Analysis and Design of Best-Effort Broadcasting Services in Cellular Networks

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***Abstract*—In this paper, we propose a novel *best-effort broadcasting service (BEBS)* scheme in cellular networks, which can be used for location-based advertising and real-time multimedia broadcasting. Unlike the conventional broadcasting service that aims to assure reliable data delivery to every user, the main objective of the proposed BEBS is to maximize the effective capacity at the cost of reliability. To this end, we introduce the notion of target reliability and formulate the problem of maximizing the capacity of BEBS under any given reliability constraint. By deriving an analytical model, we investigate the effect of target reliability on the achievable capacity. We further prove several key properties of BEBS with respect to the optimal value of target reliability and the maximum gain of the achievable capacity. To realize the maximum achievable capacity of BEBS, we propose two feedback control schemes that adjust the target reliability or modulation and coding scheme based on the estimate of relative gain of BEBS. We validate our analytical model by comparison with simulation. In addition, the simulation results confirm that the proposed schemes for BEBS significantly outperform conventional reliable broadcasting under various network configurations.**

***Index Terms*—Broadcasting service, capacity, cellular networks, reliability.**

I. Introduction

RECENTLY, multicasting and broadcasting services have come into the spotlight as emerging applications in next-generation cellular networks. They can be used for location-based mobile advertising, news/information broadcast, mobile Internet protocol television, emergency alert, and so on. To support these services, the WiMAX forum and the Third-Generation Partnership Project (3GPP) have standardized multicast and broadcast service and enhanced multimedia broadcast and multicast service, respectively [1], [2]. Compared with the unicast, multicast/broadcast (MCBC) improves wireless spectrum efficiency because multiple users can concurrently receive the identical data transmitted by a base station (BS).

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Meanwhile, spectral efficiency can be further enhanced by exploiting an adaptive modulation and coding (AMC) scheme[1]; the BS transmits data with an appropriate modulation and coding scheme (MCS) based on the channel state of the user. However, it is a challenging task to apply AMC to MCBC because the channel state may be significantly different among each user. A conventional approach to MCBC is to transmit data with the most conservative MCS such that even the user with the worst channel condition can successfully decode the data. Another conventional approach is to select a leader as the representative and to adjust MCS based on the channel feedback from the leader. It is obvious that the former cannot take advantage of AMC to improve spectral efficiency and that the latter cannot assure reliable data delivery.

In this paper, we consider a novel *best-effort broadcasting service* (BEBS) scheme. Contrary to the conventional reliable MCBC, the objective of the proposed BEBS is to maximize the capacity of a wireless channel at the cost of reliability. Our work is motivated by a simple intuition that channel efficiency can be improved by relaxing the reliability constraint, i.e., by intentionally allowing service outage for users with a poor channel condition (e.g., located at the cell edge). There exists a fundamental tradeoff between reliability and efficiency as follows. If an aggressive MCS is used for broadcasting, the amount of channel resource for supporting BEBS decreases due to the increase in the transmission rate, which improves channel efficiency. However, reliability will be degraded because the users with the poor channel condition may fail to receive the data due to the increase in the bit error rate (BER). In this context, we introduce the notion of *target reliability* and formulate the problem of BEBS as the problem of maximizing broadcasting capacity with the constraint of reliability. We derive an analytical model for BEBS to investigate the effect of target reliability on the achievable capacity. Furthermore, we show several key properties of BEBS: 1) Under a typical network configuration, BEBS always outperforms conventional reliable broadcasting in terms of broadcasting capacity, regardless of the value of target reliability; 2) the optimal value of target reliability and the maximum gain of BEBS are hardly affected by the number of users, i.e., they mostly depend on the spatial distribution of users; and 3) as the users are concentrated around the BS, it is feasible that the capacity of BEBS can be maximized even with the most aggressive MCS. Next, we propose two feedback control schemes to maximize

[1]The term of AMC is interchangeably used with *link adaptation* and *rate adaptation*, which are usually used in wireless local area networks (WLANs) based on the IEEE 802.11 standards.

the capacity of BEBS. The proposed algorithms adjust target reliability or MCS based on the estimate of broadcasting capacity without any priori information on user distribution. We perform extensive simulations and validate our analytical model by comparing with simulation results. Both analysis and simulation results confirm that the capacity of BEBS can be significantly improved by relaxing the constraint of target reliability; compared with conventional reliable broadcast, the proposed schemes for BEBS increase broadcasting capacity up to about 3.5 times under a reasonable network configuration.

In the literature, many wireless MCBC mechanisms in WLANs have been proposed, for example, [3]–[7]. They mostly focused on reliable data delivery with an effective feedback mechanism. Medium-access-control-layer broadcast protocols [3]–[5] exploit the IEEE 802.11 control frames [e.g., ready-to-send, clear-to-send, and acknowledgment (ACK)], aiming to enhance the reliability of MCBC. However, they may suffer from the hidden terminal problem or excessive retransmissions [8]. The leader-based protocol (LBP) [6] has been proposed to reduce the feedback overhead for MCBC in WLANs. This approach selects a leader among multicast receivers and allows only the leader to send an ACK frame; however, selecting the leader is a crucial problem affecting the performance of reliable MCBC. The enhanced LBP [7] adopts multiple ACK-leaders to support multimedia quality of service. Several rate adaptation mechanisms have been recently proposed to enhance the efficiency of MCBC in WLANs [9]–[12]. In [9], the auto-rate selection multicast scheme adopts the LBP so that the receiver with the lowest signal-to-noise ratio (SNR) becomes the multicast group leader, and it dynamically determines the transmission rate based on the feedback of the leader. Similarly, the approach in [10] proposes a probing-based auto-rate fall-back mechanism as a link adaptation scheme for MCBC. The mechanism proposed in [11] uses orthogonality of subcarriers in orthogonal frequency-division multiple access (OFDMA)-based wireless networks to adjust the transmission rate of MCBC. Another approach, which is called the *Threshold-T policy*, has been proposed to improve the efficiency of MCBC [12]. Before transmitting data, the sender queries the channel by individually exchanging control packets and starts transmission only when a sufficient number of members (e.g., at least T members) can successfully receive the data. The performance of the Threshold-T policy is analyzed in [13]; the optimal transmission rate is characterized, and the relationship between stability and efficiency is investigated.

The BEBS scheme proposed in this study is similar to the Threshold-T policy in that the efficiency of wireless MCBC can be improved by not intending to assure full reliable broadcasting. However, the application, system model, and protocol operation are quite different. The Threshold-T policy is applicable to multihop ad hoc networks or sensor networks where arbitrary nodes can transmit broadcasting data according to the contention-based channel access mechanism. On the other hand, BEBS is considered to be served in OFDMA-based single-hop cellular networks where only the BS is allowed to transmit broadcasting data using the dedicated channel resource. Therefore, there is little concern about delay, collision, interference, and stability. We have recently investigated the possibility of BEBS in [14]. In this paper, we significantly extend our preliminary work by analyzing the performance in depth and by proposing practical mechanisms for its realization.

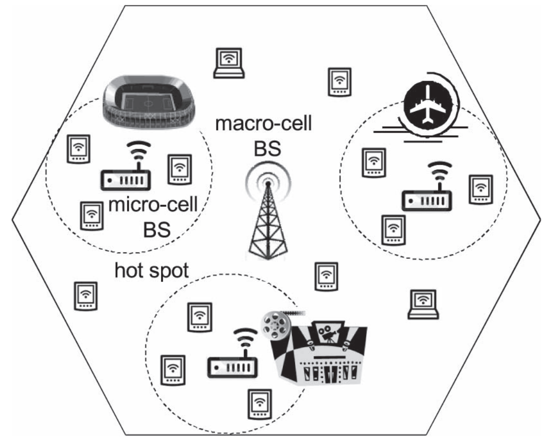

Fig. 1. Service model for BEBS in cellular networks.

