Modeling and Optimization of Network Lifetime in Wireless Video Sensor Networks

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***Abstract*—This paper studies the power consumption performance and resource allocation optimization in wireless video sensor networks. Network coding based multipath routing, network flow control and video encoding bit rate are jointly optimized, aiming to maximize the network lifetime at a given power budget and video quality requirement. Importantly, to concretely measure the network coding power utilized on error recovery, a generalized power consumption model for network coding is first developed in this paper. Through the Lagrange dual and subgradient approach, a fully decentralized algorithm is proposed to solve the target convex optimization problem. Numerical results validate the convergence and performance of the proposed algorithm.**

***Index Terms*—wireless video sensor network, network lifetime, power consumption, network coding, convex optimization.**

I. INTRODUCTION

In wireless video sensor networks (WVSNs), each sensor, equipped with battery-powered miniature video camera, is capable of capturing, processing visual information, and delivering them to the sink node over wireless channels [1]. Sensors are often assumed to be battery-irreplaceable due to their deployment in remote and unreachable locations. Therefore, minimizing power consumption to prolong the network lifetime is of paramount importance in WVSNs.

Over the past years, energy conservation mechanisms, aiming at maximizing the lifetime of wireless sensor networks have been extensively studied [2-4]. They mainly focus on minimizing the power consumption on data communication, while often neglect the power consumed in data processing. In WVSN, a video sensor is required to compress raw video of high rate to adapt to wireless transmission. In this case, energy utilized in video coding is significant and can not be neglected anymore.

Further, the relationship between power consumption of video encoding and its rate-distortion (R-D) performance is complicated and paradoxical [1]. How to balance encoding power, rate and distortion, meanwhile, make a joint optimization with network lifetime have remained vastly unexplored in WVSN.

To guarantee a reliable communication, automatic repeat request (ARQ) and forward error correction (FEC) are two common techniques for error recovery [5]. ARQ adopts feedback and retransmission scheme that is not well-suited for delay-sensitive video applications. The classical FEC scheme is done on a link-by-link basis. It requires each relay node to perform both decoding and encoding [6]. Such power consumption is tremendous and becomes impossible in large-scale WSVNs.

Network coding is proven to enhance failure resilience for both wireline and wireless networks [5]. Specifically, the combination of network coding with multipath routing may exhibit some unique advantages in coping with the unreliability: (1) It can be performed in a decentralized way, requiring no coordination among nodes; (2) It can be operated ratelessly, i.e. it can run indefinitely until successful decoding. (3) Flows of linearly independent, instead of same copies traversing multiple paths may reduce the energy wasting as well as the redundancy.

However, the existing research on network coding has concentrated on its applications and codes design. To our knowledge, its power consumption behavior has never been studied in the literature. In this study, we will establish a generalized power consumption model for network coding.

The motivation of this paper is to address the performance optimization of network lifetime and resource allocation for WVSNs. Our main contributions are as follows. First, we develop a generalized power consumption model for the video sensor node, in which video encoding, data transmission and error recovery behavior are completely considered. Second, we propose a joint optimization of video coding rate, aggregate power consumption and link rate allocation to maximize the network lifetime. In the context of error-prone wireless channels, network coding based error recovery scheme are introduced, providing reliable and high efficient transmissions. Last, using Lagrange dual and subgradient approach, we solve the target optimization problem in a fully decentralized manner.

The rest of the paper is organized as follows. Sec. II presents system model. Sec. III formulates the problem of lifetime and

The work was partially supported by NSFC grants No. 60632040, No. 60736043, No. 60802019, National High Technology Research and Development Program of China (No. 2006AA01Z322) and funds from Shanghai Science and Technology Commission (No. 08220510900).

rate allocation optimization, and proposes a decentralized algorithm over lossy WVSNs. Numerical results are presented in Sec. IV.

