Perceptual Quality-Driven Resource Allocation in Energy-Aware Wireless Video Multicasting

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Abstract—In conjunction with the rising trend towards consumption of resource-hungry multimedia content over wireless medium, efficient radio resource allocation (eRRA) represents an ongoing challenge to network operators. This paper explores the application of multicasting in light of an eRRA that considers the perceptual quality aspect of wireless video transmission such that transmission energy is minimized. A multiuser orthogonal frequency-division multiplexing (OFDM) environment is considered. The resource allocation scheme presented is based on the genetic algorithm (GA) and offers fairness through the balance of average perceptual quality and minimal total energy among all subscribers in multicasting groups. In order to assist with this balance, a utility function is introduced as a fitness function for the GA. The allocation scheme relies on a well-established video quality model (VQM) for assessment of user-perceived quality. Simulation results show that the allocation scheme helps to preserve the energy requirement at low levels despite the proportionate rise in the number of subscribers. Moreover, perceived quality is wellsecured and maintained at high levels, with a consistent increase of the utility value. Reflecting on today's consumption patterns of popular video content, adoption of the presented scheme in multicasting would help lessen the carbon footprint emitted by wireless communications, while consumers' quality of experience (QoE) is maintained.

Keywords-Multicasting; QoE; perceptual quality; resource allocation; energy; power; OFDM

I. INTRODUCTION

The recent trends in consumer demand on wireless devices show a steep rise in adoption of such devices, along with a booming consumption of resource-hungry multimedia content. In addition, convergence of the Internet and mobile devices exerts more pressure on wireless networks to offer more efficient access to multimedia, and especially video, over limited resources. This pressure becomes more insistent when consideration of customer's quality of experience (QoE) and energy-efficient communication is desired.

No doubt that QoE represents a key element to service providers nowadays; however, the increase in energy consumption in wireless communications attracted several Mahsa Pourazad Institute for Computing, Information, and Cognitive Systems (ICICS) University of British Columbia 289-2366 Main Mall Vancouver, BC, Canada, V6T 1Z4

research activities due to the environmental threat of CO_2 emissions. It is reported that 70% of mobile operator's electricity power bills are due to Radio Access Networks' (RANs) consumption [1]. The efforts to reduce energy consumption will not only reduce the carbon footprint of wireless networks, but will also lead to significant reductions in networks' operational cost.

Orthogonal frequency division multiplexing (OFDM) is a well-established technique in wireless communications due to its support for adaptive multi-user transmission at a high data rate. Therefore, OFDM has been adopted in several digital transmission systems such as IEEE 802.11a/g Wireless Local Area Network (WLAN), IEEE 802.16 Worldwide Interoperability for Microwave Access (WiMax), and Long Term Evolution (LTE). In OFDM, a high-rate data stream is split into a number of lower rate streams transmitted simultaneously over a number of subcarriers. So an individual data element normally occupies only a small part of available bandwidth since the coherent channel bandwidth is divided into many narrow sub-bands. Therefore, OFDM exemplifies a significant technique in wireless communications.

For its efficiency in multi-user environments, OFDM can be applied to unicast, broadcast, and multicast transmission modes. In unicast, each transmitted content is dedicated to a single receiver solely. In broadcast, a single content is transmitted by the base station and received by all connected users. However, in multicast, several different contents are transmitted by the base station, and each content is received by a *multicasting group*. Each group consists of subscribers who receive the designated content simultaneously. Radio resources are, therefore, allocated to each multicasting group independently. 3GPP has standardized an architecture of multicasting attributed Multimedia Broadcast Multicast Services (MBMS) [2], [3]. Radio resource efficiency is a prominent aspect of MBMS.

