Optimal Packet Scheduling in Energy Harvesting Multiple Access Channels with Common Data

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Abstract—Energy harvesting with the optimum power consumption and packet scheduling increase the lifetime and sustainability of the wireless sensor networks (WSNs) leading to green communications. Optimal packet scheduling solutions available for 2-user multiple-access channel (MAC) systems with energy harvesting transmitters do not consider the common data observed when collected sensor data is spatially or temporally correlated. Furthermore, the total received energy depends on the amount spent on the common data. In this paper, optimal packet scheduling for energy harvesting Gaussian MAC with common data is achieved by assuming the deterministic knowledge of the data and energy packets, i.e., offline solution, while also modelling the effect of the total received energy constraint. Optimum solution is achieved practically with a complex 3-level water filling algorithm. The algorithm is compared with the gradient descent search algorithm giving the global optimum solution. Furthermore, the capacity boundary region is numerically simulated by using water filling algorithm and the optimization results are compared for various points on the capacity boundary surface.

Index Terms—energy harvesting, MAC, common data, optimization, power.

I. INTRODUCTION

Energy harvesting with the optimum power adaptation and packet scheduling are significantly important for increasing the lifetime and sustainability of wireless sensor networks (WSNs) and for the green communications [1]–[4]. The scarcity and sporadic availability of the energy make it necessary the storage and the optimized utilization. Therefore, optimum energy management, data and energy transfer schemes are significantly important for WSNs.

Optimal packet scheduling in energy harvesting communication systems are achieved in various studies [5]–[9]. In [5], [6], algorithms for single-user energy harvesting communication systems are given. In [7], a directional water filling solution is given for the throughput maximization problem for a single-user fading channel with channel state information (CSI) feedback for energy harvesting finite capacity rechargeable batteries under offline and online knowledge. In [8], a two-hop relaying communication network with energy harvesting rechargeable nodes is optimized. In [9], energy usage is minimized over a wireless channel via changing packet transmission times.

The optimization for MAC schemes are achieved in [11], [2], [10]. Optimal packet scheduling is given for a 2-user MAC with energy harvesting transmitters and deterministic assumption of the data and energy packets, i.e., offline solution. In [11], the capacity region of the energy harvesting Gaussian MAC is analysed with one-way energy transfer capability while in [2], the capacity is analysed with amplitude constraints and batteryless energy harvesting transmitters. In [8], optimal continuous-time online power policies, in [13], utility maximization framework modelling using a water filling approach and in [4], the effect of storage losses are incorporated. However, these studies do not consider Gaussian MAC with common data in a capacity boundary and throughput maximization analysis and optimum scheduling framework.

Besides that, WSNs collect common data having the spatial or temporal correlation and the correlation is exploited to save the resources [14], [15]. The capacity region in a Gaussian MAC channel with common data and optimum power allocation is characterized in [16] while in [17], similar analyses are achieved for the discrete p-transmitter/q-receiver MAC with a common message. In [18], combination with joint source-channel codes and optimal policies through a memoryless fading MAC are given. In [19], the 2-user Gaussian MAC with common message (MACCM) and with conferencing encoders (MACCE) are analysed. However, there is no study combining the optimum scheduling in a Gaussian MAC with common data in an energy harvesting communication system.

On the other hand, combined data and energy transfer is utilized in energy harvesting systems. In [20], MAC with received energy constraint is analysed showing the trade-off between the data rate and the received energy. In [21], a two-way communication system is considered. In [22], MAC and two way channels with energy harvesting and cooperating transmitters are analyzed. In [23], the energy harvesting MAC relay with bidirectional energy transfer leads to a directional water filling solution. However, there is no study combining optimum scheduling and energy harvesting with received energy constraint in a Gaussian MAC with common data.

To the best of our knowledge, in this work, optimum offline packet scheduling and power policy is, for the first time, modelled, solved and leaded with the unique water filling solution in a Gaussian MAC with common data scheme. Furthermore, the modelling of the problem includes, for the first time, the constraint of the total received energy. The Karush-Kuhn-Tucker (KKT) solution is, for the first time, given for optimum packet scheduling power policy for energy harvesting transmitters in a Gaussian MAC with common data scheme. The 3-level unique water filling algorithm is, for the first time, introduced. The optimality of the water filling algorithm is shown by comparing with the gradient search iterative algorithm in a numerical simulation study. The capacity boundary region for the rates of the individual
and the common data messages is numerically simulated with the optimum solution. The optimum packet scheduling and power consumption profiles are compared by choosing various points on the surface of the capacity boundary. However, in simulation studies the total transmitted energy constraint is not taken into account and left as a future work.

The remainder of the paper is organized as the following. In Section II related work on optimum power allocation policies in energy harvesting communication systems are explored. In Section III the system model for the Gaussian MAC with common data is defined. Then, in Section IV data throughput maximization problem is defined, KKT solution, the water filling and iterative gradient descent algorithms are presented. In Section V a simulation study is performed illustrating optimum scheduling, capacity boundary and the comparison of two algorithms. Finally, in Section VI the conclusions are given and future works are pointed out.

II. RELATED WORK

Optimum online and offline packet scheduling in energy harvesting communication systems are recently investigated for single hop, MAC and broadcast systems respectively.

In [7], a directional water filling optimizes the throughput maximization problem for a single-user fading channel with additive Gaussian noise with finite capacity rechargeable batteries under offline and online knowledge. Optimal packet scheduling for single-user energy harvesting communication systems are presented in [5], [6]. In [8], a two-hop relaying communication network with energy harvesting rechargeable nodes is formulated for the offline end-to-end throughput maximization as a convex optimization problem. In [9], the energy used by a node in a wireless communication network is minimized for the packets to be sent in a given amount of time by varying packet transmission times and power levels by considering both optimum offline and online scheduling.

