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Research Article

EVALUATION OF THE ERROR PERFORMANCE OF THE IEEE802.16 STANDARD BASED ON A HIDDEN MARKOV MODEL

Shaghayegh KORDNOORI*[1], Hamidreza MOSTAFAEI[2], Mohammad Hassan BEHZADI[3]

[1]*Department of Statistics, Science and Research Branch, Islamic Azad University, Tehran-IRAN;*
ORCID: 0000-0003-1403-225X
[2]*Department of Statistics, North Tehran Branch, Islamic Azad University, Tehran-IRAN;*
ORCID: 0000-0002-5893-4653
[3]*Department of Statistics, Science and Research Branch, Islamic Azad University, Tehran- IRAN;*
ORCID: 0000-0002-1849-5588

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ABSTRACT

IEEE802.16 (WiMAX) is a standard that supports high data rate in a wide area with multi-traffic communication, low implementation and the possibility of creating broadcast, multicast and mesh networks. In this paper the Hidden Markov Model as a Discrete Channel Model has been employed to model the burst errors generated from IEEE 802.16/WiMAX; moreover, the precise Hidden Markov Models using Baum-Welch Algorithm have been obtained by estimating the optimal order of these models with comparing statistics such as Average log-likelihood, Probability of Error, $P(0^m|1)$ and Auto-Correlation function. Additionally, the parameters of the best models have been derived. The impacts of a number of Baum-Welch Algorithm iterations and the modulation order on the optimal order estimation with respect to different (T_s) were investigated using extensive simulations.
Keywords: Stochastic processes, hidden Markov model, WiMAX, error analysis, OFDM, parameter estimation.

1. INTRODUCTION

Wireless communication is an arising field which has made enormous progress in recent years. Evaluating the performance of these communication systems is vital. Therefore, techniques for simulating and modeling the channel play an important role in assessing network protocols and application functioning.

Orthogonal Frequency Division Multiplexing (OFDM) is the multicarrier transmission scheme that achieves high data integrity, high spectral efficiency, and high data throughput. It enables video and multimedia communications and has this potentiality to cope with multipath interference at the receiver and has a high degree of flexibility. OFDM is applied by a range of broadband systems such as DSL, Wi-Fi, Digital Audio/Video Broadcasting (DAB/DVB) and MediaFLO, in addition to Worldwide Interoperability for Microwave Access (WiMAX). The

* Corresponding Author: e-mail: sh_kordnourie@yahoo.com, tel: +989123866861

IEEE802.16 is a current wireless broadband standard, which is a solution to broadband Wireless Access WiMAX. Th e architecture of this standard contains one base station and many subscriber stations. It has been evolved for providing cost-effective and qualified alternatives to wireline broadband access. The IEEE802.16 standard is based on the combination of OFDM access air interface and the state of the art medium access control layer. It is a superior replacement of Wi-Fi/IEEE 802.11 in providing better coverage, bandwidth efficiency and power consumption along with supporting higher speed connection up to 70 Mbps over the distance of 30 miles. The security of IEEE 802.16 is multi-level encryption and its dynamic bandwidth allocation is good for video together with voices; moreover, it administers various traffic types with distinctive priority classes for conforming each Quality of Service conditions in downlink and uplink directions.

There is a possibility of error generation in the system when the data is sent over a data link. Therefore, it is essential to evaluate the performance of the system. Bit Error Rate (BER) is the crucial criterion that is applied in evaluating systems that transmit digital data. Some factors such performed using different ways such as the works in [1,2,3].To model burst errors in communication channels, the Hidden Markov Model (HMM) is applied more frequently. The Hidden Markov Models (HMMs) are the most common Discrete Channel Model (DCM) with memory which their theory is well established and they are analytically tractable. In these models, the data is described by supposing that it depends randomly on an underlying unobserved Markov process which explains a sequence of hidden channel states. (HMMs) make a profitable and flexible class of stochastic processes which have been used satisfactorily for a broad range of applied problems. They have become significant in a wide variety of applied fields after introducing by Baum and Petri in 1966 [4]. They are used in text recognition [5], speech recognition [6], wireless networks [7,8], Bioinformatics [9], activity recognition [10], stock forecasting [11], face recognition [12], energy sector [13], brain disease [14], machine failure detection [15], biology [16], etc. The application of HMM as one of the famous DCM methods in modeling the wireless fading channels has been undertaken in several manners for various wireless systems such as OFDM [17,18], CDMA [19,20] and GSM [21]. Evaluating the performance of the (HMM) is considerably rested on the system being followed, the type of assumed discrete channel modeling way and the fading channel. Gilbert [22] and Elliot [23] initiated the study of the HMM for bursty communication channels. In their proposed model only two states were considered which is not sufficient when the channel quality alters noticeably. Hence, Fritchman [24] improved their model by suggesting an improved state partitioned model which has more than two states. Therefore, modeling the channel using HMM compared to the real wireless channel simulation causes a huge reduction in resources, time and effort. Applying the (DCM) is essential since the Waveform channel model would require enormous computer resources and it is very high-priced for evaluating the performance of the system. The probabilistic Discrete Channel Models are computationally more powerful than the Waveform-level models which resulted from two factors: First, in (DCM) a high level of abstraction is utilized, whereas in Waveform-level model each singular block is simulated elaborately.