Efficiency of resource allocation in wireless multicasting systems has received significant research in varying contexts. Several research activities targeted the power allocation problem. Others focused on transmission throughput; however, few of them considered the quality aspect along with power in a multicasting mode. In [4], [5], a maximum throughput is distributed fairly among groups, with power as a constraint but not guaranteed to a minimum. The system sum rate is maximized to improve quality, but no measures are taken to assess the received quality. Minimizing receiver energy is achieved by minimizing the time required to receive bits [6], and by minimizing the number of received symbols [7], to increase throughput. Again, since content quality is not accounted for, higher bitrate may be offered unnecessarily. A mixture of unicast and multicast is addressed in [8], [9]; however, for multicast, minimal power is not targeted and throughput is not maximized for the sake of unicast which is given priority. Also, content quality is not accommodated. In [10], dynamic programming is used for a scalable video multicast aiming at efficient energy utilization and maximum video quality. Peak signal-to-noise ratio (PSNR) and packet success rate are used as video quality metrics; however, they lack the perceptual aspect offered by video quality models (VQM). Papoutsis et al. [11] proposed resource allocation based on allocating chunks of subcarriers to maximize throughput under limited power constraint. Yet minimal power and content quality were not addressed.

Accordingly, previous research in efficient radio resource allocation (RRA) has not adequately explored the perceptual quality aspect of wireless video multicasting such that transmission energy is minimized. However, a relevant scheme accommodating these aspects, applied to unicast transmission, is presented in [12], [13]. We take this scheme a further step and apply it in multicast. Promising results were delivered and shown to achieve acceptable levels of perceptual quality (QoE), consumed transmission energy, along with a utility that is derived for user's and service provider's mutual benefit.

The rest of this paper is organized as follows. Section II introduces the simulation system model. The methodology and allocation algorithms are described in section III. Simulation setup is outlined in section IV, and corresponding results are presented and discussed in section V. Finally, sectionVI concludes the paper.

II. SYSTEM MODEL

The wireless system considered is an adaptive multi-user multi-carrier OFDM system. Video is transmitted in a multicasting mode to a number of receivers in a single cell. A frequency selective Rayleigh fading channel with Rician absolute is assumed for the transmission environment. Accordingly, the instantaneous channel state information (CSI) corresponding to each receiver is represented by channel gains on each subcarrier.

The system model adopted in [14] considers a unicast transmission where each user receives an exclusive content over an exclusively allocated set of subcarriers. However, that model can be applied to multicast transmission scenarios. In multicasting, users become subscribers in multicasting groups since each group is transmitted an exclusive video content on exclusively assigned subcarriers. This multicasting OFDM system model is described in Figure 1. We assume that an auxiliary control channel is used to send the allocation information of bits and subcarriers. To guarantee a successful



Figure 1. Multicasting OFDM system with video transmission.

demodulation of received symbols by all mobile subscribers in a group, the worst receiver case is adopted. Therefore, on each subcarrier the minimum gain among all mobile subscribers is accounted for transmission power.

In this model we consider the modulation schemes BPSK, QPSK, 16QAM, and 64QAM, represented by 1, 2, 4, and 6 bits/symbol, respectively. However, 0 bits/symbol is used to indicate no data can be transmitted on a particular subcarrier. The simulations are based on the number of bits per second per Hertz (bps/Hz). Hence, at a given instance of time, one symbol is transmitted on each subcarrier. Therefore, the number of data bits transmitted (1, 2, 4, or 6) depends on the selected modulation.

The required transmit power for reliable reception of an OFDM symbol by the receiver is denoted r(b) [13]–[18]. This power is the minimum energy per symbol to guarantee reception and demodulation of *b* information bits/symbol when the subcarrier's gain is equal to unity.

$$r(b) = \frac{N_0}{3} \left[Q^{-1} \left(\frac{P_e}{4} \right) \right]^2 (2^b - 1) \tag{1}$$

 N_0 is the single-sided noise power spectral density level, assumed equal to unity ($N_0 = 1$). P_e is the bit-error-rate (BER), and Q^{-1} is the inverse Q function. For a number of receivers N, and a number of subcarriers S, the actual transmit power required by the $n_{\rm th}$ receiver on the $s_{\rm th}$ subcarrier is

$$Pn, s = \frac{r_n(b_{n,s})}{\alpha_{n,s}^2}$$
(2)

Whereas α is the gain on the *s*_{th} subcarrier for the *n*_{th} receiver, as given by the current channel state conditions. Thus, the minimum total transmit power is acquired by

$$P_T = min \sum_{s=1}^{S} \sum_{n=1}^{N} \frac{r_n(b_{n,s})}{\alpha_{n,s}^2}$$
(3)

On the other hand, for a number N of multicasting groups, the overall received video quality, Q_{avg} , is found by

$$Q_{avg} = max \ \frac{1}{N} \sum_{n=1}^{N} q_n(D_n) \tag{4}$$

such that $q_n(D_n)$ is the estimated video quality for receiver *n* given the average video bitrate *D*.