II. SYSTEM MODELING

A. Network Model

A static WVSN can be modeled as a directed graph $G(V,E)$, where V is the set of network nodes and E is the set of directed links between nodes. The set V consists of two disjoint subsets S and T, representing video sensor nodes and sink nodes respectively. Sensor nodes perform video capture, video encoding and packets routing. Sink nodes are destinations of WVSN. To simplify our discussion, assume that each sensor node only communicates with one designated sink node. All sensor nodes have a maximum transmission range d_x. A directed link $(i,j) \in E$ exists between node i and node j if their distance d_{ij} meets $d_{ij} \le d_x$. Suppose there exists multiple alternative paths $J(s)$ between sensor node s and its sink node. Each node s is associated with a matrix H^s to reflect the relationship between its path and related links. Let $H_{ij}^{sm} = 1$ if path $m \in J(s)$ of sensor node s uses link (i,j), or else $H_{ij}^{sm} = 0$.

B. Power-Rate-Distortion Model

According to the analytic power-rate-distortion (P-R-D) model in [1], the relationship of source coding bit rate R, coding power consumption P, and the corresponding distortion D^c can be described as:

$$D^c(R,P) = \sigma^2 e^{-\gamma \cdot R \cdot P^{\frac{2}{3}}} \quad (1)$$

where σ^2 is the input variance, γ is a model parameter related to encoding efficiency.

It is observed that a given encoding distortion can be guaranteed by controlling both the source rate and the encoding power. However, if we simply adjust the source rate or the encoding power to a very low or very high level, the encoding distortion will inevitably become large [1]. Meanwhile, the total power consumed at the sensor node will fast increase. Thus, an optimal allocation of R and P should be established to achieve the required video quality.

C. Flow Conservation and Network Coding Constraint

For any video session s originating from sensor s with source rate R^s, its information flow must flow at rate R^s to the sink node. For each link (i,j), let x_{ij}^{sm} denote the information flow rate of session s over path m, the information flow conservation constraint at each node i can be expressed as:

$$\sum_{j:(i,j)\in E} \sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ij}^{sm} - \sum_{j:(j,i)\in E} \sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ji}^{sm} = \rho_i, \ \forall i \in S$$

where
$$\rho_i = \begin{cases} R^s & \text{for } i \in S, \\ -R^s & \text{for } i \in T, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

To ensure the successful decoding, the actual physical flow rate of any session on each link should be no less than its corresponding information rate. Let f_{ij}^s represent the physical flow rate of session s on link (i,j), the relationship between information flow and physical flow can be expressed as:

$$\sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ij}^{sm} \le f_{ij}^s, \ \forall (i,j) \in E, \ \forall s \in S \quad (3)$$

D. Channel Interference Constraint

Consider a WVSN with a shared medium of capacity C. Suppose any link originating from node k will interfere with link (i,j) if $d_{ki} < (1+\Delta)d_{ij}$ or $d_{kj} < (1+\Delta)d_{ij}$. Here, $\Delta > 0$ specifies the interference range. Also define $\Psi(i,j)$ for each link (i,j) as the cluster of links that cannot transmit as long as link (i,j) is active, then the wireless network channel interference constraint can be defines as [7]:

$$\sum_{s\in S} f_{ij}^s + \sum_{s\in S} \sum_{(p,q)\in\Psi(i,j)} f_{pq}^s \le C; \ \forall (i,j) \in E \quad (4)$$

E. Power Consumption Model

The total power dissipation at a video sensor node consists of four important portions: video coding power dissipation, transmission power dissipation, reception power dissipation, and network coding power dissipation. The video coding power consumption can be computed by the P-R-D model. Following an extensively used power consumption model in wireless sensor networks [2], the transmission power consumption at a node i can accordingly be formulated as:

$$P_i^t = \epsilon_{ij} \cdot \sum_{s\in S} \sum_{j:(i,j)\in E} f_{ij}^s \quad (5)$$

where $\epsilon_{ij} = \theta + \eta \cdot (d_{ij})^\alpha$ is the transmission energy consumption cost of link (i,j), θ is the energy cost of transmit electronics, η is a coefficient term corresponding to the energy cost of transmit amplifier, and α is the path loss factor.

