Proportionally-Fair Sequencing and Scheduling for Machine-Type Communication

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***Abstract*—We consider uplink machine-type communication (MTC) from energy-constrained devices following the time division multiple access (TDMA) protocol. Conventionally, the energy efficiency performance in TDMA is optimized through multi-user scheduling, i.e., changing the transmission block length allocated to different devices. In such a system, the sequence of devices for transmission, i.e., who transmits first and who transmits second, etc., has not been considered as it does not have any impact on the energy efficiency. In this work, we consider that data compression is performed before transmission and show that the multi-user sequencing is indeed important. We propose to jointly optimize both multi-user sequencing and scheduling along with the compression and transmission rate control. Our results show that multi-user sequence optimization significantly improves the energy efficiency performance of the system, and especially the performance gain is large when the delay bound is stringent. This is advantageous for lower latency MTC.**

I. Introduction

The Internet of Things (IoT) is largely based on the energy-intensive uplink communication from energy constrained machine-type communication (MTC) devices and calls for effective energy efficient solutions [1]. In this work, the time division multiple access (TDMA) protocol is considered for the uplink MTC. The TDMA protocol allows deterministic scheduling for data transmission and other operations, such as sensing, signal detection, switching radio off, energy harvesting. Thus, TDMA is preferred for sensor networks [2] and wirelessly powered communication networks [3]. TDMA is also adopted for the IEEE 802.11ad standard and mmWave channel access in 5G networks [4].

The performance of the TDMA protocol is enhanced by optimizing the multi-user scheduling, i.e., by changing the transmission time allocated to different devices within a frame, whilst maximizing a given system objective. For example, a device allocated with a relatively longer transmission time can adapt the transmission rate for a given channel gain, to achieve better energy efficiency and vice versa. The choice of system objective involves considering the trade-off between the overall performance and the fairness among devices, e.g., in a proportionally-fair manner.

For a wireless power transfer scenario, the TDMA multi-user scheduling is optimized for the sum and max-min energy minimization objectives in [3]. Similarly, the proportional-fairness objective is considered in [5] to strike a balance between multi-user fairness and energy minimization. Similarly, in [6] the trade-off between sum throughput and energy is controlled through multi-user scheduling. In [7], the multi-user scheduling is optimized and the sum throughput is maximized for energy harvesting devices. The system energy efficiency is maximized in [8] by jointly optimizing the multi-user scheduling and transmit power subject to individual QoS requirements. *To the best of our knowledge, none of the above papers investigate multi-user sequencing.*

Moreover, for energy-constrained MTC devices, data compression schemes have been proposed in [9] and [10] to reduce the amount of data to be transmitted and thus alleviate the overall energy cost. Unlike the transmission energy cost which linearly increases with the size of data to be transmitted, the compression energy cost has a non-linear relationship with the compression ratio [11]. Owing to this non-linearity, blindly applying too much compression may exceed the energy cost of transmitting raw data, thereby losing its purpose [12], [13].

Paper Contributions: We consider a TDMA-based multi-user uplink MTC system, in which each MTC device transmits data to a base station (BS) within its allocated transmission block. We consider that the devices apply data compression before the start of their scheduled transmission block and transmit the compressed data in the allocated transmission block. The main novelty of this work lies in the proposed multi-user sequencing, i.e., the order in which the devices are scheduled for transmission in the TDMA protocol.

Conventionally, the TDMA performance is only optimized through multi-user scheduling. In particular, the order or sequence of devices has no significance, given the channel statistics do not change from one transmission block to the other. However, in our proposed system the sequence of allocating the devices to the transmission blocks affects the amount of time allowed for applying data compression.

Our investigation leads to the following technical contributions and observations:

1) We propose an approximation algorithm to solve the challenging mixed-integer nonlinear program of the multi-user sequencing and scheduling.
2) The improvement due to multi-user sequence optimization is up to 35%.

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3) The energy efficiency gain is most significant when the delay bound is stringent. Hence, the proposed scheme is advantageous for lower latency MTC.

II. SYSTEM MODEL

We consider a system consisting of N MTC devices transmitting data packets to a BS. The devices are energy-constrained, whereas the BS has no energy constraint. Each device has a data packet of a specific length which need to be transmitted within a frame of length T_{frame} (in seconds) following the TDMA protocol as shown in Fig. 1. We assume perfect synchronization among the devices [3], [5].

