Maximal Lifetime Power and Rate Allocation for Wireless Sensor Systems With Data Distortion Constraints

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***Abstract*—We address a lifetime maximization problem for a single-hop wireless sensor system (also known as a Gaussian sensor network) where multiple sensors encode and communicate their measurements of a Gaussian random source to a fusion center (FC). The FC is required to reconstruct the source within a prescribed distortion threshold. The lifetime optimization problem is formulated as a joint power, rate, and timeslot [for time-division multiple access (TDMA)] allocation problem under the constraints of the well-known rate distortion constraints for the Gaussian CEO problem, the capacity constraints of the wireless links, the energy constraints of the sensor nodes and the strict delay constraint within which the encoded sensor data must arrive at the FC. We study the performances of TDMA and an interference limited nonorthogonal multiple access (NOMA) (with single-user decoding)-based protocols and compare them against recently reported simple uncoded amplify and forward schemes under a nonorthogonal multiple access channel with complete phase synchronization. Since computing the exact capacity region for correlated sources in a multiaccess channel is difficult, we simply consider the Gaussian multiaccess capacity constraints pretending that the sensor data are independent (although they are clearly not). We show that the optimal lifetime achieved under these capacity constraints provides an upper bound on the optimal lifetime achieved by the TDMA and NOMA protocols. While the constrained nonlinear optimization problems for the TDMA and the Gaussian multiaccess cases are convex, the NOMA case results in a nonlinear nonconvex difference of convex functions (D.C.) programming problem. We provide a simple successive convex approximation based algorithm for the NOMA case that converges fast to a suboptimal lifetime performance that compares favorably against the upper bound provided by the Gaussian multiaccess case. Extensive numerical studies are presented for both static and slow fading wireless environments with full channel state information at the fusion center.**

***Index Terms*—Convex optimization, fading channels, power control, rate distortion theory, sensor networks.**

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I. Introduction

Wireless sensor networks (WSNs) have become a key technology for the 21st century due to its widespread applications in security, health, disaster response, defense, telecommunications, structural health monitoring, etc. Due to limited energy resources and a distinct lack of centralized coordination (compared to cellular networks), the usefulness of these networks can become limited unless special care is taken to optimize energy consumption in communication and computation. Optimizing the lifetime of a WSN is thus an important problem. In many typical wireless sensor network applications, a set of nodes or agents measure or collect data from a source or phenomenon of interest (e.g., temperature in a bushfire prone area or surveillance pictures of human movements, etc.) and then transmit them (possibly over a multihop relay network) to a sink or a base station where all data are collected and decisions or final estimates are made. In such a network, energy consumption is affected by such diverse parameters as choice of routes, MAC protocols, transmission scheduling, data rates, transmit power, wireless channel quality and fading, etc. Thus, to optimize the lifetime of a WSN, one really has to consider a cross-layer design. This often leads to very complicated mixed-integer nonlinear optimization problems. Some such cross-layer issues with joint power and rate control have been studied in [1] and [2]. In particular, [2] studied a joint power and rate control problem for lifetime optimization in a multihop wireless sensor network with constraints on outage induced by channel fading. In both [1] and [2], nonconvex nonlinear optimization problems were transformed into approximate convex optimization problems and solved using sophisticated convex optimization tools. Lifetime optimization with joint rate and power control in interference limited ad hoc networks has also been considered in [3], whereas some earlier work has focused on specific key issues such as maximum lifetime routing algorithms, such as [4] and [5].

However, the nature of data being communicated via the WSNs considered in the above literature as well as in many other works (that cannot be mentioned here due to space limitations) were considered to be generic, and the only constraints (if any) on the rates of data transmission were dictated by flow conservation laws and the maximum link capacities. No particular attention was paid to the nature of the source of the data and the specific task performed by the WSN. Recently, however, a lifetime maximization problem was considered with rate distortion constraints in [6]. In this paper, the specific task for the WSN is considered to be reconstruction of a remote random source. It is well known from rate distortion theory that higher data rates may allow high quality data reconstruction (e.g., in surveillance camera applications), it may also result in large amount of energy expenditure in a WSN due to multihop transmission. This inherent tradeoff between transmission rates (to achieve a certain prespecified distortion threshold) and lifetime of the WSN was studied in [6] for an interference-free WSN where transmission power was kept fixed and the only optimization variables were the data rates in the various links of the WSN. The rate distortion constraints were given by the data rate constraints derived in [7] for sensors with unequal noise variances for the well known Gaussian CEO problem. In order to make their nonlinear optimization problem tractable, the authors of [6] made some judicious linear approximations and obtained upper and lower bounds on the optimal network lifetime using linear programming methods. It was shown in [8], however, that this nonlinear optimization problem can be transformed into a convex problem by a clever variable substitution and can be solved exactly by using standard convex optimization tools such as interior point methods.

Another key constraint in data communication over wireless sensor networks is the delay incurred in receiving the data, which may be critical in many applications such as video surveillance, disaster response scenarios, or networked control applications where actuators have to take timely decisions or actions to stabilize a remotely observed system via a WSN. Delay constrained communication over wireless fading channels and associated transmission or packet scheduling problems for energy constrained wireless networks has been the focus of many recent works such as [9]–[13]. Of particular relevance to our work is [13], where the authors considered an energy optimal time scheduling problem with a strict delay constraint where a nonuniform time-division multiple access scheme (TDMA) is used for downloading fixed amounts of data from various sensors into a fusion center (FC) within a strict time duration. Another related work is [14] where a type-based estimation scheme is presented for decentralized estimation over a multiple access channel. In our paper, we consider a similar single-hop sensor network (also known as a *Gaussian sensor network*) where multiple sensors (agents) encode and transmit noisy measurements of a remote Gaussian source to an FC. The encoding rates for the various sensors can be different and are adjustable to suit the channel conditions and the delay constraint. The sensors or agents transmit their encoded data at rates which may or may not be equal to the encoding rates, depending on the multiple access scheme and the delay constraint. Each sensor is equipped with a finite amount of initial energy. The wireless channel between each sensor and the FC is taken to be static over the duration of the strict delay constraint. This delay duration is assumed to be long enough so that the maximum achievable data rate can be expressed as the Shannon capacity for that channel realization, but not too long so that the delay constraint loses its physical significance (see [13] for a similar assumption). The channels while being static during one time slot duration equal to the delay, can change randomly from one time slot to the next. In this paper, we assume that the FC has perfect channel state information (CSI) within a specific delay duration time slot, since the channel fading is assumed to be slow.

We consider a lifetime maximization problem for this sensor network with respect to transmit power and encoding rates (or transmission rates since they are related), subject to the data transmission rates satisfying the channel capacity constraints and the encoding rates satisfying the rate distortion constraints. The network lifetime is assumed to be long enough such that the sensor network is responsible for collecting measurements from the random source and transmitting them to the FC within the delay constraint a large number of times. This assumption essentially justifies the use of information theoretic capacity and rate distortion constraints in the formulation of the lifetime optimization problem. We consider both orthogonal TDMA (where an individual sensor transmits only for a fraction of the delay duration) and nonorthogonal interference limited multiple access (where all sensors transmit for the entire time slot but can create interference for each other) as the possible multiple access schemes. It is well known that computing the exact capacity region for correlated sources over a multiaccess channel is a difficult problem [15], [16]. Instead, we consider the Gaussian multiaccess channel capacity constraints assuming that the sensor data are independent (although clearly they are not since they observe the same source) and show that the optimal lifetime obtained with these constraints provides an upper bound on the achievable lifetime via TDMA and the nonorthogonal multiple access protocols. The corresponding optimization problems can be convex (Gaussian multiaccess and TDMA) or a nonconvex D.C. (difference of two convex functions) programming problem (interference limited case). We provide centralized solutions to the optimal power, rate and transmission duration (in the case of TDMA) allocation problems. The lifetime maximization problem for the Gaussian multiaccess (GMAC) case and the TDMA case can be solved globally using well known convex optimization tools. In order to solve the nonconvex optimization problem for the interference limited case, we use clever (similar to [17]) successive convex approximations of the original nonconvex optimization problem. In contrast to complex algorithms based on outer approximations or branch and bound methods [18] that take a long time to converge, we present practical algorithms that converge fast to *suboptimal* power and rate solutions for the interference limited case. Essentially, we argue that these algorithms can be run at the FC and the optimal (or suboptimal) variables can be fed back to the sensors. Energy consumption is restricted to transmission only although this framework can be readily extended to include other forms of energy consumption such as due to sensing, reception, compression and computation etc. Also, the FC is assumed to have access to replenishable energy and therefore the energy consumption in feedback is not considered. Finally, we comment that we only focus on centralized (i.e., not distributed) optimization algorithms as the number of sensing agents we can consider in such networks is small in the context of our problem. This is mainly due to the fact that the number of rate distortion constraints increases exponentially with the number of sensing nodes. Having said that, small-to-moderate-size sensor networks are currently operational in many radar and sonar applications. Also, our Gaussian sensor network can be seen as a small part of a larger hierarchical sensor network, e.g., where the network considered in this paper forms a cluster in a large sensor network consisting of many such clusters [19]. The results derived in this paper are useful in this context.

It has been recently shown in [20] and a number of subsequent papers that separate source and channel coding for minimizing distortion in a homogeneous Gaussian sensor network may not be always be a good idea. In particular, it was shown that a simple uncoded (where the sensors simply amplify and forward their noisy observations to the FC) scheme under perfect phase synchronization via a nonorthogonal multiple access scheme achieves a better scaling law than a separate source and channel coding scheme when the number of sensors grows and the total available power for the sensors grows linearly with the number of sensors. Under orthogonal multiple access, however, it has been shown that uncoded schemes perform strictly suboptimally for the Gaussian sensor network compared to separate source and channel coding schemes [21]. Hence, we compare our optimal lifetime performances achieved by the TDMA, the interference limited scheme and the GMAC (with the independent sensor data approximation) capacity achieving protocols with optimal lifetimes achieved by such uncoded schemes (for nonorthogonal multiple access).

