

Cross Layer Optimization Based on Rate Distribution in Multirate Wireless Sensor Network

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Abstract: It is important to increase the Wireless Sensor Network (WSN) lifetime, due to its limited energy resource, while meeting the constraints of applications. Recent Advances for In-Network Processing (INP) motivate many WSN applications which are based on multi rate and distributed signal processing, and therefore require the support of rate-based routing as well as MAC and link layer designs to maximize the WSN lifetime. We propose a new scheme called “Rate Distribution (RateD)”, in which the application rate constraints are distributed in the WSN based on an optimized routing scheme. An optimal RateD was achieved by forming optimal data flows under rate constraints, which was an NP-complete problem. To reduce the complexity, a near optimization solution formed and analyzed, and a practical rate-based routing selection based on rate assignment also proposed to achieve effective rate distributions. The simulation shows that this scheme significantly extends the WSN lifetime for INP applications.

Keywords: In-Network Processing, Network Lifetime, Rate-Distribution, Wireless Sensor Network

INTRODUCTION

Unlike the general-purpose Wireless Local-Area Network (WLAN) that is designed to support all types of applications, Wireless Sensor Network (WSN) operates under a set of unique resource constraints and mission-driven requirements^[1]. For example, in resource-limited WSN, an effective network operation design has to consider energy efficiency with very high priority, and the WSN must operate at least for a given mission time or as long as possible.

With respect to energy efficiency, WSN nodes should cooperatively organize the network using distributed algorithms and protocols. When a network is organized in distributed fashion, the nodes in network are not only passing on packets or executing applications programs, they are also involved in taking decisions about how to operate network. This idea makes the in-network processing^[2,3,4,5,6] a first rank design principle. For example, Aggregation, Distributed Source Coding (DSC), Distributed Compression, and Distributed and Collaborative Signal Processing are some of the enabling technologies. Recent advances in collaborative signal processing and distributed source coding has fueled effective distributed designs in WSN. Sensors’ sampling and coding rates as well as sensor data correlations have to be reflected by WSN design factors such as setting link rates, making routing decisions, etc.

DSC reduces the number of transmitted bits but still obtains the full information from all sensor reading at the sink^[7, 8]. It utilizes the correlation of data col-

lected at multiple sensors without mutual communication between these sensors, and sets the multiple coding rates at these different sensor nodes. DSC works in a unique way profoundly different from the typical data aggregation methods^[9,10,11,12,13,14]. The data aggregation method combines data flows, and attempts to remove the redundant data among them by collecting information from multiple correlated sensor nodes. In order to prevent the redundant data from flowing into the whole network, data aggregation usually has to be performed early in the local area. This results in the bottleneck problem on aggregation points and the lack of load balancing, which deteriorates the network lifetime. In DSC design, because the inherent redundancy among the information bits collected from sensor nodes is already removed, there is no need of data aggregation. DSC information bits are collected independently, separately, and at different data rates to reach the sink node for source decoding. Therefore, it is desirable for efficient WSN designs to support such multi rate data-flow in network. Due to the nature of distributed and collaborative signal processing in WSN, these multi-rate data transmission requirements in DSC are not limited to a small category of applications, but are rather general in many signal processing related WSN applications. To date, there is a lack of multi-rate WSN designs and a strong need for such efforts on the other hand, while the complexities of both sensor nodes and networks grow.

Multiple paths which each start from a single source independently can be more advantageous than a

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single aggregation path, due to the load balancing and hence the benefit for an increased WSN lifetime, so long as the interferences among paths are limited at a low level. Because of the information “non-redundancy” in DSC, it is more effective to extend WSN lifetime by balancing loads and using disjoint route transmissions for DSC, and save energy by coordinating transmission rates with distributed coding rates.

In each wireless sensor node that performs real-time coding and transmission, if the channel condition allows and the network traffic amount is not high, a lower data transmission rate can be more advantageous than the higher transmission rate with respect to the communication energy consumption. Schurgers^[4] uses the following equation for communication energy consumption analysis. In Equation (1), E_{bit} is the energy consumption, b is the constellation size, and R_s is the symbol rate. (See details about this equation in^[15]).

$$E_{bit} = [C_s \cdot (2^b - 1) + C_E + C_R \cdot \frac{R_{s,max}}{R_s}] \cdot \frac{1}{b} \quad (1)$$

From Equation (1), once symbol rate R_s is determined, the higher modulation constellation size is, the higher is data rate as well as the higher energy cost, assuming the same BER value at the receiver end. According to Equation (1), if we use different modulation schemes, lower rate transmission can achieve the energy saving. This is true since the decreasing of data rate results in longer transmission time, the power consumption used for low data rate transmission decreases much more.

