

System-Level Impact of Multi-User Diversity in SISO and MIMO-based Cellular Systems

Rahul N. Pupala

Alcatel-Lucent/Bell Labs, Murray Hill, NJ 07974, USA

Email: rahul.pupala@alcatel-lucent.com

Larry J. Greenstein (*Life Fellow, IEEE*)

ECE (WINLAB), Rutgers – The State University of New Jersey, North Brunswick, NJ 08902, USA

Email: ljg@winlab.rutgers.edu

David G. Daut (*Senior Member, IEEE*)

ECE, Rutgers – The State University of New Jersey, Piscataway, NJ 08854, USA

Email: daut@ece.rutgers.edu

Abstract— We quantify cell-wide mean throughputs of single-input-single-output (SISO) and multiple-input-multiple-output (MIMO)-based cellular systems which employ multi-user diversity (MuD). Our study considers several practical and useful system-level design dimensions, including: number of transmit/receive antennas; antenna-pattern (omni-directional or sectorized); degree of error-protection (Shannon coding, no coding or intermediate coding strategies); allowable constellation size; Rician κ -factor; number of users and scheduling algorithm (Greedy (i.e. MAX C/I), Proportional Fair, or Equal Grade of Service) in single-cell (noise-limited) and multi-cell (co-channel-interference-limited) environments.

We also provide a comparison between single-user systems having excess receive antennas and multi-user diversity systems with no excess receive antennas. Both strategies improve signal quality. Since economic costs of RF chains, mobile size and form factor limit the number of antennas a mobile receiver can have, multi-user diversity can be a more practical option. We observe that MuD with only a few scheduled users leads to comparable throughputs as receivers with excess receive antennas. By quantifying the average throughput gains that accrue from using multi-user SISO and MIMO-based cellular systems, this study serves the needs of operators to assess these promising technologies.

Index Terms—MIMO, MMSE, multipath fading, shadow fading, co-channel interference, cross-stream interference, interference cancellers, multi-user diversity, MAX, PF, EGoS

I. INTRODUCTION

Since the publication of seminal papers [1], [2] a decade ago, multi-element antenna (MEA) systems has been an area of considerable interest to the wireless communications community. Commercial interest in multiple-input-multiple-output (MIMO) systems, which employ multiple antennas at both ends of the link, grew after the successful laboratory implementation of the well-known vertical Bell-Labs layered space-time architecture

(VBLAST) [3]. VBLAST demonstrated the feasibility of the MIMO concept, delivering spectral efficiencies of 20–40 bps/Hz under indoor conditions. Later research demonstrated the different ‘modes’ of MIMO systems, notably, Diversity and Spatial Multiplexing. The diversity mode improves signal quality using the spatial resources [4]–[6]; the multiplexing mode, a chief reason for the industry’s interest in MIMO systems, increases the data rate that can be pumped through a given bandwidth. By appropriate signal processing at the transmitter and/or the receiver, several de-coupled parallel single-input-single-output (SISO) channels can be created, which greatly enhances link capacity of the MIMO channel [1], [2], [7]–[13]. A tradeoff between these modes has been established [14], and linear codes that use a combination of both modes have been discovered [15]. Relevant definitions pertaining to MIMO/MEA¹ systems appear in the Appendix A.

In much of previous MEA/MIMO research, a *link-level* view, that of point-to-point communication, is taken. More recently, a *network-level* view of a cellular system has been adopted, which permits a new form of diversity — Multi-user Diversity (MuD) [16]–[20]. MuD can be viewed as a form of selection diversity (SD), in which the base station (BS) transmits to (or receives from) a mobile station (MS) with a good channel. Diversity is possible since all users are subject to independent fading, and in a system with sufficient number of users, a ‘good’ user exists with high probability. MuD is suitable for *delay-elastic* applications, i.e., those applications that can tolerate reasonable delays, such as data (but not voice). The implication of the network view was a paradigm shift in exploiting MEA/MIMO techniques: the multi-antenna link could now be used in multiplexing mode to extract maximal rate benefit, while diversity would come from

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¹MEA links are assumed to have n transmitters and m receivers. They are denoted as MEA (n, m) or simply (n, m) .

the network itself [18], [21].

Most MuD performance studies (e.g., [18], [21]–[25]) focus only on a particular link between the transmitter and the receiver. Performance measures such as bit error rate (BER) or throughput (TP) are determined with signal-to-noise ratio (SNR) treated as a parameter, with external factors such as co-channel interference (CCI) ignored or indirectly treated using the signal-to-interference-plus-noise ratio (SINR) in place of the SNR. Some work on SISO/MEA (but not MuD) systems has been reported, however, that takes a broader view (e.g., [8]–[13]). This work determines the *distribution* of performance over a coverage area, e.g., the cumulative distributive function (CDF) of TP over the randomness of user location and shadow fading, which jointly specify the SNR value. Furthermore, in the case of multi-cell environments, it also means taking into account the CCI produced by co-channel users in other cells.

In this study, we extend the latter work to the multi-user scenario with scheduling. We quantify cell-wide mean throughputs of SISO and MIMO-based cellular systems which employ multi-user diversity, and we do so over several useful system-level design dimensions: number of transmit/receive antennas; antenna-pattern (omni-directional or sectorized); degree of error-protection (Shannon coding, no coding or intermediate coding strategies); allowable constellation size; Rician κ -factor²; number of users and scheduling algorithm (Greedy, Proportional Fair or Equal Grade of Service) in single-cell (noise-limited) and multi-cell (CCI-limited) environments. In this connection, we note that the greedy (also popularly known as MAX C/I) and the equal grade-of-service scheduling algorithms define upper and lower bounds on throughput that any useful scheduler can offer; the proportional fair scheduler is considered owing to its popularity both in industry and in academic communities.

We also provide a comparison between single-user systems having excess degrees of freedom (SU-EDoF) and multi-user diversity systems having no excess degrees of freedom (MuD-wo-EDoF). Both mechanisms attempt to improve received signal quality, as measured by the post-processing SINR. In SU-EDoF, a receiver does so by using excess receive antennas to obtain diversity and/or null one or more interfering co-channel streams on an optimal basis [26]. By contrast, MuD-wo-EDoF improves signal quality by scheduling the user with the best signal (and weakest interference), i.e., interference avoidance is an inherent feature. Since costs of RF chains, mobile size, device form factor and other practical considerations limit the number of antennas a receiver can have, multi-user diversity may be a more practical and cost-effective option. Studying the tradeoffs between SU-EDoF and MuD-wo-EDoF enriches our ability to make engineering value-judgements, while designing practical systems that use these promising technologies.

