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OPTIMIZATION ALGORITHMS FOR WIRELESS SENSOR NETWORKS TO SOLVE MAXIMIZATION PROBLEMS

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***Abstract*: The paper describes a constant time clustering algorithm that can be applied on wireless sensor networks. The scheme for rate control, scheduling, routing, and power control protocol for wireless sensor networks based on compressive sensing has been shown. Using network utility maximization formulations, cross-optimization solutions using Lagrangian multipliers in network access control and physical layers have been presented. The optimization solutions have been developed by solving the optimization model of network utility maximization. The paper presents a cross-sectional design problem that jointly maximizes network utility and lifetime. The solution to the problem leads to the optimal source rate as well as the optimal routes between each source and sink in the network. The presence of a common sink node in the network has been formulated to develop a distributed algorithm that minimizes the energy overhead in its implementation.**

***Index Terms*: Wireless sensor networks, cross layer, optimization, network utility maximization, algorithm.**

I. INTRODUCTION

Nowadays, due to the rapid advancement of the Internet in all aspects of science and technology around the world, the intention of researchers and scientists has grown to find the best localization methods for optimizing Wireless sensor networks (WSNs).

Generally, WSNs are formed of a group of small sensor nodes in order to communicate with each other in which they have been fitted by some restrictions in their memory, energy and processing capacity in wireless format.

Based on main concept of WSNs, sensor nodes by routing capabilities will be scattered in a sensor field. Also, according to location of sensor nodes, random deployment can be allowed in inaccessible areas. Yang et al., formulated optimization solutions by limiting the network topologies specified in the WUM by the NUM [1].

Wireless sensor networks have played an important role in Internet of Things. Data transfer is one of the most important features of WSNs.

The optimal transmission policy will be implemented through NUM combined with CS in transport, network, MAC, and physical layers, respectively.

While there are several ways to characterize application performance, in this paper, we characterize it using a network utility function which is the sum of individual node utility functions [2]. The utility of each node is assumed to be an increasing and strictly concave function of its source rate, thus reflecting the application performance. Distributed algorithms for solving the network utility maximization problem in the context of wired networks are studied by Low and Lapsley [3].

We consider distributed algorithms for two types of sensor networks—those with unique routes from each source to sink and, in general, with potentially multiple routes between them. Although the proposed algorithms for these two types of networks are similar in flavor, their convergence properties differ significantly. Furthermore, such differences between networks may arise in practice due to the presence or absence of a network layer routing protocol that selects unique routes between sources and sinks. Thus, the distinction between these two types of networks is interesting from both an analytical and a practical point of view.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

Khalek et al, proposed the cross-layer transmission schemes and derived joint algorithm for media access control (MAC), scheduling, and routing through optimization theory, and comprehensively studied the state of the art for wireless communication at the application, transport, network, MAC, and physical layers [4].

To achieve network optimization, improved data transmission strategies based on maximum utility or cross-layer ideas without full consideration of the sparse feature of the original data and the efficiency of the data transmission were used [5].

Sankar and Liu, have studied distributed routing algorithms and cross-design approaches to increase network lifetime. [6].

Chiang et al. developed an optimization decomposition framework [7] to design distributed protocols for the transport and network layers that enable network performance.

In this paper, we characterize it using a network utility function which is the sum of individual node utility functions [8]. The utility of each node is assumed to be an increasing and strictly concave function of its source rate, thus reflecting the application performance. Distributed algorithms for solving the network utility maximization problem [9] in the context of wired networks are studied in [10]. The network utility formulation has been used in [11], in the cross-layer design of transport, network, and radio resource layers for maximizing the throughput or network.

III. SCOPE OF WORK AND OBJECTIVES

The aim of the paper is to demonstrate a cross-sectional design problem that jointly maximizes the utility and lifetime of the network. Solving the problem leads to optimal source rates as well as optimal routes between each source and sink in the network. Through an optimization decomposition framework, we show that the cross-layer design problem is decomposed both vertically (across different layers of the protocol stack) and horizontally (between network nodes) into simpler subproblems, allowing for a fully distributed solution.

