Weighted Signed Graph (WSG) Power-aware Routing in Distributed Wireless Networks

Hemant Kumar Rath[1], Akash Chaturvedi[2], Rajan MA[3], and Anantha Simha[1]

[1]TCS Networks Lab, Bangalore 560 066, India, Email:{hemant.rath, anantha.simha}@tcs.com
[2]IIT Patna, Patna, 800 013, India, Email:lgakash@gmail.com
[3]TCS Innovation Labs, Bangalore 560 066, India, Email:rajan.ma@tcs.com

Abstract— **In this paper, we propose a Weighted Signed Graph (WSG)-based power-aware routing scheme for distributed wireless networks. It is a practically implementable and self reconfigurable distributed solution. It is an alternative and novel method to solve the constraint optimization with network lifetime and throughput in wireless networks. The proposed scheme runs independently on each wireless node and optimizes the network lifetime by invoking power-aware routing schemes. The power-aware routing scheme we propose in this paper is a modified shortest path routing (Distance Vector (DV) Routing) scheme wherein instead of path length, we employ link cost in terms of congestion and battery availability at nodes for route computation. We also propose linear as well as non-linear sectorization of available battery power at a node for sending route update packets. We perform extensive simulation using Java implementation and observe that our scheme minimizes the message passing involved in DV routing deployment. We further observe that the proposed WSG scheme out-performs the basic DV routing in-terms of throughput and lifetime of the network.**

I. Introduction

In todays world, wireless communication is becoming the de-facto communication medium at homes, work locations, malls, airports, stadiums, colleges, etc. Hand-held battery operated wireless devices capable of serving more and more applications are becoming smaller and smaller. In addition, use of wireless sensors is also an important part of todays world. Like wireless hand-held devices, wireless sensor nodes also require enhanced lifetime and higher rate of transmission. The mode of communication in both sensor and wireless hand-held devices are similar and the nodes are mainly battery powered. Therefore, without loss of generality, we consider both sensor nodes and wireless hand-held devices as wireless nodes of a wireless network. In this paper we consider a wireless distributed network as shown in Fig. 1, in which each node communicates with its neighbors for computing, communication and other services in a distributed fashion.

One of the major limiting factor of wireless networks design is the limited battery power of wireless nodes/devices. Most of these devices run on lithium-ion rechargeable batteries. These batteries have a lifetime of a few hours of active workload and about 1-2 days of idle time. To improve this crucial factor, researchers have been attempting to optimize power consumption of the node in every aspect, without compromising the Quality of Services (QoS) requirements of the applications. Therefore, design of communication protocols required for

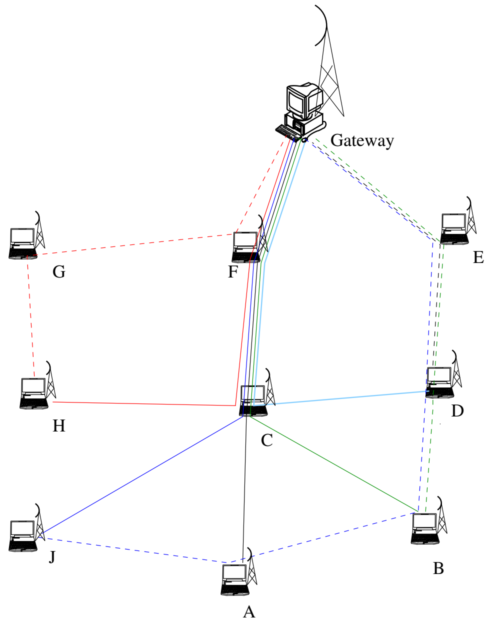

Fig. 1. Distributed Wireless Networks

wireless networks operation should be such that they are less complex and require fewer number of control messages to sustain effective communications. To achieve the above design goal, we propose a Weighted Signed Graph (WSG)-based self-optimization technique as an alternate method. This scheme optimizes the transmission rate and minimizes the battery consumption, thereby improving the lifetime of the nodes and the network. The solution we propose in this paper is a novel approach to solve a multi-objective constraint optimization problem. It is a distributed, multi-time scale self-optimization approach [1] and can be implemented using cross-layer techniques at each wireless node. In particular, we attempt to find a power efficient routing technique for distributed wireless networks and propose to achieve this using a light-weight self-optimization scheme based on signed graphs. Using the self-optimization scheme, we modify the existing Distance Vector (DV) routing scheme and compare its performance with the existing schemes. In addition, we also propose linear and non-linear sectioning of available battery power at a node and propose a practically implementable route update mechanism in the modified DV (MDV) scheme. We use available battery

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power as a measure to indicate whether the node should be considered in making routing decision or not?

