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Optimal Power Analysis for Network Lifetime Balance in Hierarchy Networks

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Abstract: Energy scarcity is one of the most critical problems that occur in wireless sensor networks compared to traditional networks. However, by using spatial correlation, which is a characteristic of wireless sensor networks due to close field sampling, we could explore the problem further and address practical solutions. Based on a new cost criterion, two algorithms for power optimization amongst hierarchy networks are presented. Their implementation and implications are discussed in detail.

Keywords: Sensor networks; Control under communication constraints; Remote sensor data acquisition; Algorithms and software; Traffic control; Analysis of heterogeneous knowledge in modelling.

1. INTRODUCTION

Wireless sensor networks have attracted enormous research attention recently because of their wide range of applications and new criteria compared to traditional networks. Limited power supply for sensor nodes is one of their typical characteristics. It generates an urgent requirement to optimize the useful life span of a sensor network under a tight power constraints as well as quality of service in wireless sensor networks. Energy aware technologies and strategies in hardware and software aspects are well researched and developed e.g.,Tsiatsis [2001],Akyildiz [2002],Howitt [2004].

Another typical characteristic brought by wireless sensor network is that the sensors measure a spatially dependent quantity in a high density network. This spatial correlation can be interpreted as information redundancy, which can be exploited to reduce data transmission requirements, and hence assist in maximizing the operational life of sensor nodes as suggested by Slepian-Wolf theory (Slepian [1973]).

By considering two characteristics above, a recent research approach is to combine network combinatorics with information theoretic ideas, joining the traditionally separate functions of coding and routing e.g., Scaglione [2002] and Cristescu [2005]. Especially for correlated sources, Slepian-Wolf theory (lossless coding) and rate-distortion theory (lossy coding) have stated that different source coding schemes will result in different routing loads through the rate allocation algorithm. Furthermore, the energy consumption in each sensor node is directly related to the data rate, hence an energy-aware rate allocation strategy strongly influences the network life span.

An attempt to optimize the life span for the overall network as well as have a best possible quality of service is approached by addressing the issue of network lifetime balance. When all the sensors exhaust their local energy supply at the same time, it is considered as the network lifetime is balanced. In Wen [2007], we developed a new cost criterion based on the idea of network lifetime balance and the energy efficiency for each sensor as well as their best possible quality of service. Under the implementation of star network topologies, it achieves better lifetime balance, longer network lifetime and more efficient energy usage compared to the minimum energy route. Here we further apply the new cost criterion into hierarchy networks. In hierarchy networks, the sensors have to consider the passing through traffic from their descendent sensors as well as their own sensing information. This leads to a much more complex optimization than is the case for star networks. We identify sufficient rate constraints and develop two algorithms to solve the sufficient rate allocation bounds for hierarchy network optimization. Their implementation and the implications of which are discussed in the context of a hierarchy network.

2. MODEL DESCRIPTION

2.1 General Model Statement

A wireless sensor network is considered as a directed graph $G(V, E)$ with a single sink, where V is the set of all nodes and E is the set of all directed links (i, j) where $i, j \in V$.

Suppose that V_0 is the single sink, the total number of sensors in the network is $|V| = N + 1$. The sensor V_{ij}^k represents Sensor i in the kth layer linking to its parent Sensor j in the $(k-1)$th layer. S is a subset of V, where $S \subset V$, $S \neq \emptyset$, $V_0 \in S^c$. In order to analyze hierarchy networks, we divide the tree topology network into three layers: the sink, the intermediate layers and the clusters, as shown in Fig.1.

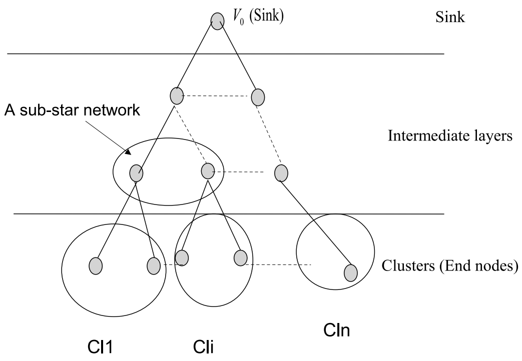

Fig. 1. Tree topology network

Each edge $e_{ij}^k \in E$ can be assigned a weight W_{ij}^k. A common traffic matrix $(N+1)\times(N+1)$ is defined with elements

$$e_{ij}^k = \begin{cases} 1, & \text{if Sensor i can directly communicate with Sensor j,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The channel between Sensor V_{ij}^k and its parent is assumed to be a DMC (Discrete memoryless channel) with a sufficient capacity C_{ij}^k and transmission rate R_{ij}^k, where $i, j \in V$.