The rest of this paper is organized as follows: In Section II, we describe the system model and the service scenario of BEBS and formulate the problem. In Sections III and IV, we present our analytical model and prove key properties of BEBS, respectively. The feedback control schemes to maximize the capacity of BEBS are proposed in Section V. Section VI presents simulation results to validate the proposed analytical model and to evaluate the performance of the proposed schemes. Finally, the conclusion follows in Section VII.

II. System Model and Problem Statement

A. *Service Scenario and System Model of BEBS*

We introduce the service model for BEBS, as shown in Fig. 1, where we consider that several microcells are deployed in hot spots within the coverage of a macrocell. BEBS is served in the microcells using a certain amount of wireless channel resource that is reserved for it. For example, BEBS can be used to transmit location-based advertising in shopping malls, movie trailers in multiplex theaters, real-time broadcasts in sports stadiums, and tour/flight information in tourist attractions/airports. We assume that the microcell BSs are used only for delivering BEBS, i.e., users in the hot spots receive broadcasting data from the microcell BS, but they transmit and receive unicast data to and from the macrocell BS. To avoid intercell interference from the macrocell to the microcells, the macrocell BS does not transmit any data frame during the time reserved for BEBS, which is similar to the concept of an almost blank subframe in heterogeneous networks discussed in 3GPP LTE-Advanced Release 10. We also consider that the macrocells are deployed with the frequency reuse factor of 1/3, to avoid interference from the neighbor macrocells to the microcells.The microcells are geographically separated from each other within the macrocell. Therefore, the resource of BEBS can be spatially reused, which improves spectral efficiency. It should be noted that BEBS can be also served by the macrocell BS without deploying microcells.

TABLE I
SET OF AVAILABLE MCSS AND CORRESPONDING CELL COVERAGES

Index (m)	Modulation (M_m-QAM)	Code rate (C_m)	Cell coverage (R_m)
1	4-QAM	1 / 12	190 m
2	4-QAM	1 / 8	169 m
3	4-QAM	1 / 4	139 m
4	4-QAM	1 / 2	114 m
5	4-QAM	3 / 4	86 m
6	16-QAM	1 / 2	70 m
7	16-QAM	3 / 4	57 m
8	64-QAM	2 / 3	44 m
9	64-QAM	3 / 4	40 m
10	64-QAM	5 / 6	35 m

We consider that a microcell BS transmits broadcasting data to N users in its cell and that the network employs OFDMA, which is the prevailing multiple-access scheme for up-to-date cellular networks. Table I lists the set of available MCSs considered in this paper. We define m ($1 \leq m \leq M$) as the index of MCS, where M is the largest index (e.g., $M = 10$). Note that the MCSs with $m = 1$ and $m = M$ correspond to the most conservative MCS and the most aggressive MCS, respectively. For each MCS m, information data bits are encoded at the coding rate of C_m, and the coded bits are interleaved and then mapped to signals with an M_m-ary (e.g., $M_m = 4$, 16, 64) quadrature amplitude modulation (QAM) scheme. We define the data rate of BEBS and the OFDMA frame duration as D (in bits per second) and T_f (in seconds), respectively; then, $B(= DT_f)$ bits are transmitted during a frame for BEBS. Note that the data rate of BEBS is determined by the contract between an advertiser and a network operator, and it is carefully engineered so that the system does not become unstable to support BEBS. Let us define ΔC_m (in bits per second) as the capacity of the OFDMA system that can be achieved by the unit channel resource, i.e., one OFDMA symbol and one subchannel, under the given MCS index m, i.e.,

$$\Delta C_m = \frac{N_{\text{sc}} C_m \log_2 M_m}{T_f}$$

where N_{sc} is the number of data subcarriers per subchannel. Then, the amount of OFDMA channel resource per frame required for supporting BEBS with MCS index m, which is denoted by M_m^{res}, becomes

$$M_m^{\text{res}} = \frac{D}{\Delta C_m}. \quad (1)$$

B. Problem Formulation

The objective of BEBS is to maximize effective broadcasting capacity, which is considered to be proportional to the number of users that successfully receive broadcasting data and inversely proportional to the amount of resources used to deliver the data. The MCS for BEBS is determined in an aggressive way by not intending to assure reliable data delivery to all the users, under the assumption that users far from the BS are probably less interested in the location-specific data delivered by BEBS. We define *target reliability*, which is denoted by η ($0 < \eta \leq 1$), such that the number of users that successfully receive broadcasting data should be at least ηN. We assume that the number of users is large enough to set target reliability to an arbitrary value. Note that the case of $\eta = 1$ is consistent with full reliable broadcasting and that $(1 - \eta)$ can be considered as the outage probability of BEBS. We define that a user receives broadcasting data successfully if the average error rate of B-bits burst is less than a certain threshold value of ε, up to which the error is recoverable by a proper error correction mechanism in the physical layer or application layer or is tolerable for real-time multimedia service, which is one of the major applications of BEBS. For this reason, we do not consider retransmissions in this study.

We define $\overline{N}^{\text{suc}}(\eta)$ and $\overline{M}^{\text{res}}(\eta)$ as the average number of successful users and the average amount of resources to support BEBS with a given target reliability, respectively, each of which accounts for reliability and efficiency. Hereafter, *broadcasting capacity* is defined as the number of successful users per resource required for BEBS, i.e., $\overline{N}^{\text{suc}}/\overline{M}^{\text{res}}$. From an economic viewpoint, the problem of maximizing broadcasting capacity under the given reliability constraint can be formulated as

$$\begin{aligned} \text{maximize} \quad & \frac{\overline{N}^{\text{suc}}(\eta)}{\overline{M}^{\text{res}}(\eta)} \\ \text{subject to} \quad & \overline{N}^{\text{suc}}(\eta) \geq \eta N \\ & 0 < \eta \leq 1. \end{aligned} \quad (2)$$

It is noteworthy that the numerator of the objective function in (2) is related to the profit that can be made by BEBS, whereas the denominator is related to the cost that should be paid for BEBS. From (2), it can be expected that decreasing η decreases $\overline{N}^{\text{suc}}(\eta)$ and $\overline{M}^{\text{res}}(\eta)$, i.e., there is a tradeoff between reliability and efficiency in setting η, and that there may exist an optimal value of η that maximizes broadcasting capacity.

III. ANALYTICAL MODEL

Here, we derive an analytical model to investigate how broadcasting capacity is affected by target reliability η. First, we derive the cell coverage for each MCS based on the wireless channel model. Then, we calculate $\overline{N}^{\text{suc}}$ and $\overline{M}^{\text{res}}$ using the cell coverage and user distribution. Note that the proposed analysis framework is flexible to account for various channel models since the derivation of broadcasting capacity is decoupled from a specific channel model.

A. Derivation of Average Cell Coverage

We define cell coverage R_m for MCS m as

$$R_m = \max \{ r | \overline{p}_m^e(r) < \varepsilon \} \quad (3)$$

where r is the distance between the BS and a user, $\overline{p}_m^e$ is the average error rate of BEBS with MCS m, and ε is the tolerable error rate. The underlying assumption behind (3) is that $\overline{p}_m^e$ mostly depends on large-scale path-loss attenuation, and thus, it monotonically increases with respect to the value of r.