In summary, the novelty of this paper lies in 1) formulation of a lifetime maximization problem for a Gaussian sensor network under the rate distortion constraints of the CEO problem and appropriate capacity constraints of the wireless multiaccess scheme (TDMA, nonorthogonal multiple access scheme (NOMA), and GMAC); 2) providing centralized algorithms for solving these optimization problems (optimal for TDMA and Gaussian multiaccess and suboptimal but fast convergent for NOMA); 3) showing that the Gaussian multiaccess capacity constraints (assuming independence between sensor data) actually provides an upper bound on the lifetime achieved by the TDMA and NOMA scheme; and 4) comparing the performance of these schemes against a simple uncoded amplify and forward scheme under nonorthogonal multiple access with complete phase synchronization via extensive simulation studies.

In the next section, we mathematically state the lifetime optimization problems with rate distortion constraints for the TDMA, the nonorthogonal interference limited case and the idealized (with independent sources) Gaussian multiaccess channel capacity constraints. We also briefly state the lifetime optimization problem using an uncoded amplify and forward scheme for the nonorthogonal multiple access case with full phase synchronization. In Section III, we provide a successive convex approximation based algorithm for solving the nonconvex optimization problem arising in the interference limited case, which is provably convergent. We also comment on the optimality issues associated with this sequential convex approximation method in relation to the original nonconvex problem. Section IV presents extensive simulation results comparing the lifetime performance of the various protocols for different rate distortion threshold requirements under static and slow fading wireless environments. Section V presents some concluding remarks and directions for future work.

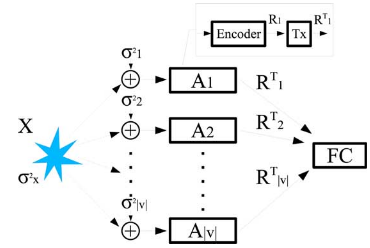

Fig. 1. Sensor network measuring a random source.

II. Problem Formulation

The single-hop wireless sensor network considered in this paper (also known as a *Gaussian sensor network*) is presented in Fig. 1 where multiple sensor nodes or agents send their information to a FC via wireless links. The set of sensor nodes is denoted by $\mathcal{V}$. The sensor nodes $\{A_1, A_2, \ldots, A_{|\mathcal{V}|}\}$ observe a discrete-time independent and identically distributed (i.i.d.) sequence $\{X_k, \ \ k \ \in \ \mathbb{N}\}$ of a Gaussian stochastic process where $X_k \ \sim \ N(0, \sigma_x^2)$. The noisy measurement (at a discrete-time instant k) at the sensor A_i is represented by $X_k + n_i(k)$ where $\{n_i(k)\}$ is also a sequence of i.i.d. random variables and $n_i(k) \sim N(0, \sigma_i^2)$. We also assume that the noise processes $n_i(k)$, $n_j(k)$ are mutually independent for $i \neq j$, $\forall k, i, j \in \{1, 2, \ldots, |\mathcal{V}|\}$. In general, the noise variances at the different sensor nodes are unequal, representing an inhomogeneous set of sensors. Agent A_i encodes information at a rate R_i and sends it to the FC at a transmission rate of R_i^T. The transmission rate and the encoding rate may or may not be the same depending on the multiple access protocol. The FC has to reconstruct the source X after receiving encoded measurements from all $|\mathcal{V}|$ sensors. We use $\log$ to denote the natural logarithm throughout the paper.

It is well known that the encoding rates from various sensors need to satisfy a set of rate distortion constraints to achieve a maximum distortion threshold. For the multisensor case, these results were obtained as the solution to the Gaussian CEO problem for the inhomogeneous sensor case in [7]. These constraints were rewritten in a slightly different form in [8] in the context of a lifetime optimization problem for a multihop sensor network. Below we quote these rate distortion constraints from [8], which can be easily shown to be convex:

$$\sum_{v\in\mathcal{W}_k} r_v + \frac{1}{2}\log\frac{1}{D_{\text{th}}} - \frac{U_k}{2} - \sum_{v\in\mathcal{W}_k} R_v \leq 0 \ k = 1, \ldots, 2^{|\mathcal{V}|} - 1$$
$$e^{U_k} - \frac{1}{\sigma_X^2} - \sum_{v\in\mathcal{V}\setminus\mathcal{W}_k} \frac{1 - e^{-2r_v}}{\sigma_v^2} \leq 0 \quad k = 1, \ldots, 2^{|\mathcal{V}|} - 1$$
$$\frac{1}{D_{\text{th}}} - \frac{1}{\sigma_X^2} - \sum_{v\in\mathcal{V}} \frac{1 - e^{-2r_v}}{\sigma_v^2} \leq 0 \tag{1}$$

where D_{th} is the maximum allowed distortion threshold after reconstruction at the FC and $\mathbf{r} \in \mathbb{R}^+$ and $\mathbf{U} \in \mathbb{R}$ are auxiliary variables. The set $\mathcal{W}$ contains all the nonempty subsets $\{\mathcal{W}_1, \mathcal{W}_2, \ldots, \mathcal{W}_{2^{|\mathcal{V}|}-1}\}$ of $\mathcal{V}$. Here, $\mathbf{R} \ = \ [R_1, \ldots, R_{|\mathcal{V}|}]'$ where $'$ denotes the transpose operation. Clearly, to achieve a distortion less than or equal to D_{th} at the FC the amount of information FC fetches from the various agents needs to be great than or equal to $\mathbf{R} = [R_1, \ldots, R_{|\mathcal{V}|}]'$ in b/s/Hz. The rate distortion region $(D_{\mathrm{th}}, \mathbf{R})$ is called achievable when the inequalities (1) hold for the pair D_{th} and $\mathbf{R}$.

Remark 1: It should be obvious from (1) that the number of rate distortion constraints grows exponentially with the number of sensing agents. This fact certainly limits the size of the sensor network that we can consider in this paper. However, as discussed before, many examples of small to moderate size sensor networks exist in currently operational radar and sonar applications. Also, our Gaussian sensor network can be seen as a small part of a larger hierarchical sensor network, e.g., where the network considered in this paper forms a cluster in a large sensor network consisting of many such clusters. It is quite conceivable that many large sensor networks of the future will have such a hierarchical structure [19]. The results derived in this paper are useful in this context.

We assume that the sensors are sensing data at constant rates and the FC has to download all data encoded by each sensor within a strict time schedule T. This delay constraint essentially implies that all data encoded by sensor A_v within a time duration T have to be received at the FC within the same time duration for all v. Note that if the sensors are transmitting all the time, such as in an interference limited scheme, then this delay constraint is equivalent to having the transmission rate equal to the encoding rate. However, if a TDMA scheme is chosen for transmission, where A_v transmits only for a duration $t_v T$, where $0 \leq t_v \leq 1$, and $\sum_v t_v = 1$, then the transmission rate $R_v^T = R_v / t_v$, which is clearly greater than the encoding rate. The channels between the sensor nodes and the FC are assumed to suffer distance based attenuation in the first instance and later we assume that the channels additionally undergo independent identically distributed Rayleigh fading. In the case of fading, the channel dynamics are assumed to be slow enough so that the maximum achievable rate of transmission for each channel is given by the Shannon capacity for that particular channel realization, which is assumed to be static within the delay duration T for all sensors. Consequently, we consider perfect CSI at the FC for the fading scenario as well.

Assuming that the vth sensor is equipped with an initial energy E_v, we define the lifetime of the network as

$$LT_{\mathrm{net}} \triangleq \min_{v \in \mathcal{V}} LT_v = \min_{v \in \mathcal{V}} \frac{E_v}{P_v^{\mathrm{avg}}} \tag{2}$$

where P_v^{avg} is the average power consumed in data transmission. This definition of lifetime denotes the minimum time before the first node runs out of energy. This definition was originally used in [4] and since then been used by many other authors. Note however, that there are many other definitions of the lifetime of a sensor network such as the time until a certain fraction of nodes survive in the network [22], or the time to the first loss of coverage etc. For a survey of these definitions, see [23]. A generalized notion of lifetime based on residual energy in sensors and channel state information is given in [24] and [25] where the network lifetime is defined as the number of data collections after which the number of active sensors in the network fall below a certain threshold. In line with this, one can similarly consider an alternative lifetime maximization problem for a Gaussian sensor network where the lifetime is defined as the time after which the network can no longer achieve a distortion lower than the specified threshold at the FC. Solving maximal lifetime rate and power allocation problems with data distortion constraints with these other definitions of network lifetime is however, beyond the scope of our current paper, as these formulations often result in either checking a combinatorially prohibitive number of possible sensor network configurations that can achieve the required distortion threshold at the FC, or alternatively, may result in multiobjective optimization problems that are difficult to solve.

Remark 2: We remark however, that for the various multiaccess schemes that we consider, the definition of lifetime that is considered in this paper (the minimum of all the individual sensor lifetimes), is not actually restrictive. It can be shown analytically (we do not include the proofs for space limitations) that according to the optimal strategy, all the sensors run out of energy at the same time for the TDMA and the uncoded amplify and forward case, and the same phenomenon is observed for the NOMA (excluding the sensors that are shut off) and the GMAC case throughout the simulations, although we do not have a proof. Finally, we add that if there was such a situation where a particular sensor ran out of energy before other sensors, then a simple suboptimal scheme to extend the network lifetime would be to apply our optimization technique successively (to the surviving sensors) until the distortion threshold can no longer be met at the FC, i.e., the optimization problem becomes infeasible. Thus, in such a case, the network operational lifetime would be given by the sum of the lifetimes achieved by the individual optimization problems.

Note also that we do not consider any other form of energy expenditure such as sensing, computation, etc., and also the energy expenditure at the FC is not taken into account since the FC is assumed to have access to a substantial energy reserve. In this paper, we seek to maximize this network lifetime (as given in (2)) subject to the rate distortion constraints, the delay constraint and the channel capacity constraints mentioned above, by optimally allocating transmit power, encoding rates and (in the case of TDMA) transmission time duration at the various sensors. These optimization algorithms are performed at the FC and the optimal variables are fed back to the sensors with negligible communication delay.

Remark 3: It is assumed here that the channel gains and noise variances at each sensor (which remain invariant for the period of data collection from the sensors) are known at the FC before it attempts to solve the optimization problem. This can be achieved via communicating training sequences (or pilot symbols) between the sensors and the FC and is a standard procedure in cellular wireless communications. See also [26] for a similar comment.