In Dong [2005], different definitions of network lifetime have been addressed. Here the network lifetime is defined as the working period till the first sensor failure. In other words, the instant that the first sensor stops working also signifies the end of the network lifetime.

2.2 Energy Model

Component	Power Consumption
Radio	50 %
Micro Processor	30 %
Sensor	10 %
Logging and Actuation	10 %

Table 1. Typical power consumption of the components in a sensor.

Table 1 shows that radios consume most of the energy, so a common power model for MAC layer of wireless sensor networks is related to the distance d_{ij}^k from transmitter(i) in kth layer to receiver(j) in $(k-1)$th layer.

In the following analysis, a similar model will be applied. To simplify the formula, we define E_{bij}^k as the energy usage per bit from Sensor i to Sensor j, which depends on the distance between them, that is

$$E_{bij}^k = e_d\{d_{ij}^k\}^\alpha. \tag{2}$$

where e_d is the energy dissipated per bit per m^2.

Therefore, the energy spent in radio transmission between Sensor i and Sensor j becomes

$$\text{Energy spent in radio transmission} = E_{bij}^k R_{ij}^k, \tag{3}$$

where R_{ij}^k is the number of bits to transmit per second.

Let each sensor node i have the initial battery energy P_{ij}^k. Considering the power usage model (3), we have

$$P_{ij}^k = E_{bij}^k R_{ij}^k t_{ij}^k, \tag{4}$$

where t_{ij}^k is the active transmission time from Sensor i to its parent Sensor j.

Our analysis is conducted in each sub-star network. Therefore, in one sub-star network the equation can be simplified into

$$P_i = E_{bi} R_i t_i. \tag{5}$$

2.3 Model Cost Function and Constraints

The energy model (5) states that the higher the data rate the more energy consumption for the sensor. The cost function is developed for power optimization by considering rate allocation.

From (5), the working time for each Sensor i is

$$t_i = \frac{P_i}{E_{bi} R_i} \tag{6}$$

We define

$$K_i = \frac{t_i}{\sum_i t_i}, \tag{7}$$

where

$$\sum_i K_i = 1 \text{ and } K_i > 0. \tag{8}$$

The cost function for a star network can be written as

$$\{R_i^*\} = \max_{\{R_i\}_{i=1}^N} \left(-\sum_i K_i \log K_i \right) \tag{9}$$

The model constraints guarantee the lossless coding rate for the sensors. Under the same constraints, the sink gathering the information from the sensor field can fully reconstruct the information for each sensor. The constraint is upper bounded by capacity and the lower bound is given by the multiple-source Slepian-Wolf theorem. Let $(X_{1i}, X_{2i}, \ldots, X_{mi})$ be i.i.d $\sim p(x_1, x_2, \ldots, x_m)$.

The complete constraints are then presented as,

$$H(X(S)|X(S^c)) \le R(S) \le \sum_{i\in S} C_i. \tag{10}$$

for all $S \subseteq \{1, 2, \ldots, m\}$ where

$$R(S) = \sum_{i\in S} R_i, \tag{11}$$

and $X(S) = \{X_j : j \in S\}$.

The following section presents a theoretical analysis of our cost function. The dual problem for our model is solved and the possible solutions for our model are discussed.

3. MODEL ANALYSIS

The cost function in (9) under the constraints (10) as well as (8) is difficult to solve directly, since the constraints of data rates are impossible to transform into an expression of K_i. However, a dual problem can be formulated and used as an upper bound for the primal problem:

$$\max_{\substack{H(X(S)|X(S^c)) \leq R(S) \leq \sum_{i \in S} C_i, \\ \sum_i K_i = 1 \ and \ K_i \geq 0}} \left(-\sum_i K_i \log K_i \right)$$

$$\leq \max_{\sum_i K_i = 1 \ and \ K_i > 0} \left(-\sum_i K_i \log K_i \right)$$

The dual problem is then defined as

$$\max_{K_i} -\sum_i^n K_i \log K_i \tag{12}$$

$$\text{s.t.} \sum_i^n K_i = 1$$

$$K_i > 0$$

The second derivative of the cost function is negative for $K_i > 0$, so the cost function is a strictly concave function of K, which guarantees a unique maximum solution within the constraints.