The BS determines the TDMA sequence and schedule and allocates frame segments (referred to as the transmission blocks) to individual devices before the start of the frame. Each device applies data compression before the start of its scheduled transmission block and then transmits the compressed data in the allocated transmission block, as shown in Fig. 1. The device allocated with the first transmission block in the frame performs both the data compression and transmission operations within its allocated transmission block. The devices switch to a power saving state when they are neither compressing nor transmitting data and consume negligible energy.

Channel model: The BS and all the devices are each equipped with an omnidirectional antenna. The distance between the ith device and the BS is d_i meters. The channel between each device and the BS is composed of a large-scale path loss, with path loss exponent α, and a small-scale quasi-static frequency-flat Rayleigh fading channel. The fading channel coefficient for the ith device is denoted as h_i. All the fading channel coefficients remain unchanged over a frame and are perfectly estimated by the BS [3], [14]. The noise is assumed to be additive white Gaussian noise (AWGN) with zero mean and variance σ^2.

MTC device sequencing and scheduling: Before each frame, the BS broadcasts a control packet which contains the sequence and schedule and the optimal compression and transmission parameters for each device. The frame duration, T_{frame}, is divided into N transmission blocks as

$$T_{\text{frame}} = \sum\nolimits_{n=1}^{N} T_n, \tag{1}$$

where T_n is the duration of nth transmission block. A device allocated with a later transmission block in the frame has more time to perform data compression. Thus, the position of the transmission block, which depends upon the multi-user sequence, affects its overall energy cost. Let us define

$$x_{n,i} = \begin{cases} 1, & \text{if } n\text{th block is allocated to } i\text{th device,} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Each transmission block is allocated to only one device, i.e.,

$$\sum\nolimits_{i=1}^{N} x_{n,i} = 1, \quad \forall n. \tag{3}$$

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$$\sum\nolimits_{n=1}^{N} x_{n,i} = 1, \quad \forall i. \tag{4}$$

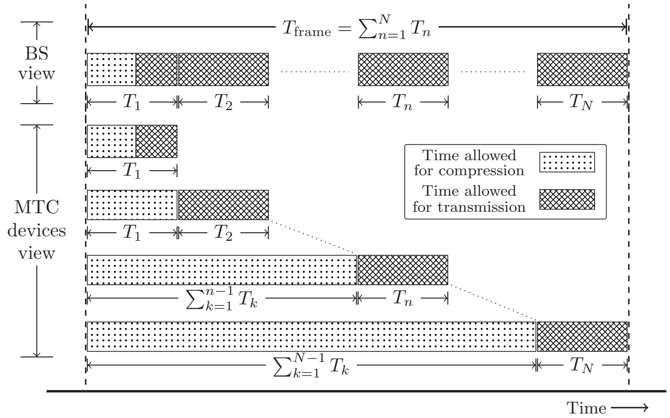

Fig. 1: Timing diagram for the compression and transmission processes within a frame of uplink MTC. For simplicity, this figure only shows the scenario with the same block length.

Compression: Before the start of transmission, each device applies data compression on its raw data. For the ith device, the D_i bits of raw data is compressed into $D_{\text{cp},i}$ bits, resulting in a compression ratio of $\frac{D_{\text{cp},i}}{D_i}$. The *compression time*, $T_{\text{cp},i}$, is defined as the time required by the ith device to compress the raw data, D_i, into the compressed data, $D_{\text{cp},i}$. We employ a generic non-linear compression cost model as proposed in [11]. The parameters of this compression model can be determined off-line for a given compression algorithm using data fitting. The compression time, $T_{\text{cp},i}$, is given as

$$T_{\text{cp},i} = \tau D_n \Big(\big(D_i^{\beta} D_{\text{cp},i}^{-\beta} \big) - 1 \Big), \tag{5}$$

where τ is the per-bit processing time and β is a compression algorithm dependent parameter that is proportional to the compression algorithm's complexity. τ depends upon the MCU processing resources and the number of program instructions executed to process one bit of data. Let P_{cp} be the power consumed by a device during the data compression process. P_{cp} is predefined for a given MTC device hardware.