Many research activities related to multi rate and power control are reported in the CDMA areas^[16, 17]. However, their primary goal is to maximize channel utilization^[18, 19] and minimize the interference and near-far effect^[20, 21]. As a result, the multi rate and power control schemes in these works are not suitable for WSN. In WSN, This energy scalability in Equation (1) compatible with data rate ensures that energy is not wasted by providing performance in excess of an application's needs. These above observations also motivate us to design efficient schemes to support In-Network Processing in WSN.

The rest of the paper is organized as the following. In Section II, we define rate distribution concept with the sensor network model. Section III forms an optimization problem under the rate constraints and provides a near optimal solution especially for INP applications. We evaluate our method in the Section VI using simulations, and draw conclusion in Section V.

Sensor Network Rate Distribution Model: We consider a large scale static sensor network, where each source sensor generates certain data coding rate and has to be relayed to the sink node. This WSN consists of large number of nodes that can dynamically vary their

transmission power. Two wireless nodes have a link in between if the sending node transmits with sufficiently high power such that the SNR at the receiving node is greater than a given threshold value. The threshold value is chosen to achieve a desired bit error rate for the given modulation scheme and data rate.

Under this sensor network setting, we will investigate on the following problems:

- If each source sensor generates data with certain coding rate, how can a route path be determined to match the coding rates requirements while achieving optimized energy savings?
- How can a whole network design be determined to satisfy the multiple sources with multiple coding rates while optimizing the network life time?
- To address these two problems, there are several issues at different layers to be considered. Some related research work in optimizing the energy and network lifetime have been done in^[22,23,24,25], however, the optimizations in those research have not considered the rate constraints for INP applications. In this paper, with respect to the INP applications, at the network layer, an optimal route has to be found. At the MAC and link layer, we need to make each node meet the constraints associated with the link bit rate, and the load balancing at each node. Clearly, there is a cross-layer problem that couples multi rate MAC, power control and routing.

Remark 1: For a given data-generating rate vector $r(r_1, r_2, \dots, r_n)$, $r_i \geq 0$, We say that rate distribution is feasible if and only if there exists a solution such that all generated data can be relayed to the sink by distributing r_i constraint in the network.

There are two types of rate distribution strategy shown in Fig. 2. One is “direct rate distribution” in Fig. 2(a), and the other is indirect rate distribution in Fig. 2(b). We assume that there are a group of sensors collaboratively measuring and detecting a target. Direct rate distribution means that each sensor directly sends their data to the sink with its individual rate via a node-disjoint path; indirect rate distribution means that sensors firstly aggregate their data into local cluster head and then send them to the sink node with multiple disjoint paths (rates are distributed from the local cluster head).

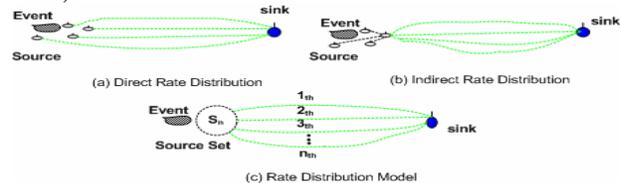


Fig. 2: Rate Distribution Model

Obviously, the direct rate distribution is more suitable for DSC applications, in which each sensor has already removed redundant information to send out; and the indirect rate distribution has positive advantages in other collaborative signal processing, in which each sensor might have redundant information and it has to be removed as early as possible when traffic data flows into network.

We generalize a common model for rate distribution in Fig. 2(c) from both direct distribution and indirect distribution. This model in Fig. 2(c) shows that there is a rate distribution source sensor set S_n , in which sensors have spatial correlations and work together to commit sensing functionality. The number of sensors in this set S_n is denoted as $|S_n|$. For the indirect distribution model example in Fig. 2(b), we only have node-disjoint multi-hop routing paths starting from the cluster head to the sink node, therefore, $|S_n|=1$, and in Fig. 2(a), $|S_n|=4$.