Second, the symbol rate of (DCM) simulation is 8-16 times of the symbol rate in the Waveform-level model. Some researches presented in [25,26,27,28,29,30,31] show the capability of (HMMs) in modeling the burst errors in the communication channel accurately. The order estimation for HMM-based models is a notable subject in the analysis. The order of the HMM presents the minimum number of hidden states which is needed to perform the modeling precisely. The physical conditions of the wireless channels play a key role in characterizing the number of states. An order estimator of HMM-based on renewal types has been demonstrated in [32]. The results concerned with the estimation of a discrete time finite alphabet stationary ergodic HMM order have been given in [33]. In [34], the impact of channel estimation errors in a CDMA system was investigated based on HMM with adaptive modulation and coding and orthogonal multicodes. The frame level errors in GSM wireless channels were modeled with different methods, including HMM in [35] and the impact of the different orders of the metric on the performance was investigated. The order estimation of binary (HMMs) in slow Rayleigh fading channels was studied in [36].

The rest of this paper is coordinated as follows. In section 2, short details about HMM along with implementation training by Baum-Welch Algorithm (BWA) is given. The discussion about the OFDM fundamentals is presented in section 3. Next, the application of the HMM in IEEE 802.16/WiMAX which is a wireless standard that adopted OFDM is exhibited. In section 4, the BER performance for this standard has been evaluated for two different OFDM system parameters with various numbers of states. The optimum number of states for (HMMs) has been achieved based on statistical measure comparisons of the original and regenerated error sequences and the simulation results are analyzed in this part. Finally, conclusions are presented.

2. MATERIALS AND METHODS

2.1. Mathematical Description

HMM is an extension of a Markov chain whose states are hidden. It is a discrete doubly stochastic model $\{(H_k, O_k)\}$, where $\{H_k\}$ denotes the hidden state sequence which is a finite state Markov chain. The O_k is conditionally independent given $\{H_k\}$ and the conditional distribution of O_k relies on $\{H_k\}$ only through H_n. Suppose $\boldsymbol{H} = \{H_n, n = 1, \dots, N_h\}$ be a Markovian process which is a set of N_h states and $\boldsymbol{O} = \{O_m, m = 1, \dots, N_m\}$ be a function of $\boldsymbol{H}$ which is a set of N_m distinct symbols such that $\boldsymbol{O} = f(\boldsymbol{H})$. Therefore, the $\boldsymbol{H}$ can be observed throughout $\boldsymbol{O}$; moreover, $\boldsymbol{A} = \{a_{ij}\}$ is a set of state transition probabilities where a_{ij} indicates the probability of moving from state H_i to state H_j i.e.,

$$a_{ij} = P[H_{t+1} = j | H_t = i], \qquad i, j = 1, \dots, N_h \tag{1}$$

$B = \{b_{H_i}(o_k)\}$ denotes the observation probabilities where $b_{H_i}(o_k)$ represents the emission probability of o_k at state H_i which k is a set of possible symbols within H_i i.e.,

$$b_{H_i}(o_k) = P[O_t = o_k | H_t = i], k = 1, \dots, N_m, i = 1, \dots, N_h \tag{2}$$

The initial set of probabilities before generating sequences of symbols is $\Pi = \pi_i$ i.e.,

$$\pi_i = P[H_1 = i], \ \ i = 1, \dots, N_h \tag{3}$$

Hence, the HMM is commonly described by parameters $(\boldsymbol{H}, \boldsymbol{O}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\Pi})$ completely. A probabilistic illustration of the first order HMM is given in figure 1.

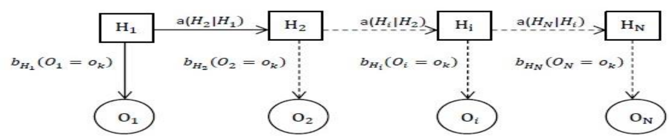

Figure 1. Probabilistic illustration of the first order HMM.

The most complicated problem related to HMM is training. This issue involves adjusting the parameters of the model $\lambda = (A, B, \Pi)$ with only the training data to meet the criterion of optimization. The Baum-Welch Forward Backward Algorithm is the most common criterion which is used to maximize the $P(\boldsymbol{O} \mid \lambda)$. This algorithm is a particular case of the EM algorithm with a noteworthy feature of robustness. The (BWA) always converges to a local maximum of the likelihood function. The forward and backward variables (until time *t*) are defined as follows, respectively:

$$\alpha_t(i) = P[\, o_1, o_2, \dots, o_t, H_t = i \mid \lambda \,] \tag{4}$$

$$\beta_t(i) = P[\, o_{t+1}, o_{t+2}, \dots, o_T \mid H_t = i, \lambda\,] \tag{5}$$

for $i = 1, \dots, N_h$. The calculations of these variables can be done by induction as illustrated in tables 1 and 2.

