A Cognitive MIMO Transceiver for Enhanced 4G and Beyond Link-Level Throughput

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***Abstract*—A novel MIMO cognitive transceiver (CTR) for LTE-downlink communication system is devised in this work. We consider the cognition concept from the perspective of providing a highly reliable communication to the mobile user anytime anywhere. Rather than handling spectrum allocation (the common perspective of cognitive radio), we consider the channel estimation as the reconfiguration parameter of the proposed CTR. The developed cognitive transceiver is capable of selecting the best channel identification scheme between the conventional least squares (LS) estimator and the recently proposed maximum likelihood (ML) estimator. the proposed CTR is also able to toggle between the conventional pilot-assisted or data-aided (DA) mode and the non-data-aided with pilot (NDA with pilot) mode that relies on both reference and data symbols to track the channel variations. The decision rules of the new CTR that identify the best combination couple of pilot-use and channel-identification modes are drawn after running extensive and exhaustive LTE-downlink link-level simulations. The proposed CTR outperforms all static transceivers, in terms of link-level performance, for any given operating conditions such as SNR, mobile speed, channel type, and channel quality indicator (CQI). The new proposed CTR offers significant link-level throughput gains against the LS channel estimator working in a pilot-assisted mode in most operating conditions and the improvement gains can reach as much as 100% at low SNR and high mobility!**

I. Introduction

Offering high data rate wireless communication is the aim of all generations of wireless systems. Multiple-input multiple-output (MIMO) technology was considered for 3G and beyond as a cost-effective solution that offers increased data rate [1]. Large-scale antennae arrays commonly known as massive MIMO are under investigation for the coming 5G standard [2]. MIMO systems allow to exploit spatial diversity and spatial multiplexing providing system performance enhancements. Spatial diversity is exploited by transmitting the signal over multiple independently fading paths. This combats the small-scale fading effects in wireless communication, but, the spectral efficiency is not enhanced. Spatial multiplexing, however, consists in transmitting independent data streams on each transmit antenna allowing an increased spectral efficiency with the cost of high inter-channel-interference (ICI) thereby requiring more complex receiver to mitigate that issue. In this paper, we capitalize on the spatial modulation as a transmission technique for our MIMO cognitive transceiver to resolve this dilemma. The spatial modulation is defined as exploiting the number of transmitting antennas as an constellation diagram in the spatial domain besides the constellation diagram in the signal domain. Each group of data bits is carrying two types of information: 1) the modulated signal (phase, amplitude or frequency) and 2) the index of the transmitting antenna [3]. As only one antenna is transmitting at a time, the ICI problem is resolved. On the other hand, the overall spectral efficiency increases by the base-two logarithm of the number of transmit antennas.

This work was supported by the Discovery Grants Program of NSERC, Discovery Accelerator Supplement Award from NSERC and the NSERC CREATE PERSWADE Research Training Program on Wireless <www.create-perswade.ca >. It is actually a continuation of a previous study published in [11], [12] and [13] as it extends the cognitive transceiver solutions developed for the SIMO transmit mode published in the aforementioned references to the MIMO case. However, this extension is far from being incremental since its requires completely new multi-antenna or multi-source signal processing solutions at the receiver side.

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The cognition concept we consider for our MIMO CTR is from the perspective of providing a highly reliable communication to the mobile user anytime anywhere. The basic idea is to allow a transceiver to rapidly adapt itself to the changing environment conditions in the aim of maximizing its performance. Rather than handling spectrum allocation (the common perspective of cognitive radio) [4]- [6], we consider the channel estimation as the reconfiguration parameter of our proposed CTR. Reliable channel estimation is key to any wireless communication system. For that purpose, reference symbols (also know as pilot symbols) are inserted in the data information to facilitate the prediction of the channel variations with the cost of data rate reduction. However, for a severe channel conditions (frequency-selective or fast fading channels), channel estimation becomes a challenging task when the pilot insertion rate becomes insufficient to allow proper tracking of the channel variations. On the other hand, for good channel conditions (high signal-to-noise-ratio, flat or slow fading channels), easy channel estimator is possible and the number of required pilots can be moderately low. Our cognitive transceiver aims to solve the aforementioned dilemmas by switching to the best channel identification scheme between the conventional least squares (LS) and the newly proposed maximum likelihood (ML) estimators.