The similar analyses are achieved for MAC schemes. In [10], the capacity region of the energy harvesting Gaussian MAC is analyzed with one-way energy transfer capability. In [11], [12], [13] optimal packet scheduling problem is solved in a 2-user MAC system with energy harvesting transmitters where the energy harvesting times and harvested energy amounts are known before the transmission. KKT solution and the generalized iterative backward water filling algorithm are presented. In [14], the capacity region of Gaussian MAC with amplitude constraints and batteryless energy harvesting transmitters are analysed. In [15], optimal continuous-time online power policies for energy harvesting MACs are presented. In [16], energy harvesting transmitter and receiver pair is considered in a utility maximization framework achieving power policy using a water filling approach. In [17], optimal transmit power policy for energy harvesting transmitters in a Gaussian MAC is presented by also considering storage losses. However, these studies do not consider the common data in an optimum scheduling and power adaptation framework and do not propose the unique water filling solution obtained when considering common data and also energy transfer.

On the other hand, data correlation in WSNs are significantly important which are exploited to save the power-bandwidth resources [14], [15]. In [16], the explicit characterization of the capacity region in a Gaussian MAC channel with common data and fading is considered. The optimum power allocation schemes that achieve arbitrary rate tuples on the boundary of the capacity region are presented and numerically computed. In [17], the capacity region of the discrete p-transmitter/q-receiver MAC coined as General MAC (GMAC) with a common message is derived. In [18], information-theoretic results and power allocation policies in combination with joint source-channel codes on the transmission of memoryless dependent sources through a memoryless fading MAC are analysed. In [19], 2-user MACCM and MACCE with CSI are analyzed. The capacity results for the Gaussian MAC with cooperative encoders and with additive interference known non-causally to both encoders are presented. However, none of these studies combine energy harvesting, optimum scheduling of transmissions and power adaptation, data rate maximization and modelling of the optimum solution including energy transfer in a Gaussian fading MAC with common data.

The optimization of both data and energy transfer at the same channel in a Gaussian MAC scheme is considered in various works. In [20], MAC with received energy constraint is analysed showing achievable trade-off between the data rate and the received energy. In [21], a two-way communication system is considered where the energy used for communication is recycled. In [22], MAC and two way channels with energy harvesting and energy cooperating transmitters are analysed for jointly optimal transmit power allocation and energy transfer policies achieving the sum-capacity. In [23], the energy harvesting multiple access relay channel with bidirectional energy transfer is optimized for the sum rate and a directional water filling solution is proposed. However, none of these studies combine common data in a Gaussian MAC, gives the optimum solution for the capacity boundary in an offline scheduling framework.

III. SYSTEM MODEL

In this paper, the Gaussian MAC has two transmitters and one receiver as shown in Fig. 1 where the components of the system model are seen [11], [12], [16].

Each user has their individual data packets and also a common message known by both transmitters. It is assumed
that energy harvesting amounts and the times are known. Similar to [1, 2], energy harvesting times are put in ascending order and the length of the time interval between two energy harvesting instants $t_n$ and $t_{n+1}$ is denoted by $L(n)$. For example, 1st user harvests $E_1(n)$ at the time instant $t_n$ and 2nd user harvests $E_2(n+1)$ at the time instant $t_{n+1}$. The users do not change the data rate in these intervals. The capacity of the data rate in a time interval $L$ with the total power $P$ is denoted by $C(P)$ and given by the following,

$$C(P) = W_{tot} \log \left(1 + \frac{P}{A}\right) L$$

where $W_{tot}$ refers the total bandwidth and the constant $A$ equals to $N_0 W_{tot} / h$ where $N_0$ is the noise spectral density and $h$ is the fixed path loss.

In this article, we assume offline solution [2]. Data packets are available at the start of each time interval, the harvested energy is stored in sensor nodes and the fading is constant and known previously. The target is to find the maximum data throughput regions for the three kinds of user data for any given deadline time $T_f$ and propose a water filling algorithm finding the optimal solution.

We can model the Gaussian MAC as the following,

$$X_i = \sqrt{P_1}X_1^i + \sqrt{P_2}P_{1,x_2}^i, \; i \in [1, 2]$$  \hspace{1cm} (2)

$$Y = H_1X_1 + H_2X_2 + Z, \; Z \sim N(0, 1)$$  \hspace{1cm} (3)

$$= h \left(\sqrt{P_1}X_1^i + \sqrt{P_2}X_2^i + \sqrt{P_0}X_0^i\right)$$  \hspace{1cm} (4)

where we assume that the fading is $H_1 = H_2 = h$ and unity throughout the formulation. The power of the correlated information can be found as $P_0 = \left(\sqrt{P_1} - P_1 + \sqrt{P_2} - P_2\right)^2$. A constant $0 \leq \rho \leq 1$ is defined such that $\mathcal{T}_1 = P_1 + \rho^2 P_0$ and $\mathcal{T}_2 = P_2 + (1 - \rho)^2 P_0$. Three independent messages are $W_0, W_1$ and $W_2$ where $W_0$ is known by both the users. The capacity region with the common data is the following [16],

$$R_1 \leq C(P_1); \; R_2 \leq C(P_2); \; R_1 + R_2 \leq C(P_1 + P_2)$$  \hspace{1cm} (5)

$$R_1 + R_2 + R_0 \leq C(P_1 + P_2 + P_0)$$  \hspace{1cm} (6)

where $0 \leq P_1 \leq \mathcal{T}_1, 0 \leq P_2 \leq \mathcal{T}_2$ and $P_0 = \left(\sqrt{P_1} - P_1 + \sqrt{P_2} - P_2\right)^2$. The capacity region $B(P_1, P_2)$ can be observed in Fig 2 for some specific $P_1 \leq \mathcal{T}_1$ and $P_2 \leq \mathcal{T}_2$. This region will be valid for both single time interval and for the overall capacity region throughout the energy harvesting process. The important boundary points on the curve are as the following [16],