Table 1. The forward stage

1. Initialization: $\alpha_1(i) = \pi_i b_i(o_1), \quad i = 1, \dots, N_h$
2.Induction: $\alpha_{t+1}(j) = \left[\sum_{i=1}^{N_h} \alpha_t(i)\, a_{ij}\right] b_j(o_{t+1}), i = 1, \dots, N_h \,; t = 1,2, \dots, T-1$
3. $P(\boldsymbol{O} \mid \lambda) = \sum_{i=1}^{N_h} \alpha_T(i)$

Table 2. The Backward stage

1. Initialization: $\beta_t(i) = 1, \quad i = 1, \dots, N_h$
2.Induction: $\beta_t(i) = \sum_{j=1}^{N_h} a_{ij} b_j(o_{t+1})\, \beta_{t+1}(j), i = 1, \dots, N_h \,; t = 1,2, \dots, T-1$
3. $P(\boldsymbol{O} \mid \lambda) = \sum_{i=1}^{N_h} \pi_i\, \beta_1(i)$

Next, the optimal state sequence related to the given observation sequence is found by defining the variable

$$\gamma_t(i) = P(\, H_t = i \mid o, \lambda\,) = \frac{\alpha_t(i)\beta_t(j)}{P(\boldsymbol{O}|\lambda)} = \frac{\alpha_t(i)\beta_t(j)}{\sum_{i=1}^{N_h} \alpha_t(i)\beta_t(j)} \tag{6}$$

In the learning problem, we introduce $\xi_t(i,j)$ to find the parameters of the model that maximize the likelihood of the training set:

$$\xi_t(i,j) = P(H_t = i, H_{t+1} = j|\mathrm{o},\lambda \tag{7}$$

$$= \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\sum_{i=1}^{N_h}\sum_{j=1}^{N_h} \alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)} \tag{8}$$

The binary error sequence δ is generated through simulation. The number of iterations for convergence to the maximum of the likelihood is determined when the variations in the value of $P(\bar{O} \mid \lambda)$ become trivial. The Forward and Backward vectors will tend to zero exponentially when the data size becomes larger. Hence, to avoid numerical underflow, the α and β should be scaled. The scaling factor (C_t) is determined as

$$C_t = \sum_{i=1}^{N_h} \alpha_t(i) \tag{9}$$

for $i = 1, \dots, N_h$ states and $t = 1, \dots, T$ bits. The value of $P(\bar{O} \mid \lambda)$ can be identified as follows:

$$P(\,\bar{O} \mid \lambda\,) = \prod_{t=1}^{T} C_t \tag{10}$$

This number is very trivial for large T and is commonly expressed as

$$\log P(\,\bar{O} \mid \lambda\,) = \sum_{t=1}^{T} log_{10}\,(C_t) \tag{11}$$

2.2. OFDM Fundamentals

OFDM is a promising modulation scheme for advanced communications networks. Many wireless standards such as WiMAX, LTE, IEEE802.11a and DVB have accepted the OFDM as a mean to expand significantly the future wireless communications. This technology is appropriate for high data rates with sufficient robustness to channel imperfections and frequency selective channels. The multicarrier structure, low symbol rate, coding and forward error correction of

OFDM make it operable in channel conditions degraded by jamming and fading. It is spectrally efficient and can combat Inter-Symbol Interference (ISI) and reduce Inter-Carrier Interference (ICI); Moreover, unlike CDMA, it can protect energy loss at frequency domain which gives additional advantages for OFDM. The orthogonality preservation methods in this model are much simpler than CDMA or TDMA. Some factors such as Multiple Input Multiple Output (MIMO), carrier aggregation, beam-forming, and space-time coding are crucial in obtaining the maximal potential of OFDM implementations. They can boost the useful capacity of a channel.

Figure 2 shows the implementation of HMM on the burst errors generated in the wireless channel for an OFDM model. The serial to parallel/parallel to serial, modulation/demodulation, Inverse Fast Fourier Transform and Fast Fourier Transform (IFFT and FFT) are included in OFDM block; moreover, to circularize the channel effect a redundancy known as Cyclic prefix is considered in OFDM schemes. The impact of both Multipath-fading and AWGN has been incorporated in the wireless channel. The error sequence as a consequence of imperfections in the transmitter, channel, and receiver is achieved by comparing the transmitted and received signal. The new error sequence is resulted by training the original error sequence by the (BWA) algorithm and its comparison with the old one is done.

