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Resource Allocation under Sequential Resource Access: Theory and Application

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***Abstract*—This paper treats the problem of optimal resource allocation over time in a finite-horizon setting, in which the resource become available only sequentially and in incremental values and the utility function is concave and can freely vary over time. Such resource allocation problems have direct applications in data communication networks (e.g., energy harvesting systems). This problem is studied extensively for special choices of the concave utility function (time-invariant and logarithmic) in which case the optimal resource allocation policies are well-understood. This paper treats this problem in its general form and analytically characterizes the structure of the optimal resource allocation policy, and devises an algorithm for computing the exact solutions analytically. An observation instrumental to devising the provided algorithm is that there exist time instances at which the available resources are exhausted, with no carry-over to future. This algorithm identifies all such instances, which in turn facilitates breaking the original problem into multiple problems with significantly reduced dimensions. Furthermore, some widely-used special cases in which the algorithm takes simpler structures are characterized, and the application to the energy harvesting systems is discussed. Numerical evaluations are provided to assess the key properties of the optimal resource allocation structure and to compare the performance with the generic convex optimization algorithms.**

I. Introduction

Consider a resource allocation problem over a finite time horizon $T \in \mathbb{N}$. The resource is made available for utilization *sequentially* over time and in *increments*. Such resource allocation models manifest in a wide range of power allocation and scheduling objectives in communication systems. For instance, in energy harvesting networks the transmitters rely partly or entirely on ambient sources in their surrounding environments. In such systems, the energy resources are available only sequentially and incrementally over time as they are harvested. Similarly, the packet transmission systems under stringent quality-of-service (QoS) constraints constitute another class of resource allocation problems in which the data packets to be transmitted arrive sequentially over time at the transmitter, while all the arriving information packets are required to be delivered to their destination by a given deadline or by using a given amount of energy.

In a time-slotted setting, we denote the incremental amount of resource made available during time slot $t \in \{1, \dots, T\}$ by $s_t \in \mathbb{R}^+$, and denote the actual amount of resource utilized during time slot $t \in \{1, \dots, T\}$ by $x_t \in \mathbb{R}^+$. The resource is assumed to be used only causally, leading to the following set of T resource utilization constraints:

$$\sum_{i=1}^{t} x_i \leq \sum_{i=1}^{t} s_i , \qquad \forall t \in \{1, \dots, T\} . \tag{1}$$

Accordingly, we denote the resource vector by $\boldsymbol{s} \triangleq [s_1, \dots, s_T]$ and denote the vector of utilized resource over time by $\boldsymbol{x} \triangleq [x_1, \dots, x_T]$. Also, we define the utility function $f_t : \mathbb{R}^+ \to \mathbb{R}^+$ as the measure of the contribution of the amount of resource utilized during time slot $t \in \{1, \dots, T\}$, i.e., x_t. We assume that all functions $\{f_t : t \in \{1, \dots, T\}\}$ are *differentiable*, *non-decreasing*, and *strictly concave*, and denote the aggregate utility gleaned over the entire time horizon by $F(\boldsymbol{x}) \triangleq \sum_{t=1}^{T} f_t(x_t)$. Based on these definitions, the resource allocation problem under the sequential access to the resource over a finite time-horizon can be formalized as

$$\mathcal{P}(\boldsymbol{s}) \triangleq \begin{cases} \max\limits_{\boldsymbol{x}} & F(\boldsymbol{x}) \\ \text{s.t.} & \sum\limits_{i=1}^{t} x_i \leq \sum\limits_{i=1}^{t} s_i , \quad \forall t \in \{1, \dots, T\} \\ & \boldsymbol{x} \succeq 0 \end{cases} . \tag{2}$$

The problem in (2), in its special cases with some constraints relaxed, subsumes an extensive body of well-understood problems, e.g., power allocation in parallel channels [1] and power allocation in single-user multi-antenna channels [2] when $\{s_i = 0 : i \in \{1, \dots, T-1\}\}$. In this paper, we leverage the structure of the convex optimization problem formalized in (2) and provide the optimal closed-form solution for the general form analytically.

A. Motivation and Related Work

In this subsection, we provide a more detailed overview of two classes of communication systems and their existing relevant literature in which resource allocation objectives can be formalized as problem $\mathcal{P}(\boldsymbol{s})$ defined in (2).

Energy Harvesting Communication Systems: These systems, in which the transmitters rely partly or entirely on ambient sources in their surrounding environments, represent one class of such communication systems in which the resource is available only sequentially. Energy harvesting networks empowered by perpetual sources of power, are especially promising alternatives to systems with lifetime-limited batteries. In such systems, nevertheless, the availability of energy becomes sporadic and temporally volatile, in which case devising optimal policies for efficient utilization of the harvested energy directly translates into how continually the communication link can be sustained by relying on the harvested energy. In such systems, optimally balancing energy consumption over time leads to solving problems of the form in (2).

Optimal resource allocation policies under different settings and objectives are studied extensively. In particular, and most relevant to the scope of this paper, in the single-user energy harvesting channels, optimal power allocation policies are studied under a number of assumptions on the battery size for storing the harvested energy (finite versus infinite), and information available regarding the causality of energy harvesting, and wireless channel fading process (slow versus fast). Specifically, the studies in [3] and [4] consider infinite-capacity batteries, establish certain properties of the optimal policies, and devise the *directional water-filling* approach to power allocation in static as well as fading wireless channels. Extensions to random channel conditions and finite-capacity batteries for static channels are studied in [5]–[7].

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Enforcing a finite battery capacity induces constraints on the policies, which are driven by the possibility of battery overflow at the instances of harvesting energy. Extensions to such finite-battery settings when facing inefficiencies in battery storage is investigated in [8]. The studies in [9] and [10] address causal and non-causal availability of the channel state information.

