Abstract—Data detection of convolutional coded differential quaternary phase shift keyed (DQPSK) signals using a predictive Viterbi algorithm (VA) based receiver, is presented for single input, multiple output - orthogonal frequency division multiplexed (OFDM) systems. The receiver has both error correcting capability and also the ability to perform channel estimation (prediction). The predictive VA operates on a supertrellis with just $S_{ST} = S_E \times 2^{P-1}$ states instead of $S_{ST} = S_E \times 2^P$ states, where the complexity reduction is achieved by using the concept of isometry (here $S_E$ denotes the number of states in the encoder trellis and $P$ denotes the prediction order). Though the linear prediction based data detection in turbo coded OFDM [1] and the bit interleaved coded (BIC) OFDM [2] systems perform better than the proposed approach in terms of bit error rate (BER) for a given signal to noise ratio (SNR), the decoding delay of the proposed approach is significantly lower than that of the BIC and the turbo coded OFDM systems.

Keywords—Supertrellis, Prediction filter, Viterbi algorithm, Isometry.

I. INTRODUCTION

OFDM has the ability to convert a frequency selective fading channel into a frequency flat channel [3]. Though the coherent detectors perform better than the linear prediction (LP)-based detectors in terms of BER [1, 4, 5], for a given SNR, coherent detectors are not throughput efficient since pilots have to be transmitted in every OFDM frame for the purpose of estimating the channel frequency response [6–8]. The throughput is defined as the ratio of the number of data symbols to the total symbols in an OFDM frame. Note that the overall rate of the transmitter in Figure 1 is $1$, that is, one bit is sent per transmission. For every data degree of correlation in the channel frequency response at the output of the fast Fourier transform (FFT) in the OFDM receiver when the length of the channel impulse response is much smaller than the FFT length. Perfect timing and carrier synchronization is assumed. Simulation results are compared against the ideal coherent detector where perfect channel-state information (CSI) is assumed. It is shown that the LP-based receiver performs close to the ideal coherent receiver. Though the BER performance of the LP-based detection in bit interleaved coded (BIC) OFDM [2] and the turbo coded OFDM systems [1] perform better than the proposed approach, the decoding delay of the proposed approach is significantly lower than that of the BIC and the turbo coded OFDM systems.

This paper is organized as follows. The notation used throughout this paper is given in Section 2. The system model is given in Section 3. The proposed linear prediction-based receiver is discussed in Section 4. In Section 5, we give the simulation results. Finally in Section 6, we give the conclusion and the scope for the future work.

II. NOTATION

In this paper, all lower-case and upper-case letters without a tilde e.g. $g_k$ represent real-valued scalar. Letters with a tilde e.g. $\tilde{h}_k$, denote complex quantities. However, complex symbols are denoted by $S_k$ (without a tilde). Boldface letters represent vectors or matrices. All letters with a hat, e.g. $\hat{X}_k$ denote the statistical estimate of $\hat{X}_k$ (or $X_k$, if it is real-valued). The $(\cdot)^*$ denotes complex conjugate, $(\cdot)^{\text{tr}}$ denotes conjugate transpose and $E[\cdot]$ denotes the expectation operation. We also assume that bit $0$ maps to $+1$ and bit $1$ maps to $-1$.

III. SYSTEM MODEL

A. Transmitter

The binary input data $g_k$ ($0 \leq k \leq L_d/2 - 1$) from the source are encoded using a rate-$r_1/r_2$ convolutional encoder. The encoded data $b_k$ is mapped to DQPSK according to the differential encoding rules [3] given in Table I to get $S_k$. The symbol stream $S_k$ is fed to a serial to parallel converter (S/P) and loaded on to the OFDM sub-carriers by an $L_d$-point inverse fast Fourier transform (IFFT) operation. The length of the cyclic prefix (CP) is equal to the length of the channel memory $L_{CP} = L_h - 1$ [3], and is inserted into the OFDM frame. Note that the overall rate of the transmitter in Figure 1 is $1$, that is, one bit is sent per transmission. For every data
bit, one coded QPSK symbol is transmitted, hence one bit of information is sent per transmission.

