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Using Centrality-based Power Control for Hot-spot Mitigation in Wireless Networks *

Parth H. Pathak, Rudra Dutta
Department of Computer Science, North Carolina State University, USA. Email: phpathak@ncsu.edu, dutta@csc.ncsu.edu

***Abstract*—When shortest path routing is employed in large scale multi-hop wireless networks, nodes located near the center of the network have to perform disproportionate amount of relaying for others. To solve the problem, various divergent routing schemes are used which route the data on center-avoiding divergent routing paths. Though they achieve better load balancing, overall relaying is increased significantly due to their longer routing paths. In this paper, we propose power control as a way for balancing relay load and mitigating hot-spots in wireless networks. Using a heuristic based on the concept of *centrality*, we show that if we increase the power levels of only the nodes which are expected to relay more packets, significant relay load balancing can be achieved even with shortest path routing. Different from divergent routing schemes, such load balancing strategy is applicable to any arbitrary topology. Also, it is shown that centrality based power control results into better throughput capacity in many different topologies.**

I. Introduction

Many of the routing protocols proposed for multi-hop wireless networks depend on shortest path routing (SPR) due to its characteristics of simplicity, robustness and scalability. It has been observed that when hop count based shortest path routing (SPR) is used for uniform node-to-node communications in a multi-hop network, certain nodes have to perform disproportionate relaying of data for others. Such *hot-spots* are often created near the center in uniform topologies and also at cluster peripheries in clustered topologies. Such increased congestion at certain nodes affects network capacity and reduces energy efficiency of energy-constrained networks.

The problem of disproportionate relaying has been addressed mainly by devising routing strategies in which routing paths intentionally try to avoid passing via center. Curved paths in curve-ball routing [1], [2], one-turn rectilinear paths in Manhattan routing [3] and edge reflection paths of outer space routing [4] are some examples of such strategies. We refer to such center-avoidance routing strategies generally as *divergent* routing. Any such divergent routing scheme increases relaying load of the nodes near the periphery of the network while taking away some relaying burden from the nodes around the center. This results into better overall load balancing. This advantage comes at a cost of various other sacrifices. Most of the divergent routing schemes depend on geometrical properties of the network (for mapping over symmetric space like torus or sphere) which limits their applicability to uniform topologies only. Routing paths in any such scheme are also longer (higher stretch factor) when compared to shortest routing paths. Moreover, divergent routing schemes sacrifice the fundamental advantages of SPR such as robustness, scalability and simplicity. In many cases, divergent routing schemes do not eliminate the hot-spots in the network because the relay load of the nodes near the center decreases moderately while the load on nodes around the periphery increases significantly. This raises an interesting question – is it possible to preserve SPR (and all its advantages) while achieving better relay load balancing?

One of the assumptions in divergent routing schemes is that all nodes operate at Compow [5] power level and routing is performed on the resultant topology. In Compow, all nodes use a uniform power level which is minimum required to maintain network connectivity. Compow achieves better concurrency in link scheduling due to lesser interference but requires more relaying at nodes because of longer routing paths. This motivates the question – is disproportional relay load distribution in multi-hop communications also a consequence of Compow power range together with SPR? And can it be dealt with using power control instead of modifying routing?

In this paper, we propose power control as a way to balance relay load in static wireless networks. We show that if the communication range of nodes are properly increased by increasing their power levels, better relay load balancing can be achieved even when routing on the shortest paths. In all cases, choosing only a small subset of nodes and increasing their power levels is sufficient to achieve load balancing that is significantly better than divergent routing schemes. The fundamental advantage of such power control based load balancing is that it preserves all the benefits of shortest path routing and still achieves significant relay load balancing. Because all the characteristics of shortest path routing is retained, such load balancing can be applied to any kind of arbitrary topologies (e.g. clustered) and traffic patterns (e.g. node-to-gateway) where divergent routing can not be applied.