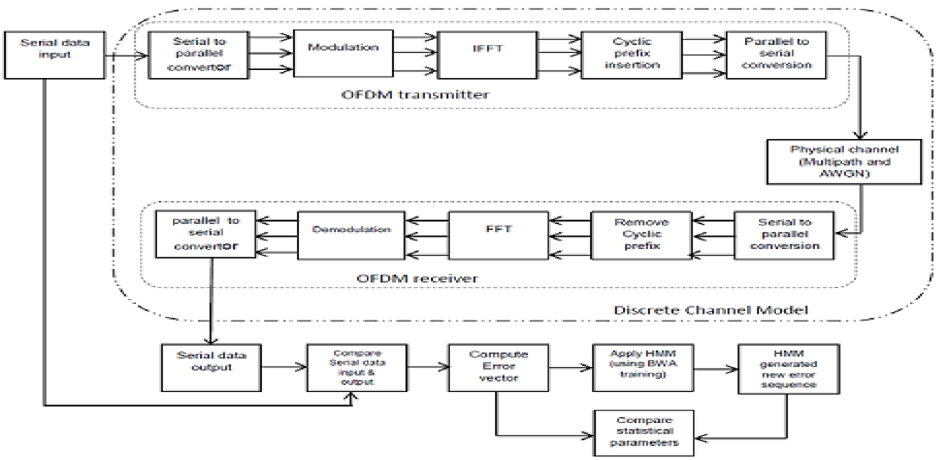

Figure 2. Block diagram for HMM implementation for OFDM

3. RESULTS AND DISCUSSION

3.1. The Simulation Results and Analysis

The Frequency selective Rayleigh fading channel is regarded for the OFDM systems. Table 3 indicates the two distinct sets of OFDM transceiver parameters which were employed in the simulation for estimating the best HMM model that generates the error sequence of waveform-level very closely. As BPSK, QPSK and 16-PSK can be used in IEEE802.16 [37] and we considered these modulations in our simulation. Sampling periods of the channel were $T_s = 10^{-3}$ and $10^{-4}(s)$. SNR (in dB) is 0-30. The path delays and Avg path power gains were with four taps. Length of error sequence and a number of iterations of BWA training were considered 200000 and 30, respectively.

The OFDM BER curve versus SNR in Frequency Selective Rayleigh fading channel from the set 1 with BPSK modulation is presented in Figure 3.

Table 3. Sets of OFDM simulation parameters

set	FFT size	Cyclic prefix length (Ncp)	Number of the pilot symbols(Np)
1	256	64	28
2	2048	96	173

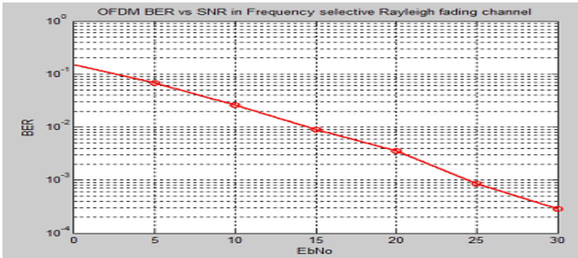

Figure 3. The OFDM BER curve versus SNR for set 1.

The error sequences which are generated from the higher value of SNR caused not only due to AWGN but also because of the multipath fading. The original error sequence and the one which was generated by the HMM are compared in terms of the Average maximum log-likelihood, $P(0^m|1)$ and the Autocorrelation function which is the most conventional technique for evaluating the HMM performance and finding the nearness between the original and HMM-generated data.

The HMMs have been trained with 30 iterations using the BWA for the original error sequence obtained from the OFDM simulation under the mentioned conditions and as a consequence new error sequences are resulted. Figure 4 depicts the average log-likelihood (defined in (11)) as a function of SNR ranged 0-30. Wide simulations were performed using various numbers of HMM states. From this figure, it is clear that for set 1 which has a fewer number of subcarriers, the HMM can be estimated more precisely. Increasing the length of training beyond 200000 only enhances the simulation time without any marked progress of the average log-likelihood and this trend is preserved.

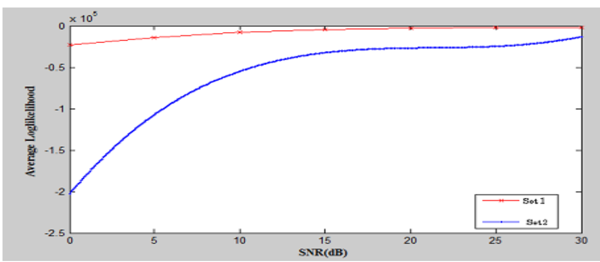

Figure 4. Average log-likelihood of 2-state HMM comparison for two sets of OFDM parameters

Figure 5 indicates the comparison of Average log-likelihood for 2-state to 5-state HMMs in the error analysis of IEEE802.16 (set1) with FFT=256. It is evident that the HMM with 3-state is the best model with an aspect of the average log-likelihood criterion.

The downgrading of average log-likelihood for the set 2 is not much and counting on a wanted precision. The obtained HMM can be a helpful substitute for the OFDM systems.

The average Error Probability is another comparison criterion which has been computed over a length of the 200000 error sequence. It can be concluded that the HMM is an acceptable fit for the two OFDM sets as compared to the original sequence. Table 4 summarizes the comparisons of different SNRs for 2-state HMM. It is evident from Table 4 that for all SNR values, the HMM can be estimated efficiently and precisely. It can be seen that the PE values for HMM and the original models remain very closely for all two sets.