TABLE I: Differential encoding rules [3]

| Dibit \((b_{k-1}b_k)\) | Decimal equivalent of the dibit \((\mathcal{D}_{b,j})\) | Phase change (in radians) |
|---------------------|---------------------------------|-----------------------------|
| 00                  | 0                               | 0                           |
| 01                  | 1                               | \(\pi/2\)                  |
| 10                  | 2                               | \(3\pi/2\)                 |
| 11                  | 3                               | \(\pi\)                     |

B. Channel Model

We assume a Rayleigh frequency selective fading channel having a uniform power delay profile [11]. Though an exponential power delay profile is more practical, we expect the uniform power delay profile to give the worst case BER performance since all channel taps (intersymbol interference (ISI) terms) have the same power. The channel is assumed to be time-invariant over each OFDM frame and varies independently from frame to frame i.e. quasi-static. For the \(l\)th diversity arm \((0 \leq l \leq N_r - 1)\), the channel impulse response \(\hat{h}_{k,l} (0 \leq k \leq L_h - 1)\) and AWGN noise \(\hat{w}_{k,l} (0 \leq k \leq L_f - 1)\) are both wide-sense stationary (WSS) circularly symmetric complex Gaussian random variables with autocorrelation given by:

\[
\begin{align*}
\frac{1}{2} E\left[ \hat{h}_{k,l} \hat{h}_{k',l'}^* \right] &= \begin{cases} 
\sigma_h^2, & \text{if } k = k' \text{ and } l = l' \\
0, & \text{otherwise}
\end{cases} \\
\frac{1}{2} E\left[ \hat{w}_{k,l} \hat{w}_{k',l'}^* \right] &= \begin{cases} 
\sigma_w^2, & \text{if } k = k' \text{ and } l = l' \\
0, & \text{otherwise}
\end{cases}
\end{align*}
\]

IV. Receiver

The output of the FFT operation at the \(l\)th diversity arm in the receiver is given by:

\[
\hat{Y}_{k,l} = \hat{H}_{k,l} S_k + \hat{W}_{k,l}, \quad 0 \leq k \leq L_f - 1, \quad 0 \leq l \leq N_r - 1
\]

where

\[
\begin{align*}
\hat{H}_{k,l} &= \sum_{i=0}^{L_h-1} \hat{h}_{i,l} e^{-j2\pi i k/L_d} \\
\hat{W}_{k,l} &= \sum_{i=0}^{L_f-1} \hat{w}_{i,l} e^{-j2\pi i k/L_d}
\end{align*}
\]

The 1-D autocorrelation of the discrete Fourier transform (DFT) of the AWGN samples is [14]

\[
\frac{1}{2} E\left[ \hat{W}_{k,l} \hat{W}_{k,m,l}^* \right] = L_d \sigma_w^2 \delta_{K,m}.
\]

where \(\delta_{K,m}\) is the Kronecker delta function defined as:

\[
\delta_{K,m} = \begin{cases} 
1, & \text{if } m = 0 \\
0, & \text{if } m \neq 0
\end{cases}
\]

The autocorrelation of \(\hat{H}_{k,l}\) is given by [14]:

\[
\tilde{R}_{\hat{H},l, m} = \frac{1}{2} E\left[ \hat{H}_{k,l} \hat{H}_{k,m,l}^* \right] = \sigma_h^2 \sum_{n=0}^{L_h-1} e^{-j2\pi nm/L_d}.
\]

Now consider

\[
\tilde{X}_{k,l} = \tilde{Y}_{k,l}/S_k.
\]

During data detection, the symbols \(S_k\) are obtained from the super trellis.

The autocorrelation of \(\tilde{X}_{k,l}\) is given by:

\[
\tilde{R}_{\tilde{X},l, m} = \frac{1}{2} E\left[ \tilde{X}_{k,l} \tilde{X}_{k,m,l}^* \right] = \tilde{R}_{\hat{H},l} + \sigma_w^2 L_d \delta_{K,m}
\]

where we have assumed that \(|S_k|^2 = \text{constant.}\)

The key idea behind this approach is to estimate (predict) \(\tilde{X}_{k,l}\) assuming \(S_k\) is known, as follows [3]:

\[
\tilde{X}_{k,l} = -\sum_{j=1}^{P} \tilde{a}_{P,j} \tilde{X}_{j-j,l}
\]

and the 1-D prediction error variance is given by [3]:

\[
\sigma_{e,P}^2 = \frac{1}{2} E\left[ |\tilde{z}_{k,l}|^2 \right] = \sum_{j=0}^{P} \tilde{a}_{P,j} \tilde{R}_{\tilde{X},-j}
\]

where \(\tilde{a}_{P,0} = 1\). In Section IV-A we give a formal derivation of the linear prediction-based receiver.