The proposed load balancing scheme does not route the data on divergent routes to avoid passing through the nodes near the center. Instead, the data is routed on the shortest paths only and the nodes which are expected to relay more packets for others are skipped or *jumped over*. In the case of uniform topologies, this results into longer hops being taken near the center which reduces the relay load burden of congested nodes without increasing the relay load of the nodes on the periphery. Longer hops in routing paths can only be achieved by controlling the communication range of nodes using power control. Power control based load balancing presented here assigns higher power levels to nodes which are expected to relay more packets. This has an underlying requirement of estimating the relay load of nodes in advance so that communication range can be assigned to them accordingly. We calculate *betweenness* centrality of nodes which assigns every node a score based on their expected relay load. The centrality value is then used to assign every node a power level which is proportional to its expected relay load. This increases the connectivity of the nodes who were expected to relay more packets previously. When shortest paths between nodes are found in this new more connected network, they pass over congested nodes, producing better load balancing.

One of the disadvantages of the divergent routing schemes is that there is a trade-off [6], [7] between length of the routing paths (path-stretch) and amount of load balancing achieved. We show that power control based load balancing does not show such a trade-off with path stretch. Instead, it is observed

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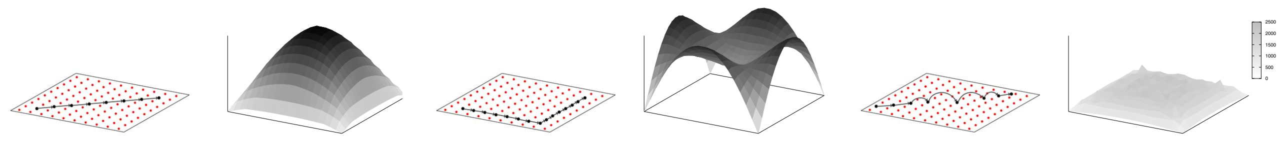


(a) Shortest path routing (b) Hot-spot generation (c) A divergent routing (d) Load redistribution (e) Centrality power control (f) Load balancing

Fig. 1: General nature of path and relay load characteristics

that load balancing and capacity sometimes show a trade-off when power control based load balancing is applied in some of the topologies. We characterize that such a trade-off is limited to the case of uniform node placement and as the node placement becomes more random and clustered, increased capacity can be achieved together with better relay load balancing. Also, in our contiguous work (currently under submission), we have shown that intelligently increasing of power levels of some nodes does not adversely affect the energy expenditure and network lifetime in stationary energy-constrained networks. Due to increased relay load balancing and reduced overall relaying, in fact such a strategy increases the network lifetime by upto 30% when compared to divergent routing schemes in wireless sensor networks. We also briefly present these results for completeness.

The rest of the paper is organized as follows - we start by explaining network model and related assumptions in Section II. Section III presents centrality based power control strategy and shows how betweenness centrality can be used for power allocation. Instead of devoting a separate section for related work, we discuss them in each individual section as and when necessary. We present several numerical results on load balancing and capacity in Section IV and conclude in Sec. V.

II. Network Model and Preliminaries

We model the network using a directed graph $G = (V, E, r)$, where V is a set of n stationary nodes and r is a set of communication range values assigned to each node in V. There exists an edge from node u to node v if their Euclidean distance $d_{uv} \leq r_u$. This allows the modeling of variable power control where each node might have a different communication range. Note that when the value of r_v is same for all $v \in V$, the resultant network graph can be considered as an undirected graph (unit disk graph) since all the edges are bidirectional. In one such case, when there is no explicit power control, all nodes are assumed to be operating at Compow power level. Compow range (r_{min}) where $r_v = r_{min}, \forall v \in V$ is defined as minimum value of common range such that G is connected. We refer to the Compow graph as G_C.

Centrality values of all nodes are determined from the Compow graph and used to assigned different power levels to different nodes. Here, increase in power levels can actually be interpreted as bounding the maximum power level of nodes. That is, if a node increases its power level, this does not mean that it will always transmit at new increased power level. If a neighbor is reachable at a lower power level, it will utilize that to communicate with it. We use path loss model of signal propagation. If transmitted signal power is P_t and distance between the transmitter and the receiver is d then received signal power (P_r) attenuates as $P_r \propto P_t(d^{-\alpha})$, where α is the path loss exponent which depends on environment ($2 \leq \alpha \leq 5$). Let β be the receiver sensitivity threshold such that signal is properly decoded at the receiver if $P_r \geq \beta$. For a node transmitting at power P_t, the communication range is the distance at which $P_r = \beta$ in absence of any other interference. Now, power level of nodes can be presented in terms of their communication range. As an example, in G_C all nodes are operating at power level $P(r_{min})$ which is necessary and sufficient to achieve communication range of r_{min} at all nodes. Now, if a node wants to increase its communication range by a factor of f, it tunes its power level to $P(f \cdot r_{min})$.