Transmission: Once the compression process is complete, each device needs to transmit its compressed data within the allocated transmission block. The *transmission time* for the ith device, $T_{\text{tx},i}$, depends upon its compressed data size, $D_{\text{cp},i}$, and its link transmission rate, R_i, as

$$T_{\text{tx},i} = \frac{D_{\text{cp},i}}{R_i}. \tag{6}$$

Here, the transmission rate, R_i, is given as

$$R_i = B \log_2 \Big(1 + \frac{\kappa P_i |h_i|^2}{\Gamma \sigma^2 d_i^{\alpha}} \Big), \tag{7}$$

where B is the bandwidth of the considered system, Γ characterizes the gap between the achievable rate and the channel capacity [3], $\kappa = \left(\frac{\lambda}{4\pi}\right)^2$ is the path loss factor, λ is the wavelength and P_i is the transmit power for the ith device. We consider the transmission power cost is composed of two components: (i) the transmit power P_i and (ii) the static communication module circuitry power P_{o}, which accounts for the operation of the digital-to-analog converter, frequency synthesizer, mixer, transmit filter, antenna circuits, etc. The transmission power cost $P_{\text{tx},i}$ for the ith device is given as

$$P_{\text{tx},i} = P_i \mu^{-1} + P_{\text{o}}, \tag{8}$$

where $\mu \in (0,1]$ is the drain efficiency of the power amplifier.

III. Optimal Multi-User Sequencing and Scheduling Scheme

The MTC devices perform two main operations (i) compression and (ii) transmission, each having individual completion time and energy cost. Recall that the device allocated with the first transmission block performs both these operations within its allocated transmission block, i.e.,

$$x_{1,i} T_{\text{cp},i} + x_{1,i} T_{\text{tx},i} \leqslant T_1, \quad \forall\, i. \tag{9}$$

For all other devices that are allocated the remaining transmission blocks, they can apply data compression on the raw data during the period between the start of the frame and the start of its allocated transmission block. This implies that

$$\sum\nolimits_{n=2}^{N} x_{n,i} T_{\text{cp},i} \leqslant \sum\nolimits_{n=2}^{N} \sum\nolimits_{k=1}^{n-1} x_{n,i} T_k, \ \forall\, i. \tag{10}$$

After compression, each device transmits the compressed data within its allocated transmission block. This implies that

$$\sum\nolimits_{n=2}^{N} x_{n,i} T_{\text{tx},i} \leqslant \sum\nolimits_{n=2}^{N} x_{n,i} T_n, \ \forall\, i. \tag{11}$$

The main problem we address is to determine the optimal length of transmission blocks allocated to devices (i.e., scheduling), the sequence of allocated transmission blocks, the compression and transmission policies for all devices. The aim is to minimize the energy consumption of the devices, under given delay and power constraints. Each device needs to know the following parameters for its operation: (i) the starting time for its compression and transmission processes, (ii) the processing time allowed for its compression and transmission processes, (iii) the optimal compression ratio, and (iv) the optimal transmission rate.

The energy cost of the ith device is given as $E_i = P_{\text{cp}} T_{\text{cp},i} + P_{\text{tx},i} T_{\text{tx},i}$. Substituting the values for $T_{\text{cp},i}$, $P_{\text{tx},i}$ and $T_{\text{tx},i}$ from (5), (6), (8) here yields

$$E_i = P_{\text{cp}} \tau \Big(\frac{D_i^{\beta+1}}{D_{\text{cp},i}^{\beta}} - D_i \Big) + \frac{B^{-1} D_{\text{cp},i}}{\log_2 \big(1 + \kappa \frac{P_i |h_i|^2}{\Gamma \sigma^2 d_i^{\alpha}}\big)} \Big(\frac{P_i}{\mu} + P_{\text{o}} \Big). \tag{12}$$

Proportionally-fair energy minimization: In the literature, there are three popular system objectives for energy minimization, which differ in terms of the overall system performance and fairness among the MTC devices. These system objectives are (i) sum energy minimization, (ii) min-max energy minimization, and (iii) proportionally-fairness energy minimization. The motivation behind the proportionally-fair energy minimization objective is to strike a balance between the system energy efficiency and the energy-fairness among the MTC devices.