A. Literature Survey

We carried out an extensive literature survey in resource allocation, optimal routing and alternative methods on optimization in wireless networks. The optimization techniques for resource allocation in wireless networks use cross-layer design paradigm [2], [3]. The earliest work in this area is related to distributed power control algorithm and its convergence is the famous Foschini-Miljanic Algorithm [4], which works well for static channels. In [5] the authors propose a heuristic scheme which requires wireless link quality estimation to find a power-aware routing, whereas in [6] the authors propose a QoS-based routing protocol which requires a-priori estimation of the bandwidth available. Both these schemes are not optimal schemes and computationally complex. Optimization problem related to routing is solved iteratively using Distance Vector (DV) routing protocols through Belman-Ford routing schemes [7], [8] or through many power-aware routing protocols presented in [9]–[11]. Moreover, as mentioned in [12], [13] the solution of the global optimization problem as in [7], [8] requires frequent message passing between the neighboring nodes. Therefore, the optimal schemes add overheads on wireless nodes in terms of extra transmission/reception and computation [2], [3]. To overcome this, we adopt a signed graph based self-optimization technique with multi-time scale approach which requires no message passing and can be executed by every node of the network. The concept of signed graph has been used very well in modeling large scale biological networks [14], [15] and to study the dynamic behavior of the complex systems such as gene regulatory system, metabolic reaction, etc. In this, the interactions, influences, inhibitions of different biological entities are represented by signed graphs. By using the notion of balancing concepts, the stability of these complex systems is analyzed [1], [14], [15].

The rest of this paper is organized as follows. In Section II, we formulate the problem and propose a novel solution for power-aware routing. In Section III, we describe the experimental setup and the topology used for our simulations. In Section III-A, we discuss the performance of our proposed solution. In Section IV, we provide concluding remarks and discuss on some of the suggestions to improve further in terms of lifetime and throughput in wireless networks.

II. Problem Formulation

We consider a distributed wireless network, the nodes of which are battery powered and are capable of transmitting information in the form of packets to any other node of the network either directly or through multi-hop communications using wireless channels. We further assume that these nodes can transmit self generated packets as well as packets received from other nodes to their final destination, without any distinction. We define *Lifetime of a node* as the duration for which the node is capable of transmitting packets to other nodes and *Lifetime of the network* as the maximum duration for which each node of the network is capable of transmitting packets to others. Lifetime of a node depends upon the power availability at that node and the rate at which it transmits to other nodes. To improve the lifetime of a node and the network, one should (i) *avoid over use of some nodes by diverting the route* and (ii) *minimize the transmission power of nodes*. Therefore, each node not only requires to determine the optimal transmission power and modulation index for packet transmission, but also needs to find an alternative route that improves the lifetime of the network. The alternative route should be such that, the cost due to congestion and battery usage is minimum and at the same time lifetime of the network is maximum. For example, though there are multiple routes available between nodes, there is a need to select a particular route such that lifetime of the network is improved and congested (bottleneck) nodes (as the central node C in Fig. 1) are by-passed. This may lead to select a longer path between nodes as shown in the figure (viz., J-A-B-E-D-Gateway is selected instead of J-C-F-Gateway).

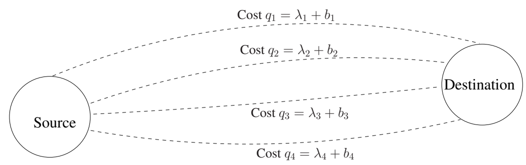

Fig. 2. Multiple Paths and Route Cost

We illustrate multi-path routing through Fig. 2 in which cost of each path between a source-destination pair is marked as q_1, q_2, q_3 and so on. Let the cost of path h be q_h, a function of the congestion cost (λ_h) and battery usage cost (b_h) associated with all the links/nodes in that path and is defined as:

$$q_h = \lambda_h + b_h, \\ \text{where,} \quad \lambda_h = \sum_l R_{lh}\alpha_l, \quad \text{and} \quad b_h = \sum_l R_{lh}B_l, \tag{1}$$

where α_l is the congestion cost of link l and B_l is the cost of battery usage/amount of battery available of node associated with link l. Routing matrix R consists of the routing nodes of the network, $R_{lh} = 1$, if path h uses link l and 0, otherwise. We now describe the shortest cost path problem as follows. Given a weighted graph $G(V, E, Q)$ (that is, a set V of vertices, a set E of edges, and a real-valued weight (cost) function $Q_l : E \rightarrow \Re$), and source-sink nodes v and v' of V respectively, find a path h (a sequence of edges) from v to a v' of V so that $\min_{h \in H} q_h$ (H: is the set of all available paths between a source-destination pair) is minimum over all paths. However, practical constraints such as maximum limit in transmission power and delay should also be accounted while finding the shortest path. Therefore, we define the modified shortest path problem [16] for wireless networks as follows:

$$\min_{h \in H} \sum_l R_{lh}(\alpha_l + B_l), \\ \text{s.t.} \quad P_{l_{Min}} \le P_l \le P_{l_{Max}} \quad \text{and} \quad t_{d_h} \le t_{d_{th}}. \tag{2}$$

The first constraint ensures that transmission power P_l on link l is bounded by minimum and maximum power $(P_{l_{Min}}, P_{l_{Max}})$ values. The second constraint ensures that the delay (t_{d_h}) associated with path h should be less than the tolerable delay $(t_{d_{th}})$ of the application/service executed by the wireless nodes.

As discussed before, the solution of the optimization problem presented in (2) can be solved iteratively using Distance Vector (DV) routing protocols through Belman-Ford routing schemes [7], [8] or power-aware routing protocols presented in [9]–[11], which requires message passing. However, we propose a novel solution in which each node senses its neighboring nodes information such as interference, routing table (from periodic broadcasts), congestion through acknowledgement packets etc., and decides the optimal transmission power and modulation index, transmission rate and next-hop information using self-optimization.

A. Self-optimization Approach

As observed in literature, obtaining an optimal solution in real-time for the system explained in (2) is difficult and often ends up with an iterated solution. Therefore, as discussed in [1], a global optimization problem of (2) can be modeled as a dynamic system as follows:

$$\begin{aligned} \dot{w} &= \Psi(w), \\ \text{where} \quad w \in \mathbb{Z}, \mathbb{Z} &\subseteq \Re^n, \Psi \in C^1(\mathbb{Z}, \Re^n), \end{aligned} \tag{3}$$

where $\mathbb{Z}$: is an open subset of n-dimensional Euclidean space over real $\Re$ and $C^1(\mathbb{Z}, \Re^n)$: is the set of functions from $\mathbb{Z} \rightarrow \Re^n$ having continuous first order derivative. Note that, the dynamic system represented in (3) can be solved through a WSG, which is the core of the paper. For completeness, we first explain WSG and its properties as follows. A WSG $G(V, E, \varrho)$ is a directed graph, where V is set of nodes and E is the set of edges : subset of Cartesian product of $V \times V$ and each edge belongs to E is associated with a weight and is defined as: $\varrho(\hat{i}, \hat{j})$:

$$\varrho(\hat{i}, \hat{j}) = \begin{cases} +\varrho_{\hat{i},\hat{j}}, \text{if } \hat{i} \text{ activates } \hat{j} \text{ at rate } \varrho_{\hat{i},\hat{j}}, \\ -\varrho_{\hat{i},\hat{j}}, \text{if } \hat{i} \text{ inhibits } \hat{j} \text{ at rate } \varrho_{\hat{i},\hat{j}}\ , \\ 0, \text{no impact.} \end{cases} \tag{4}$$

From dynamic system perspective, the system is modeled as a WSG in which parameters/variables of the system are represented as *nodes of the graph* and the interaction between the parameters are represented by edges. A signed graph is Strongly Connected Graph (SCG), if there is a path exists between every pair of nodes. If there exists a path between any two nodes of a signed graph, path sign can be computed as the product of signs of sequential edges associated along the path between them. A signed graph is balanced (and hence system(3) attains equilibrium:solution exists), if all the cycles of the graph have even number of negative signed edges.