The optimization problem of minimum power and maximum quality is shown in [12], [13] to exhibit a trade-off that required a decision maker to identify a single optimum solution. For this purpose, a utility function is proposed as follows:

$$f = max \left\{ \sum_{n=1}^{N} (q_n \cdot \omega) - \sum_{n=1}^{N} (P_n \cdot \tau) \right\}$$
(5)

 ω , τ are arbitrary parameters such that ω represents unit price of quality, and τ symbolizes unit cost of power. This is based on an assumption that a charging model exists such that the customer is charged according to the level of content quality received. Adopting the utility approach leads to a resource allocation that satisfies service provider's interest, and maintains customers' quality perception, for a lower consumption of power [12], [13].

III. MULTICASTING IN QUALITY-DRIVEN AND ENERGY-AWARE RESOURCE ALLOCATION

In a multi-user multi-carrier OFDM transmission of video content, considering the perceptual video quality and energy consumption, the allocation of wireless resources represents a challenging non-deterministic polynomial (NP-hard) problem. On one hand, video quality relies on the assigned bitrate to each receiver. On the other hand, the transmit energy required by the same bitrate depends on instantaneous channel state of each subcarrier allocated to each receiver. With the aim to minimize required energy and maximize received content quality, a trade-off between total required energy and average achievable quality is observed [12], [13]. Accordingly, the resource allocation problem has two parts: allocation of subcarriers to users, and allocation of bitrate to users based on requirement of received video. Considering the the instantaneous channel state on each user's allocated subcarrier, a multi-objective optimization problem is formulated. Hence, a scheme of wireless resource allocation that is content-aware and energy-efficient [13], is adopted to address this problem. This scheme is based on evolutionary genetic algorithms (GA) as a suitable technique to achieve a sub-optimal solution for the problem at hand.

A. Quality-Driven and Energy-Aware Resource Allocation Scheme

A high level diagram of the resource allocation scheme is illustrated in Figure 2. Once the input parameters are known to the OFDM channel, the optimization algorithms will propose



Figure 2. Main elements of the resource allocation scheme.

the most sub-optimal allocation of bitrates and subcarriers among users, which satisfy the targeted objectives of minimum energy and maximum quality for a designated utility function.

1) Video quality modeling

In Figure 2, the video quality modeling component identifies the bitrate requirement for each user such that user's perceptual quality is not compromised. For this, a mapping between video bitrate and video quality is conducted. Given the targeted video quality for a particular user, this mapping helps identify the required data bits by the user. Out of practical concerns, such a mapping may not yet exist. Therefore, we assume it is available and we follow the process designed in Figure 3 to develop it.

In this mapping process, video sequences are source coded according to the H.264 standard [19] with H.264/AVC JM Reference Software. Video source coding is performed at different quality levels with encoder's quantization parameter (QP). The bursty packet loss patterns are generated based on Gilbert-Elliot Model [20]. Video packet loss is simulated at varying levels of bit-error-rates, and is repeated at random starting positions for each video to maintain data confidence. The decoded video sequences are then assessed for perceptual quality estimation using the objective NTIA general video quality model (VOM) [21]. This model is selected based on its performance and accreditation by both ANSI [22] and ITU [23] as a video quality assessment standard. Deriving the required bitrate on this basis incorporates several quality aspects and video content characteristics into a representative bitrate. Finally, rate-distortion (R-D) diagrams are produced to reflect the required bitrate-to-quality mapping.

Since user required bitrate has been identified with the quality modeling part, the next objective is to assign this bitrate to the user's allocated subcarriers such that minimal energy is used for transmission, while per subcarrier gain is considered. The problem develops more complex in a multi-user environment. Thus, the power allocation scheme (in Figure 2) implements an evolutionary search method seeking a sub-optimal solution to the power allocation problem efficiently.



