Multimedia Sensing as a Service (MSaaS): Exploring Resource Saving Potentials of at Cloud-Edge IoTs and Fogs

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Abstract—With the popularity of multimedia sensing at cloud edges and the reducing cost of the Internet of Things (IoTs) fog devices and systems, new challenges have been posed to efficiently deal with the big data multimedia traffic generated from IoT sensing units. Specifically, in this paper we introduce the concept of Multimedia Sensing as a Service (MSaaS), and propose a generalized premium prioritization-based Quality of Experience (QoE) paradigm for wireless big-volumes-of-data (BVD) multimedia communications, with significant energy saving potentials for future multimedia IoT devices and systems. The key contribution of this new framework is its data diversity flexibility at the application layer, which could be flexibly adopted by future multimedia communication systems. Data dependencies in spatial, frequency and temporal domains are analyzed, and interaction with uplink resource allocation optimization are investigated with regards to wireless communication energy cost estimation. Extensive simulation results demonstrate that the proposed prioritization-based communication paradigm has significant energy saving potentials for BVD MSaaS wireless multimedia communications at cloud edges and fogs.

Index Terms—Wireless Multimedia Communications, Cloud Edge and Fog, Energy Efficiency

I. INTRODUCTION

Big-volume-of-data (BVD) multimedia communications poses new challenges to the last-mile wireless access, due to the popularity of smart phone-based mobile devices and multimedia sensing capabilities in modern Internet of Things (IoTs) [1]. Multimedia Sensing as a Service (MSaaS) provides valuable sources for various insights and information, such as IoT-based environmental monitoring, climate modeling and forecasting, body sensor network system-based medical decision and support, and social media content sharing, etc. However, as the “biggest” big-data, multimedia content traffic is projected to quickly increase at 62% per year, a big-data traffic that will significantly strain already overburdened mobile access network channels [2]. In addition, the energy consumption of mobile sensing devices for traffic intensive constant and continuous multimedia content sharing becomes a critical challenge.

Figure 1 illustrates typical MSaaS intensive applications with strong energy efficiency needs at the cloud edge and fog devices. In MSaaS IoT systems, the sensing units primarily produce sequences of images or videos, and upload these multimedia streams to servers in the cloud. For example, visiting tourists frequently take landscape pictures and upload them through iCloud or social media via uplink networks. Audiences at a live concert record highlight video pieces and share them with families and friends through Long Term Evolution (LTE)/5G connected social media or multimedia enriched messages. Online course videos and lecture material, as well as news media interviews could be recorded and posted to the cloud through WiFi connections and shared with participants and subscribers. These users are primarily content contributors of MSaaS. Some users play interactive cloud video games, in which the traffic intensive multimedia game information is transferred through the wireless access networks. This type of user is primarily content consumers. Some other types of users are both content generator and consumers, such as face-time users having video conversations with peers through the wireless access links.

Fig. 1. MSaaS energy efficient wireless multimedia content delivery at cloud edge IoTs and the fog.

All these users pose severe challenges for MSaaS communications. First, the mobile devices have limited battery resources, but big volumes of multimedia data consume enormous energy of source devices in wireless transmission. Second, the Quality of Experience (QoE) from the consumer side must be guaranteed and thus wireless multimedia content uploading at the provider side should enforce resource efficient communications for big data multimedia.
In this paper we propose a new multimedia communication paradigm at application layer, called generalized premium-regular concept in MSaaS, and investigate new resource allocation strategies to achieve energy efficiency gain in QoE driven wireless multimedia communications at the cloud edge and the fog. Various resource allocation strategies are thoroughly optimized with regards to this modern paradigm at the cloud edge and the fog, including smart power control, intelligent rate adaptation, versatile channel coding control, frame length adaptation and packet retransmission optimization. Furthermore, multimedia big data prioritization and dependency analysis are performed in spatial, frequency and temporal domains, respectively.

