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Correlated Data Gathering on Dynamic Network Coding Policy and Opportunistic Routing in Wireless Sensor Network

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***Abstract*—This paper studies the problem of correlated data gathering in wireless sensor networks. For a maximum network utility, an efficient data capture and transmission framework is proposed for correlated sources, where localized S-W source coding, network coding based flow control and opportunistic routing are jointly optimized. To increase the throughput and guarantee the decodability simultaneously, a dynamic network coding strategy is proposed, with which the intermediate node can easily decide whether to make a combination among the incoming flows. Also, an opportunistic routing approach is presented, which adopts a new metric (minimum congestion price) for forwarding node selection and results in a maximum utility benefit for the sensor nodes. Through the Lagrange dual and gradient approach, a fully distributed algorithm is represented. And the convergence and performance are validated by the numerical results.**

***Index Terms*—wireless sensor network, correlated data gathering, distributed source coding, network coding, opportunistic routing**

I. Introduction

Due to typically battery-powered sensor nodes, effective data gathering from sensor nodes to end sites or sink nodes is crucial for energy-constrained wireless sensor networks. When collaboratively collecting information from the same area, the sensor nodes are often densely deployed. Thus, the data collected is correlated. Compared with traditional independent data gathering, correlated data gathering provides an ideal solution for efficient resource (e.g. power and bandwidth) consumption. The motivation of this paper is to design the optimal data capture and transmission structure for correlated sources in wireless sensor networks, where the opportunistic routing and network coding based flow control are jointly considered for a network utility maximization.

Slepian-Wolf (henceforth S-W) coding, a typical distributed source coding (DSC) technique, can optimally exploit the correlation of discrete sources [1]. By using S-W coding, the data redundancy caused by the spatially correlated observations in the wireless sensor networks can be completely removed. It has been proven that the correlated data captured by the sensor nodes can be coded with a total rate not exceeding their joint entropy. This result theoretically provides the so-called S-W rate region [2] for lossless data compression. However, the determination of the S-W rate region requires each sensor node to have full knowledge of the global correlation structure. It would incur significant communication costs and even becomes impossible in large-scale sensor networks. To employ S-W coding in a realistic settings, we adopt a localized S-W coding strategy, in which S-W coding is performed locally only on the neighborhood of the sensor node [3].

The seminal work of Ahlswede et al. [4] demonstrated that network coding can achieve the capacity in single-source multiple-terminal multicast. The authors in [5] and [6] have shown that random linear network coding can achieve this capacity with high probability in a distributed manner. It is worth mentioning that such a significant throughput gain is yielded under the assumption that the packets at the receivers are decodable. In practice, Erylimaz et al. [7] proposed a routing-scheduling-coding rule to decide whether coding is to be performed according to the queues status. For the network with correlated sources, Cui et al. [8] proposed a distributed rate allocation algorithm, in which the distributed source coding and network coding are jointly optimized. Joint coding/routing optimization for correlated sources in wireless sensor networks is also discussed in [9]. Unlike the previous work, we incorporate a coding policy into the flow routing problem, with which the intermediate nodes can independently judge whether the coding operation is appropriate, and whether the decodability is guaranteed at the terminal.

In the face of highly unpredictable and lossy wireless channels, opportunistic routing emerges a promising technique that achieves higher throughput than traditional deterministic forwarding. Biswas et al. [10] proposed an opportunistic protocol ExOR to send information through multiple relays and introduce delicate scheduling policies to reduce duplicate transmission. Chachulski et al. in [11] developed an improved ExOR protocol called MORE, in which no specific scheduler is required and network coding is applied to avoid the unnecessary forwarding. However, the metric they adopted for the relay set selection is very simple (e.g. ETX metric), with little correlation to network capacity. From the perspective of optimal resource consumption, we propose an opportunistic routing protocol to construct the optimal end-to-end data path.