Figure 3. Process to map source coding bitrate to perceptual quality.

2) Power allocation scheme

The power allocation problem consists of two parts. First, allocation of subcarriers to users, such that each user is assigned a set of subcarriers on which the user experiences high channel gain. Second, within the subcarriers allocated to a particular user, the user's required bitrate is assigned to the subcarriers in a multi-modulation manner such that the total required transmit power is minimal. The aforementioned two parts are addressed with the genetic algorithm and greedy algorithm respectively [12], [13], [18].

a) Genetic algorithm

Genetic algorithms (GA) [24] emulate the theory of natural biological evolution. They represent a low-complexity methodology to attain a sub-optimal solution within acceptable timeframe. A genetic algorithm starts by searching a space of nominated solutions looking for the most fitting one. A population of solutions is updated iteratively while each solution (chromosome) is evaluated against an objective fitness function. The best fit solutions qualify to the next population where all solutions are re-evaluated. This evolutionary process continues to converge until a sub-optimal fitness is reached or a pre-defined number of iterations is performed. Hence, GAs demonstrate a suitable solution to the allocation of subcarriers to users targeting minimum transmit power [14], [16], [17].

b) Greedy algorithm

For each solution tested by the genetic algorithm, once the subcarriers allocated to a particular user are known, user required bits need to be assigned to these subcarriers considering the user's gain on each subcarrier. This is so that subcarriers requiring less transmit power are used, and those requiring more power may be unused or set free for use by other services. Therefore, a technique called greedy algorithm is used as a simple optimal solution for the bit allocation problem to subcarrier. The subcarrier which requires the least additional transmit energy is selected in each time. This process is repeated until all user bits are assigned to a set of subcarriers [14], [18], [25].

3) Global optimization algorithm

The quality-driven and energy-aware allocation scheme, presented in Figure 2, is intended to address two parts of the problem: allocation of subcarriers to users, and allocation of bitrate to users. The joint objective of both parts is to maximize users' perceived video quality through optimal bitrate selection, and to minimize total required power through optimal subcarrier and bit allocation. This joint objective is formulated in the genetic algorithm by means of structuring GA chromosomes to accommodate the two parts of the problem mentioned earlier. Thereby, a global optimization of the multi-







Figure 5. Resource allocation scheme [13].

objective optimization problem (MOOP) can be achieved by the GA chromosome in Figure 4.

The two parts of users' assigned bitrates and users' allocated subcarriers are segregated as the chromosome is decoded into discrete values. Each chromosome is evaluated against a fitness function, however as power and quality are inversely proportional, the trade-off between power and quality is addressed by a utility function. The utility function (5) is used as the fitness function to qualify fit chromosomes. Hence, the acquired suboptimal solution shall satisfy the objectives of power, quality, and utility. A schematic of the quality-driven and energy-aware allocation scheme is depicted in Figure 5.

B. Multicasting Scenario

The quality-driven and energy-aware resource allocation scheme, in Figure 5, has achieved significant results in a unicast multi-user scenario [13]. However, due to the increasing trend towards popular content among multimedia consumers, multicasting represents an appealing application to be considered by this allocation scheme. Therefore, we evaluate the scheme under different multicasting conditions.

In multicasting, a continuously varying number of users could join/leave a multicasting group. The number of multicasting groups could also vary as subscribers join different popular contents. Moreover, broadcasted content on each group can be typically different in terms of video quality characteristics, in addition to quality of service (QoS) parameters. We subject these varying conditions to the resource allocation scheme under constant and restricted channel resources (bandwidth and number of subcarriers), to test its performance.

To guarantee video content delivery to the farthest user in the radio cell, we consider the worst user case such that in a given multicasting group the least gain of each subcarrier designated for the group is considered. Hence, this would require additional power to satisfy all group subscribers. Accordingly, the CSI input to the resource allocation scheme is the lowest combination of CSIs of all subscribers in the group. Based on this, the characterization of a "user" in unicast transmission is replaced with a multicasting "group" of subscribers. From the OFDM channel point-of-view, guaranteeing the CSI of the worst subscriber is similar to a unicast transmission except that CSI of the group could be relatively lower.