The reception power consumption at a node i is given by

$$P_i^r = \xi \cdot \sum_{s\in S} \sum_{j:(i,j)\in E} f_{ji}^s \quad (6)$$

where ξ is the energy consumption cost of the radio receiver.

In the following, we will set up a generalized power consumption model for network coding.

Assume each packet consists of L bits. Let $GF(2^q)$ represent the Galois Field, then each packet can be viewed as a vector of L/q symbols over $GF(2^q)$. Also assume packets at the source are divided into generations [8], with each generation of h packets denoted as $X_1, X_2, ..., X_h$. Under random linear coding, each outgoing packet Y_i is a linear combination of the original packets. Namely, $Y_i = \sum_{j=1}^h g_{ij} \cdot X_j$, where the encoding vector **g** is randomly picked from $GF(2^q)$.

The addition over $GF(2^q)$ requires q XOR gates to act adding of two operands of q bits. For multiplication, each multiplier requires $2q^2$ XOR gates and $2q^2$ AND gates [9]. To obtain a coded packet Y_i, it is observed that, $h \cdot (L/q)$ times of multiplication and $(h-1) \cdot (L/q)$ times of addition should be performed.

Let $\varepsilon_* \cdot q^3$ and $\varepsilon_+ \cdot q$ denote the energy consumption per-bit multiplication and addition [9]. Here ε_* and ε_+ are energy consumption cost, determined by specific CMOS technology. Thus, the energy consumed on packet Y_i can be formulated as:

$$\varphi^p = \varepsilon_* \cdot q^3 \cdot h \cdot (L/q) + \varepsilon_+ \cdot q \cdot (h-1) \cdot (L/q) \quad (7)$$

Correspondingly, the power consumption cost for each bit is given by

$$\varphi = \left[\varepsilon_* \cdot q^2 \cdot h + \varepsilon_+ \cdot (h-1)\right] \quad (8)$$

Clearly, the network coding power consumption cost mainly dependents on the Galois Field size q and the generation size h. Although some improved coding strategies (e.g., XOR coding in [13]) have been proposed, we just develop a generalized model, upon which special cases can be easily deduced.

Then the network coding power consumption at a node i is formulated as:

$$P_i^{en} = \varphi \cdot \sum_{s\in S} \sum_{m\in J(s)} \sum_{j:(i,j)\in E} H_{ij}^{sm} \cdot x_{ji}^{sm} \quad (9)$$

Based on the above analysis, the total power dissipation at a sensor node i is given by

$$\begin{aligned} P_i &= P_i^s + P_i^t + P_i^r + P_i^{en} \\ &= P_i^s + \epsilon_{ij} \cdot \sum_{s\in S} \sum_{j:(i,j)\in E} f_{ij}^s + \xi \cdot \sum_{s\in S} \sum_{j:(i,j)\in E} f_{ji}^s \\ &\quad + \varphi \cdot \sum_{s\in S} \sum_{m\in J(s)} \sum_{j:(i,j)\in E} H_{ij}^{sm} \cdot x_{ji}^{sm} \end{aligned} \quad (10)$$

where P_i^s represents the video coding power of node i.

III. PROBLEM STATEMENT

A. Network Coding Scheme

To achieve a reliable transmission, we present the following network coding based error recovery scheme for WVSN.

1) At the source node, coded packets are generated from a random linear combination of original packets. These coded packets then are injected on outgoing links along multiple paths. In this way, flows traversing different paths are linearly independent rather than identical copies.

2) At the relay node, packets from different paths of the same session, can be coded again to provide diverse information. Here network coding across different sessions is forbidden to increase the reliability.

3) At the sink node, each session will be independently decoded as long as enough coded packets are received.