In practice of course, the autocorrelation \(\tilde{R}_{\tilde{X},m}\) required for generating the prediction filter coefficients is not known. Hence the autocorrelation needs to be estimated only once (see Section 4.1 in [3]). However, in this paper we assume that the receiver has perfect knowledge of the channel and noise statistics.

A. The Suboptimal Predictive Maximum Likelihood (ML) decoder [4]

The received signal at the \(l\)th diversity arm can be represented as:

\[
\tilde{Y}_l = S^{(q)} \tilde{H}_l + \tilde{W}_l, \quad 0 \leq q \leq M - 1, \quad 0 \leq l \leq N_r - 1
\]

where \(\tilde{Y}_l\) is an \(L_d \times 1\) column vector of received samples, \(S^{(q)}\) is an \(L_d \times L_d\) diagonal matrix with elements containing the \(q\)th possible QPSK symbol sequence, \(\tilde{H}_l\) is an \(L_d \times 1\) column vector of the channel DFT and \(\tilde{W}_l\) is an \(L_d \times 1\) column vector.
containing the DFT of the AWGN samples \( \tilde{w}_{k,l} \) in Figure 1 and \( M = 4 \) (QPSK constellation).

The ML detector decides in favour of \( S^{(q)} \) that maximizes the joint conditional pdf

\[
\max_q p \left( \tilde{Y}_0, \tilde{Y}_1, \ldots, \tilde{Y}_{N_r-1} | S^{(q)} \right) = \max_q \prod_{l=0}^{N_r-1} p \left( \tilde{Y}_l | S^{(q)} \right) \tag{14}
\]

where \( p(\cdot) \) denotes the probability density function, and we have assumed that \( \tilde{H}_k, \tilde{W}_l \) and hence \( \tilde{Y}_l \) are independent over \( l \). Ignoring constants and substituting for the conditional pdfs in (14), we get

\[
\max_q \exp \left( -\frac{1}{2} \sum_{l=0}^{N_r-1} \tilde{Y}_l \phi \left( \tilde{R}^{(q)} \right)^{-1} \tilde{Y}_l \right) \tag{15}
\]

where

\[
\tilde{R}^{(q)} \triangleq \frac{1}{2} E \left[ \tilde{Y}_l \tilde{Y}_l^H | S^{(q)} \right] = \frac{1}{2} S^{(q)} E \left[ \tilde{H}_l \tilde{H}_l^H \right] S^{(q)} + \sigma_w^2 L_d I \approx \frac{1}{2} S^{(q)} \phi \left( S^{(q)} \right)^{\infty} \tag{16}
\]

where we have used (3) and (6). Now, by applying Cholesky decomposition of the autocovariance matrix \( \phi \), it can be shown that (3)

\[
\phi^{-1} = \tilde{B}^{\infty} D^{-1} \tilde{B} \tag{17}
\]

where

\[
\tilde{B} \triangleq \begin{bmatrix}
1 & \cdots & 0 & \cdots & 0 \\
\tilde{a}_{l,1} & 1 & \cdots & 0 & \cdots \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\tilde{a}_{l_{d-1},1} & \tilde{a}_{l_{d-1},2} & \cdots & 1
\end{bmatrix} \tag{18}
\]

is the \((L_d \times L_d)\) matrix of predictor coefficients with \( \tilde{a}_{i,j} \) being the \( j^{th} \) coefficient of the optimum \( i^{th} \)-order predictor and the \((L_d \times L_d)\) matrix

\[
D \triangleq \begin{bmatrix}
\sigma_{e,0}^2 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & \sigma_{e,L_d-1}^2
\end{bmatrix} \tag{19}
\]

where \( \sigma_{e,k}^2 \) is the 1-D prediction error variance of the optimum \( k^{th} \)-order predictor as given by (12) and \( \sigma_{e,0}^2 = R_{\tilde{H} \tilde{H}^H,0} \approx R_{\tilde{X} \tilde{X},0} \) at high SNR.