For single-user scenarios, cell-wide average throughput

²Normally, K is used instead of κ , but, we use K here for the number of users sharing the channel.

per-user is typically used as a performance metric. For multi-user scenarios, wherein a channel is shared over many simultaneous users, a more appropriate metric is cell-wide average throughput *per-channel*. For the single-user case, ‘channel’ and ‘user’ are synonymous, and the metric continues to remain relevant³. We do not consider specific and precise metrics for fairness and stability. Even so, these considerations do enter our discussion, since they are prevalent in the literature. Essentially, when the throughput per-channel differences between the various scheduling algorithms are small, a sub-optimal scheduler may be used, trading a small throughput loss for greater ‘fairness’ or ‘stability’.

This paper is organized as follows. The system model and simulation platform are discussed in Section II, and numerical results are presented in Section III. Section IV offers a comparison between excess receive antennas and multi-user diversity, while Section V summarizes our work and presents some key conclusions.

II. SYSTEM MODEL AND SIMULATION PLATFORM

We have developed a system-level simulation platform for computing the throughputs of multi-user SISO/MEA cellular systems which employ network scheduling. The test-bed is sufficiently general to allow us to work with the several key system-level parameters noted earlier.

A. Network-level Description: Base Station Viewpoint (MAC-layer)

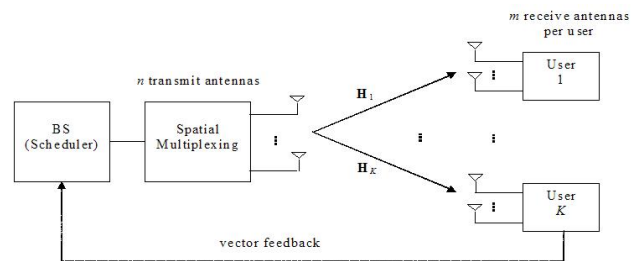


Figure 1. A multiuser scheduling system with n transmit antennas at the BS and m receive antennas at each MS. The scheduler can employ any user selection algorithm. In this study, the Greedy (MAX), Proportional Fair (PF) and the Equal Grade of Service (EGoS) schedulers are considered.

Fig. 1 shows a wireless system with a base station serving K downlink mobile stations. Each user MS tracks its individual channel from the BS, and sends a measure of the channel quality index (CQI) to the BS. The BS schedules any one user in a given time slot depending

³The reader is cautioned against attempting conversion from the per-channel metric to an ‘equivalent’ per-user metric (e.g., by dividing the per-channel metric by the number of users). MuD leads to gains that are logarithmically proportional to the number of users. Since, the per-user metric normalizes this figure by the number of users, it will cast multi-user diversity in poor light. We take the view that such a conversion is inappropriate, since multi-user diversity applies only for *delay-elastic* applications. Users are willing to wait, and are scheduled only when a channel becomes available.

on the present CQI, past transmissions to all users, and fairness/latency requirements.

In this study, perfect and instantaneous feedback of the CQI from each MS to the BS is assumed. The full-buffer traffic model is used; i.e. users always have data to receive, and all transmissions are initiated at the start of the simulation (i.e., users cannot ‘enter’ or ‘leave’ a set of users being serviced by the BS).

Three scheduling algorithms are considered — Greedy (MAX), Proportional Fair (PF) and Equal Grade of Service (EGoS). By evaluating the performance of two extreme schedulers (MAX, EGoS), we attempt to obtain a perspective on the performances realized by a range of useful schedulers. The PF scheduler is considered as a representative and widely popular example. In what follows,

- $CQI(k, t)$ denotes the vector CQI for user k at time instant t . Achievable substream-throughput vector (if k is scheduled at time t) is used for CQI ⁴.
- $SCQI(k, t)$ denotes the user’s sum-CQI (the summation is over all sub-streams), and is a scalar quantity.
- $TP(k, t)$ denotes the throughput of user k at time instant t . Note that $TP(k, t)$ differs from $SCQI(k, t)$, since only 1 of K users is scheduled at every time instant.

1) *MAX*: Schedules the user with maximum SCQI. Thus,

$$k^*(t) = \arg \max_k SCQI(k, t) \quad k = 1, 2, \dots, K \quad (1)$$

where $k^*(t)$ denotes the user selected at time t . MAX is optimum from a throughput standpoint, in that no other algorithm can achieve more throughput. However, it ignores the past transmission history of all users, and hence, is unfair and biased in that aspect.

2) *EGoS*: Schedules that user who has been relatively starved throughput-wise over a time-window that extends to the indefinite past. Thus,

$$k^*(t) = \arg \min_k \sum_t TP(k, t) \quad k = 1, 2, \dots, K \quad (2)$$

EGoS can be considered to be the ultimate *throughput-fair* scheduler, since it allows each user to catch-up with other users, regardless of their channel conditions.

3) *PF*: All other schedulers will lead to performances that will be bracketed by the above two schedulers. We use the well-known PF scheduler [17], [20] as an example of one that attempts a better balance between throughput performance and fairness. Thus,

⁴We note that, although a single scalar quantity such as the total link-capacity would suffice as CQI information for user scheduling, a vector CQI is needed for adaptive transmission reasons. See Appendix B.

$$k^*(t) = \arg \max_k \frac{SCQI(k, t)}{\overline{TP}(k, t)} \quad k = 1, 2, \dots, K \quad (3)$$

where $\overline{TP}(k, t)$ is a measure of the mean throughput of link k over a window extending from t back to the indefinite past⁵. $\overline{TP}(k, t)$ is updated using an exponentially weighted Infinite Impulse Response (IIR) filter as

$$\overline{TP}(k, t+1) = \beta * \overline{TP}(k, t) + \delta(k^*, k) * SCQI(k, t) \quad (4a)$$

$$\delta(k^*, k) = \begin{cases} 1 & k^* = k \\ 0 & else \end{cases} \quad (4b)$$

where, δ is the Kronecker delta (sifting) operator, and β is the decay rate (or forgetting factor). We use $\beta = 0.98$ in the simulations, corresponding to an effective averaging window of 50 transmissions. This is a reasonable number for getting an accurate running mean.