The proportionally-fair objective achieves some level of fairness among devices by providing each device with a performance that is proportional to its signal power attenuation conditions. This is achieved by reducing the opportunity of the devices with low signal power attenuation, getting more share of system resources to the weak devices. More system resources are allocated to the devices when their instantaneous signal power attenuation is low relative to their own signal power attenuation statistics. Thereby, proportional-fairness is achieved without compromising much energy efficiency performance. Since the signal power attenuation fluctuates independently for different devices, this strategy effectively exploits multi-user diversity. This can be achieved by minimizing the sum of logarithmic energy cost function of the individual devices [14], i.e., $\sum_{i=1}^{N} \log(E_i)$, where E_i is defined in (12).

Optimization problem: The optimization problem for the proposed scheme is formulated as follows

$$\underset{\substack{P_i,\, D_{\text{cp},i},\, T_n,\\ x_{n,i},\, \forall\, n,i}}{\text{minimize}} \quad \sum\nolimits_{i=1}^{N} \log \Big(E_i \big(P_i, D_{\text{cp},i}\big) \Big) \tag{13a}$$

$$\text{subject to} \quad \sum\nolimits_{n=1}^{N} T_n = T_{\text{frame}}, \tag{13b}$$

$$x_{1,i} \tau \Big(\frac{D_i^{\beta+1}}{D_{\text{cp},i}^{\beta}} - D_i \Big) + \frac{x_{1,i} B^{-1} D_{\text{cp},i}}{\log_2 \big(1 + \kappa \frac{P_i |h_i|^2}{\Gamma \sigma^2 d_i^{\alpha}}\big)} \leqslant T_1, \quad \forall\, i, \tag{13c}$$

$$\sum_{n=2}^{N} x_{n,i} \tau \Big(\frac{D_i^{\beta+1}}{D_{\text{cp},i}^{\beta}} - D_i \Big) \leqslant \sum_{n=2}^{N} \sum_{k=1}^{n-1} x_{n,i} T_k, \quad \forall\, i, \tag{13d}$$

$$\sum_{n=2}^{N} x_{n,i} \frac{B^{-1} D_{\text{cp},i}}{\log_2 \big(1 + \kappa \frac{P_i |h_i|^2}{\Gamma \sigma^2 d_i^{\alpha}}\big)} \leqslant \sum_{n=2}^{N} x_{n,i} T_n, \quad \forall\, i, \tag{13e}$$

$$\sum\nolimits_{i=1}^{N} x_{n,i} = 1, \qquad \forall\, n, \tag{13f}$$

$$\sum\nolimits_{n=1}^{N} x_{n,i} = 1, \qquad \forall\, i, \tag{13g}$$

$$0 \leqslant P_i \leqslant P_{\max}, \qquad \forall\, i, \tag{13h}$$

$$D_{\min,i} \leqslant D_{\text{cp},i} \leqslant D_i, \qquad \forall\, i, \tag{13i}$$

$$0 \leqslant T_n \leqslant T_{\text{frame}}, \qquad \forall\, n, \tag{13j}$$

$$x_{n,i} \in \{0,1\}, \qquad \forall\, n, i, \tag{13k}$$

where (13d) and (13e) are obtained by substituting the values of compression and transmission time from (5) and (6), in to inequalities (9), (10) and (11), respectively. $P_{\max}$ is the maximum transmit power constraint for each device. $D_{\min,i}$ is the lower bound on the compressed data size for the ith device. Thus, the maximum compression that can be applied is given by the minimum compression ratio defined as $\frac{D_{\min,i}}{D_i}\, \forall\, i$. The maximum compression ratio depends on the nature of the data and the system application. Note that a device may not fully utilize its allocated transmission block, depending upon its optimal compressed data size and/or the transmission rate.

IV. Solution Approach

The optimization problem in (13) is a mixed-integer nonlinear program which is non-convex in its natural form. Therefore, it is very challenging to determine the globally optimal solution or even to determine if the globally optimal solution exists [15].

Lemma 1. *For each multi-user sequence, the optimization problem in* (13) *can be transformed into an equivalent convex sub-problem. The globally optimal solution for one of these equivalent sub-problems which minimizes the objective function in* (13) *is the globally optimal solution of problem* (13).