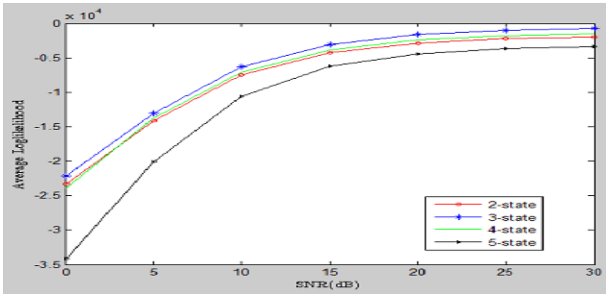

Figure 5. Comparison of Average log-likelihood for 2-state to 5-state HMM with the IEEE 802.16 (set 1) parameters

Table 4. Probabilities of Error (PE) for different SNRs and 2-state HMM in sets 1 and 2 of OFDM parameters

	SET1		SET 2	
SNR(dB)	**PE Original**	**PE HMM**	**PE Original**	**PE HMM**
0	0.0708	0.0711	0.0731	0.0729
5	0.0334	0.0329	0.0309	0.0307
10	0.0125	0.0120	0.0106	0.0106
15	0.0045	0.0045	0.0033	0.0033
20	0.0016	0.0016	9.4712e-04	9.8884e-04
25	5.3000e-04	5.3000e-04	2.8672e-04	2.5499e-04
30	1.1500e-04	1.2000e-04	6.1105e-05	1.9976e-05

Figure 6 demonstrates the comparison of PE for the original error data with 2 states to 5 state HMMs for different SNR values of IEEE 802.16 parameters (set 1). It can be concluded that the performance is improved by enhancing the order of the HMM. The estimated error sequences from the HMMs were in addition compared with the Original error sequence in terms of the Autocorrelation function (ACF) and Error-free run distribution. The ACF is the most common technique for estimating the order and evaluating the performance of HMMs. In the IEEE802.16 (set 1) with SNR=5 dB and $T_s = 10^{-3}$s, the MSE of ACFs (with 50 lags) for the error sequences generated and the original error sequence were 0.003955 and 0.003952, respectively. Hence, the 3-state HMM is lightly less and can estimate the Original error sequence more precisely.

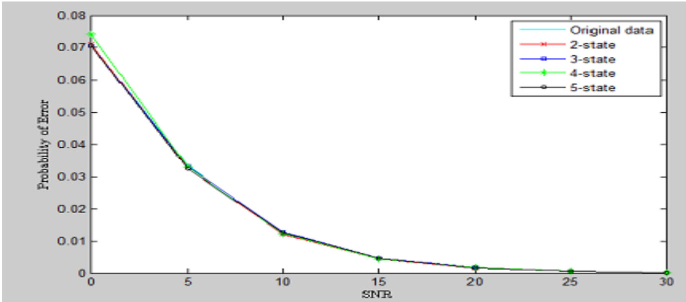

Figure 6. Comparison of PE values for HMM with a different number of states and a wide range of SNRs for set 1 of OFDM parameters.

Figure 7 shows the Error-free run distribution comparison for the original and 2-state along with 3-state HMM-generated error sequences. Although both HMM trends are close to the trend of original error sequence but it is evident that the 3-state HMM is much closer to the Original error trend. Therefore the 3-state HMM can model the IEEE802.16 of OFDM system adequately. Table 5 summarizes the optimum estimated parameters A, B, Π at different values of SNRs for the 3-state HMM model with (set 1) simulation parameters. The iteration was considered 30 for BWA training. The error bursts obtained in the OFDM Frequency selective Rayleigh fading channel can be characterized by these estimated parameters.

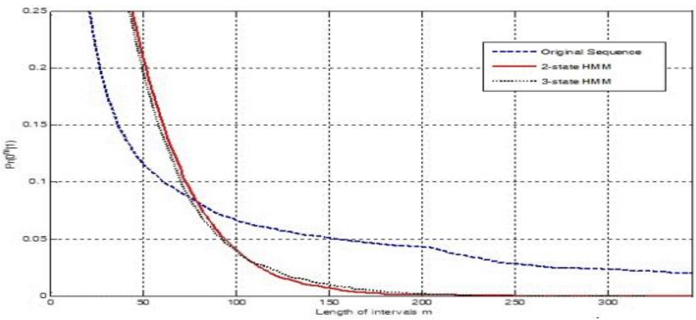

Figure 7. Comparison of the Error-free run distributions for the Original and HMMs generated error data at SNR = 5 and T_s = 10^{-3}s for set 1 of OFDM parameters.