$$Q = (0, 0, C(P_{0,2}^*)); \; S = (C(P_1^*), 0, C(P_{0,2}^*) - C(P_1^*))$$  \hspace{1cm} (7)

$$T = (C(P_1^*), C(P_{1,2}^*) - C(P_1^*), C(P_{0,2}^*) - C(P_{1,2}^*))$$  \hspace{1cm} (8)

where $P_{0,2}^* = P_0 + P_1 + P_2, P_{1,2}^* = P_1 + P_2$. The points V and U can be obtained in the same manner with S and T by changing the roles of the user 1 and 2. It is proved in [16] that all the points on the capacity region of Gaussian MAC can be achieved by some point on the line segment $T - U$ of $B(P_1, P_2)$ for some $0 \leq P_1 \leq \mathcal{T}_1, 0 \leq P_2 \leq \mathcal{T}_2$ and are the union of $C(\mathcal{T}_1, \mathcal{T}_2) = \bigcup_{P, \rho \in \mathcal{R}} C_f(P, \rho)$ where $C_f(P, \rho)$ is the set of $R_1, R_2, R_0$ in (5) and the set $F$ is the following,

$$F = \left\{ (P, \rho) : \; P_0, P_1, P_2 \geq 0, 0 \leq \rho \leq 1, \; P_1 + \rho^2 P_0 \leq \mathcal{T}_1, P_2 + \rho^2 P_0 \leq \mathcal{T}_2 \right\}$$  \hspace{1cm} (9)

It is stressed out that the boundary surface of $C(\mathcal{T}_1, \mathcal{T}_2)$ can be found with the following optimization problem which will be used throughout the paper,

$$\max_{R, P, \rho} \mu_1 P_1 + \mu_2 P_2 + \mu_0 R \; \text{s.t.} \; R \in C_f(P, \rho)$$  \hspace{1cm} (10)

Since $C_f(P, \rho)$ has a capacity boundary surface as in Fig 2 we can find Q, S and T points by using (7-8). V and U can be found by swapping the roles of two users. It is observed that for various $\mu$ values, various boundary points maximize $C(\mathcal{T}_1, \mathcal{T}_2)$ as in the following,

$$\mu_0 \geq \max(\mu_1, \mu_2) \rightarrow Q; \; \mu_1 \geq \mu_2 \geq \mu_0 \rightarrow T$$  \hspace{1cm} (11)

$$\mu_1 \geq \mu_0 \geq \mu_2 \rightarrow S; \; \mu_2 \geq \mu_1 \geq \mu_0 \rightarrow U$$  \hspace{1cm} (12)

$$\mu_2 \geq \mu_0 \geq \mu_1 \rightarrow V$$  \hspace{1cm} (13)

where $U : (C(P_{1,2}^* - C(P_2), C(P_2), C(P_{0,2}^*) - C(P_{1,2}^*)$ and $V : (0, C(P_2), C(P_{0,2}^*) - C(P_2))$. It is known that $C_f(P, \rho)$ is a convex region [2, 11, 16] leading to convex solution of the optimal offline scheduling capacity. Then, based on the optimization method for a single time interval in [16], the optimal scheduling will be achieved which maximizes the overall capacity region for some specific energy harvesting scenario. The overall capacity of a number of time intervals is found by summing the capacities in each time interval similar to the MAC scheduling framework in [2] where no common data is assumed. Then, the points on the capacity or the maximum data throughput will be obtained by changing $\mu_{1,2,3}$ and maximizing $C(\mathcal{T}_1, \mathcal{T}_2)$.
IV. DATA THROUGHPUT MAXIMIZATION AND OPTIMUM POWER POLICY

The points on the 3-D capacity curve of $R_0, R_1, R_2$ are found by using the cases $\mu_1 \geq \mu_2 \geq \mu_0$, $\mu_1 \geq \mu_0 \geq \mu_2$, $\mu_0 \geq \max(\mu_1, \mu_2)$ for the half part of the curve \[16\]. The other half part can be found by changing the roles of the nodes and $\mu_1$ and $\mu_2$. Firstly, the optimization problem is defined, then, KKT conditions are written similar to the study in \[2\] with the difference of the incorporation of the common data and the constraint for the total received energy. Then, the water filling algorithm for the KKT solution will be presented. The iterative gradient descent algorithm gives the global solution and it is compared with the water filling algorithm.

A. Capacity Maximization Problem

Optimization problem is defined for three different rate tuples given in \[11\] [2], \[16\].

1) $\mu_1 \geq \mu_2 \geq \mu_0$:

$$\max \sum_{k=1}^{3} \text{OF}_{1,k}$$  \hspace{1cm} (14)

s.t. positive power and the sharing constraint for $P_0$,

$$P_1(n), P_2(n), P_0(n) \geq 0, 0 \leq \rho(n) \leq 1; 1 \leq n \leq N$$  \hspace{1cm} (15)

causality constraints for the the total energy,

$$\sum_{n=1}^{N} P_1(n)L(n) - E_1^{T,1} = 0; \sum_{n=1}^{N} P_2(n)L(n) - E_2^{T,1} = 0$$  \hspace{1cm} (16)

where $P_1(n) = P_1(n) + \rho_2^2 P_0(n)$, $P_2(n) = P_2(n) + (1 - \rho(n))^2 P_0(n)$, $E_1^{T,i} = \sum_{n=i+1}^{N} E_{j,n}$ for $j = \{1, 2\}$, for the consumed energies in the time interval $[i, N]$ for $i \geq 2$,

$$\sum_{n=i}^{N} P_1(n)L(n) + E_1^{T,i} \leq 0; \sum_{n=i}^{N} P_2(n)L(n) + E_2^{T,i} \leq 0$$  \hspace{1cm} (17)

and the total received power constraint,

$$\sum_{n=1}^{N} \rho(n)(\theta - \rho(n))P_0(n)L(n) + E_{th} \leq 0$$  \hspace{1cm} (18)