II. Context-aware modes for the cognitive transceiver

A. DA or pilot-assisted mode

Pilot symbols are inserted according to a predetermined mapping known by the receiver. They are used in the receiver side for synchronization purpose and to estimate the wireless channel.

1) LS channel estimator: The conventional LS channel estimator consists of estimating the channel by minimizing the squared error between the received and the known transmitter pilot symbols. Let $y_{i,\mathrm{DA}}^{t_x,r_x}$ denote the received signal from the transmit antenna t_x to the receiving antenna r_x, on pilot sub-carrier i among N_{pilot} pilot sub-carriers at the OFDM pilot symbol index t. In the remaining of the paper, the time index t and the transmitting and receiving antennas index are omitted for simplification and without loss of generality since when an antenna t_x is transmitting a pilot symbol on resource element (i,t), all other transmitting antennas are not transmitting at that resource element. The transmitted pilot symbol $x_{i,\mathrm{DA}}$ is related to $y_{i,\mathrm{DA}}$ as follows:

$$y_{i,\mathrm{DA}} = h_i x_{i,\mathrm{DA}} + n_i \qquad i = 0, 1, ..., N_{pilot} - 1 \tag{1}$$

where h_i is the complex channel coefficient and n_i is a zero-mean Gaussian noise. Equation (1) can be written in matrix format as:

$$\mathbf{y}_{\mathrm{DA}} = \mathbf{X}_{\mathrm{DA}}\mathbf{h} + \mathbf{n} \tag{2}$$

where $\mathbf{X}_{\mathrm{DA}} = \mathrm{diag}\left\{x_{0,\mathrm{DA}}, x_{1,\mathrm{DA}}, \ldots, x_{N_{pilot}-1,\mathrm{DA}}\right\}$, $\mathbf{h} = [h_0, h_1, ..., h_{N_{pilot}-1}]^T$, and $\mathbf{n} = [n_0, n_1, ..., n_{N_{pilot}-1}]^T$ is the i.i.d complex zero-mean Gaussian noise vector. The LS algorithm aims at minimizing $(\mathbf{y}_{DA} - \mathbf{X}_{DA}\mathbf{h})^{\dagger}(\mathbf{y}_{\mathrm{DA}} - \mathbf{X}_{\mathrm{DA}}\mathbf{h})$ ($\dagger$ denotes matrix Hermitian transpose) to estimate the frequency response of the channel. This minimization leads to estimating the channel coefficients at pilot subcarriers as follows: [7]:

$$\widehat{\mathbf{h}}_{\mathrm{LS}} = \mathbf{X}_{\mathrm{DA}}^{-1}\mathbf{y}_{\mathrm{DA}}, \tag{3}$$

where $\mathbf{A}^{-1}$ denotes the inverse of the matrix $\mathbf{A}$. The channel coefficients at non-pilot subcarriers are subsequently approximated by interpolation [10]. This approximation is not accurate in the case of high user velocity, which corresponds to a fast fading channel. In this case, the pilots spacing may not be sufficient, which results in inaccurate tracking of the channel variations. Reducing the pilot spacing would increase the pilot overhead and therefore would result in a deterioration of the throughput.

2) ML estimator: In this work, the ML channel estimator proposed in [8] is considered. This DA channel estimator tracks the variations in the channel for each OFDM symbol using a polynomial expansion of order $(J-1)$. In fact, the channel over each $\{r^{th}\}_{r=1}^{N_r}$ antenna branch and the i^{th} subcarrier, in a MIMO system (note here that when an antenna t_x transmits a pilot symbol on resource element (i,t) all other transmit antennas do not transmit on that resource element which recalls a SIMO system), is modeled as follows [9]:

$$h_{i,r}(t_n) = \sum_{j=0}^{J-1} c_{i,r}^{(j)} t_n^j + REM_J^{(i,r)}(t_n). \tag{4}$$