Remark 2: For a given data-generating rate vector $r(r_1, r_2 \dots r_n)$, $r_i \geq 0$, in source sensors S_n , the rate distribution is optimal if and only if there exists a solution such that all generated data can be relayed to the sink by distributing r_i constraints so that the network lifetime (e.g., the time until any node runs out of energy) is maximized.

We assume that the optimal rate distribution is to address sensor networks where multiple sensors cooperate on the same task, and network is static or changes very slowly, thus the optimization can be pre-calculated and configured during the network planning stage. It can also be done by a central node, which informs the optimal rate distribution information to other nodes when the network configuration needs to be updated. Therefore, it is clear that our goal is to find a solution for the optimal rate distribution by a cross layer optimization in the joint MAC and routing design scheme.

Equation (2) and (3) are close form relationships between the desirable BER and transmit power, for BPSK, QPSK and QAM modulations respectively, which can be straightforwardly derived from [5,12,13]:

$$P_S^{BPSK,QPSK} = R_s \cdot b \cdot \left[\text{erfc}^{-1}(2 \cdot BER) \right]^2 \cdot \frac{N_0}{A} \quad (2)$$

$$P_S^{M-QAM} = \frac{1}{3} \cdot R_s \cdot b \cdot (b^2 - 1) \cdot \left[\text{erfc}^{-1} \left(\frac{1}{2} \cdot \left(1 - \frac{1}{b} \right)^{-1} \cdot BER \right) \right]^2 \cdot \frac{N_0}{A} \quad (3)$$

When modulation scheme is determined, symbol rate R_s and constellation size b is also determined accordingly. Desirable BER is a system parameter, pre-defined by the system. Gaussian noise power intensity N_0 is a system constant value. Channel attenuation with

antenna gain A can be calculated from lower layer. As a result, the transmit power can be calculated from Equation (2) and (3). We assume that each sensor periodically performs measurements. Denote the data rate from node i to node j as $R_{i,j}$. Therefore, without losing generality, for BPSK, QPSK and M-QAM modulation, we can characterize the transmission power and receiver power as follows:

For BPSK and QPSK:

$$P^{transmit}(i, j) = \delta(i, j) \cdot R_{ij} \quad (4)$$

For M-QAM:

$$P^{transmit}(i, j) = \omega_{ij}(b) \cdot R_{ij} \quad (5)$$

For BPSK, QPSK and M-QAM:

$$P^{receive}(j) = \sum_{k \in N_i} \rho \cdot R_{kj} \quad (6)$$

where $\delta(i, k) = C_1 \cdot \left[\text{erfc}^{-1}(2 \cdot BER) \right]^2 \cdot \frac{N_0}{A}$, the typical value of ρ is 50 nJ/b,

$$\omega_{ik}(b) = C_2 \cdot (b^2 - 1) \cdot \left[\text{erfc}^{-1} \left(\frac{1}{2} \cdot \left(1 - \frac{1}{b} \right)^{-1} \cdot BER \right) \right]^2 \cdot \frac{N_0}{A}$$

And C_1 and C_2 are the constant value. We denote the data rate generated at each node i as G_i ,

$i = 1, 2, \dots, N$. For constant source rate G_i , $1 \leq i \leq N$, we can formulate the optimal rate distribution problem in (7) (8) and (9) under rate constraints. Denote T_i as the sensor i lifetime. Then, we have the following data rate equations and energy constraints for each node i , $1 \leq i \leq N$.

$$\sum_{k \in M_i} R_{ki} + G_i = \sum_{k \in N_i} R_{ik} \quad (7)$$

$$\left(\sum_{k \in M_i} \delta(i, k) R_{ik} + \sum_{k \in N_i} \rho R_{ki} \right) \cdot T_i < E_i \quad (8)$$

$$\left(\sum_{k \in M_i} \omega_{ik}(b) R_{ik} + \sum_{k \in N_i} \rho R_{ki} \right) \cdot T_i < E_i \quad (9)$$

$$b = 1, 2, \dots, N$$

Among them, M_i is a set of neighbor nodes of i which sends data traffic to node i , N_i is a set of neighbor nodes of i which receives data traffic from node i . Equation (7) states, at each i , that the data traffic G_i generated by node i , plus the amount of total received data traffic from others sent to i , are equal to the total bit rate transmitted from i . The second set of N inequalities in (8) and (9) state that the energy required to receive and transmit all these data traffic at each node i , at the end of sensor lifetime T_i , cannot exceed its energy constraint.