Now, we derive $\overline{p}^e_m$ as a function of r. As described in the IEEE 802.16m performance evaluation methodology [15], we consider the log-distance path loss based on the COST 231 HATA model for urban environment. Then, the path loss at distance r, i.e., $PL(r)$, is represented as

$$PL(r)[\text{dB}] = 35.2 + 35\log_{10}(r) + 26\log_{10}(f/2.0) + S_\sigma \quad (4)$$

where f is the carrier frequency, which is set to 2.5 GHz in this study, and S_σ is a normal random variable with zero mean and standard deviation σ to model the effect of shadowing. Let us denote the transmission power of the BS and the background noise power in dBm as P_{tx} and P_{noise}, respectively. Then, the average value of the SNR, i.e., $\overline{\gamma}$, can be expressed with the average path loss, i.e., $\overline{PL}(r)$, as

$$\overline{\gamma}\,[\text{dB}] = P_{\text{tx}} - \overline{PL}(r) - P_{\text{noise}}. \quad (5)$$

In addition, we consider the Rayleigh fading model to account for small-scale fading caused by nonline-of-sight signals with different delays. The probability density function of the instantaneous SNR over the Rayleigh fading channel is given as

$$p(\gamma) = \frac{1}{\overline{\gamma}} \exp\left(-\frac{\gamma}{\overline{\gamma}}\right), \qquad (\gamma \geq 0). \quad (6)$$

For each MCS and its corresponding modulation scheme, we can represent the BER, i.e., $b_m(\gamma)$, over the additive white Gaussian noise channel [16]. In the case of M_m-ary QAM with Gray-coded assignment, b_m becomes

$$b_m(\gamma) = \frac{1}{\log_2 M_m}\left[1 - \left[1 - \left\{2\left(1 - \frac{1}{\sqrt{M_m}}\right) \cdot Q\left(\sqrt{\frac{3}{M_m - 1}\gamma}\right)\right\}\right]^2\right] \quad (7)$$

where $Q(x)$ is the complementary Gaussian error function, i.e., $Q(x) = 1/\sqrt{2\pi}\int_x^\infty e^{-t^2/2}dt$. We assume that the channel status does not significantly change during one frame and that the hard-decision Viterbi decoding algorithm is used at the receiver. Then, we can get the error probability for a B-bits burst with MCS m, which is denoted by $p^e_m(\gamma)$ from (7). The details can be found in [17]. Finally, the average error probability can be calculated as

$$\overline{p}^e_m = \int_0^\infty p^e_m(\gamma)p(\gamma)d\gamma \quad (8)$$

Fig. 2 shows $\overline{p}^e_m$ versus r when $D = 1$ Mb/s and $T_f = 5$ ms. This figure shows that $\overline{p}^e_m$ is an increasing function of r and can be used to determine the cell coverage (R_m) once ε is given. Table I lists R_m obtained in this way with $P_{\text{tx}} = 20$ dBm (100 mW) and $\varepsilon = 0.05$.

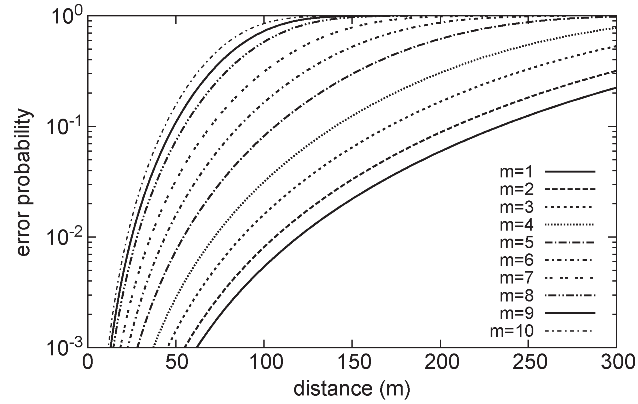

Fig. 2. Average error probability of B-bits burst ($\overline{p}^e_m$) versus distance between the BS and the MS (r).

B. Calculation of $\overline{N}^{\text{suc}}$ and $\overline{M}^{\text{res}}$

Let us define P_m as the probability that a user is located with the distance of r from the BS such that

$$P_m = \begin{cases} \text{Prob}[R_{m+1} < r \leq R_m], & \text{if } m = 1, 2, \ldots, M-1 \\ \text{Prob}[r \leq R_m], & \text{if } m = M \end{cases} \quad (9)$$

which can be determined from the spatial distribution of users and the average cell coverage obtained in the previous section. Note that $R_{m+1} < R_m$, i.e., R_m decreases if a more aggressive MCS is used. We also define P^{in}_m and P^{out}_m as the probabilities that a user is located such that $r \leq R_{m+1}$ and $r > R_m$, respectively, i.e.,

$$P^{\text{in}}_m = \sum_{i=m+1}^{M} P_i, \qquad m = 1, 2, \ldots, M-1$$
$$P^{\text{out}}_m = \sum_{i=1}^{m-1} P_i, \qquad m = 2, 3, \ldots, M. \quad (10)$$

We assume that when MCS m is used, a user receives broadcasting data successfully as long as $r \leq R_m$; otherwise, if $r > R_m$, it fails to receive the data.[2] Thus, P^{out}_m represents the probability that a user fails to receive the data with a given MCS m. Let us denote $N_f(\eta)$ as the maximum allowable number of users that fail to receive broadcasting data, i.e., $N_f(\eta) = \lfloor N \cdot (1-\eta) \rfloor$, where $\lfloor x \rfloor$ is the largest integer that does not exceed x.

We consider the following three cases depending on the locations of users.

- Case 1: k ($N_f < k \leq N$) users are located such that $R_2 < r \leq R_1$, whereas the remaining $N - k$ users are located such that $r \leq R_2$.
- Case 2: k ($0 \leq k \leq N_f$) users are located such that $r > R_M$, whereas $N - k$ users are located such that $r \leq R_M$.
- Case 3: Among N users, 1) k ($0 < k \leq N_f$) users are located such that $r > R_m$, 2) j ($N_f - k \leq j \leq N - k$) users are located such that $R_{m+1} < r \leq R_m$, and 3) the

[2]This assumption is valid in the sense of average, and it is made for the tractability of analysis. However, it is dropped in the simulations by using a practical error model that considers the effects of fading and shadowing.

remaining $N-k-j$ users are located such that $r \leq R_{m+1}$.

The BS determines MCS such that the number of unsuccessful users does not exceed $N_f f(\eta)$; thus, the MCS index for these three cases should be 1, M, and m $(1 < m < M)$, respectively. Accordingly, the probability that the BS selects MCS m, i.e., $P_m^{\text{sel}}(\eta)$, can be obtained as

$$P_m^{\text{sel}}(\eta) = \begin{cases} \sum_{k=N_f(\eta)+1}^{N} \binom{N}{k} (P_m^{\text{in}})^{N-k} (P_m)^k, & \text{for } m=1 \\ \sum_{k=0}^{N_f(\eta)} P_m^{\text{ig}}(k), & \text{for } 2 \leq m \leq M. \end{cases} \quad (11)$$

Here, $P_m^{\text{ig}}(k)$ denotes the probability that the BS selects MCS m under the condition that the number of unsuccessful users is k $(0 \leq k \leq N_f(\eta))$, which can be represented as

$$P_m^{\text{ig}}(k) = \begin{cases} \binom{N}{k} (P_m^{\text{out}})^k \left[\sum_{j=N_f(\eta)+1-k}^{N-k} \binom{N-k}{j} (P_m)^j \cdot (P_m^{\text{in}})^{N-k-j} \right], & \text{for } 2 \leq m \leq M-1 \\ \binom{N}{k} (P_m)^{N-k} (P_m^{\text{out}})^k, & \text{for } m=M. \end{cases} \quad (12)$$

From (9)–(12), $\overline{N}^{\text{suc}}(\eta)$ and $\overline{M}^{\text{res}}(\eta)$ can be calculated as

$$\overline{N}^{\text{suc}}(\eta) = NP_1^{\text{sel}}(\eta) + \sum_{m=2}^{M} \sum_{k=0}^{N_f(\eta)} (N-k) P_m^{\text{ig}}(k) \quad (13)$$

$$\overline{M}^{\text{res}}(\eta) = \sum_{m=1}^{M} M_m^{\text{res}} P_m^{\text{sel}}(\eta). \quad (14)$$

Finally, the broadcasting capacity in (2) can be evaluated from (13) and (14). We will validate this analytical model and further investigate the effect of η via simulations in Section IV-A.