QoS-constrained Systems: Optimizing the efficiency of packet transmission systems under stringent quality-of-service constraints is another class of resource allocation problems solving which is equivalent to the problem in (2). In such systems, the data packets to be transmitted arrive sequentially over time at the source and all the arriving information packets requires to be delivered to their destination by a given deadline or by using a given amount of energy. For instance, the studies in [11], [12] consider minimizing the energy-cost used to transmit data packets through wireless channels subject to given delay or other quality of service constraints. Maximizing the transmission throughput of an energy- or time-constrained transmitter over fading channels is studied in [13]. Under a fixed delay constraint, a transmission schedule that maximizes the battery life-time is derived in [14], while the study in [15] considers minimum-energy scheduling problems over fading multiple-access and broadcast channels. Also, the recent study in [16] analyzes proactive content caching from an energy efficiency perspective. Moreover, a scheduling algorithm with real-time constraints was presented in [17].

II. Optimal Solution: Properties and Algorithm

The objective in this section is to analytically characterize $\boldsymbol{x}^*$, which we define as the solution to $\mathcal{P}(\boldsymbol{s})$. The solution $\boldsymbol{x}^*$ is unique since all the constraints are linear and the utility function is strictly concave. We start by considering the *offline* resource allocation problem, in which the resource vector $\boldsymbol{s}$ and the utility functions $\{f_t : t \in \{1,\dots,T\}\}$ are known *deterministically*. We characterize the optimal solution *analytically*, and then discuss the generalization to the settings in which these terms bear stochastic uncertainties in Section II-H.

A. Algorithm for Finding the Optimal Solution

We start by providing an algorithm that identifies the exact solution to $\mathcal{P}(\boldsymbol{s})$, discuss its complexity in Section II-B, present an overview of the scheme of the proofs in Section II-C, and present the detailed steps of the analysis for establishing its optimality properties in sections II-D and II-E. In these latter two subsections, specifically, we show that the optimal solution $\boldsymbol{x}^*$ has two key properties, which constitute the main structure of Algorithm 1 for analytically solving $\mathcal{P}(\boldsymbol{s})$. The first property is that the set of optimal values $\{x_1^*,\dots,x_T^*\}$ can be partitioned into d mutually exclusive subsets separated at time instants $t \in \{u_1,\dots,u_d\}$, which we can find analytically. We denote these subsets by

$$\{x_1^*,\dots,x_{u_1}^*\}, \quad \{x_{u_1+1}^*,\dots,x_{u_2}^*\}, \quad \dots \quad \{x_{u_{d-1}+1}^*,\dots,x_T^*\}\ , \tag{3}$$

where we show that each subset can be characterized analytically and independently of the rest. Built on this observation, secondly, we show that among all the constraints of $\mathcal{P}(\boldsymbol{s})$, i.e.,

$$\sum_{i=1}^{t} x_i \ \le\ \sum_{i=1}^{t} s_i\ , \qquad \forall t \in \{1,\dots,T\}\ . \tag{4}$$

the constraints corresponding to $t \in \{u_1,\dots,u_d\}$ hold with *equality*, and all others hold with *strict inequality*. Finally, based on these two properties we show that finding $\boldsymbol{x}^*$ via solving $\mathcal{P}(\boldsymbol{s})$ reduces to solving a number of problems with a similar structure, but with reduced dimension.

The detailed steps of solving $\mathcal{P}(\boldsymbol{s})$ are provided in Algorithm 1. This algorithm receives the resource vector $\boldsymbol{s}$ as its input and produces the optimal resource allocation solution $\boldsymbol{x}^*$. It consists of one outer loop (lines 3-13) the purpose of which is progressively determining the indices of the time instants $\{u_i : i \in \{1,\dots,d\}\}$. Each of the d outer loops involves an inner loop (lines 6-9), which finds a part of the optimal solution, and specifically in the iteration i of the outer loop, the inner loop finds the optimal values $\{x_i^* : i \in \{u_{i-1}+1,\dots,u_i\}\}$. This inner loops within the i^{th} iteration solve optimization problems $\mathcal{Q}_{u_{i-1}\to t}(\boldsymbol{s})$ for all values of $t \in \{u_{i-1}+1,\dots,T\}$, where corresponding to each pair $m<n$ we have defined the auxiliary problem

$$\mathcal{Q}_{m\to n}(\boldsymbol{s}) \triangleq \begin{cases} \max\limits_{\boldsymbol{x}} & \sum\limits_{i=m+1}^{n} f_i(x_i) \\ \text{s.t.} & \sum\limits_{i=m+1}^{n} x_i = \sum\limits_{i=m+1}^{n} s_i\ , \quad \forall t \in \{1,\dots,T\} \\ & \boldsymbol{x} \succeq 0 \end{cases}, \tag{5}$$

It is noteworthy that $\mathcal{Q}_{m\to n}(\boldsymbol{s})$ has a unique globally optimal solution, since its utility function is strictly concave.

Algorithm 1 - Solving $\mathcal{P}(\boldsymbol{s})$ for any given resource vector $\boldsymbol{s}$

1: **input** $\boldsymbol{s}$
2: **initialize** $t=1$, $d=0$ and $u_0=0$,
3: **while** $u_d \le T-1$
4: $\quad d \leftarrow d+1$
5: $\quad$ **set** $\mathcal{A}_d \triangleq \{u_{d-1}+1,\dots,T\}$
6: $\quad$ **for** $t \in \mathcal{A}_d$
7: $\quad\quad$ set $\boldsymbol{w}^{d,t}$ as the solution to $\mathcal{Q}_{u_{d-1}\to t}(\boldsymbol{s})$
8: $\quad\quad$ set $q^{d,t} \triangleq \min\left\{\frac{\mathrm{d}f_i}{\mathrm{d}x}(w_i^{d,t}) : i \in \{u_{d-1}+1,\dots,t\}\right\}$
9: $\quad$ **end for**
10: $\quad u_d \triangleq \arg\max_{t\in\mathcal{A}_d} q^{d,t}$ (if not unique, select the smallest[a])
11: $\quad v_d \triangleq \max_{t\in\mathcal{A}_d} q^{d,t}$
12: $\quad \boldsymbol{z}^d \triangleq \boldsymbol{w}^{d,u_d}$
13: **end while**
14: **for** $i \in \{1,\dots,d\}$
15: $\quad$ **for** $t \in \mathcal{D}_i = \{u_{i-1}+1,\dots,u_i\}$
16: $\quad\quad x_t \triangleq z_t^i$
17 : $\quad$ **end for**
18 : **end for**
19: **output** $\boldsymbol{x}$, d, $\{u_i : i \in \{1,\dots,d\}\}$ and $\{v_i : i \in \{1,\dots,d\}\}$

[a] For the convenience in the analyses, throughout the rest of the paper we assume that u_d is unique. In case that it is not unique, by selecting the smallest choice all the analyses remain valid.