The proposed formulation exploits the presence of a common sink node in the network to design a distributed algorithm that minimizes the energy overhead in its implementation. By studying the distribution of proportionally fair rates in networks, we discuss practical design implications through analysis and numerical simulations.

IV. SYSTEM MODEL

We present a model of power dissipation in nodes and various algorithms for wireless sensor networks.

A wireless sensor network consists of nodes that can communicate with each other via wireless links. One way to support efficient communication between sensors is to organize the network into several groups, called clusters, with each cluster electing one node as the head of cluster.

Many clustering algorithms for sensor networks were proposed in the last few years. Younis and Fahmy proposed HEED (Hybrid Energy-Efficient Distributed clustering) as a probabilistic clustering algorithm [12]. An improved version of HEED was offered by researchers Hesong Huang and Jie Wu [13].

The pseudo code of the extended algorithm (called the Extended HEED) is shown in Fig. 1. In the first round the core algorithm is used, where each node will check if its cost is the least among its neighbors. If it is the node with the lowest cost, it will set itself as core head, otherwise, it will set the least cost neighbor a core.

After the core election, the cluster head election will exclude the non-core nodes. The entire election process (step II in the pseudo code) repeats until the values for *CHprob* of all nodes reach 1.

In the final round, final CHs are considered as CHs, and tentative CHs non-CHs.

Fig. 2 shows an example of the Extended HEED. There are 500 nodes deployed in a 100 £ 100 area, with a transmission range of 10 and an initial *CHprob* of 0.01. The algorithm takes 7 rounds and elects 64 CHs (represented by black nodes).

```
I. Initialize
1. SnbrÃ fv: v lies within my cluster rangeg
2. Broadcast Snbr
3. is final CH Ã FALSE
4. Get the node ID of the least cost node among its
neighbors
5. set the node as my core
II. Repeat
(Exactly same as original algorithm)
UNTIL CHprevious = 1
III. Finalize
1. If(is final CH = FALSE)
2. If ((SCH Ã v: v is a final CH) 6= ;)
3. my cluster heade Ã least cost(SCH)
4. join cluster(cluster head ID, NodeID)
5. Else
6. find the least cost node among its neighbors as
CH
7. If (cluster head ID = NodeID)
8. Cluster head msg(NodeID, final CH, cost)
9. Else
10. join cluster(cluster head ID, NodeID)
11. Else Cluster head msg(NodeID, final CH, cost)
```

Fig. 1. clustering algorithms for sensor networks

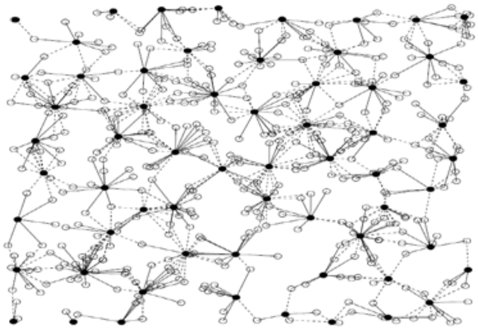

Fig. 2. The result of Extended HEED

A solid line represents a wireless link connecting a non-CH (represented by white nodes) and its corresponding CH. A dotted line represents a link between a non-CH to a CH of a neighboring cluster. In some rare occasions, two CHs are neighbors, which is also represented by a solid line.

Thus an extended probabilistic algorithm for Hybrid Energy-Efficient Distributed clustering (HEED) adds two more steps to eliminate a large quantity of nodes, and only potential candidates can survive to participate in the cluster head election, it is more efficient than the original HEED.

V. DIRECT PATHFINDING PROBLEM

According to He et al, the proposed WSN algorithm. This method uses the Lagrangian multiplier method to solve the problem of cross-layer optimization, so that we can jointly achieve optimal speed control, planning, routing and power control [14].

The cross-layer optimization model

$$M_r^i(H_j^i(t) = e^{-H_j^i(t)}$$

is approximately convex if the entropy satisfies $e^{-H_j^i(t)} \approx 1 - H_j^i(t)$.