where objective function (OF) for the point $T$ is following,

$$\text{OF}_{1,1} = -\mu_0 \sum_{n=1}^{N} C(P_0(n) + P_1(n) + P_2(n))$$  \hspace{1cm} (19)

$$\text{OF}_{1,2} = -(\mu_2 - \mu_0) \sum_{n=1}^{N} C(P_1(n) + P_2(n))$$  \hspace{1cm} (20)

$$\text{OF}_{1,3} = -(\mu_1 - \mu_2) \sum_{n=1}^{N} C(P_1(n))$$  \hspace{1cm} (21)

\[16\] - \[17\] include the causality constraints such that the consumed energy from the time $t_i$ to $t_N$, i.e., $\sum_{n=1}^{N} (P_1(n) + \rho_2^2 P_0(n))L(n)$ , is larger than the total harvested energy in that interval, i.e., $E_1^{T,i}$, assuming that the energy stored and harvested before $t_i$ can be used. \[18\] is the constraint for the total received power obtained using \[16\] as follows,

$$\sum_{n=i}^{N} (P_1(n) + P_2(n) + P_0(n)L(n)) \geq E_{Targ}$$  \hspace{1cm} (19)

$$E_{Tot} - 2 \sum_{n=1}^{N} \rho(n)(\rho(n) - 1)P_0(n)L(n) \geq E_{Targ}$$  \hspace{1cm} (20)

$$\sum_{n=1}^{N} \rho(n)(1 - \rho(n))P_0(n)L(n) \leq -E_{th}$$  \hspace{1cm} (21)

where $E_{Targ}$ is the targeted total received power, $E_{Tot} = \sum_{n=0}^{N} (E_1,n + E_2,n)$ is the total harvested energy and $E_{th} \triangleq (E_{Targ} - E_{Tot}) / 2$.

2) $\mu_1 \geq \mu_0 \geq \mu_2$: The constraints will be similar to the first case except $P_2$ will be set to zero. In this case, the sum $\sum_{k=1}^{2} \text{OF}_{2,k}$ coming from the point $S$ in \[12\] maximizes the capacity and $P_2$ is equal to zero throughout the optimization. Therefore by equalizing $P_2$ equal to zero in \[15\] - \[21\], the optimization problem can be achieved not written in explicit detail. $\text{OF}_{2,1}$ and $\text{OF}_{2,2}$ are defined as follows,

$$\text{OF}_{2,1} = -\mu_0 C(P_0(n) + P_1(n))$$  \hspace{1cm} (22)

$$\text{OF}_{2,2} = -(\mu_1 - \mu_0)C(P_0(n))$$  \hspace{1cm} (23)

B. Karush-Kuhn Tucker Solution

Maximization problems are solved by using KKT multipliers for 3 different cases \[11\], \[2\]. Since $C_f(P, \rho)$ or the summation of OFs lead to convex solution \[16\] for a single time interval and the maximum departure region obtained for a set of time intervals in a Gaussian MAC setting leads to convex solution for the optimal offline scheduling capacity \[2\]. KKT solution will also lead to unique global optimum.

1) $\mu_1 \geq \mu_2 \geq \mu_0$:

$$\max \sum_{k=1}^{10} \text{OF}_{1,k}$$  \hspace{1cm} (25)

s.t. KKT multipliers are positive or zero,

$$\lambda_{m,n} \geq 0, n \in [2, N], m \in [1, 2]$$  \hspace{1cm} (26)

$$\lambda_{m,n} \geq 0, n \in [1, N], m \in [3, 8]$$  \hspace{1cm} (27)

positive power constraints and the constraint for $P_0$ and $\rho$ in \[15\], causality constraints for the harvested and consumed energies in \[16\] for the total energies,

$$\lambda_{1,1} \left( -\sum_{n=1}^{N} P_1(n)L(n) + E_1^{T,1} \right) = 0$$  \hspace{1cm} (28)

$$\lambda_{2,1} \left( -\sum_{n=1}^{N} P_2(n)L(n) + E_1^{T,2} \right) = 0$$  \hspace{1cm} (29)
and for the consumed energies in the time interval $[i, N]$, $i \in [2, N]$

$$\lambda_{1,i} \left( -\sum_{n=1}^{N} \frac{P_1(n)}{\lambda_{1,i}} L(n) + \sum_{n=1}^{N-1} E_{1,n} \right) = 0 \quad (30)$$

$$\lambda_{2,i} \left( -\sum_{n=1}^{N} \frac{P_2(n)}{\lambda_{2,i}} L(n) + \sum_{n=1}^{N-1} E_{2,n} \right) = 0 \quad (31)$$

the multiplications of KKT multipliers with the inequalities in \([15]\) for $i \in [2, N]$, \(\lambda_{3,n} \rho_n = \lambda_{4,n} (\rho_n - 1) = \lambda_{5,n} P_1(n) = 0 \quad (32)\)

$$\lambda_{6,n} P_2(n) = \lambda_{7,n} P_0(n) = 0 \quad (33)$$

and the total received power constraint,

$$\lambda_8 \left( -\sum_{n=1}^{N} \rho(n)(1 - \rho(n)) P_0(n) L(n) + E_{th} \right) = 0 \quad (34)$$

where the components of OF corresponding to the point $T$ are defined in \([19, 21]\). The ones for the causality constraints is, \(\text{OF}_{1,m} = \sum_{i=2}^{N} \left[ \lambda_{k,i} \left( -\sum_{n=1}^{N} \frac{P_k(n)}{\lambda_{k,i}} L(n) + E_{T,i}^T \right) \right] \quad (35)\)

where $[k, m] = [1, 4]$ or $[2, 5]$, the ones regarding \([32, 33]\) is,

$$\text{OF}_{1,6} = L(n) \left( \sum_{n=1}^{N} \lambda_{3,n} (-\rho_n) + \sum_{n=1}^{N} \lambda_{4,n} (\rho_n - 1) \right) \quad (36)$$