B. Computational Complexity

The significance of obtaining the optimal solution $\boldsymbol{x}^*$ *analytically* is the substantial reduction in the computational complexity. To furnish the relevant context, we remark that since the utility functions are strictly concave, the generic approaches in convex optimization can be readily applied to the problem at hand. In particular, the primal-dual interior-point (IP) methods are known to be extremely efficient and capable of handling large-scale non-linear problems. From a computational perspective, the complexity of IP methods is shaped primarily by two factors, namely the desired level of accuracy in the solution they provide (i.e., closeness to the optimal solution) and the nature of the utility functions (e.g., linear or quadratic). In the IP methods, it is well-investigated that for *linear* utility functions, the computational complexity scales at the rate $O(\sqrt{T}\ln\frac{1}{\epsilon})$, where

T is the dimension of the problem and ϵ accounts for the error of the solution provided by the IP method, i.e., the difference between the optimal solution and the solution provided by the IP method. For *non-linear* utility functions, which is the case in this paper, the complexity is higher, and except for special cases (e.g., quadratic) the general complexity is unknown. On the other hand, Algorithm 1 provides the *exact* optimal solutions, which corresponds to guaranteeing that $\epsilon = 0$ for the output of Algorithm 1, achieving which by the IP method results in theoretically *unbounded* computational complexity. The same trend is true for other numerical approaches as well, and in Section IV we provide numerical comparisons between the computational complexities. Finally we remark that the complexity of Algorithm 1 is $O(T)$, since in the worst case it has T iterations. Each iteration involves solving a problem of the form $\mathcal{Q}_{m\to n}(\boldsymbol{s})$. The solution to $\mathcal{Q}_{m\to n}(\boldsymbol{s})$ often has a closed-form when the utility functions are specified, and as a result as it is customary, the computational complexity is considered negligible.

C. Scheme of the Proofs

Before proceeding to the details of the proofs, we provide a scheme of the steps involved. The objective is to characterize the key properties of $\boldsymbol{x}^*$ as the optimal solution of $\mathcal{P}(\boldsymbol{s})$. For the analytical purposes, we construct another resource allocation vector $\tilde{\boldsymbol{x}}$ as the output of Algorithm 1 when its input $\boldsymbol{s}$ is replaced by $\boldsymbol{x}^*$. It is noteworthy that this serves merely as an auxiliary solution which we are not interested in computing, but rather we investigate its properties. Specifically, we show the following properties for $\tilde{\boldsymbol{x}}$:

1) From the construction of $\tilde{\boldsymbol{x}}$, it can be readily verified that $\tilde{\boldsymbol{x}}$ satisfies all the constraints of $\mathcal{P}(\boldsymbol{s})$. As a result due to the optimality of $\boldsymbol{x}^*$, the utility corresponding to $\tilde{\boldsymbol{x}}$ cannot exceed the utility corresponding to $\boldsymbol{x}^*$, i.e., $F(\boldsymbol{x}^*) \geq F(\tilde{\boldsymbol{x}})$. This is established in Lemma 2.
2) Also, from the construction of $\tilde{\boldsymbol{x}}$, we prove that $F(\boldsymbol{x}^*) \leq F(\tilde{\boldsymbol{x}})$. This is established in Lemma 3.
3) By leveraging the results of lemmas 2 and 3 we subsequently have $\tilde{\boldsymbol{x}} = \boldsymbol{x}^*$. This implies that if we initiate Algorithm 1 with $\boldsymbol{x}^*$, it will produce the same vector $\boldsymbol{x}^*$ as its output. This is established in Theorem 1.
4) Finally, we show that initiating Algorithm 1 with inputs $\boldsymbol{s}$ and $\boldsymbol{x}^*$ results in the same resource allocation vectors. This is formalized in Theorem 2, which in conjunction with Theorem 1 establishes that the output of the Algorithm 1 is the unique desired vector $\boldsymbol{x}^*$.

Besides these main items, we also show that $\tilde{\boldsymbol{x}}$ and the value of the utility functions corresponding to this resource allocation vector have a number of algebraic properties established in lemmas 1, 4, and 5, which $\boldsymbol{x}^*$ also inherits due to the observation that $\boldsymbol{x}^* = \tilde{\boldsymbol{x}}$.

D. Grouping the Constraints

We start the analysis by showing that the set of the optimal values $\{x_1^*, \dots, x_T^*\}$ has the key property that this set can be partitioned into smaller subsets, such that the elements within one subset are closely related. These properties are established via lemmas 1-5. For this purpose, we first establish a number of properties for $\tilde{\boldsymbol{x}}$, which is the output of Algorithm 1 when its input $\boldsymbol{s}$ is replaced with the optimal solution $\boldsymbol{x}^*$. It is noteworthy that it is not our objective to actually compute $\tilde{\boldsymbol{x}}$, but rather we aim to show that when such an auxiliary term is constructed according to the rules specified in Algorithm 1, it satisfies certain desired properties. Hence, the purpose of generating $\tilde{\boldsymbol{x}}$ is only proving the properties, as a result of which, this process does *not* involve knowing the optimal solution $\boldsymbol{x}^*$, or actually computing $\tilde{\boldsymbol{x}}$.

In order to construct $\tilde{\boldsymbol{x}}$, Algorithm 1 admits $\boldsymbol{x}^*$ as its input, and based on that *successively* partitions the set of constraints $\{\sum_{i=1}^t x_i \leq \sum_{i=1}^t s_i : t \in \{1, \dots, T\}\}$ into d disjoint subsets of constraints. Specifically, it returns time indices $0 = u_0 < u_1 < \cdots < u_d = T$, and partitions the set $\{1, \dots, T\}$ into d disjoint sets:

$$\mathcal{D}_i \triangleq \{u_{i-1}+1, \dots, u_i\} \ , \qquad \text{for} \quad i \in \{1, \dots, d\} \ . \tag{6}$$

Furthermore, this algorithm computes the metrics $\{v_i : i \in \{1, \dots, d\}\}$ and assigns v_i to the set $\mathcal{D}_i$. Once the dominant constraints are known, solving $\mathcal{P}(\boldsymbol{x}^*)$ reduces to solving a collection of smaller problems in the form of $\mathcal{Q}_{u_{i-1}\to u_i}(\boldsymbol{x}^*)$ defined in (5). The properties of $\tilde{\boldsymbol{x}}$ are formalized in the following lemmas.