The remainder of this paper is organized as follows. Section II introduces the related works and gives the novelty of the new energy efficiency resource allocation strategy proposed in this paper. In Section III, we analyze data dependencies in spatial, frequency and temporal domains. Sections IV formulates the resource allocation problem at the cloud edge IoTs and fogs. Section V shows our simulations, followed by the conclusions in Section VI.

II. RELATED WORKS

Fog computing is a promising solution to address the ubiquitous user demand on high-quality mobile service and accommodate the explosive growth of mobile video traffics. It enables applications on billions of already connected devices to run directly at the IoT edge. Consideration of energy efficient wireless multimedia communications has been extensively researched in the literature, however, big data mobile multimedia traffic pose new challenges to the modern cloud edge and fog for both mobile devices and access communication protocols. Research in [3] provides a comprehensive literature survey of cloud multimedia challenges with mobile devices. A case study of a cloud media centric platform was also presented. Another comprehensive survey in [4] was conducted to summarize contemporary rich media applications in mobile cloud. Research in [5] proposed a new concept of Sensing as a Service (S2aaS) in cloud computing, in which smart phone users provide sensing services to the cloud under certain data source incentives. Resource allocation issues and quality of service scheduling challenges were discussed in [6] for mobile media cloud. The research in [7], introduces a blind scheduling algorithm in mobile cloud media to cope with the situations of unknown demand rates and service times. Significant effort have been put on reducing multimedia traffic. At the multimedia source data compression side, research in transform domains such as exploring wavelet tree roots [8] [9] and tree structure nodes [10] [11] have been performed in image compression. In those, the transform domain coefficient magnitude distribution provides desirable quality progression for lower layers to perform Unequal Error Protection (UEP) and allocate communication resources. The tree structures and bit-plane layers of wavelet or cosine coefficients could be efficiently compressed and the bit streams with lower precision embedded into the bit streams with higher quality layers. Research in spatial domain typically utilize quad-trees [12] [13] to present low frequency large flat areas and background information in the pictures, as well as the high frequency variations and edges in boundaries of the objects. Due to its support of flexibly transforming block sizes, quad-tree has been widely used in the most recent High Efficient Video Encoding (HEVC) techniques for Ultra High Definition (UHD) pictures and videos. The quad tree decomposition of picture partitioning for temporal motion prediction and residual coding in MPEG-H/H.265/HEVC is more flexible than that in H.264/MPEG-4 AVC [14]. The complexity and cost of HEVC video coding was also discussed in [15]. Various resource allocation schemes regarding prioritizing image or video packets and adapting communication settings have been reported in the literature as well. Authors in [16] propose research in resource allocation strategies to protect different quality layers in order to improve quality - latency performance. Research in [17] proposed a latency constrained solution for multimedia quality optimization with link layer retransmission adaptation and retry control. Research in [18] developed a different link layer packet retry scheme to improve quality enhancement and to reduce bandwidth consumption.

However, most of the above research focus on latency bounded multimedia delivery over wireless networks or scheduling algorithms within the cloud, while the energy efficiency considerations were largely ignored for mobile devices at the cloud edge and the fog. Furthermore, with the challenges of UHD big multimedia data traffic generated by MSaaS source devices, traditional packet prioritization with granularity of quality layers and conventional resource allocation with a single network strategy adaptation are not able to efficiently handle big data energy efficient multimedia communications. In our preliminary work in [19], we formalize a new premium-regular concept and explained the details of how to separate premium and regular information from application layer compression algorithms at the transform domain. In this paper, we specifically study the new energy efficiency resource allocation strategies at the cloud edge and the fog, while utilizing high level application layer positing and regular concepts.

III. APPLICATION LAYER MSaaS BIG MULTIMEDIA DATA PREPARATION

The essential challenges of BVD for MSaaS at the cloud edge and the fog are two folds. First, the big volume of multimedia must be prioritized efficiently; and here we utilize the generalized premium-regular concept to present such priority. Second, the uplink traffic especially MSaaS multimedia content should be efficiently delivered to the cloud with energy efficient resource allocation methods; and here we investigate resource allocation strategies corresponding to premium-regular diversified multimedia traffic priorities. .