where, $t_n = nT_s$ and T_s is the sampling period. The order $J-1$ of the polynomial expansion is Doppler-dependent and is obtained from [8]. $c_{i,r}^{(j)}$ is the j^{th} coefficient of the channel polynomial approximation over the i^{th} sub-carrier and the r^{th} branch. The term $REM_J^{(i,r)}(t_n)$ denotes the remainder of the Taylor series expansion. This term can be made sufficiently small by selecting a sufficiently small approximation window. Therefore, an accurate approximation of the channel coefficients can be obtained as follows [8]:

$$h_{i,r}(t_n) = \sum_{j=0}^{J-1} c_{i,r}^{(j)} t_n^j. \tag{5}$$

For simpler and clearer representation, the sub-carrier index is removed in the following analysis.
Reducing the order $J-1$ in (4) significantly reduces the computation complexity since a smaller size matrix inversion will be needed. To reach this objective, the newly proposed DA ML estimator partitions the entire observation window into K local approximation windows of the same size. following this partition, the probability density function (pdf) of each of the locally-observed vectors, $\mathbf{y}_{\mathrm{DA}}^{(k)}$, parametrized by $\mathbf{c}_k$, is maximized:

$$p\left(\mathbf{y}_{\mathrm{DA}}^{(k)};\mathbf{c}_k|\mathbf{B}_k\right) = \frac{1}{(2\pi\sigma^2)^{N_{\mathrm{DA}}N_r}} \exp\left\{-\frac{1}{2\sigma^2}\left[\mathbf{y}_{\mathrm{DA}}^{(k)} - \mathbf{B}_k\mathbf{c}_k\right]^H\left[\mathbf{y}_{\mathrm{DA}}^{(k)} - \mathbf{B}_k\mathbf{c}_k\right]\right\}, \tag{6}$$

where $\mathbf{c}_k$ is a vector containing the unknown approximation polynomial coefficients over the k^{th} approximation window (i.e., for all the antenna branches) defined as $\mathbf{c}_k = [\mathbf{c}_{k,1}^T, \mathbf{c}_{k,2}^T, ..., \mathbf{c}_{k,N_r}^T]^T$ with $\mathbf{c}_{k,r} = [c_{k,r}^{(0)}, c_{k,r}^{(1)}, ..., c_{k,r}^{(J-1)}]^T$ where $c_{k,r}^{(j)}$ is the j^{th} coefficient of the channel polynomial approximation over the i^{th} sub-carrier, the k^{th} approximation window and the r^{th} branch and σ^2 defines the noise variance. In (6), $\mathbf{y}_{\mathrm{DA}}^{(k)} = [\mathbf{y}_{1,\mathrm{DA}}^{(k)}\, \mathbf{y}_{2,\mathrm{DA}}^{(k)} \ldots \mathbf{y}_{N_r,\mathrm{DA}}^{(k)}]^T$ with $\mathbf{y}_{r,\mathrm{DA}}^{(k)}$ being the received pilot samples over the antenna element r within the k^{th} approximation window, i.e., $\mathbf{y}_{r,\mathrm{DA}}^{(k)} = \left[y_r^{(k)}(t_1)\, y_r^{(k)}(t_2) \ldots y_r^{(k)}(t_{P_{\mathrm{DA}}})\right]$. P_{DA} is the number of pilot symbols in each approximation window which is covering N_{DA} pilot and non-pilot received samples. N_{DA} is Doppler-dependent approximation window size, which can be optimized as was shown in [8]. Moreover $\mathbf{B}_k$ is a $P_{\mathrm{DA}}N_r \times JN_r$ block-diagonal matrix defined as $\mathbf{B}_k = \mathrm{blkdiag}\{\mathbf{A}_k\mathbf{T}, \mathbf{A}_k\mathbf{T}, ..., \mathbf{A}_k\mathbf{T}\}$. Here, $\mathbf{A}_k$ is the $P_{\mathrm{DA}} \times P_{\mathrm{DA}}$ diagonal matrix of the transmitted pilot symbols within the k^{th} observation window, i.e., $\mathbf{A}_k = \mathrm{diag}\{a_k(t_1), a_k(t_2), ..., a_k(t_{P_{\mathrm{DA}}})\}$, and $\mathbf{T}$ is a Vandermonde matrix given by:

$$\mathbf{T} = \begin{pmatrix} 1 & t_1 & \ldots & t_1^{J-1} \\ 1 & t_2 & \ldots & t_2^{J-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & t_{P_{DA}} & \ldots & t_{P_{DA}}^{J-1} \end{pmatrix}. \tag{7}$$