We add that Round-Robin (RR) is another plausible scheduler. RR is a fair scheduler from a service-time perspective. However, it is known that for users with independent and identically distributed (i.i.d.) fades, the benefit of multi-user diversity is lost when RR is employed [21]. On the other hand, it is also known that PF best balances between the conflicting tradeoffs — offering service-time fairness to all users (in the asymptotic sense), while optimizing user performance at the same time [20], [27].

B. Link-level Description: Mobile Station Viewpoint (PHY-layer)

While the simulation platform developed in this study is quite general with respect to system and channel parameters, most numerical results were obtained using the parameters detailed in Table I. The various assumptions invoked in developing the platform are outlined here.

1) *Channel Model*: We consider three cases for Rician κ -factor, namely, $\kappa = 0$ (Rayleigh fading, i.e., only the scatter component); $\kappa = 10$ (dominant specular component); and κ a function of distance. The κ -factor typically decreases as the MS moves farther away from the BS, and the variation of κ with distance assumed here for the third case is given in Table II.

The complex baseband channel gain between the j th transmit antenna of a given base station and the i th receive antenna of a given user-terminal is modeled by

$$h_{ij} = \sqrt{A \left(\frac{d_0}{d} \right)^\Gamma} s \left[\sqrt{\frac{\kappa}{\kappa+1}} e^{j\phi} + \sqrt{\frac{1}{\kappa+1}} z_{ij} \right] \quad (5)$$

where,

⁵Our averaging formula for $\overline{TP}(k, t)$ is slightly different from the formula introduced in [17], [20].

TABLE I.
PARAMETER VALUES USED IN THE SYSTEM SIMULATIONS.

Cell Geometry	Hexagonal Array with side $R = 1000$ m
Carrier Frequency	$f_c = 2$ GHz
System Bandwidth	$W = 5$ MHz
Path Loss Exponent	$\Gamma = \begin{cases} 2 & 30 \leq d \leq 100\text{m} \\ 3.7 & \text{else} \end{cases}$
Shadow Fading	Lognormal, with Standard Deviation $\sigma = 8$ dB
Multipath Fading	Rician, with κ -factor = 0 (Rayleigh), 10, or a function of Transmit-Receive (T-R) distance (see Table II)
Antenna Pattern	Omnidirectional, or Uniform over 120°
Thermal Noise Density	$N_0 = -174$ dBm/Hz
Mobile Terminal's Noise Figure	$N_F = 8$ dB
Transmit Power	$P_T = 5$ W
Median cell-boundary SNR	$\rho = 20$ dB

TABLE II.
VARIATION OF RICIAN κ -FACTOR AS A FUNCTION OF BS-MS SEPARATION DISTANCE (PERCENTAGES SPECIFY THE DISTANCES RELATIVE TO THE CELL RADIUS).

Distance %	0-5	5-15	15-25	25-35	35-45	45-55	55-65	65-75	75-85	85-100
Rician κ	10	9	8	7	6	5	4	3	2	0

- d is the link length, Γ is the path loss exponent, and A is the median of the path gain at reference distance d_0 ($d_0 = 100$ m in the simulations).
- $s = 10^{S/10}$ is a log-normal shadow fading variable, where S is a zero-mean Gaussian random variable with standard deviation σ dB.
- κ is the Rician κ -factor for the given base-to-mobile path.
- $\phi = 2\pi d/\lambda$ is the phase shift of a line-of-sight (LOS) plane wave from the transmitter to the receiver. $\lambda = c/f_c$ is the wavelength. We assume that for a given transmit-receive pair, all LOS paths have the same length.
- z_{ij} represents the phasor sum of scattering components for the (i, j) path which are assumed to be zero-mean, unit-variance, i.i.d. complex Gaussian random variables.

We assume a base station height of $h = 30$ m above ground. For receivers located close to the ground, the direct path has a length $d = [r^2 + h^2]^{1/2}$, where r is the distance along the ground from the receiver to the base station. This implies that all Transmitter-Receiver (T-R) distances are 30 m or greater. We use a loss exponent of 2.0 (free space loss) for distances close to the base station (30 – 100 m), and 3.7 for distances beyond 100 m. We also apply shadow fading regardless of the T-R distance. This has been shown to be an empirically reasonable model [28]. For antenna sectoring, perfect beams are assumed instead of shaped antenna patterns.

2) *Simplifying System Assumptions:* We invoke assumptions often made in conjunction with MEA systems [1], [2]: (i) narrowband signaling, (ii) quasi-static (block) fading, (iii) long burst interval, and (iv) independently faded complex Gaussian path gains. This permits

a mathematical representation for the SISO/MEA cellular system⁶ as follows

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{Z}, \quad (6)$$

where $\mathbf{X} \in \mathbb{C}^{7n}$, $\mathbf{Y} \in \mathbb{C}^m$, are transmit (serving and interfering) and receive signal vectors, $\mathbf{H} \in \mathbb{C}^{m \times 7n}$ is the channel gain matrix, and $\mathbf{Z} \in \mathbb{C}^m$ is a thermal noise vector, that is Gaussian distributed with zero-mean and one-sided power spectral density (PSD) N_0 . Since the noises corrupting the different receive antennas are independent, $\mathbf{Z}$ has an autocorrelation matrix $N_0 \mathbf{I}_{m \times m}$, with $\mathbf{I}_{m \times m}$ being the identity matrix.

We assume only one tier of interferers around the serving BS (Fig. 2). This assumption is made to simplify the simulations and is slightly optimistic. However, the rapid decay of signal power with distance makes this assumption reasonable. Moreover, we offset it with the pessimistic assumption that all co-channel interferers are transmitting all the time. (In the single-cell case co-channel interferers are not present, and $\mathbf{H} \in \mathbb{C}^{m \times n}$).

We assume an adaptive transmission algorithm that perfectly adapts the transmission on each transmit antenna (via the constellation size) according to the instantaneous radio channel and interference conditions. It is possible for different transmit antennas to choose different bit rates (constellation sizes), although all transmissions operate at the same symbol rate. The procedure to compute the optimum size of the transmit constellations appears in the Appendix B.

Since cell-site (macro) diversity has been shown to have minimal impact on mean throughput calculations

⁶Following explanation offered in the Introduction, configurations employing Transmit Diversity are not considered. Hence, configurations that have more transmit than receive antennas ($n > m$) are excluded from this study.