Let $q$ denote the quality of a coding unit (i.e. a frame in H.264 or H.265 video, or bit plan layer packet of a wavelet or cosine transformed image), $W$ denote the total number of coding units, and $\Theta$ denote the map from premium information $\bar{i}$ to another coding unit of regular information $\bar{j}$ depending on the successful decoding of unit $\bar{i}$ with quality $q$. This
application layer MSaaS multimedia data preparation problem is translated to a complex selection problem, the objective of which is to find the “best coding unit” with the highest $q^*$.

$$q^* = \arg \max_{i=1...W} \left\{ q_i + \sum_j \Theta_j (q_i) \right\}$$  \hspace{1cm} (1)

In a single picture or image, the premium information denotes the crucial tree structures in the transform domain, or contours and shapes in the spatial domain. In a temporal domain video sequence, the premium information presents the intra coding frames and those important coding units serving as reference data for other packets.

A. Transform Domain Data Preparation

In transform domain multimedia premium-regular separation, the key issue is to separate crucial premium blocks from the less important regular blocks. After Discrete Cosine Transform (DCT) or Discrete Wavelet Transform (DWT) transforms, the large valued coefficients will be concentrated to upper left corners and small valued coefficients will be quantized to zeros during bit plane coding. The tree structures present the premium information and the tree leaves present regular information, which could be captured via a light weighted premium-regular partition algorithm. For more details please refer to our preliminary work [19], which is also a conference version of this paper. It is worth noting that transform domain data preparation is the so far most typical approach to prioritize data due to the superb concentration performance on transforms.

B. Spatial Domain Data Preparation

With the availability of more and more new mobile computing devices at the cloud edge and fog, simple and fast processing of source data is preferred. In spatial domain we propose to directly identify essential premium information of the pixels in a low cost fashion, and compress the lightening regular information in an efficient fashion. We utilize quad-tree as the driving algorithm to partition important premium blocks and unimportant regular blocks. Figure 2 illustrates the concept of premium and regular partitioning in the spatial domain. Unlike computer generated graphic pictures, natural picture and digital images carry semantic information through low frequency large flat areas and high frequency edges. In general, the high frequency edges are more important in presenting the premium information and semantic meaning of the picture. However, the locations of edge information typically are determined by the large flat areas when run length coding is involved. In addition, the large flat areas have higher impacts on the decoding distortion measured in Root Mean Square Error (RMSE), due to the large number of pixels involved in each single block. As a result, losing large flat areas is equivalent of messing up with the premiums, and the regular information will be useless even if they are transmitted correctly. The large flat areas such as the backgrounds could be efficiently represented in quad tree decomposition.

Algorithm 1 describes the quad tree decomposition process for a single image or an HEVC intra-frame coding style picture. Quad tree based picture decomposition has been widely used in image compression, and recently has been revisited as a desirable candidate for H.265 HEVC intra-mode compression. Unlike MPEG-4 H.264 compression standard with fixed sizes of Macro Blocks (MBs), H.265 employing quad tree with adaptive sizes of MBs can approximate the semantic meaning of the objects with better granularity. After quad tree decomposition, the large flat areas including a large number of pixels will be presented by a small number of large MBs, and the high frequency edges with few pixels will be presented with a large number of small MBs. This type of inequality and unbalance provide a unique opportunity for energy efficient big data multimedia communications at the cloud edges and fogs. Due to the spatial independency of various MBs in the quad tree decomposition, the problem of finding the best coding unit could be simplified as follows:

$$q^* = \arg \max_{i=1...W} \{ q_i \}$$  \hspace{1cm} (2)

The total per picture quality $Q$ could also be expressed in a simplified additive fashion:

$$Q = \sum_{i=1}^{W} q_i$$  \hspace{1cm} (3)

Algorithm 1: Quad tree decomposition for premium and regular partitioning.