By nullifying the partial derivative of (6), the the channel coefficients estimates over all the receiving antenna branches can be obtained by:

$$\widehat{\mathbf{c}}_{k,\mathrm{DA}} = \left(\mathbf{B}_k^{\dagger}\mathbf{B}_k\right)^{-1}\mathbf{B}_k^{\dagger}\mathbf{y}_{\mathrm{DA}}^{(k)}, \tag{8}$$

The DA ML estimates for the channel coefficients at pilot and non-pilot positions are consequently obtained by injecting the estimates of the polynomial coefficients from (8) back into (4).

TABLE I
PARAMETERS USED IN THE LINK-LEVEL SIMULATIONS.

Number of User Equipment	1
Channel Bandwidth (MHZ)	1.4
Carrrier Frequency (GHZ)	2.1
Frame Duration (ms)	10
Sub-carrier Spacing (kHz)	15
FFT size	128
Number of subcarriers/RB	12
OFDM Symbols/subframe	7
Transmit mode	2×2 MIMO
Channel type	PedA, PedB, VehA, and VehB

B. NDA with pilot or hybrid mode

Accurate channel modelling is essential for reliable communication. However, this task becomes very challenging in the case of fast receiver mobility and significant surrounding scatterers' motion. These parameters result in a hard to track fast-varying channels. Indeed, pilot symbols, which are often inserted far apart, in the time-frequency grid, are not sufficient to estimate the channel behaviour. In the following, this paper proposes to use the information carried in data symbols in a hybrid channel identification scheme in order to enhance the system performance.

MIMO systems are among the most promising transmission techniques enabling the high data rate and high spectral efficiency demanding by future wireless communication systems. For that purpose, we extend our previous work on SIMO systems [11]- [13] to MIMO systems. However, increasing the capacity for MIMO systems exploiting spatial-multiplexing requires transmitting multiple independent data streams over the antennas which causes high Inter Channel Interference (ICI). On the other hand, the number of transmit antenna do not improve spectral efficiency when exploiting the spatial diversity for MIMO systems. Given the aforementioned dilemmas, we choose the spatial modulation technique for our new MIMO cognitive transceiver. The basic idea of spatial modulation is to map each group of data bits into two types of information: 1) the modulated signal (phase, amplitude or frequency) and 2) the number of the transmitting antenna. The overall spectral efficiency is hence increased by the base-two logarithm of the number of transmit antennas. The MIMO system is then equivalent to a SIMO system with variant transmit antenna and for which the transmit antenna index carries an information.

1) NDA w. pilot RLS estimator: At OFDM symbol $t+1$ received from transmit antenna t_x, we use preceeding transmitted signals from the same antenna as a training sequence of t symbols. We assume that the index of transmit antenna t_x is perfectly known for the denoted "perfect RLS" transceiver version. For the "RLS" channel estimation based transceiver, the index of the transmit antenna t_x is estimated using the Maximum Receive Ratio Combining (MRRC). Then, the channel estimate for each transmit antenna t_x, $\widehat{\mathbf{h}}_{t+1}$, at OFDM symbol $t+1$ is obtained using the weighted LS method as follows [14]:

$$\widehat{\mathbf{h}}_{t+1} = \underset{\widehat{\mathbf{h}}}{\operatorname{argmin}} \sum_{w=1}^{t} \beta_w \|\mathbf{y}_w - \widehat{\mathbf{h}}\mathbf{q}_w x_w\|^2, \qquad (9)$$