$$\text{OF}_{1,7} = - \left( \sum_{n=1}^{N} \lambda_{5,n} P_1(n) + \sum_{n=1}^{N} \lambda_{6,n} P_2(n) \right) L(n) \quad (37)$$

regarding the total received power constraint,

$$\text{OF}_{1,8} = \lambda_8 \left( -\sum_{n=1}^{N} \rho(n)(1 - \rho(n)) P_0(n) L(n) + E_{th} \right) \quad (38)$$

and the ones for the total consumed and the harvested power,

$$\text{OF}_{1,m} = \lambda_{k,1} \left( -\sum_{n=1}^{N} \frac{P_k(n)}{\lambda_{k,1}} L(n) + E_{T,k}^T \right) \quad (39)$$

where $[k, m] = [1, 9]$ or $[2, 10]$. Taking the derivative with respect to $P_1(n)$, $P_2(n)$, $P_0(n)$, $\rho(n)$ and equalizing to zero give the following KKT equalities for $j \in [1, N]$,

$$\text{P}_{1,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} = \frac{\lambda_{1,j} P_0^i(j)}{1 + P_0'(j) + P_1'(j) + P_2'(j)} \quad (40)$$

$$\text{P}_{2,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} = \frac{\lambda_{2,j} P_0^i(j)}{1 + P_0'(j) + P_1'(j) + P_2'(j)} \quad (41)$$

$$\text{P}_{0,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} \quad (42)$$

where \(\lambda_{m,j} = \lambda_{1,1} - \sum_{i=2}^{2} \lambda_{m,i} \) with $m = [1, 2]$, \(\mu_i^i = \mu_i W_{rank} / A, P_0'(j) = P_0(j) / A\). If $0 < \rho_j < 1$, the following can be obtained,

$$\rho_j = \frac{2 \lambda_{2,j} P_0^i(j) + \lambda_8}{2 \lambda_{2,j} P_0^i(j) + 2 \lambda_{1,j} + 2 \lambda_8} \quad (43)$$

Putting into \([42]\) the equation becomes as the following,

$$\text{P}_{0,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} = g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) - \lambda_{7,j} \quad (44)$$

where \(g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) \) is defined as \(g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) \) defined as \(4 \lambda_{1,j} P_0^i(j) \lambda_{2,j} P_0^i(j) - \lambda_8^2 \) \(4(\lambda_{1,j} P_0^i(j) + \lambda_{2,j} P_0^i(j) + \lambda_8) \quad (45)\)

The KKT multiplier regions for the single time interval can be found with a similar approach in \([16]\) and are given in Appendix A. The total transmitted energy constraint is also added to the formulas as different from the version in \([16]\).

The constraints and the components of the objective functions for the other 2 cases are found with a similar approach to the case 1. Therefore, in the following, the only final expressions will be presented without the detailed explanation.

2) \(\mu_1 \geq \mu_0 \geq \mu_2\): Similar to the approach performed for the case-1 and taking the derivative with respect to $P_1(n)$, $P_0(n)$, $\rho(n)$ gives the following for $j \in [1, N]$,

$$\text{P}_{1,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} + \frac{\mu_0^{i} - \mu_0^i}{1 + P_1'(j) + P_2'(j)} = \lambda_{1,j} P_0^i(j) \quad (47)$$

$$\text{P}_{0,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} = \lambda_{1,j} P_0^i(j) \quad (48)$$

where \(g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) \) is defined as \(g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) \) defined as \(4 \lambda_{1,j} P_0^i(j) \lambda_{2,j} P_0^i(j) - \lambda_8^2 \) \(4(\lambda_{1,j} P_0^i(j) + \lambda_{2,j} P_0^i(j) + \lambda_8) \quad (49)\)

If $0 < \rho_j < 1$, the following can be obtained,

$$\rho_j = \frac{2 \lambda_{2,j} P_0^i(j) + \lambda_8}{2 \lambda_{2,j} P_0^i(j) + 2 \lambda_{1,j} + 2 \lambda_8} \quad (50)$$

Putting into \([43]\) the equation becomes as the following,

$$\text{P}_{0,j} : \frac{\mu_0^{i}}{1 + P_0'(j) + P_1'(j) + P_2'(j)} = g(\lambda_{1,j} P_0^i(j), \lambda_{2,j} P_0^i(j), \lambda_8) - \lambda_{7,j} \quad (51)$$

3) \(\mu_0 \geq \max(\mu_1, \mu_2)\): After defining the optimization problem and similarly taking the derivative with respect to $P_0(n)$, $\rho(n)$, equalization to zero gives the following KKT
equalities for \( j \in [1, N] \),

\[
P_{0,j} : \frac{\mu_0}{1 + P_{0}^j(j)} = g(\lambda_{1,j}^p, \lambda_{2,j}^p, \lambda_8) \tag{52}
\]

\[
= \lambda_{1,j}^p \rho_j^2 + \lambda_{2,j}^p (1 - \rho_j)^2 - \lambda_8 (1 - \rho_j) \rho_j \tag{53}
\]

\[
\rho_j : \rho_j = \frac{2 \lambda_{2,j}^p + 2 \lambda_{1,j}^p + 2 \lambda_8}{2 \lambda_{2,j}^p + 2 \lambda_{1,j}^p + 2 \lambda_8} \tag{54}
\]

Now, the water filling algorithm satisfying KKT solutions will be developed.

C. Optimal Water filling Algorithm

The water filling algorithm has the similar structure for different constant multiplier \( \mu \) values but with different number of water levels and types. Therefore, the case for \( \mu_1 \geq \mu_2 \geq \mu_0 \) is analysed and explained as an illustrative example. The case for the single time epoch leads to 8 different regions defined with respect to the KKT multipliers \[16\]. In a correlated setting, different from the previous studies \[1, 2\], there will be comparison of two time intervals where each one is optimized with respect to the current total energy and in different regions of KKT multipliers.