The Li and Wang, created the Lagrangian problem by resting the speed, power and route constraints as follows [15]:

$$\boldsymbol{L}\,(x_i\ (t), f_i^j\ (t), I_i^j\ (t), E_i(t), \delta_i, \alpha_i, \beta_i, \gamma_i\ )$$
$$= \sum_{i=1}^{N} U\,((x_i\ (t), f_i^j\ (t), I_i^j\ (t), E_i(t))$$
$$+\delta_i(t)\,(x_i\ (t)\ +\ \sum_{j\in\gamma_i} r_{ji}(t))\ -\ \sum_{j\in B_i} r_{ji}(t))$$
$$+\alpha_i\,(t)\,(\,f_i^j\ (t) - (x_i\ (t)\ - \sum_{j\in\gamma_i} r_{ji}(t)) \tag{1}$$
$$+\beta_i\,(t) M_r^j\ (H_j^i(t) - e^{-H_j^i(t)}\ )$$
$$+\ \gamma_i\ (t) = (\ \hat{\mathrm{E}}(\mathrm{t}) -\ \textstyle\sum_{i=1}^{N} E_i\ (t)),$$

where $\delta_i, \alpha_i, \beta_i, and\ \gamma_i$ are Lagrangian multipliers with the conservation constraints. Because L(.) is only piecewise differentiable, used the distributed sub-gradient method. $\mathrm{x}_i(t)$ is the linear function of the transmission vector $\gamma(t)$ and the temporal entropy

$$\mathrm{x}_i(t) = \frac{v_j^i(\gamma(t), H_j^i(t))}{B}. \tag{2}$$

The temporal entropy $H_j^i(t)$ at time t is calculated as follows:

$$H_j^i(t) = M_j^i(t) ln \frac{1}{M_j^i(t)}, \tag{3}$$

where $M_j^i(t)$={ N_i (t)=j} denotes the transmission probability at time *t* from node *I* to *j*. The proposed algorithm takes into account the need to distribute speed, power, link capacity, and route as well as for node i. In the theorems of the Li and Wang, it has been proved that this algorithm has optimal properties.

VI. RESULTS

Assume that in a self-tuning network, the sensor nodes can change the source frequency depending on the application demand. Associated with each source n is a function Un(xn) that is continuously differentiable, increasing, and strictly concave in xn. The utilities are assumed to be additive, so the network utility is defined as the sum of the utilities of the individual nodes. The network utility maximization (NUM) problem is described as follows:

$$\max_{x\,\in\,X} \textstyle\sum_{n=1}^{N} U_n\ (X_n). \tag{4}$$

The polyhedral constraint set X together with the strictly concave objective function results in a unique maximizer x* in (1) that is Pareto optimal [14].

However, nodes in sensor networks are energy-constrained, and higher data rates lead to greater energy dissipation in data sensing, transmission, and reception. Thus, maximizing network utilization may result in widely varying energy dissipation levels across nodes and may lead to network outages in short periods of time.

We consider a distributed algorithm for solving the utility-lifetime maximization problem (5)

$$\max_{(x,v)\epsilon x_v}\ \textstyle\sum_{n=1}^{N} U_n\ (X_n) - M(u), \tag{5}$$

when each sensor node can have multiple paths to sink (R ≥ N).

$$\max_{x\,\in\,I_x, y\,\in\,I_y, u\,\in\,I_u}\ \textstyle\sum_{n=1}^{N} U_n\ (X_n) - M(u),$$

$$\text{subject to, } P_y = X \quad B_y \le c\ ,\ F_y \le \mathrm{e}\ . \tag{6}$$

Since (6) represents a convex optimization problem with only linear constraints, strong duality holds and we can obtain the primal optimal solutions indirectly by first solving the dual problem. We introduce Lagrange multipliers $\eta\epsilon\mathrm{R}^{\mathrm{N}}, \lambda\epsilon\mathrm{R}_{+}^{\mathrm{I}}, \mu\epsilon\mathrm{R}_{+}^{\mathrm{N}}$ to formulate the Lagrangian dual function corresponding to primal problem (6) as below:

$$\boldsymbol{C}\,(\eta, \lambda, \mu) = \max_{x\,\in\,I_x, y\,\in\,I_y, u\,\in\,I_u} \textstyle\sum_{n=1}^{N} U_n\ (X_n) -$$
$$- M(u)\ +\ \eta^t(\,P_y -\ X\ )\ ,$$
$$\lambda^t\,(B_y - c) -\ \boldsymbol{\mu}^t\ (F_y \text{ - eu}). \tag{7}$$