IV. Properties of the Best-Effort Broadcasting Service

Here, we show several key properties of BEBS by deriving a simple approximate model under various user distributions. Although the analytical model in Section III can be used to obtain the values of $\overline{N}^{\text{suc}}(\eta)$ and $\overline{M}^{\text{res}}(\eta)$ numerically, it is neither suitable to give an insight regarding the performance of BEBS nor applicable to get the optimal value of η and the maximum achievable capacity of BEBS. Therefore, we introduce a new performance index and a simple yet effective analytical model.

A. Performance Index and Spatial Distribution of Users

We define a *relative gain of BEBS* as the performance measure as

$$G(\eta) = \frac{\overline{N}^{\text{suc}}(\eta)/\overline{M}^{\text{res}}(\eta)}{N^{\text{suc}}(1)/M^{\text{res}}(1)} \quad (15)$$

i.e., the value of broadcasting capacity with the given η divided by that with η of 1 (full reliable broadcasting). Note that $G(\eta)$ in (15) can be rewritten as

$$G(\eta) = \left(\frac{\overline{N}^{\text{suc}}(\eta)}{N}\right) \left(\frac{M^{\text{res}}(1)}{\overline{M}^{\text{res}}(\eta)}\right) \quad (16)$$

since $N^{\text{suc}}(1) = N$. For $\eta < 1$, the first term on the right side of (16) is less than 1, and it evaluates the loss from which BEBS suffers due to the decrease in reliability, whereas the second term becomes larger than 1, and it accounts for the achievable gain by BEBS due to the increased efficiency of channel resource.

Next, we consider the following three representative distributions of users:

- uniform distribution;
- stationary distribution of random waypoint model (RWPM)[3];
- exponential distribution.

Note that the RWPM [18] is widely used as a mobility model in wireless networks. According to the RWPM distribution, the users are more concentrated around the BS, compared with the uniform distribution. By considering that the microcell BS for BEBS is usually installed in a hot spot with crowded users, the RWPM distribution is more reasonable than the uniform distribution. In addition, the exponential distribution is considered to investigate the performance of BEBS in an extreme case where most users are located close to the BS.

We define $F_{R,1}(r)$, $F_{R,2}(r)$, and $F_{R,3}(r)$ as the cumulative distribution functions (cdfs) for these three distributions, i.e.,

$$\begin{aligned} F_{R,1}(r) &= \left(\frac{r}{R_{\max}}\right)^2, && \text{for uniform} \\ F_{R,2}(r) &= 2\left(\frac{r}{R_{\max}}\right)^2 - \left(\frac{r}{R_{\max}}\right)^4, && \text{for RWPM} \\ F_{R,3}(r) &= 1 - e^{-\lambda\left(\frac{r}{R_{\max}}\right)}, && \text{for exponential} \end{aligned} \quad (17)$$

where $R_{\max}$ is the maximum cell radius with the most conservative MCS, i.e., $R_{\max} = R_1$. Since r for the exponential distribution is not bounded, λ is determined such that $F_{R,3}(R_{\max}) = 1 - \delta_R$ (we set $\delta_R = 0.01$), i.e., $\lambda = -\log(\delta_R)$. Fig. 3 shows cdfs with respect to the normalized distance $(r/R_{\max})$ for the three distributions of users, along with their mean and median values.

B. Approximate Model

We now derive $G(\eta)$ as a function of η in a closed form. For this purpose, we make the following assumptions.

A1) The number of users is large, and the distance between a user and the BS follows the independent and identically distributed random variable whose cdf is given as (17).

[3]In this paper, we do not directly consider the mobility of users, but we consider the stationary distribution when users move according to the RWPM.

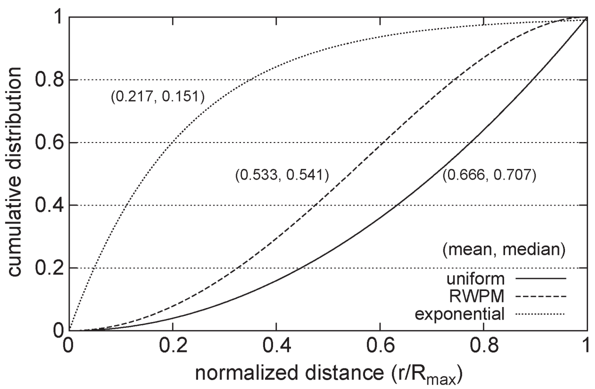

Fig. 3. Cumulative distribution and statistics of the normalized distance between the BS and the MS.

A2) It is feasible to satisfy the reliability requirement by adjusting MCS based on the channel feedback (e.g., SNR) or acknowledgment.

A3) The number of MCSs is sufficiently large so that the change in M_m^{res} becomes continuous and infinitesimal.

These assumptions are reasonable under the following rationale. We consider that BEBS is usually served in the place and time where and when users are crowded. The effect of the number of users will be investigated through simulations in Section VI. In cellular networks, the mobile station (MS) usually reports channel quality, or the BS may estimate it indirectly. The number of MCSs is expected to increase due to new emerging modulation and coding technologies, and M_m^{res} gradually changes as the number of MCSs increases.

Let us define r_B as the distance within which at least ηN users can successfully receive broadcasting data. With the assumptions made, we can relate r_B with η as

$$F_R(r_B) = \eta, \text{ for} R_{\min}(= R_M) \leq r_B \leq R_{\max}(= R_1) \quad (18)$$

and we can represent and approximate $\overline{N}^{\mathrm{suc}}(\eta)$ as

$$\overline{N}^{\mathrm{suc}}(\eta) = (1 + \delta_N(\eta))\, \eta N \approx \eta N \quad (19)$$

for $\eta_{\min} \leq \eta \leq 1$, where $\eta_{\min} = F_R(R_{\min})$. Next, we represent $\overline{M}^{\mathrm{res}}$ in terms of r_B. Note that $\overline{M}^{\mathrm{res}}(r_B)$ is a monotonically increasing function with respect to r_B with the assumption of (A3). It is possible to accurately model $\overline{M}^{\mathrm{res}}(r_B)$ by using elaborate and complex curve-fitting methods (e.g., in the form of high-order polynomial, exponential, power, or Gaussian formula). However, they are neither easy to mathematically handle nor effective to understand the relationship between parameters. For the tractability of analysis, we approximate $\overline{M}^{\mathrm{res}}$ as an exponential function with two parameters, i.e.,

$$\overline{M}^{\mathrm{res}}(r_B) \approx \alpha e^{\beta r_B}. \quad (20)$$

The values of α and β in (20) can be determined from two extreme points of r_B, i.e., $\overline{M}^{\mathrm{res}}(R_{\min}) = M_M^{\mathrm{res}}$ and $\overline{M}^{\mathrm{res}}(R_{\max}) = M_1^{\mathrm{res}}$, and thus

$$\alpha = e^{-\frac{\Delta R}{\Delta R - 1}\log \Delta M^{\mathrm{res}}} M_1^{\mathrm{res}}$$
$$\beta = \frac{1}{R_{\max} - R_{\min}} \log \Delta M^{\mathrm{res}} \quad (21)$$

where $\Delta R = R_{\max}/R_{\min}$, and $\Delta M^{\mathrm{res}} = M_1^{\mathrm{res}}/M_M^{\mathrm{res}}$. From extensive numerical validation, we verified that the approximation of $\overline{M}^{\mathrm{res}}$ in (20) and (21) has a comparable mean square error (MSE), compared with various complex curve-fitting methods that minimize the MSE. Finally, we approximate $G(\eta)$ as a function of η from (15) and (18)–(21) as

$$G(\eta) = \eta e^{\beta(R_{\max} - g(\eta))} \quad (22)$$

where $g(\eta) = F_R^{-1}(\eta) = r_B$. It is important to note that 1) $g(\eta)$ always exists regardless of user distribution because $F_R(\cdot)$ is the cdf of a random variable and that 2) $G(\eta)$ given in (22) is differentiable with respect to η.