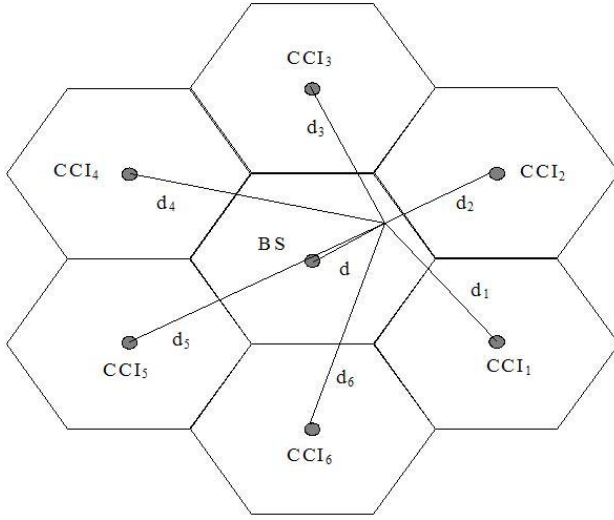


Figure 2. Plot of an interference-limited system, showing the serving and co-channel base stations. Regular hexagonal geometry with side $R = 1000$ m is assumed.

[9], [10], it is not used in the simulations, i.e., for simplicity, we assume that users communicate with the base station that is the nearest, not necessarily the strongest. Finally, perfect channel estimation, perfect T-R synchronization, and perfect instantaneous feedback are also assumed. These simplifications focus the problem on the essential issues we wish to investigate.

3) Array Processing: Depending on the availability of channel state information (CSI) at the transmitter, it is possible to design transmit-adaptation (e.g. eigen-beamforming) and receive-adaptation (e.g., minimum mean-square error) array processing strategies. Since we assume CQI but not CSI feedback to the transmitter, only the receive-adaptation scheme is discussed here. The minimum mean-square error (MMSE) scheme uses uniform power allocation among the n transmit antennas. To analyze MMSE reception, the analyst takes into account the path gains from all BSs — serving and interfering — in the channel gain matrix ($\mathbf{H} \in \mathbb{C}^{m \times 7n}$). Received data streams are separated by computing a linear combination of the received signals using a set of weights that achieves the minimum mean-square error between the output estimate and the true signal sample. Thus, we have that

$$\hat{\mathbf{X}} = \mathbf{W}^H \mathbf{Y}. \quad (7)$$

The performance index for a given weight matrix is

$$\zeta(\mathbf{W}^H) \triangleq E \left[\sum_{j=1}^n |\epsilon_j|^2 \right] = E \left[\sum_{j=1}^n |x_j - \hat{x}_j|^2 \right] \quad (8)$$

where x_j is the j th transmitted signal. The expectation in (8) is taken with respect to the noise and the statistics of the data sequences. The weight matrix $\mathbf{W}$ that yields the

minimum mean-square error is [10]

$$\mathbf{W} = \mathbf{A}^{-1} \mathbf{H}, \quad (9a)$$

$$\mathbf{A} = \mathbf{H} \mathbf{H}^H + \frac{\sigma^2}{P_T/n} \mathbf{I}_{m \times m}. \quad (9b)$$

The post-processing SINR on the j th decoded stream can be shown to be [8], [10]

$$\gamma_j = (\mathbf{H}_j)^H \mathbf{R}_j^{-1} (\mathbf{H}_j), \quad j = 1, 2, \dots, n \quad (10)$$

where

$$\mathbf{R}_j = \sum_{l=1, l \neq j}^{7n} (\mathbf{H})_l (\mathbf{H})_l^H + \frac{\sigma^2}{P_T/n} \mathbf{I}_{m \times m} \quad (11)$$

and $(\mathbf{H})_j$ is the j th column of $\mathbf{H}$. (For the noise-only (single-cell) case, the summation will have n terms, instead of $7n$).

4) Link Throughput Bounds: The per-user data throughput is the sum of the throughputs of the sub-streams. We determine the throughput T_j of sub-stream j for two extreme cases:

- **Ideally Coded Signals** – The throughput is upper-bounded by the Shannon capacity,

$$T_j = \log_2 (1 + \gamma_j). \quad (12)$$

- **Uncoded Signals** – Assuming error detection in each block, the throughput is

$$\begin{aligned} T_j(M_j) &= (1 - BLER_j) \log_2(M_j) \\ &= (1 - BER_j)^L \log_2(M_j) \end{aligned} \quad (13)$$

where $\log_2(M_j)$ is the number of bits per symbol in stream j , BER_j is the bit error rate for stream j , and $BLER_j$ is the corresponding block error rate for L -bit blocks. In this study $L = 500$ bits is assumed, though the results are robust for values of L over a wide practical range [10].

We wish to simplify (13) to the form of (12) for convenience of calculation. Under the simplifying assumption that the channel undergoes quasi-static block fading, it is possible to regard the channel as *AWGN conditioned on the instantaneous gains*. For QAM modulation, we can then use the procedure in [9]–[11] to bring this to the form

$$T_j = \max T_j(M_j) \approx \log_2 \left(1 + \frac{\gamma_j}{6.4} \right). \quad (14)$$

Thus, the curve for uncoded transmission is 8 dB ($= 10 \log_{10}(6.4)$) shifted from the curve for perfectly-coded (Shannon) transmission. A variety of practical coding strategies can then be modeled by using other shifts less than 8 dB.

5) *Simulation Trials*: For the purpose of averaging throughput over a cell, we conduct 500 trials in a simulation. In any given trial, K users are distributed at random locations uniformly over the cell/sector. A given trial assigns a location, shadow-fade combination to each user, and user locations are uncorrelated. In each trial, users experience 1000 different multipath fades⁷. Thus, there are 500,000 quasi-static-block-fade transmission intervals in all. In this study, we consider both limited and unlimited constellation sizes. For the limited constellation case, modulations up to 16-QAM (leading to a symbol rate of up to 4 bits/symbol) are considered. This maximum is practical for present-day cellular implementations⁸.

III. NUMERICAL RESULTS

Figs. 3–6 show the cell-wide average throughputs that are offered by MMSE systems for the many dimensions we considered. We show only a sample listing, instead of presenting throughputs over all dimensions, to keep the discussion useful and concise. Our initial discussion refers to the case of a Rician κ -factor of $\kappa = 0$ and omnidirectional antennas. Any deviations we make from this baseline case in subsequent paragraphs will be so noted.