We consider the two usual multiple access schemes: an orthogonal TDMA and a nonorthogonal interference limited case. Since it is difficult to exactly compute the multiaccess channel capacity region with correlated sources (the sensors in our problem observe the same source and hence transmit correlated measurements), we consider the capacity region for an idealized Gaussian multiaccess channel assuming the sensors are independent. We show that the optimal lifetimes achieved by the TDMA and the nonorthogonal interference limited case are upper bounded by the lifetime achieved under (idealized) the Gaussian multiaccess capacity constraints. We also compare the optimal lifetime performance for the three cases above (which essentially employ separate source and channel coding) with the performance of a corresponding optimal lifetime solution for a simple uncoded (amplify and forward) system under nonorthogonal multiple access [20]. In the next section, we present the nonlinear optimization problems for the above four schemes.

A. TDMA System

A recent study [27] has shown that a pulsed operation of each sensor battery can increase the yield of a battery, as it affects how energy is being drained from the battery. This implies that a TDMA based scheme may be more energy efficient than other protocols [22]. In a TDMA based transmission scheduling scheme, we allow the sensor node/agent A_v to transmit during a fraction t_v of the available time slot (which is also taken to be equal to the delay duration within which all data have to be downloaded into the FC). Clearly, we have $\sum_{v\in\mathcal{V}} t_v \leq 1$. As alluded to earlier, the transmission rate of node v is decided by the encoding rate R_v in (1) and allocated timeslot t_v, and is given by R_v/t_v. In addition, the rate of transmission is upper bounded by the discrete-time Shannon capacity (assuming full CSI at the FC) in nats per channel use such that

$$\frac{1}{2}\log\left(1+\frac{g_vP_v}{N_0}\right) \geq \frac{R_v}{t_v} \tag{3}$$

where P_v is the transmission power for the vth sensor node, g_v denotes the propagation gain of the wireless channel between node v and the FC, and N_0 is the average power of the background noise at the FC receiver.

Combining all the constraints (rate distortion, delay and capacity constraints) and the objective function (2), we have the following optimization problem for the TDMA scheme:

$$\begin{aligned} &\max_{\mathbf{t},\mathbf{P},\mathbf{R}} LT_{\text{net}} \quad \text{s.t. } \frac{E_v}{P_vt_v} \geq LT_{\text{net}} \quad v=1,\ldots,|\mathcal{V}| \\ &\frac{1}{2}\log\left(1+\frac{g_vP_v}{N_0}\right) \geq \frac{R_v}{t_v} \quad v=1,\ldots,|\mathcal{V}| \\ &\sum_{v\in\mathcal{V}} t_v \leq 1 \\ &\{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\} \\ &\mathbf{t},\mathbf{P},\mathbf{R} \succeq 0. \end{aligned} \tag{4}$$

It can be easily shown to be a nonlinear nonconvex optimization problem. However, one can transform this nonconvex problem to a convex optimization problem by defining the following variables: $\bar{q} = 1/LT_{\text{net}}$, $\bar{P}_v = t_vP_v$. One can then rewrite the energy and capacity constraints and transform the above nonconvex optimization problem into the following convex formulation, which can be solved by well established convex optimization tools based on interior point methods.

$$\begin{aligned} &\min_{\bar{q},\mathbf{t},\bar{\mathbf{P}},\mathbf{R}} \bar{q} \quad \text{s.t.} -\bar{q}E_v + \bar{P}_v \leq 0, \quad v=1,\ldots,|\mathcal{V}| \\ &t_v\left(\exp\frac{2R_v}{t_v}-1\right) - \frac{g_v}{N_0}\bar{P}_v \leq 0, \quad v=1,\ldots,|\mathcal{V}| \\ &\sum_{v\in\mathcal{V}} t_v \leq 1 \\ &\{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\} \\ &\bar{q},\mathbf{t},\bar{\mathbf{P}},\mathbf{R} \succeq 0. \end{aligned} \tag{5}$$

B. Interference Limited System

In the interference limited scheme, all sensors transmit throughout the entire delay duration, and hence there always exists interference from other sensors which degrade the quality of reception at the FC. The capacity constraint on the transmission rate is then given by (note that here transmission rate is the same as the encoding rate)

$$\frac{1}{2}\log\left(1+\frac{g_vP_v}{\sum\limits_{k\neq v} g_kP_k + N_0}\right) \geq R_v. \tag{6}$$

Note that in this formulation, each sensor sees the interference created by other sensors as noise and hence this scheme is nonorthogonal as opposed to the TDMA scheme. We assume the FC uses single-user decoding rather than the more complex joint multiuser decoding. We call this simple multiple access scheme (6) NOMA in the rest of the paper.

Clearly, one can obtain better channel capacity and consequently, better network lifetime by considering multiple access schemes such as CDMA with multiuser detection such as linear minimum mean square error (LMMSE) receivers [28] or other more complex nonlinear receivers such as successive interference cancellation (SIC). Lifetime optimization problems for CDMA with complex multiuser detection schemes is beyond the scope of the current work and will be studied in a separate paper. We emphasize, however, that the optimization technique developed in this paper for the interference limited case can be easily extended to cope with such problems.

Note that the energy requirements in the NOMA system are different to the ones in TDMA, since all sensor nodes are transmitting throughout the entire time the network is alive. Therefore, for all v, we have $E_v/P_v \geq LT_{\text{net}}$.

In summary, the lifetime maximization problem in the NOMA case is given by

$$\begin{aligned} &\max_{\mathbf{P},\mathbf{R}} LT_{\text{net}} \quad \text{s.t. } \frac{E_v}{P_v} \geq LT_{\text{net}} \quad v=1,\ldots,|\mathcal{V}| \\ &\frac{1}{2}\log\left(1+\frac{g_vP_v}{\sum\limits_{k\neq v} g_kP_k + N_0}\right) \geq R_v, \quad v=1,\ldots,|\mathcal{V}| \\ &\{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\} \\ &\mathbf{P},\mathbf{R} \succeq 0. \end{aligned} \tag{7}$$

This optimization problem is nonlinear and nonconvex. In Section III, we will propose a successive convex approximation based methodology to solve the optimization problem given by (7).

C. Upper Bound on the Network Lifetimes of TDMA and Noma Schemes

It is obvious that in the problem we consider, the sensor nodes communicate to the FC via a Gaussian multiaccess channel. Note however though that the various sensors observe the same source and thus their observations are highly correlated. It is well known that obtaining the exact capacity region for a multiaccess channel with correlated sources is a difficult task [15], [16]. Although it is expected that the multiaccess capacity region for correlated sources will be larger than that with independent sources, we still consider the capacity region of the Gaussian multiaccess channel (pretending the sensors to be transmitting independent data) and show that the network lifetime achieved within these capacity constraints provides an upper bound on the optimal network lifetimes achieved by the TDMA and NOMA schemes described before. The capacity region for the Gaussian multiaccess channel (assuming independent sources) is given by (with normalized bandwidth $W = 1$) [29]

$$\left\{ \sum_{v\in\mathcal{W}_k} R_v \le \frac{1}{2}\log\left(1+\frac{\sum_{v\in\mathcal{W}_k} g_v P_v}{N_0}\right), \text{ where } \mathcal{W}_k \in \mathcal{W}, \quad k=1,2,\ldots,2^{|\mathcal{V}|}-1 \right\}. \tag{8}$$

Henceforth, we call this the idealized Gaussian multiple access channel (GMAC). Accordingly, the lifetime optimization problem for the idealized GMAC case can be described as

$$\begin{aligned} &\max_{\mathbf{P},\mathbf{R}} LT_{\text{net}} \\ \text{s.t.} \quad & \frac{E_v}{P_v} \ge LT_{\text{net}} \quad v=1,\ldots,|\mathcal{V}| \\ & \sum_{v\in\mathcal{W}_k} R_v \le \frac{1}{2}\log\left(1+\frac{\sum_{v\in\mathcal{W}_k} g_v P_v}{N_0}\right), \; k=1,\ldots,2^{|\mathcal{V}|}-1 \\ & \{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\} \\ & \mathbf{P},\mathbf{R} \succeq 0. \end{aligned} \tag{9}$$

The nonlinear optimization problem (9) can be converted to a convex minimization problem simply after a single-variable substitution $\bar{q} = 1/LT_{\text{net}}$:

$$\begin{aligned} &\min_{\mathbf{P},\mathbf{R}} \bar{q} \qquad \text{s.t.} \quad P_v - E_v\bar{q} \le 0 \quad v=1,\ldots,|\mathcal{V}| \\ & e^{\sum_{v\in\mathcal{W}_k} 2R_v} - \frac{\sum_{v\in\mathcal{W}_k} g_v P_v}{N_0} - 1 \le 0, \quad k=1,\ldots,2^{|\mathcal{V}|}-1 \\ & \{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\} \\ & \mathbf{P},\mathbf{R},\bar{q} \succeq 0. \end{aligned} \tag{10}$$

Therefore, the rate and power allocation problems for the idealized GMAC with rate distortion constraints can be solved using standard convex optimization tools. It can be shown in a fairly straightforward manner that the optimal lifetime solution of (10) provides an upper bound for the optimal solutions achieved by the TDMA and NOMA schemes, as the following result states. The proof can be found in the Appendix for the TDMA and the NOMA cases. For a simple intuitive explanation of this result, see [30, Ch. 6, pp. 232–233].

Proposition 1: The optimal lifetime solution to the convex optimization problem for the idealized GMAC capacity region given by (10) provides an upper bound to the optimal lifetime solutions for nonconvex optimization problems for the TDMA and the NOMA cases given by (4) and (7), respectively.

Remark 4: It should be noted that the exact capacity region for the Gaussian sensor network considered in this paper is difficult to compute, and thus the optimal achievable lifetime performance under these exact capacity constraints is also unknown. However, the bound derived above (using an idealized Gaussian MAC channel assuming independent sources) is still useful for various reasons. Instead of computing the performance with TDMA and NOMA schemes separately, one could simply use this bound to overestimate the TDMA and NOMA performance. And since the NOMA problem is nonconvex, and the global optimum cannot be found, the suboptimal solution presented in the paper (Section III) can be compared against this upper bound. We also believe that Proposition 1 is an interesting result in its own right.