Our main contributions in this paper are as follows. First,

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we develop an efficient data gathering framework for correlated sources, where localized S-W source coding, network coding based flow control and opportunistic routing are jointly optimized. Second, to increase the throughput and guarantee the decodability simultaneously, a dynamic network coding strategy is proposed, with which the intermediate node can easily decide whether to make a combination among the incoming flows. Further, an opportunistic routing approach is presented, which adopts a new metric (minimum congestion price) for forwarding node selection and results in a maximum utility benefit for the sensor nodes. Last, using Lagrange dual and gradient approach, we solve the target optimization problem in a fully decentralized manner.

The rest of this paper is organized as follows. Sec. II presents the network model, related constraints and formulates the problem. A distributed solution of the optimization problem is then demonstrated at Sec. III. Sec. IV and Sec. V describes the details above the proposed coding strategy and opportunistic routing. Numerical results are presented in Sec. VI, and we conclude this article at the last section.

II. Problem Formulation

A. Network Model and Flow Constraints

The wireless sensor network can be modeled as a directed graph $G = (V, E)$, where $V = S \cup T$ is the set of nodes, E is the set of wireless links, and $S = \{s_1, s_2, ..., s_{N_s}\}$ and $T = \{t_1, t_2, ..., t_{N_t}\}$ denote the set of sensor nodes and sink nodes, respectively. Each node $i \in V$ has a radio range d_i and can communicate with other nodes within its range. Each link $(i, j) \in E$ has a fixed capacity $c_{(i,j)}$.

Suppose that there exist multiple paths from a sensor node to the sink nodes. Let $J(s,t)$ denote the set of paths from sensor s to sink t. For any t, let $R_s^{t,m}$ be the transmission rate from s over path m ($m \in J(s,t)$). Moreover, let $g_{ij}^{s,t,m}$ represent the information flow rate of link (i,j) allocated by s over path m. Thus, for any node $i \in V$, we have the following flow conservation constraints,

$$\sum_{j:(i,j)\in E} g_{ij}^{s,t,m} - \sum_{j:(j,i)\in E} g_{ji}^{s,t,m} = \sigma_i^{s,t,m}, \tag{1}$$

$$\text{where} \quad \sigma_i^{s,t,m} = \begin{cases} R_s^{t,m} & : \text{ if } i = s, \\ -R_s^{t,m} & : \text{ if } i = t, \\ 0 & : \text{ otherwise.} \end{cases}$$

B. Distributed Source Coding Model

Sensor nodes can be viewed as N_s discrete memoryless source and their output values X_i, $i = 1, ..., N_s$ are drawn identically distributed from a joint distribution $p(X_1, ..., X_{N_s})$. Let R_i denote the encoding rate of sensor s_i. For each sensor node, we define a neighborhood. When a sensor node determines its encoding rate, it only considers the data correlation with those sensors within the range of its neighborhood, rather than in the entire network. As a result, the localized S-W region is loosed as

$$\mathcal{R}_{\mathcal{SW}} = \{[R_1 R_2 ... R_{N_s}] : \; R_i \geq H(X_i|N_i)\} \tag{2}$$

where N_i is a subset of the sensors within the neighborhood of sensor i.

C. Network Coding Constraints

With network coding, flows from different source to different sink are allowed to share the network capacity by coding together at the intermediate node. For any intermediate node i that receives flows at the information flow rate $g_{ij}^{s,t,m}$, if network coding is applied, the actual physical flow f_{ij} sent by node i to its next hop j is only to be the maximum of the received information flows. That is

$$f_{ij} = \begin{cases} \max\limits_{s,t,m} g_{ij}^{s,t,m} & \text{if network coding is applied,} \\ \sum\limits_{s,t,m} g_{ij}^{s,t,m} & \text{otherwise.} \end{cases} \tag{3}$$

D. Problem Statement

Assume each sensor node i is characterized by a utility function $U(R_i)$ that is concave increasing in its transmission rate R_i. Our goal is to maximize the aggregate utility by joint optimization of source coding, network coding and opportunistic routing for all the correlated sources. Combining the above rate admissibility constraints, our optimization problem can be formulated as

$$\textbf{P1:} \qquad \text{maximize} \quad \sum_{i\in S} U(R_i)$$

s.t.

