from 0 to 25 dB. From the results shown in Figure 2, it is easy to infer that PF-EKF bears superior performance compared to RLS. Further, as one would expect, MSE decreases with lesser Doppler spread .

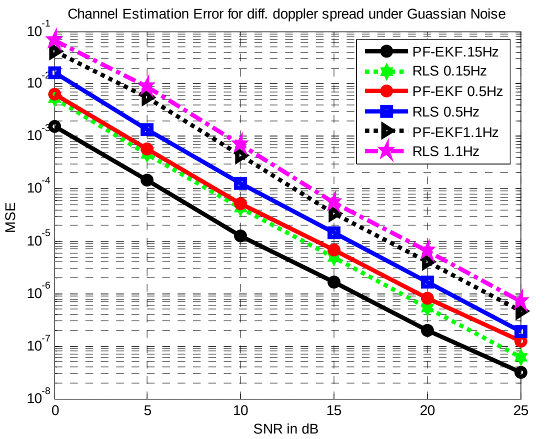

Figure 2: MSE vs SNR for Channel estimation under different Doppler spread for Gaussian Noise HF Channel

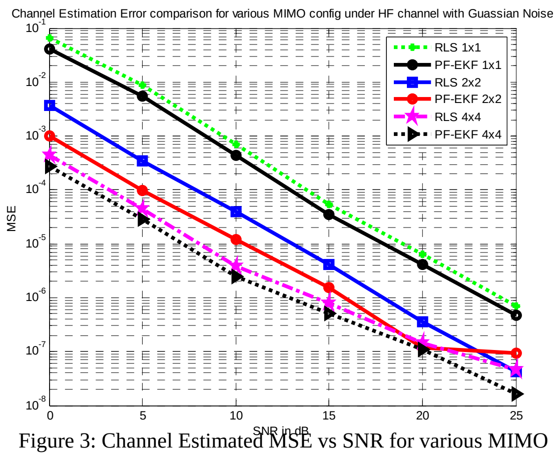

Figure 3: Channel Estimated MSE vs SNR for various MIMO configurations

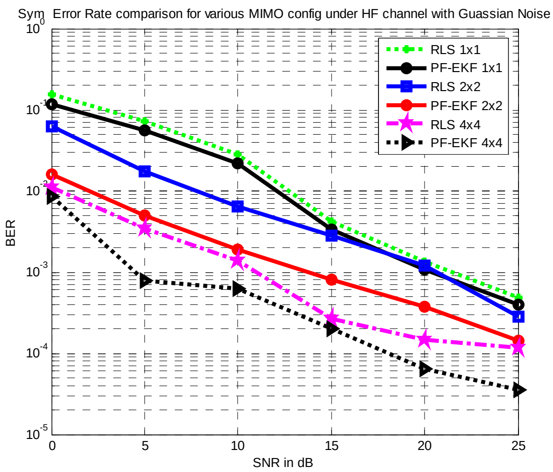

Figure 5: BER vs SNR for various MIMO configurations under Gaussian Noise

E. Simulation studies were conducted to analyze the performance of MIMO with different configuarations of transmitter and receiver antennas. Figures 3 and 4 illustrate the relative comparison of MSE of MIMO and SISO configuration under Gaussian noise and Non-Gaussian noise scenario respectively. In the simulation, the Doppler spread of 1.1 Hz has been assumed. From the results of figure 3 and 4, it can be seen that MIMO configuration exhbits lower MSE compared to SISO. Further, MSE obtained through PF-EKF is lower compared to that of RLS algorithm.

F. In addition to the MSE performance, the symbol error rate is also computed for various MIMO configurations as well as SISO.The BER results are plotted in Figures 5 and 6 for Gaussian Noise and Non-Gaussian Noise conditions respectively. The results of Figures 5 and 6 clearly demonstrate that MIMO configurations have desirable feature of lower BER relative to SISO. Also, the PF-EKF algorithm yields better performance than the RLS.

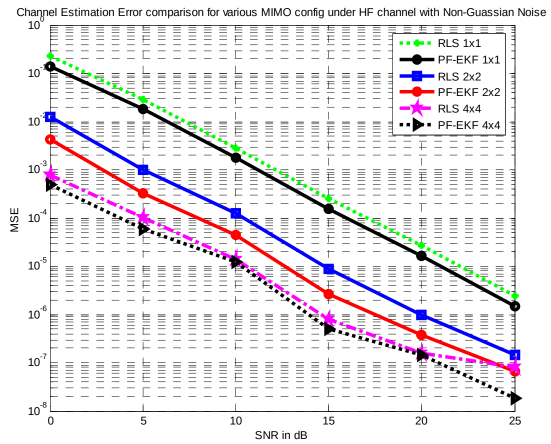

Figure 4: Channel Estimated MSE vs SNR for various MIMO configurations under Non-Gaussian Noise

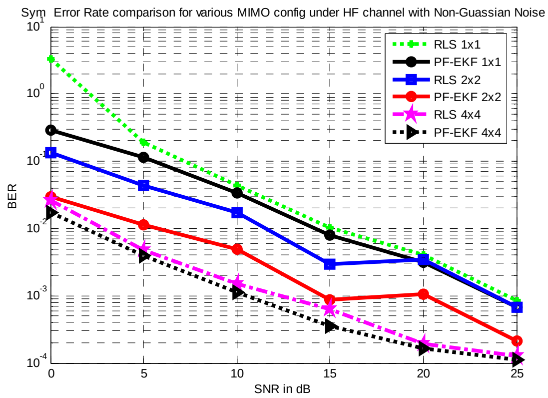

Figure 6: BER vs SNR for various MIMO configurations under Non-Gaussian Noise

G. The results on MSE illustrated in Figures 3 and 4 reveal that PF-EKF algorithm performs better than RLS. For higher MIMO configurations, there is an improvement in MSE. Comparison of MSE results of PF-EKF with RLS for 4x4 antenna configurations indiacate a gain improvement of on average of 2-3 dB for Gaussian Noise condition. Similarly for Non-Gaussian scenario, the corresponding gain improvement is about 1-3 dB. It is pertinent to point that the above data on gain improvement of PF-EKF refers to low SNR (below 7dB).