We use uniform node-to-node traffic pattern for simulation and analysis. In uniform node-to-node traffic, every pair of source and destination communicate with amount of traffic which is uniform across all such pairs. With the consideration of dense node distribution, greedy geographical routing (where packet is forwarded to the neighbor which is nearest to the destination) also becomes shortest path routing and we use both names interchangeably. We assume that the nodes are stationary and there is no consideration of mobility in this work.

III. Centrality-based Power Control

Conceptual difference between load balancing using divergent routing and power control is depicted in Fig 1. It can be observed that divergent routing schemes (Fig. 1c, 1d) transfers much of the relay burden onto the nodes around the periphery. In power control based load balancing (Fig. 1e, 1f), data is forwarded on shortest path only but nodes in hot-spot regions are skipped or *jumped over*. This results into longer hops taken near the center hot-spot in uniform topologies. To achieve such longer hops, nodes which are expected to relay more packets should be assigned high power levels and larger communication range. If the relay load at every node can be estimated, then a node can be assigned power levels proportional to its estimated load. This increases the connectivity of the nodes which were likely to relay more packets previously. When shortest paths between nodes are found in this new more connected network, they pass over congested nodes, producing better load balancing. The mentioned heuristic has an underlying requirement for accurately estimating the relay probability of nodes for any given topology which we discuss next.

A. Modeling Relay Load

Techniques for modeling and estimating relay load have been limited to uniform topologies with assumptions like continuous density of nodes. One of the first few such approaches was presented in [1] where relay load probability of a node was derived as a function of its (Euclidean) distance from the center of the network, when routing over the shortest paths between the nodes. It is possible to show that nodes at same distance from the center can have different relay load if the topology is even slightly non-uniform. Similarly, [8] presented

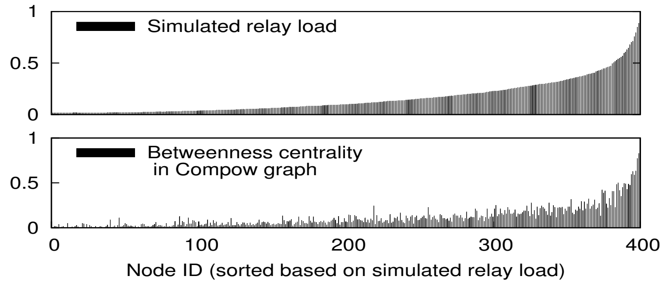


Fig. 2: Comparison of simulated relay load of nodes and their centrality values in Compow graph (all normalized with maximum value, n=400 randomly distributed in unit square)

Voronoi cell based technique in which it was shown that relay load of a node is a function of perimeter of its Voronoi cell, its location in the network and the traffic pattern in consideration. Even with assumptions of uniform node-to-node traffic pattern and node distribution, Voronoi tessellation based model might not always be sufficient because nodes adjacent to each other in network graph might not always have neighboring Voronoi cells. Such techniques do not always accurately estimate the relay load because they rely on geometrical properties of the network and not the underlying network connectivity.

1) Betweenness Centrality: We are interested in devising a relay load estimation technique which relies on properties of network graph. Centrality indices [9] proposed for analysis of large network assign relative importance or status to every node in the network based on certain characteristic of interest. One such centrality named betweenness [10] of a node depends on how many end-to-end shortest paths between other nodes of network actually pass through it. In node-to-node uniform traffic, a node is likely relay more data for others if it falls on relatively more number of shortest paths between other nodes. For a network graph G, if S_{xy} is number of shortest paths between vertices x and y and $S_{xy}(v)$ denotes number of shortest paths between x and y which pass through vertex v, then betweenness centrality of v (denoted by $(b(v))$) is

$$b(v) = \sum_{x \neq y \neq v \in V} \frac{S_{xy}(v)}{S_{xy}} \tag{1}$$

The fraction in (1) (also known as *pair-dependency*) can be interpreted as the probability that vertex v will be relaying data between vertices x and y. Betweenness centrality of a node can be regarded as measure of how important a node is in carrying out relaying of data for other nodes.