1) $\displaystyle\sum_{j:(i,j)\in E} g_{ij}^{s,t,m} - \sum_{j:(j,i)\in E} g_{ji}^{s,t,m} = \sigma_i^{s,t,m}, \quad \forall i \in V,$

2) $\displaystyle\sum_{m\in J(s,t)} R_s^{t,m} \geq H(X_s|N_s), \qquad \forall s \in S,\; t \in T,$

3) $\displaystyle\sum_{m\in J(s,t)} R_s^{t,m} \leq \text{min-cut}(s,t), \qquad \forall s \in S,\; t \in T,$

4) $f_{ij} = \begin{cases} \max\limits_{s,t,m} g_{ij}^{s,t,m} & \text{if network coding is applied,} \\ \sum\limits_{s,t,m} g_{ij}^{s,t,m} & \text{otherwise,} \end{cases}$

5) $f_{ij} \leq c_{ij}, \qquad \forall (i,j) \in E.$

where $R_i = \sum_{t\in D(i)} \sum_{m\in J(i,t)} R_i^{t,m}$. For each sink node $t_i \in T$, the total incoming traffic flows from a source must be less than the minimum cut capacity from the source to itself, as represented in constraint 3). We introduce $H_{ij}^{s,t,m}$ to reflect the relationship between its paths and the corresponding links. Let $H_{ij}^{s,t,m} = 1$ if path m of sensor s to the sink t uses link (i,j), otherwise $H_{ij}^{s,t,m} = 0$. Therefore, constraint 1) can be re-written as

$$g_{ij}^{s,t,m} = H_{ij}^{s,t,m} \cdot R_s^{t,m}, \qquad \forall i \in V \tag{4}$$

Also, we relax constraint 4) by $g_{ij}^{s,t,m} \leq f_{ij}$.

III. Distributed Solution

By using Lagrangian dualization, we relax constraints 1)-4) and obtain the Lagrangian dual problem:

$$\textbf{P2:} \qquad \text{minimize} \quad g(\alpha, \beta, \gamma, \lambda)$$

$$\text{s.t.} \qquad \beta \geq 0,\; \gamma \geq 0,\; \lambda \geq 0. \tag{5}$$

with partial dual function

$$
\begin{aligned}
&\mathbf{L}(\mathbf{R},\mathbf{g},\alpha,\beta,\gamma,\lambda)\\
&=\sum_{i\in S}U(R_i)+\sum_{(i,j)\in E}\sum_{s\in S}\sum_{t\in T}\sum_{m\in J(s,t)}\alpha_{ij}^{s,t,m}\cdot(g_{ij}^{s,t,m}\\
&-H_{ij}^{s,t,m}\cdot R_s^{tm})+\sum_{s\in S}\sum_{t\in T}\beta_s^t\cdot(\sum_{m\in J(s,t)}R_s^{t,m}-H(s|N_s))\\
&-\sum_{s\in S}\sum_{t\in T}\gamma_s^t(\sum_{m\in J(s,t)}R_s^{t,m}-\text{min-cut}(s,t))\\
&-\sum_{(i,j)\in E}\sum_{s\in S}\sum_{t\in T}\sum_{m\in J(s,t)}\lambda_{ij}^{s,t,m}\cdot(g_{ij}^{s,t,m}-f_{ij})
\end{aligned}
\tag{6}
$$

where α, β, γ and λ are Lagrange multipliers.