When one of the nodes, e.g., first node, transmits energy from the time step \( j \) to the next time step \( j + 1 \), then the corresponding KKT multiplier in \[30\] \[31\] becomes zero and the equality \( \lambda_{1,j}^p = \lambda_{1,j+1}^p \) is satisfied. On the other hand, if the optimum scheduling includes no energy transfer from some node then \( \lambda_{1,j}^p \geq \lambda_{1,j+1}^p \) should be satisfied. Therefore, in the algorithm, at each time step, both of the nodes are experimented one by one to transmit energy and whether the water-level equalities/inequalities and the corresponding equalities/inequalities for \( \lambda_{1,j}^p, \lambda_{0,j}^p, \lambda_{2,j+1}^p, \lambda_{2,j}^p, \lambda_{2,j+1}^p \), are satisfied based on the regions of two time steps shown in the Tables \[11\] in Appendix-B. For example, if 1st user is chosen in a time step-j to transmit energy to the next time step as a possible candidate of optimum solution, and assume that the region in time step- \( j \) is 5 and the region in the time step-j+1 is 2, then, based on Table-II and \( \lambda_{1,j}^p = \lambda_{1,j+1}^p \), the following should be satisfied if the transfer leads to the optimum solution,

\[
W_1(j) = \lambda_{1,j}^p \geq W_1(j+1) = \lambda_{1,j+1}^p - \lambda_{6,j+1}^p \tag{55}
\]

\[
W_2(j) = \lambda_{2,j}^p - \lambda_{6,j}^p \leq W_2(j+1) = \lambda_{2,j+1}^p - \lambda_{6,j+1}^p \tag{56}
\]

\[
W_3(j) \geq W_3(j+1) \tag{57}
\]

\[
\lambda_{1,j}^p = \lambda_{1,j+1}^p; \quad \lambda_{2,j}^p \geq \lambda_{2,j+1}^p \tag{58}
\]

where \( W_3(j) = g(\lambda_{1,j}^p, \lambda_{2,j}^p, \lambda_8) \) and \( W_3(j+1) = g(\lambda_{1,j+1}^p, \lambda_{2,j+1}^p, \lambda_8) \). Then, by looking at the difference between water levels and using an iterative weighted search algorithm, water levels are optimized. The comparison tables regarding the water levels can be seen in Tables-III and IV in Appendix-B. Here, similar to \[1, 2, 10\], an iterative backward water filling procedure is applied as shown in Algorithm-I. The water filling algorithm checks the energy transfer for both of the levels in a more complicated manner compared with the previous versions where one of the nodes is assumed to have fixed scheduling. Since the correlated power also depends on the power profile of both users in equalizing water levels, here both of the nodes are optimized at the same time. Now, the gradient descent algorithm is introduced which will be a comparison test-bed for the water filling solution as an algorithm converging to the global maximum.

D. Iterative Gradient Descent Algorithm

It is known that \( C_f(P, \rho) \) is a convex region \[2, 11\]. Global solution is found by iterative gradient search by optimizing the scheduling for the first node with the other fixed, then, the reverse is applied. The iterative nature of the water filling algorithm in \[2\] is shown to converge to the global optimum. Therefore, the same iterative technique is applied in this article. The optimization continues iteratively, until the overall data throughput increase after each iteration is below some threshold. Assuming \( N \) time steps, firstly, the gradient of the overall throughput \( C(E) \) is found as the following,

\[
\nabla C(E) = \frac{\partial C(E)}{\partial E_1}, \frac{\partial C(E)}{\partial E_2}, \ldots, \frac{\partial C(E)}{\partial E_N} \tag{59}
\]

where the partial derivatives are found as the following, e.g., for the first node,

\[
\frac{\partial C(E)}{\partial E_1} = C(E_1, \ldots, E_{1,n} + \Delta E, \ldots, E_{2,N}) - C(E) \tag{60}
\]

and \( E = [E_{1,1}, E_{1,2}, \ldots, E_{1,N}, E_{2,1}, E_{2,2}, \ldots, E_{2,N}] \) is the available energy at each time step for each node. The direction maximizing the gradient is found by computing the directional derivative for all the possible energy scheduling cases for the chosen node at the current iteration. The possible energy scheduling cases \( d_s = [d_1, d_2, \ldots, d_N]^T \) are found by finding all the combinations of the rows of the matrix \( D \) of dimension \( N \times N \) which has the value \(-1\) at the index \((i, i)\) and \((i, i+1)\) and all the other values are zero at the row \( i \). For each direction vector \( d = \Delta E d_s \) with some \( \Delta E \), the directional derivative is calculated by \( d^T \nabla C(E) \). After finding the direction for the maximum increase, the energy transfer \( d \) is applied. The transfer continues until no further increase in the capacity is observed. The same iteration is
Algorithm 2: Gradient Descent Scheduling Algorithm

while $\Delta E > \Delta E_{thr}$ do
    $\Delta E = \Delta E/2$;
    while The increase in capacity $C(E)$ is above some threshold do
        for all node num = 1 to 2 do
            Compute the gradient for energy transfers of the node num
            Find the direction $d$ for the maximum directional derivative and perform
            the energy scheduling
        end for
    end while
end while

| Parameter | Meaning                  | Value |
|-----------|--------------------------|-------|
| $W_{Tot}$ | Total bandwidth          | 1 MHz |
| $N_0$     | Noise                    | $10^{-19}$ W/Hz |
| $h$       | (Path Loss)              | $10^{-11}$ |
| $E_1$     | First user harvested energies | [3 6 10] mJ |
| $E_2$     | Second user harvested energies | [4 11 6] mJ |
| $t_1$     | First user harvesting times | [0 2 6] seconds |
| $t_2$     | Second user harvesting times | [0 5 8] seconds |
| $T_f$     | Final time               | 11    |
| $A$       | Constant $N_0 W_{Tot} / h = 0.01$ |
| $N$       | Number of time intervals | 5     |

then repeated for the second node. The iterations continue by decreasing $\Delta E$ incrementally until below some threshold $\Delta E_{thr}$. The algorithm is presented in Algorithm 2. Since the algorithm computes all the possibilities, it is expected to converge to the global optimum. This method is compared with the performance of the water filling algorithm.