Applying the Lagrange multiplier method, the solution of the dual problem is

$$K_i = \frac{1}{n}. \tag{13}$$

.

The upper bound of the maximum solution for the primal problem can be achieved when

$$t_1 = t_2 = \ldots = t_n. \tag{14}$$

Assuming that for any i, the weight is $W_i = \frac{P_i}{E_{bi}}$, (14) then becomes

$$\frac{W_1}{R_1} = \frac{W_2}{R_2} = \ldots = \frac{W_n}{R_n}. \tag{15}$$

The derivative of t_i with respect to R_i is given by

$$\frac{\partial t_i}{\partial R_i} = -\frac{W_i}{R_i^2} \tag{16}$$

The derivative is negative (16) within the constraints, and therefore the working time for each Sensor i monotonically increases while R_i decreases, i.e.,

Three possibilities can occur under the constraints in (10):

- **Unique solution:** There exists only one pair of R values satisfying (15). The primal problem can achieve its maximum upper bound within the constraint region. This set of rates is the optimal solution for the primal problem.
- **Non-unique solutions:** Multiple sets of R value satisfy (15) within the constraints in (10). The primal problem can achieve its maximum upper bound with various rates within the constraint region. Multiple solutions occur because the cost function does not guarantee the longest sensor working period by balancing the network lifetime. However, we are able to choose the solution with the longest sensor working period due to the monotonic decreasing relationship between t_i and R_i as shown in (16).
- **No solution for the dual problem:** No R value satisfies (15) within the constraints in (10). The primal problem cannot reach its maximum upper bound. However, a suboptimal solution can be found due to the concavity of the cost function. As in the multiple solutions case above, the longest sensor working period can still be considered.

The cost criterion has been implemented in the context of a star network topology in Wen [2007]. The simulation results further proved that all the sensors efficiently use their own energy supply to achieve a maximal life span for the overall network in comparison to the minimum energy route. In the next section, we address the implementation method of our cost criterion, prove the sufficient rate constraints and develop two algorithms in hierarchy networks.

4. ALGORITHMS FOR HIERARCHY NETWORKS

Slepian-Wolf constraints are based on the idea of DSC (Discrete Source Coding), which only considers the necessary coding rate for the information of each sensor itself, does not include the rate spent on passing through traffic. In the network power analysis, it ignores a large proportion of data rate, which the intermediate sensor nodes have to pass through the lower layer data to their upper layer. Namely, a sensor node in the intermediate layers carries the duty of a 'sensor' as well as a router.

In order to overcome the drawback of Slepian-Wolf constraints, the network is divided into different layers (shown in Fig.1) and the analysis focuses on the sub-star networks. A suitable algorithm needs to consider a data rate to transfer a sensor's own field information as well as allocate sufficient data rate for its descendent nodes. The algorithm developed below is imposing on the entropy chain rule and the Slepian-Wolf theorem to reduce the minimum required data sent from the end nodes and intermediate nodes. Furthermore, it balances the network lifetime by implementing our cost criterion.

The criteria of sufficient data rate for each sub-star network, which is different from a single star network, is provided and proven here. We assume that the covariance matrix C_s of the sources are known. So the minimum lossless rate for a sub-star network $V_{ij}^k,\ i = 1, 2, \ldots$ considering the upper layer correlation is

$$H\left(V_{1j}^k, V_{2j}^k, \ldots, V_{nj}^k \ |\text{all the nodes from layer 1 to (k-1)}\right). \tag{17}$$

We will prove that the total rate for each sub-star network is large enough to reconstruct the lossless information at the sink.

Proof. The sufficient total rate for reconstructing the whole field information at the sink is the joint entropy

$H(\text{all the sensor nodes})$.