Proof: For brevity we omit the details of the proof. Please see [16] for the proof. ■

Approximation approach: Let us now propose an alternative problem modelling approach to handle the binary constraints, which targets a more computationally feasible implementation. Note that for a real variable $x_{n,i} \in [0,1]$, we have $x_{n,i} \geqslant x_{n,i}^2, \ \forall n,i$. To this end, we can write

$$\begin{aligned} x_{n,i} \in \{0,1\} &\Leftrightarrow x_{n,i} - x_{n,i}^2 = 0 \\ &\Leftrightarrow \big(x_{n,i} \in [0,1] \ \& \ x_{n,i} - x_{n,i}^2 \leqslant 0\big), \forall n,i, \end{aligned} \tag{14}$$

and adopt the approach of [17–20] to rewrite (13k) as

$$\sum\nolimits_{n=1}^{N} \sum\nolimits_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right) \leqslant 0, \tag{15}$$

$$0 \leqslant x_{n,i} \leqslant 1, \quad \forall n,i. \tag{16}$$

In this way, we relax the binary variables $x_{n,i} \in \{0,1\}, \forall n,i$, in (13) to real variables $x_{n,i} \in [0,1], \forall n,i$, and introduce a cost function that penalizes the objective in (13) to impose $x_{n,i} = x_{n,i}^2, \ \forall n,i$ [18]. Therefore, the binary to real variable transformation leads to the following equivalent problem

$$\begin{aligned} \underset{\substack{P_i,\, D_{\text{cp},i},\, T_n,\\ x_{n,i},\, \forall\, n,i,}}{\text{minimize}} \quad & \sum_{i=1}^{N} \log\left(E_i\right) + \Lambda \sum_{n=1}^{N}\sum_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right) \\ \text{subject to} \quad & \text{(13b)} - \text{(13e)},\ \text{(13h)} - \text{(13j)},\ \text{(16)}, \end{aligned} \tag{17}$$

where $\Lambda \geqslant 0$ is a constant penalty factor. The term $\sum_{n=1}^{N} \sum_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right)$ in (17) is the penalizing function on violation of the binary constraints over the energy minimization objective. Its magnitude quantifies the degree of violation from the binary constraints. Λ embodies the cost of this violation from the binary values $x_{n,i}, \forall n,i$. The minimizer of (17) will satisfy the binary constraints, $x_{n,i} \in \{0,1\}, \forall n,i$, for a finite value of Λ, i.e., the penalization is exact [15]. Thus, the optimization problems defined in (13) and (17) are equivalent, and the same optimal solution minimizes both the objective functions for a suitable value of Λ [18].

The non-negative term $\sum_{n=1}^{N} \sum_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right)$ in (17) decreases to 0 as $\Lambda \to +\infty$. Ideally, we need this term to be zero, and for that we would have to derive the optimal value of the penalty factor, Λ^*. For practical computational feasibility, let us introduce a numerical tolerance level such that it is acceptable to have $\sum_{n=1}^{N} \sum_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right) < \epsilon$, where ϵ is very small and Λ is sufficiently large. Following [17] and [18], in our numerical experiments we found $\Lambda \geqslant 200$ is large enough to satisfy a tolerance level of $\epsilon = 10^{-6}$ such that $\sum_{n=1}^{N} \sum_{i=1}^{N} \left(x_{n,i} - x_{n,i}^2\right) \leqslant \epsilon$.

Note that the penalty function in (17) is non-convex in $x_{n,i}, \ \forall n,i,$. Consider a non-convex quadratic function $g(x) \triangleq x - x^2$, where $x \in [0,1]$. If we apply the first-order Taylor series expansion at a given point $x^{(j)} \in [0,1]$, we can obtain

Algorithm 1 Iterative Approach for Multi-User Sequencing and Scheduling Optimization