C. Proof of Several BEBS Properties

Here, we prove several key properties of BEBS using the approximate analytical model. Let us denote η^* and G^* as the optimal value of η and the maximum value of $G(\eta)$, respectively.

Proposition 1.1: In the case of uniform distribution, there exists a unique $\eta^*(\eta_{\min} < \eta^* < 1)$, if $2 < \log \Delta M^{\mathrm{res}} < 2(\Delta R - 1)$, i.e.,

$$\eta^* = \left(\frac{2}{\beta R_{\max}}\right)^2 \quad (23)$$

and the corresponding maximum gain is

$$G^* = \left(\frac{2}{\beta R_{\max}}\right)^2 e^{\beta R_{\max} - 2}. \quad (24)$$

Proof: Due to space limitations, we present the outline of proof. From (17)–(22), it can be shown that the derivative of $G(\eta)$ is a strictly decreasing function of η in its feasible region and that there exists a unique η^* that makes the derivative zero, i.e., maximizes $G(\eta)$. Moreover, such a η^* exists in its feasible region with the given conditions on ΔM^{res} and ΔR, and G^* can be straightforwardly derived from (22). The details can be found in [17]. ■

Proposition 1.2: In the case of RWPM distribution, there exists a unique η^* in its feasible region if $1 < \log \Delta M^{\mathrm{res}} < \Delta R - 1$.

Proof: The proof is similar to the case of uniform distribution, which can be found in [17]. ■

Proposition 1.3: In the case of exponential distribution, there exists a unique η^* in its feasible region if

$$\eta^* = \frac{1}{1+\rho} > 1 - e^{-\frac{\lambda}{\Delta R}} \quad (25)$$

where $\rho = \beta R_{\max}/\lambda$, and the maximum gain is

$$G^* = \frac{1}{1+\rho}\left(\frac{\rho}{1+\rho}\right)^{\rho} e^{\beta R_{\max}}. \quad (26)$$

Proof: The proof is omitted due to space limitations. (See [17] for further details.) ■

Corollary 1: The values of η^* and G^* are independent of the number of users but mostly depend on the distribution of users.

TABLE II
OPTIMAL VALUE OF TARGET RELIABILITY (η^*) AND THE MAXIMUM ACHIEVABLE RELATIVE GAIN (G^*) OBTAINED FROM ANALYSIS AND SIMULATION

method	uniform		RWPM		exponential	
	η^*	G^*	η^*	G^*	η^*	G^*
anal	0.26	2.13	0.42	3.54	0.56	17.45
apprx	0.23	2.01	0.34	3.61	0.57	17.16
sim	0.28	2.21	0.39	3.57	0.57	17.16

Proof: As shown in (22), $G(\eta)$ does not depend on the number of users. Therefore, η^* and G^* are not affected by the number of users. ■

Before proceeding to the next proposition, we present and compare the analysis and simulation results regarding η^* and G^*. We use the configuration of R_m and M_m^{res} given in Table I and (1), i.e., $R_{\min} = 35$ m, $R_{\max} = 190$ m, $M_1^{\text{res}} = 630$, and $M_M^{\text{res}} = 21$, where $D = 1$ Mb/s, $T_f = 5$ ms, and $N_{\text{sc}} = 48$, and set $N = 100$. The details about the simulation configuration are given in Section VI. Table II lists η^* and G^* obtained by the following three methods:

i) `anal`: exhaustive search using the analytical model in Section III;

ii) `apprx`: direct calculation based on the approximate model in this section;

iii) `sim`: exhaustive search from the simulation results.

From the results in Table II, we can make the following observations.

- There is no significant difference between the values of η^* and G^* obtained by different methods, which confirms that the approximate model is effective to estimate η^* and G^*.
- As the users are more concentrated around the BS, both η^* and G^* increase.
- In the case of exponential distribution, $\eta^*(= 0.52)$ derived from the approximate model becomes smaller than $\eta_{\min}(= 0.57)$, i.e., the condition in (25) is not satisfied. Therefore, $G(\eta)$ is maximized with $\eta_{\min}$, i.e., even the most aggressive MCS maximizes the gain of BEBS.[4]

Proposition 2: As the users are more concentrated around the BS, the relative gain is magnified, regardless of the value of η.

Proof: From (22), we can see that $G(\eta)$ is proportional to η and inversely proportional to $g(\eta)$ $(= F_R^{-1}(\eta) = r_B)$. Note that the parameters of β and $R_{\max}$ in (22) are determined by R_m and M_m^{res}, irrespective of the user distribution. As the users are concentrated around the BS, for any given η_o, the value of $g(\eta_o)$ decreases, resulting in the increase in $G(\eta)$, which agrees with the intuition.

Specifically, consider the three user distributions given in (17) and Fig. 3. For most range of $\eta(< 0.99)$, $g_1(\eta) > g_2(\eta) > g_3(\eta)$ since $F_{R,1}(r_B) < F_{R,2}(r_B) < F_{R,3}(r_B)$. Consequently, it is obvious from (22) that

$$G_1(\eta) < G_2(\eta) < G_3(\eta) \tag{27}$$

where G_1, G_2, and G_3 are the relative gains of BEBS for the uniform, RWPM, and exponential distributions, respectively. ■

[4]In the case of exponential distribution, the values for `apprx` in Table II are obtained with $\eta^* = \eta_{\min}$.

Proposition 3: Consider that there exists a feasible η^* and the following condition is satisfied:

$$\Delta M^{\text{res}} > (\Delta R)^2. \tag{28}$$

Compared with conventional reliable broadcasting, BEBS improves broadcasting capacity by relaxing target reliability regardless of the value of target reliability, i.e.,

$$G(\eta) > 1, \qquad \text{for } \eta_{\min} \le \eta < 1. \tag{29}$$

Proof: Since $G_1(\eta) < G_2(\eta) < G_3(\eta)$ as shown in (27), we only need to show that $G_1(\eta) > 1$. As already shown in Proposition 1.1, $G_1(\eta)$ is a unimodal and concave function with respect to $\eta(\eta_{\min} \le \eta \le 1)$. Thus, $G_1(\eta)$ has the minimum value when η is either $\eta_{\min}$ or 1. It is trivial that $G_1(1) = 1$ by the definition in (15), and $G_1(\eta_{\min})$ becomes

$$G_1(\eta_{\min}) = \left(\frac{R_{\min}}{R_{\max}}\right)^2 e^{\beta(R_{\max}-R_{\min})} = \frac{\Delta M^{\text{res}}}{(\Delta R)^2} > 1 \tag{30}$$

if $\Delta M^{\text{res}} > (\Delta R)^2$. Consequently, $G(\eta) > 1$ for $\eta_{\min} \le \eta < 1$. ■

Corollary 2: Even BEBS with the most aggressive MCS outperforms conventional reliable broadcasting in terms of broadcasting capacity, if $\Delta M^{\text{res}} > (\Delta R)^2$.