We focus on the 1st layer and 2nd layer.

$$\begin{aligned}
&\{H(V_{11}^2, V_{21}^2, \ldots, V_{n1}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1) \\
&+H(V_{12}^2, V_{22}^2, \ldots, V_{n2}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1) \\
&+\cdots + H(V_{1j}^2, V_{2j}^2, \ldots, V_{nj}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1)\} \\
&+H(V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1) \\
\geq & \qquad (18) \\
&\{H(V_{11}^2, V_{21}^2, \ldots, V_{n1}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1, \text{all } V_{ij}^2, \text{when } j \neq 1)+ \\
&H(V_{12}^2, V_{22}^2, \ldots, V_{n2}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1, \text{all } V_{ij}^2, \text{ when } j \neq 1,2) \\
&+\cdots + H(V_{1j}^2, V_{2j}^2, \ldots, V_{nj}^2 | V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1)\} \\
&+H(V_{1s}^1, V_{2s}^1, \ldots, V_{ns}^1)
\end{aligned}$$

By the chain rule for entropy, the right-hand side of Equation (18) equals the joint entropy of all the sensors in the 1st and 2nd layers, i.e., $H(\text{all the sensors in 1st and 2nd layers})$.

Applying the same method from the nth layer to the first layer, together with recursion, the total sum of all the sub-star networks' rates is greater than the $H(\text{all the sensor nodes})$. Thus the total rate is sufficient for reconstructing the whole field information at the sink. ∎

In each sub-star network, we therefore apply the Slepian-Wolf constraints conditioning on all the upper layer nodes. For each node, the rate is sufficient for full reconstruction at the sink, i.e.,

$$R(S) \geq H(X(S)|X(S^c), \text{all the upper layer nodes}). \quad (19)$$

Together with the bottom-to-top approach, the lower bound for $R(S)$ is its own sufficient rate plus its descendent nodes' rates.

$$R(S) \geq H(X(S) \mid X(S^c), \text{all the upper layer nodes}) + \sum_{i=\text{S's descendent nodes}} R(V_i). \quad (20)$$

The lower bound of each sub-star network is given above, and now we consider the upper bound of the constraints. In order to obtain lossless reconstruction, each intermediate node should have enough bandwidth (rate) allocated to its own information. The maximum capacity for the sum of its descendent nodes' rates is

$$R(S) \leq C_{ij}^k - H(V_{ij}^k \mid \text{all the nodes from layer 1 to (k-1)}). \quad (21)$$

Assuming the capacity C_{ij}^k is large enough, the algorithm for calculating suitable capacity of a sub-star network among intermediate layers is given as follows

ALGORITHM I

Step 1 if

$$\sum_i C_{ij}^{k+1} > C_j^k - H(V_j^k \mid \text{all nodes from layer 1 to (k-1)}), \quad (22)$$

where $i \in$ the $(k+1)$th layer sensors with parent node Sensor j in kth layer, then the values are reset as,

Step 1a firstly,

$$\sum_i C_{ij}^{k+1} = C_j^k - H(V_j^k \mid \text{all nodes from layer 1 to (k-1)}), \quad (23)$$

Step 1b then recalculate each node capacity,

$$\hat{C_{ij}^{k+1}} = \frac{W_i}{\sum_i W_i} \sum_i C_{ij}^{k+1}. \quad (24)$$

where W_i is the weight $W_i = \frac{P_i}{E_{bi}}$. Now compare the new $\hat{C_{ij}^{k+1}}$ value and its previous value and choose the smaller value as the new C_{ij}^{k+1}.

Step 2 Compare all C_{ij}^{k+1} with its lower bound required reconstruction rate, i.e.,

$$\begin{aligned}
&(H(V_{ij}^k | \text{all nodes from layer 1 to (k-1)}) \\
&+ \sum_{\text{descendent nodes of i}} H(V_{ji}^{k+1} | \text{all nodes from layer 1 to k}) \\
&+ \ldots \qquad (25)
\end{aligned}$$

which includes its descendent layers' rates. Choose the larger value as C_{ij}^{k+1}.

If there is any C_{ij}^{k+1} (e.g., $i = 1, 2, \ldots, l$) using its lower bound, then a new $\sum_i C_{ij}^{k+1}$ is equal to previous $\sum_i C_{ij}^{k+1}$ (calculated from **Step 1a**) minus the C_{ij}^{k+1}. Go back to **Step 1b** and recalculate the rest of the nodes. Otherwise, break (Stop the algorithm calculation for the sub-star network.).