Now, the maximization rule in (15) can be expressed as

\[
\min_q \sum_{l=0}^{N_r-1} \tilde{Y}_l \phi \left( \tilde{S}^{(q)} \right)^{\infty} B^{\infty} D^{-1} B \left( \tilde{S}^{(q)} \right)^{-1} \tilde{Y}_l \equiv \min_q \sum_{l=0}^{N_r-1} \sum_{k=0}^{L_d-1} \begin{bmatrix} z_{0,l}^{(q)} \\ z_{1,l}^{(q)} \\ \vdots \\ z_{L_d-1,l}^{(q)} \end{bmatrix}^2 \tag{20}
\]

where the prediction error \( z_{k,l}^{(q)} \) is an element of

\[
\begin{bmatrix}
z_{0,l}^{(q)} \\
z_{1,l}^{(q)} \\
\vdots \\
z_{L_d-1,l}^{(q)}
\end{bmatrix} \triangleq \tilde{z}^{(q)} = B \left( \tilde{S}^{(q)} \right)^{-1} \tilde{Y}_l \tag{21}
\]

Assuming that a \( P^{th} \)-order predictor completely decorrelates noise, (20) can be written as

\[
\min_q \sum_{l=0}^{N_r-1} \sum_{k=0}^{L_d-1} \frac{z_{l,k}^{(q)} z_{l,k}^{(q)*}}{2 \sigma_{e,k}^2} + \sum_{l=0}^{N_r-1} \sum_{k=p}^{L_d-1} \frac{z_{l,k}^{(q)} z_{l,k+p}^{(q)*}}{2 \sigma_{e,p}^2} \tag{22}
\]

Note that the first double summation in (22) denotes the “transient” part and the second double summation denotes the “steady state” part. Observe also that the predictor coefficients in (13) correspond to the autocorrelation of the channel frequency response. In practice, the predictor coefficients are obtained from the autocorrelation of \( \tilde{X}_{k,l} \). Finally we note that the complexity in (22) increases exponentially with \( L_d \).

In the Subsection [IV.C] we present the predictive VA, whose complexity increases linearly with \( L_d \).
B. Supertrellis Construction

In Section IV (just after (7)), we mentioned that the symbols $S_k$ are not known, and in practice they are obtained from a supertrrellis. Consider the predictive VA in Figure 1. The inner decoder trellis must be modified to a supertrellis which incorporates the memory of the prediction filter.

Assume that the $r_2$ coded bits from the inner rate-$r_1/r_2$ convolutional encoder (in this work $r_1 = 1$, $r_2 = 2$) are mapped to an $M$-ary ($M = 2^m$) constellation according to the set partitioning rule, e.g. $S_{0,j,h} = \mathcal{M}(\mathcal{I}_{0,j})$ (see Figure 2). Here, $\mathcal{I}_{0,j} (0 \leq \mathcal{I}_{0,j} \leq 2^m - 1)$ is the decimal equivalent of the $n$ coded bits $b_kb_{k-1}\ldots b_{k-n+1}$ in Figure 1 and is referred to as the input code digit. Note that since the supertrrellis is a periodic structure, we have removed the subscript $k$ in $S_k$ and replaced it with $S_{i,j,h}$. The subscript "i" in $S_{i,j,h}$ refers to the $i^{th}$ memory element of the prediction filter (the 0th element is the input), the subscript "j" refers to the present supertrrellis state and "h" denotes the next supertrrellis state. Observe that the symbol sequence $S_k$ in Figure 1 corresponds to one of the paths through the supertrrellis.

Now consider Figure 3. Note that

$$\{\mathcal{M}(\mathcal{I}_{0,j}), \mathcal{M}(\mathcal{I}_{1,j}), \ldots, \mathcal{M}(\mathcal{I}_{P,j})\}$$

(23)

in Figure 3 is a valid encoded symbol sequence. In (23), the subscript $P$ refers to a $P^{th}$-order prediction filter and $j$ refers to the $j^{th}$ supertrrellis state, as will be explained later.