We have organized our figures as follows: Figures 3 and 4 consider the single- and multi-cell cases respectively for the (1, 1) configuration; while figures 5 and 6 do the same for the (3, 3). Figures 7 and 8 refer to (3, 3) with sectorized antenna patterns.

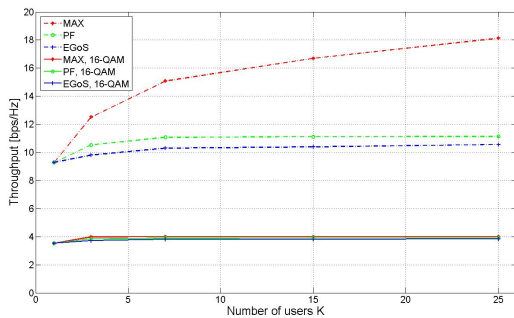


Figure 3. Mean throughput as a function of number of users for the (1, 1) system, single-cell environment, $\kappa = 0$, and omnidirectional antennas. Throughputs are plotted for all three scheduling algorithms, for both unlimited constellation (with ideal coding) and limited constellation size (16-QAM).

Effect of Number of Users and Scheduling Algorithm:

It is known that at the link-level, multi-user diversity with network scheduling leads to gains that grow as $O(\log K)$. Referring to Figs. 3–6, we see that this is also the case for system-level simulations for unlimited constellation sizes (although the scalar multipliers, and lower order terms, are different for different scheduling algorithms).

⁷Since Rayleigh fading has significant density at the tail, 1000 realizations are needed for statistical stability.

⁸The state-of-art is 16-QAM for mobile wireless systems, and 64-QAM for fixed wireless systems.

It is clear that MAX leads to higher gains with increasing K , while EGoS leads to limited gains. In some cases (the multicell scenarios), EGoS leads to throughput *loss* rather than gain. This is readily explained by the fact that EGoS is a “poor man’s” scheduling algorithm. It penalizes users with better channels to allow users with poor channels to catch up. This leads to a situation in which users with weak channels determine the overall scheduler performance.

The PF scheduler, in contrast to the EGoS scheduler, always leads to gains with increasing number of users. It is also evident from the figures that PF with $\beta = 0.98$ leads to curves parallel to those for EGoS in the mid-to-high region of K . Different values of β can lead to a range of ‘tunable’ PF schedulers, although, $0.90 \leq \beta < 1.00$ is a practical range⁹.

As explained earlier, MAX leads to very good gains as compared to EGoS and PF. However, it is a biased/greedy algorithm, which may not serve well for environments having quality of service (QoS) requirements. EGoS attempts throughput fairness, while PF attempts to strike a balance between cell-wide throughput and fairness. However, as will be seen shortly, EGoS can also be useful under practical circumstances.

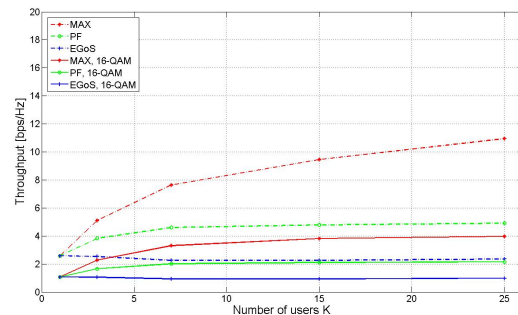


Figure 4. Mean throughput as a function of number of users for the (1, 1) system, multi-cell environment, $\kappa = 0$, and omnidirectional antennas. Throughputs are plotted for all three scheduling algorithms, for both unlimited constellation (with ideal coding) and limited constellation size (16-QAM).

Effect of Co-Channel Interference: In the single-cell scenario, multi-user diversity improves the signal (channel) quality, while in the multi-cell case, it has room to perform an additional function: that of interference avoidance [20]. This means that we can expect better gains with increasing K for the multi-cell case. This is indeed so, as evidenced by a comparison between Fig’s. 3 and 4 or 5 and 6; i.e.,

$$\frac{TP_{single-cell, K=25}}{TP_{single-cell, K=1}} < \frac{TP_{multi-cell, K=25}}{TP_{multi-cell, K=1}}.$$

SINRs in the single-cell case (20 dB to 60 dB) are much higher than those in the multi-cell case (−5 dB to

⁹With $0.90 \leq \beta < 1.00$, the effective averaging window is 10 transmissions or greater, which is sufficient for averaging purposes. For $\beta < 0.90$, exponential averaging will have an extremely short memory.

25 dB), leading to correspondingly lower throughputs for the latter. MAX and EGoS curves display more or less similar trends for the single and multi-cell cases, whereas PF yields better gains (the PF curve moves away from EGoS, closer to the MAX curve) for the multi-cell case.

Effect of Degrees of Freedom: In a (1, 1) system, multi-user diversity improves the operating SINR. In a (3, 3) system, multi-user diversity improves both the operating SINR, as well as the available degrees of freedom of the system. In other words, the entire channel subspace structure (the number, as well as values of the eigen-space) is improved [18].

Note that neither the SISO (1, 1), nor the MIMO (3, 3) system have excess degrees of freedom. It is clear that, although we see a substantial increase in mean throughput for the MIMO (3, 3) system as compared to the SISO (1, 1) system, we cannot expect the increase to be three-fold, despite the creation of three parallel decoupled streams at the receiver. This is because the available degrees of freedom (receive antennas) are used to combat cross-stream interference (XSI), even at the cost of noise enhancement. Also, each transmit antenna in the (3, 3) system now uses only 1/3 the total transmit power as compared to the SISO system.

Similar trends are seen for both single and multi-cell cases. Note the change in scale of the y-axis for the (3, 3) configuration (Figs. 5, 6) as compared to the (1, 1) configuration (Figs. 3, 4).

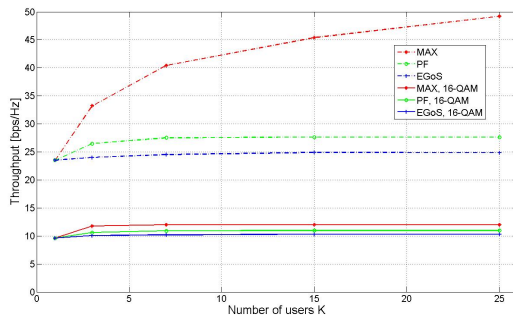


Figure 5. Mean throughput as a function of number of users for the (3, 3) system, single-cell environment, $\kappa = 0$, and omni-directional antennas. Throughputs are plotted for all three scheduling algorithms, for both unlimited constellation (with ideal coding) and limited constellation size (16-QAM). (Note the change in the vertical scale relative to Figures 3 and 4).