where the channel variation $\langle$ is approximated to the D^{th} order Taylor series expansion according to the OFDM symbol instance m, i.e.: $\langle_w \simeq \sum_{d=0}^{D} w^d \langle^{<d>} = \mathbf{h}\mathbf{q}_w$ with $\mathbf{q}_w \triangleq [w^0\mathbf{I}_{N_r}, w^1\mathbf{I}_{N_r}, ..., w^D\mathbf{I}_{N_r}]^T \in \mathbb{R}^{(D+1)\times 1}$. In (9) $\beta_w \in \mathbb{R}$ stands for a weighting coefficient given by $\beta_w = \lambda^{t-w}$ where $\lambda \in \mathbb{R}$ is referred to as a forgetting factor. The exponential weighted RLS algorithm is implemented as follows:

$$\begin{aligned}
\boldsymbol{\zeta}_t &= \boldsymbol{\Phi}_{t-1}^{-1}\mathbf{q}_t x_t \in \mathbb{C}^{(D+1)\times 1},\\
\alpha_t &= \frac{1}{\lambda + \boldsymbol{\zeta}_t^{\dagger}\mathbf{q}_t x_t} \in \mathbb{R},\\
\boldsymbol{\Phi}_t^{-1} &= \lambda^{-1}\boldsymbol{\Phi}_{t-1}^{-1} - \lambda^{-1}\alpha_t\boldsymbol{\zeta}_t\boldsymbol{\zeta}_t^{\dagger} \in \mathbb{C}^{(D+1)\times(D+1)},\\
\mathbf{e}_t &= \mathbf{y}_t - \widehat{\mathbf{h}}x_t \in \mathbb{C}^{N_r\times 1}\\
\widehat{\mathbf{h}}_{t+1} &= \widehat{\mathbf{h}}_t + \alpha_t\mathbf{e}_t\boldsymbol{\zeta}_t^{\dagger} \in \mathbb{C}^{N_r\times(D+1)}.
\end{aligned}$$

For initialization, $\widehat{\mathbf{h}}_1$ is considered to be identically zero and $\boldsymbol{\Phi}_0^{-1}$ is set to $\varrho\mathbf{I}_{N_r(D+1)}$ where $\varrho \gg 1$ is a constant with sufficiently large value. Moreover, x_1 is assumed to be a pilot symbol. The channel estimate $\widehat{\mathbf{h}}_{t+1}$ is then used to detect the $(t+1)^{th}$ symbol x_{t+1}.

2) NDA w. pilot ML estimator: Similarly to the RLS channel estimator, We assume that the index of transmit antenna t_x is perfectly known for the denoted "perfect NDA ML with pilot" transceiver version. The transmit antenna index is estimated for the denoted "NDA ML with pilot" using the MRRC. Given the transmit antenna index, the MIMO system recalls a SIMO system. The expectation maximization (EM) based ML estimator is then the iterative algorithm used as presented in [8] for SIMO systems. Pilot and data symbols are jointly used by the EM algorithm for channel variation tracking. As described in Section II-A2, firstly, pilot symbols are used for channel coefficients prediction on each pilot symbol for each pilot sub-carrier. Then the channel coefficients on non-pilot symbols are estimated by applying the EM algorithm on all received symbols from transmit antenna t_x. The iterative EM algorithm consists on two operations using as initialization $\widehat{\mathbf{c}}_{k,\mathrm{DA}}$ deduced in (8) using pilot symbols only.

• Expectation step (E-Step):

On the E-Step, all the possible transmitted symbols $\{a_m\}_{m=1}^{M}$, where M is the modulation order, are considered by the pdf function presented in (6). We iterate the objective function at each iteration q for every N_{NDA} sized approximation window as follows:

$$Q(\mathbf{c}_k \mid \widehat{\mathbf{c}}_k^{(q-1)}) = -N_{\mathrm{NDA}} N_r \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{r=1}^{N_r}\left(M_{2,k}^{(r)} + \sum_{n=1}^{N_{\mathrm{NDA}}} \alpha_{n,k}^{(q-1)} |\mathbf{c}_{r,k}^T \mathbf{t}(n)|^2 - 2\beta_{r,n,k}^{(q-1)}\mathbf{c}_{r,k}\right), \quad (10)$$

where $M_{2,k}^{(r)} = E\{|y_{r,k}(n)|^2\}$ is the second-order moment of the received samples over the r^{th} receiving antenna branch,