Table 5. Estimated parameters for three state-HMMs error generation for IEEE 802.16 (set 1)

SNR / Parameters	0	5
A	$\begin{bmatrix} 0.7384 & 0.1230 & 0.1386 \\ 0.4965 & 0.2710 & 0.2325 \\ 0.3778 & 0.4611 & 0.1611 \end{bmatrix}$	$\begin{bmatrix} 0.7630 & 0.1135 & 0.1235 \\ 0.5454 & 0.2525 & 0.2021 \\ 0.4182 & 0.4376 & 0.1442 \end{bmatrix}$
B	$\begin{bmatrix} 0.9950 & 0.8380 & 0.7922 \\ 0.0050 & 0.1620 & 0.2078 \end{bmatrix}$	$\begin{bmatrix} 0.9994 & 0.9024 & 0.8952 \\ 0.0006 & 0.0976 & 0.1048 \end{bmatrix}$
Π	$[0.0000 \quad 0.0613 \quad 0.9387]$	$[0.9699 \quad 0.0205 \quad 0.0096]$
SNR / Parameters	**10**	**15**
A	$\begin{bmatrix} 0.7384 & 0.1246 & 0.1370 \\ 0.5475 & 0.2549 & 0.1976 \\ 0.4050 & 0.4491 & 0.1459 \end{bmatrix}$	$\begin{bmatrix} 0.7215 & 0.1321 & 0.1464 \\ 0.5419 & 0.2592 & 0.1989 \\ 0.3918 & 0.4590 & 0.1492 \end{bmatrix}$
B	$\begin{bmatrix} 0.9999 & 0.9649 & 0.9639 \\ 0.0001 & 0.0351 & 0.0361 \end{bmatrix}$	$\begin{bmatrix} 0.9999 & 0.9882 & 0.9875 \\ 0.0001 & 0.0118 & 0.0125 \end{bmatrix}$
Π	$[0.7949 \quad 0.1071 \quad 0.0980]$	$[0.6327 \quad 0.1715 \quad 0.1958]$
SNR / Parameters	**20**	**25**
A	$\begin{bmatrix} 0.7164 & 0.1342 & 0.1494 \\ 0.5414 & 0.2599 & 0.1987 \\ 0.3883 & 0.4616 & 0.1501 \end{bmatrix}$	$\begin{bmatrix} 0.7144 & 0.1351 & 0.1505 \\ 0.5406 & 0.2604 & 0.1990 \\ 0.3867 & 0.4628 & 0.1505 \end{bmatrix}$
B	$\begin{bmatrix} 1.0000 & 0.9959 & 0.9957 \\ 1.0000 & 0.0041 & 0.0043 \end{bmatrix}$	$\begin{bmatrix} 1.0000 & 0.9986 & 0.9986 \\ 0.0000 & 0.0014 & 0.0014 \end{bmatrix}$
Π	$[0.5649 \quad 0.1935 \quad 0.2416]$	$[0.5400 \quad 0.2012 \quad 0.2588]$
SNR / Parameters	**30**	
A	$\begin{bmatrix} 0.7134 & 0.1355 & 0.1511 \\ 0.5402 & 0.2607 & 0.1991 \\ 0.3859 & 0.4634 & 0.1507 \end{bmatrix}$	
B	$\begin{bmatrix} 1.0000 & 0.9997 & 0.9997 \\ 0.0000 & 0.0003 & 0.0003 \end{bmatrix}$	
Π	$[0.5299 \quad 0.2044 \quad 0.2657]$	

The influence of the number of iterations on the order estimation of HMM has been assessed for the waveform level simulation for IEEE 802.16 (set 1) with $T_s = 10^{-3}$ and 10^{-4}s.

The ACFs (with 30 lags) were computed for comparing the Original error data and HMM-generated error sequences with different states. The closest HMM generated error sequence to the Original one was chosen according to the MSE of ACFs. The results are given in figures 8-9 and table 6. It can be seen that for a specific T_s, the order of HMMs decreases with increasing in the number of (BWA) training iterations.

Table 6. The required minimum number of hidden states for the different number of iterations and various T_s values

T_s	Number of iterations			
	25	50	75	100
10^{-3}	6-state	6-state	6-state	2-state
10^{-4}	6-state	6-state	6-state	2-state

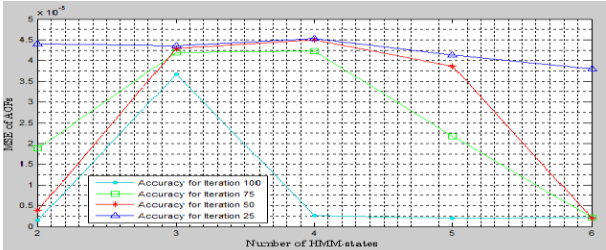

Figure 8. Accuracy vs. number of states for IEEE 802.16 with $T_s = 10^{-3}$s for set 1 of OFDM parameters