Let $S_E$ denote the number of encoder states. For any given present convolutional encoder state $\mathcal{E}_i (0 \leq i \leq S_E - 1)$, there are $2^m = N$ possible encoded symbols. Hence, starting from any particular encoder state, there are $N^P$ ways in which a prediction filter of order $P$ can be populated (see Figure 3). Therefore, the total number of ways in which a $P^{th}$-order predictor can be populated is $S_E \times N^P$ which is also equal to the number of supertrrellis states. Therefore

$$S_{ST} = S_E \times N^P.$$  

(24)

Let $\mathcal{F}_m (0 \leq m \leq N^P - 1)$ denote the prediction filter state. Supertrellis state is given by $\mathcal{I}_{ST,j}$, where

$$j = i \times N^P + m, \quad 0 \leq j \leq S_E \times N^P - 1.$$  

(25)

Symbolically, the supertrellis state can be represented as:

$$\mathcal{I}_{ST,j} : \{\mathcal{E}_i; \mathcal{F}_m\}.$$  

(26)

Let us represent the prediction filter state $\mathcal{F}_m$ by an $N$-ary $P$-tuple as follows:

$$\mathcal{F}_m : \{N_1, m \ldots N_{P,m}\}$$  

(27)

where the input digits are denoted by

$$N_t \in \{0, \ldots, N - 1\} \quad \text{for} \ 1 \leq t \leq P$$  

(28)

such that

$$m = \sum_{i=1}^P N_{P+1-t,m}N^{t-1}$$  

(29)

is the decimal equivalent of the $N$-ary, $P$-tuple in (27).

$\mathcal{F}_m$ is actually the input sequence to the encoder in Figure 3 with $N_{P,m}$ being the initial input digit. Let $\mathcal{E}_a (0 \leq s \leq S_E - 1)$ be the encoder state corresponding to the input digit $N_{P,m}$. The code digit sequence corresponding to the supertrrellis state $\mathcal{I}_{ST,j}$ is generated as follows:

$$\mathcal{E}_a, N_{P,m} \rightarrow \mathcal{E}_a, \mathcal{I}_{P,j} \quad \text{for} \ 0 \leq a < S_E, 0 \leq \mathcal{I}_{P,j} < M$$

$$\mathcal{E}_a, N_{P-1,m} \rightarrow \mathcal{E}_a, \mathcal{I}_{P-1,j} \quad \text{for} \ 0 \leq b < S_E, 0 \leq \mathcal{I}_{P-1,j} < M$$  

(30)

which means: the encoder at (starting) state $\mathcal{E}_a$ with input digit $N_{P,m}$ yields the code digit $\mathcal{I}_{P,j}$ and the next encoder state $\mathcal{E}_a$ and so on. We repeat this procedure till the last input digit, to get:

$$\mathcal{E}_a, N_{I,0,m} \rightarrow \mathcal{E}_a, \mathcal{I}_{I,0,j} \quad \text{for} \ 0 \leq c < S_E, 0 \leq \mathcal{I}_{I,0,j} < M$$

$$\mathcal{E}_a, N_{0,m} \rightarrow \mathcal{E}_a, \mathcal{I}_{0,j} \quad \text{for} \ 0 \leq f < S_E, 0 \leq \mathcal{I}_{0,j} < M,$$

(31)

Thus, the prediction filter is populated with a valid encoded symbol sequence as given in (23).