B. Optimization Problem

In this work, we aim to seek the maximum network lifetime and optimal rate allocation for a WVSN, where the initial power budget of video sensors and the required video quality are given. Mathematically, it can be formulated as follows:

P1: $\text{maximize} \quad \min_{i\in S} T_i$ (11)

subject to

1)

$$\sum_{j:(i,j)\in E} \sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ij}^{sm} - \sum_{j:(j,i)\in E} \sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ji}^{sm} = \rho_i, \ \forall i \in S$$

2) $\sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ij}^{sm} \le \left(1-p_{ij}\right) \cdot f_{ij}^s, \ \forall (i,j) \in E, \ \forall s \in S$;

3) $\sum_{s\in S} f_{ij}^s + \sum_{s\in S} \sum_{(p,q)\in \Psi(i,j)} f_{pq}^s \le C, \ \forall (i,j) \in E$;

4) $T_i = E_i / P_i, \ \forall i \in S$;

5) $\sigma^2 e^{-\gamma \cdot R^s \cdot (P^s)^{\frac{2}{3}}} \le D_s, \ \forall s \in S$.

Assuming that each sensor node i has an initial energy E_i, the lifetime of sensor node i can be formulated as $T_i = E_i / P_i$. Also assume all video sensors are of equal importance. Hence, the network lifetime of WVSN is given by: $T_{net} = \min_{i\in S} T_i = \min_{i\in S} E_i / P_i$.

Constraint 2) illustrates the relationship between information flow and physical flow over lossy channels. Unlike the error-free channel defined in Eq. (3), we take the packet loss into account. At any link (i,j) with packet loss rate of p_{ij}, the actual transmission rate of the coded (physical) flows requires to be no less than the information flow rate. Under such condition, the coded flows may provide sufficient information for the sink node to recover the original information flow.

Furthermore, considering a small probability of linear correlation among coded packets over $GF(2^q)$, we introduce a slack factor $\kappa (\kappa > 1)$ and let $\kappa \sum_{m\in J(s)} H_{ij}^{sm} \cdot x_{ij}^{sm} = (1-p_{ij}) f_{ij}^s$. Then, f_{ij}^s becomes a dummy variable and can be expressed by functions of x_{ij}^{sm}.

$$f_{ij}^s = \sum_{m\in J(s)} \eta_{ij} \cdot H_{ij}^{sm} x_{ij}^{sm} \quad (12)$$

where we let $\eta_{ij} \triangleq \kappa / (1-p_{ij})$ to simplify the expression.

Constraint 4) is not convex and usually hard to solve. So we introduce a new variable $t_i = 1/T_i$ and make a equivalent transformation of $E_i t_i = P_i$. Actually, t_i can be regarded as the normalized power consumption of node i with respect to its energy budget E_i. Maximizing the minimum lifetime of all sensor nodes is therefore equivalent to minimize the maximum normalized power consumption over all sensor nodes.

Constraint 5) reflects the relationship of the encoding rate, encoding power and encoding distortion, where D_s is the upper bound of the received video distortion for session s.

Therefore, Problem **P1** can be re-written as:

P2: $\text{minimize} \quad \max_{i\in S} t_i$ (13)

subject to

1)

$$\sum_{j:(i,j)\in E}\sum_{m\in J(s)} H_{ij}^{sm}\cdot x_{ij}^{sm} - \sum_{j:(j,i)\in E}\sum_{m\in J(s)} H_{ij}^{sm}\cdot x_{ji}^{sm} = \rho_i,\ \forall i\in S$$

2)

$$\sum_s\sum_m \eta_{ij}H_{ij}^{sm}x_{ij}^{sm} + \sum_s\sum_{(p,q)\in\Psi(i,j)}\sum_m \eta_{pq}H_{pq}^{sm}x_{pq}^{sm} \le C, \forall (i,j)\in E$$

3) $$E_i t_i = P_i^s + \sum_{s\in S}\sum_{j:(i,j)\in E}\sum_{m\in J(s)} \eta_{ij}\epsilon_{ij}\cdot H_{ij}^{sm}x_{ij}^{sm} + \sum_{s\in S}\sum_{j:(i,j)\in E}\sum_{m\in J(s)} \eta_{ij}\xi\cdot H_{ij}^{sm}x_{ji}^{sm} + \sum_{s\in S}\sum_{m\in J(s)}\sum_{j:(i,j)\in E} \varphi\cdot H_{ij}^{sm}x_{ji}^{sm},\quad \forall i\in S$$

4) $\log\,(\sigma^2/D_s)/\gamma\cdot(P^s)^{\frac{2}{3}} \le R^s,\ \forall s\in S.$

Problem **P2** is a convex optimization problem, as the objective function and the constraint sets are convex [10]. Traditional centralized solutions require global information and coordination among all nodes, which is sometimes infeasible in practice. In the following section, we will develop a fully distributed solution based on Lagrange dual theory [11].