Lemma 1. *When Algorithm 1 is initiated with $\boldsymbol{x}^*$, for all $m \in \{1, \dots, d\}$ and $t \in \mathcal{A}_m \triangleq \{u_{m-1}+1, \dots, T\}$, we have*

$$\begin{array}{ll} \frac{\mathrm{d}f_i}{\mathrm{d}x}(w_i^{m,t}) \ = \ \lambda_{m,t} \ , & \forall i \in \{u_{m-1}+1, \dots, t : w_i^{m,t} > 0\} \\ \frac{\mathrm{d}f_i}{\mathrm{d}x}(w_i^{m,t}) \ > \ \lambda_{m,t} \ , & \forall i \in \{u_{m-1}+1, \dots, t : w_i^{m,t} = 0\} \end{array} , \tag{7}$$

where we have defined $\boldsymbol{w}^{m,t} \triangleq [w_1^{m,t}, \dots, w_T^{m,t}]$, and $\lambda_{m,t} \in \mathbb{R}_+$ is a strictly positive real constant. Furthermore we have $q^{m,t} = \lambda_{m,t}$.

Lemma 2. *Vector $\tilde{\boldsymbol{x}}$ generated by Algorithm 1 satisfies all the constraints of $\mathcal{P}(\boldsymbol{s})$.*

Lemma 3. *The vector $\tilde{\boldsymbol{x}}$ satisfies $F(\tilde{\boldsymbol{x}}) \geq F(\boldsymbol{x}^*)$, and the equality holds if and only if $\boldsymbol{x}^* = \tilde{\boldsymbol{x}}$.*

The results of lemmas 1-3, collectively, establish the optimality of $\tilde{\boldsymbol{x}}$ generated by Algorithm 1, which is formalized by the following theorem.

Theorem 1. *By initiating Algorithm 1 with $\boldsymbol{x}^*$ as the optimal solution to $\mathcal{P}(\boldsymbol{s})$, the vector $\tilde{\boldsymbol{x}}$ generated by Algorithm 1 is equal to the optimal solution of $\mathcal{P}(\boldsymbol{s})$, i.e., $\tilde{\boldsymbol{x}} = \boldsymbol{x}^*$.*

E. Dominant Constraints

By leveraging the results in the previous subsection, which essentially partition the set of all constraints into a collection of d disjoint constraint sets, next we provide additional properties for these sets of constraints. Specifically, we show that in each of the given d sets, at least one constraint holds with equality, which we refer to as the *dominant* constraint. These d dominant constraints are the only constraints needed to characterize the optimal solution to $\mathcal{P}(\boldsymbol{s})$. The following lemma represents an intermediate and instrumental step towards characterizing the set of dominant constraints of $\mathcal{P}(\boldsymbol{s})$. In particular, it establishes a connection among the derivative measures $q^{d,t}$ and v^d defined in Algorithm 1.

Lemma 4. *The sequence $\{v_1, v_2, \dots, v_d\}$ is strictly decreasing.*

We remark that the indices $\{u_i : i \in \{1, \dots, d\}\}$ and their associated constraint indices $\{v_i : i \in \{1, \dots, d\}\}$ have significant physical meanings in resource allocation. Specifically, the elements of $\{u_i : i \in \{1, \dots, d\}\}$ specify the time instances at which all the resources arrived by that time instance are consumed in their entirely. At other time instances, a fraction of the available resources is reserved for being consumed in the future time instances. This observation is formally demonstrated in the following lemma. Also, the measures $\{v_i : i \in \{1, \dots, d\}\}$ are the derivatives of the utility functions at the optimal solution $\boldsymbol{x}^*$ over time. Specifically, for all the indices in the range $t \in \mathcal{D}_{i+1}$, the derivatives of all the utility terms f_t at the non-zero optimal values of $\boldsymbol{x}^*$ are all the same, and equal to v_i, i.e., for to the set $\mathcal{D}_i$ is defined in (6) we have

$$v_i = \frac{\mathrm{d}f_t(x_t)}{\mathrm{d}x_t} \ , \quad \forall t \in \mathcal{D}_{i+1}, \quad \text{and} \quad \forall x_t \neq 0 \ .$$

Lemma 5. *Under the optimal solution $\boldsymbol{x}^*$, all the inequality constraints with indices included in $\{u_m : m \in \{1, \dots, d\}\}$ hold with equality, i.e.,*

$$\forall m \in \{1, \dots, d\} : \qquad \sum_{i=1}^{u_m} x_i^* \ = \ \sum_{i=1}^{u_m} s_i \ . \tag{8}$$

F. Initiating $\boldsymbol{x}^*$ via Algorithm

By leveraging the results of Lemma 4 and Lemma 5 in this subsection, we poof the optimality of Algorithm 1 for obtaining $\boldsymbol{x}^*$. So far we have shown that if we modify Algorithm 1 such that instead of inputting $\boldsymbol{s}$ we input the resource vector $\boldsymbol{x}^*$, then the output will be in fact the optimal solution $\boldsymbol{x}^*$. Next we show that initiating Algorithm 1 with either $\boldsymbol{x}^*$ or $\boldsymbol{s}$ yields the same output. The underlying insight is that this algorithm depends on $\boldsymbol{x}^*$ primarily for determining the metrics $\{v_i : i \in \{1, \dots, d\}\}$ and their associated constraint indices $\{u_i : i \in \{1, \dots, d\}\}$. By invoking the result of Lemma 5, we next show that for determining the sets $\{v_i : i \in \{1, \dots, d\}\}$ and $\{u_i : i \in \{1, \dots, d\}\}$, alternatively, we can also use the resource vector $\boldsymbol{s}$, based on which subsequently we can show that the outcome of Algorithm 1 based on the input $\boldsymbol{s}$ will be in fact the optimal solution $\boldsymbol{x}^*$. Insensitivity of Algorithm 1 to the choice of $\boldsymbol{x}^*$ by $\boldsymbol{s}$ as the input is formalized in the next lemma.