Effect of Antenna Sectorization: Antenna sectorization is an interference suppression technique. Co-channel interference is reduced by using antenna beam patterns and frequency coloring [29], [30]. By contrast, multi-user diversity is an interference avoidance technique, which also improves channel subspace structure (by avoiding ill-conditioned channels). Since antenna sectorization cannot improve channel structure, it is clear that multi-user diversity is the superior technique, particularly for a system with many users. Antenna sectorization and multi-user

diversity can be used in conjunction, since their goals are not necessarily conflicting. It stands to reason that as the number of users increases, the combined gain will have diminishing benefit, with multi-user diversity playing an increasingly major role.

From Figs. 6 and 7, for a reuse factor of 1, using sectorized antennas leads to about a two-fold improvement in throughput over omni-directional antennas for the single-user case¹⁰.

As the number of users is increased, the benefit due to antenna sectorization gradually decreases for all three schedulers, as was expected. As a percentage, sectorization leads to far more improvement in EGoS performance as compared to MAX and PF.

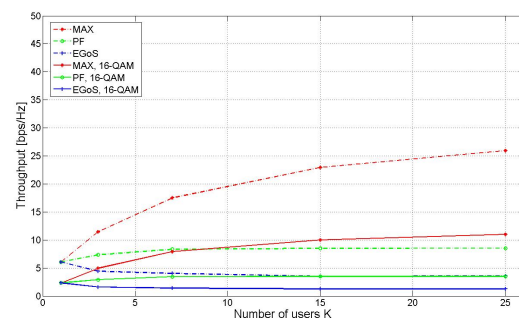


Figure 6. Mean throughput as a function of number of users for the (3, 3) system, multi-cell environment, $\kappa = 0$, and omni-directional antennas. Throughputs are plotted for all three scheduling algorithms, for both unlimited constellation (with ideal coding) and limited constellation size (16-QAM). (Note the change in the vertical scale relative to Figures 3 and 4).

Effect of Rician κ -Factor: It is known that, in the presence of a strong specular component ($\kappa \sim 10$) the mean throughput of SISO (1, 1) systems increases [1], [9], [11], [22]. Adding users and scheduling algorithms results in the following changes: mean throughput increases slightly ($\sim 3\%$) for the MAX scheduler, decreases slightly ($\sim 5\%$) for PF, and decreases moderately ($\sim 9\%$) for EGoS, over all K . Similar trends hold for the single- and multi-cell cases.

For the MIMO (3, 3) system, going from $\kappa = 0$ to $\kappa = 10$ leads to a substantial decrease in capacity [1], [9], [11], [22]. However, as the number of users is increased, the losses are reduced. This can be explained by the inherent property of multi-user diversity to choose the relatively best channel. Loss reduction with increasing number of system users is the highest in MAX, followed in order by PF and EGoS.

Mean throughput values for Rician fading with κ -factor a function of distance (Table II) are bracketed those obtained for $\kappa = 0$ and $\kappa = 10$, closer to those obtained using $\kappa = 10$.

¹⁰This is consistent with results from conventional systems (using three-sector antennas enables cellular system planners to bring down the reuse factor from 12 to 7, which amounts to a similar throughput increase [30, Ch. 3]).

Effect of Coding: For the single-cell case, for both (1, 1) and (3, 3) systems, the reduction in throughput at $K = 1$, for uncoded signals relative to Shannon coded signals is about 20% [11], [31]. As the number of users is increased, we experience a decrease in the throughput loss for uncoded transmission. Throughput loss at $K = 25$ is about 15% for the MAX scheduler, 22% for PF and 25% for EGoS.

For the multi-cell case, the coding loss at $K = 1$ for both (1, 1) and (3, 3) systems is about 40–50% [11], [31]. At $K = 25$, the losses are about 25%, 45% and 50%, for MAX, PF and EGoS respectively.

Thus, at higher K , there is improvement for MAX, but not for PF and EGoS in both the single- and multi-cell cases.

This can be explained as follows: Loss due to uncoded transmission depends on the operating SINR. For the single-cell case, the operating SINR is high, hence the throughput loss is comparatively low, and comparable percentage losses are recorded by all three schedulers. On the other hand, operating SINRs are significantly lower for the multi-cell case, hence throughput losses are higher. Multi-user diversity has the inherent property of seeking users with good SINRs; however, this applies to the MAX scheduler more than to the PF and EGoS schedulers. Depending on past transmission history, PF and EGoS schedulers may not be able to choose the best user. Hence, they lead to correspondingly less improvement.

For sectorization, SINRs, and hence coding losses observed, will be bracketed by the single-cell and multi-cell cases above.

Effect of Limited Constellation Sizes: Whereas unlimited constellation size provides insight to the potentially achievable throughputs the system can offer, it is also necessary to look into throughputs that practical systems can actually realize. Figs. 3–6 give some illustrative results. Limiting the transmit alphabet size to 16-QAM amounts to capping throughput at $4n$ bps/Hz. The effect is to reduce the potential benefit from increasing number of users in the system, particular choice of scheduling algorithm, and antenna sectorization.

Compared to the case of unlimited constellation sizes, we notice a substantial throughput loss for both (1, 1) [Fig. 3 for single-cell, Fig. 4 for multi-cell] and (3, 3) systems [Fig. 5 for single-cell, Fig. 6 for multi-cell]. Throughput saturation (due to constellation size capping) is almost immediate ($K = 3$) for the single-cell case. For the multi-cell case, throughput leveling occurs at $K = 7$ for PF and EGoS, and the differences between the throughputs offered by the scheduling algorithms are substantially reduced.

Since throughput per-cell differences between the various schedulers are negligible for the single-cell case, and significantly reduced even for the multi-cell case, it becomes reasonable to view these findings through the prism of other metrics. In this context, we note the following: EGoS can be more suitable than MAX

and PF for the single-cell case [Figs. 3 and 5] since it is the ultimate throughput-fair scheduler; MAX may be unsuitable since it is biased, while PF may be unsuitable since it is *not* stable¹¹ [32]. For the multi-cell case, PF may be more suitable than MAX, depending on QoS requirements [Figs. 4 and 6]. This observation has important implications for current state-of-the-art systems that can support signal constellations up to 16-QAM.