D. Simple Uncoded Amplify and Forward Scheme

It has been shown recently that for a Gaussian sensor network under a nonorthogonal multiple access scheme, it is better for the sensors to simply amplify and forward their noisy data to the FC [20]. With identical sensor noise variance and total power in all sensors increasing linearly with the number of sensors, [20] shows that this simple analog amplify and forward scheme outperforms (minimum distortion achieved decreases as $1/|\mathcal{V}|$ rather than $1/\log|\mathcal{V}|$ where $|\mathcal{V}|$ is the number of sensors) any scheme based on separate source and channel coding and is asymptotically optimal (i.e., when $|\mathcal{V}| \to \infty$). See also [31] for some generalizations of these results. This technique has been further investigated in the context of minimizing total power consumption in [26] and energy efficient joint estimation in [32] for Gaussian sensor networks. Note, however, that under an orthogonal multiple access scheme, separate source and channel coding scheme is optimal for a Gaussian sensor network and the above mentioned uncoded amplify and forward scheme performs strictly suboptimally [21].

It is implicitly assumed in the above papers however, that there is complete phase synchronization amongst the sensors such that the received data from all the sensors add up coherently at the FC. This point has been commented on in [26] and also further qualified in [33]. In the case of fading channels, in the absence of perfect phase synchronization, this simple amplify and forward scheme can only perform near-optimally if the fading distributions satisfy a nonzero mean condition [34] or enough number of sensors enjoy fading channels with such a nonzero mean condition [33].

We stress, however, that complete phase synchronization amongst sensors (which is equivalent to distributed transmit beamforming if the channels are modelled as complex entities) is extremely difficult to achieve in practice. For example, complete phase synchronization is almost impossible in underwater acoustic sensor networks [35]. See [36] and [37] for discussions on complexity of incorporating distributed transmit beamforming in wireless networks and effect of random phase errors on the network performance. It is important to keep in mind therefore that large performance gains as promised by such simple uncoded schemes may not be feasible in practical sensor networks.

For comparison purposes, we provide an equivalent lifetime optimization problem formulation for the uncoded amplify and forward case under the nonorthogonal multiple access scheme in this section. In this scheme, the ith sensor amplifies its own noisy data by a scaling factor $\sqrt{P_i/(\sigma_X^2+\sigma_i^2)}$. The mean square distortion at the FC is then given by D_{uc} where

$$\frac{1}{D_{uc}} = \frac{1}{\sigma_X^2} + \left(\sum_{i=1}^{|\mathcal{V}|} \frac{g_i P_i \sigma_i^2}{\sigma_X^2+\sigma_i^2} + N_0\right)^{-1} \left(\sum_{i=1}^{|\mathcal{V}|} \sqrt{\frac{g_i P_i}{\sigma_X^2+\sigma_i^2}}\right)^2. \tag{11}$$

The equivalent lifetime optimization problem can therefore be stated as

$$\min_{\bar{q},\mathbf{P}} \bar{q} \qquad \text{s.t.} \quad -\bar{q}E_v + P_v \leq 0, \quad v = 1,\ldots,|\mathcal{V}|$$
$$D_{uc} \leq D_{\text{th}}$$
$$\mathbf{P}, \bar{q} \succeq 0 \tag{12}$$

where D_{uc} is given by (11) above and $\bar{q}$ denotes the inverse of the network lifetime.

We use a MATLAB-based optimization routine ("*fmincon*") to solve this problem. In Section IV, we provide a comparative study amongst the optimal lifetime achieved by this scheme and the separate source and channel coding based TDMA, NOMA and the idealized GMAC schemes via simulation studies.

III. Successive Convex Approximations for the Nonconvex NOMA Problem

In Section II, we formulated the lifetime optimization problem with the rate distortion constraints for the NOMA environment which resulted in a nonlinear nonconvex optimization problem. In fact, by suitable variable transformations, one can pose this nonconvex problem as a D.C. (representing difference of convex functions) programming problem which can be converted to a corresponding canonical D.C. programming problem. Canonical D.C. problems can be solved by outer approximation and branch and bound methods [18]. However, the complexity of D.C. programming is NP hard and convergence time is quite long [38]. In our work, we adopt a simpler strategy and approximate the original nonconvex problem (7) with a sequence of convex approximations. For a similar sequential convex optimization algorithm for power and rate allocation in an interference limited MANET, see [17]. Starting at a suitably chosen initial point, we solve an approximate convex problem and then use the results of this optimization procedure to obtain a new convex approximation of the original nonconvex problem. Thus, this method leads to a sequence of convex problems which can be shown to converge (under certain conditions) to a suboptimal solution. Below, we describe this successive convex approximation algorithm in detail for the NOMA case.

It was shown in [8] that the rate distortion constraints are convex in $\mathbf{R}$, $\mathbf{r}$, and $\mathbf{U}$. We now consider the energy and capacity constraints for the nonconvex NOMA problem (7).

Suppose we make the following variable transformations:

$$LT_{\text{net}} = e^{q}, \quad t_v = e^{\tilde{t}_v}, \quad P_v = e^{\tilde{P}_v} \quad v = 1,\ldots,|\mathcal{V}|. \tag{13}$$

Accordingly, the energy constraints in (7) can be represented in q, and $\tilde{P}_v$ as follows (after taking logarithm of both sides) $q + \tilde{P}_v - \log(E_v) \leq 0 \quad v = 1,\ldots,|\mathcal{V}|$, which is obviously convex.

Now define an auxiliary variable $Q_v, v = 1,\ldots,|\mathcal{V}|$ such that the capacity constraint can be rewritten as

$$R_v \leq \frac{1}{2}\log(1+e^{Q_v}) \quad \text{and} \quad e^{Q_v} \leq \frac{g_v e^{\tilde{P}_v}}{\sum\limits_{k\neq v} g_k e^{\tilde{P}_k} + N_0}.$$

Taking log on both sides of the inequalities, we can rewrite the above set of constraints as

$$\log(R_v) - \log\left(\log(1+e^{Q_v})\right) + \log 2 \leq 0$$
$$\log\left(\frac{N_0}{g_v}e^{Q_v-\tilde{P}_v} + \sum_{k\neq v}\frac{g_k}{g_v}e^{Q_v+\tilde{P}_k-\tilde{P}_v}\right) \leq 0.$$

Here, the second set of constraints are convex as they are in the standard *log-sum-exponential* form. It is the first set of constraints that are not convex. It is easy to demonstrate that $\log\left(\log(1+e^{Q_v})\right)$ is a concave function in Q_v. However, note that $\log R_v$ is not convex, in fact, it is concave. Note that each of these nonconvex capacity constraints can be written as a difference of two convex functions and hence the original nonconvex problem can be converted to a canonical D.C. problem. Our strategy, however, is to approximate $\log R_v$ by a convex expression (as in [2]). Consider the tangent line that touches the concave curve $\log R_v$ at the point $(R_0, \log R_0)$. The equation representing this tangent line is obviously given by $y = x/R_0 + \log R_0 - 1$ where x refers to the R_v axis. Consider another point $(R, \log R)$ nearby and the corresponding point on the tangent line with an ordinate value of $H_R = a_v R + b_v$, where $a_v = 1/R_0$ and $b_v = \log R_0 - 1$.

Clearly, $H_R \geq \log R$ since the tangent lies above the concave $\log R_v$ curve. It is now easily seen that if one satisfies the constraint

$$a_v R_v + b_v - \log\left(\log(1+e^{Q_v})\right) + \log 2 \leq 0, \; v = 1,\ldots,|\mathcal{V}| \tag{14}$$

with an appropriately chosen (a_v, b_v), then the original NOMA capacity constraint is also satisfied. Thus, in general, a suboptimal solution to the original nonconvex lifetime maximization with rate distortion constraints in the NOMA case can be found by solving the following convex optimization problem:

$$\min_{q,\tilde{\mathbf{P}},\mathbf{R},\mathbf{Q}} -q \qquad q + \tilde{P}_v - \log(E_v) \leq 0 \quad v = 1,\ldots,|\mathcal{V}|$$
$$a_v R_v + b_v - \log\left(\log(1+e^{Q_v})\right) + \log 2 \leq 0 \quad v = 1,\ldots,|\mathcal{V}|$$
$$\log\left(\frac{N_0}{g_v}e^{Q_v-\tilde{P}_v} + \sum_{k\neq v}\frac{g_k}{g_v}e^{Q_v+\tilde{P}_k-\tilde{P}_v}\right) \leq 0 \quad v = 1,\ldots,|\mathcal{V}|$$
$$\{\mathbf{R} : \text{(1) holds for distortion threshold } D_{\text{th}}\}$$
$$\mathbf{R} \succeq 0. \tag{15}$$

A. Successive Convex Approximation Algorithm Based on Updating of Tangent Points

In the previous section, we illustrated how the nonconvex NOMA optimization problem can be converted to an approximate convex optimization problem by suitably choosing an initial point around which a tangent approximation is made, such that the resulting convex problem is feasible. Once this convex (approximate) problem is solved, the resulting rate R_v can then be used as a new point of approximation to form a new approximate convex problem. Thus, one can form a sequence of convex approximations where the solution from the previous stage becomes the point of tangent approximation for the next stage. Below, we show that this sequence of convex approximations results in a sequence of optimal solutions that asymptotically converge to unique steady-state values, provided that the initial convex approximate problem is feasible. In practice, one can stop this successive convex approximation method once a certain accuracy is reached in the optimal solution values.

Theorem 1: Suppose after solving the approximate convex problem (15) k successive times, the logarithm of the inverse of the optimal lifetime value is given by $p^{(k)}$, i.e., $p^{(k)} = -q^{(k)}$, where $q^{(k)}$ is the logarithm of the achieved optimal lifetime value after solving k successive convex approximations. If the initial convex approximation is feasible resulting in an optimal inverse lifetime $p^{(1)}$, then the sequence $\{p^{(k)}\}$ converges to a (not necessarily unique) steady-state value p^*.

Proof: Suppose the feasible region for the kth convex approximate optimization problem is $\mathcal{F}^{(k)}$. As above, the superscript k means 'after k updates'. We will show that sequence $\{p^{(k)}\}$ is nonincreasing and lower bounded, and consequently it converges.