C. Fully Distributed Algorithm

To decouple Problem **P2** into a set of subproblems with distributed solutions, we relax constraint sets and formulate the following Lagrangian:

$$\begin{aligned}\mathbf{L}(\mathbf{t},\mathbf{x},\mathbf{P},\mathbf{R},\lambda,\mu,\nu,\omega) &= \max_{i\in S} t_i \\ &+ \sum_{i\in S}\lambda_i\Big(\sum_{j:(i,j)}\sum_m H_{ij}^{sm}x_{ij}^{sm} - \sum_{j:(j,i)}\sum_m H_{ij}^{sm}x_{ji}^{sm} - \rho_i\Big) \\ &+ \sum_{(i,j)}\mu_{ij}\Big(\sum_s\sum_m \eta_{ij}\cdot H_{ij}^{sm}x_{ij}^{sm} + \sum_s\sum_{(p,q)}\sum_m \eta_{pq}\cdot H_{pq}^{sm}x_{pq}^{sm} - C\Big) \\ &+ \sum_{i\in S}\nu_i\Big(P_i^s + \sum_s\sum_{j:(i,j)}\sum_m \eta_{ij}\epsilon_{ij}\cdot H_{ij}^{sm}x_{ij}^{sm} + \sum_s\sum_{j:(i,j)}\sum_m \eta_{ij}\xi\cdot H_{ij}^{sm}x_{ji}^{sm} - E_i t_i\Big) \\ &+ \sum_s \omega_s\Big(\log\,(\sigma^2/D_s)/\gamma\cdot(P^s)^{\frac{2}{3}} - R^s\Big)\end{aligned}\tag{14}$$

where λ, μ, ν and ω are Lagrange multipliers.

The corresponding Lagrange dual function is

$$\mathbf{g}(\lambda,\mu,\nu,\omega) = \inf_{\mathbf{t},\mathbf{x},\mathbf{P},\mathbf{R}} \mathbf{L}(\mathbf{t},\mathbf{x},\mathbf{P},\mathbf{R},\lambda,\mu,\nu,\omega)\tag{15}$$

The Lagrange dual problem of Problem **P2** is then defined as:

$$\begin{aligned}&\text{maxmize}\quad g(\lambda,\mu,\nu,\omega)\\ &\text{subject to}\ \ \mu\succeq 0,\ \omega\succeq 0\end{aligned}\tag{16}$$

Since the objective function of the primal problem (13) is not strictly convex, the dual function (15) may not be differentiable everywhere. We hence use a subgradient algorithm to update the primal and dual variables.

At the n-th iteration, the primal variables are updated as follows,

$$\begin{aligned}t_i(n+1) &= \Big[t_i(n)+\dot{t}_i\Big]^+ = \Big[t_i(n)+\tau_1(n)\frac{\partial\mathbf{L}}{\partial t_i}\Big(t_i(n)\Big)\Big]^+\\ x_{ij}^{sm}(n+1) &= \Big[x_{ij}^{sm}(n)+\dot{x}_{ij}^{sm}\Big]^+ = \Big[x_{ij}^{sm}(n)+\tau_2(n)\frac{\partial\mathbf{L}}{\partial x_{ij}^{sm}}\Big(x_{ij}^{sm}(n)\Big)\Big]^+\\ P^s(n+1) &= \Big[P^s(n)+\dot{P}^s\Big]^+ = \Big[P^s(n)+\tau_3(n)\frac{\partial\mathbf{L}}{\partial P^s}\Big(P^s(n)\Big)\Big]^+\\ R^s(n+1) &= \Big[R^s(n)+\dot{R}^s\Big]^+ = \Big[R^s(n)+\tau_4(n)\frac{\partial\mathbf{L}}{\partial R^s}\Big(R^s(n)\Big)\Big]^+\end{aligned}\tag{17}$$