The algorithm calculates the most suitable capacity for each sub-star network among intermediate layers, while considering sufficient rate for its descendent nodes. We note that the capacity for each link does not need to be recalculated in the first layer and the end node layer (nth layer).

We now analyze the network Capacity in each layer and each link from the top to bottom applying **ALGORITHM I** as the upper bound together with the cost function and constraints' lower bounds presented in Equation (9) and (20).

There is an alternative algorithm (**ALGORITHM II**) option for the capacity analysis, which is using the minimum-required total sum rate of each sub-star network as the capacity-sum's upper bound.

From the expressions of two algorithms, it can be stated that **Algorithm I** intends to give the lower layers looser bounds in order to achieve more balance in the lower layers. **Algorithm II** intends to use the minimum sufficient construction rates in lower layers, which can extend the critical nodes' (upper layer nodes) working period. It can achieve a longer network lifetime by sacrificing the lower layer's balance. Both of these algorithms do guarantee lossless coding and transmission.

5. NUMERICAL EXAMPLES

Example 1. The topology has a depth of three (See Figure 2). The intermediate nodes have their own data to transmit as well as the data from their descendent nodes.

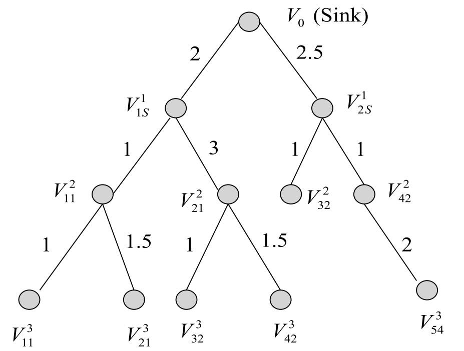

Fig. 2. Tree topology network with a depth of three

$V = \{V^1_{1s}, V^1_{2s}, V^2_{11}, V^2_{21}, V^2_{32}, V^2_{42}, V^3_{11}, V^3_{21}, V^3_{32}, V^3_{42}, V^3_{54}\}$. We assume that all the sensors have the same initial energy $P = 100$. Each sensor information is encoded with rate 5 *bits/sec* independently (without using Distributed Source Coding).

The covariance matrix follows the expression,

$$E[V^k_{ij} V^{\hat{k}}_{\hat{i}\hat{j}}] = \begin{cases} 1, & i = \hat{i},\ j = \hat{j}\ and\ k = \hat{k}, \\ 0.5, & i \neq \hat{i}\ or\ j \neq \hat{j}\ or\ k \neq \hat{k}. \end{cases} \quad (26)$$

The original channel capacities are $C^1_{is} = 30$, $C^2_{ij} = 20$, $C^3_{11} = C^3_{21} = 15$ and $C^3_{32} = C^3_{42} = C^3_{54} = 8$.

Part 1

We analyze the network from top to bottom applying **Algorithm I** to calculate the upper bound for each layer:

$C^1_{1s} - H(V^1_{1s}) = 25 < C^2_{11} + C^2_{21} = 40$, So reset $C^2_{11} + C^2_{21} = 25$ and

$$C^2_{11} = \frac{W^2_{11}}{W^2_{11} + W^2_{21}} (C^2_{11} + C^2_{21}) = 22.5$$
$$C^2_{21} = \frac{W^2_{21}}{W^2_{11} + W^2_{21}} (C^2_{11} + C^2_{21}) = 2.5 \quad (27)$$

$C^2_{11} = 22.5 >$ previous $C^2_{11} = 20$, thus we choose $C^2_{11} = 20$. Moreover, C^2_{21} is smaller than the sufficient reconstruction rate, i.e.,

$$H(V^2_{21}|V^1_{1s}, V^1_{2s}) + H(V^3_{32}|V^1_{1s}, V^1_{2s}, V^2_{11}, V^2_{21}, V^2_{32}, V^2_{42}) + H(V^3_{42}|V^1_{1s}, V^1_{2s}, V^2_{11}, V^2_{21}, V^2_{32}, V^2_{42}) = 5.0414. \quad (28)$$

We reset $C^2_{21} = 5.0414$, then $C^2_{11} = 25 - 5.0414 = 19.9586$. Using the same algorithm, we can obtain

$$C^2_{32} = C^2_{42} = 12.5$$
$$C^3_{11} + C^3_{21} = 18.2040$$
$$C^3_{32} + C^3_{42} = 3.2868 \quad (29)$$
$$C^3_{54} = 8$$