V. NUMERICAL SIMULATION RESULTS

In this section, the proposed solutions and the algorithms are numerically simulated for parameters shown in Table I. The users harvest energy at 3 time instants at the specified time instants. Furthermore, the constraint for the total received energy is not simulated and left as a future work, i.e., $\lambda_8$ in (34), (38), (42 - 44), (48 - 54) is taken as zero. In Fig. 3, the scatter plot of the capacity boundary at the final time $T_f$ is shown for both the water filling algorithm and the gradient descent search algorithm. It can be observed that they form almost the same surface proving the optimality of both the methods. The surface formed from the scattered points is shown in Fig. 4 which resembles the capacity boundary surface for the single time interval as shown in Fig. 2. Furthermore, the comparison between the surfaces formed from the scatter plots of the water filling and the gradient descent search algorithm is shown in Fig. 5. The surfaces are formed for specific $(R_1, R_2)$ pairs and the corresponding $R_0$ is compared. It is observed that they give almost the same values except the limiting regions where $R_0$ decays to zero due to the finite number of $\mu_1, \mu_2, \mu_0$ samples. The water filling behaviour and the power consumption profiles of the users are seen in Figs. 6-9 for various regions corresponding to $(\mu_1, \mu_2, \mu_0)$. As shown in Fig. 6 when $\mu_1 \geq \mu_2 \geq \mu_0$ with $\mu_0$ comparable...
with common data scheme. KKT solution is presented and the total received energy is decreased. It can be observed that the harvested energies for each user are shown with the total energy and the rate for the common data which leads to the maximum received energy goes to the messages (Fig. 6). Received energy for each message and the received total energy for $\mu_1 = 1.1$, $\mu_2 = 1$, $\mu_0 = 0.9$ comparable to $\mu_1$ and $\mu_2$ or $\mu_0 \geq \max(\mu_1, \mu_2)$. Energy (Joule) for $\mu_1 = 1.1$, $\mu_2 = 1$, $\mu_0 = 0.9$ with $\mu_1$ comparable to $\mu_1$ and $\mu_2$ or $\mu_0 \geq \max(\mu_1, \mu_2)$.

In this paper, optimum offline packet scheduling and energy consumption policy is developed for 2-user Gaussian MAC with common data scheme. KKT solution is presented and a water filling algorithm is presented achieving the optimum solution. The water filling algorithm includes 3-level water filling and specific complicated structure due to the regional behaviour of KKT multipliers in Gaussian MAC with common data. In the offline modelling and solution of the packet scheduling problem, the constraint of the total received energy is taken into account. Optimum water filling algorithm is compared with the gradient descent search algorithm which gives the global optimum solution. It is observed that both solutions are very close and optimal. In addition, the capacity boundary region for the individual and common data rates are obtained with simulations of the optimum solution and various points on the surface of the capacity boundary are compared. The fundamentals of the optimal packet scheduling for the MAC scheme with common data is established which can improve the performance of WSNs where highly correlated data exists. Finally, the effect of the total received power constraint and the extension of the work to both data and

VI. CONCLUSION

Fig. 6. Received energy for each message and the received total energy for $\mu_1 = 1.1$, $\mu_2 = 1$, $\mu_0 = 0.9$ comparable to $\mu_1$ and $\mu_2$ or $\mu_0 \geq \max(\mu_1, \mu_2)$.

Fig. 7. Consumed and harvested energies for each user and for the total, for $\mu_1 = 1.1$, $\mu_2 = 1$, $\mu_0 = 0.9$ with $\mu_0$ comparable to $\mu_1$ and $\mu_2$ or $\mu_0 \geq \max(\mu_1, \mu_2)$.

Fig. 8. Consumed and harvested energies for each user and for the total, for $\mu_1 = 6$, $\mu_2 = 1$, $\mu_0 = 0.9$ with $\mu_1 \gg \mu_2$, $\mu_0$ and $\mu_0$ comparable to $\mu_2$.

Fig. 9. Received energy for each message and the received total energy for $\mu_1 = 6$, $\mu_2 = 1$, $\mu_0 = 0.9$ with $\mu_1 \gg \mu_2$, $\mu_0$ and $\mu_0$ comparable to $\mu_2$. Energy (Joule)
energy transfer are left as a future work.

APPENDIX A
KKT Multiplier Regions and Solutions

The following definitions are used next, $g = g(\lambda_1, \lambda_2, \lambda_3)$, $\alpha \equiv (\mu_2 - \mu_1) / (\lambda_2 - g)$, $\beta \equiv (\mu_1 - \mu_2) / (\lambda_1 - \lambda_2)$, $\gamma \equiv (\mu_0 - \mu_1)(g - \lambda_1)$. The regions are defined for varying $(\lambda_1, \lambda_2)$ with the corresponding solutions. $R_1$ refers to the case where the power values are 0 and skipped in the solutions. $R_i$ refers the region, and $S_i$ refers the solution in that region.