With the decomposition method proposed in [13], the dual function $g(\alpha,\beta,\gamma,\lambda)$ can be decomposed into two separate subproblems:

P2-1:

$$
\begin{aligned}
\min\sum_{(i,j)\in E}\sum_{s\in S}\sum_{t\in T}\sum_{m\in J(s,t)}&[\lambda_{ij}^{s,t,m}\cdot(g_{ij}^{s,t,m}-f_{ij})-\alpha_{ij}^{s,t,m}g_{ij}^{s,t,m}]\\
\text{s.t.}\qquad f_{ij}\le c_{ij}\qquad&\forall(i,j)\in E.
\end{aligned}
\tag{7}
$$

P2-2:

$$
\begin{aligned}
\max\sum_{s\in S}\sum_{t\in T}\sum_{m\in J(s,t)}&[U(R_s^{t,m})+(\beta_s^t-\gamma_s^t\\
&-\sum_{(i,j)\in E}\alpha_{ij}^{s,t,m}\cdot H_{ij}^{s,t,m})\cdot R_s^{t,m}]
\end{aligned}
\tag{8}
$$

Subproblem **P2-1** is a rate control problem [14] at the transport layer. Apart from its distributed solution, we will judge whether network coding at the intermediate node suffices to reconstruct all the sources error-free at the terminals. To do that, a dynamic coding strategy will be detailed in Sec. IV.

In subproblem **P2-2**, let $\varphi_s^{t,m}\triangleq\beta_s^t-\gamma_s^t-\sum_{i,j}H_{ij}^{s,t,m}\cdot\alpha_{i,j}^{s,t,m}$, then the target becomes a maximum $U(\mathbf{R})+\varphi\cdot\mathbf{R}$. It requires each sensor to transmit its data along the paths that yields the maximum transmission rate $\mathbf{R}$. Therefore, we will present an opportunistic routing scheme for constructing the optimal routing paths in a fully distributed manner in Sec. V.

It is observed that these two subproblems are solved separately and coordinated by the Lagrange multipliers. Here we use a gradient algorithm to update the dual variables. At the n-th iteration, the dual variables are updated by:

$$\alpha_{ij}^{s,t,m}(n+1)=[\alpha_{ij}^{s,t,m}(n)+\theta_\alpha\cdot(g_{ij}^{s,t,m}-H_{ij}^{s,t,m}\cdot R_s^{t,m}(n))]^+ \tag{9}$$

$$\beta_s^t(n+1)=[\beta_s^t(n)-\theta_\beta\cdot(\sum_{m\in J(s,t)}R_s^{t,m}-H(s|N_s))]^+ \tag{10}$$

$$\gamma_s^t(n+1)=[\gamma_s^t(n)+\theta_\gamma\cdot(\sum_{m\in J(s,t)}R_s^{t,m}-\text{min-cut}(s,t))]^+ \tag{11}$$

$$\lambda_{ij}^{s,t,m}(n+1)=[\lambda_{ij}^{s,t,m}(n)+\theta_\lambda\cdot(g_{ij}^{s,t,m}-f_{ij})]^+ \tag{12}$$

where θ_α, θ_β, θ_γ and θ_λ are positive step size, and $[\cdot]^+$ denotes the projection onto the set of non-negative real numbers.

IV. Control for Network Coding

Although network coding allows the link to be shared by the flows belonging to different source-sink pairs, how and when to perform network coding still remains an open problem. In the follows, we propose a coding policy that exploits the network coding advantage while guaranteeing decodability at the destinations.

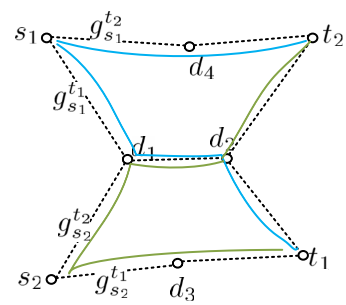

Fig. 1. The topology of the wireless sensor network

As shown in Fig. 1, sensor s_1 transmits the data to sink t_1 and t_2 through path $s_1-d_1-d_2-t_1$ and $s_1-d_4-t_2$, while s_2 sends the data to these two sinks along path $s_2-d_3-t_1$ and $s_2-d_1-d_2-t_2$. Clearly, flow from s_1 to t_1 shares link (d_1,d_2) with flow from s_2 to t_2. Without network coding, the achievable rates $g_{s_1}^{t_1}$ and $g_{s_1}^{t_1}$ of these two flows satisfy