The whole constraints for each sub-star network can be calculated, for example, (V^2_{11}, V^2_{21})'s sub-star network constraints are

$$R(V^3_{11}) + R(V^3_{21}) + H(V^2_{11}|V^1_{1s}, V^1_{2s}, V^2_{21}) \leq R(V^2_{11}) \leq 20 \text{ (the original capacity)}$$

$$R(V^3_{32}) + R(V^3_{42}) + H(V^2_{21}|V^1_{1s}, V^1_{2s}, V^2_{11}) \leq R(V^2_{21}) \leq 20 \text{ (the original capacity)} \quad (30)$$

$$R(V^3_{11}) + R(V^3_{21}) + R(V^3_{32}) + R(V^3_{42}) + H(V^2_{11}, V^2_{21}|V^1_{2s}, V^2_{11}) \leq R(V^2_{11}) + R(V^2_{21}) \leq C^3_{11} + C^3_{21} = 18.2040$$

Similarly the constraints for all the other sub-star networks can be obtained while calculating from the bottom layer to the top layer. Together with the Model II cost function, we have

$R(V^3_{11}) = 3.6722$	$R(V^2_{11}) = 20$	$R(V^1_{1s}) = 26.8345$
$R(V^3_{21}) = 1.6321$	$R(V^2_{21}) = 4.9949$	$R(V^1_{2s}) = 17.1718$
$R(V^3_{32}) = 1.6547$	$R(V^2_{32}) = 3.3512$	
$R(V^3_{42}) = 1.6321$	$R(V^2_{42}) = 3.3512$	
$R(V^3_{54}) = 1.6434$		

The network lifetime is 0.9316, and the bottleneck is the 1st layer sub-star network. The number of balanced sub-star networks is 4.

Part 2 We now analyze the network from bottom to top applying **Algorithm II** to calculate the upper bound for each layer.

We use the minimum required total sum of rates in each sub-star network as the capacity sum's upper bound, for example

$$R(V^3_{11}) + R(V^3_{21}) + H(V^2_{11}|V^1_{1s}, V^1_{2s}, V^2_{21}) \leq R(V^2_{11}) \leq 20 \text{ (the original capacity)}$$

$$R(V^3_{32}) + R(V^3_{42}) + H(V^2_{21}|V^1_{1s}, V^1_{2s}, V^2_{11}) \leq R(V^2_{21}) \leq 20 \text{ (the original capacity)} \quad (31)$$

$$k \leq R(V^2_{11}) + R(V^2_{21}) \leq k,$$

where $k = R(V^3_{11}) + R(V^3_{21}) + R(V^3_{32}) + R(V^3_{42}) + H(V^2_{11}, V^2_{21}|V^1_{2s}, V^2_{11})$.

Similarly the constraints for all the other sub-star networks can be obtained while calculating from the bottom layer to the top layer. Together with the Model II cost function, we have

$R(V^3_{11}) = 1.6434$	$R(V^2_{11}) = 5.0301$	$R(V^1_{1s}) = 13.4296$
$R(V^3_{21}) = 1.6321$	$R(V^2_{21}) = 4.9836$	$R(V^1_{2s}) = 8.5298$
$R(V^3_{32}) = 1.6434$	$R(V^2_{32}) = 1.7546$	
$R(V^3_{42}) = 1.6321$	$R(V^2_{42}) = 3.3515$	
$R(V^3_{54}) = 1.6434$		

The network lifetime is 1.8616, and the bottleneck is still the 1st layer sub-star network. The number of balanced sub-star networks is 1.

Compared with **Algorithm I**, the network lifetime is extended, but the number of balanced sub-star networks decreases.

From Example 1, **Algorithm II** achieves a better lifetime by sacrificing lower layer balance level as expected. However, the cost function still tries to balance the sub-star network within the tight constraints. The network lifetime achieved by **Algorithm II** is the longest possible lifetime for the network.

Algorithm I achieves better network balance in all layers and better data quality by sacrificing the critical nodes' working period (usually equal to the network lifetime). We can now see the tradeoff between data rate and network lifetime. Compared with **Algorithm II**, we can use a parameter α, $\alpha > 0$, to achieve looser bounds for the lower layers than **Algorithm II**, and a longer network lifetime than **Algorithm I**.

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