1: **Initialization**: Set iteration count $j = 0$. Set initial point for $x_{n,i}^{(j)} = 0.5, \forall n,i$. Select a reasonably high penalty value $\Lambda = 200$ and low tolerance value $\epsilon = 10^{-6}$.
2: **while** $\sum_{n=1}^{N} \sum_{i=1}^{N} \left(x_{n,i}^{(j)} - \left(x_{n,i}^{(j)}\right)^2\right) \geqslant \epsilon$ **do**
3: Solve (19) using point $x_{n,i}^{(j)}, \forall n,i$ and get solution parameters Z_i^*, $D_{\text{cp},i}^*$, T_n^*, $x_{n,i}^*, \forall n,i$.
4: Update point $x_{n,i}^{(j+1)} = x_{n,i}^*, \forall n,i$
5: Update iteration count $j = j+1$
6: **end while**

the convex lower bound on $g(x)$ as [20]

$$x\big(1 - 2x^{(j)}\big) + \big(x^{(j)}\big)^2 \leqslant x - x^2. \tag{18}$$

Similarly, the convex lower bound on the penalty function can also be given as

$$\sum_{n=1}^{N}\sum_{i=1}^{N} \left(x_{n,i}\big(1-2x_{n,i}^{(j)}\big)+\big(x_{n,i}^{(j)}\big)^2\right) \leqslant \sum_{n=1}^{N}\sum_{i=1}^{N} \left(x_{n,i}-x_{n,i}^2\right).$$

Moreover, substitute $Z_i = \ln\left(1+\kappa\frac{P_i|h_i|^2}{\Gamma\sigma^2 d_i^\alpha}\right)$, $V_i = \ln\left(D_{\text{cp},i}\right)$, and $Z_{\max} = \ln\left(1+\kappa\frac{P_{\max}|h_i|^2}{\Gamma\sigma^2 d_i^\alpha}\right)$ in (17). Accordingly, for a given point $x_{n,i}^{(j)} \in [0,1]$, the global upper bound minimization for problem (17) is given as

$$\underset{\substack{Z_i,\, V_i,\, T_n,\\ x_{n,i},\, \forall\, n,i,}}{\text{minimize}} \quad \sum_{i=1}^{N} \log\left(E_i\right) + \Lambda \sum_{n=1}^{N}\sum_{i=1}^{N} \left(x_{n,i}\big(1-2x_{n,i}^{(j)}\big)+\big(x_{n,i}^{(j)}\big)^2\right) \tag{19a}$$

subject to (13b), (13j), (16),

$$x_{1,i}\left(\frac{\tau D_i^{\beta+1}}{\exp\left(\beta V_i\right)} - \tau D_i\right) + \frac{x_{1,i} B^{-1} \ln(2)}{Z_i \exp\left(-V_i\right)} \leqslant T_1, \quad \forall i, \tag{19b}$$

$$\sum_{n=2}^{N} x_{n,i}\left(\frac{\tau D_i^{\beta+1}}{\exp\left(\beta V_i\right)} - \tau D_i\right) \leqslant \sum_{n=2}^{N}\sum_{k=1}^{n-1} x_{n,i} T_k, \quad \forall i, \tag{19c}$$

$$\sum_{n=2}^{N} x_{n,i} \frac{\exp\left(V_i\right)\ln(2)}{B Z_i} \leqslant \sum_{n=2}^{N} x_{n,i} T_n, \quad \forall i, \tag{19d}$$

$$0 \leqslant Z_i \leqslant Z_{\max}, \qquad \forall i, \tag{19e}$$

$$\ln(D_{\min,i}) \leqslant V_i \leqslant \ln(D_i), \qquad \forall i, \tag{19f}$$

where $b_i = \frac{\Gamma\sigma^2 d_i^\alpha \ln(2)}{\mu B \kappa |h_i|^2}$, $c_i = \frac{\mu\kappa|h_i|^2 P_o}{\Gamma\sigma^2 d_i^\alpha} - 1$. It can be shown that (19) is jointly convex in $Z_i, V_i, T_n, x_{n,i}, \ \forall\, n,i$.

Implementation: Algorithm 1 outlines the steps to find the solution to the nonconvex problem (13) by iteratively solving the convex problem (19). In the first iteration, $j = 1$, problem (19) is solved using the initially guessed points, $x_{n,i}^{(j)}, \forall n,i$. The solution for the jth iteration $x_{n,i}^*, \forall n,i$ is used as an initial point for next iteration $j+1$. This process is repeated until convergence is achieved. The final solution yields the optimal parameters for multi-user sequencing and scheduling and compression and transmission rates for problem (13) due to its equivalence to problem (19).