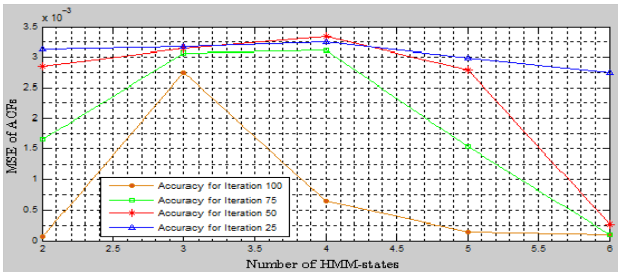

Figure 9. Accuracy vs. number of states for IEEE 802.16 with $T_s = 10^{-4}$s for set 1 of OFDM parameters

In order to describe different data rates for various needs in IEEE 802.16, there are many modulation schemes which are applied with OFDM such as BPSK, QPSK, and 16-PSK. In fact, the system becomes more apt to errors when the points on the constellation become greater. The impact of the modulation scheme on the order estimation of HMM has also been investigated. The results are exhibited in figures 10-13, for 256 FFT keeping the SNR as 5 dB and $T_s = 10^{-4}$ s. The error sequence length was taken as 200000. Comparison of the Original and HMM generated error sequences has been performed to evaluate the increase in the order of PSK based IEEE 802.16 with the measures of ACF and error-free interval distribution.

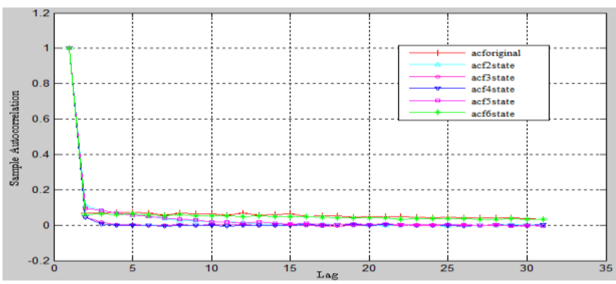

Figure 10. ACF versus SNR with BPSK modulation for set 1 of OFDM parameters.

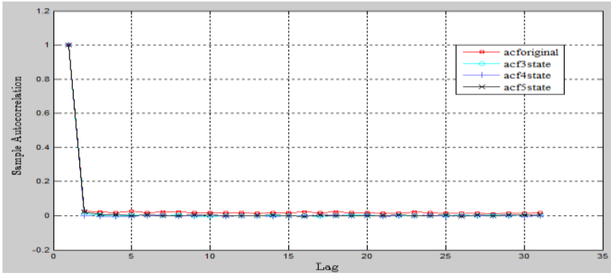

Figure 11. ACF versus SNR with QPSK modulation for set 1 of OFDM parameters.

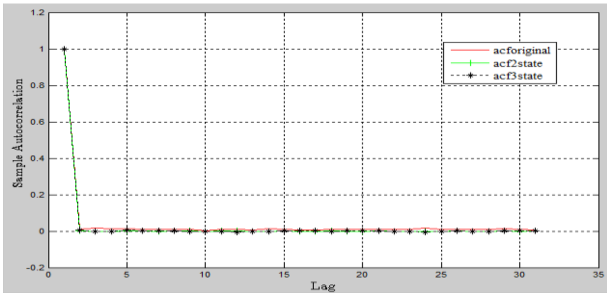

Figure 12. ACF versus SNR with 16-PSK modulation for set 1 of OFDM parameters.

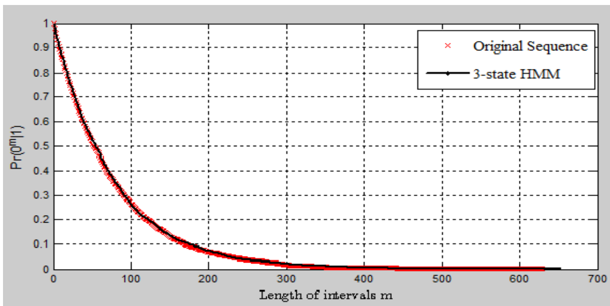

Figure 13. The error-free interval for set 1 OFDM parameters with 16-PSK modulation.

The obtained minimum number of hidden states of HMMs for various M-Ary PSK modulation schemes is given in table 7. It is clear that when the number of errors is increased by enhancing the constellation size, the pattern in that errors can be detected simply by the HMM; moreover, with the increase of constellation size, the required minimum number of hidden states was decreased.

Table 7. The required minimum number of hidden states for the different number of iterations and various T_s values

PSK-modulation	Required minimum number of hidden states
BPSK(M=2)	6
QPSK(M=4)	5
16-PSK(M=16)	3

In addition, the results concerning the order estimation of HMM in different PSK modulation can be determined precisely by computing the MSE of ACFs. Figure 14 represents the progress of modeling precision with an increased number of states in the HMM for the BPSK and QPSK modulation based IEEE 802.16 WiMAX. It validates the results of table 7.