Rate Distribution Optimization: At the routing layer, our objective is to maximize the network lifetime T while (11) and (12) or (13) are satisfied. We formulate

the flow routing problem into the following optimizations.

$$T = \min(T_i) \quad (10)$$

Max T

s.t.

$$\sum_{k \in N_i} R_{ik} - \sum_{k \in M_i} R_{ki} = G_i \quad (11)$$

$$\left(\sum_{k \in M_i} \delta(i, k) R_{ik} + \sum_{k \in N_i} \rho R_{ki} \right) \cdot T_i - E_i \leq 0 \quad (12)$$

Or
$$\left(\sum_{k \in M_i} \omega_{ik}(b) R_{ik} + \sum_{k \in N_i} \rho R_{ki} \right) \cdot T_i - E_i \leq 0 \quad (13)$$

The above problem is based on the constant G_i . If the G_i is time-variable, it is expressed as $G_i(t)$. Assume each sensor measures data and generates constant data rate periodically. Suppose that the transmission rate and power do not change within each period τ , and neither does the data rate generated by sensors. During the l^{th} period, we denote the time length for link i to j as t_{ij}^l with the transmission rate R_{ij}^l . At each node, we use

$P_{ij}^{\text{transmit}}(l)$ to denote transmit power needed for transmission satisfying a target BER from node i to node j at the l^{th} period. So the average power consumption can be expressed in (14).

$$P_{\text{average}}^i(l) = \sum_{j \in N_i} P_{ij}^{\text{transmit}}(l) \cdot t_{ij} / \tau + \sum_{j \in M_i} P_{ji}^{\text{receive}}(l) \cdot t_{ji} / \tau \quad (14)$$

Thus for the time varied data rate problem, we could convert it to the following problem:

$$T = \min(N_i \cdot \tau) \quad (15)$$

Max T

s.t.

$$\sum_{l=1}^{N_i} P_{\text{average}}^i(l) \cdot (N_i \cdot \tau) \leq E_i \quad (16)$$

$$\sum_{k \in M_i} R_{ki}(l) - \sum_{k \in N_i} R_{ik}(l) = G_i(l), l = 1, 2, \dots, N_i \quad (17)$$

Those above problems can not be solved by polynomial time, which are NP hard because the objective function is the max-min problem. However, for this optimization problem under the time variable rate constraints, we can find a NEAR optimization solution by exploring the rate distribution characteristics in INP applications. In INP applications, it is reasonable that there are very small group of sensor nodes that generate the sensing data, compared with the large size network. Several space-correlated sensor nodes report the data to sink node. In such kind of large scale static network, there are just very small data traffic compared with the network size, and most of the sensors play a role in relaying data without generating data themselves when a small group of sensors report the data to the sink node.

Let us denote $S\{s_1, s_2, \dots, s_k\}$ as the source sensor group set, k is the number of source sensors. Denote a $F\{f_1, f_2, \dots, f_m\}$ set which includes all the other m number of sensors except for sensors in S . Sensors in F only are intermediate nodes forwarding data in the network. Therefore, for sensors in F set, we can derive (18), which states that the incoming data rate should be equal to the outgoing data rate for node i .

$$\sum_{k \in M_i} R_{ik}(l) = \sum_{k \in N_i} R_{ki}(l), l = 1, 2, \dots, N_i, i \in F \quad (18)$$

Based on (17), we can derive the power consumption at the l^{th} period τ

$$\begin{aligned} P^i(l) &= \sum_{j \in M_i} \omega_{ij}(b) R_{ij}(l) + \sum_{j \in N_i} \rho R_{ji}(l) \\ &= (\omega_{ij}(b) + \rho) \cdot \sum_{j \in M_i} R_{ij}(l) \end{aligned} \quad (19)$$

The T maximization problem (Max T) in the previous section can be converted to minimization problem (Min R).

$$R = \max \left(\sum_{j \in M_i} R_{ij}(l) \right) \quad (20)$$

Min R

s.t.