- *Monotonicity*: Suppose $[q^{(k)}, R^{(k)}, \tilde{P}^{(k)}, Q^{(k)}]$ is the optimal allocation scheme to the kth convex approximation. Therefore, the parameters for the tangent approximation in the next round will be $a_v^{(k+1)} = 1/R_v^{(k)}$, $b_v^{(k+1)} = \log R_v^{(k)} - 1$, where $v = 1, \ldots, |\mathcal{V}|$. We now show that $[q^{(k)}, R^{(k)}, \tilde{P}^{(k)}, Q^{(k)}]$ is within the feasible region $\mathcal{F}^{(k+1)}$ for the next iteration.

$$\begin{aligned} a_v^{(k+1)} R_v^{(t)} &+ b_v^{(k+1)} - \log\left(\log(1+e^{Q_v^{(k)}})\right) + \log 2 \\ &= \frac{1}{R_v^{(k)}} R_v^{(k)} + \log R_v^{(k)} - 1 - \log\left(\log(1+e^{Q_v^{(k)}})\right) + \log 2 \\ &= \log R_v^{(k)} - \log\left(\log(1+e^{Q_v^{(k)}})\right) + \log 2 \\ &\leq a_v^{(k)} R_v^{(k)} + b_v^{(k)} - \log\left(\log(1+e^{Q_v^{(k)}})\right) + \log 2 \leq 0. \end{aligned}$$

The last inequality follows from the fact that $\log R_v^{(k)} \leq a_v^{(k)} R_v^{(k)} + b_v^{(k)}$ by virtue of the tangent approximation after the $(k-1)$st iteration of the successive convex approximation scheme. Combining this with the fact that all the other constraints hold for the solution $[q^{(k)}, R^{(k)}, \tilde{P}^{(k)}, Q^{(k)}]$, we can conclude that

$$[q^{(k)}, R^{(k)}, \tilde{P}^{(k)}, Q^{(k)}] \in \mathcal{F}^{(k+1)}.$$

Since $p^{(k+1)}$ is the logarithm of the inverse optimal lifetime after $k+1$ updates, we have $p^{(k+1)} \leq p^{(k)}$.

- *Boundedness*: Note that once the network is activated, we can easily find $P_{v'}$ for at least one activated sensor node v', where $P_{v'} > 0$. This implies that the lifetime of the network has a finite upper bound, since the initial node energy values are finite. It then follows that $p^{(k)}$ is lower bounded by a finite lower bound.

In summary, as a nonincreasing lower-bounded sequence (with a finite lower bound) $\{p^{(k)}\}$ converges (asymptotically) to a steady-state value p^* which implies that $q^{(k)}$ also converges to a steady-state value and by uniqueness of the solution to each of the approximate convex problems, all other variables of optimization converge to their respective steady-state values. Note that the choice of the first convex approximation may dictate the final steady-state values, hence uniqueness of the steady-state solutions cannot be guaranteed in general. ■

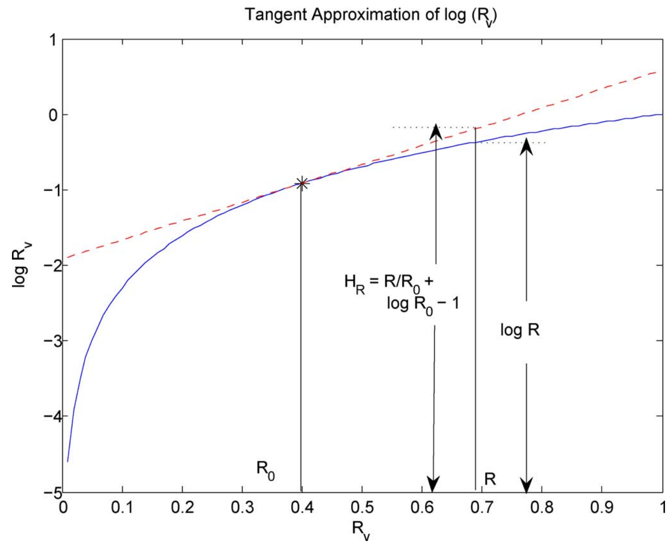

Fig. 2. Convex approximation for $\log R_v$.

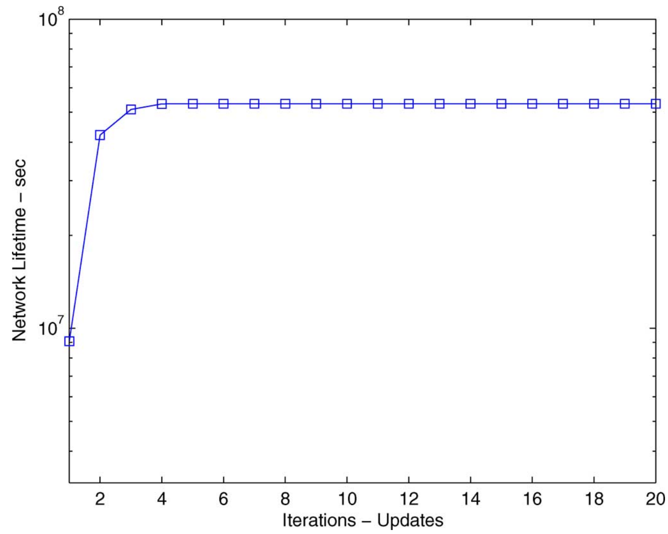

Fig. 3. Convergence of lifetime for the NOMA based WSN: $D_{\text{th}} = -1$ dB.

Although it is difficult to provide analytical results regarding the speed of convergence, we illustrate via simulations below that the successive convex approximation algorithm converges quite rapidly. These simulation results are for a six sensor network the details of which can be found in Section IV. Fig. 3 illustrates the convergence for the NOMA case, where it is seen that after only four or five updates, the successive convex approximation based algorithm yields solutions within a reasonable accuracy. Recall that convergence is guaranteed as long as the problem is feasible at the initial iteration. These simulation results were achieved both by the MATLAB-based *fmincon* program and well known Barrier Method based interior point techniques [39].

B. Local Optimality of the Successive Convex Approximation Algorithm

In Section III-A, we proved the convergence of our sequential convex optimization method, i.e., as long as the first convex (approximate) optimization problem is feasible, the algorithm will converge to a (in general) suboptimal solution. In this section, we show that when the successive convex approximation algorithm converges to a steady-state solution, this solution is actually satisfies the Karush–Kuhn–Tucker (KKT) conditions for the original nonconvex optimization problem (7). Below, we provide a sketch of the proof of this result.

The full-version of the (approximate) convex optimization problem for NOMA system is given by

$$
\begin{aligned}
&\min_{q,\tilde{\mathbf{P}},\mathbf{Q},\mathbf{R},\mathbf{r}} -q \qquad q+\tilde{P}_v-\log(E_v)\le 0 \quad v=1,\ldots,|\mathcal{V}|\\
&a_vR_v+b_v-\log\big(\log(1+e^{Q_v})\big)+\log 2\le 0 \quad v=1,\ldots,|\mathcal{V}|\\
&\log\Big(\frac{N_0}{g_v}e^{Q_v-\tilde{P}_v}+\sum_{k\neq v}\frac{g_k}{g_v}e^{\tilde{P}_k-\tilde{P}_v}\Big)\le 0 \quad v=1,\ldots,|\mathcal{V}|\\
&\sum_{v\in\mathcal{W}_k} r_v+\frac{1}{2}\log\frac{1}{D_{\rm th}}-\frac{U_k}{2}-\sum_{v\in\mathcal{W}_k}R_v\le 0 \quad k=1,\ldots,2^{|\mathcal{V}|}-1\\
&e^{U_k}-\frac{1}{\sigma_X^2}-\sum_{v\in\mathcal{V}\setminus\mathcal{W}_k}\frac{1-e^{-2r_v}}{\sigma_v^2}\le 0 \quad k=1,\ldots,2^{|\mathcal{V}|}-1\\
&\frac{1}{D_{\rm th}}-\frac{1}{\sigma_X^2}-\sum_{v\in\mathcal{V}}\frac{1-e^{-2r_v}}{\sigma_v^2}\le 0\\
&\mathbf{R},\mathbf{r}\succeq 0. \qquad (16)
\end{aligned}
$$

We denote the steady-state solution to this optimization problem (i.e., when the sequence of convex approximations has converged) as $(q^*,\tilde{\mathbf{P}}^*,\mathbf{Q}^*,\mathbf{R}^*,\mathbf{r}^*,\mathbf{U}^*)$. Note also that after convergence, $a_v = 1/R_v^*$ and $b_v = \log R_v^* - 1$. The strong feasibility of this convex problem and the convexity of the objective function and constraints imply that Slater's condition holds. Therefore, there exists at least one set of Language multipliers $(\boldsymbol{\lambda}^E,\boldsymbol{\lambda}^C,\boldsymbol{\lambda}^Q,\boldsymbol{\lambda}^{R1},\boldsymbol{\lambda}^{R2},\boldsymbol{\lambda}^{R3})$ corresponding to the energy, the two capacity, and the three rate distortion constraints respectively, associated with the Lagrangian function for the final convex approximate optimization problem. As Langrange multipliers, they are equal to zero when the corresponding constraints are not active, and nonnegative otherwise.

Note that the only difference between the convex approximation (16) above and the original nonconvex problem (7) lies in the (tangent) approximated second constraint above. All other constraints and the objective function are identical. Since after convergence, $a_v = 1/R_v^*$ and $b_v = \log R_v^* - 1$, it is trivial to show that the aforementioned steady-state solution $(q^*,\tilde{\mathbf{P}}^*,\mathbf{Q}^*,\mathbf{R}^*,\mathbf{r}^*,\mathbf{U}^*)$ and the associated Lagrange multipliers satisfy the KKT necessary optimality conditions for the original nonconvex optimization problem (7). Note that this *does not necessarily guarantee* that the steady-state solution $(q^*,\tilde{\mathbf{P}}^*,\mathbf{Q}^*,\mathbf{R}^*)$ is a *local optimum* for the original nonconvex optimization problem (7). However, one can check numerically whether this steady-state solution satisfies further sufficient second order optimality conditions and some constraint qualification criteria (see [40, Proposition 3.3.2, p. 314]). If it does, then the solution is a local optimal point for the nonconvex NOMA problem (7). However, it is difficult to prove analytically that this steady-state solution will always be a locally optimal solution of the nonconvex NOMA problem. Instead, we compare the lifetime performance of this successive convex approximation scheme against the upper bound provided by the lifetime performance of the Gaussian MAC optimization problem (10) via extensive simulation studies reported in Section IV.