Lemma 6. *Denote the set of constraint indices yielded by Algorithm 1 when it is initiated by $\boldsymbol{x}^*$ by $\{u_i : i \in \{1, \dots, d\}\}$, and denote the counterpart set when in Algorithm 1 is initiated with $\boldsymbol{s}$ by $\{\bar{u}_i : i \in \{1, \dots, \bar{d}\}\}$. We have $\{u_i : i \in \{1, \dots, d\}\} = \{\bar{u}_i : i \in \{1, \dots, \bar{d}\}\}$.*

Based on the result of Lemma 6, in the following theorem we establish the optimality of Algorithm 1, that is it produces $\boldsymbol{x}^*$ with it is initiated with input $\boldsymbol{s}$.

Theorem 2. *By admitting $\boldsymbol{s}$ as its input, Algorithm 1 generates the optimal solution of $\mathcal{P}(\boldsymbol{s})$.*

G. Homogeneous Utility Functions

In this subsection we consider the settings in which the utility functions are all identical, i.e., $f_t = f$ for all $t \in \{1, \dots, T\}$. While in such settings we can solve $\mathcal{P}(\boldsymbol{s})$ directly via Algorithm 1, nevertheless, by leveraging the homogeneity structure, this algorithm can be significantly simplified. Specifically, we show that the inner loop that solves an optimization problem for all the future time instances (lines 6-9) can be avoided, and the indices of the dominant constraints and the associated resource allocation scheme can be found directly based on $\boldsymbol{s}$. Specifically, in the following lemma, we show that the set of dominant constraints $\{u_m : m \in \{1, \dots, d\}\}$ can be found without solving the optimization problems of the form $\mathcal{Q}_{u_{d-1} \to t}(\boldsymbol{s})$, unlike in the general form.

Lemma 7. *For problem $\mathcal{P}(\boldsymbol{s})$ with identical utility function $f_t = f$, the indices of the dominant constraints $\{u_m : m \in \{1, \dots, d\}\}$ are given by*

$$u_m \ = \ \arg \min_{t \, \in \, \mathcal{A}_m} \ \frac{1}{t - u_{m-1}} \sum_{i=u_{m-1}+1}^{t} s_i \ . \tag{9}$$

Based on the result of Lemma 7, we provide Algorithm 2 as a simpler algorithm for obtaining the optimal solution $\boldsymbol{x}^*$ to the problem in (2) with homogeneous utility functions by admitting the resource vector $\boldsymbol{s}$ as the input. The optimality of the outcome of the algorithm $\boldsymbol{x}^*$ is stated in Theorem 3.

Algorithm 2 - Computing $\boldsymbol{x}^*$ under homogeneous utility functions

input $\boldsymbol{s}$
initialize $d = 0$ and $u_d = 0$
while $u_d \leq T - 1$
  $d \leftarrow d + 1$
  set $\mathcal{A}_d \triangleq \{u_{d-1} + 1, \dots, T\}$
  $u_d = \arg\min_{t \, \in \, \mathcal{A}_d} \ \frac{1}{t - u_{d-1}} \sum_{i=u_{d-1}+1}^{t} s_i$
  $\beta_d \triangleq \frac{1}{u_d - u_{d-1}} \sum_{i=u_{d-1}+1}^{u_d} s_i$
end while
$\boldsymbol{x}^* = \sum_{m=1}^{d} \ \beta_m \cdot \left[\mathbb{0}_{u_{m-1}} \ , \ \mathbb{1}_{u_m - u_{m-1}} \ , \ \mathbb{0}_{T - u_m}\right]$

Theorem 3. *The optimal solution to the problem $\mathcal{P}(\boldsymbol{s})$ under homogeneous utility functions is yielded by Algorithm 2, and takes the closed form $\boldsymbol{x}^* = \sum_{m=1}^{d} \ \beta_m \cdot \left[\mathbb{0}_{u_{m-1}} \ , \ \mathbb{1}_{u_m - u_{m-1}} \ , \ \mathbb{0}_{T - u_m}\right]$. where $\mathbb{0}_\ell$ and $\mathbb{1}_\ell$ are ℓ-dimensional vectors of all zeros and all ones, respectively.*

We comment that a similar solution structure is provided in [18] for treating the problem of optimal power allocation over a point-to-point *static* channel in an energy harvesting system.

H. Stochastic Uncertainties

In this subsection we consider a class of utility functions and resource vectors the true values of which are known only causally, and otherwise bear stochastic uncertainties. We show that solving this class of stochastic problems can be reduced to solving problems of the form in (2). To formalize such settings, we assume $\{s_t : t \in \{1, \dots, T\}\}$ are independent and identically distributed (i.i.d.) random variables unknown non-causally. Furthermore, to capture the uncertainties in $f_t(x)$ we assume that the function depends on an unknown random variable α_t, and denote it by $f_t(x, \alpha_t)$. We also assume that f_t is concave in its both arguments. Given these notations, a stochastic account of (2) can be formalized by optimizing the *expected* value of the aggregate utility subject to *chance* constraints on the availability of the resource, i.e.,

$$\mathcal{Q}(\gamma) \triangleq \left\{ \begin{array}{ll} \max\limits_{\boldsymbol{x}} & \sum\limits_{t=1}^{T} \ \mathbb{E}_{\alpha_t}[f_t(x_t, \alpha_t)] \\ \text{s.t.} & \mathbb{P}\left(\sum\limits_{i=1}^{t} x_i \leq \sum\limits_{i=1}^{t} s_i \right) \ \geq \ \gamma \ , \quad \forall t \in \{1, \dots, T\} \\ & \boldsymbol{x} \ \succeq \ 0 \end{array} \right. . \tag{10}$$