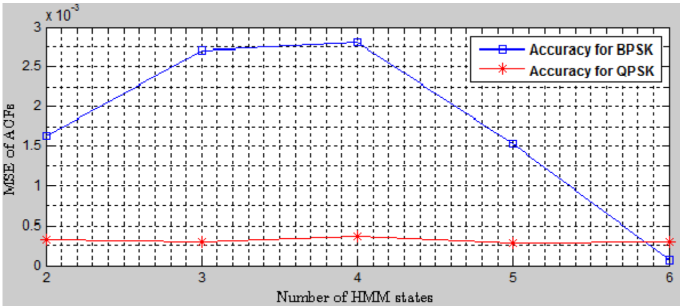

Figure 14. MSE of ACFs for different modulation with set 1 OFDM parameters.

At last, the parameters A, B, Π of HMM for IEEE 802.16 with different modulation were estimated by 30 iterations of (BWA) according to the optimal number of hidden states which obtained before. The results are summarized in table 8. These estimated parameters can be adequately applied in the analysis and design of protocols and applications since they are completely identified by the error bursts generated in a wireless fading channel.

Table 8. The estimated HMM parameters for the optimum states with different PSK modulation (T_s =10^{-4}s; SNR = 5dB)

Modulation	HMM parameters
BPSK	$A=\begin{bmatrix} 0.4067 & 0.0097 & 0.2871 & 0.1363 & 0.1588 & 0.0014 \\ 0.8088 & 0.0316 & 0.0174 & 0.0614 & 0.0497 & 0.0311 \\ 0.1947 & 0.0454 & 0.3828 & 0.1920 & 0.1691 & 0.0160 \\ 0.1353 & 0.0062 & 0.1695 & 0.1308 & 0.5485 & 0.0097 \\ 0.3945 & 0.0179 & 0.0715 & 0.1042 & 0.4105 & 0.0014 \\ 0.0048 & 0.0006 & 0.0099 & 0.0007 & 0.0012 & 0.9828 \end{bmatrix}$
	$B=\begin{bmatrix} 0.9955 & 0.9424 & 0.9982 & 0.9920 & 0.9980 & 0.8926 \\ 0.0045 & 0.0576 & 0.0018 & 0.0080 & 0.0020 & 0.1074 \end{bmatrix}$
	$\Pi = [0.4418 \quad 0.0000 \quad 0.1215 \quad 0.0469 \quad 0.3898 \quad 0.0000]$
QPSK	$A=\begin{bmatrix} 0.6868 & 0.0456 & 0.0234 & 0.0166 & 0.2276 \\ 0.6538 & 0.1192 & 0.1622 & 0.0533 & 0.0115 \\ 0.1029 & 0.2655 & 0.1875 & 0.1339 & 0.3102 \\ 0.4192 & 0.2644 & 0.0548 & 0.0671 & 0.1945 \\ 0.3599 & 0.3103 & 0.0865 & 0.0809 & 0.1624 \end{bmatrix}$
	$B=\begin{bmatrix} 0.9961 & 0.9730 & 0.8168 & 0.8611 & 0.9795 \\ 0.0039 & 0.0270 & 0.1832 & 0.1389 & 0.0205 \end{bmatrix}$
	$\Pi = [0.9722 \quad 0.0272 \quad 0.0000 \quad 0.0000 \quad 0.0006]$
16-PSK	$A=\begin{bmatrix} 0.7128 & 0.1355 & 0.1517 \\ 0.5342 & 0.2623 & 0.2035 \\ 0.3828 & 0.4645 & 0.1527 \end{bmatrix}$
	$B=\begin{bmatrix} 0.9985 & 0.9726 & 0.9590 \\ 0.0015 & 0.0274 & 0.0410 \end{bmatrix}$
	$\Pi = [0.0000 \quad 0.0000 \quad 1.0000]$

4. CONCLUSION

The most frequently used model for channels with memory is the Markovian models. In this paper, the application of HMM as a (DCM) in the wireless channel has been shown. This model was estimated for error bursts in IEEE 802.16/WiMAX based on OFDM technology. Considerable simulative analyses have been employed to conclude precise HMM-based (DCM) after the order i.e. the minimum number of hidden states has been estimated by BWA iterative training for various OFDM system parameters and SNR conditions. According to a variety of criteria such as log-likelihood, AutoCorrelation Function, Average Error Probability, and error-free interval probability distribution along with the simulation results, it can be concluded that the suggested HMMs can approximate the features of the Original error sequence very closely. The applications of IEEE 802.16 (WiMAX) have significantly increased recently due to rapid deployment, low cost and advanced characteristics of OFDM technology. Therefore the proposed HMM can apply as a potent tool for modeling and evaluating the statistics of burst error sequences. The roles of the input sample period of the signal, the modulation order and the number of iterations in BWA training in order estimation were investigated. Increasing the number of iterations will lead to a decrease in the required optimal number of states. The order of

PSK modulation has a profound influence on the minimum number of hidden states required; Furthermore, Increasing the order of modulation reduces the order and complexity of HMM. The parameters of HMM for the optimum states with different PSK modulation in IEEE802.16 were estimated.

Reducing the computational burden and including the potential of making accurate with a high-speed study of higher level protocols are the most notable advantages of HMM compared to the physical layer simulation.

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