IV. MULTI-USER DIVERSITY SYSTEMS WITH NO EXCESS DEGREES OF FREEDOM VS. SINGLE-USER SYSTEMS WITH EXCESS DEGREES OF FREEDOM

We now provide a brief comparison between single-user systems employing excess degrees of freedom (SU-EDoF), and multi-user diversity systems having no excess degrees of freedom (MuD-wo-EDoF). Both mechanisms attempt to improve received signal quality, as measured by the post-processing SINR, and use of one technique does not preclude using the other (i.e., it is possible to combine multi-user diversity with excess degrees of freedom (MuD-EDoF)).

In SU-EDoF, a receiver uses excess antennas achieving diversity to combat fading, or to suppress one or more co-channel interference streams, or a combination of both [26]. SU-EDoF is a *radio-layer* technique, and can be used for all application types (delay-elastic, as in data applications, or delay-intolerant as in voice applications). By contrast, multi-user diversity schedules the user with the best signal quality, i.e., interference avoidance is inherently achieved. However, multi-user diversity (both MuD-EDoF and MuD-wo-EDoF) is applicable only to delay-elastic applications, wherein the scheduler selects one user for transmission. Viewed from this perspective, multi-user diversity may be considered as a *cross-layer technique* in which the radio (PHY)-layer continually educates the medium access control (MAC)-layer. Since multi-user diversity is able to improve the channel subspace structure (by avoiding ill-conditioned channels), a capability which SU-EDoF does not have, it can be the superior technique, particularly in a system having many users.

We now discuss how MuD-wo-EDoF may be used in lieu of SU-EDoF, thereby leading to a reduction in the number of receive antennas, while offering comparable or greater throughput¹². We have seen previously that, EGoS leads to small gains for the single-cell scenario, and moderate loss for the multi-cell scenario, as a function of number of users K . Hence, EGoS cannot be used as a scheduler in MuD-wo-EDoF to compete against SU-EDoF. Similarly, we have seen that the PF scheduler has curves that are nearly parallel to those of EGoS with higher multi-user diversity gains. This implies that the PF scheduler can be used with MuD-wo-EDoF to compete against SU-EDoF wherein the excess degrees of freedom in SU-EDoF are few (e.g. one). When excess degrees of

¹¹A stable algorithm always results in bounded queue lengths under any conceivable traffic scenario.

¹²Since there is a reduction in the number of receive antennas, there is considerable impact, since it affects all mobiles.

freedom in SU-EDoF are many, e.g. MIMO (3, 6), the MAX scheduler should be used.

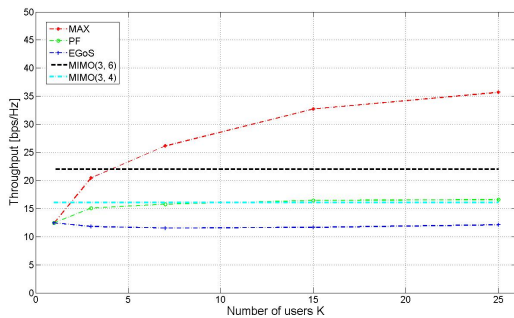


Figure 7. Mean throughput as a function of number of users for the (3, 3) system, with unlimited constellation sizes and ideal coding, multi-cell environment, $\kappa = 0$, and sectorized antennas. Throughputs for all three scheduling algorithms are plotted. The upper horizontal line is for the single-user MIMO (3, 6) system (no multi-user diversity), while the lower horizontal line is for the single-user MIMO (3, 4) system.

Fig. 7 illustrates a representative example, where the upper horizontal line indicates the performance of the single-user MIMO (3, 6) system, and the lower horizontal line indicates the performance of the single-user MIMO (3, 4) system. These systems are able to suppress up to 3 and 1 interfering streams, respectively. We see that a MuD-wo-EDoF system incorporating the MAX scheduler, with 2 or more users can offer equal or better performance than the single-user MIMO (3, 4) system, while 4 or more users are needed to achieve performance equal to or better than that for single-user MIMO (3, 6). With a MuD-wo-EDoF system incorporating a PF scheduler, 10 or more users are needed to compete with a single-user MIMO (3, 4) system. A PF-based MuD-wo-EDoF system cannot compete with a single-user MIMO (3, 6) system, no matter how large K is.

The above comparisons hold even for the case of limited constellation sizes, as seen in Fig. 8. In this case, however, the differences, in terms of design choices and their consequences, are markedly reduced.

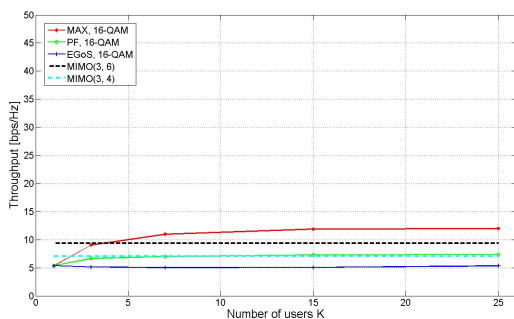


Figure 8. Mean throughput as a function of number of users for the (3, 3) system, with limited constellation size (16-QAM), multi-cell environment, $\kappa = 0$, and sectorized antennas. Throughputs for all three scheduling algorithms are plotted. The upper horizontal line is for the single-user MIMO (3, 6) system (no multi-user diversity), while the lower horizontal line is for the single-user MIMO (3, 4) system.

V. SUMMARY AND CONCLUSIONS

We have evaluated the throughput performance of SISO and MIMO-based cellular systems which employ multi-user diversity over several useful system-level design dimensions. By evaluating the performance of two extreme schedulers (MAX, EGoS), we have been able to obtain a perspective on the performances realized by a variety of useful schedulers. The PF scheduler was also considered as a representative and widely popular example. Our chief observation is that, although the various dimensions are important considerations for SISO and MEA systems, the potential benefits need to be weighed in the context of limited signal constellations that are prevalent in present day practical systems. Since per-channel throughput differences were negligible for the single-cell case, and dramatically reduced for the multi-cell case, other metrics (fairness and stability) were employed to get another perspective on the findings. There, EGoS seemed a reasonable choice for the single-cell case, and PF seemed reasonable in multi-cell scenarios when delay tolerance was allowed.