Proof: It is trivial from (30). ■

V. CONTROL MECHANISM FOR THE BEST-EFFORT BROADCASTING SERVICE

Here, we propose control mechanisms to realize the gain of BEBS. First, we consider a simple baseline mechanism that determines MCS to satisfy the given target reliability. Then, we elaborate this mechanism and propose two dynamic feedback control schemes to maximize the benefit of BEBS.

A. Baseline Scheme

The baseline scheme controls MCS to meet the requirement of target reliability. We assume that the MS periodically reports its SNR to the BS via a dedicated control channel. Then, the BS keeps track of the SNR and maintains its average value ($\overline{\gamma}$). Similar to the AMC for unicast, the BS maintains a table containing the minimum threshold value of the SNR for each MCS to assure that the average error rate can be maintained below the given target value of ε. The BS makes the list of users that are sorted in the decreasing order of $\overline{\gamma}$ and selects a representative that corresponds to the η-percentile of user in terms of SNR. Then, the BS selects the largest MCS such that the SNR of the representative becomes larger than the minimum threshold value for the selected MCS. To cope with the estimation error and/or the rapid change in SNR, the BS may determine the MCS for BEBS in a conservative manner by setting a safety margin for the SNR. This way, the average packet error rate for at least ηN users becomes lower than ε, implying that target reliability can be assured while attaining the maximum allowable channel efficiency. From the viewpoint of maximizing broadcasting capacity, the key point is how to set the value of η. As already shown in Table II, η^* highly depends on the user distribution. Therefore, to make this scheme practical and effective, the precondition is empirical estimation of the user distribution, which is costly and erroneous.

B. Two Feedback Schemes

We propose two feedback schemes to remove the drawback of the baseline scheme. Without estimating user distribution, the first scheme dynamically controls the value of η, and the second scheme directly controls MCS instead of controlling η.

1) Adaptive Control of Target Reliability: The first scheme periodically updates the value of η so that $G(\eta)$ can be maximized. The BS estimates $\overline{N}^{\mathrm{suc}}(\eta)$ and $\overline{M}^{\mathrm{res}}(\eta)$ for every monitoring interval of T_s based on the feedback of channel status (e.g., SNR); a user is assumed to successfully receive broadcasting data if its SNR is larger than the threshold value.[5] Let us define $\eta[k]$ as the value of η used during time interval $t = [(k-1)T_s, kT_s]$ and define $\widetilde{G}(\eta[k])$ as the estimate of relative gain during the same time interval, which can be calculated from $\overline{N}^{\mathrm{suc}}(\eta)$ and $\overline{M}^{\mathrm{res}}(\eta)$ as in (16). Based on the values of $\widetilde{G}(\eta[k])$ and $\widetilde{G}(\eta[k-1])$, the BS updates the value of η at $t = kT_s$ as

$$\eta[k+1] = \eta[k] + \left(K_p \frac{\widetilde{G}(\eta[k]) - \widetilde{G}(\eta[k-1])}{\eta[k] - \eta[k-1]}\right)_{-}^{+} \quad (31)$$

where K_p is a constant control parameter. Note that the large value of K_p contributes to enhance responsiveness at the cost of control stability. In (31), $(x)_{-}^{+} = \max(\min(x, \Delta+), \Delta-)$, which limits the change of η to the upper and lower bounds ($\Delta+$ and $\Delta-$) for improving stability. The update rule of η in (31) is similar to the gradient descent algorithm, which is a well-known optimization algorithm to find a maximum (or minimum) of a function. As shown in (31), η increases or decreases depending on the value of $\Delta\eta[k]$ $(= \eta[k] - \eta[k-1])$ and $\Delta\widetilde{G}(\eta[k])$ $(= \widetilde{G}(\eta[k]) - \widetilde{G}(\eta[k-1]))$. For example, if the relative gain is increased due to the decrease in η, then η continues to be decreased (i.e., $\Delta\widetilde{G}(\eta[k]) > 0$, and $\Delta\eta[k] < 0 \rightarrow \eta[k+1] < \eta[k]$); otherwise, if the decrease in η rather decreases the gain, then η will be increased (i.e., $\Delta\widetilde{G}(\eta[k]) < 0$ and $\Delta\eta[k] < 0 \rightarrow \eta[k+1] > \eta[k]$). The underlying design rationale of this scheme is that there exists a unique η^* that maximizes concave function $G(\eta)$, which is already confirmed in Section IV-C.

We further elaborate the update rule of η. To relieve the effect of the estimation error of $\widetilde{G}$ and its temporary abnormal change, the estimate of $\widetilde{G}(\eta[k])$ is averaged in the form of exponentially weighted moving average as

$$\overline{G}(\eta[k]) = w\widetilde{G}(\eta[k]) + (1-w)\overline{G}(\eta[k-1]) \quad (32)$$

where $w (0 < w < 1)$ is a weight factor. When updating η in (31), we replace the values of $\widetilde{G}(\eta[k])$ and $\widetilde{G}(\eta[k-1])$ with those of $\overline{G}(\eta[k])$ and $\overline{G}(\eta[k])$, respectively.

[5]The BS may accurately estimate $\overline{N}^{\mathrm{suc}}(\eta)$ with a reliable acknowledgment mechanism instead of channel status feedback. However, it is a challenging problem to design an acknowledgment mechanism for broadcasting service, which is out of the scope of this study.

2) Direct Control of MCS: Compared with the first proposed scheme, this scheme also makes use of the estimate of relative gain, but it directly controls MCS, instead of controlling η. Let us denote $m[k]$ as the index of MCS for broadcasting during the time interval between $(k-1)Ts$ and kTs. Similar to the update rule of η in the first scheme, the BS controls the MCS index at $t = kT_s$ as

$$m[k+1] = \begin{cases} \min(m[k]+1, M), & \text{if } \mathrm{sgn}(\Delta m[k])\Delta\overline{G}(\eta[k]) > G_{\mathrm{th}} \\ \max(m[k]-1, 1), & \text{if } \mathrm{sgn}(\Delta m[k])\Delta\overline{G}(\eta[k]) < -G_{\mathrm{th}} \\ m[k], & \text{if } |\Delta\overline{G}(\eta[k])| \le G_{\mathrm{th}} \end{cases} \quad (33)$$

where $\Delta m[k] = m[k] - m[k-1]$, $\mathrm{sgn}(x) = 1$ or -1 if $x \ge 0$ or $x < 0$, respectively, and G_{th} is a threshold value. According to (33), if the aggressive (conservative) MCS contributes to increase the relative gain, a more aggressive (conservative) MCS will be used in the next control interval. To avoid the unnecessary fluctuation in MCS, it is not changed as long as the difference between the relative gains estimated for two consecutive monitoring intervals is less than the threshold of G_{th}. To prevent $\overline{G}(\eta)$ from being remained at the nonmaximal value, we propose to reinitialize the update procedure of the MCS index occasionally.