It can be readily verified that the function $\bar{f}_t(x) = \mathbb{E}_{\alpha_t}[f_t(x, \alpha_t)]$ is concave in x. Also, by denoting the cumulative distribution function of $\sum_{i=1}^{t} s_i$ by G_t, the stochastic constraints can be rewritten as $\sum_{i=1}^{t} x_i \leq G_t^{-1}(1-\gamma)$. Moreover, by setting $\gamma_1 \triangleq G_1^{-1}(\gamma)$, defining

$$\gamma_t \ \triangleq \ G_t^{-1}(1-\gamma) - G_{t-1}^{-1}(1-\gamma) \ , \qquad \forall t \in \{2, \dots, T\} \ , \tag{11}$$

and noting that $G_t(x) \geq G_{t-1}(x)$ for all $t \in \{2, \dots, T\}$, it can be readily verified that the solution of $\mathcal{Q}(\gamma)$ can be found by solving the problem $\mathcal{P}(\boldsymbol{s})$ since $\mathcal{Q}(\gamma) = \mathcal{P}([\gamma_1, \dots, \gamma_T])$.

III. Application: Energy Harvesting Systems

In this section we discuss the application of the general approach developed in Section II to the problem of power allocation in a single-user point-to-point communication channel in which the transmitter's battery is equipped with an energy harvesting unit, gathering its power entirely from ambient sources in its surrounding environment. Hence, power, as the resource, is made available for transmission only sequentially and incrementally over time. For this purpose, consider a time-slotted transmission over a single-antenna channel in which the channel input at time $t \in \{1, \dots, T\}$ is denoted by X_t, and the output is given by

$$Y_t = h_t \cdot X_t + N_t , \qquad \text{for} \quad t \in \{1, \dots, T\} , \tag{12}$$

where h_t denotes the channel coefficient at time $t \in \{1, \dots, T\}$, and N_t accounts for additive white Gaussian noise distributed according to $\mathcal{N}_{\mathbb{C}}(0, 1)$. In this model, x_t denotes the transmission power at time $t \in \{1, \dots, T\}$ and s_t denotes energy increments harvested at time t. Throughout the analysis we assume that the battery has infinite capacity.

A. Sum-rate Maximization in Fading Channels

By setting the utility function as $f_t(x_t) \triangleq \log(1 + \alpha_t \cdot x_t)$ where $\alpha_t \triangleq |h_t|^2$, the optimal power consumption scheme over time for the purpose of maximizing the sum-rate capacity in this energy harvesting system can be obtained via solving

$$\mathcal{P}(\boldsymbol{s}) = \begin{cases} \max\limits_{\boldsymbol{x}} & \sum\limits_{t=1}^{T} \log(1 + \alpha_t \cdot x_t) \\ \text{s.t.} & \sum\limits_{i=1}^{t} x_i \le \sum\limits_{i=1}^{t} s_i , \quad t \in \{1, \dots, T\} \\ & \boldsymbol{x} \succeq 0 \end{cases} . \tag{13}$$

For solving $\mathcal{P}(\boldsymbol{s})$ we can directly apply Algorithm 1, which can identify the set of the dominant constraints recursively. In each recursion cycle, the algorithm solves a power allocation problem that is equivalent to optimizing power allocation across independent parallel channels and can be solved via the well-known water-filling algorithm. Nevertheless, when there is more structure to be leveraged, solving such power allocation problems can be avoided, and the indices of the dominant constraints, and the associated power allocation schemes can be found directly. Hence, for a general fading model, the optimal solution of $\mathcal{P}(\boldsymbol{s})$ consists of identifying the dominant constraints indexed by $\{u_i : i \in \{1, \dots, d\}\}$ in conjunction with applying the water-filling algorithm d times for solving $\mathcal{Q}_{u_{i-1} \to u_i}(\boldsymbol{s})$. We remark that the indices $\{u_i : i \in \{1, \dots, d\}\}$ mark the instances at which the entire energy available at those instances is exhausted, and there is no energy carry-over to the following instances. The fact that the optimal solution involves elements similar to water-filling is pointed out and discussed in details in [4], and the result in this paper complements this observation by determining the exact time intervals $\{u_{i-1}+1, \dots, u_i\}$ over which the optimal power solution is the water-filling solution of $\mathcal{Q}_{u_{i-1} \to u_i}(\boldsymbol{s})$. In the following corollary, we also address a special cases of interest, in which the fading process can be time-varying, but the rate of variations is small enough to be bounded by a measure specified by the variations of the harvested energy over time. Specifically, if the deviations of $\frac{1}{\alpha_t}$ from their average $\frac{1}{T}\sum_{t=1}^{T}\frac{1}{\alpha_t}$ are smaller than the average harvested energy $\frac{1}{T}\sum_{t=1}^{T} s_t$, i.e., when

$$\frac{1}{\min_t \alpha_t} \le \frac{1}{T}\sum_{t=1}^{T}(s_t + \frac{1}{\alpha_t}) , \tag{14}$$

then the structure of Algorithm 1 simplifies significantly, as specified in the following corollary and Algorithm 3. It is noteworthy that a static channel (i.e., α_t constant) satisfies (14) and power allocation in static channels can be also determined by Algorithm 3.

Corollary 1 (Slowly Fading Channels)**.** *For a fading model that satisfies* (14)*, for the optimal solution of $\mathcal{P}(\boldsymbol{s})$ the time instants at which the available resources are exhausted are given by*

$$u_m = \arg\min_{t \in \mathcal{A}_m} \frac{1}{t - u_{m-1}} \cdot \sum_{i=u_{m-1}+1}^{t} \left(s_i + \frac{1}{\alpha_i}\right) . \tag{15}$$

Based on the result of Corollary 1, we provide Algorithm 3 as a simple approach to obtain the optimal power allocation $\boldsymbol{x}^*$ to the problem in (13) by admitting the vector of harvested energy $\boldsymbol{e}$ as an input. For the convenience in notation, we define the channel power gain vector as $\boldsymbol{\alpha} \triangleq [\alpha_1, \dots, \alpha_T]$. The optimality of the provided power allocation $\boldsymbol{x}^*$ is stated in Theorem 4.