where $\tau_1(n) \backsim \tau_4(n)$ are positive step sizes, and $[\cdot]^+$ denotes the projection onto the set of non-negative real numbers. The partial derivatives of the above primal variables are given by

$$\begin{aligned}\dot{t}_i &= \begin{cases}\tau_1(t_i)(1-\nu_i\cdot E_i), & \text{if } t_i(n)=\max_{j\in S} t_j(n)\ ;\\ -\tau_1(t_i)\cdot\nu_i\cdot E_i, & \text{otherwise}\ .\end{cases}\\ \dot{x}_{ij}^{sm} &= \tau_2(x_{ij}^{sm})\Big(\lambda_i-\lambda_j+\mu_{ij}\cdot\eta_{ij}+\nu_i\cdot\eta_{ij}\cdot(\epsilon_{ij}+\xi)\Big)\\ \dot{P}^s &= \tau_3(P^s)\Big(\nu_s - \frac{2\omega_s\log\,(\sigma^2/D_s)}{3\gamma(P^s)^{\frac{5}{3}}}\Big)\\ \dot{R}^s &= \tau_4(R^s)(-\omega^s-\lambda^s)\end{aligned}\tag{18}$$

Similarly, the dual variables are updated by

$$\begin{aligned}\lambda_i(n+1) &= \Big[\lambda_i(n)+\tau_5(n)\Big(\sum_{j:(i,j)}\sum_m H_{ij}^{sm}x_{ij}^{sm}(n) - \sum_{j:(j,i)}\sum_m H_{ij}^{sm}x_{ji}^{sm}(n)-\rho_i\Big)\Big]^+\\ \mu_{ij}(n+1) &= \Big[\mu_{ij}(n)+\tau_6(n)\Big(\sum_s\sum_m \eta_{ij}\cdot H_{ij}^{sm}x_{ij}^{sm}(n) + \sum_s\sum_{(p,q)\in\Psi(i,j)}\sum_m \eta_{pq}\cdot H_{pq}^{sm}x_{pq}^{sm}(n)-C\Big)\Big]^+\\ \nu_i(n+1) &= \Big[\nu_i(n)+\tau_7(n)\Big(P_i^s(n)+\sum_s\sum_{j:(i,j)}\sum_m \eta_{ij}\epsilon_{ij}\cdot H_{ij}^{sm}x_{ij}^{sm}(n) + \sum_s\sum_{j:(i,j)}\sum_m \eta_{ij}\xi\cdot H_{ij}^{sm}x_{ji}^{sm}(n)-E_i t_i(n)\Big)\Big]^+\end{aligned}\tag{19}$$

where $\tau_5(n) \backsim \tau_8(n)$ are positive step sizes.

The update of the primal and dual variables can solve three correlated subproblems, i.e., rate control problem, energy conservation problem and P-R-D balance problem. The rate control is mainly performed by the update of x_{ij}^{sm}, where μ_{ij} can be viewed as the congestion price at link (i,j). For each link (i,j), if the total demand exceeds the supply C, namely, the capacity of wireless shared-medium is not sufficient to support current data flows travelling within a cluster, the price μ_{ij} will rise to reduce the allocated rate x_{ij}^{sm}. Or else, μ_{ij} will decrease to attract more flows to occupy the free bandwidth.

The energy conservation at each sensor is achieved by adjusting the value of x_{ij}^{sm} and t_i, with ν_i working as the energy consumption cost. If the total energy utilized at node i exceeds the current energy budget, ν_i will rise. As a response, the communication rate x_{ij}^{sm} will slow down to save the energy. Meanwhile, the normalized power consumption t_i will rise, signifying the reduction of the lifetime. Otherwise, the opposite changes will happen.

At each source node s, the balance between the encoding rate and the encoding power is maintained by ω_s and ν_s. For a required video distortion, the excessive increase of R^s or P^s will raise the value of ω_s and ν_s, which simultaneously impose an inverse impact on R^s and P^s. The decrease of R^s and P^s will likewise pull down ω_s and ν_s. Such interaction iteratively functions, till an optimal balance is established between R^s and P^s.