$$((\omega_{ij}(b) + \rho) \cdot \sum_{j \in M_i} R_{ij}(l)) \cdot T_i - E_i \leq 0 \quad (21)$$

Therefore, in order to optimize sensor network lifetime, we attempt to find route paths between source and sink that can reduce the flow rate on each sensor, which means that optimal rate distribution must find lower rate route path under source rate constraints. K node (link) disjoint source-destination paths in a network is a suitable solution for this problem, because lower rate can be achieved on each of sensors for load balancing and lower source rate constraints. Finding K node (link) disjoint path has been well studied in graph theory. It is a polynomial $O(kN^2)$ running time algorithm.

To be practical, we propose a rate selection scheme based on the link rate assignment method. The link rate of each hop i on the route path is denoted as r_i . Because of the limited memory constraints and rate requirements, the node transmission rate on the route path must be more than or equal to the individual source node coding rate. We also observe from Equation (1), once symbol rate R_s is determined, the higher modulation constellation size is, the higher is data rate, and the higher is the energy cost, assuming the same BER value at the receiver end. Therefore, In order to pursue opti-

mal rate distribution, we demand that nodes with more residual power energy should be assigned with higher transmission rate, and lower transmission rate should be associated to the nodes with less residual power energy. Equation (22) shows the data rate being assigned on the sensor is proportional to the residual energy of each sensor, C is a constant value.

$$r_i = C \cdot E_i^{residual} \quad (22)$$

In INP applications, a group of sensors generate data with multiple data rates and transmit them to the sink node.

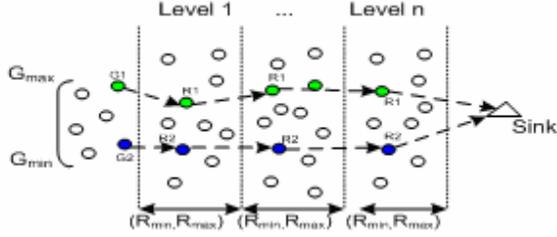


Fig. 3: n-level routing selection

As is shown in Fig. 3, we can separate the sensors between the source sensor group and sink node into n levels according to their distance to the sink. Sensors at each level will be assigned with data rates according to their residual energy. For example, in the i^{th} level, the sensor residual energy is in $[E_{\min(i)}^{Residual}, E_{\max(i)}^{Residual}]$, therefore, the m^{th} sensor in i^{th} level will choose r_m as calculated in (23).

$$r_m = G_{\min} + \frac{E_{\max(i)}^{Residual} - E_m^{Residual}}{E_{\max(i)}^{Residual} - E_{\min(i)}^{Residual}} (G_{\max} - G_{\min}) \quad (23)$$

After each sensor determines its rate according to its residual energy and level, each sensor will choose its next hop node in the next level based on its rates. Sensors always choose the next hop node that has the same rate or the closest value. If some nodes at the same level have been assigned the same rate, a probability-based next hop route selection will be applied. This routing selection scheme guarantees that each individual source node in the source group can find node-disjoint path while satisfying their rate constraints.

Simulation and Evaluation: The evaluation metrics are defined as follows. The desirable BER is $-50\text{db}(10^{-5})$; the noise power density N_0 is the product of Boltzmann constant 1.38×10^{-23} and equivalent noise temperature Tn . We generally assume the noise temperature is normal room temperature 290K,

and the noise power density value 4×10^{-21} J/Hz. The antenna gain together with the channel attenuation factor A is 10^{-9} . The frequency bandwidth is 1 MHz. These simulation parameters are specified in Table 1. The energy expenditure per unit information transmission from node to is

$$e_{ij}^t = P^{transmission} \cdot \frac{1}{R} + \epsilon_{amp} \cdot d_{ij} \quad (24)$$

And

$$e_{ij}^r = e^{recieve} \quad (25)$$

where $e^{recieve} = 150\text{nJ/bit}$, which is the energy consumed in the transceiver circuitry. $\epsilon_{amp} = 100\text{pJ/bit}/m^4$ is the energy consumed at the output transmitter antenna. $p^{transmission}$ is the transmit power and can be calculated by either (5) or (6) in Section II. R denotes the data rate between node i and j .