H. From the Figures 5 and 6, it is seen that PF-EKF algorithm performs better than RLS for both Gaussian and Non-Gaussian noise conditions. There is an improvement in BER with higher MIMO configuration. This is to be expected due to diversity factor in STBC. A gain improvement of 0.8-1dB gain is noticed in the PF-EKF relative to RLS for 4x4 antenna configurations under Gaussian Noise Channel. For lower MIMO configuration (2x2), the corresonding improvement in the gain is of the order of 0.2 to 0.5 dB gain for Gaussian Noise scenario . For Non-Gaussian Noise scenario the gain improvement is of the order of 0.5 to 0.8dB at lower SNR using PF- EKF.

Figure 7 shows the comparison of the Estimated Channel response obtained through the RLS and PF-EKF algorithms for :

Normalized Doppler Spread 1.1 Hz
Order of AR model 3
SNR =10 dB
Noise Distribution: Gaussian noise.
Number of data bits=4000
Multipath=3

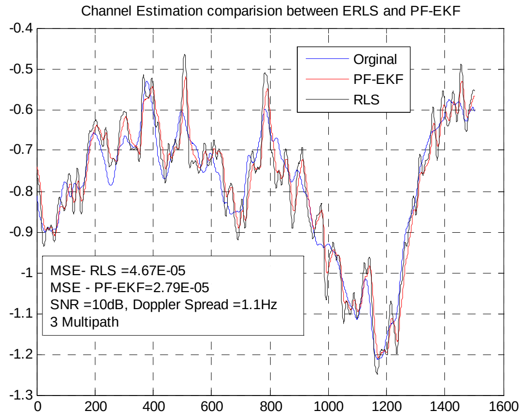

Figure 7: Comparison of channel Estimation based RLS and PF-EKF

It is found that PF-EKF estimates the channel states more accurately compared to RLS. The variance of estimated channel state by RLS is 4.67E-05. The corresonding variance through PF-EKF is 2.79E-05 and thereby proving the better performance of PF-EKF.

The HF channel capacity estimated for 2x2 MIMO configurations is compared with an ideal Shannon channel capacity is shown in table II. In these simulations, Doppler spread of 1.1 Hz with 3 multipath have been assumed for the modeling of the simulated HF channel.

$$C = \log_2(\det(\frac{\rho}{M_T} HH^H + I_{N_R}) bps/Hz \quad (39)$$

Where ρ the signal to noise ratio, H is the measured channel matrix, H^H is the conjugate transpose of this matrix.

V. CAPACITY COMPARISON

The results illustrated in Table II clearly spell out the influence of the channel estimation on the channel capacity. From Table II, it is evident that the PF-EKF exhibits a better channel estimation performance than the RLS algorithm for all MIMO configurations.

Table II: Capacity Comparison between RLS and PF-EKF for 2x2 MIMO

SNR dB	Capacity bit/sec/hz		
	Ideal Shannon 2x2 MIMO	RLS	PF-EKF
0	2.0	1.7807	1.8113
5	4.1147	3.7391	3.76480
10	6.9188	6.32733	6.3491
15	10.055	8.91599	8.94696
20	13.3164	12.73805	12.74209
25	16.61875	15.76779	15.77185

VI. CONCLUSION

This paper presents an analysis of MIMO based HF channel invoking Particle Filtering. The proposed PF based analysis has been demonstrated to show an improved performance in comparison to that obtained with RLS algorithm. The noteworthy feature of the paper is the treatment of even a Non-Gaussian noise in estimating the HF channel state. In addition, the influence of MIMO configurations on the performance of HF channel has also been investigated. The performance of various MIMO configurations has been compared with that of SISO also. This paper convincingly substantiates the benefit in lieu of incorporating dynamic Bayesian modelling technique for use in estimating a rapidly changing MIMO HF channel.

It is inferred from the simulation studies, that the performance of the channel estimation with the PF-EKF algorithm is superior to the RLS and other techniques with affordable computational complexity even in low SNR scenario. The results presented in this paper indicate that the PF algorithms can be handled with a better trade off between computational complexities and desirable performance suitable for HF communication system. The results of the simulation studies proves that the PF based HF channel estimation algorithm out performs the other algorithm like RLS in Gaussian noise conditions. While the prior algorithms have been unable to treat the Non-Gaussian noise condition, the proposed PF algorithm is demonstrated to deal with these scenarios. The simulation results of the MIMO based HF channel with PF confirm that there is a degradation in the channel performance under Non-Gaussian noise conditions. However the degradation is relatively small in comparison to Gaussaian Noise condition. Treating SISO as a limiting case of MIMO of 1x1 configuration, this paper has established the enhanced performannce of PF-EKF algorithm in estimating the BER and MSE. The BER results of these computations favorably compare with those of the prior published work [2].The results of RLS algorithm also exhbit lower BER in comparison to [2]. .

The analysis of this paper has a strong potential to form a firm basis to treat the Non linear time dispersive HF channel which is the current subject of research of the authors.

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