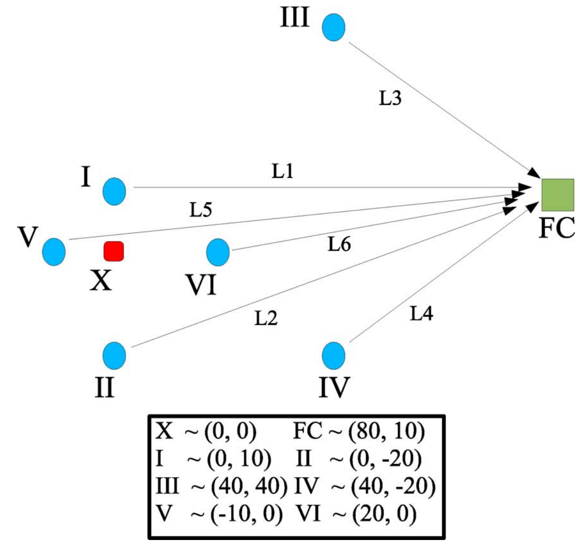

Fig. 4. Wireless detection system with six sensors (Unit: meters).

TABLE I
SIMULATION PARAMETERS.

loss factor n	3
σ_0^2	0.01
σ_X^2	10
N_0	1×10^{-12}(Watts)
$E_v, v = I, II, III, IV, V, VI$	1000(Joules)

IV. Simulation Studies

In this section, we carry out extensive simulation studies mainly focusing on a six-sensor single-hop network where each sensor is connected via a wireless link to the FC. The geometric configuration of this network is given in Fig. 4, where the variance of the measurement is based on the distance between the source X (representing the random phenomenon) and the sensor itself, $\sigma_v^2 = \sigma_0^2 d_{Xv}^2$ [6]. The propagation gain for the wireless channel between the sensors and the FC is proportional to the line-of-sight (LOS) distance with loss factor n. The distance parameters for the simulation studies with the six-sensor network can be derived from Fig. 4, where the coordinates of the source, the sensors and the FC are given. All other relevant parameters are provided in Table I below.

A. Static Propagation Gain

In this subsection, we assume that the link propagation gains between the sensors and the FC are deterministic and depend only on the distances between the sensors and the FC with a loss factor of $n = 3$.

In Fig. 5, we first illustrate the network lifetime achieved as the results of the three optimization problems (5), (10), and (15) for the six-sensor situation. We also compare these results against the network lifetime achieved by the uncoded amplify and forward scheme stated as the optimization problem

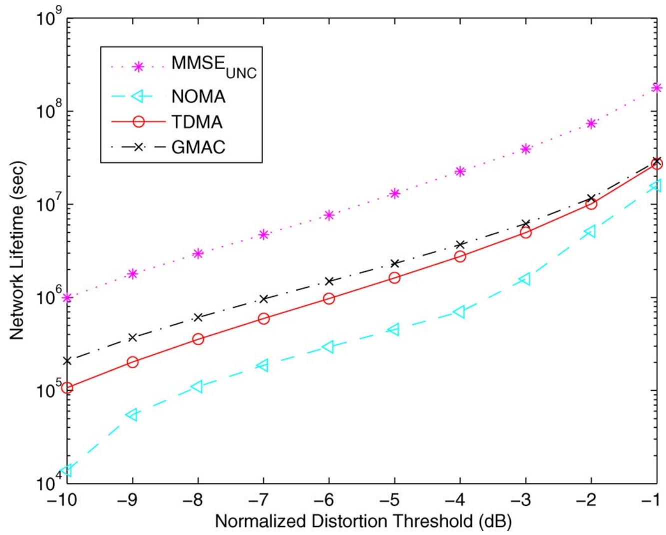

Fig. 5. Lifetime for the network with 6 sensors.

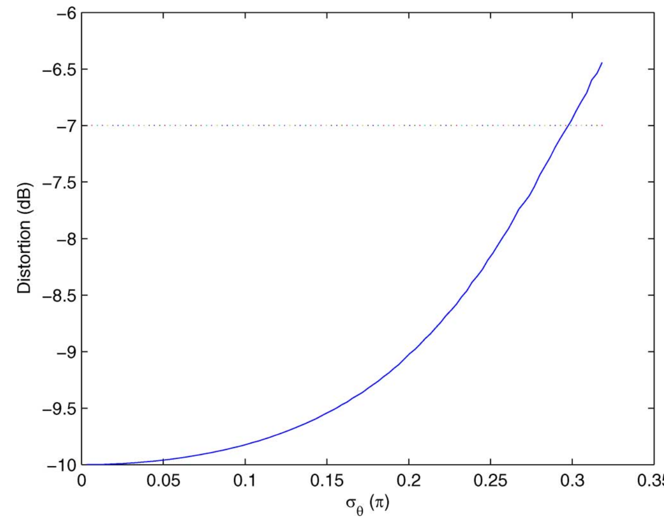

Fig. 6. MMSE distortion with phase error for the uncoded amplify and forward scheme.

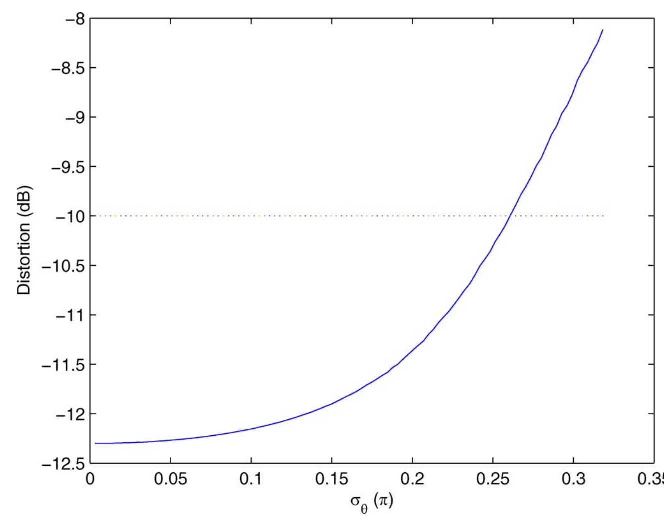

Fig. 7. MMSE Distortion with phase error for the uncoded amplify and forward scheme.

(12). The uncoded amplify and forward scheme (denoted by $\mathrm{MMSE}_{\mathrm{UNC}}$ in Fig. 5) performs better than the TDMA/NOMA schemes and the upper bound provided by the idealized GMAC scheme as well. Increasing channel noise or decreasing SNR at the sensors, etc., was seen to decrease the lifetime for all schemes, while keeping the order of the achieved optimal lifetimes intact for the various schemes. This may give the impression that one must therefore favour uncoded amplify and forward transmission under nonorthogonal multiple access to TDMA/NOMA based schemes in these circumstances. However, the uncoded amplify and forward scheme is not as simple to implement as it is made out to be. One of the major difficulties of achieving the performance as depicted in Fig. 5 by the uncoded scheme is maintaining full phase synchronization at the sensor transmitters (which is equivalent to implementing fully distributed beamforming for complex channels), specially for time-varying fading channels.

Below we present a study where the uncoded amplify and forward lifetime maximization scheme is tested under random phase errors in the received signals from the sensors. We assume that the phase error in each of the received signals at the FC follows an identical and mutually independent Gaussian distribution with variance σ_θ^2 and zero mean. The uncoded amplify and forward optimal power allocation scheme is implemented assuming no phase error, simply using the real channel gain. The random phase errors for the received signal from each sensor are generated 100 000 times, and the resulting mean square error (MSE) distortion is obtained averaging over these 100 000 trials. Figs. 6 and 7 illustrate how the mean square error distortion achieved by the uncoded amplify and forward scheme increases quickly as σ_θ increases, starting from a base distortion threshold of $-$ 12.3 dB and $-$10 dB, respectively. It is seen that when σ_θ exceeds 0.25π, the MSE distortion achieved by the uncoded amplify and forward scheme exceeds its counterpart achieved by the GMAC case (which is close to the performance achieved by the TDMA scheme). This fact tells us that the phase error should be considerably small in order to guarantee that the uncoded amplify and forward schemes will outperform the GMAC, TDMA, and NOMA schemes.

In addition, another study [27] has shown that a pulsed operation of each sensor battery can increase the yield of a battery, as it affects the battery's energy drainage pattern. This implies that a TDMA based scheme may be more energy efficient than other protocols (including an uncoded scheme under nonorthogonal multiple access) [22]. Therefore, while the uncoded scheme offers a promising (but perhaps impractical) performance gain to aspire to, the separate source and channel coding based schemes such as TDMA and NOMA provide useful simple alternatives which are easier to implement.

As also expected, the network lifetimes for TDMA (optimal) and NOMA (suboptimal) are upper-bounded by the solutions achieved by the constraints defined by the idealized GMAC capacity region. The suboptimal solutions obtained by the sequential convex approximations for the NOMA case performs reasonably well, as compared to this upper bound provided the globally optimal solution to the idealized Gaussian MAC case. In these simulations, although TDMA seems to perform better than the suboptimal solutions to NOMA, note that this does

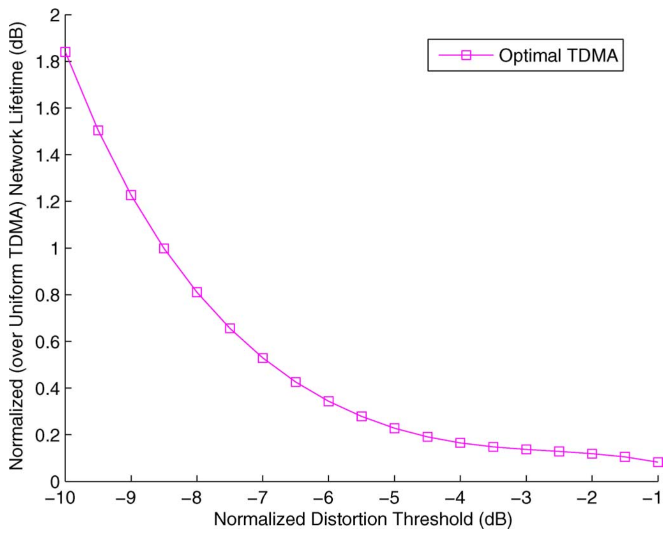

Fig. 8. Advantage of optimal TDMA over uniform TDMA.