TABLE I: System Parameter Values.

Name	Sym.	Value	Name	Sym.	Value
Amplifier's drain efficiency	μ	0.35	Max. transmit power	P_{max}	0 dB
Scale parameter for channel gain	ς	1	Wavelength	λ	0.333 m
Compression processing power	P_{cp}	24 mW	No. of devices	N	5
Comm. module circuitry power	P_{o}	82.5 mW	Bandwidth	B	1 MHz
Practical modulation power gap	Γ	9.8 dB	Packet size	D_i	{310,500,100,80,200} kbits
Minimum compression ratio	$\frac{D_{\text{min},i}}{D_i}$	0.4	Distance	d_i	{40,15,31,49,22} m
Per-bit processing time	τ	7.5 ns/b	Noise spectral density	N_0	−174 dBm
Compression cost parameter	β	5	Pathloss exponent	α	4

V. Numerical Results

The values for the parameters shown in Table I are adopted for numerical results, unless specified otherwise. Algorithm 1 is implemented in AMPL, which is popular for modelling scheduling problems. A model for the proposed problem is developed in the AMPL environment and the Couenne (convex over and under envelopes for nonlinear estimation) solver [21], [22] is used to solve the problem. The Couenne solver guarantees the globally optimal solution if such a solution exists and we have this condition fulfilled from Lemma 1.

Let us define system energy cost as the total energy cost of all the devices, i.e., $\sum_{i=1}^{N} E_i$. Moreover, the energy efficiency gain, $\mathbb{G}_{\text{ee}}$, provided by a given scheme A over scheme B be defined as the percentage decrease in the system energy cost of scheme B, $\sum_{i=1}^{N} E_{i,B}$, in comparison to the system energy cost of scheme A, $\sum_{i=1}^{N} E_{i,A}$, and it is given as

$$\mathbb{G}_{\text{ee}} = \frac{\sum_{i=1}^{N} E_{i,B} - \sum_{i=1}^{N} E_{i,A}}{\sum_{i=1}^{N} E_{i,B}}. \tag{20}$$

We compare the performance of the proposed optimal scheme with the following systems:

1) *State-of-the-art* which we label as the benchmark scheme. To the best of our knowledge, the recent works [3], [5], [8], [14] are the most relevant to our proposed scheme. We adopt the multi-user scheduling and transmission rate design policies proposed by these schemes for our considered system model except that data compression and multi-user sequencing are not employed. Thus, in the benchmark scheme the multi-user sequence is fixed but the transmission block length of any device is flexible and can be optimized. This scheme does not include data compression and multi-user sequencing optimization. The transmission rate and the transmission block length (scheduling) are jointly optimized for the given proportionally-fair energy minimization objective for a fixed sequence and without employing data compression. The strategy followed to optimize the multi-user scheduling and transmission rate policies for this benchmark scheme is essentially the same as in the state of the art [3], [5], [8], [14].

2) *Sub-optimal Scheme:* In this scheme compression is employed but, unlike the optimal scheme, does not consider multi-user sequencing. For the sub-optimal scheme, the multi-user sequence is fixed and unchanged from one frame to the next. However, the transmission block length of any device is flexible, and hence is optimized. In this scheme, the transmission rate, compression ratio, and the transmission block length (multi-user scheduling) are jointly optimized for the proportionally-fair energy minimization objective for a fixed multi-user sequence (i.e., $\{x_{n,i}, \forall n, i\}$ is known).

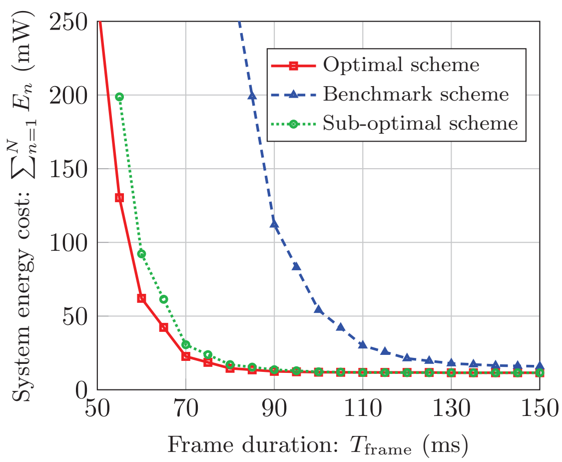

Fig. 2: System energy cost under given power constraints.