IV. SIMULATION

A. Multicasting

A multicast transmission scenario is simulated for a single cell multi-carrier OFDM channel. We assume a 4 MHz OFDM channel with 32 subcarriers. As shown in Figure 6, we simulate from 1 up to 4 multicasting groups, and in each group from 1 up to 15 subscribers. As subscribers could joint/leave a group at any point in time, simulations start by a single subscriber in each group and increment one subscriber at a time until the total number of subscribers in the group is 15. A different video content is broadcast to each group; however, to maintain consistency the same video is used for the same group in each scenario, utilizing the same channel resources. Two levels of bit-error-rate, 10^{-5} and 10^{-3} , are tested.

Since we consider frequency selective Rayleigh fading channels with Rician absolute in this testing, we generate 100 sets of instantaneous channel state information (CSI) per subscriber. For data confidence, the power allocation scheme is simulated over all the sets and an average power calculation is calculated.

B. Genetic Algorithm

The parameters used in the genetic algorithm are listed in Table I. Total length of a binary chromosome changes according to the number of multicasting groups simulated in each scenario. In one-group and three-group scenarios, the binary representation would offer a group number that does not exist, e.g. group-2 or group-4. This issue is resolved by replacing those binary digits with a randomly generated and evenly distributed group numbers that conform to the number of groups being simulated.

The utility function parameters, unit price of quality, ω , and unit cost of power, τ , in (5), are identified based on a heuristic approach. This approach depends on practical conditions of, QoE ≈ 0.85 , and, BER=10⁻⁵. Under these conditions the maximum value of the utility function in (5) is found by iteratively increasing the ratio, ω / τ .



Figure 6. Simulated multicasting scenarios.

TABLE I. GA SIMULATION PARAMETERS

Parameter	Value
Binary chromosome length for a group bitrate	5 (bits)
Binary chromosome length for subcarriers	64 (bits)
Total length of binary chromosome, β	69, 74, 79, 84 (bits)
Population size, γ	40 (chromosomes)
Percentage of population survivors, δ	0.5
Mutation rate (R_m)	0.15
Number of iterations	1000

C. Video Rate–Distortion Diagrams

A standard definition video (720×576 spatial resolution) of 200 frames, is assigned to each multicasting group as follows: *Break dance* – Group 1, *GT Fly* – Group 2, *Interview* – Group 3, *Tractor* – Group 4. The selected video sequences hold different attributes of motion, content, and temporal resolution.

Based on the process described earlier in Figure 3, rate– distortion (R–D) diagrams are produced [13] for bit-error-rates 10^{-5} and 10^{-3} . This is needed to identify the quality level for a given average video bitrate in the resource allocation scheme. However, this average bitrate is considered a *representative* rate of the video sequence at any particular point in time. This is because the resource allocation scheme is designed on instantaneous basis, i.e. resources are allocated at a given point in time, and adaptively reallocated at the next point in time.

Out of practical concerns, we simulate a range of bitrates for each video based on practical high/low limits of video quality, since QoE is unlikely to score beyond these limits. The bitrate limits are defined such that $0.4 \le \text{QoE} \le 0.95$.

V. RESULTS AND DISCUSSION

In the results we compare the four multicasting scenarios by observing utility, power, and quality for the same number of total subscribers in each scenario. This total can be represented by several patterns as we assume subscribers join/leave groups from one simulation to another. Therefore, we plot the average utility, power, or quality for the number of equal totals simulated. Thus the error bars depict a standard deviation from the average.

A. Exhaustive Search

To comprehend the solution space of the simulated scenarios, an exhaustive testing of all possible solutions in the four tested scenarios is depicted in Figure 7. Each solution represents a different bitrate allocation to each group. A range of all possible bitrates per group is tested. For comparison purposes, a fixed total number of 12 subscribers is considered in each scenario. Hence, the number of subscribers per multicasting group is 3, 4, 6, and 12 subscribers for the 4-groups, 3-groups, 2-groups, and 1-group scenarios, respectively. Figure 7 shows the corresponding minimum total power and achievable average quality of each solution. In each scenario in Figure 7, the upper-left Pareto frontier provides the



Figure 7. Search space by GA for a total of 12 subscribers (BER=10⁻⁵).

non-dominant best set of optimal solutions, which satisfy lower power and higher quality. The quality-driven and energy-aware resource allocation scheme [13] employs utility function (5) as a decision maker to identify one best solution along the Pareto frontier. It is apparent from Figure 7 that under same constraints of wireless resources, as the number of multicasting groups increases the demand on required power increases, whereas the operational window of quality can be maintained across the four scenarios at the expense of power.