Betweenness centrality is a structural index of the graph, that is if H is isomorphic to G ($G \simeq H$), then betweenness centrality satisfies the condition: $\forall v \in V : G \simeq H \Rightarrow b_G(v) = b_H(\phi(v))$. Also, betweenness of nodes change considerably with changes in edge set of network graph which may require frequent recalculations. This is not a concern here since we do not consider any mobility of nodes. As described in [9], straightforward usage of Dijkstra's algorithm for computing betweeneness of nodes can have running time of $O(n^3)$. Brandes's algorithm [11] can compute betweenness of all nodes in $O(nm)$ time for unweighted graphs and $O(nm + n^2 \log n)$ for weighted graphs, where m is number of edges in the graph. In terms of n, this does not impose significant computational cost for moderate to large sized networks (400-1000 nodes). While in terms of m, as it is described below, betweenness centrality is required to be determined in the Compow graph which is a relatively sparser graph ($m \ll n(n-1)$). Fig. 2 shows betweenness centrality of nodes and compares it with their actual simulated relay load in Compow graph when employing uniform node-to-node traffic pattern and SPR.

B. Centrality-based Power Control

Following steps describe how betweenness indices are used to assign power levels to nodes.

1) For a given V, first Compow range (r_{min}) is determined and $G_C = (V, E_C, r_{min})$ is created.
2) Betweenness centrality of all nodes in G_C are calculated using Brandes's algorithm and are normalized using $\max\{b(v) \mid v \in V\}$.
3) Every node $v \in V$ is assigned a power level (P_v) as: $P_v = P_{min} + (b(v) \cdot (P_{max} - P_{min}))$, where $P_{min} \geq P(r_{min})$ to guarantee connectivity and $P_{max} \geq P_{min}$. Even if $P_{max} = P_{min} = P(r_{min})$, resultant graph is at least G_C.

Any such assignment is uniquely referred as $\psi(P_{min}, P_{max})$ and resultant more connected graph of betweenness centrality based power assignment is called G_B. We often set $P_{min} = P(r_{min})$ and vary $P_{max} = P(f \cdot r_{min})$ using a factor $f \geq 1$. In such case, P_{min} and P_{max} are dependent on r_{min} which is a property of V, only control parameter is f which we refer as *growth factor*. For any reasonable value of f, ψ results into increased power levels and communication range of nodes which were expected to relay more packets. Nodes near the center in uniform topologies have higher betweenness and are assigned higher power levels. As shown in Fig. 1f, this allows them to *jump over* other nearby congested neighbors. If a source and a destination are on opposite side of each other over the periphery, packet from source first starts progressing along shorter hops. As it reaches near the center, long-distance transmissions occur which results into longer hops, followed by fewer shorter hops at the end. This results into subsequent reduction of relay load of nodes near the center without increasing relay burden on nodes on periphery.

Foremost advantage of such load balancing using power assignment is that it can be applied to any kind of arbitrary topology like clustered where divergent routing mechanisms can not be applied. Also, centrality measure of nodes can be calculated for any specific set of shortest paths pertaining to traffic pattern of interest, which makes the mechanism applicable for load balancing in any other traffic patterns (e.g. node-to-sink uniform). The complexity of the scheme is dominated by the complexity of centrality algorithm, and Brandes's algorithm performs well even with moderately large networks as we saw above. The presented scheme is static and centrality calculation is necessary only once. The only necessary requirement of the scheme is that the nodes should be able to vary their power levels as per the centrality based calculations. Note that the proposed power control is centralized and its distributed extensions are discussed in future work. Fig. 3 shows the impact of growth factor on load balancing in a 20 x 20 grid network. As discussed before, P_{min} is set to $P(r_{min})$ and $P_{max} = P(f \cdot r_{min})$. Initially, when $f = 1$, $P_{max} = P_{min}$ and resultant topology is a Compow graph of V. In such