Now, given the supertrrellis state $\mathcal{I}_{ST,j}$ and the input digit $N_{0,m}$ in (31), the next supertrrellis state $\mathcal{I}_{ST,h}$ can be obtained as follows:

$$\mathcal{I}_{ST,h} : \{N_{0,m}, N_{1,m} \ldots N_{P-1,m}\}$$

$$h = f \times N^P + l \quad 0 \leq f < S_E, 0 \leq l \leq N^P - 1, 0 \leq \mathcal{I}_{ST,h} \leq S_E \times N^P - 1.$$  

(32)

To summarize

$$\mathcal{I}_{ST,j}, N_{0,m} \rightarrow \mathcal{I}_{ST,h}, \mathcal{I}_{0,j}$$  

(33)

which means: the supertrrellis state $\mathcal{I}_{ST,j}$ with input digit $N_{0,m}$ gives the code digit $\mathcal{I}_{0,j}$ and the next supertrrellis state $\mathcal{I}_{ST,h}$. Note also that according to the notation in (26)

$$\mathcal{I}_{ST,h} : \{\mathcal{E}_j; \mathcal{F}_l\}.$$  

(34)

The supertrellis for a 1st-order predictor ($P = 1$) and the rate-1/2 encoder given in Table II is given in Table III.

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1In this section we assume that the DQPSK mapper in Figure II is absent. The need to have a DQPSK mapper will be explained in Section IV-C1.
C. The Predictive Viterbi algorithm [3, 5, 17]

Let \( v_{k,m,n} \) denote the branch metric at time instant \( k \) corresponding to the transition from state \( m \) to state \( n \). We have

\[
v_{k,m,n} = \sum_{l=0}^{N_r-1} \left| \hat{z}_{k,m,n,l} \right|^2 = \sum_{l=0}^{N_r-1} \sum_{j=0}^{P} \hat{a}_{P,j} \hat{Y}_{k-j,l}/S_{j,m,n} \tag{35}\]

where \( S_{0,m,n} \) denotes the input symbol corresponding to the transition from state \( m \) to \( n \) and the data \( S_{j,m,n} \) are the contents of the prediction filter of state \( m \).

1) Complexity Reduction using Isometry [1, 3, 5]: Consider the error signal \( \hat{z}_{k,m,n,l} \) in (35):

\[
\hat{z}_{k,m,n,l} = \hat{X}_{k,l} - \hat{X}_{k,l} = \sum_{j=0}^{P} \hat{a}_{P,j} \hat{Y}_{k-j,l}/S_{j,m,n} = \frac{1}{S_{0,m,n}} \sum_{j=0}^{P} \hat{a}_{P,j} \hat{Y}_{k-j,l} \times S_{0,m,n}/S_{j,m,n}. \tag{36}\]

Note that \( \left| \hat{z}_{k,m,n,l} \right|^2 \) is independent of \( S_{0,m,n} \) (due to isometry [4]) and is dependent only on the phase changes between \( S_{j,m,n} \) and \( S_{0,m,n} \). In particular, the all-zero and all-one sequence \( g_k \) yield the same magnitude squared error \( \left| \hat{z}_{k,m,n,l} \right|^2 \), and are hence indistinguishable.

In general it is clear from (36) that two symbol sequences

\[
S^{(v)} = \{ \ldots s_{k-1}^{(v)} s_{k}^{(v)} s_{k+1}^{(v)} \ldots \} \tag{37}\]

and

\[
S^{(w)} = \{ \ldots s_{k-1}^{(w)} s_{k}^{(w)} s_{k+1}^{(w)} \ldots \} \tag{38}\]

are isometric if

\[
S^{(w)} = e^{j\phi} S^{(v)} \tag{39}\]

where \( \phi \) is a constant phase. This implies that we need to differentially encode \( b_k \) at the transmitter. However, when differential encoding is done then \( \mathcal{M}(\mathcal{A}_k) \neq S_k \) (see Figure 3 and Section IV-B).

Now consider (36). Note that \( S_{0,m,n}/S_{1,m,n} \) is a function of the input code digit \( \mathcal{I}_{0,j} \) in Figure 3 (see also Table 1).

Mathematically, this can be stated as

\[
\frac{S_{0,m,n}}{S_{1,m,n}} = f_1(\mathcal{I}_{0,j}). \tag{40}\]

Similarly in (36)

\[
\frac{S_{0,m,n}}{S_{2,m,n}} = f_2(\mathcal{I}_{0,j}, \mathcal{I}_{1,j}) \tag{41}\]

where \( f_2(\mathcal{I}_{0,j}, \mathcal{I}_{1,j}) \) is some function of \( \mathcal{I}_{0,j} \) and \( \mathcal{I}_{1,j} \) in Figure 3 depending on the differential encoding rules in Table 1.