The parameters of the dynamic system with their interactions is represented through a Directed Signed Graph (DSG). The DSG is constructed through system observations, known facts and learning methods. For the problem defined in (2) and (3), we consider a snapshot of topology for routing scenario in Fig. 3 and construct the corresponding signed graph in Fig. 4; η: life time of the network, x_i: rate of transmission, P_i: transmission power and CO_i: congestion indication at node i. Note that, η is a goal variable, x_i and P_i are control variables and CO_i is a state variable. For simplicity, we have not included modulation index (m_i) in the signed graph. The construction of the WSG (Fig 4.) is illustrated with the help of Fig. 3. W.r.t. the topology, node i receives packets from its neighbors $(j-1)$, s and $(l-1)$ and forwards these packets to their destination d through any one of the available routes (via j or any other neighbor k). Note that node i is also capable of transmitting its own packets to any or all of its six neighbors. We assume that at a time instant t, the next hop for the packets received from nodes $(j-1)$, s and $(l-1)$ at node i is node j. However, as time progresses and more and more packets are transmitted (increase in x_i), P_i as well as CO_i increase. Let w_{xp}, w_{xco} be the cost (weight of the edge) associated between x_i and P_i and x_i and CO_i respectively. Note that w_{xp} and w_{xco} are not the same. The $(+)$ sign is due to the fact that x_i activates P_i and CO_i. As P_i and CO_i increase, cost of the path through node j increases resulting a trigger in route change R at node i; next hop for node i is changed from j to k or to any other neighbor. Due to this, battery usage of node j gets reduced whereas the battery usage of neighbor k gets increased. As the usage of node k increases, lifetime of the node as well as the network decreases; $(-)$ sign between B_j, B_k and η. The dotted paths in the WSG shows that there is a possibility of change in sign as the route changes. This process continues and new routes are triggered automatically till the convergence is achieved.

We use Multi Time Scale (MTS) WSG approach for the convergence analysis and solution of the optimization problem is proposed. At each time scale, the system is represented as a DSG and the optimization problem is solved independently. Specifically in this paper, we use two time scales T_1 and T_2 for the given system presented in (2) and (3) and solve using DSG in T_1 and T_2; $T_1 < T_2$. In this approach, x_i, P_i and CO_i are updated in timescale T_1, whereas route (R), battery usage/cost B_j and B_k are updated in T_2. Since the route matrix R is unchanged for a duration of T_2, the DSG generated is balanced. As the cost of the path changes, new routes are obtained resulting in new balanced DSGs in each T_2. Note that, the WSG we obtain here is balanced at the network level, not at the node level; resulting in converged solution by the network. We present the pseudo code of this scheme in Algorithm 1. In this, instead of solving the global optimization problem as in (2), each wireless node solves an equivalent local optimization problem and maximize node lifetime η_l, thereby maximize network lifetime η. Each node updates its transmission power P_l, modulation index m_l and Routing matrix R such that throughput is maintained and lifetime is optimized. The proposed algorithm is a less complex as compared to any optimization based approach. Therefore, it is implementable and can save resources in terms of energy and computing power.

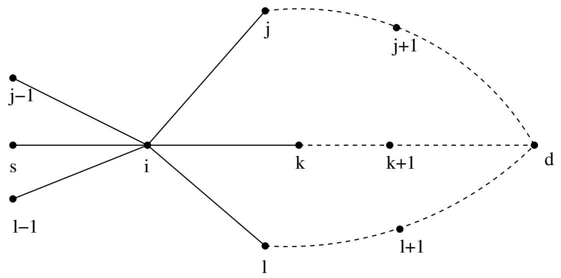

Fig. 3. Multiple Paths at a Node

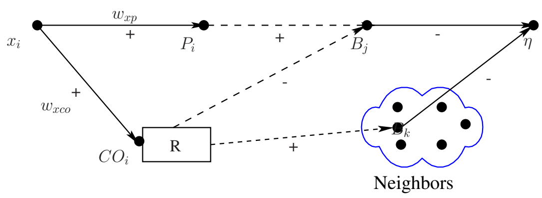

Fig. 4. WSG at a Node

Algorithm 1 : Multi Time Scale Self-optimization Algorithm for Power-aware Routing