According to Eq. (18), the update of t_i at each sensor node requires the global information of all nodes. Obviously, this algorithm is not fully distributed. Thus, we use a simple approach, to replace the max norm by an k-norm [12].

$$\max_{i\in S} t_i = \|t\|_\infty \approx \|t\|_k = \Big(\sum_{i\in S} t_i^k\Big)^{1/k} \quad (20)$$

Also, we make some transformation on the objective function of Problem **P2**, and formulate the following approximate problem.

P3: $\quad \text{minimize} \quad \|t\|_k^k$

subject to Constraint sets as in Problem **P2**.

The calculation of t_i at the n-th iteration is then changed to

$$t_i(n+1) = \Big[t_i(n) + \tau_1(n)\Big(k \cdot t_i(n)^{(k-1)} - \nu_i(n)\cdot E_i\Big)\Big]^+ \quad (21)$$

Clearly, all the updating steps of Problem **P3** can be decentralized performed using only the local information.

D. Implementation of Distributed Algorithm

To implement the proposed distributed algorithm, each link and each sensor node is considered as a processor of a distributed computation system. Assume that the processor for link (i,j) keeps track of variables x_{ij}^{sm} and μ_{ij} , while the processor for node s keeps track of variables t_s, R^s, P^s, λ_s and ν_s. A decentralized implementation of the proposed algorithm can be summarized in Fig. 1.

Initialization:

- set $n=0$, and $x_{ij}^{sm}(0)$, $t_s(0)$, $R^s(0)$, $P^s(0)$, $\mu_{ij}(0)$, $\lambda_s(0)$, $\nu_s(0)$ to some non-negative value for all i, j, s, m;

At times $n = 1, 2, ...,$

At link (i,j)**:**

- Receives $\lambda_s(n)$ and $\nu_s(n)$ from all nodes use link (i,j);
- Fetches $\mu_{ij}(n)$ stored in the local processor;
- Updates rate $x_{ij}^{sm}(n)$ and congestion price $\mu_{ij}(n)$;
- Broadcasts the new price $\mu_{ij}(n)$ to all nodes use link (i,j);

At sensor node s**:**

- Receives from the network the price $\mu_{ij}(n)$;
- Fetches $\lambda_s(n)$ and $\nu_s(n)$ stored in the local processor;
- Updates $t_s(n)$, $R^s(n)$, $P^s(n)$, and price $\lambda_s(n)$, $\nu_s(n)$;
- Broadcasts the new price $\lambda_s(n)$ and $\nu_s(n)$ to all links.

Fig. 1. Implementation of the proposed distributed algorithm.

IV. NUMERICAL RESULTS

In this section, we present simulation results to demonstrate the performance of the proposed distributed algorithm. Consider a static WVSN in which 9 video sensor nodes and one sink nodes are randomly deployed in a square region of 50m×50m. The maximum transmission range d_x for each node is 25m. The parameters for the power consumption model are set as [2]: $\gamma = 55.54W^{(3/2)}/Mbps$, $\eta = 1.3\times 10^{-8} J/Mb/m^4$, $\sigma^2 = 3500$, $\theta = 0.5J/Mb$, $\alpha = 4$, $\xi = 0.5J/Mb$. The initial power of each sensor node is $5MJ$. The capacity of the wireless shared-medium is $0.2Mbps$. Each sensor nodes is allowed to perform random linear network coding over $GF(2^8)$ with a generation size of 50. In our simulations, we use a standard test video sequence "Coastguard" with a frame rate of 30 fps, CIF (352x288) resolution, and a GOP-length of 32 frames.

Fig. 2 shows the evolution of the normalized power consumption t_i at each sensor node, where the upper bound of the encoding distortion D_s in PSNR is 28.13. Here all step sizes are diminishing style and equally set to $\tau_i(n) = 0.15/n^{-2}$. It is observed that all of the normalized power consumption reaches the optimal values after 221 iterations, which means the proposed algorithm converges with a fast speed. Although a constant step size is more convenient in practice, the algorithm will only converge to some suboptimal solution around the optimum. Using a diminishing step size, the convergence to the optimum can be well guaranteed.