Theorem 4. *For a quasi-static fading model that satisfies* (14)*, power allocation $\boldsymbol{x}^*$ yielded by Algorithm 3 is the optimal solution to the problem $\mathcal{P}(\boldsymbol{s})$ in* (13)*.*

Algorithm 3 - Optimal power allocation $\boldsymbol{x}^*$ over fading channels

input $\boldsymbol{s}$
initialize $d = 0$ and $u_d = v_d = 0$
while $u_d \le T - 1$
  $d \leftarrow d + 1$
  set $\mathcal{A}_d \triangleq \{u_{d-1} + 1, \dots, T\}$
  $u_d = \arg\min\limits_{t \in \mathcal{A}_d} \frac{1}{t - u_{d-1}} \cdot \sum\limits_{i=u_{d-1}+1}^{t} \left(s_i + \frac{1}{\alpha_i}\right)$
  $\beta_d \triangleq \frac{1}{u_d - u_{d-1}} \sum\limits_{i=\bar{u}_{d-1}+1}^{u_d} (s_i + \frac{1}{\alpha_i})$
end while
for $t \in \{1, \dots, T\}$
  set $x_t^* \triangleq \beta_j - \frac{1}{\alpha_t}$, where $j = \inf\{u_i : u_i \ge t\}$
end for

B. Special Cases

In this subsection we present two special cases that specialize the sum-rate optimization of interest to the two special cases studies in Section II, namely homogeneous utility functions and utility functions with stochastic uncertainties.

Example 1 (Homogeneous Utility Functions)**.** In the context of energy harvesting, the utility functions turn out to be homogeneous when the fading process is static and the fading coefficients do not vary over time, i.e., $\alpha_1 = \cdots = \alpha_t = \alpha$, as a result of which the utility functions remain unchanged over time, i.e., $f_t(x) = \log(1 + \alpha x)$.

Example 2 (Stochastic Uncertainty)**.** When the fading coefficient α_t is random and unknown to the transmitter, the utility function $f_t(x, \alpha_t) = \log(1 + \alpha_t x)$, which is concave in both α_t and x, becomes also random and unknown. Based on the discussion in Section II-H, the expected utility function $\bar{f}_t(x) = \mathbb{E}_{\alpha_t}[f_t(\alpha_t, x)] = \mathbb{E}_{\alpha_t}[\log(1 + \alpha_t x)]$ is concave in x, and as result the stochastically-constrained power allocation problem can be solved via solving (10).

IV. Numerical Evaluations

In this section, we present numerical evaluations to highlight the structure and the properties of Algorithm 1 provided in Section II and compare its performance with the generic numerical algorithms for solving convex problems. Throughout the simulations we pursue two objectives. First, we aim to numerically assess the structure of the optimal solution given in lemmas 4 and 5, and assess the number of the variations of the dominant constraints, as well as the utility value with respect to different resource arrival processes. Secondly,

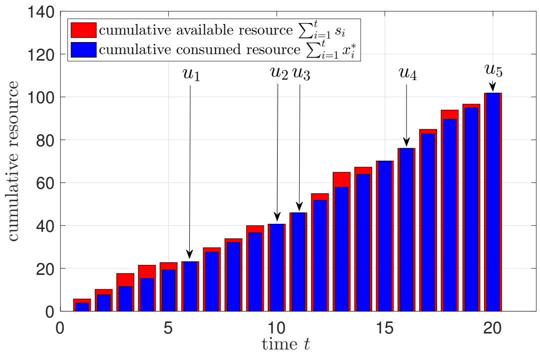

Fig. 1: Resource arrival and allocation.

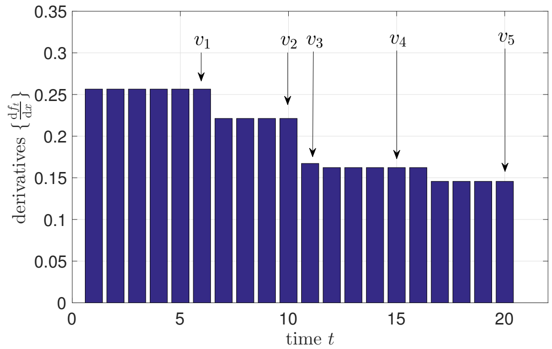

Fig. 2: Derivative measures $\{\mathrm{d}f_t/\mathrm{d}t\}$.

we compare the structure of the optimal solution and the performance yielded by the optimal solution characterized with those yielded by two generic convex optimization approaches, namely the interior point (IP) method and the Matlab CVX solver.

Throughout the simulations we focus on the slowly-fading energy harvesting application specified in Section III. In this model the utility function at time t is $f_t(x_t) = \log(1 + |h_t|^2 x_t)$, where the channel coefficients h_t follow a Rayleigh fading and are distributed according to $\mathcal{N}_{\mathbb{C}}(0, 1)$. The amount of energy harvested at different time slots, i.e., $\{s_t : t \in \{1, \dots, T\}\}$, randomly varies over time, and for the purpose of implementation we consider three different models for the energy arrival process, namely $\text{Unif}(0, 2\eta)$, $\text{Exp}(\frac{1}{\eta})$, and $\text{Poisson}(\eta)$, where η denotes the average resource arrival rate.