The optimization problems of both the benchmark and the sub-optimal scheme can be formulated and solved in similar ways as done for the optimal scheme. We do not present the details here, but they can be found in [16].

Validation: Let us first carry out a comparative analysis of the proposed scheme with the benchmark scheme (which represents existing state-of-the-art work). Fig. 2 plots the system energy cost, $\sum_{i=1}^{N} E_i$, versus the frame duration, T_{frame}, for the system parameters in Table I. The system energy cost is plotted with the proposed optimal scheme and benchmark scheme in Fig. 2. When compared with the benchmark scheme, the proposed optimal scheme exhibits significant performance superiority. This shows that employing both multi-user sequence and compression optimization provides notable gains in the energy efficiency, especially in the lower latency regime.

The energy efficiency gain, $\mathbb{G}_{\text{ee}}$, provided by the proposed optimal scheme over benchmark scheme is plotted in Fig. 3. It is shown that the gain is comparatively significant (between 27% to 95%), for the considered range of delay when the system is feasible for benchmark scheme (between 80 ms to 150 ms). For the benchmark scheme, the device energy cost is reduced by adapting the minimum required transmit power level under given channel conditions. However, reducing transmission rate through transmit power only helps up to a certain level and any further reduction does not improve the energy

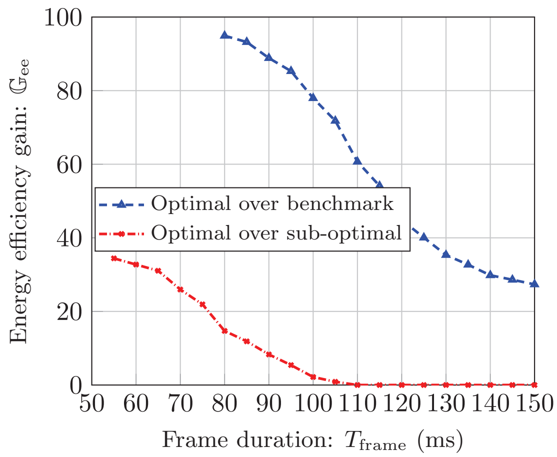

Fig. 3: Energy efficiency gain performance for the optimal scheme over the sub-optimal scheme and benchmark scheme.

efficiency. Hence, in general, it is not optimal to transmit at the lowest transmission rate. Note that for the proposed optimal scheme the lower bound delay has a much smaller value as compared to the benchmark scheme.

Impact of Multi-User Sequencing: Let us now illustrate the advantage of the multi-user sequencing. In both optimal scheme and sub-optimal schemes, the multi-user scheduling and compression are optimized. However, they differ in an important aspect that the multi-sequencing is employed by the proposed optimal scheme and not by sub-optimal scheme, which uses a fixed multi-user sequence.

From Fig. 2, the proposed optimal multi-user sequencing and scheduling scheme clearly outperforms the sub-optimal scheme. Intuitively, it was expected that the multi-user sequencing will always provide non-negative gains. However, the gains are notable for a wide range of delay when the system is feasible for the sub-optimal scheme as shown in Fig. 3. Also, in the lower latency regime the gains are significantly high, between 12% to 35% for the delay range from 55 ms to 85 ms. On the other hand, for a less stringent delay constraint, employing the multi-user sequencing will not pay off. At the same time, it can be concluded that the data compression provides significant gains for all types of delay constraints.

VI. Conclusion

In this paper, we have investigated the joint optimization of sequencing and scheduling in a multi-user uplink MTC scenario, considering adaptive compression and transmission rate control design. Our results have showed that the proposed optimal scheme outperforms the schemes without multi-user sequencing and improves energy efficiency by up to 35% under the given maximum transmit power and delay constraints. The energy efficiency gain of multi-user sequence optimization is paramount under a stringent delay bound. Thus, multi-user sequence optimization makes the TDMA-based multi-user transmissions more likely to be feasible in the lower latency regime subject to the given power constraints.

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