$$g_{s_1}^{t_1}\le\min(c_{s_1d_1},c_{d_2t_1}),\quad g_{s_2}^{t_2}\le\min(c_{s_2d_1},c_{d_2t_2}), \tag{13}$$

$$g_{s_1}^{t_1}+g_{s_2}^{t_2}\le c_{d_1d_2}. \tag{14}$$

When network coding is allowed, flow rate $g_{s_1}^{t_1}$ and $g_{s_2}^{t_2}$ may be increased. More precisely, we can make linear combinations (e.g. XOR operation) over flow s_1-t_1 and s_2-t_2 at node d_1, and then multicast the coded flows to both sink t_1 and t_2. Let g_{NC} be the rate at which flows are coded at d_1, and $g^{t_1t_2}\triangleq g_{NC}-g_{s_1}^{t_2}+g_{NC}-g_{s_2}^{t_1}$ denote the flow gain by network coding. To guarantee the coded flows can be decoded at the destination, we have

$$g^{t_1t_2}\ge\max(g_{s_1}^{t_1},g_{s_2}^{t_2}) \tag{15}$$

After acquiring the required flow information from the upstream nodes s_1 and s_2 and the downstream node d_2, according to Eq.15, d_1 can decide whether to apply network coding or not. Specifically, if t_1 and t_2 can respectively receive the data form sensor s_2 and s_1, and $g^{t_1t_2}$ is no less than $\max(g_{s_1}^{t_1},g_{s_2}^{t_2})$, network coding is performed. Otherwise, network coding would never be used.

We now extend this decision rule to a generic network with multiple-source multiple-sink. For each sink $t_j\in\mathbf{t}$, source node $s_i\in\mathbf{s}$ can transmit data to t_j through the same intermediate node d at flow rate $g_{s_i}^{t_j}$, where $\mathbf{t}$ is a subset of sink nodes and $\mathbf{s}$ is a subset of source nodes. If network coding is allowed, we gain flow gain as:

$$g^{\mathbf{t}}=\sum_{t_j\in\mathbf{t}}(g_{NC}-\sum_{s_k\in(\mathbf{s}-s_i)}g_{s_k}^{\prime t_j}) \tag{16}$$

where $g_{s_k}^{\prime t_j}$ is the flow sink t_j gain from s_k over the paths without the intermediate node d. Therefore, network coding can be applied at the intermediate node to increase the throughput if the following conditions are satisfied:

$$g'^{t_j}_{s_k} > 0 \text{ and } g^{\mathbf{t}} \geq \max_{s_i \in \mathbf{s}; t_j \in \mathbf{t}} g^{t^j}_{s_i}. \quad (17)$$

V. Opportunistic Routing

A. Forwarding Candidates Selection

In this section, we will develop an opportunistic routing framework based on problem **P2-2**, upon which the optimal transmission structure for a maximum network utility can be easily derived. The proposed protocol is divided into three stages: the selection of the forwarding candidates, the transmission acknowledgment, and the flow control based on network coding.

As illustrated in Sec. III, the optimization objective of problem **P2-2** is to maximize $U(\mathbf{R}) + \varphi \cdot \mathbf{R}$. If we look φ as the benefit that the sensor can obtain by sending a unit flow, then $\varphi \cdot \mathbf{R}$ can represent the total benefit s achieves at a data rate of $\mathbf{R}$. Therefore, for a given $\mathbf{R}$, each sensor would choose a candidate subset from all its neighboring nodes with lower link congestion price α for a higher benefit φ.