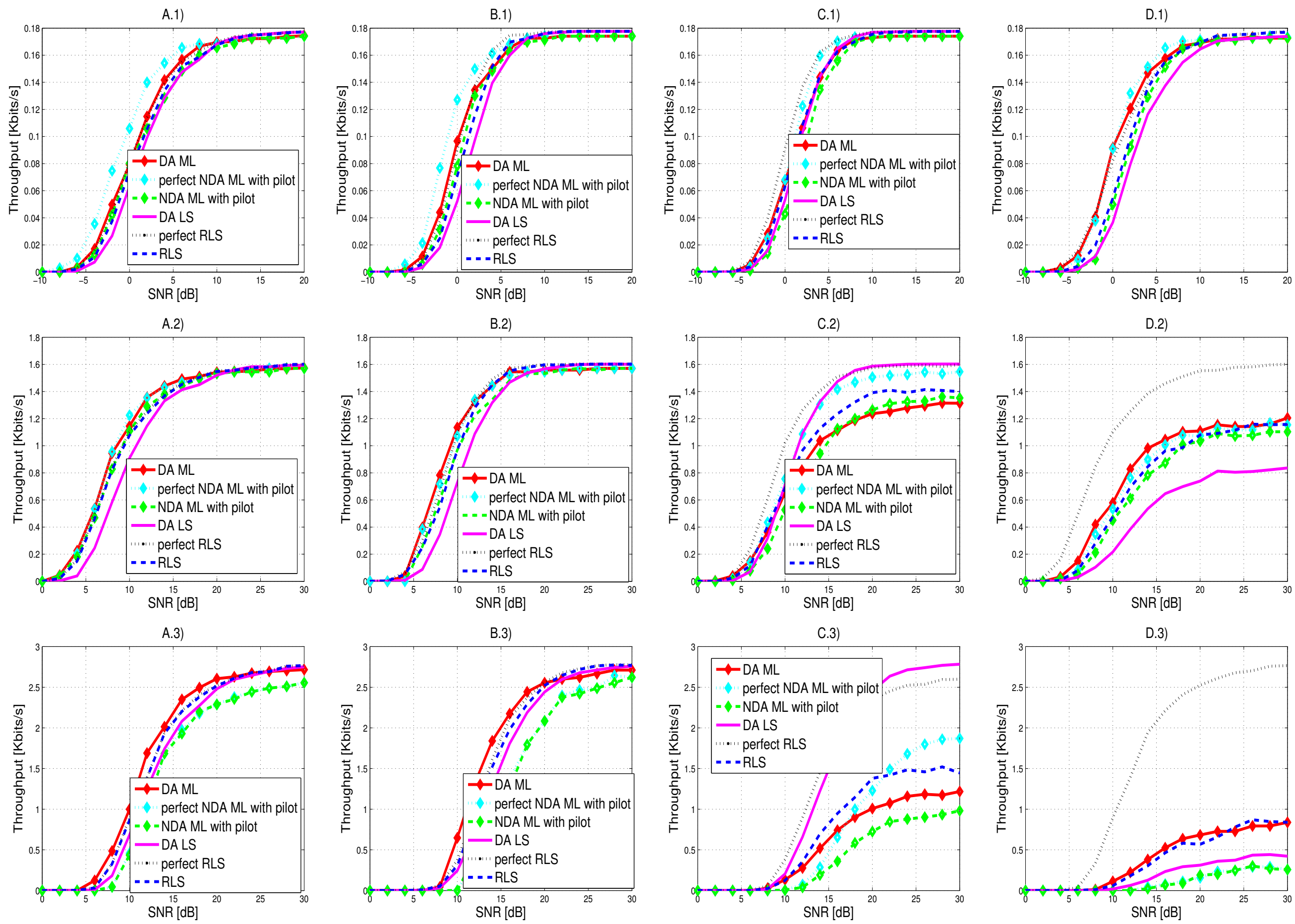

Fig. 1. Simulation results in terms of link-level throughput for MIMO LTE on the downlink for A) PedA channel/speed=2 km/h, B) PedB channel/speed=2 km/h, C) VehA channel/speed=100km/h, D) VehB channel/speed=30 km/h, and 1) CQI=1 for QPSK, 2) CQI=7 for 16QAM, and 3) CQI=10 for 64QAM.