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Initial time scales: $t_{l_1}, t_{l_2}, T_1, T_2$
Input: $P_l, P_{l_{Min}}, P_{l_{Max}}, \delta T_1, \delta T_2$
Initialize: $R, m_l, x_l, \eta_l \forall l$
while TRUE **do**
  $T_2 \leftarrow t_{l_2}$
  while $(T_2 \geq 0)$ **do**
    $T_1 \leftarrow t_{l_1}$
    while $(T_1 \geq 0)$ **do**
      Send and Receive packets
      $T_1 \leftarrow T_1 - \delta T_1$
    end while
    Update P_l and m_l s.t. x_l and η_l are maximum
    Update t_{l_1}
    $T_2 \leftarrow T_2 - \delta T_2$
  end while
  Update Routing table R based on lifetime of the paths, s.t. η_l is maximum
  Update P_l and m_l s.t. x_l is maximum/transmitted without any delay
  Update t_{l_2}
end while

We now use the above algorithm and modify the route update and route selection mechanism of the Distance Vector (DV) Routing scheme for Sensor Networks as discussed below.

B. Modified Distance Vector (MDV) Routing

In MDV, we compute dynamic routing between the source-destination nodes, such that the route cost between them is minimized. We use cost of the link instead of path length as the parameter for route computation. Cost between the nodes are functions of available battery power and congestion/usage of the link. Congestion cost α_l at a link is modeled as the probability of packet drop due to buffer overflow as in [12]. We compute the battery cost B_l as follows:

Since the route broadcast packets also impacts the lifetime of the network, instead of regular updates for every data packet transmission, we propose to broadcast update packets only when there is a change in the battery power level of a node. For this, we define both linear and non-linear divisioning/sectioning of the battery power available at a node. This is illustrated in Fig. 5. Our battery cost function increases/decreases in a step wise manner as battery power decreases/increases. In addition to this, we also propose that instead of sending the amount of battery power available though the broadcast packets, we send the section number (Section 1, Section 2, .. Section N, etc.) such that number of bits required to represent this information is minimized (and hence the size of the broadcast packet). In linear sectorization, width of each sector $W = \frac{B_{Max} - B_{Min}}{N}$, where B_{Max} is the maximum battery power of a node, B_{Min} is the threshold battery power required for a node to operate and N is the number of sectors considered. In non-linear sectorization, sector width is an increasing non-linear function; width of n^{th} sector $W_n = f_n \times (n-1) + c$, where f_n is the slope of the non-linear function at n^{th} sector (can take the slope of an exponential function) and c is a constant (positive real number) depends upon the value of the threshold and minimum power required to transmit one packet. Battery powers in same section/range have same cost and the cost function is inversely proportional to the battery power of the threshold value of the section. Hence, in linear and non-linear sectorization the cost of available battery power at sector n is $\frac{1}{B_{Min} + W \times (n-1)}$ and $\frac{1}{B_{Min} + \sum_{y=1}^{n-1} W_y}$ respectively. Note that cost changes only when the available battery power changes from one section to another.

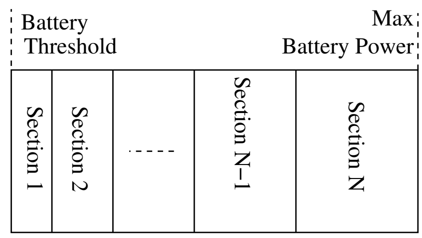

Fig. 5. Non-Linear Sectorization of Available Power

When a node processes a packet, it consumes some power in the process of forwarding it to the next node. This consumption of power depends on the distance between the sender and receiver node and the path-loss due to shadowing. The routing decisions are taken on the basis of remaining lifetime[1] of nodes between the source and destination and

[1]Lifetime of a node depends upon the power availability at that node and the rate at which it transmits to other nodes. Hence probability of node failure increases with packet transmission and decrease in power level.

congestion in the link. Since we select a route with minimum cost, nodes having less available battery power shall not be selected for transmission and thus its battery shall not get depleted early. Each node maintains a routing table with the next-hop and the least known cost for each destination of the network. A node computes its cost of transmission and advertises battery power information to its neighbors using the normal routing broadcasts of DV Algorithm. For power-aware mechanism (MDV), we implement self-optimization techniques and update the power level for transmission of packets. Each participating node computes its new cost and compares with the existing cost; updates the route information only if the new cost is lesser than the existing and then forwards newly updated information to its neighbors. When node's battery power reaches a minimum threshold level it stops broadcasting information (available battery power) to its neighbors. Thus the neighbors do not hear any message from it anymore and assume that the node is power depleted, link is broken and packets can not be delivered through that node. Nodes update their tables with new entries whenever there is a change in the battery power of neighbors.