B. Relative Utility

Figure 8 shows average utility value as the total number of subscribers is increased in each scenario. Utility value by itself is irrelevant since we are interested in the relative levels of utility as influenced by the number of subscribers. From the linear relations in Figure 8 we conclude that multicasting with the suggested resource allocation scheme [13] is more advantageous (from the service provider's point-of-view) when lower number of multicasting groups is operated. This is referred to the higher cost of power as the number of groups increases. Since the more groups are operated the less the spectrum becomes available per group, and also required power by groups is accumulated. Yet the scheme [13] maintains a steadily increasing utility value as more subscribers join the operating groups.



C. Required Transmit Energy

Figure 8. Average utility as subscribers join muticasting groups (BER=10⁻⁵).

diagram in Figure 9. In 1-group and 2-groups scenarios, the required transmit power is maintained almost constant by the allocation scheme [13] regardless of the increasing number of subscribers. This is desired since utility will increase as subscribers join while cost of power is fixed. However, in 3groups scenario we observe a slight increase of power as subscribers join. Furthermore, in 4-groups scenario the rise of power becomes considerable. This trend could continue if more groups were simulated. This behavior is attributed to the limited number of subcarriers. Up until 2 groups the available subcarriers were sufficient to accommodate increasing subscribers, but starting with 3 groups more power was required on existing subcarriers to compensate for the less available subcarriers. This efficient maintainability of the required power given limited available resources is due to the resource allocation scheme [13].

Due to the same spectrum limitation in addition to accumulation of required power by groups, and the worst user case adopted for multicasting, a higher number of groups requires considerable higher energy as seen in Figure 9.

The range of required power represented by error bars in Figure 9 indicates that as the number of groups increases the resource allocation scheme [13] seeks a wider space of solutions to satisfy the maximum utility objective. Hence, error bars stretch when more groups are accommodated.

D. Perceptual Quality (QoE)

Video quality diagram in Figure 10 demonstrate the effectiveness of the resource allocation scheme [13] with its objective to maintain high levels of perceived video quality by the user. Almost in all multicasting scenarios user's perceptual quality is maintained. However, the more groups accommodated the slightly lower quality is experienced. This is a result of the decision maker's design in the allocation scheme [13], which gives priority to the utility value. In order to satisfy maximum utility value, the scheme considers cost of power and revenue of quality instantaneously, and therefore could lower average quality to avoid higher cost of greater power.

The mild fluctuations in quality as indicated by the error bars in Figure 10, reassures the capability of the allocation scheme [13] to maintain quality even with the rising number of subscribers.



Figure 9. Average required total energy as subscribers join muticasting groups (BER=10⁻⁵).



Figure 10. Average quality perception as subscribers join muticasting groups (BER=10⁻⁵).

VI. CONCLUSIONS

This paper has discussed the application of multicasting in an energy-efficient radio resource allocation scheme that is driven by video quality as perceived by the end user. The scheme is also based on utility function maximization in the interest of service providers. The application in multicasting has shown a linearly rising utility, a steadily controlled energy requirement, and maintained high levels of perceptual quality as the number of subscribers increases in different multicasting scenarios. An overall observation of the results suggests that resource allocation scheme attains a significant the accomplishment in achieving its multi-objective optimization when applied in wireless video multicasting. Since popular video content is becoming increasingly desired by consumers, adoption of this scheme in multicasting would help limit the carbon footprint emitted by wireless communications, while consumers' QoE is guaranteed. It is suggested that this work is extended in the future to multi-cell environment. Hence, the allocation scheme would require further intelligence for implementation in a distributed system, especially when optimization in multicasting is intended.

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