Fig. 3 compares the power consumption on error control using network coding and link-by-link FEC scheme, respectively. The encoding power consumption cost of network coding is calculated as $1.2\times 10^{-4} J/Mb$ in terms of Eq. (8), with $\varepsilon_* = 3.7\times 10^{-5} mW/MHz$, $\varepsilon_+ = 3.3\times 10^{-5} mW/MHz$ [9]. The FEC encoding and decoding power consumption cost are set to $8\times 10^{-5} J/Mb$ and $2.1\times 10^{-4} J/Mb$ [6]. We can find that network coding performs better than FEC based error control scheme. Using FEC scheme, each relay node consumes a large amount of energy on encoding and decoding operation.

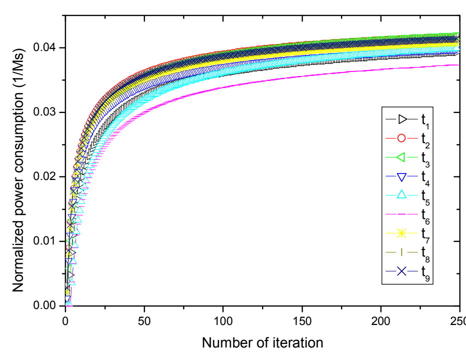

Fig. 2. Performance of normalized power consumption.

In contrast, only the intersecting relay nodes on different paths for the same sink requires to perform network coding, and network decoding is never required at any relay node. Moreover, FEC scheme introduces redundant check codes which also require more power than network coding.

Fig. 4 shows the relationship between the video quality requirement measured as PSNR and the achievable maximum network lifetime, where the packet loss rate of each link changes from 0.05 to 0.5. It can be seen that the quality and the lifetime is a paradoxical property pair. High-quality video is achieved at the cost of network lifetime. On the contrary, the network lifetime can be prolonged by moderately degrading the received video quality. Further, the increase of the packet loss rate will lead to more retransmissions and consume more energy on network coding and transmission, which inevitably results in the reduction of the network lifetime.

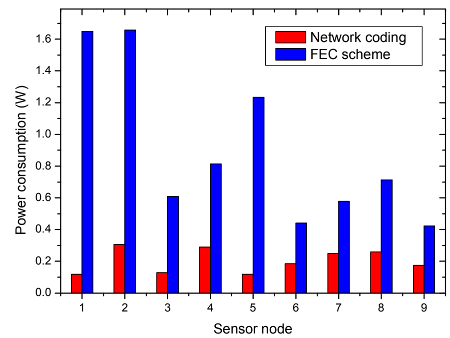

Fig. 3. Comparison of power consumption on network coding and FEC scheme.

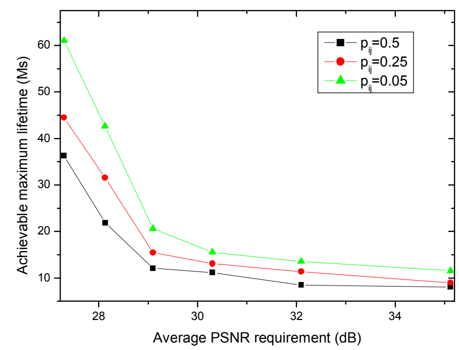

Fig. 4. Relationship between video quality requirement and achievable maximum network lifetime.

V. CONCLUSION

This paper investigates a network lifetime optimization for WVSNs, where the network employs link rate allocation, network coding based error control, multipath routing as well as video encoding rate to jointly optimize the network lifetime. To evaluate the energy consumed by network encoder, a generalized network coding power consumption model is established. It specifies the relationship of Galois Field size and generation size with the network coding power consumption cost. We develop a fully decentralized algorithm by Lagrange dual and subgradient approach to solve the objective convex problem. Numerical results validate the proposed algorithm from the convergence and performance optimization.

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