Table 1: Data Rate and Modulation Scheme Parameters

Data Rate (Mbps)	Modulation Scheme	Transmit Power (mW)	Transmit Energy (1m)
1	BPSK	0.036	36nJ/bit
2	QPSK	0.073	36.5nJ/bit
4	16-QAM	0.812	20.6nJ/bit
6	64-QAM	2.868	40.78nJ/bit
8	256-QAM	6.915	81.25nJ/bit

We start with a simple simulation Scenario 1. In this scenario, four nodes (1,2,3,4) are deployed in the prismatic shape, node 1 generates data at the 2, 4, 8Mbps. Fig. 4 (b) shows Minimum Hop(MH) routing path, Fig. 4 (c) shows the Minimum Total Energy(MTE) Routing path, and Fig. 4 (d) shows the RateD routing path.

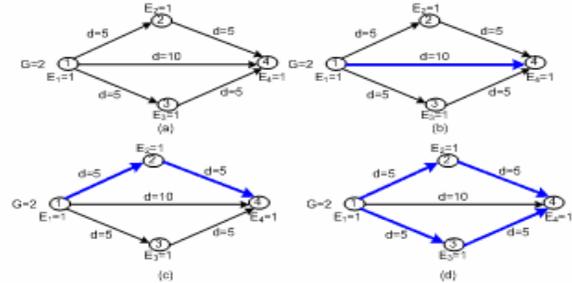


Fig. 4: MTE, MH, and Rate Distribution in Prismatic topology

The distance of each pair of links except for link (1-4) is 5 meters, and link (1-4) is 10 meters. The simulation result shows that the network lifetime is reduced with the increased data rate of source sensor. However, MTE and RateD has achieved longer network lifetime

than MH. This is because MTE finds a minimum energy path, and RateD distributes the rate into two distributed lower rate paths. From Fig. 5, we can see that RateD achieve longest network lifetime at both low and high rates. Based on the basic model in Fig. 6, we test more complex scenarios, considering a network of 28 nodes (see Fig. 6) over a 80×80 square meter area. Assume that the transmission range of each node is limited within 15 m. The rate distribution is constrained by the transmission power range, so we assume that topology has no significant dynamic changes.

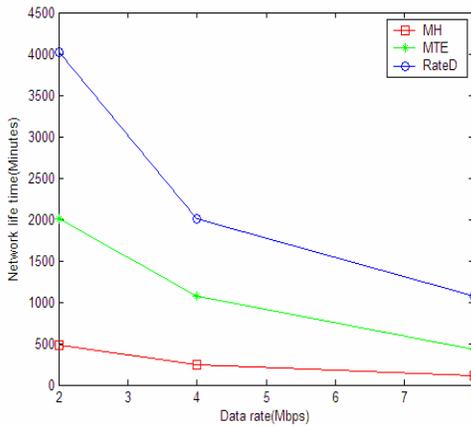


Fig. 5: Network Lifetime in MH, MTE and RateD in Prismatic topology

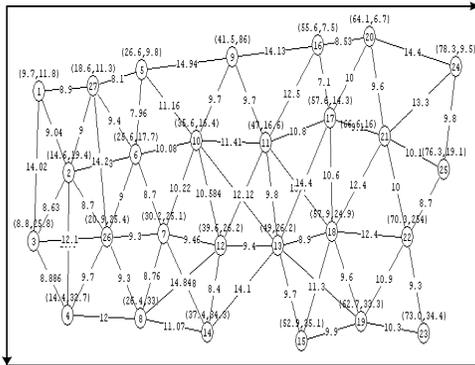


Fig. 6: 80×80 Square Simulation Topology

In Fig. 6, each node has been marked by its coordinates as well as link distances. We use Grin Graph theory software to look for the MH, MTE and RateD route paths, and compare the one-source, two-source and three-source sensors scenarios, the result is shown in the Fig. 7, 8, and 9. In those graphs, the vertical coordinate value represents the network lifetime, the horizontal coordinate value is the data rate of each source