A. Constraint Groups

The key structure of the solution to $\mathcal{P}(\boldsymbol{s})$ is that it can be reduced by partitioning $\{x^*, \dots, x_T^*\}$ into d disjoint sets, where the values in each set are related (their respective functions have same derivatives) and can be computed independently of each other. The set $\{u_i :\in \{1, \dots, d\}\}$ specifies the time instances at which all the available resources are exhausted. In order to demonstrate this numerically, we set the time horizon to $T = 10$, and generate one realization of the harvested energy vector $\boldsymbol{s}$. We solve the problem $\mathcal{P}(\boldsymbol{s})$ for this realization, and in Fig. 1 plot the variations of $\sum_{i=1}^{t} x_i^*$ over time to asses the optimal properties stated in lemmas 4 and 5. For this evaluation we consider $\text{Unif}(0, 2\eta)$ as the energy arrival process, with $\eta = 5$. The light (red) bar at time t shows the level of available resources at time t, and the dark (blue) bar depicts the amount of available resources to be consumed at time t. It is observed that at certain time instants the two bars have exactly same heights indicating the available resources are exhausted. These time instants occur at $\{u_1, u_2, u_3, u_4, u_5\} = \{6, 10, 11, 16, 20\}$. We have also evaluated the variations of $\sum_{i=1}^{T} x_i$ for the solution $\boldsymbol{x}$ provided by the CVX solver as well as the IP method, where we have observed that the solutions match with the optimal solution with high accuracy (albeit with higher complexity analyzed in Section IV-B). Furthermore, for the same system realization used for the evaluations in Fig. 1, the variations of the derivatives of the utility functions, i.e., $\{\mathrm{d}f_t/\mathrm{d}t : t \in \{1, \dots, T\}\}$ are depicted in Fig. 2. It shows two main properties associated with the derivative measures $\{v_i : i \in \{1, \dots, d\}\}$. First, the solutions in the range $\{u_i + 1, \dots, u_{i+1}\}$ have the same derivatives, and secondly, the metrics $\{v_i : i \in \{1, \dots, d\}\}$ are strictly decreasing over time. These values are marked in Fig. 2.

B. Computational Complexity

An important practical advantage of $\{x^*, \dots, x_T^*\}$ is that the elements in each partition are computed independently of each other. This leads to significant reduction in the computational complexity since instead of solving a T-dimensional problem we face solving a number of problems with dimensions much smaller than T. To compare the complexity of Algorithm 1 with those of CVX solver and IP method, we consider the setting of Section IV-A, and provide Table I, which demonstrates the processing times of the algorithm for different values of T and three energy arrival processes (uniform, exponential, and Poisson). This table shows that the algorithm, in designing which the structure of the problem is taken into account, is considerably faster than the CVX solver and the IP method.

Table I: Computational time in seconds

T \ s_t	Unif (0,10)			Exp $(\frac{1}{30})$		
	Alg. 1	IP	CVX	Alg. 1	IP	CVX
10	29×10^{-6}	0.11	1.84	51×10^{-6}	0.15	1.75
100	31×10^{-6}	0.87	11.25	55×10^{-6}	0.87	10.55
1000	42×10^{-6}	2.09	443.70	77×10^{-6}	2.08	376.23

C. Number of Partitions

Figure 3 depicts the variations of the number of partitions d with respect to different rates of energy arrival η under three different processes, and for different problem dimensions $T = 10, 50, 100$. It is observed that for a given T, d remains rather insensitive to energy arrival process, and the the average arrival rate η. The underlying reason is that the expected values of $\{u_i : i \in \{1, \dots, d\}\}$ do not depend on the exact distribution of the resource arrival process, and rather they depend on the relative changes of these distributions over time. When the distributions are identical over time, as is the case in this setting, their exact choices do not have a significant impact. As a result, varying the energy arrival rate η does not affect the average values of $\{u_i : i \in \{1, \dots, d\}\}$, and subsequently, the expected value of d.

Additionally, increasing T has two opposing effects on d. On the one hand it increases the spacing between the consecutive time indices in $\{u_i : i \in \{1, \dots, d\}\}$. The reason underlying this is that according to Algorithm 1, these time indices are determined by selecting the maximum derivative measure, $q^{d,t}$, for every $t \in \mathcal{A}_i$ and $i \in \{1, \dots, d\}$. Thus, by increasing the time horizon T, the maximum values of the derivative measures, $q^{d,t}$, appear, on average, at later time instances. This effect tends to decrease d. On the other hand, a larger T is expected to lead to a larger number of constraint groups.

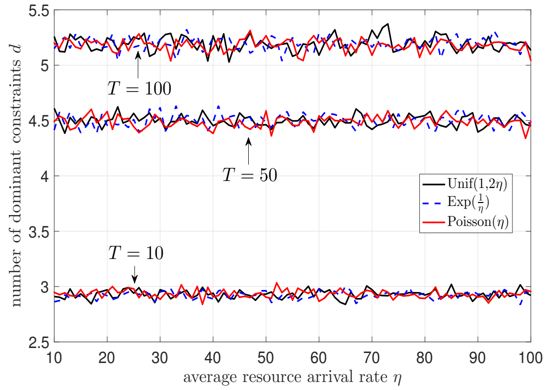

Fig. 3: Average d versus η.

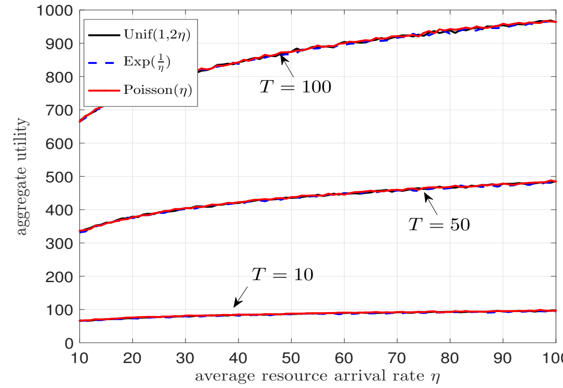

Fig. 4: Aggregate utility versus η.

Figure 3 shows the combined effect of these two opposing trends is in favor of an increasing trend for d.

V. Conclusion

In this paper, we have analyzed and solved the problem of optimal resource allocation over time, with the resource becomes available sequentially and incrementally over time. Such problems in their general forms subsume a wide range of conventional resource allocation problems in communication systems (e.g., resource allocation over parallel channels), and have direct application in certain applications in which resources are accessible sequentially (e.g., energy harvesting and quality-constrained systems). First, we have established certain key properties of the optimal solution, based on which we have proposed an algorithm for obtaining the solution. A key observation has been that there exist time instants at which the available resource is entirely utilized, and characterizing the optimal solution depends on identifying those instants. The proposed algorithm provides closed-form characterization of these instants. Furthermore, we have shown that the proposed algorithm can be applied to a stochastic version of the resource allocation problem, in which only the statistical properties of the resource arrivals are known. Moreover, we have applied the obtained optimal solution to identify a closed-form optimal power allocation policy under energy harvesting constraints over the single-user fading channels. Finally, we have provided numerical evaluations to depict the key properties of the optimal resource allocation policy and to also compare the performance with those of generic convex optimization algorithms.

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