Continuing in this manner we find that

\[
\frac{S_{0,m,n}}{S_{P,m,n}} = f_P(\mathcal{I}_{0,j}, \mathcal{I}_{1,j}, \ldots, \mathcal{I}_{P-1,j}). \tag{42}\]

Thus, we find from (42) that the metric in (36) is a function of only \( P-1 \) digits in the memory, with \( \mathcal{I}_{0,j} \) being the input digit. Thus the number of states in the trellis with differential encoding is only \( M^{P-1} \) instead of \( M^P \).

The VA operates as follows. Let \( C_n \) denote the set of states that converge to the state \( n (0 \leq n \leq S_{ST}-1) \). Let \( \mu_{k,n} \) denote the path metric at time instant \( k (0 \leq k \leq L_d - 1) \) and state \( n \).

1) Set initial values as \( k = 0 \) and \( \mu_{0,n} = 0 (0 \leq n \leq S_{ST}-1) \), since we assume that the receiver does not know the starting state.
2) Increase time \( k \) by 1.
3) Compute the path metrics at each state \( n \) as

\[
\mu_{k,n} = \min_{m \in C_n} \{ v_{k,m,n} + \mu_{k-1,m} \}. \tag{43}\]

a) Store the survivor for each state \( n \).
b) Identify the state having the minimum \( \mu_{k,n} \), and trace back along the survivor path and release a symbol corresponding to time \( k-D_v \), where \( D_v \) is the decoding delay of the VA.
c) Increase \( k \) by 1.
d) Go to step 3 until time \( k = L_d \).
Since the overall rate is 1, the average SNR per bit for each receive diversity arm is defined as [14, 15]:

$$\text{SNR per bit} = N_r \times E \left[ |\tilde{H}_{k, l} S_k|^2 \right]$$

$$= \frac{N_r \times \left( L_h \times 2\sigma_f^2 \right) \times |S_k|^2}{L_d \times 2\sigma_w^2}.$$  (44)

### TABLE II: Simulation parameters

| Parameter                  | Value |
|----------------------------|-------|
| Frame size $L_d$           | 1024  |
| Channel memory $L_h - 1$   | 9     |
| Length of the cyclic prefix $L_{CP}$ | 9     |
| Decoding delay of the VA $D_v$ | 30    |
| No. of frames simulated    | $10^5$|
| Receiver antennas         | 4     |
| 1D channel fade variance $\sigma_f^2$ | 0.5   |
| Generator matrix for the encoder | $\begin{bmatrix} 1 & 1+D^2 \\ 1+D^2 & 1+D^2 \end{bmatrix}$ |

### TABLE III: Unnormalized supertrellis for the inner code, for a first-order ($P = 1$) prediction order and a rate-1/2 encoder given in Table II

| Present supertrellis state $j$ (time $n$) | Input $N_{0,m}$ | Next supertrellis state $h$ (time $n+1$) |
|------------------------------------------|-----------------|----------------------------------------|
| 0                                        | 0               | 0                                      |
| 0                                        | 1               | 5                                      |
| 1                                        | 0               | 5                                      |
| 1                                        | 1               | 5                                      |
| 2                                        | 0               | 4                                      |
| 3                                        | 1               | 1                                      |
| 2                                        | 1               | 1                                      |
| 3                                        | 0               | 4                                      |
| 3                                        | 1               | 1                                      |
| 4                                        | 0               | 6                                      |
| 4                                        | 1               | 3                                      |
| 5                                        | 0               | 6                                      |
| 5                                        | 1               | 3                                      |
| 6                                        | 0               | 2                                      |
| 6                                        | 1               | 7                                      |
| 7                                        | 0               | 2                                      |
| 7                                        | 1               | 7                                      |

The simulation parameters are given in Table II. The BER performance of the linear prediction-based data detection in convolutional coded OFDM systems using predictive VA is given in Figure 4. The LP-based receiver for convolutional coded SIMO-OFDM performs close to the ideal coherent receiver.

### VI. CONCLUSION

We have shown that the LP-based receiver performs close to the ideal coherent receiver. Future work can be focused on increasing the bit rate using $M$-ary constellations.

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