VI. Model Validation and Performance Evaluation

Here, we validate our analytical model of BEBS derived in Section III and its several properties asserted in Section IV by comparing with simulation results. We also carry out simulations to compare the performance of several approaches aiming to enhance broadcasting capacity. By considering the channel model and the configuration of the microcell in the IEEE 802.16m performance evaluation methodology [15], we set several parameters as follows: $P_{\mathrm{tx}} = 20$ dBm, $P_{\mathrm{noise}} = -104$ dBm, $\sigma = 1.1$ dB, $N_{\mathrm{sc}} = 48$, $T_f = 5$ ms, and the channel bandwidth is set to 10 MHz. The wireless channel is modeled considering path loss, Rayleigh fading, and shadowing. The burst error rate is obtained by means of exponential effective SNR mapping [15]. Unless otherwise stated, N and ε are set to 100 and 0.05, respectively. The simulation time is set to 100 s (20 000 frames), and the simulation results are averaged over ten simulation runs where users are randomly placed according to the spatial distribution model, as described in Section IV-A.

A. Model Validation

We establish the following three performance indexes:

- Reliability: $\overline{R}^{\mathrm{suc}}(\eta) = \overline{N}^{\mathrm{suc}}(\eta)/N$, i.e., the ratio of users that successfully received broadcasting data among all the users;
- Efficiency: $\overline{C}^{\mathrm{eff}}(\eta) = B/\overline{M}^{\mathrm{res}}(\eta)$, i.e., the average number of bits that can be served in a frame with a unit

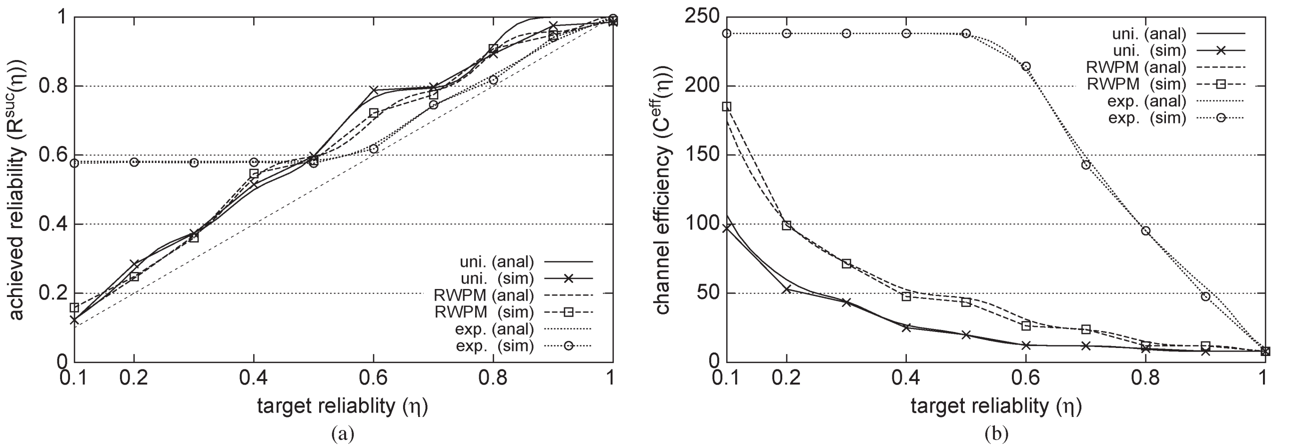

Fig. 4. Effect of target reliability (η) on the (a) achieved reliability ($\overline{R}^{\mathrm{suc}}$) and (b) channel efficiency ($\overline{C}^{\mathrm{eff}}$).

OFDMA resource consisting of one symbol and one subchannel;

- Capacity: $G(\eta)$, i.e., the relative gain of BEBS. It is measured according to (15).

We compare these performance indexes obtained from the analytical model with those measured from the simulation where the baseline scheme is adopted to control MCS.

As shown in Fig. 4(a), $\overline{R}^{\mathrm{suc}}(\eta)$ monotonically increases with respect to $\eta(> \eta_{\min})$, and it is always larger than η (denoted as the dotted straight line) for the entire range of η regardless of the user distribution, which confirms that BEBS satisfies the reliability constraint. There are no remarkable differences 1) between analysis and simulation and 2) between the case of uniform distribution and the case of RWPM distribution. However, in the case of exponential distribution, we observe that $\overline{R}^{\mathrm{suc}}(\eta)$ is unchanged from $\eta_{\min}$ $(= 0.57)$, as long as $\eta \leq \eta_{\min}$. On the other hand, $\overline{C}^{\mathrm{eff}}(\eta)$ is shown in Fig. 4(b). As was expected, $\overline{C}^{\mathrm{eff}}(\eta)$ decreases as $\eta(> \eta_{\min})$ increases, which implies that efficiency is degraded to achieve the required reliability. In the case of exponential distribution, $\overline{C}^{\mathrm{eff}}(\eta)$ remains constant if $\eta < \eta_{\min}$ because the most aggressive MCS is used in this case. Unlike $\overline{R}^{\mathrm{suc}}(\eta)$, the value of $\overline{C}^{\mathrm{eff}}(\eta)$ in the case of RWPM distribution is notably higher than that in the case of uniform distribution, since more aggressive MCSs are used in the case of RWPM distribution to satisfy the reliability constraint. If $\eta > 0.6$, $\overline{C}^{\mathrm{eff}}(\eta)$ slightly changes in the case of uniform distribution; however, it remarkably decreases in the case of exponential distribution. In addition, the analysis results agree well with the simulation results, regardless of user distribution.

Next, we investigate the relative gain of BEBS, i.e., $G(\eta)$. Fig. 5 shows three different values of $G(\eta)$ for a given user distribution, which are obtained from 1) the analytical model in Section III (`anal`), 2) the approximate model in Section IV-B (`apprx`), and 3) simulation with the baseline scheme (`sim`). In Fig. 5, we observe that the values of $G(\eta)$ obtained from `anal` are tightly close to those obtained from `sim`, which reconfirms the validity of the analytical model. Although there exists a nonnegligible difference between $G(\eta)$ of `apprx` and that of `sim`, the approximate model is still effective to derive η^* and G^*. Recall that the values of η^* and G^* are listed in Table II.

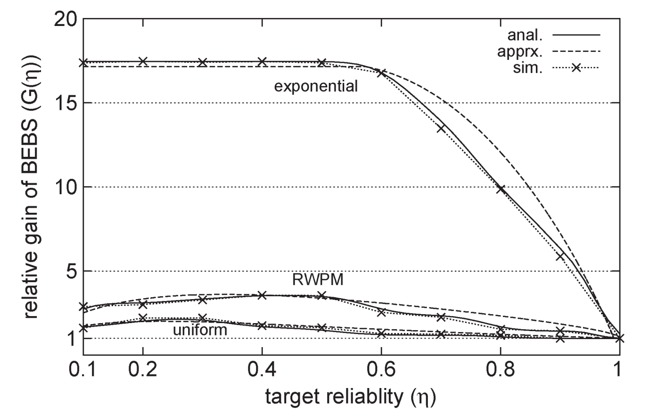

Fig. 5. Relative capacity gain of BEBS, compared with full reliable broadcasting.

TABLE III
COMPARISON OF MCS DISTRIBUTION FOR SEVERAL BEBS SCHEMES

algorithm	MCS3	MCS4	MCS5
OPT-R	-	0.81	0.19
ADAPT-R	0.03	0.75	0.22
ADAPT-MCS	0.17	0.64	0.09

The results in Fig. 5 validate the properties proved with the approximate model in Section IV-C.

- In the cases of uniform and RWPM distributions, there exists a unique η^* $(> \eta_{\min})$, and $G(\eta)$ is concave. On the other hand, in the case of exponential distribution, $\eta^* < \eta_{\min}$, and thus, the maximum gain is achieved with the most aggressive MCS, and $G(\eta)$ monotonically decreases as η $(> \eta_{\min})$ increases.
- $G_1(\eta)$ (uniform) $< G_2(\eta)$ (RWPM) $< G_3(\eta)$ (exponential), in almost all the range of η.
- $G(\eta) > 1$, regardless of the value of η and user distribution.