$\mathbf{t}(n) = [1, t_n, t_n^2, ..., t_n^{J-1}]^T$ and:

$$\alpha_{n,k}^{(q-1)} = \sum_{m=1}^{M} P_{m,n,k}^{(q-1)} |a_m|^2, \tag{11}$$

$$\beta_{r,n,k}^{(q-1)}(\mathbf{c}_{r,k}) = \sum_{m=1}^{M} P_{m,n,k}^{(q-1)} \Re\{y_{r,k}^*(n) a_m \mathbf{t}^T(n)\mathbf{c}_{i,k}\}, \tag{12}$$

where, $P_{m,n,k}^{(q-1)} = P(a_m \mid \mathbf{y}_k(n); \widehat{\mathbf{c}}^{(q-1)})$ is the *a posteriori* probability of a_m at iteration $(q-1)$ that is calculated based on Bayes' formula as follows:

$$P_{m,n,k}^{(q-1)} = \frac{P(a_m) P\left(\mathbf{y}_k(n) | a_m; \widehat{\mathbf{c}}_k^{(q-1)}\right)}{P\left(\mathbf{y}_k(n); \widehat{\mathbf{c}}_k^{(q-1)}\right)}. \tag{13}$$

Since the symbols are assumed to be equally likely transmitted, we have $P(a_m) = \frac{1}{M}$ and therefore:

$$P\left(\mathbf{y}_k(n); \widehat{\mathbf{c}}_k^{(q-1)}\right) = \frac{1}{M} \sum_{m=1}^{M} P\left(\mathbf{y}_k(n) | a_m; \widehat{\mathbf{c}}_k^{(q-1)}\right). \tag{14}$$

- Maximization step (M-Step):

On the M-Step, we maximize the objective function given in (10) with regards to $\mathbf{c}_k$:

$$\widehat{\mathbf{c}}_k^{(q)} = \underset{\mathbf{c}_k}{\operatorname{argmax}}\, Q(\mathbf{c}_k | \widehat{\mathbf{c}}_k^{(q-1)}). \tag{15}$$

New accurate approximation polynomial coefficients estimates are then provided as follows:

$$\widehat{\mathbf{c}}_{r,k}^{(q)} = \left(\sum_{n=1}^{N_{\text{NDA}}} \mathbf{t}(n)\mathbf{t}^T(n) \right)^{-1} \sum_{n=1}^{N_{\text{NDA}}} \lambda_{r,n,k}^{(q-1)} \mathbf{t}(n). \tag{16}$$

In (16), $\lambda_{r,n,k}^{(q-1)}$ is given by:

$$\lambda_{r,n,k}^{(q-1)} = \left[\widehat{a}_k^{(q-1)}(t_n) \right]^* y_{r,k}(t_n), \tag{17}$$

in which

$$\widehat{a}_k^{(q-1)}(t_n) = \sum_{m=1}^{M} P_{m,n,k}^{(q-1)} a_m, \tag{18}$$

is the soft symbol estimate at iteration $q-1$ and $\mathbf{t}$(n) $= [1, t_n, t_n^2, ..., t_n^{J-1}]^T$.