1. Load picture into array $P|\dim [X, Y]$ with resolution dimension of $X \times Y$.
2. Perform quad tree decomposition $[\Omega_{x,y}] Z_0 = \Xi \{ P|\dim [X, Y] \}$, where $\Omega$ denotes a two dimension matrix of the $x$ and $y$ premiums of a specific MB, $Z$ denotes the one dimensional vector of the MB sizes, and $\Xi$ denotes the operation of quad tree decomposition.
3. Calculate relative RMSE distortion reduction for each MB,

$$q_k = \frac{\sqrt{\sum_{i=0}^{Z_k} \sum_{j=0}^{Z_k} (I_{i,j} - f_{i,j})^2}}{X \cdot Y},$$

where $I_{i,j}$ is the intensity of the pixel at premiums $(i,j)$.
4. Prioritize MBs based on the relative RMSE distortion reduction: $\forall m \in Z, n \in Z$, if $q_m < q_n$ then exchange the order of the $m$-th MB and the $n$-th MB.
5. Perform rate-optimized truncation based on resource requirement $R$ and resource translation function $\Re$, by finding the maximum integer threshold $t$, such that $R \geq \sum_{i=0}^{t-1} \Re |Z_i|$ and $R < \sum_{i=0}^{t} \Re |Z_i|$. 

**Fig. 2.** Spatial domain premium regular concept with quad tree decomposition.
C. Temporal Domain Data Preparation

Because a video flow is a sequence of compressed pictures, the above solution can be seamlessly applied to intra-frame video coding. The major concern with video premium-regular separation is finding the premium-regular concept in inter-frame coding. In the next generation MPEG-H HEVC H.265 and MPEG-4 H.264 Advanced Video Coding (AVC) standards, inter-frame prediction, equal or unequal Code Block (CB) sizes, quantization levels and motion vector estimation all contribute considerably to the overall reduction of bit rate and increase of video compression ratio. Such performance gain is associated with the overhead of decreased error resilience; because B and P framed sizes are decoding dependencies of I frames and large-size CBs, losing I frames or large-size CBs in the wireless channel inevitably renders the B and P frames non-decodable. In other words, I frames and large-size CBs serve as the reference “premium blocks”, and B and P frames primarily code the small-size CB residues and motion vectors as “regular blocks”.

![Figure 3](image-url)  
**Figure 3.** Temporal domain dependency analysis of video coding.

Figure 3 shows the temporal domain premium-regular concept in video coding dependency analysis. Typically the compressed I frames serve as the reference marks for decoding of P and B frames, and thus have similar avalanche error propagation effect as the premium information in image compression. The P and B frames serve as similar roles of the regular information in image compression and decoding. In this figure we illustrate six basic coding modes for modern MPEG-4 and MPEG-H compression standards. The choice of the coding modes leads to the various tradeoffs between rate and distortion, and between energy efficiency and QoE.

IV. Resource Allocation Prioritization at the Cloud Edge IoTs and Fogs

Nowadays the resource allocation strategies for network communication and wireless protocol have been pushed to the cloud edge, in order to take the advantage of geographic proximity of coordinative services nodes. In addition, fog computing [20] has been recently proposed as a future candidate for leveraging mobile device’s and smart gateway’s computing and power resources in cloud edge data services. With the availability of high power smart gateways and smart mobile phones as the fog nodes, together with proper incentives provided by the carriers or service providers, resource allocation scenarios will be primarily one or two hops between the user mobile devices, smart gateways, and the intermediate relays. In this paper we address the fundamental challenges of energy efficiently MSaaS multimedia transmission between user mobile devices and smart gateways.