We also compared single-user MIMO systems that use excess degrees of freedom (SU-EDoF) and those that use multi-user diversity without excess degrees of freedom (MuD-wo-EDoF). Here, among scheduler choices, it is clear that EGoS is not a viable candidate; that PF has limitations in the number of excess receive antennas it can compete against in SU-EDoF based systems; and, that MAX is the best option in terms of cell-wide throughput.

In general, for applications that are delay-tolerant, a MuD-wo-EDoF system with a large number of users can deliver substantially higher throughputs than SU-EDoF links. This is especially when using SU-EDoF with only one extra antenna, but applies even to the case of up to three. Finally, the amount of improvement using MuD-wo-EDoF instead of SU-EDoF decreases with increasing limits on constellation size.

APPENDIX A DEFINITIONS

- 1) Array processor: the unit at the receiver, which attempts to separate the received streams in the face of cross-stream interference (XSI) and co-channel interference (CCI) as optimally as possible.
- 2) Degrees of Freedom: the number of decomposable parallel SISO channels that can be created after array processing. It equals the rank of the channel gain matrix $\mathbf{H}$, and is upper-bounded by $\min(n, m)$.
- 3) Excess Degrees of Freedom: the excess number of receive elements over transmit elements, i.e., $m - n$. When the receive array has at least as many antenna elements as the transmit array, we can receive all of the transmitted streams at the receiver after array processing.

APPENDIX B SIMULATION APPROACH

The intention in this study is to compute throughput statistics of several SISO/MIMO configurations in a multi-user scenario (employing network diversity scheduling) for various design options. Highlights of the steps involved are as follows:

- 1) Distribute K MSs in cell (uniform random uncorrelated locations), and generate channel matrices $\mathbf{H}_1, \dots, \mathbf{H}_K$ as given by (5).
- 2) $\forall k$, compute post-processing SINR for each substream j , assuming MMSE reception ((10)-(11)).
- 3) $\forall k$, compute the throughput for each substream j ((12), (14)). This is the vector CQI for user k .
- 4) $\forall k$, compute $SCQI = \sum_{\text{substreams}} CQI$.
- 5) Schedule user $k^*(t)$ (Equations (1), (2), (3)), and update his cumulative throughput ($\sum_t TP(k^*, t)$).
- 6) Update the averages ((4)) of all users.
- 7) Compute the average cell-wide multi-user throughput over 500 locations (each with lognormal shadow fading) and 1000 multipath fades per location.

At the beginning of each block-fade interval, pilot signals are transmitted to estimate the receiver array weights. The receiver then determines the constellation size (M) from the substream post-processing SINRs, and communicates this information to the transmitter. Based on CQI, past transmission history, delay/latency constraints and the particular scheduling algorithm in use, a particular user is selected for transmission. Adaptive modulations at each transmit antenna then quickly select the corresponding optimal QAM constellation. The channel remains known throughout, since estimation-feedback-adaptation occurs within the block fade interval. By assumption, we exclude all overheads (pilot signaling, channel estimation at receiver, feedback and signal-adaptation) from our throughput computation procedure.

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Rahul N. Pupala received the B.E. degree in Computer Engineering from Victoria Jubilee Technical Institute (VITI), Bombay in 1994, the M.S. degree in Computer Science in 2003, and the Ph.D. in Electrical Engineering in 2008 both from Rutgers - The State University of New Jersey. From 1994 to 1999, he worked in the software industry. He is currently at Alcatel-Lucent/Bell Labs, Murray Hill, NJ, responsible for PHY & MAC layer innovations for LTE-Advanced.

His research interests include Distributed Computing, Computer Networks, Signal Processing and Wireless Communications.



Larry J. Greenstein received the BS, MS and PhD degrees in electrical engineering from Illinois Institute of Technology in 1958, 1961 and 1967, respectively. From 1958 to 1970, he was at IIT Research Institute, where he worked on radio frequency interference and anti-clutter airborne radar. He joined Bell Laboratories in Holmdel, NJ in 1970. Over a 32-year career, he conducted research in digital satellites, point-to-point digital radio, optical transmission techniques and wireless communications.

For 21 years during that period (1979–2000), he led a research department renowned for its contributions in these fields. Since 2002, he has been a research professor at Rutgers University’s WINLAB, working on PHY-based security techniques, MIMO-based cellular systems, broadband power line systems, cognitive radio and channel modeling.

Dr. Greenstein is an IEEE Life Fellow, an AT&T Fellow, a recipient of the IEEE Communications Society’s Edwin Howard Armstrong and Joseph LoCicero Awards, and co-author of several award-winning papers, including the IEEE Donald G. Fink Prize Paper Award. He has served on numerous editorial boards and technical program committees and was, and is now again, the IEEE Communications Society’s Director of Journals.



David G. Daut (S76-M80-SM88) received the B.S.E.E. from the New Jersey Institute of Technology (1976) and the M.S.E.E. and Ph.D. degrees from Rensselaer Polytechnic Institute (1977, 1981). He joined Rutgers University in 1980. He has served as Director, ECE Graduate Program (1991–1999) and as Director, Engineering Computer Center (1989–1998). He had served as Chairman of the Electrical and Computer Engineering Department from 1986 to 1988 and again from 1997 to

2006. Currently, a Professor of Electrical and Computer Engineering, his teaching and research activities are in the areas of communications and information systems.

His present research activities are focused on data/bandwidth compression techniques in the context of image coding and transmission, including: combined source and channel encoding of image data; digital communication system performance evaluation using different modulation and channel coding strategies in conjunction with both Gaussian and fading channel characterizations; wireless communication systems; the application of rate-distortion theoretic principles to the design of data and image transmission systems; and, optical communications systems employing Dense Wavelength Division Multiplexing in the presence of fiber nonlinearities. He has authored numerous journal and conference papers and was a co-recipient of the IEEE Communications Society Rice Prize Paper Award (1984).

Dr. Daut is an IEEE Senior Member and a member of Sigma Xi, Tau Beta Pi, Eta Kappa Nu as well as the Association for Computing Machinery, Optical Society of America, and the Society of Photo-Optical Instrumentation Engineers. He served as an elected member of the IEEE Board of Directors (Division III) during 1998 and 1999. In 2009 he served as General Co-Chair for the IEEE Sarnoff Symposium, Princeton, NJ.