III. Simulation Setup and Results

In this paper, we simulate a downlink communication for LTE MIMO system with 2 transmit antennas at the base station and 2 receive antennas at the mobile station. We present some of the used link-level parameters in table I. Our new MIMO CTR aims to switch between the best channel prediction algorithm (LS or ML) and the best pilot-use mode (DA pr NDA with pilot) for any of the given propagation channel

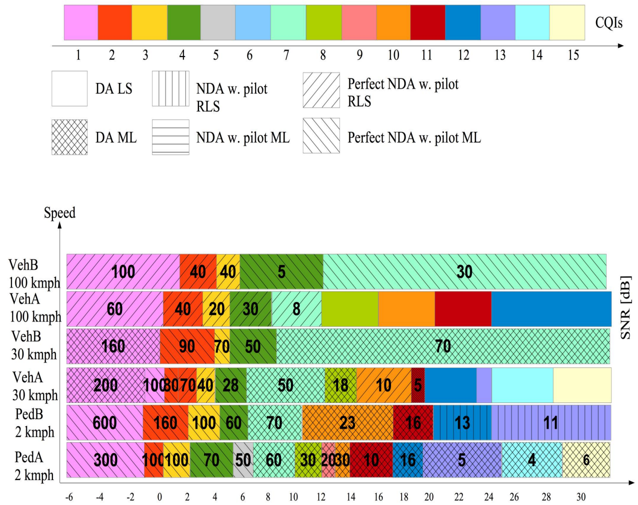

Fig. 2. MIMO cognitive transceiver throughput gain percentages (our benchmark is the DA LS) and decision rules (best channel estimation algorithm and pilot-use mode) for different propagation channel conditions (SNR/CQI, channel types and mobile speeds).

parameters: SNR, channel model type, mobile speed, and CQI value. For that purpose, we consider a Pedestrian slow-fading channels for a mobile speed of 2 km/h and a Vehicular fast-fading channels for mobile speeds of 30 km/h and 100 km/h. We simulate type A and B channels for respectively flat-fading and frequency selective channels. The CQI carries the information about the modulation order and the channel coding rate to be used to the base station during each subframe. The CQI values range from 1 to 15 defining six, three, and six coding rates for QPSK, 16QAM, and 64QAM modulations, respectively. We assume a perfect knowledge of the SNR and CQI parameters on the receiver side. Only throughput results of CQI 1 (QPSK), CQI 7 (16QAM) and CQI 10 (64QAM) are shown due to lack of space. As shown in Fig. 1.A) , the ML outperforms the DA LS estimator for all modulation schemes. Fig. 2 shows that the perfect NDA ML with pilot reaches a throughput gain as high as 300% in the low SNR region over the PedA channel. This is because modelling the channel with Taylor series remains accurate when the channel experiences flat fading. Fig. 1.B) shows that the ML estimator outperforms the DA LS for QPSK and 16QAM modulation schemes with a throughput gain over 600% in low SNR region as shown in Fig. 2. Fig. 2 shows that for a medium mobile speed with flat fading (VehA) channel, DA ML offers a gain as high as 200% in low SNR region. We also note that the perfect NDA with pilot channel estimate schemes (both ML and RLS) offer a significant throughput gain for this type of channel. This is due to the fact that relying on data symbols jointly with pilot symbols enhances channel estimation when time variations are significant. The same conclusions are deduced for the VehB (frequency selective) channel with medium mobile speed as shown in Figs. 1.D) and 2. Figs. 1.C) and 2 show that the perfect NDA with pilot RLS reaches a throughput gain over 60% for VehA channel for high mobile speed. For the VehB channel and a mobile speed of 100 km/h, Fig.2 reveals a gain as high as 100% that is offered by the perfect NDA with pilot RLS as compared to DA LS in terms of link-level throughput, in the low SNR region. For the same channel type and mobile speed, Figs 1.C) and 2 suggest that the perfect NDA with pilot ML version offer throughput gains rising up to 30% in the high SNR region for 16QAM modulation scheme.

IV. Conclusion

In this paper, we were able to generalize the new cognition concept developed for the SIMO transmission mode to the MIMO case. The simulation results show that our new MIMO CTR offers a significant link-level throughput gains by switching between two different channel estimators (ML and LS) and two different pilot-use modes (conventional DA and NDA with pilot) depending on different propagation channel conditions in terms of channel speed, channel type, SNR, and CQI. The throughput gains achievable by the new context-aware CTR are noticeable in most operating conditions reaching as much as 100% at low SNR and high mobility.

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