A. Resource Allocation Problem Formulation

Once the unique pattern of premium-regular based data prioritization at the higher layer is established, cross-layer design at the lower layers can be guided as a complex communication resource allocation problem. The communication resources can generally be divided into five categories: transmission power, data rate, and Forward Error Correction (FEC) channel coding at physical layer, and packet length and Automatic Repeat reQuest (ARQ) limit at link layer. We will develop a unified premium-based resource allocation methodology to achieve optimal multimedia transmission quality while guaranteeing wireless communication energy efficiency.

The overall MSaaS resource allocation methodology can be formulated as an energy-constrained quality optimization problem. Given a certain communication energy budget, the proposed solution will optimize multimedia quality, by adjusting communication resource parameters such as power and modulation unequally between crucial premium information and unimportant regular information. Let $\lambda$ denote the premium information truncation point, e.g. the threshold of numbers of important image blocks. One truncation point is used to divide an image into premium packets and regular packets. Two truncation points are used to divide a video sequence into premium frames, medium premium frames, and regular frames. If $\bar{R}$ denotes the resource matrix (i.e., $\bar{R} = [r_0, r_1, \ldots]$), where each $r$ denotes a resource parameter such as modulation constellation size, transmission power, packet size, etc.), then the lower layer resource allocation problem can be formulated as follows to maximize the overall quality $Q(\lambda, R)$ for $N$ available images or video sequences under optimization consideration.

$$
\left\{ \lambda_i, R_{\text{premium},i}, R_{\text{regular},i} \right\} = \arg \max \left\{ \sum_{i=1}^{\infty} Q(\lambda, R) \right\} \quad \forall i, i = 1, 2, \ldots, N
$$

s.t.

$$
\sum_{i} R_i \leq R_{\text{max}} \quad \text{and} \quad 0 \leq \lambda \leq \sum_{i} K
$$

The received quality of each coding unit $i$ depends on the contribution quality $q_i$ if it is successfully received and the successful received probability $\zeta$. The total quality for $N$ images is the quality sum of each frame, which includes $W$ coding units, i.e.,

$$
Q(\lambda, R) = \sum_{i} \sum_{j} q \times \zeta
$$

where $\zeta$ is a packet’s contribution rate to the overall multimedia quality with $\zeta = (1 - \xi) \prod_{j} \Theta_{j}(\xi_j)$. It is related
Through the scheduling of communication resources at the cloud edge, IoTs and fog will not involve many hops as those in ad-hoc networks. The communication pattern will be typically one or at most two hops between the mobile sensing device and the access smart gateway. We also assume the smart devices can handle resource allocation in an optimal way.

In this section we perform studies on simulation and performance analysis. We use quad tree decomposition and the domain video encoder. The default transmission data bandwidth is 120 dB, medium loss as 100 dB, and low loss as 90 dB. Depending on the energy consumption, the aggregated information quality (AIQ) is defined as the successfully delivered distortion reduction quality gain per unit of energy consumption.

The layer 2 link retransmission and packet fragmentation could be applied to further reduce the packet error rate to $\xi = \xi_1$, due to the retransmission and error correction capability of the protocol layer. Let $\xi$ denote the packet error rate after decoding and let $\xi_1$ denote the function of choosing $n$ out of $m$ elements, then the packet error rate after error correction could be reduced to follows due to spatial redundancy:

$$\xi = \sum_{(n, m)} \binom{m}{n} \xi_1^n (1 - \xi_1)^{m-n}$$

where $\binom{m}{n}$ is the number of all possible values of parameter $n$.

The computation complexity can be approximated as $[12]$: $L = \frac{2^{\tau} - 1}{\tau} \cdot \text{enf} - 2$. The resource allocation problem is formulated and solved using a genetic algorithm.

The proposed truncation-point-optimized resource allocation method is described as Algorithm 2. Let $R$ denote the packet header overhead, and $B_t$ denote the frequency of channel selection. Let $B_w$ denote the bandwidth, and $B_r$ denote the frequency of channel selection. The resource allocation problem can be formulated as $\hat{R}$, which is the packet error rate. The computation complexity can be approximated as $[12]$: $L = \frac{2^{\tau} - 1}{\tau} \cdot \text{enf} - 2$. The resource allocation problem is formulated and solved using a genetic algorithm.