sensor. From Fig. 7, 8, and 9, we can see that for each scenario, the network lifetime is reduced with the increased data rate and number of source sensors. This is because there is more traffic at each rate. However, RateD has achieved longer network lifetime than both MH and MTE. In Fig. 7 for one single source, MTE and RateD have achieved longer network lifetime than MH, both of them increases 87%, 103% and 88% lifetime more for the source rate 2, 4, 8 Mbps than MH. This is because the MH has to increase its transmit power to achieve required BER when the hop distance is not the shortest distance (energy), then it does not save energy. However, for the RateD and MTE, both of them find the shortest routing path in terms of the energy consumption instead of the MH path, which can significantly extend the network lifetime. We also find that the MTE has the same performance with respect to the network lifetime for the single source, because RateD does not use the multiple route path due to single source sensor, then RateD extend the network lifetime in this scenario only by minimizing the total energy consumption, which is as same as the MTE routing. However, for the two sources in Fig. 8, the RateD has more advantages than both MH and MTE, and it has extended 195%, 250%, 240% more network lifetime than the MH. It also has extended 96%, 96% and 71% network lifetime more than the MTE. This is because the RateD is not only to extend network lifetime by achieving the energy savings with lower rate transmission, but also by finding multiple lower rate node (or Link) disjoint paths in the network and balance the energy consumptions, the similar performance achievement can be seen in Fig. 9. Here, the RateD has extended the network lifetime 20%, 19% and 27% more, separately at the source rate 2Mbps, 4Mbps, and 8Mbps than the MTE. It also extends the network lifetime 200%, 189% and 210% more than the MH.

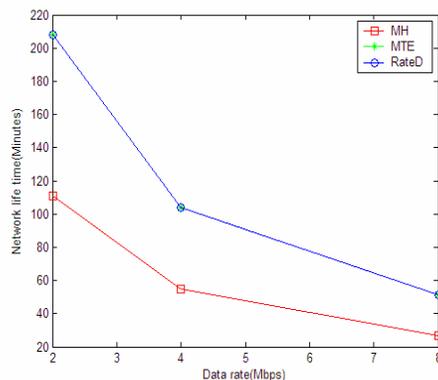


Fig. 7: One source sensor at 2, 4, 8 Mbps

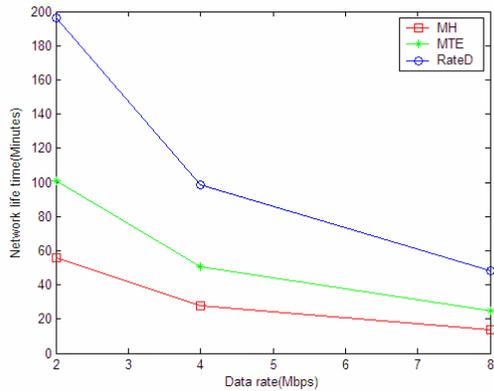


Fig. 8: Two sources sensor at 2, 4, 8 Mbps

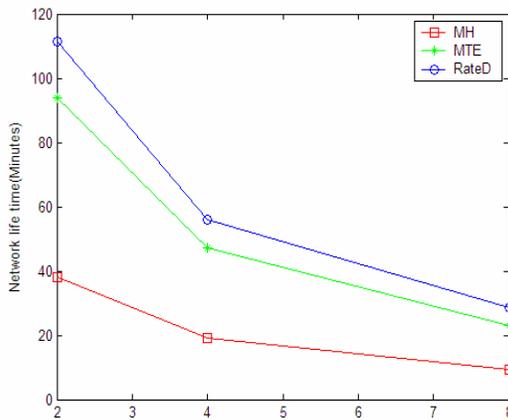


Fig. 9: Three source sensor at 2, 4, 8 Mbps

CONCLUSIONS

In this paper, we have explored the characteristic of multiple rates in In-Network Processing applications and defined a new concept called “Rate Distribution” based on the dynamic link rate assignment in the static WSN, which suggests that the sensor network distribute the application rate constraints efficiently based on solving an optimization problem of joint routing, MAC and link layer scheme. We form a rate distribution network model for INP as an optimization problem, which is targeted to extend the network lifetime by distributing the load, and to achieve energy savings by low rate transmission.

Since the optimal problem is NP-complete, to reduce the algorithm complexity, a near optimization model with respect to the INP is analyzed and a practical and simple rate-based routing selection scheme for rate distribution is suggested. The simulation results show that, with a dynamic link rate assignment and optimal rate distribution, the network lifetime has been extended.

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