For the first case, i.e., $\mu_1 \geq \mu_2 \geq \mu_0$, the KKT multiplier regions and solutions for the power variables are the following,

$$R_1 = \{ \mu_1 < \lambda_1 : i \in [1, 2], g > \mu_0 \}$$

$$R_2 = \{ \mu_i - \mu_0 + g < \lambda_i : i \in [1, 2], \frac{\mu_0}{g} > 1 \}$$

$$R_3 = \{ \mu_1 > \lambda_1, g > \frac{\mu_0}{\mu_1}, \frac{\mu_2}{\lambda_1} > \frac{\mu_2}{\mu_1} \}$$

$$R_4 = \{ \mu_1 - \mu_2 < \lambda_1 - \lambda_2, g > \frac{\mu_0}{\mu_2}, \lambda_2 < \mu_2 \}$$

$$R_5 = \{ \frac{\mu_0}{g} > 1, \gamma > \alpha, P_{0,1} > 0 \}$$

$$R_6 = \{ \frac{\mu_0}{g} > 1, \lambda_1 - \lambda_2 > \frac{\mu_0}{\mu_1}, \mu_2 > 0, \mu_0 > 0 \}$$

$$R_7 = \{ \frac{g}{\lambda_2} > \frac{\mu_0}{\mu_2}, \frac{\mu_2}{\lambda_2} > 1, \lambda_2 < \frac{\mu_2}{\mu_1}, P_1 > 0 \}$$

$$R_8 = \{ \frac{\mu_0}{g} > \beta > 1, \alpha > 1, P_{0,2} > 0 \}$$

For the case of $\mu_0 \geq \max(\mu_1, \mu_2)$, the solution is given by $P_0 = \frac{\mu_0}{g} - 1$.

APPENDIX B
Comparison Table of Water Levels

Let us define $g(j) \triangleq g(\lambda_{i,j}^p, \lambda_{2,j}^p, \lambda_8)$. Then, for the case $\mu_1 \geq \mu_2 \geq \mu_0$, 3 water levels to be compared are the following,

$$W_1 = \frac{\mu_0}{1 + P_1 + P_2 + P_0} + \frac{\mu_2 - \mu_0}{1 + P_1 + P_2} + \frac{\mu_1 - \mu_2}{1 + P_1}$$

$$W_2 = \frac{\mu_0}{1 + P_1 + P_2 + P_0} + \frac{\mu_2 - \mu_0}{1 + P_1 + P_2}$$

$$W_3 = \frac{\mu_0}{1 + P_1 + P_2 + P_0} + \frac{\mu_0}{1 + P_1 + P_0}$$

while for the case $\mu_1 \geq \mu_0 \geq \mu_2$, 2 water levels to be compared are the following,

$$W_1 = \frac{\mu_0}{1 + P_1 + P_0} + \frac{\mu_1 - \mu_0}{1 + P_1}$$

and finally, for the case $\mu_0 \geq \max(\mu_1, \mu_2)$, the water level to be compared is $W_1 = \frac{\mu_0}{1 + P_1 + P_0}$. The water levels and the regions for these cases are shown in Table B.

For different optimized regions in the neighbouring time intervals $n$ and $n - 1$, with respect to the specific node transferring energy, the equalities/inequalities to be satisfied for the optimum solutions are seen in Table C for the case $\mu_1 \geq \mu_2 \geq \mu_0$ where the first node transfers energy and in Table D where the second node transfers energy. The cases for $\mu_1 \geq \mu_0 \geq \mu_2$ and $\mu_0 \geq \max(\mu_1, \mu_2)$ are not shown due to space limitations.
### Table II
The KKT multiplier regions and the water levels for time step \( j \) for varying \( (\mu_1, \mu_2, \mu_0) \)

| \( \mu_1 \geq \mu_2 \geq \mu_0 \) | \( R_2 \) | \( R_4 \) | \( R_5 \) | \( R_6 \) | \( R_7 \) | \( R_8 \) |
|---|---|---|---|---|---|---|
| \( P_1 \) | 0 | \( > 0 \) | 0 | \( > 0 \) | 0 | \( > 0 \) |
| \( P_2 \) | 0 | 0 | \( > 0 \) | 0 | \( > 0 \) | 0 |
| \( P_3 \) | \( > 0 \) | 0 | 0 | \( > 0 \) | \( > 0 \) | \( > 0 \) |
| \( W_1 \) | \( \lambda_{1,j} - \lambda_{5,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} - \lambda_{5,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} - \lambda_{5,j} \) | \( \lambda_{1,j} \) |
| \( W_2 \) | \( \lambda_{2,j} - \lambda_{6,j} \) | \( \lambda_{2,j} - \lambda_{6,j} \) | \( \lambda_{2,j} - \lambda_{6,j} \) | \( \lambda_{2,j} - \lambda_{6,j} \) | \( \lambda_{2,j} - \lambda_{6,j} \) | \( \lambda_{2,j} - \lambda_{6,j} \) |
| \( W_3 \) | \( g(j) \) | \( g(j) - \lambda_{7,j} \) | \( g(j) \) | \( g(j) - \lambda_{7,j} \) | \( g(j) \) | \( g(j) - \lambda_{7,j} \) |

### Table III
The KKT multiplier regions and the optimality conditions for time steps \( j \) and \( j+1 \) when the 1st node transfers energy, \( \mu_1 \geq \mu_2 \geq \mu_0 \)

| \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) |
|---|---|---|---|---|---|
| \( W_1(j+1) \) | \( R_{2,4,6} \) | \( R_{3,5,7,8} \) | \( x \) | \( \leq \) | \( \geq \) |
| \( W_2(j+1) \) | \( R_{2,4,6} \) | \( R_{3,5,7,8} \) | \( x \) | \( \leq \) |

### Table IV
The KKT multiplier regions and the optimality conditions for time steps \( j \) and \( j+1 \) when the 2nd node transfers energy, \( \mu_1 \geq \mu_2 \geq \mu_0 \)

| \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) | \( \lambda_{1,j} \) |
|---|---|---|---|
| \( W_1(j+1) \) | \( R_{2,3,5} \) | \( R_{4,6,7,8} \) | \( x \) | \( \leq \) |
| \( W_2(j+1) \) | \( R_{2,3,5} \) | \( R_{4,6,7,8} \) | \( x \) | \( \leq \) |

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