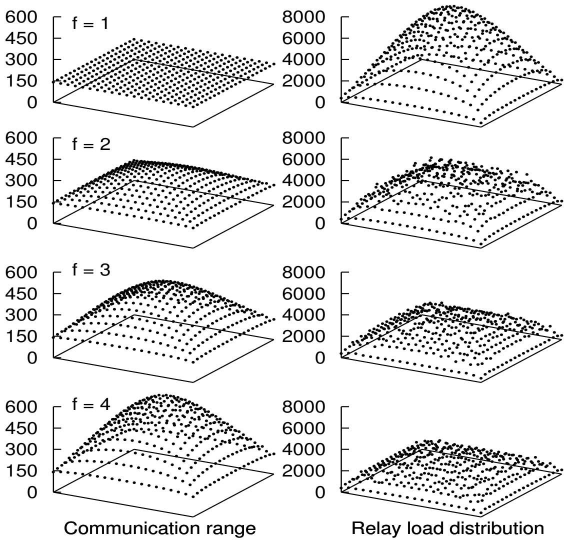


Fig. 3: Effect of growth factor on load balancing in 20x20 grid

case, there is no explicit effect of centrality values because growth factor is set to 1 and relay load distribution displays hot-spots near the center. When growth factor increases, the actual difference between maximum and minimum power level assigned in the network also increases. This results into higher power levels and communication ranges for nodes which have higher betweenness centrality and are expected to relay more packets. As can be observed in Fig. 3, central nodes are now assigned higher power levels which results into better load balancing. The growth factor f is a tunable parameter here and its value can be decided based on several factor which we discuss later.

IV. Numerical Results

Three sets of simulation results are presented to confirm the claims of load balancing using centrality-based power control. In the first set, load balancing strategy is applied to different kinds of topologies. We also compare its load balancing performance to existing divergent routing schemes. Next, we show how the load balancing affects the attainable capacity in different topologies. At the end, we briefly present energy-efficiency and network lifetime results for sensor networks.

A. Load Balancing

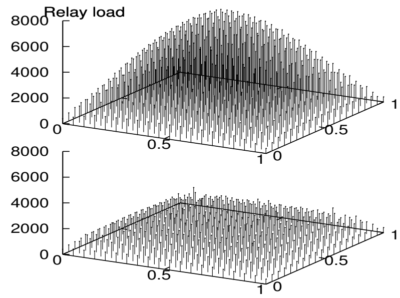
Fig. 4a shows the nature of load balancing achieved by using SPR in G_C and centrality based more connected graph G_B. We use 20×20 grid and set the growth factor $f = 6$. That is, if $b(v)$ was the betweenness centrality of a node v, operating at power level $P(r_{min})$ in G_C, in G_B, it is assigned power level $P_v = P(r_{min}) + (b(v) \cdot (P(6 * r_{min}) - P(r_{min})))$. As expected, relay load distribution in G_C clearly shows hot-spots near the center. In G_B, even with shortest path routing, relay load is very well distributed among nodes.

Next, we analyze the effect of growth factor on load balancing achieved by $\psi(P_{min}, P_{max})$ power control. We consider grid (Fig. 4b), random (Fig. 4c) and clustered topologies (Fig. 4d). Random topologies ($n \approx 400$) are modeled as homogeneous Poisson point processes while clustered topologies ($n \approx 300$) are generated using Mateŕn cluster process [12]. Shortest path routing is used with node-to-node uniform traffic pattern. In all cases, maximum power level P_{max} is varied by growth factor f using $P_{max} = P(f * r_{min})$. We set minimum power level P_{min} to $P(r_{min})$. Whenever random topologies are considered, results are presented for 30 instances of random topology with 95% confidence interval. Here relay load is defined as number of packets a node has to relay for other nodes. It is observed that even for small growth factor, relay load balancing improves significantly in all topologies. Though initial decrease in maximum, average and standard deviation of relay load is more significant, it consistently decreases with higher values of f. In clustered topologies, nodes providing inter-cluster connectivity become traffic bottlenecks and resultant relay load distribution can be highly disproportionate. Divergent routing based load balancing schemes are not applicable in such clustered topologies. As can be observed, ψ achieves significantly better relay load balancing in clustered topologies even for very small values of f.