1) Complexity Analysis: The complexity of the general DV algorithm is difficult to compute, as it suffers from count-to-infinity problem due to the presence of loops in the network. With Time to Live (TTL) concepts for the messages, we eliminate this problem. For a network with N nodes, in which, every node has k neighbors (k-connected network), the complexity of our algorithm depends on the battery power dissipation of the nodes and if δb_r^i is the rate of battery level/step change of the node i, the the complexity of our algorithm is given by $O(\frac{k*N}{\delta b_r^{avg}})$, where δb_r^{avg} is the rate of average battery level/step change. For power unaware DV routing algorithm, $\delta b_r^{avg} = 1$, Thus the complexity of power aware DV routing algorithm is less when compared to power unaware DV by a factor of δb_r^{avg} on an average. In the next section, we implement the proposed scheme and analyze its performance through extensive simulations.

III. Experimental Evaluation

We now describe the simulations that are performed to evaluate the proposed power-aware routing. All the simulations are conducted using Java based implementation of sensor networks. We consider a wireless network topology as illustrated in Fig. 6; node 1 and 6 are source and destination respectively. Each node of our simulation is a wireless node and is capable of generating, forwarding and receiving packets. Each node can update its transmission power, modulation index and next-hop based on the route information. We assume that node 1 sends data packets to node 6 at a rate of 60 packets/minute and there are two intermediate routes exist between node 1 and node 6. The distances between the directly connected nodes (one-hop) are assumed to be same. Both the source and the destination nodes have more battery power than intermediate nodes such that they won't get power depleted before the intermediate nodes. We implement basic wireless channel model for the simulation. The path loss exponent due to distance is set to $\gamma = 4$. We consider Additive White Gaussian Noise (AWGN) with Power Spectral Density (PSD) N_0 = 0.35 (4.5 dB/Hz). The shadowing is modeled as Log-normal with mean zero and standard deviation (σ) 8 dB.

We assume fixed size data packets and power consumed by a packet depends on the size of the packet and distance between communication nodes. Update packets are small in size as compared to data packets. We also assume that each node spends 0.5, 0.1 units of power to transmit a data and update packet respectively. The minimum power required at a node to operate is 5 units ($B_{Min} = 5$ and $B_{Max} = 100$ units). When a node is idle, it is not being used in packet transmission, then there wont be any loss in nodes battery power. At the start of the simulation we consider two different cases of battery availability - (i) *fixed power availability: node 1 and node 6 have 100 units of power and others have 40 units each* and (ii) *random power availability (between 40 to 100 units)*. For the comparison, we implement the (i) classical Distance Vector (DV) scheme (shortest path routing) without any power control, (ii) Modified Distance Vector (MDV) routing (power-aware routing), (iii) MDV with linear and (iv) MDV with non-linear sectorization of available power at each node. In linear sectorization, we use uniform sections at a range of 10 units ($W = 10$ units), i.e., Section 1: 5.5 - 15.5, Section 2: 15.5 - 25.5 units and so on. In non-linear sectorization, we use non-uniform sections at a range of 5 - 20 units; Section 1: 5.5 - 10.5, Section 2: 10.5 - 15.5, Section 3: 15.5 - 25.5, Section 4: 25.5 - 37.5, Section 5; 37.5 - 53.5, Section 6: 53.5 - 70.5, Section 7: 70.5 - 90.5 and Section 8: 90.5 - 100 units.