The dual function can be decomposed into the following three subproblems:

$$C\ (\eta, \lambda, \mu) =\ \lambda^t\, c +\ C_1\ + C_2\ (\eta, \lambda, \mu) + C_3\ (\eta, \lambda, \mu),$$

where

$$c_1\ (\eta, \lambda, \mu) =$$
$$= \max_{x\,\in\,I_x, y\,\in\,I_y, u\,\in\,I_u} \textstyle\sum_{n=1}^{N} U_n\ (X_n) -$$
$$- \eta^t(\,P_y - X\ ), \tag{8}$$

$$C_2(\eta, \lambda, \mu) = \max_{y\,\in\,I_y}\ (\eta^t\, P -\ \lambda^t\, B - \mu^t F)y\ =$$
$$= \begin{cases} 0\ if \eta^t\, P \le\ \lambda^t\, B + \mu^t F \\ \infty,\ \ \text{otherwise} \end{cases}, \tag{9}$$

$$C_3(\eta, \lambda, \mu) = \max_{u\,\in\,I_u} \eta^t\ (\text{e u}) \text{ - } M(u). \tag{10}$$

The dual problem corresponding to the primal problem in (6) is then given by min C(η, λ, μ) subject to

$$\lambda \ge 0, \mu \ge 0, \eta^{\mathrm{t}}\,\mathrm{P} \le\ \lambda^{\mathrm{t}}\,\mathrm{B} + \mu\text{^}\mathrm{t}\,. \tag{11}$$

Each of the three subproblems (8), (9), and (10) evaluates variables corresponding to different layers of the protocol stack and thus they represent a vertical decomposition of the primal problem (6). The cross-layer interaction between the different layers is coordinated through the dual variables and the distributed algorithm presented below represents a further horizontal decomposition.

The dual objective function (7) is not differentiable because the objective function (6) is not strictly concave in all first variables. Therefore, a subgradient-based descent approach is used to solve the dual problem (11). Using Danskin's theorem [17], the subgradients (η, λ, μ) of the dual objective function ∂D (η, λ, μ) can be obtained from the set of maximizers Z = {(x, y, v) } (7).

From (9), if $y_{\boldsymbol{r}^*} > 0$ for some $\boldsymbol{r}^* \in$ R(n), then for all other routes $\boldsymbol{r}' \in$ R(n),

$$\eta_n = (\lambda^t\, B + \mu^t\ F)_{r^*} \le\ \ (\lambda^t\, B\ \ - + \mu^t\ F)_{r'}\ . \tag{12}$$

Interpreting λ and μ as link congestion price and node lifetime price, respectively, the route-price of route r is given by $(\lambda^t B + \boldsymbol{\mu}^t\ F)$.

From (12), all routes from a node with nonzero flows have an equal cost, which is the minimum cost of a route compared to other routes from the same node.

Thus, the routing algorithm involves each node choosing a source rate based on the minimum route cost. Finally, we summarize the distributed algorithm for networks with multipath routing. At the kth iteration:

- source rate and route flow update: Each node *n* computes the minimum route-price among all its routes and updates its source rate as below:

$$x_n\ (k+1) = \left[U_n^{\prime -1}\ \ ((\lambda^t B + \boldsymbol{\mu}^t\ F)_{r^*} \right]_{x_n^{max}}^{x_n^{max}} \quad (13)$$

- link and node prices update: Using subgradient-based descent, each node n updates its node-price μn and link-prices λl, where l is an outgoing link from the node along any of its routes to the sink η_n and λ_l

$$\lambda_l\ (k+1) = \left[\lambda_l(k) - \alpha(c - \sum_{r \epsilon R(l)} y_r(k) \right]^+,$$

$$\eta_n = \lfloor \eta_n(k) - \alpha(e_n v(k) - \textstyle\sum_r F_{nr} y_r(k) \rfloor^+, \quad (14)$$

where α > 0 is a constant scalar step size.