During the node selection procedure, the congestion price $\alpha^{s,t,m}_{ij}$ for each link (i,j) is computed by its originator i according to the flow rate over link (i,j) from s to sink t on the m-th path. And the originator i acknowledges the congestion price $\alpha^{s,t,m}_{ij}$ to its neighbors. All the originators record the congestion price to the corresponding sink node. Then, when a source node s transmits its data to a sink node t, it firstly broadcasts a RTS (request to send) frame to its downstream neighbors. As a response, each receiver replies a CTS (clear to send) frame to its upstream nodes containing its link state information, especially the congestion price $\alpha^{s,t,m}_{ij}$. According to the feedbacks, the source node s chooses the appropriate neighbor subset and constructs m paths to the sink t, where each relay node involved in the subset joins the path respectively. The relay node also chooses its downstream nodes according to the congestion price. This process is repeated until the sink node replies the RTSs. And for each path, the source node gains a benefit $\varphi^{t,m}_{s}$ to sink node t and assigns an appropriate rate $R^{t,m}_{s}$ for that path.

B. Sensor Node

In the proposed opportunistic routing mechanism, each sensor in the forwarding list would also firstly broadcast a RTS frame to its neighboring nodes for detecting the status of the wireless channels. Meantime, the sensor node can determine its data transmission rate according to the data correlation with the sensors in its candidate subset. And the lower rate bound of the localized S-W required can be achieved simultaneously.

During data gathering, the sender would inform its forwarder by attaching a header to each data packet which reports the packet's code vector, the generation ID [6] belongs to, the source and destination IP address and the list of nodes which could participate in forwarding it. The sender keeps transmitting the coded packets of the current generation until it is recovered at the destination, and then it moves to the next generation.

C. Candidate Relay

Each sensor computes the congestion price which can be updated according to its local information. After receiving the RTS frame, the sensor would report its current status to the sender for the candidate set selection. In order to avoid the data collision, the sensor will delay a random time before sending back the CTS.

Once the set of the forwarder is determined by the sender, each relay node determines whether to forward the received packets directly or perform network coding to increase the throughput in terms of the proposed decision rule. For this reason, the CTS would also contain the information of its local storage. Fig. 2 describes the structure of the CTS frame where the local information is included.

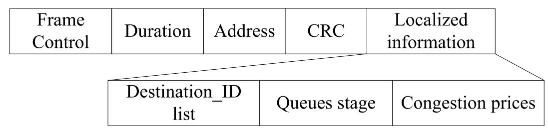

Fig. 2. The format of CTS frame

D. Destination

At the sink node, when enough linearly independent packets of a generation are received within a given period, this generation is assumed to be successfully received. Then an acknowledge (ACK) is sent to the source node. Or else, a negative acknowledge (NACK) is sent back.

VI. Simulation Results

In this section, we conduct numerical experiments to evaluate the performance of the proposed algorithm. We consider a wireless network with 8 sensor nodes and 2 sink nodes shown in Fig.3. As all the sources are identically distributed, we assume that $H(s_i) = 0.5Mbps$ and $H(s_1|N_{s_1}) = 0.2Mbps$, $H(s_2|N_{s_2}) = 0.2Mbps$, $H(s_3|N_{s_3}) = 0.3Mbps$, $H(s_4|N_{s_4}) = 0.3Mbps$, $H(s_5|N_{s_5}) = 0.4Mbps$, $H(s_6|N_{s_6}) = 0.4Mbps$. Also, suppose that all the sensors have the same utility function $U(R_i) = \ln(R_i)$.

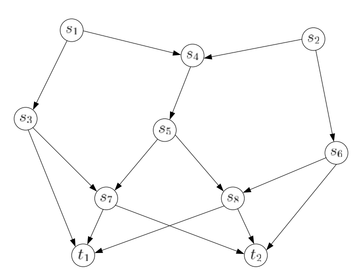

Fig. 3. The topology of wireless sensor network

Fig. 4 shows the convergence behavior of the source rate for each sensors with a fixed stepsize $\theta = 0.1$. We set the capacity of each link $c_l = 1Mbps$. It can be seen that the rates approach the optimal value after 100 iterations. Since the sensors which are far from the sink nodes can construct more paths to the sink nodes, these sensors can have higher transmission rates.