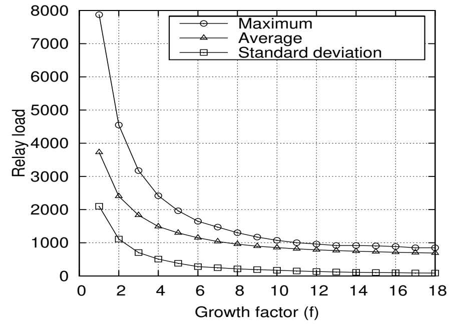
Now, we compare the ψ with other well-known divergent routing schemes. Load balancing of greedy routing in centrality based power controlled topology is compared with the load balancing of greedy routing in Compow topology (G_C) and three well-known divergent routing schemes, namely outer space routing [4], Manhattan routing [3] and curve-ball routing [1]. In outer space routing, packets are first forwarded towards the periphery of the network and is then reflected back from some intermediate node towards the actual destination. In Manhattan one-turn routing, source forwards the packet to an intermediate node which is near the intersection of horizontal/vertical lines passing through the source and destination. In curve-ball routing, network plane is first mapped on a sphere and shortest paths on sphere are then mapped back to the plane. This results into center-avoiding curved routing paths. All divergent routing schemes are also employed in G_C.

Fig.4e shows the results of load balancing in a 400 nodes network and uniform node-to-node traffic pattern. We use growth factor $f = 6$ in ψ as described in Section III-B. Centrality based power control mechanism achieves significantly better load balancing compared to greedy and divergent routing schemes. Divergent routing schemes increase the average relay load of nodes when compared to greedy routing but decreases the overall deviation, which shows better load balancing. On the other hand, ψ decreases the standard deviation of relay load substantially without even increasing the average relay load. In most cases, ψ achieves upto 50% better load balancing than divergent routing schemes which is a useful practical result.

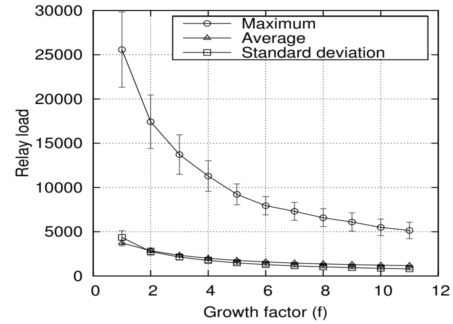
Fig. 4f shows comparison of average routing path stretch and distance stretch between the same set of schemes. Average routing path stretch can be defined as average ratio of hop-length of routing paths in any load balancing scheme to hop-length of the shortest routing path. Average distance stretch can be defined as average ratio of Euclidean length of a routing path (summation of length of all of its hops) to actual Euclidean distance between source and destination. This measures on an average how much routing paths of a scheme deviates from the straight line between the endpoints. All the divergent routing schemes increase path and distance stretch compared to greedy routing in Compow graph. Different



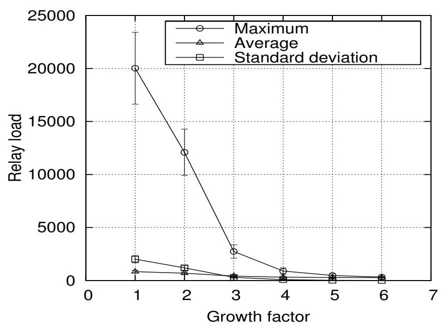
(a) Nature of load balancing using ψ



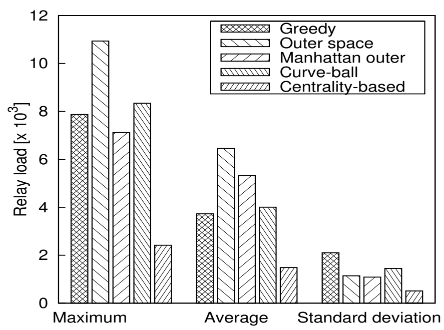
(b) Load balancing using ψ in grid (n=400)