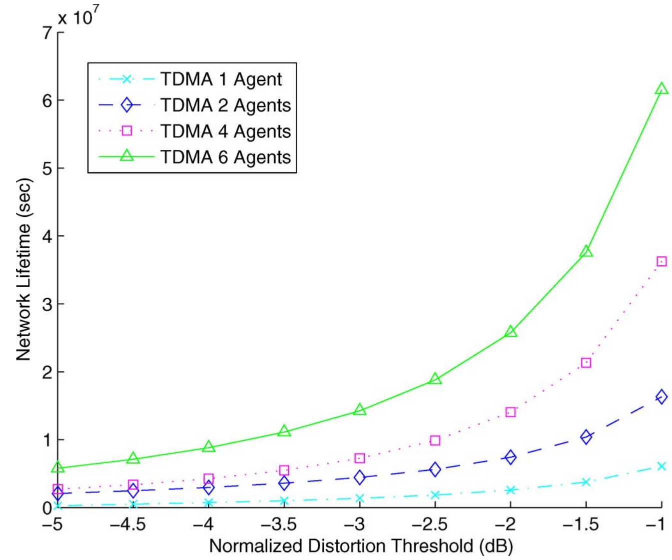

Fig. 9. Lifetime for the TDMA-based wireless sensor network.

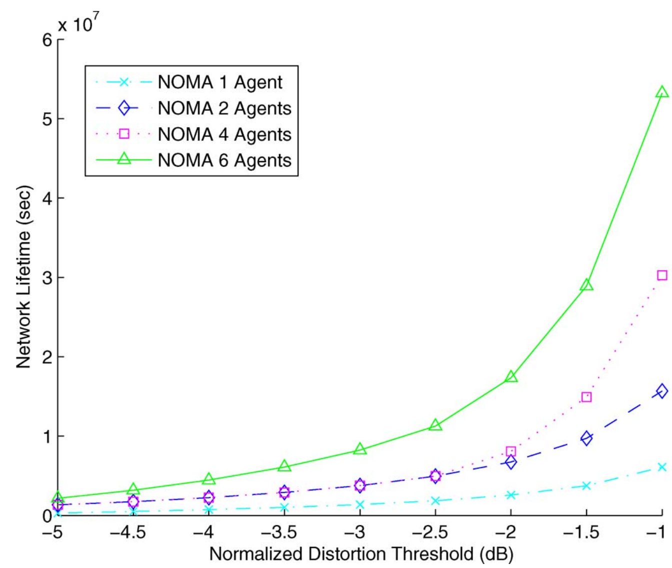

Fig. 10. Lifetime for the NOMA-based wireless sensor network.

not necessarily indicate that TDMA will always perform better than NOMA, since the globally optimal solution to NOMA is unknown. Increasing channel noise or decreasing SNR at the sensors, etc., was seen to decrease the lifetime for all schemes, while keeping the order of the achieved optimal lifetimes intact for the various schemes.

Fig. 8 demonstrates the normalized improvement the network can achieve through an optimal TDMA scheme as opposed to a uniform TDMA scheme, where each sensor transmits for an equal 1/6th portion of the time. The x axis is the normalized distortion threshold given by $10\log(D_{\rm th}/\sigma_X^2)$. In the uniform TDMA case, the length of the activated time is the same for each sensor, hence the lifetime depends on the most power-consuming agent. On the other hand, optimal scheduling improves the performance by adaptively tuning the length of the individual sensor timeslots. Clearly, since uniform TDMA is a special case of a nonuniform TDMA, the optimal scheduling always performs better than uniform TDMA. However, when the distortion constraint is stricter, the improvement achieved by the optimal scheduling is more evident—since a lower distortion threshold requires higher transmission rate, the optimal assignment of timeslot fractions gives more flexibility to the network to improve its lifetime. performance of the network. Clearly, the normalized value of the optimal lifetime over that achieved by the uniform TDMA scheme decreases as the distortion threshold is relaxed.

We also study how the optimal time-slot assignment changes (in the optimal TDMA case) as a sensor moves from a position close to the source to a position that is close to the FC. Figs. 11 and 12 illustrate the results for the four-sensor (I, II, III, IV) case in the TDMA scenario when Sensor I moves horizontally from (0, 10) to (75, 10), all the other sensors being fixed. When Sensor I moves closer and closer to the FC and away from the source, the sensor noise increases with increasing distance from the source whereas the corresponding propagation gain and consequently the channel quality to the FC increases. As these two factors have a conflicting effect on the network lifetime, it is clearly seen in Fig. 11 that the network lifetime reaches an optimal point when it is still close to the phenomenon, and decreases dramatically after that. Fig. 12 illustrates that the amount of the time fraction allocated to Sensor I displays a similar behavior, as the sensor measurements become more and more noisy, Sensor I is allocated less and less time for transmission despite its enhanced channel quality to the FC. In this case, Sensor II is allocated increased time for transmission as the measurements of Sensor I become poorer. Sensors III and IV enjoy a modest increase in their allocated time fraction since their positions are neither close to the phenomenon nor the fusion center.

Figs. 9 and 10 illustrate the relationship between the network lifetime and the number of sensor nodes (agents) in the system for the TDMA and the NOMA case respectively, where the network consists of 1({II}), 2 ({I, II}), 4({I, II, III, IV}), and 6({I, II, III, IV, V, VI}) sensors along with the FC. In general, the network lifetime increases as the rate distortion requirement is

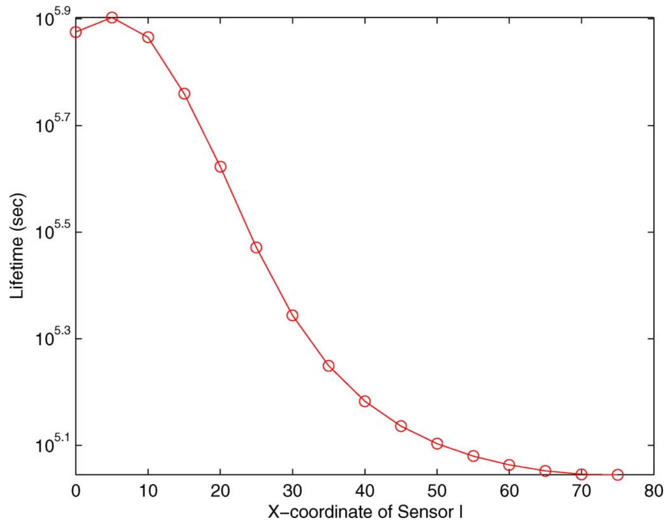

Fig. 11. Lifetime for the (4 sensor) TDMA based wireless sensor network with mobile sensor 1.

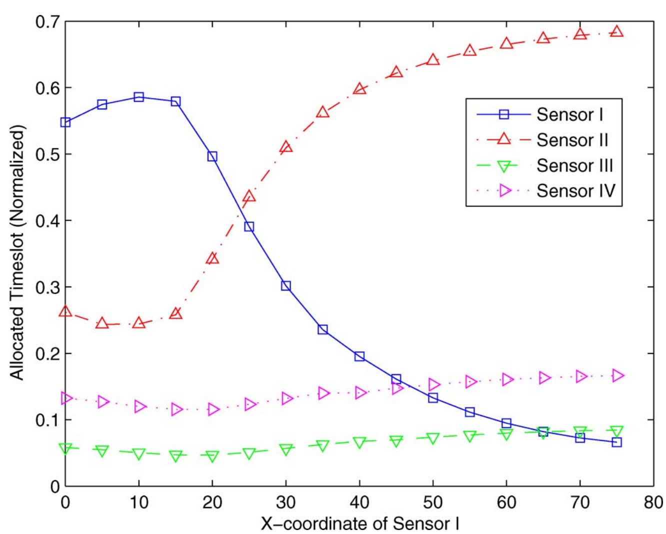

Fig. 12. Normalized sensor transmission timeslots for the (four-sensor) TDMA-based wireless sensor network with mobile sensor 1.

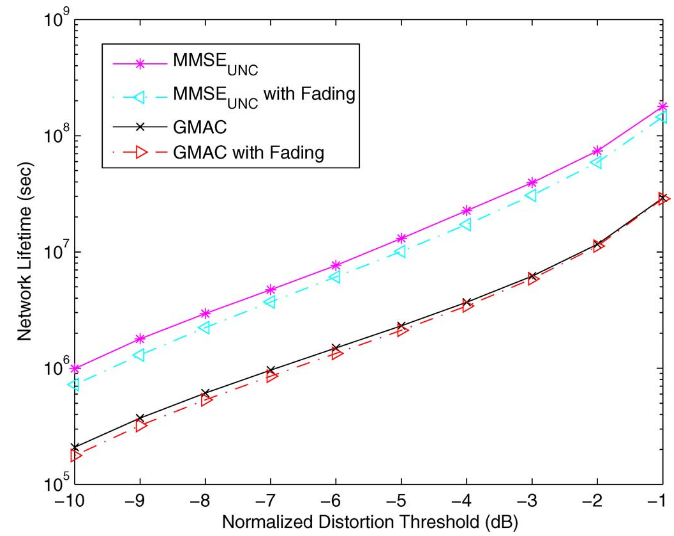

Fig. 13. Lifetime performance in Rayleigh fading – idealized GMAC and uncoded amplify and forward ($\mathrm{MMSE_{UNC}}$).

relaxed. Also, in general, increasing the number of sensors in the TDMA case helps to extend the network lifetime due to the diversity available to the network. However, note that this is not always the case in the NOMA scheme, e.g., in the normalized distortion threshold domain of (−5 dB, −2.5 dB) in the NOMA system, increasing the number of sensors from two to four does not give any advantage in lifetime performance, as shown in Fig. 10. The reason is simple: nodes III and IV are too far from the phenomenon and hence it is not wise to use those two sensors when the distortion threshold is strict. Therefore, the optimal solution for the four-sensor case is to shut down node III and IV in order to eliminate the interference to the receiver. On the other hand, when the distortion threshold is less strict, the performance of the four-sensor system will be better than that of the two-sensor one.

B. Slow Fading Environment

In this subsection, we assume that the wireless link gains between the sensors and the FC are not only path loss dependent, but also randomly varying due to slow Rayleigh fading. Under this assumption, the fading is slow enough so that even though the channel is random, it can be accurately estimated at the FC and used to compute the optimal power, rate, etc., which are fed back to the sensors. We assume that the propagation gain between the vth node and the FC is effected by Rayleigh fading parameters F_v, where F_v has an exponential distribution with unity mean (without loss of generality), and g_v (as before) represents the path loss dependent part. As a result, one can rewrite the channel capacity constraints for the TDMA, NOMA and the Gaussian multiaccess problems by replacing g_v with $g_v F_v$ for the vth sensor. The same can be said for the channel gains in the uncoded amplify and forward case.