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80 dB. Channel coding rate is scaled between zero, 3.125%, 6.25%, 12.5%, 18.75% and 25%.

Figure 4 shows the test image and video of the proposed algorithms in this paper. We utilize standard “camera man” image as the input of spatial domain premium and regular information partitioning. The quad tree structure decomposition can ideally present large flat areas as premium information, and the fine details as the regular information. Similarly, we use foreman video sequence as the input of the temporal video compression codec. The premium and regular concept is brought up to higher frame dependency level for video. The role of I frames in video is similar to the role of premium packets in images, which is crucial for decoding process; P frames are less important, and B frames are the least important.

Figure 5 illustrates the importance of premium packets and regular packets, for various premium and regular partitioning decision thresholds. One spatial domain raw image will be compressed into two packets: premium packet and regular packet without going through the wavelet or cosine transforms. The decision threshold value is the number of premium codes blocks treated as important blocks, and in the figure we show four different choices of thresholds: 128, 256, 374, and 512. Larger number of decision threshold means that more premium blocks are incorporated into the premium packet, and thus leading to a bigger premium packet including more semantic content information and a smaller regular packet with less detail information. The quality of each packet is measured in reduction of Root Mean Square Error (RMSE), meaning how much quality reduction it will be if the packet is lost in the wireless transmission. From this figure we can see, by increasing the decision threshold, both premium packet quality and the premium packet length are increased; in the meanwhile the regular packet quality and size are both decreased. When we consider normalized RMSE as the per bit quality gain of the packet, we can see that the premium packet is much more important than regular packet.

Figure 6 shows the temporal domain video frame quality prioritization, with different number of inter/P frames between coded intra/I frames. The individual picture level quality contributions in terms of Peak Signal to Noise Ratio (PSNR) are similar for both I and P frames, however, the packet sizes of intra frames are typically five to six times bigger than inter frames. When mode inter frames are chosen to code the pictures, the percentage of quality contribution of important intra frames decreases, and the percentage of intra frame traffic also reduce. The percentage of important intra frames will play a major role in resource allocation, tuning the quality and energy tradeoff.

Figure 7 shows the DIQ of the raw data using various physical layer resource allocation strategies, including channel coding rate, transmission power, and data rate. Information quality of raw data is defined as the successfully transmitted information bits per unit of energy consumption. We also consider three channel loss conditions and their impacts on resource allocation efficiency. Each resource allocation index represents a combined choice of transmission power, data rate, and channel coding rate, starting from low profile to high profile. Transmission power is scaled from $10$ mW.
to 40 mW with seven steps leading to seven major peaks in these figures, and data rate is scaled with three steps leading to three sub-peaks, and channel coding rate is in the inner loop with six steps. From these figures we can see, the highest peaks of information quality are resulted from choosing lowest power and highest rate, with high channel coding rates applied in high channel loss scenarios and low channel coding rates applied in low channel loss scenarios. Power control and rate adaptation could be very effective in providing raw data packet information quality with limited energy, channel coding is very effective in achieving high information quality, reducing the communication error rate by slightly adding certain redundancy.

In Figure 8 we illustrate the DIQ of various resource allocation strategies primarily at link layer, including packet size and packet retransmission limit. Due to its effectiveness in controlling the bit errors and achieving high information quality, the channel coding rate is also included in this simulation. Six major peaks in these figures represent six steps of channel coding rates, and six sub-peaks within each peak represent six steps packet length choices. The packet retransmission limit is within the inner loop with three steps. From these figures we can see, channel coding rate is very effective in controlling the information quality at various channel loss scenarios, in conjunction with packet length control. At high channel loss scenario, higher channel coding rates effectively improve the successfully delivered data bits per unit of energy consumption. In each sub-peak, shorter data packet length is favored in high channel loss scenario, since shorter packets are more robust in error prone environment. In medium channel loss scenarios, reducing channel coding rate to the middle peaks can reduce extra redundancy bits and thus reduce extra communication energy consumption. We also observed that, higher channel coding rate with longer packet lengths, or lower channel coding rate with shorter packet lengths are favored in the medium channel loss scenario. In low channel loss scenario, lower channel coding rates with longer packet sizes are favored. The performance peak of information quality occurs when the lowest channel coding rate and longest packet length are chosen. This is due to their superb performance in combating with the wireless channel errors.