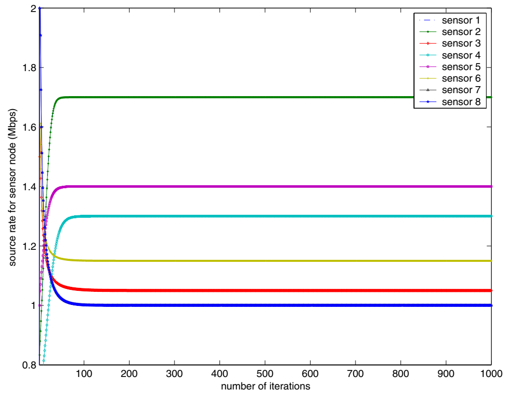

Fig. 4. The evolution of source rates versus the number of iteratons

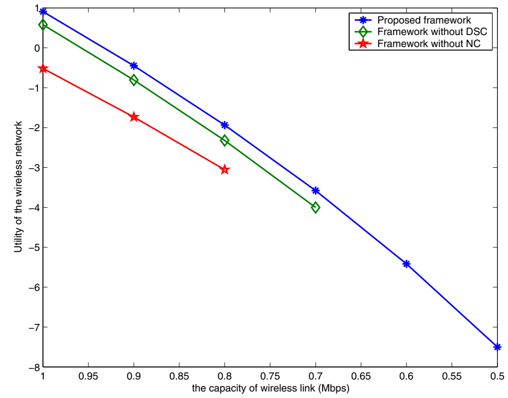

Fig. 6. Performance comparison on network utility

Therefore, sensor 1 and sensor 2 have higher rates than sensor 7 and sensor 8.

Fig. 5 compares the source rate each sensor node can achiever under the proposed framework to the framework without network coding. Clearly, for resource-constrained sensor network, there are distinct rate gains when network coding is applied at the intermediate nodes.

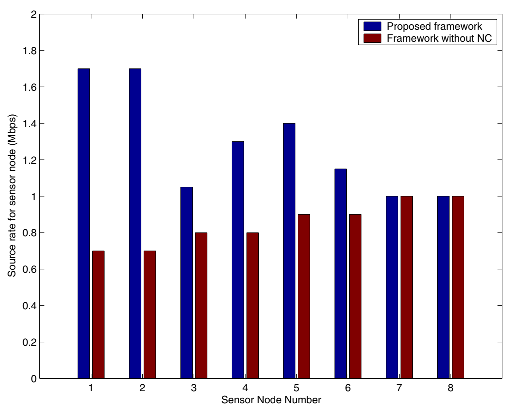

Fig. 5. Performance Comparison on optimal source rate

Performance comparison on the network utility is depicted in Fig. 6. We can see that the network utility in the proposed framework is larger than other two schemes where either DSC or network coding is not allowed. Without DSC, the achievable rate region for each sensor is higher than the one with DSC. Correspondingly, the total energy consumption of the network would be increased. Moreover, for a given source rate region, when we reduce the average wirless link capacity, the entire network controlled by the proposed strategy can still function well. In contrast, the network with the other two schemes would be gradually in congestion, and finally be out of work.

VII. Conclusion

In this paper, we investigate the problem of efficient correlated data gathering in wireless sensor networks where a distributed resource allocation framework is constructed based on a network utility maximization problem. The localized S-W coding is adopted at the sensor nodes to compress the redundant information. For each intermediate node, a dynamic network coding strategy is applied that allows this node to independently decide whether to combine the incoming flows. Moreover, an opportunistic routing strategy is proposed for data path construction, in which a new metric for minimum congestion price is introduced. Finally, the performance of the proposed framework is validated though the numerical simulation results.

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