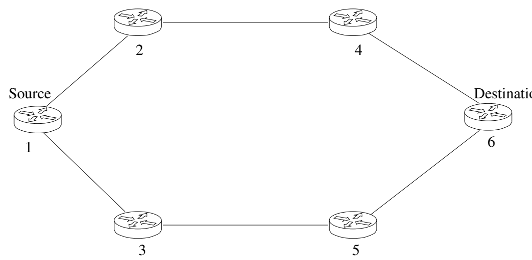

Fig. 6. Simulation Topology

A. Performance Evaluation

In this section, we compare the performance of all the four routing schemes we implement in our simulation. We consider parameters such as (i) lifetime of first depleted node, (ii) average lifetime of the nodes and (iii) average number of route update packets sent by each scheme. We observe from Fig. 7, that the lifetime of the first depleted node is highest in MDV non-linear sectorization, whereas it is lowest in the classical DV routing (power-unaware); over 90% improvement in lifetime of the first depleted node. We also observe that non-linear sectorization improves lifetime over liner sectorization by 7% and over the MDV (simple power-aware routing) by 10%. We also observe similar improvement in average lifetime of the nodes in Fig. 8; around 34%, 13% and 4% improvement in average lifetime over power-unaware, MDV and MDV linear sectorization schemes respectively. The improvement in lifetime proves our claim that self-optimization improves lifetime of the network and that of individual nodes. For each scheme, we also plot the number of route packet updates communicated during the simulation in Fig. 9 and observe that MDV transmits highest number of routing updates (because small change in the battery power due to node operation trigger route updates), whereas MDV linear sectorization transmits lowest number of update packets. We also observe that the increase in the number of update packets in MDV non-linear scheme as compared to that of MDV linear scheme is due to the fact that number of sectors in non-linear sectorization is more than that of linear sectorization. By choosing different lengths of sectors, we can still improve the number of updates and hence in throughput of the system. Note that there is a reduction of approximately 60% in number of update packets for MDV linear/non-linear sectorization over the classical DV scheme.

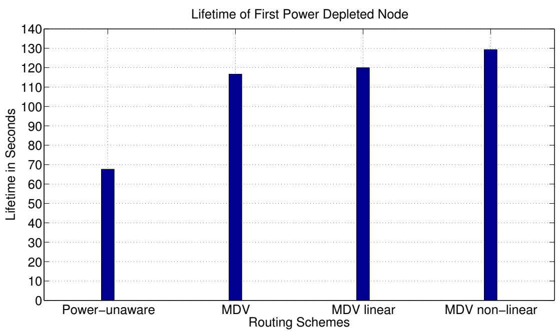

Fig. 7. Lifetime of First Depleted Node

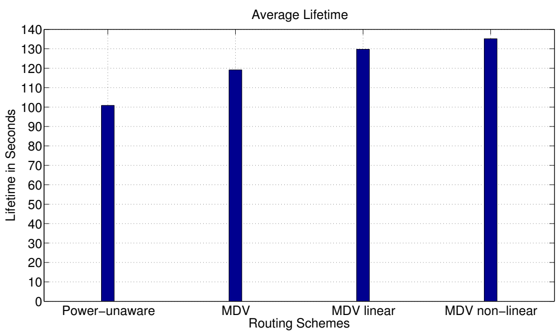

Fig. 8. Average Lifetime of the Nodes

IV. Conclusion

In this paper, we propose a self-optimization technique which can be implemented at each individual node for power-aware routing. This technique is a computationally simple, scalable and practically implementable solution. Our scheme improves lifetime of the individual nodes, that of the network and at the same time minimizes the number of route updates, thereby improving the throughput of the networks in a time bound manner. We also propose linear and non-linear sectorization of available battery power which further improves the lifetime and throughput of the network. Our scheme is

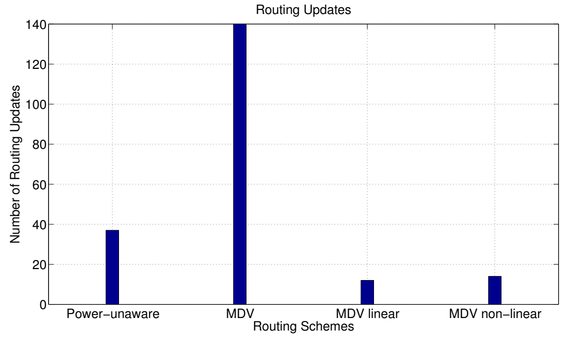

Fig. 9. Number of Route Updates

agnostic to the existing protocols defined by TCP/IP protocol stack and can be implemented using cross-layer techniques in wireless networks in which Physical (PHY), Media Access Control (MAC), Network and Transport layers of the TCP/IP protocol stack can participate. Though the proposed scheme is applicable to distributed networks, we plan to extend this to centralized networks in the future.

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