For constant step size as in the above algorithm show that the (arithmetic) averages of the primal and dual iterates approach the optimal solutions for large number of iterations, provided the subgradients are bounded and the step size is chosen small enough. Since the primary variables in our model are bounded, the subgradients are bounded, and the simulation results show that the primary and dual variables approach optimal values within a finite number of iterations.

The optimal source rates, route flows, and network lifetime are plotted in Fig.3, Fig. 4, and Fig. 5, respectively.

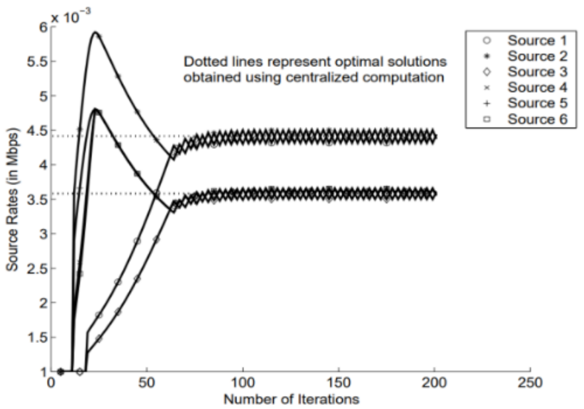

Fig. 3. Distributed Algorithm 2: Source rates

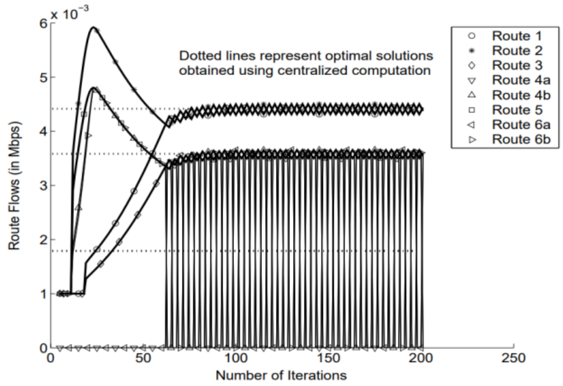

Fig. 4. Distributed Algorithm 2 (multipath routing): Route flows

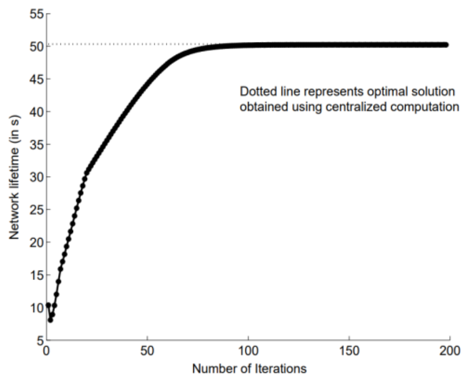

Fig.5. Distributed Algorithm 2 (multipath routing): Network lifetime

VII. CONCLUSION

The article showed the analysis of clustering and joint control algorithms for maximization in wireless touch networks. It was focused on a joint optimization strategy based on CS in physical, MAC, network, and transport layers.

This article presented the implementation of a cross layer optimization design for data transmission in WSNs consisting of rate control, scheduling, routing, and power control. Taking into account the relationships among rate, routing, link capacity, and energy allocation, NUM was proposed for efficient data transmission and optimal solutions were solved by the Lagrangian multiplier method.

The performance of the proposed algorithm, in theory and practice, perfectly achieved the desired solutions. We used framework networks with proportional rate distribution and studied practical design issues by characterizing the optimal utility trade-off curve by showing numerical simulations of the proposed distributed algorithms. In the case of multipath routing, since each node could have routes to multiple sinks, the weighted node-prices could be communicated to every sink so that the network inverse-lifetime update was computed by all sinks in the network.

Alternatively, by forming a spanning tree within the network with a particular sink as its root, the weighted

weighted node-prices only needed to be communicated to this sink which computed the network lifetime updates. The analysis and proposed algorithms in this paper could also be extended to other generalizations of the system model involving multiple commodities in the network. Finally, the methodology proposed in this paper was generally applicable to any energy-constrained wireless network.

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