Fig. 13 shows the optimal network lifetime obtained by the idealized Gaussian MAC capacity-limited case and the uncoded amplify and forward scheme. Since the idealized GMAC capacity constrained region provides a network lifetime that acts as an upper bound (for a given channel realization), we only show the results for the idealized GMAC and the uncoded case in this graph in order to save on computation time. These simulation studies are carried out for the six-sensor configuration under slow Rayleigh fading (as described above) where the results are averaged over 1000 fading realizations. In order to make a fair comparison between the fading and no fading cases, the simulation results in Fig. 5 (no fading) for idealized GMAC and the uncoded case are repeated here. In Fig. 13, all the lifetime curves in dotted lines represent the numerical results for the original nonfading cases, while those with solid curves represent the lifetimes achieved under a slow Rayleigh fading environment. It is clear that the lifetime performance is comparable between the ones with and without such effects. Although fading shortens the network lifetime as a result of increasing transmission power to combat fading, the diversity available by using multiple sensors helps the network allocate resources to the sensors with better channel conditions and hence offset the power loss and extend the network lifetime.

V. Conclusion

In this paper, we studied the lifetime performance of a single-hop sensor network with a small number sensors and a centrally coordinating FC, where the task of the network is to reconstruct a remotely observed random Gaussian source. We provided a centralized joint power and rate optimization algorithm under the energy, wireless link capacity, delay and rate distortion constraints. The various multiple access protocols studied were TDMA, a nonorthogonal interference limited protocol NOMA and the ideal Gaussian MAC capacity achieving protocol. Convex optimization methods were used to find the optimal lifetime solutions for the TDMA and the Gaussian MAC case, whereas for the NOMA case, the original nonconvex optimization problem was approximated by a series of sequential convex approximations which were proved to converge to a steady-state solution, a KKT point of the original problem. Extensive simulation studies were performed to compare the performance of these various protocols. We also compared the network lifetime performance of these separate source and channel coding based schemes against the performance of a recently proposed uncoded amplify and forward scheme. While this uncoded scheme is seen to perform better, difficulties related to its implementation render the TDMA/NOMA based schemes as attractive alternatives which are easier to implement. This fact is illustrated through evaluating (via simulations) the performance of the uncoded amplify and forward scheme in the presence of random phase noise, where the performance is seen to deteriorate quickly as the phase noise variance increases.

Future work includes a study of the lifetime performance of the CDMA protocol with appropriate multiuser detectors, extension of centralized algorithms to distributed ones (specially in the case of a network with large number of sensors), and to the case of fast fading channels with partial channel information at the FC (or the sensors).

Appendix

Proof of Proposition 1 – TDMA Case: Consider the TDMA optimization problem given by (4) and the Gaussian MAC optimization problem given by (10) and note that it is the capacity constraints that set them apart.

Suppose the TDMA optimization problem has been optimized with respect to t_v, $v = 1, 2, \ldots, |\mathcal{V}|$ only and the resulting optimal solutions are given by t_v^*, $v = 1, 2, \ldots, |\mathcal{V}|$ Consider any nonempty subset $\mathcal{W}_k$ of $|\mathcal{V}|$. Note that feasibility of the solutions t_v^*, $v = 1, 2, \ldots, |\mathcal{V}|$ implies that $\sum_{v\in\mathcal{W}_k} t_v^* \le 1$ (in fact it can be shown that $\sum_{v\in\mathcal{V}} t_v^* = 1$). This implies that summing over the TDMA capacity constraints: $R_v \le (1/2)t_v^* \log(1 + g_v P_v/N_0)$ for $v \in \mathcal{W}_k$, we get

$$\begin{aligned}\sum_{v\in\mathcal{W}_k} R_v &\le \frac{1}{2}\sum_{v\in\mathcal{W}_k} t_v^* \log\left(1+\frac{g_v P_v}{N_0}\right)\\ &\le \frac{1}{2}\log\left(1+\sum_{v\in\mathcal{W}_k}\frac{t_v^* g_v P_v}{N_0}\right)\\ &\le \frac{1}{2}\log\left(1+\sum_{v\in\mathcal{W}_k}\frac{g_v \bar{P}_v}{N_0}\right),\ \forall k = 1,\ldots,2^{|\mathcal{V}|} \end{aligned}\tag{17}$$

where $\bar{P}_v = t_v^* P_v$ and the second last inequality follows as a special case of Jensen's inequality.

Using the transformation $\bar{P}_v = t_v^* P_v$ one can now rewrite the energy constraints in the TDMA problem as $E_v/\bar{P}_v \ge LT_{\text{net}}$, $\forall v \in \mathcal{V}$, where $\bar{P}_v \ge 0$. Denote $\bar{\mathbf{P}} = (\bar{P}_1, \bar{P}_2, \ldots, \bar{P}_{|\mathcal{V}|})$.

Therefore the new transformed TDMA problem (after optimizing over t_v) can be written as

$$\begin{aligned}&\max_{\bar{\mathbf{P}},\mathbf{R}} LT_{\text{net}} \quad \text{s.t.}\ \frac{E_v}{\bar{P}_v} \ge LT_{\text{net}} \quad v = 1,\ldots,|\mathcal{V}|\\ &\frac{1}{2}t_v^*\log\left(1+\frac{g_v\frac{\bar{P}_v}{t_v^*}}{N_0}\right) \ge R_v \quad v = 1,\ldots,|\mathcal{V}|\\ &\{\mathbf{R} : (1) \text{ holds for distortion threshold } D_{\text{th}}\}\\ &\bar{\mathbf{P}}, \mathbf{R} \succeq 0.\end{aligned}\tag{18}$$

Clearly, the capacity constraints in the above problem imply (due to inequality (17)) the capacity constraints in the Gaussian MAC problem. Hence, an optimal solution of the TDMA problem (4) belongs to the feasible set of the Gaussian MAC problem (10). Therefore, the optimal lifetime obtained from the Gaussian MAC problem is equal or greater than that obtained by an optimal solution of the TDMA problem.

Proof of Proposition 1 – NOMA Case: Consider the capacity constraints in the NOMA problem (7) and the Gaussian MAC optimization problem given by (10).

Summing over the NOMA capacity constraints over $v \in \mathcal{W}_k$, (for a given k), we get

$$\begin{aligned}\sum_{v\in\mathcal{W}_k} R_v &\le \frac{1}{2}\sum_{v\in\mathcal{W}_k}\log\left(1+\frac{g_v P_v}{N_0+\sum\limits_{l\ne v} g_l P_l}\right)\\ &\le \frac{1}{2}\sum_{v\in\mathcal{W}_k}\log\left(1+\frac{g_v P_v}{N_0+\sum\limits_{l\ne v,\, l\in\mathcal{W}_k} g_l P_l}\right)\\ &= \frac{1}{2}\sum_{v\in\mathcal{W}_k}\log\left(1+\frac{x_v}{1+\sum\limits_{l\ne v, l\in\mathcal{W}_k} x_l}\right)\end{aligned}\tag{19}$$

where $x_v = g_v P_v/N_0$, $v \in \mathcal{W}_k$.

Now, denote by $Z_k = |\mathcal{W}_k|$, where $|\mathcal{W}_k|$ denotes the number of elements in the set $\mathcal{W}_k$. Note that the sum on the left-hand side of the last equality of (19) can be written as $(1/2)\sum_{v=1}^{Z_k}\log(1+ x_v/(1+\sum_{l=1, l\ne v}^{Z_k} x_l))$. The rest of the proof just shows that the above sum is less than or equal to $(1/2)\log(1+\sum_{v=1}^{Z_k} x_v) = (1/2)\log(1+\sum_{v\in\mathcal{W}_k} x_v)$ when $x_v \ge 0$, $\forall v \in \mathcal{W}_k$. This follows by induction.

For $Z_k = 2$, it is easy to show that

$$\left(1+\frac{x_1}{1+x_2}\right)\left(1+\frac{x_2}{1+x_1}\right) \le 1 + x_1 + x_2,\ x_1, x_2 \ge 0.$$

Now assume that for $Z_k = N_z$,

$$\prod_{i=1}^{N_z}\left(1+\frac{x_i}{1+\sum\limits_{\substack{l=1\\ l\ne i}}^{N_z} x_l}\right) \le \left(1+\sum_{v=1}^{N_z} x_v\right).$$

This implies

$$\prod_{i=1}^{N_z+1}\left(1+\frac{x_i}{1+\sum\limits_{\substack{l=1\\l\neq i}}^{N_z+1}x_l}\right) = \left\{\prod_{i=1}^{N_z}\left(1+\frac{x_i}{1+\sum\limits_{\substack{l=1\\l\neq i}}^{N_z}x_l}\right)\right\}\left(1+\frac{x_{N_z+1}}{1+\sum\limits_{l=1}^{N_z}x_l}\right)$$
$$\leq \left(1+\sum_{v=1}^{N_z}x_v\right)\left(1+\frac{x_{N_z+1}}{1+\sum\limits_{l=1}^{N_z}x_l}\right) \leq \left(1+\sum_{v=1}^{N_z+1}x_v\right).$$

Obviously, it follows by induction that

$$\frac{1}{2}\sum_{v=1}^{Z_k}\log\left(1+\frac{x_v}{1+\sum\limits_{\substack{l=1\\l\neq v}}^{Z_k}x_l}\right) \leq \frac{1}{2}\log\left(1+\sum_{v=1}^{Z_k}x_v\right) = \frac{1}{2}\log\left(1+\sum_{v\in\mathcal{W}_k}x_v\right).$$

This result implies that any $(R_v, P_v), v = 1, \ldots, Z_k$ that satisfy the NOMA capacity constraint, also satisfies the corresponding Gaussian MAC capacity constraint. Since this result is true for all $k = 1, 2\ldots, 2^{|\mathcal{V}|} - 1$, and all the other constraints are the same for both the NOMA and the Gaussian MAC problems, any feasible solution to the NOMA problem is included within the feasible set of the Gaussian MAC problem. Clearly, the optimal lifetime solution provided by the Gaussian MAC formulation is better or equal to that provided by the NOMA formulation.

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