B. Performance Comparison

Now, we compare the performance of the following BEBS schemes.

- FIX $-$ R: This is the baseline scheme with the fixed value of $\eta = 0.8$, which is almost twice larger than η^* in the case of RWPM. This is considered to be a conservative scheme.

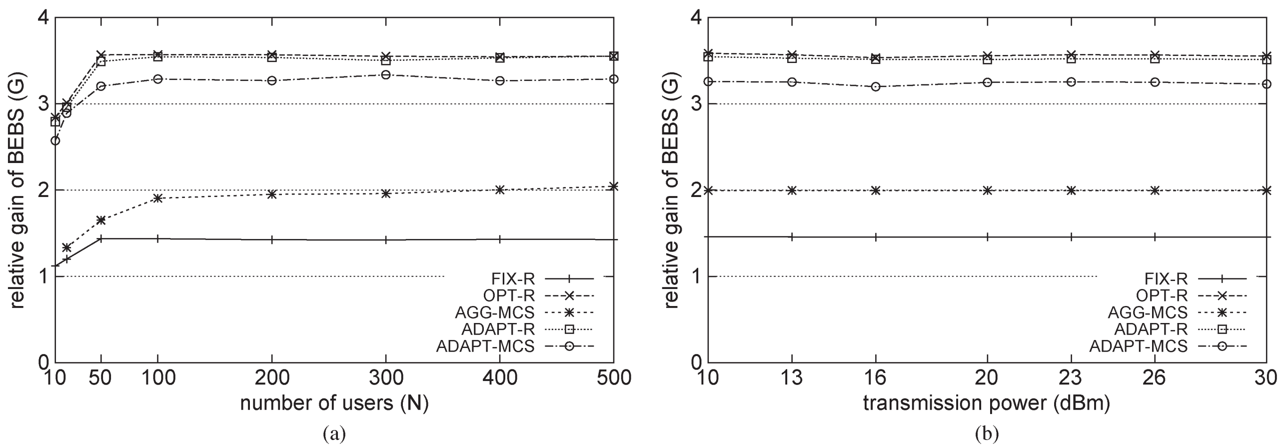

Fig. 6. Comparison of relative gain for several schemes. (a) Effect of the number of users. (b) Effect of transmission power.

- $\mathtt{OPT-R}$: This is considered to be an ideal scheme from the viewpoint of the relative gain, where the value of η is set to the optimal value obtained from the analytical model.
- $\mathtt{AGG-MCS}$: This scheme always uses the most aggressive MCS to minimize the resource for broadcasting at the cost of reliability. This is the extreme case opposite to full reliable broadcasting.
- $\mathtt{ADAPT-R}$: This is the proposed scheme in Section V-B; the value of η is adjusted to maximize G. The parameters of this scheme are set to $K_p = 0.01$, $w = 0.8$, $\Delta+ = 0.1$, $\Delta- = -0.1$, and $T_s = 0.5$ s, and the initial values of η are set to 0.5.
- $\mathtt{ADAPT-MCS}$: This is another proposed scheme, where the MCS is dynamically adjusted. The threshold value of $G_{\rm th}$ is set to 0.03, and the initial MCS is set to the median one.

We do not present the result of full reliable broadcasting (i.e., $\eta = 1$), since its relative gain was nearly equal to 1 in most cases. The control parameters in $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ were determined in a trial-and-error manner. Here, we focus on the case of RWPM because it is considered to be the most reasonable distribution of users in cellular networks.

First, we compare the MCS distribution of $\mathtt{OPT-R}$ and those of $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ to evaluate how $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ adjust MCS close to the ideal value. As shown in Table III, $\mathtt{OPT-R}$ selects MCS4 and MCS5 with the probability of 0.81 and 0.19, respectively, and $\mathtt{ADAPT-R}$ also selects them with the comparable probability. However, $\mathtt{ADAPT-MCS}$ selects MCSs in a more conservative way compared with $\mathtt{OPT-R}$. In addition, we observed from simulations that $\mathtt{ADAPT-R}$ controls η around the optimal value, but it slightly fluctuates due to the coarse granularity of MCS control and the nature of the random wireless channel. Similarly, we observed that the MCSs determined by $\mathtt{ADAPT-MCS}$ change among MCS3, MCS4, and MCS5.

Next, we investigate how the relative gain of BEBS changes depending on the number of users and transmission power. We observe the effect of N in Fig. 6(a). As we can expect from Corollary 1 in Section IV-C, Fig. 6(a) shows that the relative gains for all the schemes are almost immune to the values of N ranging from 10 to 500. There is an insignificant difference among $\mathtt{OPT-R}$, $\mathtt{ADAPT-R}$, and $\mathtt{ADAPT-MCS}$; the relative gains of $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ are smaller than that of $\mathtt{OPT-R}$ by at most 2% and about 8%, respectively. These results confirm that both proposed schemes almost achieve the maximum available gain regardless of the number of users. Compared with reliable broadcasting, $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ improve broadcasting capacity by about 3.5 and 3.3 times, respectively. It is important to note that $\mathtt{AGG-MCS}$ outperforms $\mathtt{FIX-R}$, i.e., G of $\mathtt{AGG-MCS} \approx 1.92$ while G of $\mathtt{FIX-R} \approx 1.43$. This result indicates that even the most aggressive MCS improves broadcasting capacity. If the value of N is small, the relative gains of all the schemes decrease, as shown in Fig. 6(a). This is due to the coarse control granularity of target reliability or MCS. However, even in the case of $N = 10 \sim 20$, the relative gains of $\mathtt{ADAPT-R}$ and $\mathtt{ADAPT-MCS}$ are close to that of $\mathtt{OPT-R}$, and they are still higher than that of $\mathtt{FIX-R}$ by about 2.3–2.5 times.

Fig. 6(b) shows the effect of transmission power ($P_{\rm tx}$), which is considered as one of the key factors affecting the performance of BEBS. Note that we recalculate R_m for each case of $P_{\rm tx}$. Due to the increase in $P_{\rm tx}$ from 10 dBm (10 mW) to 30 dBm (1000 mW), the cell coverage ($R_{\max}$ $(= R_1)$) increases from 95 to 356 m, according to the analysis in Section III-A. Here, we set N to 100, and they are located within the cell coverage. Similar to N, $P_{\rm tx}$ hardly affects G, as shown in Fig. 6(b). These results confirm the robust performance of the proposed scheme realizing the benefit of BEBS. In summary, the performance of BEBS mostly depends on the user distribution and target reliability, while it is almost immune to the number of users, transmission power, and transmission coverage.

VII. Conclusion

We have introduced the novel service model of BEBS in cellular networks and have formulated the problem as maximizing broadcasting capacity by relaxing the reliability constraint. Although the problem seems simple and intuitive, we have derived the analytical model, with which we can quantitatively investigate the effect of target reliability on the achievable capacity of BEBS and rigorously prove several key properties of BEBS. Moreover, we have proposed practical feedback control schemes that can maximize the capacity of BEBS.

The simulation results have validated the analytical model and confirmed that the proposed schemes for BEBS can remarkably improve broadcasting capacity, compared with conventional reliable broadcasting. This study provides a basis for BEBS by proving its potential benefit. We expect that BEBS can be extended to layered video broadcasting in cellular or satellite networks and that its performance will be further enhanced by jointly adjusting MCS and transmission power, which can be a subject of future work.

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