Figure 9 shows the AIQ gain of the proposed resource allocation with premium and best effort regular prioritization for spatial domain image partitioning. The prioritization of packet resource allocation for video could be seamlessly applied in a similar way. To illustrate the effect of the six resource allocation parameters $\lambda, P_t, G, M, K, H$, we adjust the rest five parameters between premium and regular information by fixing one of them. We investigate three channel loss scenarios: high, low, and medium. In the proposed resource allocation packet prioritization, channel coding resource allocation with prioritization leads to higher AIQ at picture level. Such AIQ performance is higher in those lower channel loss scenarios.

Parameters $P_t, G, M, K, H$ have the effect in controlling and recovering the channel bit errors. In Figure 9 (a), resource is allocated with smart gateway assisted decisions: premium packets will be allocated with high coding rates, and best effort regular packets will be allocated with lower coding rates. We find that lower block decision threshold in spatial domain image partitioning leads to higher AIQ gain using the proposed resource allocation prioritization. This is because the lower block decision threshold will lead to fewer premium data blocks but with higher quality contribution for each premium block. On the other hand, although there are a large number of unimportant regular blocks, they will be delivered with best effort approach with lower prioritization to save the energy cost. When the important block decision threshold increases, more blocks with less importance and lower quality contribution will be treated as premium blocks, and thus AIQ performance of prioritized and non-prioritized resource allocations are getting closer, due to the decreased concentration of importance level for premium packets. The prioritization of premium blocks and
best effort regulars provides a simplified approach to achieve energy efficient QoE in wireless multimedia services.

Figure 9 (b)-(f) demonstrate the effect of transmission power, modulation constellation size, redundancy encoding bits, packet length, and retransmission limit. We find that the modulation scheme has the biggest effect on improving AIQ, with FEC rate and packet length followed, while the ARQ technique has no effect on AIQ enhancement. From Figure (b), we can see that increasing the transmission power results in reduced AIQ. This is because the higher power means bigger energy consumption. And with the deployment of other techniques like modulation, FEC and ARQ, the increasing speed of energy consumption is more than the speed of quality enhancement. Thus it is best to use as low as transmission power. From Figure (d) and (e), the positive or negative effect of FEC rate and packet length is related with the channel loss factor. From Figure (f), the performance has hardly any changes when different retry limit is used, since the modulation constellation size and the FEC rate have been optimally selected to cancel channel bit errors. Another reason is that ARQ increases both the energy consumption and the transmission latency. It is not acceptable for the long-distance multimedia transmission with strict energy constraint, even it is simpler to implement than FEC, which recovers errors by putting more redundancy bits in the transmitted data.

VI. CONCLUSION

In this paper we have proposed a new resource allocation framework for big data MSaaS at the cloud edges IoTs and fogs. In this proposed approach, data dependencies in spatial, frequency and temporal domains are analyzed, and interaction with uplink resource allocation optimization are investigated with regards to wireless communication energy cost estimation. Energy efficiency and QoE were investigated with various resource allocation strategies, and the impacts of flexible channel coding rate were studied. Application layer prioritization of premium and best effort regular packets was designed in conjunction with link layer and physical layer resource allocation strategies for multimedia sensing users. Simulation results demonstrated that the proposed new MSaaS framework with prioritization of premium packets and best effort regular packets has significant energy efficiency potentials for big data multimedia communications.
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