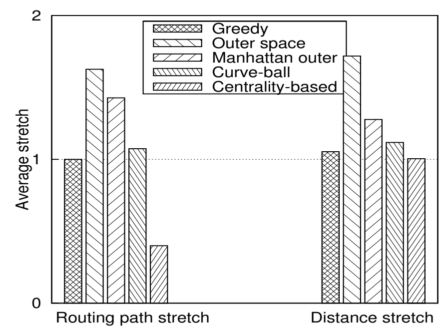
(c) Load balancing, ψ random topologies ($n \approx 400$)



(d) Load balancing, ψ clustered topologies ($n \approx 300$)



(e) Relay load compared to divergent routing



(f) Path characteristics compared to divergent routing

Fig. 4: Effects of centrality based power assignment ψ

from this, ψ actually reduces path stretch below one. This is because power control increases network connectivity which reduces number of hops required to be taken to reach the destination. Also, ψ reduces distance stretch when compared to Compow graph because increased connectivity makes end-to-end shortest paths deviate less from the straight line. It is generally believed that when divergent routing is used for load balancing, stretch factor and load balancing ratio are inversely proportional to each other [7]. As shown in [6], divergent routing strategy which has stretch factor of σ with compared to shortest path routing, can achieve load balancing ratio of $O(\sqrt{n/\sigma})$. But when power control is used for load balancing, it is in fact possible to reduce stretch factor together with load balancing ratio, using shortest paths only.

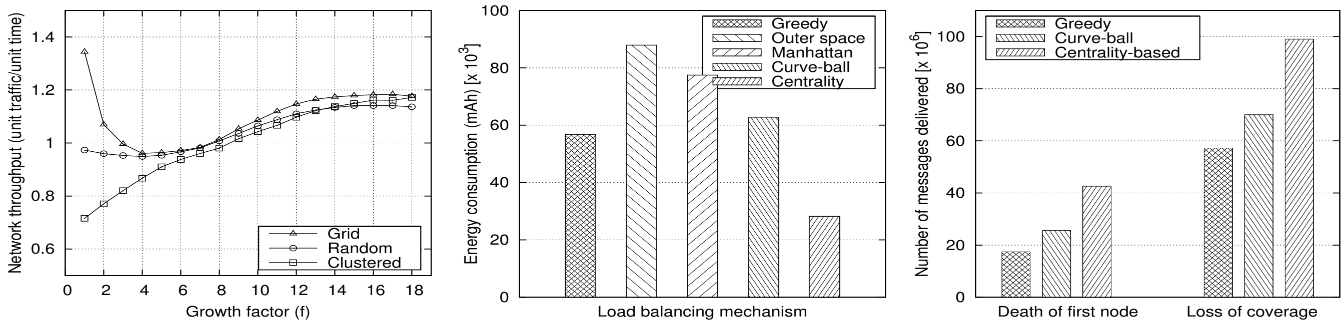
B. Throughput Capacity

Increasing power levels of nodes certainly results into better load balancing, but it also affects achievable spatial reuse and throughput. Increasing communication range and connectivity of nodes using power control results in longer links which causes interference in a larger area, reducing simultaneous transmissions. In this section, we show that centrality based power control also increases throughput capacity in random and clustered topologies under uniform node-to-node traffic. In case of uniform topologies such as grid, centrality based power control shows a trade-off between load balancing and throughput capacity.

We use spatial reuse TDMA-based greedy link scheduler [13] for generating time slotted, conflict-free and feasible link transmission schedule. The end-to-end traffic demand between nodes is represented using a traffic demand matrix (T_R). Once the shortest path routing is performed, T_R yields per-link transmission matrix (T_X). We assume that there is a central controller entity which performs link scheduling. In the operation of greedy scheduler, first all links of T_X are sorted based on their interference score. Interference score of a link is the number of other links with whom the given link interferes and hence can not be scheduled simultaneously. Then scheduler chooses the first link in order to be scheduled in the current slot and tries to add more and more non-interfering links greedily until no more links can be added to the slot. The procedure repeats until all transmission requests of T_X are satisfied. [13] showed that such a scheduler has the time complexity of $O(m \cdot n \cdot T)$, where $T = \Sigma_{i=0}^{n} \Sigma_{j=0}^{n} T_{X_{ij}}$. If the total offered load $G = \Sigma_{i=0}^{n} \Sigma_{j=0}^{n} T_{R_{ij}}$ and greedy scheduler requires S slots to schedule all the links, the network throughput is G/S traffic units per unit time. The TDMA scheme used here is centralized and we assume that there is tight synchronization between nodes, and resultant TDMA schedule is distributed to the nodes without any additional delay. Such an idealistic TDMA scheme is appropriate to study performance of centrality based power control which is the central focus of the work.

We assume that simultaneous transmissions on two links uv and xy results into collision-free data reception at the receivers *iff* $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{uv})$ and $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{xy})$, where d_{xy} is the distance between nodes x and y and interference ratio $\Delta = 2$. As an example, in coarse-grained TDMA, if every slot is 1 second and channel goodput (B) is approximately 6 Mbps (as in 802.11b without RTS/CTS) in absence of interference, then resultant throughput with above mentioned TDMA scheduler is $(G/S) * B$.

Fig. 5a shows the aggregate network throughput for three different topologies. In case of grid, increasing the growth factor results into initial decrease of capacity followed by an increase. Even though load balancing improves with increase in growth factor, highest capacity is achieved at $f = 1$ in case of grid topology. This is because highest spatial reuse is achieved at $f = 1$ in case of grid and spatial reuse gradually



(a) Throughput capacity with centrality power control (b) Total energy expenditure (n=1000) (c) network lifetime comparison (n=1000)

Fig. 5: Network capacity and energy efficiency with centrality power control

decreases after that. On contrary, in case of random and clustered topologies, increasing growth factor also increases the throughput capacity along with better load balancing. As expected, random and clustered topologies achieve lower throughput compared to grid case. In random topologies, increasing power levels of certain nodes decreases the spatial reuse, but it also increases the connectivity among nodes. This results into many of the source nodes directly reaching the destination nodes and average routing path length decreases. The positive effect of reduced number of transmissions dominates the negative effect of reduced spatial reuse, and overall throughput capacity improves.

In clustered topologies, inter-cluster links become traffic bottlenecks and they are required to be scheduled large number of times. This results into decreased throughput. Now, as the growth factor increases, more and more inter-cluster links are established which share the burden of previously bottleneck links and also improve the opportunity of spatial reuse. Due to better load balancing and improved spatial reuse, increasing growth factor in clustered topologies also increase the throughput. Since most of the real world topologies are either random or clustered, centrality based power control can yield good benefits of load balancing and capacity in them. Also, decision of choosing appropriate value of f depends on the network topology along with some of the realistic factors such as maximum power level of radios etc.

C. Energy Efficiency and Network Lifetime

Though it may appear that power control based load balancing may not be very energy efficient when compared to battery-operated networks like sensor networks, actually increasing connectivity using centrality indices turns out to be more energy efficient than other divergent routing schemes. This is due to the fact that it it achieves a balance between the nodes which have to transmit more number of times but with lower power levels and the nodes having to transmit at higher power levels but lesser number of times. We use CC2420 (widely used in sensors like MICAz motes) radio chip specifications for transmit power levels and respective distance with 100% packet reception rate. Fig. 5b compares the energy expenditure of various schemes under uniform node-to-node traffic. Centrality based power control reduces number of hops while routing on shortest paths which is proven to be more energy efficient (results confirm to [14]). Similarly, Fig. 5c compares the two measures of network lifetime – death of first node and loss of coverage. Here data is exchanged between randomly chosen source and destination nodes until battery of a node depletes (death of first node). Similarly, loss of coverage lifetime is marked as the time when set of co-located nodes deplete their batteries in relaying and there is a certain area within network boundary which is not covered by any sensor node. As can be observed, significant improvements are achieved in network lifetime using centrality based power control due to better relay load balancing and reduced overall relaying.

V. Conclusions and Future Work

In this paper, we proposed centrality based selective power control scheme which achieves better relay load balancing compared to other divergent routing schemes. Since the current scheme is centralized, we are devising a distributed protocol in which nodes can dynamically learn and share their centrality values based on back-logged queue lengths (relay load), and can adjust the power levels accordingly to mitigate the hot-spots. The protocol will be implemented on our mesh network testbed using the capabilities of MadWiFi device driver.

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